Essays in Behavioral Finance

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Max Erik Suchanek

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Hamburg

Referentin/Referent: Prof. Dr. Matthias Pelster

Korreferentin/Korreferent: Prof. Dr. Antje Mahayni

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1 Synopsis

1.1 Introduction

Behavioral Finance, a field dedicated to understanding investors' decision-making processes, reveals the pervasive influence of behavioral biases that deviate from rational market assumptions. The impact of Behavioral Finance spans various fields of Finance such as Banking, Corporate Finance, or Investment. Within the field of investments, a large literature studies the trading behavior of individual investors on capital markets.
The goal of this dissertation is to contribute to the literature in Behavioral Finance that focuses on the investment behavior of individuals. More specifically, the dissertation contributes to this literature from two important perspectives and considers (i) individuals' personality traits and (ii) social interactions between individuals.

Various personality assessments emerged over the decades, among which the big five taxonomy established itself as a popular choice for researchers. It results from factorial analyses based on a linguistic approach, assuming existing vocabulary can fully describe personality traits (De Raad & Mlačić, 2017). This personality assessment was first explicitly hypothesized in 1961 (De Raad, 2000) and quickly gained in popularity since then. It covers the personality dimensions of openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Several extensions of this model emerged over the years. A widely established example is the honesty-humility trait of the HEXACO personality assessment. Past literature often thematized big five personality traits in connection with behavioral biases, a form of irrational decision making, whereas other personality traits such as the "dark triad" initially received less attention.
Lately, however, the concept of dark personality traits, namely narcissism, Machiavellianism, and psychopathy have received increased attention in financial research. The dark triad (Paulhus & Williams, 2002) shows hereby a significant correlation with aggressive reporting at the managerial level (Majors, 2016), tendencies towards gambling (Jones, 2013), and riskier behavior overall (Crysel, Crosier, & Webster, 2013).
This underlines the relevance of dark personality traits for financial decision making. Yet, a transfer of the dark personality traits towards behavioral biases in the investment decision making process is still missing. This dissertation aims to provide a starting point to fill this void.

A second aspect of Behavioral Finance is the impact of social interactions onto investment decision making. As social interactions play an important role in everyone's daily life, research elaborated their relationship within the financial realm. Many studies showed that within a social setting, investors behave differently by changing their investment preferences (De Bondt, Mayoral, & Vallelado, 2013). Noteworthy hereby is that individuals' behavior in social interactions, and how individuals are affected by social interactions, also depend on their personality traits. Agreeable individuals for instance are more willing to follow investment advice of others (Tauni, Yousaf, & Ahsan, 2020).
Interestingly, the dark triad is also associated with specific behavioral patterns that manifest in social situations. Seeking social admiration, for instance, can be considered a facet of narcissism. Dark triad personality traits and their connection to investors within social interactions is still unexplored, opening the opportunity for further research.
The impact of social interactions on financial markets has also been highlighted in recent events. In

January 2021, the GameStop short squeeze - when a group of private investors, predominantly organized on the social news aggregator Reddit, coordinated to drive up the stock price of GameStop corporation - captured the world's attention for three important reasons: First, its duration surpassed that of other short squeezes, which typically last just one or two days. Second, it was not only limited to a single but also other companies. Lastly, the pivotal role of social interactions among investors played a significant role in these market events.

These distinctions provide a unique context to examine the social behavior of private investors in volatile market conditions. While literature focused on GameStop itself in connection with textual sentiment (Long, Lucey, Xie, & Yarovaya, 2023), it leaves room to expand the discussion towards other stocks, as well as the intent dimension of social interactions. Elaborating the goals of users posting certain content at a given time, besides knowing the mood in which it was published might further explain the events.

In summary, this dissertation aims to analyze the relationships between personality traits, behavioral biases, and social interactions in the realm of investment decision making of individuals. Doing so, it contributes to the existing literature in several ways.

Besides adding to the existing literature, the results of the dissertation may also have practical implications. For instance, it might be helpful to consider personality assessments as part of client investment profiles to provide individuals better guidance in their investment processes.

1.2 Literature review

1.2.1 Investment decision making and personality traits

The big five personality traits show significant relationships with risk attitudes (Bucciol & Zarri, 2017; Thomas, Goel, & Agrawal, 2020), investment horizon (De Bortoli, da Costa Jr, Goulart, & Campara, 2019; Mayfield, Perdue, & Wooten, 2008), choice of financial instruments (Oehler, Wendt, Wedlich, & Horn, 2018), and behavioral biases such as overconfidence and the disposition effect (Baker, Kumar, Goyal, & Gaur, 2019; Kubilay & Bayrakdaroglu, 2016; Lin, 2011; Schaefer, Williams, Goodie, & Campbell, 2004).

In addition to these personality traits, Paulhus and Williams (2002) established the concept of the dark triad, incorporating narcissism, Machiavellianism and psychopathy to cover malevolent personality traits. From a financial perspective, the dark triad is usually thematized in a less investment-related manner. Instead, the literature explores the intersection of psychopathy and individual financial success, which can result from the improved job performance of individuals with psychopathic traits (Babiak, Neumann, & Hare, 2010; Benning, Venables, & Hall, 2018; Howe, Falkenbach, & Massey, 2014). High levels of psychopathy are hereby associated with a stronger emphasis on financial success and a tendency to link happiness and life satisfaction to material possessions (Glenn, Efferson, Iyer, & Graham, 2017). Moreover, psychopathy can predict the propensity to take general financial, investment, and gambling risks, primarily to avoid loss (Sekścińska & Rudzinska-Wojciechowska, 2020). A body of literature connecting psychopathy to popular investment biases such as herding, or the disposition effect still needs to be developed.

When examining the relationship between Machiavellianism and finance, the literature reveals a tendency towards manipulative behavior in the context of fraudulent financial reporting. Individuals who hold favorable attitudes towards misreporting and who possess higher levels of Machiavellianism are more prone to engage in such deceptive practices (Jones, 2013; Murphy, 2012; Mutschmann, Hasso, & Pelster, 2022). Besides a higher likelihood of misreporting, Machiavellians also bear a smaller emotional burden than others. This suggests that they might behave differently to reach their financial goals, even though there is no association between Machiavellianism and financial risk-taking dimensions according to recent

literature (Sekścińska & Rudzinska-Wojciechowska, 2020).
Like psychopathy, narcissism is associated with gambling (Jones, 2013), whereas narcissists perceive money as a means of influencing and impressing others (Lim & Teo, 1997). This perception indicates that even the motivation to strive for financial success depends on personality traits. In summary, the dark triad is connected to increased risk attitudes and the underlying motivation to acquire wealth. However, only a few studies investigate investment decision making at the capital market in connection with the dark triad (Foster, Reidy, Misra, & Goff, 2011; Pelster, Hofmann, Klocke, & Warkulat, 2023; Sekścińska & Rudzinska-Wojciechowska, 2020);. When doing so, the significant relationship with risk-seeking behavior seems to transition into the investment realm, such that narcissists are prone to engage in riskier stocks with higher volatility than their peers (Foster et al., 2011). Furthermore, Sekścińska and Rudzinska-Wojciechowska (2020) showed that investors with high narcissism or psychopathy typically hold a large proportion of stocks in their portfolios. Pelster et al. (2023) show, that even professional risk managers high in dark triad personality traits tend towards actively varying the size of their hedge ratios and the timing of their derivatives transactions based on their market views, personal preferences, attitudes, or skills. This so-called selective hedging can result in major losses for companies.
Existing literature on behavioral finance has not yet fully integrated dark personality traits into investment matters despite their substantial correlation with, for instance, an individual's risk attitude. A few pioneering studies, such as those mentioned above, have slowly entered this realm.

