Master Thesis

Excuse-using when your actions turn against you: an empirical study on investors in the stock market

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1. Introduction

People use numerous excuses in many situations in their day to day lives. Excuses aim to reduce personal responsibility for questionable events (Snyder & Higgings, 1988a). In 2016, Oxford University graduate Faiz Siddique sued the university for one million pounds because he allegedly received bad teaching (BBC, 2018). The 38-year-old claimed that this lowered his job opportunities and corresponding salary. This is just one of many examples where individuals use excuses to avoid taking responsibly for the negative consequences of their own decision-making or actions. Such behaviour may be also be used by people who fail at work, or people who are overweight and use excuses for explaining them not being fit or healthy.

Besides the use of excuses, many other types of behaviour and psychological definitions are involved in the avoidance of responsibility for one's actions. In recent literature, behaviour displayed to distance one's persona from negative effects resulting from one's decisions and actions are outlined within the following topics. Wilful ignorance: the deliberate avoidance of information and facts about the impact of a decision or action, is one example of such behaviour (Grossman & Van Der Weele, 2013). Wilful ignorance may for instance be used to ignore pollution when driving a car, or disregard your bank's investments in the weapons industry. This behaviour may also take place inside a person's own mind and is referred to as self-deception. By denying facts, exaggerating the truth or simply lying to oneself, a person is able to justify their wrongdoing having negative consequences (DeWeese-Boyd, 2017). Recent literature on CEO overconfidence (i.e. Malmendier & Tate, 2015) describes CEO's that exaggerate their abilities in their own minds. As a consequence, mergers and acquisitions (M&As) may become less profitable than expected. Another way that avoids taking responsibility for personal negative outcomes is by simply shifting the blame to someone or something else (Bartling & Fischbacher, 2012). In football and other team sports for instance, it often occurs that one defence player blames another for the other team scoring a goal.

These various types of behaviour may sometimes be beneficial to the user. Self-deceiving behaviour may for instance lead to a better self-image and reduced anxiety about an uncertain future (Schwardmann & Van Der Weele, 2019). This could be the case when soldiers who took a life in battle claim that they were following orders. Furthermore, using an excuse has been associated with a lower degree of damage to the excuse-maker's identity, reduced negative sanctioning and reduced depression (Schenkler, Pontari et al., 2001). Also, shifting the blame may protect a person's image in the case of delegating decisions (Bartling & Fischbacher, 2012).

So why does excuse-using pose a problem? Research shows that deliberate avoidance of responsibility via excuses is a cause of irritation and is perceived negatively by society (Weiner & Amirkhan et al., 1987). Excuse-using could also have negative effects on the person's own character by undermining three major human qualities: being trustworthy, the quality of being able to bring about an effect and being motivated by good will towards others (Schlenker, Pontari et al., 2002).

In addition, there are more negative consequences resulting from responsibility avoiding behaviour. Wilfully ignoring important facts and circumstances may lead to bad decision-making and outcomes. A CEO of an oil company may ignore information about a leaking pipeline to protect the company's profit. A stock market investor may deceive himself by rationalizing a stock's potential and losing his family's savings. A professional athlete who deliberately shifts the blame for an error to his teammates may end up without a contract. A manager that always blames others for his shortcomings and therefore remains in the same place, is not updating his behaviour in the future. These are all examples of negative consequences arising from such behaviour and stress the importance of identifying such behaviour.

In the literature above, helpful insights, definitions, positive and negative aspects of the various types of human behaviour such as increased self-esteem and reduced trustworthiness are described. However, the existence of empirical research on a relation between negative outcomes arising from errors in decision-making or wrongdoing and excuses used using is thin.

Trading on the stock market provides an excellent environment for witnessing successes and errors made in human decision-making. The results of a person's actions, i.e. buying or selling of stocks, are directly visible and can be quantified in terms of profit/loss. In addition, increasing internet usage and availability of text data has led to an increase of literature with text data methodology. Pang, Lee et al. (2002) use text data for designing a model which classifies movie reviews as positive or negative. Relating this to the stock market, many people provide insights into their experiences, their reasoning and strategies for buying and selling through the use of comments on fora or likewise, hence providing a very good possibility for observing human behaviour. Many others used sentiment in Tweets to explain stock returns (Bollen, Mao et al., 2011; Rao & Srivastava, 2012). Using this method and data enables an analysis where excuse using behaviour could be observed.

Therefore, this thesis aims to contribute to expanding the empirical research mentioned above, by analysing the use of excuses by investors in the stock market. This thesis also provides a framework which could be applied onto other situations in which people may use excuses, such as the work and study related examples described earlier.

The central question in this thesis is as follows: are investors in the stock market more likely to find alternative explanations (with regard to the fundamentals) for changes in stock value when the stock price is decreasing as opposed to increasing? To answer this question, online text obtained from the microblogging website StockTwits is used as data. A sample of 55,591 posts related to 21 publicly traded firms are analysed for a period of 14 trading days. This provides a rich source of data written by real investors who share their thoughts, opinions, mood and sentiment (Gentzkow, Kelly et al., 2019). Examples of posts where users provide alternative explanations could be that they blame manipulation for a price decrease but do not mention this manipulation when it increases the stock price. Another possibility could be that a CEO is blamed when stock prices decrease and lauded when stock returns are positive.

Finding a relation between incurring losses and investors using excuses may make investors more conscious about their behaviour. Psychological research claims that increased consciousness and awareness is often associated with behavioural change (Ludwig & Brown et al., 2020). This could lead to a higher focus on the real cause of their losses, such as a lack of knowledge and expertise. The remainder of this thesis is organized as followed. In the next chapter, literature related to several aspects of responsibility avoidance is elaborated. Chapter 3 will ground the hypotheses of this thesis. Chapter 4 explains the methodology that is used to obtain the data and the dataset itself. In chapter 5, the method used for testing the hypothesis is outlined. Chapter 6 summarizes the most important results. Finally, the conclusion and discussion are outlined in chapter 7.

2. Literature review

Scientific literature from many disciplines (e.g. psychology, economics, medicine and law) contributed research related to avoid taking responsibility for negative outcomes of one's decisions or actions. The main concepts involved aim to develop an understanding of this avoidance, are self-deception, wilful ignorance, shifting the blame and excuses. Although literature uses different denomination for the concepts, they may have a similar meaning. These concepts are interrelated through the common purpose of diminishing the negative implication of people's performance (Snyder, Higgins et al., 1983). These concepts in general and findings related to responsibility and investment will be elaborated in the following.

2.1 Wilful ignorance

Wilful or strategic ignorance is deliberately choosing to remain uninformed about negative externalities arising from actions and decisions (Grossman & Van Der Weele, 2017). Applying this general definition to corporate scandals and fraud, CEOs and board members often claim that they are not aware of what happened further down the hierarchy (Bartling, Engl et al., 2014). For example, in scandals such as Enron and Watergate, those responsible strategically ignored information from lawyers, accountants and advisors (Simon, 2005). In this way, those responsible for the negative consequences could use plausible deniability instead of taking responsibility and trying to find a solution. By using an experimental research design, Kajackaite (2015) compared participants, that knew about the negative consequences following from their decisions, with a subset where subjects choose to remain uninformed. Results showed that the participants who choose to ignore the negative consequences by remaining uninformed, exerted a significant 23.64% higher effort on a task than the participants that did know. This means that within this experiment, wilful ignorance caused people to increase their effort and therefore not taking the negative effects of their actions into account.

2.2 Self-deception

Closely related to wilful ignorance, but more focused on an individual's own mental process, is self-deception. The most common way to deceive someone is telling an outright lie. Deception could be extended by many forms including obfuscating or exaggerating the truth or casting doubt on the truth. Von Hippel & Trivers (2011) claim that these forms of deception could also be used for deceiving a person's own mind. By deceiving their own mind, people can use the positive outcomes resulting from negative behaviour and therefore maintain a positive view about themselves (Chance, Norton et al., 2011). Since self-deception could be applied to numerous situations, this paper focusses on the most relevant: self-deception used for not admitting that one's choices or actions have turned against one and self-deception used for overestimating one's abilities. An important example of this phenomena is regret avoidance, which is defined as an action among investors that refuses them to accept a loss on an investment that turned against them (Coval, Hirchleifer et al., 2004; Bailey & Kinerson (2005). Investors often do not want to take responsibility for their failed investment and feel a desire to undo a certain action (Reb & Connolly, 2009). Additionally, in an experiment where participants made the same decision in several rounds, Reb & Connolly (2009) found evidence that those who rejected feedback continued to make poor decisions. Following this reasoning, investors may not learn from their failure and remain in their suboptimal behaviour trap.