1.2.2 Investment decision making in social interactions

Besides personality traits, there are exogenous factors that influence the investment decision-making process of an individual. These influences can be of social nature and are often rooted in psychological concepts like group thinking (Janis, 1972) and group polarization (Isenberg, 1986). Notably, peers impact investors' choices concerning entering the stock market (Hong, Kubik, & Stein, 2004), the selection of financial instruments (Zhang, Fang, Jacobsen, & Marshall, 2018), the timing of market entry (Kaustia & Knüpfer, 2012) and foster the appearance of behavioral biases.
This includes phenomena like the disposition effect, where investors hold on to losing stocks and sell winners rather early (Shefrin & Statman, 1985). The disposition effect as such a bias has widely been explained by investor type (Garvey & Murphy, 2004), investment experience (Chen, Kim, Nofsinger, & Rui, 2007), gender (Brooks & Zank, 2005) and age (Dhar & Zhu, 2002). To measure this effect, (Weber & Camerer, 1998) present an experiment design which is widely applied in literature (Sornette, 2009).
Considering the disposition effect, (Heimer, 2016) demonstrate that investors who trade in open public settings experience a higher disposition effect compared to those in standard trading environments without social interactions among traders. He argues that social investors, driven by the active efforts to project a positive image, may further increase their disposition effect, asserting that a successful appearance enhances their ability to persuade others. Adding to the social context, findings from Pelster and Hofmann (2018) suggest that "leader" traders, i.e., investors who are being followed in a social setting, are more susceptible to the disposition effect compared to investors who are not followed by other traders. The sense of group responsibility paired with a fear of losing their followers might explain these results. Such social concerns can also be used to explain the results of Hermann, Mußhoff, and Rau (2019), where they found that subjects without prior trading experience exhibited significantly higher disposition effects when trading for others.
Based on the arguments around social concerns and image preservation, the extreme facet of narcissism as part of the dark triad may drive the disposition effect as well. Individuals might prioritize admiration over the monetary value of trading profits. Therefore, one could expect a tradeoff between the social admiration that an individual receives and the monetary payoffs.

Despite the extensive literature and a solid measurement instrument to assess the disposition effect, current research leaves still room to further explain the effect in connection with admiration seeking. The dissertation hereby develops the hypothesis that individuals with narcissistic personality traits are also more susceptible to such biases.

Furthermore, peer effects extend to online communities such as Reddit, where observing and analyzing these social interactions among potential investors presents inherent challenges for both researchers and the financial service industry. Hereby, textual sentiment analysis emerged as a focal point for understanding the nuanced dynamics of social interactions in financial markets. It initially described the categorization of a text into positive or negative sentiments by assigning numerical values to each word (Li, 2010). Textual sentiment can affect the performance of speculative assets (Long et al., 2023), lead to euphoria, and contribute to behavioral biases, like investment overconfidence (Nofsinger, 2005), especially during volatile markets. This can make investors more susceptible to emotions and irrational behavior (Bollen & Mao, 2011).

The accessibility and ease of obtaining textual sentiment data have dramatically increased in recent years. With the advent of lexicons specifically tailored for this purpose, researchers now have a robust toolkit for extracting information from vast amounts of text. However, the validity of textual sentiment measures remains an ongoing topic of discussion in the research community. Although substantial progress has been made in refining sentiment analysis techniques, challenges persist in ensuring that these measures accurately reflect the underlying sentiment in financial texts (Kearney & Liu, 2014). The inherent complexity of human language, including sarcasm, irony, and context-dependent expressions, can pose difficulties for sentiment classification. While the field of machine learning algorithms has emerged to tackle these classifications beyond the single-word level (Kearney & Liu, 2014), dictionary-based approaches remain valid, particularly in the case of specific languages or vocabularies (Long et al., 2023).

Moreover, textual sentiment analysis demonstrated a degree of stability and consistency in the results across various studies (Kearney & Liu, 2014). For GameStop, a major firm of interest during these events, textual sentiment correlated significantly with stock performance metrics such as trading volume and returns (Anand & Pathak, 2022; Betzer & Harries, 2022). However, this relationship was only observable during the first price peak of the stock price in January and February 2021 and only for this specific stock, leaving room for more research focused on generalizability.

Besides this need to generalize findings beyond a single stock, existing literature did not cover yet the intent dimension of social interactions. A popular intent of the short squeeze events of 2021 for instance was to hold on to the investments disregarding any fluctuations in pricing. The specific expressions of "diamond hands", which was widely used in research and news, influenced investors in light of peer effects. Furthermore, these specific postings might be motivated by achieving strategic complements, triggering a short squeeze event. Investors following this advice, holding on to their investments could actively reduce trading volume and increase prices. This possible influence motivates a combined approach between sentiment and intent in explaining social interactions in volatile markets.

1.3 Overview of papers

This thesis bridges the existing research gaps in the realm of behavioral finance by presenting a cumulative dissertation comprising three scientific papers:

- Suchanek, Max (2021). The Dark Triad and Investment Behavior. *Journal of Behavioral and Experimental Finance, 29*, 100457.
- Suchanek, Max, & Liêu, Minh-Lý (2022). The Disposition Effect and Admiration Seeking. *Review of Financial Economics, 40* (2), 200–234.

- Suchanek, Max (2023). Social Interactions in Short Squeeze Scenarios. *International Review of Economics & Finance, 91*, 898-919.

Each paper focuses on a distinct type of empirical research: survey, experiment, or archival study.
The first two studies contribute to the primary research involving the collection and application of data within the context of predefined research objectives (Borenstein, Cooper, Hedges, & Valentine, 2009). The third method utilizes real-life data without framing or interaction effects.
All primary research papers obtain explicit permission from participants, thereby ensuring voluntary participation (Lowe & Zemliansky, 2011). Confidentiality and anonymity were safeguarded by assigning unique participant codes and avoiding the collection of personal identifying data.
The second study introduced a variable compensation framework that can be affected if participants fail certain attention checks. It incorporates an auction in which participants bid for funds received from a trading game. In light of this, an ethics review board was approached, and the request underwent a favorable evaluation on July 7, 2020.
These studies employ deductive reasoning, outline existing theories based on secondary literature, formulate hypotheses, collect and analyze data, and ultimately accept or reject the hypotheses (Johnson-Laird, 1999). They can be put into the positivism paradigm outlined by Weber (2004) due to fitting theoretical assumptions e.g. about method, type of data, validity and reliability.
On the topic of determining the research population and sampling strategy, each study outlines the process in context of previous literature elaborating also size and quality of chosen samples. In case of such sampling, the studies discuss the criteria for acceptable sample size (Sudman, 1976) and surpass the minimum size requirements of Collins, Onwuegbuzie, and Jiao (2007).
This thesis also addresses the issue of publication bias, a researcher's tendency to favor studies with the desired outcomes for publication purposes. Striving to publish significant findings offers several advantages, including quicker and more frequent publication opportunities and an increased likelihood of acceptance by high-impact journals (Stanley, 2005). These advantages contributed to the systematic representation of insignificant findings in the literature. The second study addresses this publication bias by publishing partially insignificant findings.