When zooming in on corporate executives, self-deception is researched in the form of CEO overconfidence. Overconfidence is described as the difference between a person's beliefs about their abilities and their actual abilities (Pikulina, Renneboog et al., 2017). CEO overconfidence is often linked to the excessive drift of spending cash-flow on acquisitions (Malmendier & Tate, 2005). The overconfidence of CEOs may apply to other investors as well. Grinblatt & Keloharju (2009) found that overconfident investors trade more frequently. Investors that trade a lot may be more likely to experience reduced earnings (Kirchler & Maciejovsky, 2002). Additionally, overconfident investors may ultimately lead to poor investment performance (Trinugroho & Sembel, 2011). Concluding to this type of behaviour, investors and people in general use self-deception to maintain a positive view about themselves, avoid the feeling of regret, and overestimate their abilities. Those reasons for using this behaviour are closely related to the avoidance of responsibility and are of importance for a deeper understanding of the behavioural concepts described earlier.

2.3 Shifting the blame

Alternative behaviour for responsibility avoidance is shifting the blame to someone or something else. Bartling & Fischbacher (2012) did research on shifting the blame by delegating decisions and the responsibility that comes with them. In a dictator game, the authors found that responsibility was shifted to the delegee who ended up making the decision. An example where the blame is shifted elsewhere is the hiring of interim management for handling reorganizations (Bartling & Fischbacher, 2012). Additionally, Steffen & Williams (2018) found evidence for delegating decisions as well. In their experimental approach they concluded that participants were more likely to let others choose for them when choices felt difficult. The delegation of decisions and shifting responsibility may be beneficial in the case of hiring experts. Property owners often hire local managers to oversee their real estate because they are better informed about local demand (Dai & Lewis et al., 2006).

In relation to stock market investment, investors often try to shift the blame to fund managers or brokers in the case of negative returns (Chang, Solomon et al., 2016). Furthermore, one of the goals of hiring a third party to do your investments or dirty work in general, is the avoidance of responsibility for personally negative outcomes (Hamman, Loewenstein et al., 2010). This reasoning supports the general purpose of shifting the blame by diminishing the negative implication of one's actions.

2.4 Excuses

Lastly, the use of excuses in order to avoid responsibility is of importance. Excuses are defined as "self-serving explanations that aim to reduce personal responsibility for questionable events, thereby disengaging core components of the self from the incident" (Schlenker, Pontari et al., p. 4, 2001). According to Snyder & Higgins (1988), individuals using excuses perceive two interrelated benefits: an excuse will maintain an individual's positive image and gives a sense of control. Literature claims that, among other less relevant benefits, using excuses reduces the feeling of shame, guilt and remorse and defers punishment for failure (Taylor & Brown, 1988). Those benefits reflect the tendency among scientists, where excuse-using is mostly a productive mean for dealing with difficulty (Pontari, Schlenker et al., 2002). However, Pontari et al. (2002) pointed out that excuse making causes frustration in society and contributes to formation of opinions on those who use excuses, to be unreliable and irresponsible. This negative perception of one's character may lead to adverse effects of a person's own concept of his or her self-image (Tyler & Feldman, 2007). Connecting this to the behaviour of investors, those who always come up with an excuse for their negative return will be perceived negatively. Besides the external perception, investors will not correct for ongoing weaknesses and lead to avoiding tasks that might have been learned when taking responsibility (Pontari et al., 2002).

2.5 The overlap with sentiment analysis

The methodology and data sources in this thesis are overlapping with research related to sentiment analysis. Sentiment analysis is defined as the computational treatment of opinions and sentiments obtained from text data (Medhat & Hassan et al., 2014). This is often done by assigning sentiment scores to all the words. For instance, the word "joy" will score high on positive and happy categories and low on negativity. When all the words received a score, the total sentiment score of a document could be calculated.

In order to clarify the similarities, differences and positioning of this thesis within the existing literature, related literature on the method is described. Oliveira, Cortez et al. (2013) used microblogging data from StockTwits for predicting stock return and volatility and found scarce evidence for a relation. Other authors (e.g. Mittal & Goel, 2012) used tweets scraped from Twitter as sentiment indicator. The text (i.e. tweets or posts) is often classified using sentiment scores for each word or by machine-based learning algorithms. These algorithms analyse and learn from similarities in text and use these patterns to classify the comments (Rathi, Malik et al., 2018). Although these analyses give helpful insights related to the methodology, many models are threatened by reversed causality. The variables investor sentiment and stock return are affecting one another simultaneously. Using excuses as a dependent variable instead of investor sentiment solves this endogeneity problem. Including excuses rather than sentiment means that the focus lies on human behaviour and its causes, which is different to an individual's emotions.

3. Hypotheses

After elaborating the different behavioural concepts above, it is also crucial to get a sense of what actual cause changes in stock prices. The groundwork laid by Malkiel & Fama (1970) states that a firm's stock price reflects all available information about that company. Information about the performance of a company is summarized in financial statements supplied by accountants, which are processed and used for decision-making by investors (Williams & Ravenscroft, 2015). These decisions lead to buy or sell orders and therefore changes in the price of a stock. Early research by Ball & Brown (1968) directly connected information supply to change in stock prices. Other types of information provided by a firm's management could for instance relate to its activities, goals or capital requirements. The types of information described above are often referred to as a firm's fundamentals.

Besides a firm's fundamentals, investors in the stock market claim that many other aspects have an influence on the price of a firm's stock. Due to the countless reasons one may give for changes in stock prices, the most frequent and important explanations will be explained briefly. Users on StockTwits often use the trading volume of a stock as a reason for price changes. Literature on the relation between trading volume and stock return is mixed. Some authors (e.g. Chandrapala, 2011) found a positive relation between trading volume and stock returns, others did not find evidence for an effect. For instance, in an analysis of stock markets in China, Europe and the US, Lee & Rui (2000, 2002) found no evidence for a causal effect. Another often heard claim is that large institutions as hedge funds and investment banks are able to affect stock prices. Some support for these claims comes from literature on analyst recommendations (who in some cases work at large investment banks or institutions), which found abnormal stock returns on the days that analysts gave buy recommendations for a specific stock (Kumar & Chaturvedula et al., 2009). Other ways in which large institutions may affect stock prices could be trough a short squeeze. In this situation, investment banks, hedge funds or other parties hold a short position in a stock in order to profit from price decreases (Allen & Haas et al., 2019). When the stock price increases, shares have to be bought in the market to prevent larger losses. This demand will increase stock prices even more creating a snowball effect.

Returning to the different forms of behaviour, several arguments related to investor behaviour could be made. Investors may deceive their own minds by exaggerating facts or hold unrealistic beliefs about an organization that they have invested in. Investors blame external parties for their losses and often overestimate their own investment knowledge. Furthermore, investors want to avoid feelings of shame, guild and remorse by using excuses. Following this reasoning, one may expect that investors will use excuses for negative outcomes of their actions. These negative outcomes are negative returns on their investments in the stock market. This relation grounds hypothesis 1, which aims to test the effect of daily negative returns on investor excuse-using:

H1: A decrease in the value of stock x will lead to a significant larger frequency of alternative explanations and excuses provided used by individuals that possess stock x

The negative relation in hypothesis 1 may also work in the other direction. The different forms of psychological behaviour may also be used when stock prices increase. It could be that investors care less about alternative explanations when it benefits them in the form of stock increases. When stock prices increase, people may wilfully ignore facts or explanations that oppose this increase. Therefore, in hypothesis 2, the effect of a general increase will be analysed:

H2: An increase in the value of stock x will lead to a significant lower frequency of alternative explanations and excuses provided used by individuals that possess stock x

When considering the magnitude of negative and positive effects following from investor decisions, one may expect that excuse-using frequency may be different for various degrees of stock reductions. The theorem of loss aversion, for instance, claims that the subjective weight of a loss is heavier than the same amount of gain (Brenner & Rottenstreich et al., 2007). Additionally, microeconomic literature on an individual's utility and payoff describes the existence of nonsatiation (Rabin, 1998). This means that possessing more of something is preferred over less. Following this reasoning, one may argue that investors prefer less loss over more loss. This builds the foundation for hypothesis 3 and 4, where the effect of the magnitude of stock increases and decreases will be tested:

H3: The size of the effect varies with the decrease in value
H4: The size of the effect varies with the increase in value

4. Methodology

Over the last decade, social media, microblogging, review websites and other personal online expressions became a major source of data where information with regards to communication, human interaction and emotions could be collected (Gentzkow, Kelly et al., 2019). The data in this paper is obtained by using web scraping, which is a process of automatically collecting data from websites through programming language (Bradley & James, 2019). Specific data such as tweets, comments on a forum, or entire articles on a news website could be collected. Via the programming script, conditions and specific subjects could be added to scrape the text data that fits a certain criterion. A Python, R or other programming language script that simulates the process of collecting the data is used. Every step that is required for manually selecting the text of interest will be included in the script: visiting the targeted website, taking the appearance of ads and other banners into account, log into a user account, switch through different pages of the website and scroll up and down in order to load more information on a webpage. After that the script automatically simulates the process, a place of storage for the data should be included. Often this is a Structured Query Language (SQL) database, which stores the data on a computer hard drive or in the cloud. The stored data could be exported to several statistical programs (e.g. Stata or R-studio) or as specific files. After collecting the requested data, a cleaning process is used to eliminate irrelevant elements as interpunction, usernames, blanc spaces, and certain stop-words that hold no meaning. When a clean data set remains, other variables can be implemented into the data set to perform analyses on causal relation or building predicting models.

4.1 Data sources

The data source that is used to collect text comments from investors is the stock market forum StockTwits. This is a financial platform with more than 200,000 users that can post 140-character messages related to a certain stock. By using a self-written Python programming script, comments are scraped from the watchlist timeline on StockTwits, which can be edited to a user’s interests. Depending on the amount of comments posted at that moment, the script runs on x minute intervals. The obtained observations are transferred to a PostgreSQL database and included an id number, the exact moment of when this comment was posted, the stock that the comment related to and the text itself. When the scraping process is complete, the raw data will be saved as a Comma Separated Value (CSV) file which enables further analysis in the statistical programming software R Studio.

4.2 Dependent variable: the operationalization of excuses

The most challenging aspect of this paper is to classify a certain comment or post as an excuse. This will be done by the occurrence of one or multiple words in an observation (a comment written by an individual on StockTwits). When one or multiple words occur, an observation is classified as an excuse.

When no match is found, the observation will be classified as no excuse. The word or combination of words will form the fundament of the classification and should be selected carefully.

In order to increase the internal validity and obtain a higher degree of objectivity, this selection process will contain the following steps. In order to get a sense of how to distinguish between excuses, alternative explanations and logical explanations, a survey will be conducted. Hereafter and taking the responses into account, logical words and phrases directly related to excuse-using and shifting the blame are included. Finally, common terms related to market manipulation will be analysed and selected. The selection process of a word or the words will be elaborated on in the following.

The first step contains creating and distributing the survey, where 20 statements related to failing and bad outcomes were presented to 135 random respondents using Amazon Mechanical Turk in an online survey (see appendix 1). Respondents rated the statements on a scale from 1 to 5: 1 meaning that the statement was a logical explanation and 5 meaning that the statement was a very bad excuse. In order to control for consistency, statements related to university, career and health were added. Also, several control statements containing legitimate reasons for failing an objective (i.e. “I can’t attend your birthday party because I have COVID-19”).

The results of the survey are mixed but still useful. For instance, 66.99% percent of the respondents think that the phrase “the stock is manipulated by the government” is an excuse. With regard to shifting the blame, 58.40% of the respondents believed that blaming their neighbour for a bad stock tip is an excuse. On the other hand, 38.99% believed that blaming analysts was an excuse and 34.23% thought that blaming the investment channel was an excuse. After getting a sense of how to distinguish between valid explanations and excuses, this information is replenished. Logical excuse and blame-shifting expressions like “it was not my fault” and “I blame person x for this” are added to the excuse classification process.

Finally, the phrases or words related to types of market manipulation will be included. An example is a “pump and dump”, where owners of the stock distribute false information about the stock, which leads to price increases and finally to the same owners selling the stock at a large profit (Bloomberg, 2020). Although these types of manipulation may occur, claiming that manipulation is the cause of an investor’s loss, without the existence of evidence is considered an excuse. Related to shifting the blame, terms where users blame the CEO of firms in the sample are included as well.

The words that are often related to excuse-using behaviour are used to form a single word and n-grams. An n-gram is a phrase that holds a combination of n words. This thesis will mostly hold a maximum of 2 words because the benefits of using more words are diminishing (Gentzkow, Kelly et al., 2019). The resulting n-grams will be used as criteria for the classification of an excuse. This happens when words from the n-gram match the words in an observation. In table 1, all the unigrams, bigrams and trigrams that are used in the classification process are outlined.

Table 1: Summary of the n-grams used
for the classification of a comment

Unigrams	Bigrams	Trigrams
blamed	institutions dump	sell by institutions
blame	institutions sell	dump by institutions
blaming	pump dump	
manipul	market misunderstood	
manipulation	insider trading	
manipulate	painting tape	
manipulated	paint tape	
cheating	wash trading	
cheat	wash trade	
cheated	bear raiding	
cheater	cornering market	
conspire	corner market	
conspiring	stock bashing	
conspired	lure squeeze	
conspiracy	price fixing	
fault	ramping market	
churning	ramp market	
pools	quote stuffing	
runs	front running	
spoofing	short distort	

4.3 Dependent variable: Sample and data preparation

Once PostgreSQL database containing all collected comments was exported to a CSV file and imported into R studio, the raw data frame including 79,219 observations was prepared for further use. First, all double observations arisen from the scraping process were removed from the data. After this a filter was used to exclude all comments that were replies to other users. Finally, posts related to firms that were not in the sample were removed as well. This resulted in a data frame with 56,759 observations.
In the second stage, the content of the posts was cleaned in order to prepare the text for the classification of excuses. In the original content of the comments, many irrelevant elements such as numbers, emojis, punctuation, special characters, URLs, pictures and videos existed. Those elements were removed, and all text was transformed to lower case characters. Observations that solely existed of those elements ended up empty and were therefore removed from the sample.
In order to capture the meaning of each post, common words described as “stop words” are removed (Gentzkow, Kelly et al., 2019). Stop words include articles and copulatives (“the”, “a”, “and”, “or”), which have little meaning on their own. Observations that ended up empty after this process were removed from the sample. This resulted in a sample size of 55,591 observations.

In the final step of cleaning the text data, the words in a post were stemmed. This means that different forms of a word are transformed to their root (e.g. “lovely”, “loving” and “loved” are changed into “love”) using a word stemming algorithm. After implementing this final step, the text data was clean and prepared for the classification analysis.
Now, the text data is prepared for the classification of an excuse. As described under the methodology section, excuse will be classified through n-grams and single words. The words and n-grams are collected in an excel file (classification list), where each row contains a word or n-gram. Subsequently, a Python script is used to compare words and n-grams in each comment to the classification words and n-grams in the excel file. If a match occurs, a comment is classified as an excuse and the variable $EXCUSE_i$ will have value 1. When a comment exists of words or n-grams that do not exist in the classification list, the variable $EXCUSE_i$ will be 0.

4.4 Independent variable: Stock return

Since the obtained text data contains the date and time of the original post, connecting it to daily stock returns is possible. The daily stock and market prices are obtained via the Compustat database and the derived daily returns are calculated using the following formula:

$$R_{it} = \ln\left(P_{i,t}\right) - \ln\,(P_{it-1})$$

Here, P_{it} is the closing price of stock i at time t and P_{it-1} is the closing price of the previous day. The return of $Stock_i$ will be used to three different ways. First, the daily stock return creates a binary variable for daily losses below a certain level. Second, the daily returns are used to create a control variable that captures the monthly return and is described below. Finally, the daily return as calculated under R_{it} will be used as a numeric value.