1.4 Data and methodology

1.4.1 The dark triad and investment behavior

Collecting data of personality traits using online surveys is widely established (Donnelly, Iyer, & Howell, 2012; Fox & Rooney, 2015; Migliore, 2011). Besides gathering information on the big five assessment, this method can further be enhanced by the dirty dozen questionnaire to capture the dark triad (Jonason & Webster, 2010). The dirty dozen questions can then be interspersed with other personality-related questions to minimize the potential influence of question order on the responses (McFarland, 1981). Due to the number of biases and personality traits, this study requires the use of a more restricted personality assessment compared to the existing literature, where singular personality traits are correlated with behavioral biases. Niszczota (2014), for instance, looked specifically into openness for experience dimension in connection with home bias and was able to use a more detailed assessment of this trait. Therefore, before using these data, internal reliability and consistency of the scales need to be assessed (Jonason & Webster, 2010).
Lütje and Menkhoff (2007) demonstrate that surveys can measure behavioral biases like for instance the home bias. Similar like Gort (2009); Nosić and Weber (2010); Park, Konana, Gu, Kumar, and Raghunathan (2010) for overconfidence and from Kanojia, Singh, and Goswami (2022) for herd behavior.

The survey can then be organized into three distinct sections: demographics, investment decision-making, and an evaluation of the dark triad personality traits.
To address the validity of the data, specific problems that might occur when gathering it need to be addressed beforehand: One of these specific issues for online surveys is the one of multiple submissions (Tuten, Urban, & Bosnjak, 2002). A unique worker ID linked to the subject's user account will prevent this issue. As the survey can be restricted to only unique worker IDs, the only way to submit multiple times would be via creating multiple user accounts. Besides this mitigation method, the wide geographic coverage is a significant advantage of such online survey methods (Evans & Mathur, 2005).
For the analysis step, the dark triad serves as the independent variable, whereas the biases are endogenous variables.
I develop three models, each incorporating a different combination of variables: The basic model includes only three biases as dependent variables and the dark triad as the explanatory variable. The subsequent models add sociodemographic factors, such as sex, age, and education, and financial factors, such as investment horizon and information frequency, to examine their potential influence. The data can further be divided based on nationality to run regressions accordingly, looking into potential changes of the results. When comparing the sample size with existing literature, the study aims to gather a number of participants that is in range with similar studies like 201 (Donnelly et al., 2012), 281 (Holden, Dennie, & Hicks, 2013), 441 (Charness, Yoon, Souders, Stothart, & Yehnert, 2018), or 800 (Fox & Rooney, 2015), supporting the applied sample size and technique.

1.4.2 The disposition effect and admiration seeking

Data for this study are gathered via the previously presented portfolio management experiment of Weber and Camerer (1998) to assess the disposition effect of the participants. Afterwards, a personality assessment takes place to get data on the necessary personality traits. These questions include the ten-item personal inventory of the big five dimensions (TIPI-G) (Gosling, Rentfrow, & Swann Jr, 2003), the honest-humility dimension of the HEXACO personality assessment (Ashton, Lee, & De Vries, 2014), and the dark triad personality assessment measured with the Dirty Dozen (Jonason, Kaufman, Webster, & Geher, 2013).
After the trading game, each participant has a certain balance in the virtual currency, depending on their achieved performance available. In addition, the participants also know their place on a leaderboard. They can participate in a sealed-bid English auction, measuring their willingness to pay for admiration with a unique certificate as bidding item. Because the certificate owner has the possibility of posting it on social media, it can result in admiration from peers. Funding for participating in this auction was determined by balancing the stock-trading round beforehand. In particular, the maximum value that participants can bid on is their final balance after the stock trading game. O-Tree, which is an open-source platform software that can be used to technically integrate these dimensions into one framework. It allows the usage of many advantageous features, such as not requiring installation and having low costs and high scalability (Chen, Schonger, & Wickens, 2016).
This methodological framework can effectively address the prevailing research constraints highlighted in Sekścińska and Rudzinska-Wojciechowska (2020). The authors relied on participants declaring their intentions while explaining that an experimental setting might reveal more accurate results. This study can provide such actual results, yielding insights into the real behavior of participants within an experimental environment, as opposed to relying on survey-based methods.

1.4.3 Social interactions in volatile markets

To demonstrate the influence of social interactions on stock performance metrics in volatile markets, the last study will connect archival data from the social news aggregator Reddit to data on stock performance metrics. The data ranging from 01.12.2020 to 30.09.2021 cover major market movements of so-called "short-squeezed" stocks. These stocks were highly prominent on social media such as Twitter and Reddit, especially during late January and February (Lyócsa, Baumöhl, & Výrost, 2022).
However, this study extends the timeframe beyond the initial short-squeeze events to add another argument for generalizability. To cover social interactions, submissions from /r/wallstreetbets and /r/GME are included. Owing to the prominence of submissions relative to comments on Reddit (Medvedev, Lambiotte, & Delvenne, 2019), the dataset excludes user-generated comments. Stock performance in the form of volume and closing prices on an hourly intraday basis is obtained from Finnhub.io for the most prominent stocks in the subreddit /r/wallstreetbets, namely, GME, AMC, NOK, and BB (Lyócsa et al., 2022). With these textual and stock data in place, a vector autoregression (VAR) model can derive causal findings by applying the Granger Causality and impulse response functions (IRF). Commonly used checks for stationarity and autocorrelation ensure that the time-series data used in the model satisfies statistical properties. These checks ensure the validity and reliability of the VAR models (Hendry & Juselius, 2000). Based on the underlying multivariate VAR model, the analysis uses a VAR Granger causality test involving multiple variables. The VAR model considers the interactions and feedback effects among variables, allowing for a comprehensive examination of the causal relationships between them. Afterwards, the IRFs provide further insight into the dynamics of the model. They analyze the dynamic effects of shocks on variables by showing how a unit shock to one variable affects all variables in the system over time. IRFs provide a structured way to study the short- and long-term interactions between variables, allowing for a deeper understanding of a system's response to shocks (Lütkepohl, 2010). Further, IRFs show relative changes and not absolute magnitudes; therefore, they do not allow for any argument about economic magnitude.
From a data-driven standpoint, this study extends the temporal scope to encompass volatile short-squeezed stocks throughout 2021. Second, it includes different social interaction data by adding another popular subreddit. Third, it enhances the scope of stock selection. Using an established methodology previously used by researchers, this study also applies instruments for causality observation.

1.5 Results

1.5.1 The dark triad and investment behavior

Suchanek (2021) focuses on the relationship between dark triad personality traits on behavioral biases in investment decision-making. Three prominent biases – home bias, overconfidence, and herd mentality – are discussed and assessed using a questionnaire and set into relationships with personality traits.
This study contributes to existing literature in several ways. It includes psychopathy, Machiavellianism and narcissism in addition to normal personality traits, whereas prior studies by, for example, (Durand, Newby, Tant, & Trepongkaruna, 2013; Nga & Ken Yien, 2013; Zaidi & Tauni, 2012) focus on personality traits outside the dark triad.
First, the study discerned a noteworthy dissimilarity in the manifestation of dark triad traits between US and non-US subjects. While the dark triad personality traits were more pronounced among individuals of non-US nationality, they did not show a significant relationship with behavioral biases. However, when looking at the sample of US nationals, the dark triad personality traits show a significant relationship with the investment decision-making of US individuals despite their seemingly less pervasive nature compared

to other nationalities.

Among US participants, higher scores on the dark triad scales were indicative of heightened proclivity towards overconfidence and herd mentality biases. Intriguingly, a higher dark triad score corresponded to reduced exposure to home bias.

These findings are contextualized within the framework of cross-cultural variation. This study postulates that the exceptional economic growth experienced by the US in the past has forged a profound and distinctive relationship between its society and the concept of money. Notably, the US exhibits the highest degree of individualism, as defined by Hofstede's cultural dimension, among the nations considered. Consequently, the impact of culture on investment behavior extends to dark personality traits. Thus, the discerned distinctions between US and non-US subjects can be attributed to the divergent fundamental underpinnings of investment decision-making, where dark personality traits assume a more salient role for US individuals while being marginalized for their non-US counterparts.

In conclusion, this study illuminates the intricate associations between the dark triad personality traits and behavioral biases in investment behavior. These findings emphasize the importance of considering the interplay between personality traits and biases in different cultural contexts. Such insights enhance our understanding of the nuanced drivers of investment behavior and have implications for practitioners seeking to optimize decision-making processes in finance.

This study underscores the imperative for an expanded investigation into the intricate interplay between dark personality traits and behavioral biases, with particular consideration of cultural and national differentials. Understanding these relationships can enhance the assessment of client investment decisions and improve investment outcomes.

1.5.2 The disposition effect and admiration seeking

Suchanek and Liêu (2022) examines the disposition effect and its connection to personality traits, including a concept to assess willingness to pay for social admiration. This study provides additional insights into this bias and contributes to the ongoing discussion of personality traits and behavioral biases.

The findings align with the existing literature on a descriptive level in a sense that for instance male subjects exhibit a greater tendency towards psychopathy than female subjects do (Jonason & Davis, 2018). Furthermore, women tend to display higher levels of extroversion than men do (Costa Jr, Terracciano, & McCrae, 2001; Schmitt, Realo, Voracek, & Allik, 2008; Weisberg, DeYoung, & Hirsh, 2011). For normal personality traits, the findings correspond to those in Chapman, Talbot, Tatman, and Britton (2009); Samek (2017). In addition, the distribution of the dark triad personality traits in the samples overlaps with the previous findings of Preotiuc-Pietro, Carpenter, Giorgi, and Ungar (2016). Finally, a significant association is observed between overconfidence and personality traits, which corresponds to Schaefer et al. (2004).

In addition to the descriptive level replicating different significant correlations among observed attributes, the main part of the analysis shows neither a significant willingness to pay for admiration in connection with the dark triad nor any influence of personality traits on the disposition effect.

The regression models examining the relationship between the big five personality traits and disposition effect revealed non-significant differences across all subscales. These results contrast with those of Lin (2011), who found a significant relationship between conscientiousness and the disposition effect, as well as a significant positive relationship between neuroticism and the disposition effect. These discrepancies may stem from variations in the measurement instruments and methodologies used in different studies comparing the results of experimental and questionnaire-based approaches.

In terms of admiration-seeking behavior, the regression models with the dark triad and honesty-humility traits as exogenous variables showed no significant relationship between these traits and the willingness

to pay for admiration. These results suggest that there is no significant willingness among individuals to pay for admiration and that personality traits do not significantly influence auction behavior in this context.
Nevertheless, regression models featuring the big five personality traits reveal a substantial correlation between agreeableness and augmented bidding magnitudes. This finding, confirming Grebitus, Lusk, and Nayga Jr (2013) partially, indicates that individuals high in agreeableness are more likely to pay a higher amount for an auction price, potentially driven by their inclination to view bidding as an offer rather than a competition.
Overall, this study provides valuable insights into the interplay between the disposition effect, personality traits, and admiration-seeking behaviors.

1.5.3 Social interactions in volatile markets

Suchanek (2024) focuses on the social interactions in volatile markets by looking into three dimensions of investor behavior. First, looking into specific kinds of user submissions in the communities to influence trading behavior motivated by triggering a short squeeze scenario. Such submissions include call investors holding on to their trading positions regardless of current price movements; thus, short sellers need to rebuy their shares at current rates. The second dimension covers the textual sentiments of submissions. The third section examines stock performance metrics.
Using a tripartite approach, this study augments existing insights into sentiment and stock performance metrics while illuminating novel dimensions within submission content and motivations.
For textual sentiment, the literature differs in findings from negative sentiment associated with contemporary and next-day abnormal returns (Chen, De, Hu, & Hwang, 2014) to positive messages predicting negative returns (Antweiler & Frank, 2004), to no influence, where the value of the stock index on a given day is not related to the sentiment level in Internet messages on the next day (Das & Chen, 2007). The third study did not find a significant relationship between textual sentiment and returns but showed a positive bidirectional Granger-causality with the trading volume of the GME stock, confirming the existing literature (Checkley, Higón, & Alles, 2017; Wu, Liu, Zou, & Weng, 2022).
Regarding stock performance metrics, the findings add up with Clark (1973), who find no significant relationship between logged returns and volume.
Foremost among the contributions to the literature, however, is the incisive analysis of submission intent dimensions, which showed that in the case of a positive shock in diamond hand submissions, the GME and BB's trading volumes dropped after delays of 10 and 3 hours, respectively. However, when GME-specific diamond hand submissions originated from the /r/wallstreetbets community, no significance was found. This shows that the /r/GME community seemed to follow the appeal to hold its investments, resulting in reduced order volume. Different subreddits and stock constellations can lead to variations in behavior and responses to the same intent or concept of diamond hands.
Furthermore, the findings are robust when controlling for the number of submissions reflecting the subreddit's activity.

1.6 Conclusion

This dissertation contributes to two important areas of behavioral financing. It provides new insights into the discussion around personality traits and their connection to behavioral biases, as well as social interactions between investors.
It combines the dark triad with investment decision-making in the context of behavioral biases by considering the herding, home bias, overconfidence, and the disposition effect.

In addition to an observable significant relationship in the data of the empirical survey setting, the disposition effect also appears in the experimental setting while being significantly correlated with selected personality traits. Here, participants showed no significant willingness to pay for admiration in an auction setting to receive a participant certificate designed to be shared on social media.