4.5 Control variables

As described in the opening paragraph of this thesis, people use numerous excuses and have various motivations for using them. This means that other variables and events may also have an effect of the number of excuses used. By using control variables in the regression model, some of these effects may be accounted for. Also, the effect of the characteristics of different firms on excuse-using is captured through specific firm variables as the price/earnings-ratio and a firm’s beta. Differences in these variables may have an effect the type of investors and therefore excuse-using. The data of the variables are obtained via Compustat. The control variables and the argumentation about why they are included are described in the following.

The first control variable that is included is a stock's trading volume, which is described as the number of transactions between buyers and sellers of a stock (Karpoff, 1986). A high (low) trading volume means a large (small) amount of changes in ownership and therefore activity related to the stock. Trading volume is also often associated with a stock's volatility (Chen, Firth et al., 2001). Volatility and trading volume are measures that reflect firm features and may therefore affect the use of excuses and posting behaviour in general.

In order to correct for the overall performance of the company that is analysed, the price/earnings-ratio (P/E-ratio) is included as a control variable. The P/E-ratio gives an indication of future performance and is measured as the stock price divided by the earnings per share (Anderson & Brooks, 2005). Investors that invest in stocks with positive future returns may change their excuse-using behaviour. Also, different types of firms (growth stocks versus value stocks) could be separated through the P/E-ratio (Beneda, 2002). The effect of firms as for instance Tesla Inc., where stock prices are mostly based on their potential could therefore control for different types of investors and changes in excuse-using.

The third control variable which is include in the analysis is beta. According to the Capital Asset Pricing Model (CAPM), a stock's risk compared to the market portfolio is reflected in the stock's beta or ß (Campbell & Vuolteenaho, 2003). A beta that is smaller (larger) than 1 indicates that a stock is less (more) volatile than the market in which the stock is listed. Varied levels of volatility and risk may attract investors that have a different attitude towards risk. Different attitudes toward risk may affect the degree of which these investors blame others or use excuses. In order to capture the effect of these different types, beta will be added as a control variable.

The return of the last 20 trading days $stock_i$ at time t will also be used to control for the short-term results of daily returns. One may expect that a positive monthly return mitigates the effect of daily negative returns on the use of excuses for those who hold stocks long-term.

Finally, the average return of the index will be included as a control variable. This controls for the overall sentiment of a given day. If a particular stock decreases while the entire market increases, one may expect that investors in that stock feel worse than if it is an overall red day in the markets. Changes in the frequencies of which investors use alternative explanations and excuses could result from this.

4.6 Model specification

In order to test the hypotheses that will be used to answer the research question, four different models are estimated using Ordinary Least Squares (OLS) and Logistic regressions. Due to the nature of the data, a double clustering based on day and firm, of standard errors is applied in order to prevent biased estimations. First, the effect of the binary independent variable stock return smaller than -1% on the binary dependent variable excuses will be estimated in model 1. Secondly, the effect of the binary independent variable stock return greater than +1% on the binary dependent variable excuses will be estimated in model 2. In model 3, the effect of actual daily percentage return of a stock on excuse using will be estimated both for positive return and negative return. Each model will be extended with the control variables outlined in section 3.

Model 1a

The first model will estimate the effect of a < -1% decrease in value of $stock_i$ on the frequency of excuses used.

$$EXCUSE_i = \beta_0 + \beta_1\, NEGATIVERETURNDUMMY_i + \varepsilon_i$$

where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ is classified as an excuse and 0 otherwise. $NEGATIVERETURNDUMMY_i$ is a binary variable with value 1 if the return of $stock_i$ on day t has a return < -1% and value 0 otherwise.

Model 1b

In the extended version of model 1a, the market and firm specific control variables trading volume, P/E-ratio and beta will be added. Also, the monthly return of a stock and the daily index return will be implemented in the model so that the effect of long-term investors and overall market sentiment is captured. This results in the following estimated model.

$$\begin{aligned} EXCUSE_i = \beta_0 + \beta_1 NEGATIVERETURNDUMMY_i + \ \beta_2 VOLUME_i + \beta_3 PERATIO_i + \beta_4 BETA_i \\ + \beta_5 RETURNINDEX_i + \beta_6 RETURNMONTH_i + \ \varepsilon_i \end{aligned}$$

Where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ is classified as an excuse and 0 otherwise. $NEGATIVERETURNDUMMY_i$ is a binary variable with value 1 if the return of $stock_i$ has a return < -1% and 0 otherwise. $VOLUME_i$ is the trading volume of $stock_i$ on day t, $PERATIO_i$ is the P/E-ratio of $stock_i$, $BETA_i$ is the beta of $stock_i$, $RETURNINDEX_i$ is the daily return of the index in which $stock_i$ is listed, and finally $RETURNMONTH_i$ is the return of $stock_i$ over de last 20 trading days.

Model 2a

The second model will estimate the effect of a > +1% increase in value of $stock_i$ on the frequency of excuses used. This results in the following estimated model

$$EXCUSE_i = \beta_0 + POSITIVERETURNDUMMY_i + \ \varepsilon_i$$

Where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ is classified as an excuse and 0 otherwise. $POSITIVERETURNDUMMY_i$ is a binary variable with value 1 if the return of $stock_i$ on day t has a return > +1% and value 0 otherwise.

Model 2b

As under model 1, model 2 will be extended with the control variables trading volume, P/E-ratio, beta, daily index return and monthly stock return. This results in the following model.

$$EXCUSE_i = \beta_0 + \beta_1 POSITIVERETURNDUMMY_i + \ \beta_2 VOLUME_i + \beta_3 PERATIO_i + \beta_4 BETA_i \\ + \beta_5 RETURNINDEX_i + \beta_6 RETURNMONTH_i + \ \varepsilon_i$$

Where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ is classified as an excuse and 0 otherwise. $POSITIVERETURNDUMMY_i$ is a binary variable with value 1 if the return of $stock_i$ on day t has a return > +1% and value 0 otherwise. $VOLUME_i$ is the trading volume of $stock_i$ on day t, measured. $PERATIO_i$ is the P/E-ratio of $stock_i$, $BETA_i$ is the beta of $stock_i$, $RETURNINDEX_i$ is the daily return of the index in which $stock_i$ is listed, and finally $RETURNMONTH_i$ is the return of $stock_i$ over de last 20 trading days.

Model 3a

The third model will estimate the effect of the actual negative change in daily returns in value of $stock_i$ on the frequency of excuses used. This means that only observations where daily stock returns are smaller than 0 are included in the model. This results in the following estimated model

$$EXCUSE_i = \beta_0 + NEGATIVECHANGERETURN_i + \ \varepsilon_i$$

Where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ that is classified as an excuse and 0 otherwise. $NEGATIVECHANGERETURN_i$ is the daily percental change in the price of $stock_i$, given that this return is negative.

Model 3b

As under the first two models, model 3 will be extended by the control variables trading volume, P/E-ratio, beta, index return on that day and monthly stock return. This results in the following model.

$$EXCUSE_i = \beta_0 + \beta_1 NEGATIVECHANGERETURN + \ \beta_2 VOLUME_i + \beta_3 PERATIO_i + \beta_4 BETA_i \\ + \beta_5 RETURNINDEX_i + \beta_6 RETURNMONTH_i + \ \varepsilon_i$$

Where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ is classified as an excuse and 0 otherwise. $NEGATIVECHANGERETURN_i$ is the daily percental change in the price of $stock_i$, given that this return is negative. $VOLUME_i$ is the trading volume of $stock_i$ on day t. $PERATIO_i$ is the P/E-ratio of $stock_i$, $BETA_i$ is the beta of $stock_i$, $RETURNINDEX_i$ is the daily return of the index in which $stock_i$ is listed, and finally $RETURNMONTH_i$ is the return of $stock_i$ over de last 20 trading days.

Model 4a

The third model will estimate the effect of the actual positive change in daily returns in value of $stock_i$ on the frequency of excuses used. This means that only observations where daily stock returns are larger than 0 are included in the model. This results in the following estimated model

$$EXCUSE_i = \beta_0 + POSITIVECHANGERETURN_i + \varepsilon_i$$

Where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ that is classified as an excuse and 0 otherwise. $POSITIVECHANGERETURN_i$ is the daily percental change in the price of $stock_i$, given that this return is positive.