By extending the framework to social interactions between investors, this dissertation shows that social media influences stock performance metrics and vice versa for specific stocks and social communities. It also shows a significant relationship between sentiment and stock volumes.

Overall, the results elaborate on the relationship between behavioral biases and dark personality traits and further how social interactions between investors can influence stock markets in significant ways. This raises the question of whether and how regulatory bodies want to include personality and social interactions in their investor protection guidelines.

This dissertation proposes various practical applications for these findings regarding regulatory standards. In the past, behavioral biases have also been integrated in regulatory decision making, for instance by enhancing reporting standards, such as in the case of home bias, international operating companies were required to simplify their balance sheet structure to make it more understandable to investors (Beneish & Yohn, 2008). On an individual level, financial institutions might also benefit from enhancing client investment profiles beyond the regulatory standard (Bellofatto, D'Hondt, & De Winne, 2018) to include personality assessments of the clients to enhance client service levels.

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2 The dark triad and investment behavior

The dark triad and investment behavior

Max Suchanek[1]

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Abstract

This paper studies the influence of dark personality traits, machiavellianism, narcissism and psychopathy on several behavioral biases. Using survey data and a multiple linear regression framework, a relationship between the dark triad and home bias, overconfidence and herd mentality was found on a data set of 298 individuals. The relation is particularly pronounced for US nationals. US subjects with more pronounced dark traits are more vulnerable to overconfidence and herd mentality, but less affected by the home bias.

Keywords: Dark triad, personality traits, behavioral biases, investment behavior

2.1 Introduction

Behavioral biases in financial decision making have been widely analyzed regarding demographic factors and risk attitude (Lin (2011); Bhandari and Deaves (2006); Nosić and Weber (2010)). Yet, the link between these biases and a subject's personality, was only recently established through selected psychological models like the big-five-personality-model or other single selected personality traits by Rzeszutek (2015) or Baker, Kumar, and Goyal (2019). This study adds to this stream of the literature and study the relation between dark personality traits, machiavellianism, narcissism and psychopathy, and investors' overconfidence, home bias, and herd mentality.

Over recent years the concept of this "*dark triad*" gained more and more popularity. With topics like internet trolling, the noticeable behavior of CEOs and politicians, dark personality traits became present in the media. With a light, still reliable methodological way of assessing these dark personality traits through the so-called dirty dozen, (Jonason & Webster, 2010) the inclusion into the context of behavioral finance seems to be a next step research needs to take. Despite the rising interest for dark personality traits and the possibility for an easy assessment, research has not yet considered the link to behavioral biases. This study closes this existing research gap by focusing on the concept of the dark triad and setting it into context of appearance and strength of important behavioral biases. Hereby, the focus is on home bias, overconfidence and herd mentality. Overconfidence and herd behavior count to the investors' ten most common mistakes (Ritholtz, 2012). Home bias is taken into consideration because of the anticipated diversified portfolio investors would hold according to modern portfolio theory (Ardalan, 2018). Research has defined home bias as one of the six major puzzles in international macroeconomics

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(Obstfeld & Rogoff, 2001) and it "*is still prevalent in most countries*" (Ardalan, 2018). Furthermore, it allows to observe how the dark triad affects asset allocation. Overconfidence is considered since it is one of the most studied behavioral biases (Billett & Qian, 2008; Chen, Kim, Nofsinger, & Rui, 2007; Doukas & Petmezas, 2007; Forbes, 2005). Finally, current trends like social investing and social trading are fostering the interaction between investors (Pelster & Hofmann, 2017). This connectivity paired with rising impact of social media in terms of financial decision making (Deringer, 2012) leads our focus on the herd mentality bias. Beside the popularity in research and society these biases were selected due to the expected correlation with certain character traits explained in the later sections of this paper. With an expected correlation in mind, it is highly relevant to investigate the impact of character traits on these biases.

The data of this study was gained by conducting an online survey over the online marketplace 'Amazon-MTurk'. The dataset was divided in a US and Non-US nationality sample to study potential variation across cultures. This cross-cultural comparison is based on the results of previous research (Raihani & Deutchman, 2017) which showed significant difference for US and Non-US subjects in scoring for dark personality traits. Furthermore, there are significant differences for the appearance of biases across cultures. Investment portfolios in countries with a higher degree of masculinity and long-term orientation showed less home bias (Anderson, Fedenia, Hirschey, & Skiba, 2011).

By conducting multiple linear regression analysis, the analysis showed that the dark triad is more pronounced for Non-US subjects and has no significant influence on behavioral biases. For subjects with US nationality, however, the dark triad affects the financial decision making in a significant way, even though the trait seems to be less disseminated compared to other nationalities. The dark triad is significantly correlated to overconfidence, the home bias, and herd mentality. The higher a US-subject scored on the dark triad scale, the higher was the manifestation of the biases overconfidence and herd mentality. At the same time, a higher dark triad is related to less exposure of the home bias.

These results might be to explain with taking cross culture variations into account: With an outstanding economic growth in the past, the US anchored their special relationship with money deep in their society. According to Hofstede (2001) the cultural dimension of individualism, was the highest for the US. The effect of culture in shaping investment behavior can now also be found for dark personality traits. Therefore, our findings may be explained by a different fundamental base for financial decision making for US-subjects compared to other nationalities. Dark personality traits are included in financial decisions for US but excluded for Non-US subjects because of cultural background. The shown individualism expresses in financial decision making also within dark personality traits being more significant in it.

To understand the existing research on personality traits, the paper continues with a short literature review. Then, the concept of the dark triad is introduced by creating a stereotype for each personality trait. One part of this is the context of cultural, nationality and gender-based differences. Hereinafter, these personality traits are set into the financial context. With this understanding of the dark triad in mind, the paper describes the data and methodology used for the analysis. In the next section, the findings were described. The final section discusses the results and the practical usage of the findings.

2.2 Literature Review

By reviewing current literature, this section highlights the link between personality traits and behavioral biases. Baker et al. (2019) examine the relation between the big five personality traits and overconfidence, disposition effect, anchoring, representativeness, mental accounting, emotional bias and herding for Indian individual investors. They show that four personality traits are significantly associated with the selected

biases and that agreeableness is the only one with no significant influence. For instance, extroverted investors orient their decisions on past performance as well as the group's opinion and are therefore more exposed to especially the herding bias. Furthermore, the authors show that the personality trait neuroticism has a significant influence on all selected biases. These findings are consistent with previous research done by Lin (2011) and Sadi, Asl, Rostami, Gholipour, and Gholipout (2011).

In a similar vein, Rzeszutek (2015) studied the influence of the Eysneck's personality traits (impulsivity, venturesomeness and empathy) and selected behavioral biases (overconfidence, mental accounting and sunk-cost fallacy) with a sample of retail investors from the polish market. Within the included personality traits, only venturesomeness was statistically significant and influenced the rationality of the investors' decisions in the way that a higher level was associated with lower probability of behavioral biases.

This study adds to this literature by extending the existing relationship between personality traits and behavioral biases to the dark triad.