Model 4b

Model 4 will be extended by the control variables trading volume, P/E-ratio, beta, index return on that day and monthly stock return. This results in the following model.

$$\begin{aligned} EXCUSE_i = \beta_0 + \beta_1 POSITIVECHANGERETURN + \beta_2 VOLUME_i + \beta_3 PERATIO_i + \beta_4 BETA_i \\ + \beta_5 RETURNINDEX_i + \beta_6 RETURNMONTH_i + \varepsilon_i \end{aligned}$$

Where $EXCUSE_i$ is a binary variable with value 1 if a comment about $stock_i$ is classified as an excuse and 0 otherwise. $POSITIVECHANGERETURN_i$ is the daily percental change in the price of $stock_i$, given that this return is positive. $VOLUME_i$ is the trading volume of $stock_i$ on day t. $PERATIO_i$ is the P/E-ratio of $stock_i$, $BETA_i$ is the beta of $stock_i$, $RETURNINDEX_i$ is the daily return of the index in which $stock_i$ is listed, and finally $RETURNMONTH_i$ is the return of $stock_i$ over de last 20 trading days.

5. Data and descriptive statistics

The next section will describe the firms used in the sample and corresponding statistics in order to obtain a sense of the data set. Thereafter is outlined how the data is obtained and processed into a data frame.

5.1 Summary statistics: Comments and stock return

In this thesis a sample of 16 publicly-traded firms listed on the S&P500 index in a three-week period[1] in January 2021 were analysed. These firms are banks, airlines, oil and gas companies, automobile producers or active in the technological industry. With the exception of Martin Luther King Day on Monday the 18th of January, the stock market was open, which resulted in 14 trading days to be analysed. Also, during the last two weeks of the observation period, five United-States (US) firms with a more volatile nature were added to the sample. This was done to include possible effects of firms that held a higher degree of risk. These are firms operating within the industries of green energy, artificial intelligence, marihuana or electrical vehicles. On the 14 trading days, comments that included the firm name or ticker tag of firms in the sample were scraped from StockTwits between approximately 14.00 and 24.00 Central European Time (CET). This time frame captured comments that were posted one and a half hour pre and post market opening hours. Table 1 summarizes the sample described above.

Table 2: Summary statistics of the comments and the daily stock return

		Comments		Daily stock return	
Firm name	Obs.	Excuse	No excuse	Mean	St. dev
ALPHABET INC	277	2	275	0,116%	2,393%
AMERICAN AIRLINES GROUP INC	1964	33	1931	0,903%	4,013%
APPLE INC	9689	95	9594	-0,005%	2,385%
CHEVRON CORP	93	0	93	-0,477%	2,247%
CITIGROUP INC	276	3	273	-0,856%	2,593%
DELTA AIR LINES INC	229	3	226	-0,377%	2,808%
EXXON MOBIL CORP	627	7	620	-0,098%	2,591%
FACEBOOK INC	4036	31	4005	-0,251%	2,585%
FORD MOTOR CO	2868	16	2852	1,121%	3,631%
GENERAL MOTORS CO	1072	5	1067	1,164%	4,246%
GEVO INC	11144	60	11084	5,978%	19,078%
GOLDMAN SACHS GROUP INC	591	0	591	-0,482%	1,705%
JPMORGAN CHASE & CO	773	1	772	-0,397%	1,361%
LITHIUM AMERICAS CORP	1016	10	1006	0,139%	10,268%
MARATHON OIL CORP	371	7	364	-0,299%	4,648%
OCCIDENTAL PETROLEUM CORP	319	1	318	-0,007%	5,401%
PALANTIR TECHNOLOG INC	9152	126	9026	2,383%	7,723%
SOUTHWEST AIRLINES	93	1	92	-0,478%	2,221%
SUNDIAL GROWERS INC	9938	122	9816	1,270%	9,799%

[1] 11th of January until the 1st of February

UNITED AIRLINES HOLDINGS INC	373	1	372	-0,566%	3,630%
XPENG INC -ADR	690	13	677	0,417%	7,501%
	55591	537	55054		

5.2 Summary statistics: Control variables

After classifying the comments, the stock and firm related control variables are added to the data frame. Daily stock volume and closing price, the P/E-ratio and the market capitalization of all the firms in the sample are collected for the 14 trading days. The daily closing price is used to calculate daily stock return. After this, the return of the companies over the last 20 trading days, which is approximately one calendar month, will be calculated[2] and included as a column in the data frame as well. Finally, the return of the index in which a firm is listed will be used in combination with the stock return to calculate beta. Beta is calculated using the following formula: $Beta_i = \frac{Cov(R_i, R_m)}{Var(R_i)}$ where R_i is the daily return of $stock_i$ and R_m is the daily return of the index in which the stock is listed. Table 2 summarizes the statistics of the control variables.

[2] $R20days_i = \ln(P_{i,t}) - \ln\,(P_{i,t-20})$

Table 3: Summary statistics of the control variables

			Trading volume (mln.)		P/E - ratio		Index return		20 Day return	
Firm name	Obs.	Beta	Mean	St. dev	Mean	St. dev	Mean	St. dev	Mean	St. dev
ALPHABET INC	14	1,96	2174094	838036	34,84	1,32	-0,21%	1,07%	4,12%	3,91%
AMERICAN AIRLINES GROUP INC	14	0,57	81822689	77718948	-1,12	0,07	-0,21%	1,07%	-0,63%	7,35%
APPLE INC	14	1,01	115496907	27718921	39,84	2,45	-0,21%	1,07%	2,89%	2,41%
CHEVRON CORP	14	1,09	10023027	2125948	-14,91	0,47	-0,21%	1,07%	5,88%	2,92%
CITIGROUP INC	14	0,96	23434631	5662460	12,67	0,41	-0,21%	1,07%	4,38%	6,10%
DELTA AIR LINES INC	14	1,75	13822087	3673734	-2,15	0,19	-0,21%	1,07%	-0,93%	2,89%
EXXON MOBIL CORP	14	0,92	30557766	6719756	60,83	2,03	-0,21%	1,07%	11,98%	2,81%
FACEBOOK INC	14	1,31	26179618	5889530	29,14	1,97	-0,21%	1,07%	-3,58%	4,84%
FORD MOTOR CO	14	1,81	110918076	53524539	-263,05	17,98	-0,21%	1,07%	16,55%	7,65%
GENERAL MOTORS CO	14	1,93	38420865	13663328	22,98	1,43	-0,21%	1,07%	21,36%	6,40%
GEVO INC	14	4,69	61119444	40470962	-8,42	2,39	-0,07%	1,26%	106,01%	12,79%
GOLDMAN SACHS GROUP INC	14	0,39	3743855	1184984	13,83	3,05	-0,21%	1,07%	13,69%	7,29%
JPMORGAN CHASE & CO	14	0,52	16335016	4066711	17,59	0,59	-0,21%	1,07%	9,39%	5,51%
LITHIUM AMERICAS CORP	14	2,21	9579295	7059672	-61,54	6,13	-0,28%	1,03%	67,12%	17,01%
MARATHON OIL CORP	14	0,54	30209067	4414382	-5,57	0,33	-0,21%	1,07%	17,54%	6,76%
OCCIDENTAL PETROLEUM CORP	14	0,89	21121170	6362793	-1,36	0,08	-0,21%	1,07%	18,25%	6,55%
PALANTIR TECHNOLOG INC	14	2,62	75624276	56448927	334,23	57,76	-0,28%	1,03%	12,32%	21,94%
SOUTHWEST AIRLINES	14	1,15	7771447	2765109	-15,03	2,95	-0,21%	1,07%	1,36%	3,58%
SUNDIAL GROWERS INC	14	1,14	519658871	530480224	-0,25	0,03	-0,07%	1,26%	33,64%	10,52%
UNITED AIRLINES HOLDINGS INC	14	1,42	15737056	6710939	-7,10	0,31	-0,21%	1,07%	-3,51%	4,18%
XPENG INC -ADR	14	3,47	24020009	11716684	-78,18	5,03	-0,28%	1,03%	14,78%	11,07%

6. Results

In this section the results from the two regressions of each model are discussed. In the first part the results from the OLS estimation of the models are described. Next, the results of the logit estimation of the models are outlined. Lastly, the estimated models are used to test the hypotheses and their robustness will be checked.

6.1 Results of the OLS estimations

Table 4: OLS regression of model 1 and 2

The dependent variable in this regression is a binary variable that is 1 if an observation is classified as an excuse and 0 otherwise. Daily return < -1% is a binary variable that is 1 if the stock return is smaller than minus 1 percent and 0 otherwise. Daily return > +1% is a binary variable that is 1 if the stock return is larger than 1 percent and zero otherwise.

	Model 1A	Model 1B	Model 2A	Model 2B
Daily return < -1%	0.00427**	0.00395**		
	(2.68)	(2.92)		
Daily return index		-0.102		-0.0944
		(-1.54)		(-1.48)
Log trading volume		0.00139*		0.00171**
		(2.47)		(3.30)
P/E-ratio		0.0000126*		0.0000137*
		(1.98)		(2.17)
Beta		-0.000837		-0.000543
		(-0.75)		(-0.48)
Return 20 days		0.000523		0.000409
		(0.13)		(0.10)
Daily return > +1%			-0.00430**	-0.00470***
			(-2.75)	(-3.40)
Constant	0.00769***	-0.0169	0.0115***	-0.0196*
	(7.67)	(-1.67)	(10.90)	(-2.02)
Observations	55591	55591	55591	55591

t statistics in parentheses
The standard errors in all models are clustered
* p<0.05; ** p<0.01; *** p<0.001

In the first OLS regression, the effect of a decrease in stock return on the dependent variable excuse-using will be analysed. The first column of table 3 presents the estimated coefficient and the corresponding significance ($p < 0.01$) of the binary variable daily return < -1%. Consistent with the expectations that formed the hypotheses of this thesis, the coefficient is of a positive nature. This means that the model describes a negative relation between stock return and excuse-using: if a stock's daily return is smaller than -1%, it is more likely that investors write excuse related comments. After summarizing the descriptive statistics of the sample, it became clear that the proportion of excuses within the sample was small. This could elucidate the relatively small coefficient estimated in model 1A.

In model 2A the effect of an increase in stock return on the dependent variable excuse-using is outlined. Column (3) presents the estimated coefficient of the binary variable daily return > 1%. This coefficient is of negative nature, which indicates that a daily stock return larger than 1% lead to lower excuse-using by investors on that day.

After capturing the isolated effect of the negative daily return dummy variable, the control variables were added in model 1B. The regression specification of these control variables is outlined in the second column of table 3. The first control variable with a significant effect ($p < 0.05$) is the logarithmic transformation of trading volume. The coefficient describes a positive relation between a stock's trading volume and excuse-using by investors. The extent to which a stock changes ownership captures the degree of activity around a stock and may clarify the positive nature of the coefficient. The other firm specific control variable with a significant effect ($p < 0.05$) on excuse-using is the P/E-ratio. The coefficient of this variable signifies a positive relation between a firm's P/E-ratio and excuse-using by its investors.

Investors in firms that are characterized by high stock prices relative to their earnings performance are using excuses more frequently. This effect may exist due to a higher degree of stock pricing based on a firm's future expectations rather than a firm's current performance. When comparing these types of valuation, one may expect that the former hold more uncertainty than the latter, which could lead to disappointing outcomes and more excuse-using. The effect of the remaining control variables index return, beta and monthly return on excuse-using is insignificant. The daily return of the corresponding index of a stock was included to capture the effect of overall sentiment on that day. An overall green day and a negative return on the stock might increase excuse-using. This reasoning is not confirmed by the sample used in this thesis. The same holds for the variable beta: the expectation that stocks with a volatile nature lead to larger price movements and investor excuse-using is not confirmed. Finally, the return of a stock over the last 20 trading days did not have a significant effect. This control variable was included to capture longer term stock returns which could mitigate the effect of daily stock returns. One may expect that if a stock increases heavily prior to a day of loss, investors will use less excuses because their overall return was still positive. A possible explanation could be that investors mostly write messages related to what occurs at that particular moment.

Table 5: OLS regression of model 3 and 4

The dependent variable in this regression is a binary variable that is 1 if an observation is classified as an excuse and 0 otherwise. In model 3A and 3B, only observations where the daily return of a stock is smaller than -1% are included. In model 4A and 4B, only observations where the daily return of a stock is larger than +1% are included.

	Model 3A	Model 3B	Model 4A	Model 4B
Daily return of stock	0.0178	-0.0329*	0.00420	-0.00207
	(1.63)	(-2.11)	(0.69)	(-0.25)
daily return index		-0.182**		0.0189
		(-2.67)		(0.11)
Log trading volume		0.00207*		0.00195*
		(2.30)		(2.37)
P/E-ratio		0.0000189		0.0000148*
		(1.44)		(2.17)
Beta		0.000466		-0.00182
		(0.25)		(-1.11)
Return 20 days		-0.00791		0.00479
		(-1.14)		(0.75)
Constant	0.0129***	-0.0275	0.00665***	-0.0274
	(8.62)	(-1.57)	(4.76)	(-1.95)
Observations	25673	25673	24200	24200

t statistics in parentheses
The standard errors in all models are clustered
* p<0.05; ** p<0.01; *** p<0.001"

Instead of the binary variable included in models 1 and 2, the actual percentage change of stock return will be included in model 3 and 4. Analysing daily stock returns as the actual percentage change made it possible to capture the effect of the magnitude of stock returns. Similar as under model 1, the isolated effect of daily stock return on excuse-using was estimated first. The effect of a daily return, where only values smaller than -1% were included, is estimated in the first column of table 4 and resulted in an insignificant (p = 0.106) negative relation with the dependent variable excuse. Interpretation of this coefficient is that negative (positive) stock returns of greater magnitude result in more (less) frequent

excuse-using by investors. Due to the relatively scarce quantity of excuse-using in the sample, the coefficient is small.
Adding the control variables to the isolated model results to a different outcome. The sign of the coefficient of daily stock return (smaller than minus 1%) changed from positive to negative. Also, the coefficient is significant ($p < 0.05$). Possible explanations for the change of sign might be that a lot of the explanatory power of the coefficient is now captured in the control variables. Trading volume ($p < 0.05$) and the index return ($p < 0.01$) have a significant positive relation with excuse-using and P/E-ratio, 20 day return and beta show no significant effect on excuse-using.

Finally, the effect of positive percentage change of stock return larger than plus 1% is outlined under the third and fourth column. Again, the isolated effect is estimated first and subsequently the control variables are added. In both models, the coefficient of the variable stock return larger than plus 1% is insignificant. This means that no statistically significant relation between positive stock returns and excuse-using is found using this estimation method. When analysing the control variables, similar results regarding the variables P/E-ratio and trading volume could be observed. Both variables have a significant effect on excuse-using.

6.2 Results of the Logistic estimations

Table 6: Marginal effects of Logistic regression of model 1 and 2

The dependent variable in this regression is a binary variable that is 1 if an observation is classified as an excuse and 0 otherwise. Daily return < -1% is a binary variable that is 1 if the stock return is smaller than minus 1 percent and 0 otherwise. Daily return > +1% is a binary variable that is 1 if the stock return is larger than 1 percent and zero otherwise. The values in each column are the marginal effects of a change in the independent variable on the dependent variable excuse (i.e. the change in the probability of the occurrence of an excuse when an independent variable changes).

	Model 1A	Model 1B	Model 2A	Model 2B
Daily return < -1%	0.00427**	0.00421**		
	(2.64)	(3.13)		
daily return of index		-0.0840		-0.0742
		(-1.43)		(-1.33)
Log trading volume		0.00144*		0.00183**
		(2.18)		(2.84)
P/E-ratio		0.0000127*		0.0000140*
		(2.08)		(2.28)
Beta		-0.000679		-0.000302
		(-0.52)		(-0.22)
Return 20 days		-0.000894		-0.00120

		(-0.19)		(-0.25)
Daily return > +1%			-0.00450**	-0.00527***
			(-2.58)	(-3.41)
Observations	55591	55591	55591	55591

t statistics in parentheses
The standard errors in all models are clustered
*p<0.05; ** p<0.01; *** p<0.001

Due to the binary nature of the dependent variable excuses, the results of a logistic regression will be presented in this section. Similar to the estimation of the OLS models, an isolated effect of the dummy variable daily return < -1% will be estimated first. The coefficient presented under the first column of table 4 describes a significant ($p > 0.01$) effect of the negative return dummy variable on excuse-using. Since we are using a logistic model, the marginal effects of the coefficients were calculated in order to interpret the results. This translates into a 0.427% increase in excuse-using when daily stock returns are smaller than -1%. When adding the control variables in model 1B, the effect of the dummy return variable on excuse-using increases to 0.421%. The control variables log trading volume ($p < 0.01$) and P/E-ratio ($P < 0.05$) have a significant positive effect on excuse-using. A one percent increase in trading volume increases the probability that an excuse is used by 0.144%. The P/E-ratio increases the probability of excuse-using by investors with 0.00127% per increase of 1.