2.3 The dark triad

The "*dark triad*" as construct of three dark personality dimensions consists of machiavellianism, narcissism and psychopathy was introduced by Paulhus and Williams (2002). In order to paint a picture of individuals with these personality traits, the following section explains them one by one. First, there will be a definition and short excurse on the origin of the personality trait. Afterwards, features of the addressed trait will be shown. At last, with a complete picture of the concept, the translation into financial context will be made.

2.3.1 Machiavellianism

Machiavellianism dates to the advisor of the reigning Medici family named Niccolo Machiavelli in the early 16th century. Core belief within his advices can be narrowed down to "*the end justifies the means*". (Jones & Paulhus, 2009). This motive enhanced the political agenda at the time to unethical decision making like lying or bribery. A self-initiated manipulative behavior of other individuals (Christie & Geis, 1970) and opportunism in interpersonal relationship described henceforth a machiavellian on individual level. According to the authors, machiavellianism consists out of three core dimensions: the intention to manipulate others, a cynical view on a person's nature and the disregard for common morality understanding. In addition to the manipulative behavior, individuals high in machiavellianism tend to keep knowledge for themselves (Liu, 2008).

Beside the political concept and manifestations in individual's behavior, gender plays a diversified role: Christie and Geis (1970) discovered higher machiavellianism scores for men while Rayburn and Rayburn (1996) found a higher female score. In more recent literature of Webster and Harmon (2002) there were similar machiavellianism scores for both genders. These gender differences seem to depend on the experiment design and used scale.

Manifestation of machiavellianism differs also between cultures: Since the concept of measuring machiavellianism was widely studied in the western civilization historically, Hwang and Marsella (1977) showed in their research case for Chinese and American college students that older measurements of machiavellianism (Mach IV) might lack conceptual and behavioral equivalency.

Furthermore, machiavellianism has become one of the most popular personality dimensions in studying career development and leadership behavior: Hereby, classical research focuses on students in the business area as possible future leaders. Research by Elias and Farag (2010) showed that students expressed

a higher love of money tended to be machiavellians. With this finding the authors proposed to leadership instructors that they should focus on ethical environment in finance. This focus should lead to a reduction on the "win-at-all-costs" mentality. On the other hand, Bloodgood, Turnley, and Mudrack (2007) found that after taking only one business ethics course, the machiavellian view of the participants had not changed significantly. Similar research conducted by Ritter (2006) focused as well on changing machiavellianism and unethical behavior through an ethics training. In the short run this might have a small effect for female - but no effect for male students his work states.

2.3.2 Narcissism

Narcissism dates to the Greek mythos of Narziss who felt in love with his own reflection while bending over a pond. He plunged into the water when he tried to kiss it. John Tzetzes describes it as "*grandiose sense of self-importance and entitlement; [...] preoccupied with fantasies of unlimited success, power, brilliance or ideal love; generally lack empathy; may not recognize the needs and feelings of others; and may consciously or unwittingly exploit others.*" (Corry, Merritt, Mrug, & Pamp, 2008). Within this statement, there are three main facets of narcissism derived: Exploitative/ entitlement, leadership/ authority and grandiose/ exhibitionism. These facets were instrumentalized over the narcissistic personality inventory (NPI) from Raskin and Hall (1979) which is the most popular used instrument for measuring narcissism in non-clinical environment. Out of these facets, narcissism manifests itself in self-centered, entitled, domineering as well as distrustful, neurotic and introverted behavior (Miller, Lynam, Hyatt, & Campbell, 2017).

There was no significant difference between genders observed in early years of researching narcissism. However, Philipson (1985) stated the disproportionate representation of men during his time as a reason for further research on gender differences. According to (Grijalva et al., 2015) men tend to be more narcissistic than women – an effect that was stable for a U.S. college student sample over time and across age groups.

In addition, there is the facet of collective narcissism: It expands the basic concept beyond individual behavior into group dynamics. This type cannot be narrowed down to only similar cultural or ethnical aspects of a group. It includes a strong ingroup-love and outgroup hate.

For an ethnical and cultural view on narcissism, Pickard, Barry, Wallace, and Zeigler-Hill (2013) showed with their results that Afro-American subjects scored higher than Caucasian ones. In this study, the ethnical aspect of narcissism could only be shown with a relatively small magnitude. For nationality aspects, Gordon (2018) states that Americans view themselves as more narcissistic than other nations. In addition to that respondents from other countries tend to agree with this affiliates this finding to the more individualistic attitude of Americans. statement. The author affiliates this finding to the more individualistic attitude of Americans. This is also reinforced by Jonason et al. (2017), who found that "*America was the most narcissistic [country] [...] whereas Japan was the least*".

2.3.3 Psychopathy

Research differentiates between clinical and empirical (non-clinical) psychopathy: Clinical aspects of psychopathy originate from the early studies of Cleckley, an American psychiatrist who collected conversations with patients in his publication "*Mask of Sanity*" in 1941 (Cleckley, 1982). The title states the main concept of an outwards normally acting individual but an internal calamitous behavior. This concept is also known as the so-called shallow affect – the hiding or absence of emotions (Viding, McCrory, & Seara-Cardoso, 2014). Whereas non-clinical psychopathy goes back to the Hare Psychopathy Checklist (PCL-R) which is a standardized framework of the psychiatric diagnostic. This checklist instrumental-

izes the psychopathic personality characteristics with previously collected information as a basis. The higher an individual performs on the Hare scale the more psychopathic characteristics can be found. This concept makes the PCL-R more usable for research purpose.

Psychopaths behave grandiose, arrogant, callous, dominant, superficial, and manipulative on individual level (Hare, 2006). Furthermore, psychopathy includes personality traits like emotional detachment and guiltlessness (Fowles & Dindo, 2009). Looking at gender specific manifestations of psychopathy is complicated by the segregating design of experiments pointed out by Efferson and Glenn (2018): In many studies the authors reviewed males and females were separated in the analysis part. Another aspect beside the design of the experiments is also the application of the different psychopathy scales in which females are included with a lower threshold. These aggravations in a possible comparison are already found in Nicholls and Petrila (2005) who stated the difficulty to separate socio-cultural effects and narrow down psychopathic differences to gender only. Both overviews pointed out the need for further research of especially female psychopathy.

A similar picture can be found for an ethical view: Cooke, Kosson, and Michie (2001) as well as Skeem, Edens, Camp, and Colwell (2004) found no significant differences in levels of psychopathy for Caucasian and African American subjects.

2.3.4 Dark triad in financial context

With the influence of the dark triad personality traits on individual level in mind, the next step is to crystallize the role on financial decision making. In a wider setting, Sekscinska and Rudzinska-Wojciechowska (2019) provided a literature overview of the relationship between the dark triad and risk-taking and gambling. Here the authors include not only financial risk-aspects but also the tendency to substance use and behavior in the road traffic. Beside the risk-taking there have also been studies of direct connection between financial related topics and the dark triad: One example mentioned by the authors is the importance for narcissistic individuals to reach economic goals - stated by Roberts and Robins (2000). But this goal-driven behavior regarding the wealth itself would not be the primary motive, but the associated power and prestige that comes with it (Ng, Tam, & Shu, 2010). The presentation of money and material possessions are especially important for narcissists according to Pilch and Górnik-Durose (2016). Foster, Misra, and Reidy (2009) showed the preference for stocks rather than bonds for narcissists. A weak avoidance motivation in connection with a strong approach motivation were predominant for this preference. This behavior could also be demonstrated by Foster et al. (2011): In a study the authors created a business game where the participants had to manage a portfolio for five weeks. Led by the heightened approach motivation, narcissists preferred investments in more volatile stocks. This aggressive/ risk seeking investment strategy did not pay-off in the end and so narcissisms ended up with significant less money compared to the other participants. Beside the literature focus on the choice of investment instruments, Rose (2007) showed also positive associations between narcissism and compulsive buying behavior. This buying behavior can also transfer to investment decisions.

Another example of psychopathy in finance context lies within the behavior of certain CEOs. That is because they tend to block upward mobility and financial security for the working-class Americans Eidelson (2019). This behavior is strongly related to psychopathy. Prominent example of this psychopathy within leadership positions comes from Randy Miller - responsible for Amazons vendor relations in Europe. According to Stone (2013) he "*took an almost sadistic delight in pressuring book publishers to give Amazon more favorable financial terms*" (Stone, 2013). Stone states that Miller would prompt to raise prices of the book publishers work, take them off the recommendation lists or promote competing titles in order to get better conditions.

Despite the known influence of machiavellianism, narcissism and psychopathy on financial decision-making and the shown relevant influence from personality traits on behavioral biases, there is no connection between the two concepts in place.

2.4 Behavioral biases

Due to the growing number of behavioral biases (Barberis & Thaler, 2002) a focus for deeper research is needed. This paper focusses on three popular biases described in more details within the next section.

2.4.1 Home bias

Within home bias subjects are more likely to trade with other subjects in the same geographical area rather than outside of it (Lin & Viswanathan, 2016). In an investment context, this describes higher exposure to stocks of companies located in the individual's home country. One of the main reasons for home bias is often stated in transaction costs that would come up for an international investment. Results from Domowitz, Glen, and Madhavan (2002) and Warnock (2002) on the other hand suggest that transaction costs are not directly related to home bias Another foundation of this bias lies within the believe of the individual to be more experienced and informed about the home market. Lastly the necessary currency differences leading to foreign exchange risk. Therefore, investing in the home market seems more affordable and secure. This behavior results in an inadequate portfolio allocation by creating country and/ or currency specific bulk risks. Multiple factors influence the appearance and strength of this bias as well: Existing cross-border boundaries like changing the exchange in a stock-order result in higher prices or exchange rate risk (Ke, Ng, & Wang, 2010).

2.4.2 Overconfidence

Defined as the systematic misjudgment of own abilities and competence. Being overconfident in investment decisions leads to the engagement into riskier positions. As stated, overconfidence receives lots of attention within behavioral finance (Billett & Qian, 2008; Chen et al., 2007; Doukas & Petmezas, 2007; Forbes, 2005). It can be found in two forms: There is the kind of overconfidence arising from self-serving bias, where individuals assign success to their own behavior (Myers, 2014). On the other hand, there is illusory superiority, which is the case when an individual overestimates their own skills (Hoorens, 1993). In this paper, the focus is on illusory superiority.

There are differences in overconfidence on nationality level: Acker and Duck (2008) found that Asians are consistently more overconfident than the British. This trend of Asian overconfidence was also shown in comparison to individuals from United States (Li & Fang, 2004). Furthermore, it was shown that individuals heading firms headquartered in Christian countries that encourage individualism, within Hofstedes cultural dimensions were most extensively overconfident (Ferris, Jayaraman, & Sabherwal, 2013).

2.4.3 Herd mentality

Herd mentality describes the circumstance of subjects being influenced by others in order to behave likewise. Outcome of this bias can be a facilitation of bubble building in the financial market. E.g. the crypto bubble end of 2018 with prices of cryptocurrencies driven by herding behavior (Calderon, 2018). Jones 2017 specifically focuses on the herd mentality for Americans. With a derivation from history he shows how particular herd events have manifested in the American society like the "*California Gold Rush, the race to Kansas (Bleeding Kansas), slavery from 1854–1861, and the Panic of 1893, [...] to*

the Red Scare of the 1940s and 1950s" (Jones, 2013a). Due to this quick sequence of these events that promoted herd mentality within the US, this bias takes up a special role for Americans.

2.5 Dataset and methodology

2.5.1 Data collection

The data for this study was collected using an online survey on the crowdsourcing marketplace Amazon-MTurk. Data was collected from 08th June 2019 to 31st August 2019 with two filters in place on the data platform itself: First, survey participants or "workers" in the providers terminology had to be older than 21 years. Additionally, they had to be employed in the banking and financial services industry. After collection of the data, a cleanup was performed. Every individual that had no complete data on dark triad personality traits or refused to answer responses (e.g. by always marking the first answer field in the questionnaire and leaving free text fields empty) was extracted. This resulted in a final dataset of 298 participants.

To address the validity of this data collection methodology, the following paragraph explains specific problems that might occur when using it. One of these specific issues for online surveys are multiple submissions (Tuten et al., 2002). A unique worker ID linked to the subject's user account prevented this issue for the chosen provider. With this in place, the survey was restricted to only unique worker IDs. The only way still to submit multiple times would be over multiple user accounts on the provider's platform. There was no further mitigation for this possible misbehavior of the participants.

There were no restrictions in terms of nationality for the data collection. Here the advantage of the online survey came into play regarding wide geographic coverage (Evans & Mathur, 2005). Furthermore, data collection on personality traits by using an online survey is widely established e.g. by Donnelly et al. (2012), Migliore (2011) or Fox and Rooney (2015).

The questionnaire consisted of 30 questions in total, divided into (1) six questions about the meta data and demographics, (2) four questions about behavioral finance and (3) the assessment of the dark triad personality traits with the dirty dozen (Jonason & Webster, 2010)and other personality trait related questions. The dirty dozen questions were scattered among the character questions. This was to reduce the influence of the answers regarding the order of the questions.

2.5.2 Variables

Dark triad: The dark triad was assessed over the single dimensions with the dirty dozen questionnaire from Jonason and Webster (2010). Here, a Likert scale instrumentalized the different personality traits machiavellianism, narcissism and psychopathy to numerical values 1-5. The average out of the three dark triad elements was merged into one key figure for each subject. Hereby, the variable ranges from 1 to 5 (for this method see also Jonason and Webster (2010)). To check the internal reliability and consistency, Cronbach's alpha was determined in Table 2.1: A result of 0.85 for the dark triad single scale showed no violation of internal consistency for the scale selected. This value is comparable with Jonason and Webster (2010) who reached 0.83 for a combined dark triad variable. Beside the key figure of the dark triad, similar results were found for the separate parts. Due to the omitting of double-barreled questions in the questionnaire like "*I tend to not be too concerned with morality or the morality of my actions*" (Jonason & Webster, 2010) also psychopathy scored relatively high in this survey. The comparative paper solved this problem in conducting another study by rephrasing the question, resulting in a "*markedly stronger α for the psychopathy subscale*" (Jonason & Webster, 2010) (0.77). Since no combined or single

instrument scored less than 0.7, they are valid for further analysis. Furthermore, no instrument scored an alpha above 0.95, so there seems to be no redundancy in place.