In the third and fourth column, the results of the binary variable larger than 1% are outlined. In both models, the coefficient of the binary variable is of negative nature. This means that when stock return is larger than 1%, there is 0.45% - 0.527% lower chance that a comment on that stock is an excuse.

Table 7: Marginal effects of the Logistic regression of model 3 and 4

The dependent variable in this regression is a binary variable that is 1 if an observation is classified as an excuse and 0 otherwise. In model 3A and 3b, only observations where the daily return of a stock is smaller than -1% are included. In model 4A and 4B, only observations where the daily return of a stock is larger than +1% are included. The values in each column are the marginal effect of a change in the independent variable on the dependent variable excuse (i.e. the change in the probability of the occurrence of an excuse when an independent variable changes).

	Model 3A	Model 3B	Model 4A	Model 4B
Daily return of stock	0.0200	-0.0455*	0.00393	-0.00134
	(1.44)	(-1.96)	(0.73)	(-0.15)
Daily return of index		-0.198**		0.0317
		(-2.71)		(0.25)
Log trading volume		0.00226*		0.00175*
		(2.15)		(2.40)

P/E-ratio		0.0000197		0.0000152*
		(1.64)		(2.12)
Beta		0.000428		-0.00184
		(0.20)		(-1.08)
Return 20 days		-0.00992		0.00446
		(-1.39)		(0.67)
Observations	25673	25673	24200	24200

t statistics in parentheses
The standard errors in all models are clustered
* p<0.05; ** p<0.01; *** p<0.001"

The first two columns of table 6 estimate the effect of daily return as a numerical value below minus 1% using a logistic estimation method. In the model without the control variables, an insignificant (p = 0.150) negative relation between stock return and excuse-using is estimated. When adding the control variables, the reliability of the daily stock return coefficient increases and is statistically insignificant (p < 0.05). Analysing the positive daily return, no significant effect of positive stock returns (larger than 1%) was found.

After summarizing the results of the analysis, conclusions related to both hypotheses in this thesis could be drawn. The models estimated using OLS and Logistic estimation methods are presenting similar results: the negative return dummy variable has a significant effect on excuses used by investors. Therefore, no evidence is found for rejecting hypothesis 1: a *decrease in the value of stock x will lead to a significant larger frequency of excuses used by individuals that possess stock x.*

After analysing the effect of a negative return binary variable, the same analysis was performed for positive return. Both estimation methods provided evidence for a significant coefficient of the binary variable stock return larger than 1 percent. This means that there is no evidence for rejecting hypothesis 2: *An increase in the value of stock x will lead to a significant lower frequency of alternative explanations and excuses provided used by individuals that possess stock x.*

When applying the results of the estimations of the effect of daily stock return as a numerical value, the following conclusion could be drawn: small support for a significant effect of this variables was found using both estimation methods. Using values below minus 1 percent resulted in a significant coefficient of the variable daily stock return under both estimation methods. This means that is no evidence is found for rejecting hypothesis 3, *The size of the effect varies with the decrease in value* and will therefore be rejected.

Finally, when analysing the results obtained from the models, conclusions regarding hypothesis 4 could be drawn. Both estimation techniques and models provided insignificant coefficients and therefore hypothesis 4, *The size of the effect varies with the decrease in value*, will be rejected.

The evidence for accepting hypothesis 1, hypothesis 2, hypothesis 3 and rejecting hypothesis 2 is based on robust statistical methods. Due to the nature of the sample, with comments related to 14 firms over 14 days, a correction for clustered standard errors is applied. This led to acceptable standard deviations and corresponding t-values relative to an analysing without clustered standard errors. In two of the variables, market capitalization and trading volume, a skewness in their distributions was solved by logarithmic transformation. Furthermore, no multicollinearity in the control variables used in models 1B and 2B exists (see appendix 3). Finally, the data was treated as panel data in order to analyse the differences with OLS and Logistic estimations. Each firm had a number of comments related to the firm for each day in the sample. Some of those comments were classified as an excuse and were assigned a value of 1, others were classified as no excuse and were classified as zero. By aggregating the data to a proportion for excuse using with regard to total comments on a given day, all 21 firms had an excuse proportion for 14 days. This data set could be treated as panel data where the firms were the economic entity i and time t was represented by the days. All extended models (1B, 2B, 3B, 4B) were estimated using a fixed effects regression (see appendix 4). This resulted in similar coefficients as compared to OLS and Logistic estimations and had one significant variable: the dummy variable positive return > 1% in model 2B. All other stock return variables were insignificant.

7. Conclusion and discussion

In this thesis the excuse-using behaviour of investors in the stock market is studied. The main focus of the thesis is to identify a relation between excuses used by investors and negative returns on stock investments. This question is answered by using text data scraped from the microblogging investment website StockTwits. Small messages written by individuals with an interest in the stock market are analysed. These messages are subject to a binary classification process that label each comment as either an excuse or no excuse. From this classification process the dependent variable is formed.

The effect of daily stock return on excuse-using by investors is estimated with OLS and Logistic estimation methods. Firm specific control variables are included to distinguish between firm characteristics and capture alternative effects on the dependent variable.

The following results related to four hypotheses were interpreted to answer the research question. Hypothesis (1) tests the effect of negative stock return on excuse-using with a binary variable for stock return smaller than minus 1%. Hypothesis (2) tests the effect of negative stock return on excuse-using with a binary variable for stock return smaller than minus 1%. After analysing our sample and estimating the models, evidence for support for these two hypotheses was found. This means that investors use a higher frequency of excuses when daily return is smaller than minus one percent. The same applied for positive return larger than plus 1 percent: significantly more excuses are observed within the data. The effect of this negative relation is strengthened by the control variables trading volume and P/E-ratio. This may be explained by the degree of activity and therefore popularity around a stock which also leads to a higher posting frequency. The P/E-ratio describes that investors use more excuses when investing in growth stocks. This could be attributed to the reasoning that growth stocks are valued based on expectations rather than current performance. This valuation is subject to a higher degree of risk which may lead to more excuse-using when returns decrease.

While interpreting the results regarding hypothesis (3) and (4), which test the effect of the magnitude of the stock return using the actual numeric daily stock return, evidence for less excuse-using when daily stock returns were larger was found. In the other direction, evidence for a relation between the negative magnitude of stock return and excuse-using by investors was not found.

There are several considerations to be taken into account, with respect to the data and methodology, when interpreting these findings. With regard to the nature of the data source, several flaws should be considered. Since the data is written by anonymous users, it is uncertain whether the text is written by investors who actual possess the stock. Also, there is a possibility that users post unserious and biased comments in order to provoke actions from other users, which could support their own interest. The people that post on StockTwits may be special and characterized differently than traditional stock investors. Every person with an internet connection is able to post when and what they want, which means that no expertise related to stock investment should be assumed.

Also, some characteristics of the dataset and analysis thereof should be addressed. First, the amount of comments per firm suffers from skewness: there are 11,144 observations related to Gevo Inc. and 277 observations related to Alphabet Inc. This means that the results are for the greater part based on firms with a relatively large number of observations. Performing the fixed effects regression made it clear that the results deviated from the OLS and Logistic regressions. Also, as outlined in the methodology section, the operationalization of the dependent variable was challenging. The method of classifying an excuse is based on words and n-grams, giving an indication of the nature of a comment, however absolute certainty does not exist. Therefore, in future research a machine-based learning classification process based on a larger sample could strengthen the analysis. Here, mainly the creation of and classification by a subjective training data set could provide more reliable results. Then, a final note can be made about the operationalization of stock return. When critically reviewing, one may argue that using daily returns are not sufficient. Due to fluctuations in stock return during a day, comments may not correspond to the stock return based on the closing price of a stock. This could lead to biased estimations. Therefore, the methodology of this thesis could be improved by matching comments with stock returns on that exact moment.

Finally, several remarks with regards to the timeframe of this thesis can be made. Due to the limited time in which this thesis was written, the number of days that were analysed are limited. Increasing the number of days may lead to more reliable results. Important to note is that parallel to the scraping period, the stock markets witnessed a new phenomenon. Large amounts of individuals united through a sub forum on Reddit called “wallstreetbets”. These people conspired together and bought large amounts of stocks as GameStop corp. and AMC entertainment, which increased prices by more than a thousand percent. It is unclear which firms exactly were “victims” of this actions, but it might be the case that firms used in this sample were among their interests. This should be considered when interpreting the results of this thesis.

Considering these limitations and looking past these problems, this thesis contributes to existing literature. First, the literature on the psychological concepts of wilful ignorance, self-deception, shifting the blame and excuse-using is outlined and applied on investor behaviour. This creates a higher degree of consciousness related to such behaviour among stock market investors. Elaborating these concepts leads to more clarity on the differences between and consensus about various forms of human behaviour. Secondly, operationalizing variables based on text data to provide empirical evidence on behaviour as excuse-using is extending current literature. The framework provided in this thesis could be used to research relations between human behaviour and economic phenomena. This may contribute to the development of an even more pluralistic view of the field of economics.

This methodological approach could be applied to other aspects of human lives where one uses excuses for bad decisions or actions. Fruitful areas are gamblers using online chatrooms and course evaluation forms written after a student participated in an exam. Lastly, the identification of a negative relation between negative stock return and excuse-using by investors may lead to more awareness. With the increased popularity of stock investment and brokers without any commission fee, more awareness of the risks of stocks should be known. Investors should focus on proper due diligence, risk levels and the understanding of the numerous products available rather than using excuses afterwards.

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Appendices

Appendix 1: Results of the survey

#	Question	an excuse		neutral		a valid explanation		Total
1	"I did not finish my homework because my dog ate it"	86.54%	135	10.26%	16	3.21%	5	156
2	"I am late because my train was delayed"	8.28%	13	19.75%	31	71.97%	113	157
3	"I can not come to your birthday party because I have COVID-19"	5.10%	8	10.83%	17	84.08%	132	157

#	Question	a very cheap excuse		a cheap excuse		neutral		a logical explanation		a very logical explanation		Total
1	"I do not have time to exercise and therefore I am overweight"	25.00%	39	44.23%	69	15.38%	24	10.26%	16	5.13%	8	156
2	"I do not agree with the university curriculum and therefore dropped out of university"	21.57%	33	30.72%	47	18.95%	29	23.53%	36	5.23%	8	153
3	"People did not understand the news related to my investment and therefore the stock decreased in value"	13.46%	21	30.13%	47	28.85%	45	23.72%	37	3.85%	6	156
4	"I am fired from my job because my qualifications do not fit this type of job"	6.41%	10	16.67%	26	18.59%	29	44.87%	70	13.46%	21	156
5	"The stocks in my portfolio plummeted because of the COVID-19 pandemic"	1.28%	2	6.41%	10	13.46%	21	51.28%	80	27.56%	43	156
6	"I have been misinformed about nutrition and therefore I am overweight"	18.99%	30	36.71%	58	20.25%	32	22.78%	36	1.27%	2	158
7	"I am losing money on my investment because the stock that I hold is manipulated by insiders with more information"	8.28%	13	20.38%	32	25.48%	40	35.67%	56	10.19%	16	157
8	"Healthy food is too expensive and therefore I have to eat unhealthy food which makes me overweight"	31.01%	49	37.97%	60	17.09%	27	9.49%	15	4.43%	7	158
9	"The company has a bad strategy and therefore my stocks reduced in value"	5.10%	8	12.74%	20	26.11%	41	45.22%	71	10.83%	17	157
10	"I am fired from my job because my boss does not like me"	13.38%	21	29.30%	46	28.66%	45	22.93%	36	5.73%	9	157
11	"Fake news is driving the value of my investments down"	8.86%	14	28.48%	45	24.68%	39	36.08%	57	1.90%	3	158
12	"I am not able to exercise because of my knee injury"	4.43%	7	7.59%	12	12.03%	19	37.97%	60	37.97%	60	158
13	"The value of the stock decreased because the market misunderstood the earnings report"	4.46%	7	24.84%	39	28.66%	45	31.85%	50	10.19%	16	157
14	"I am more of a practical person who wants to work with his\her hands and therefore I dropped out of university"	11.39%	18	11.39%	18	29.11%	46	39.24%	62	8.86%	14	158
15	"I am losing money on my investment because the stock that I hold is manipulated by large mutual/hedge funds"	4.43%	7	19.62%	31	25.32%	40	41.14%	65	9.49%	15	158

#	Question	a very cheap excuse		a cheap excuse		a logical explanation		a very logical explanation		Total
1	"The stock is manipulated by the government"	23.30%	24	43.69%	45	23.30%	24	9.71%	10	103
2	"My neighbor recommended the stock, I already told him it was a bad idea"	18.58%	21	39.82%	45	32.74%	37	8.85%	10	113
3	"The CEO of this company is incompetent. He/she led the company into the ground"	3.48%	4	32.17%	37	56.52%	65	7.83%	9	115
4	"Regulation on this company is increasing the costs and driving down profit"	3.33%	4	20.83%	25	63.33%	76	12.50%	15	120
5	"The stock is just having a bad day. This is normal"	5.79%	7	18.18%	22	58.68%	71	17.36%	21	121
6	"Profit taking is the reason that my stocks went down"	6.73%	7	36.54%	38	47.12%	49	9.62%	10	104
7	"The negative sentiment is driving the price of my stocks down"	8.94%	11	25.20%	31	53.66%	66	12.20%	15	123
8	"The analyst who recommended the stock said the price would increase"	11.02%	13	27.97%	33	48.31%	57	12.71%	15	118
9	"The investment channel mentioned this stock as an opportunity"	10.81%	12	23.42%	26	54.95%	61	10.81%	12	111

Appendix 2: Tests for multicollinearity of the control variables

Variable	VIF	1/VIF
Return 20 days	5.84	0.171152
Beta	5.69	0.175788
Log trading volume	1.31	0.765990
P/E-ratio	1.28	0.781834
Daily return of index	1.13	0.886706
Daily return < -1%	1.02	0.975841
Mean VIF	2.71	

Appendix 3: Results of the fixed effect model

The dependent variable in this regression is a binary variable that is 1 if an observation is classified as an excuse and 0 otherwise. Daily return < -1% is a binary variable that is 1 if the stock return is smaller than minus 1 percent and 0 otherwise. Daily return > +1% is a binary variable that is 1 if the stock return is larger than 1 percent and zero otherwise. In model 3B, only observations where the daily return of a stock is smaller than -1% are included. In model 4B, only observations where the daily return of a stock is larger than +1% are included.

	Model 1B	Model 2B	Model 3B	Model 4B
Daily return < -1%	0.00285			
	(1.34)			
daily return of index	-0.131	-0.120	-0.199	-0.146
	(-1.33)	(-1.26)	(-1.39)	(-0.72)
Log trading volume	0.00217*	0.00265**	0.00211	0.00308*
	(2.26)	(2.64)	(1.20)	(2.14)
P/E-ratio	0.0000157	0.0000168	0.00000960	0.0000346*
	(1.33)	(1.37)	(0.50)	(2.44)
Beta	0.00175	0.00194	0.000820	0.00439*
	(1.17)	(1.25)	(0.35)	(2.20)
Return 20 days	-0.00755	-0.00733	-0.00660	-0.0160*
	(-1.27)	(-1.20)	(-0.63)	(-1.99)
Daily return > +1%		-0.00463*		
		(-2.11)		
Daily return of stock			-0.0557	-0.00527
			(-0.90)	(-0.17)
Constant	-0.0316	-0.0374*	-0.0289	-0.0517*
	(-1.93)	(-2.19)	(-0.95)	(-2.09)
Observations	279	279	115	96

t statistics in parentheses
The standard errors in all models are clustered
* p<0.05; ** p<0.01; *** p<0.001