Home bias: This survey measures home bias with the question of how many percent of its wealth a subject invests into international shares. Defining the term international as belonging to a company not based in the subject's home country. Taking the reciprocal value resulted in a measurement of the home bias. Similar measurement and questionnaire formulations were used by the UBS/Gallup Investor Optimism Index (1996 - 2002), Lütje and Menkhoff (2007).

Overconfidence: In this survey the overconfidence was measured with the question how the subject would rate the success rate of their investment decisions compared with their peers on a Likert scale. This approach in question construction is commonly used by e.g. Nosić and Weber (2010), Park et al. (2010) and Gort (2009). For both, US and Non-US subjects, a similar behavior was found: Beside the concentration around the average, there is a tendency for the subjects to find themselves on the right side of the distribution. The strength of this seems to not vary across the samples.

Herd mentality: Herd mentality was assessed by asking subjects how rumors in the market affect their own decision making on a Likert scale. This question extracted from Vidyapith (2015) was part of a way larger set of questions targeting the measurement of herd mentality. Both samples are homogeneously distributed for this bias.

Methodological approach: To see the influence from dark triad on behavioral biases, multiple linear regression models were constructed. Where dark triad was the independent variable and the biases acted as endogen variable. Home bias is rational scaled (1-100), while a Likert scale measures the other two biases. For some questions in the dark triad, a recoding had to take place due to the formulation of the question. This standard procedure is part of the dirty dozen methodology and means that some values were mirrored due to negative questions. Three models were designed to see if the assumed influence is consistent by including different variables: The basic regression model includes only the three biases as dependent variable and dark triad as the only explanatory variable. The next model was structured by enhancing the basis model with the socio-demographic factors gender, age and education. The third model enhanced the second with financial factors: Investment horizon, measures how long a subject is willing to invest without a cash-out event. Information frequency refers to the degree of how updated a subject is with current market behavior. The first step was to divide the sample on the level of nationality. Afterwards the regressions were run with the variables stated above.

2.6 Findings

This paragraph describes the findings in the descriptive statistics and for each regression model. Figure 2.1 shows the differentiation of the data set into 190 subjects with US - and 108 with other nationalities (e.g. Indian, German, Swiss). For the US nationality sample, a slightly more left skewed distribution could be observed for dark triad. US dark triad was indeed significant different from the Non-US distribution with a Mann-Whitney-U p-value of 0.0004599. These findings correspond with e.g. Deutchman and Raihani (2017) who find also that Non-US (in their case Indians) scored higher on dark triad traits than subjects from the US. Despite the higher sample size of the US sample, there were significantly more subjects with very little manifestation of dark triad compared to the Non-US sample. In addition, there was a higher amount of Non-US subjects with high value in the dark triad sample. Five subjects scored between four and five points on the dark triad scale, while in the US sample only three were represented in this bucket. This is remarkably since there were nearly double subjects in the US sample.

The dark triad key figure is correlated with home bias, overconfidence and herd mentality, shown in Figure 2.2. The herd mentality for the US sample, however, shows the strongest correlation between biases and dark triad from both samples.

For home bias in Table 2.2, US subjects showed a higher exposure to home bias than Non-US subjects. This effect comes from the larger tail of people not exposed to home bias at all in the Non-US sample. For them, a more parabola-like distribution was found. In addition, the values in the center of the distribution were more distinct for this sample. The distribution of overconfidence displayed in Figure 2.3 showed no significant difference between US and Non-US nationality. This picture carries on for herd mentality, pointed out in Figure 2.4.

To run the regression analysis, other external variables were included: Gender, as binary variable, education, salary and the information frequency on financial matters of the subject as ordinal scaling variables. Before going over to the results of the regression analysis, the general overview of all variables in the descriptive view on Table 2.3 showed, that for Non-US subjects the average dark triad was higher than for US subjects. This is also fitting for every single trait of it. Both sample sets showed similar distribution regarding age. Considering that AmazonMTurk workers are supposed to be slightly younger than the US population (Casler, Bickel, & Hackett, 2013). Regarding biases, the US sample showed higher home bias on average. The subjects stated their portfolio allocation in the beginning of the financial part. There was no significant relationship between narcissism and investment into stocks rather than bonds. Here the data could not confirm Foster et al. (2009).

In the basic regression model, shown in Table 2.4, dark triad did not influence the biases in the Non-US sample but for the US sample. The home bias exposure shrinks with increasing dark triad personality. Overconfidence and herd behavior are positively influenced by dark triad. These directions are valid for all three datasets.

For the second model in Table 2.5, the full, as well as both subsamples show no influence from gender and age on the selected biases. Dark triad still significantly influences the behavioral biases for subjects in the US sample. Only significant influence can be found with education as additional variable within the US sample.

The full model in Table 2.6 added two financial factors - investment horizon and information frequency - that had impact on the relationship: herd behavior and overconfidence were influenced by the investment horizon for the complete dataset. For US and Non-US neither one of the financial factors had an influence on the biases. Furthermore, the dark triad influence was still shown in the US subsample, but only for home- and overconfidence bias. By adding the investment horizon as external variable, the herd mentality bias lost its significance for the US sample. Throughout the adding of more and more external factors, the US sample showed more significant exposure to the dark triad regarding the three biases.

2.7 Discussion and conclusion

Existing literature has shown the significant influence of personality traits onto behavioral biases in financial decision making. This study complements to previous research by unveiling the relationship between the dark triad's personality traits and the appearance of behavioral biases.

First, the data shows a significant negative influence of dark triad onto the appearance of home bias for Americans. A higher overall score, in the combination of machiavellianism, narcissism and psychopathy, leads to less exposure.

Second, the analysis reveals that Americans with higher score in dark personality traits are more exposed to overconfidence and herd mentality compared to Non-US citizens. This effect was significant for several multiple regression models and none of the control variables from demographic or finance area changed the relationship.

The analysis did not find any significant influence of the dark triad for individuals non-US nationality. Overconfidence might be explained by the drive of narcissism in the dark triad: Individuals with a more entitling and self-loving behavior will tend to overconfidence, also in financial matters. This correlates with results from e.g. Jones (2013b) where narcissism predicted greater losses.

On home bias, Graham, Harvey, and Huang (2009) stated "*investors who feel competent trade more often and have a more internationally diversified portfolio*" and therefore are not so likely to fall for home bias. This feeling of competence is rooted in the narcissism personality trait of the dark triad. The current study shows that a high degree of dark triad is likely to reduce the exposition to home bias and adds therefore to Graham et al. (2009). People who care more convinced about their competence are more likely to invest internationally.

Beside these findings, the study is subject to limitations: For home bias, the complexity of financial instruments is not fully exhausted due to the convention of a simple questionnaire. The issue with accessing home bias in a simple question like this comes with the complexity of financial instruments: Funds that note their value in USD might be investing in a multi-national portfolio with different currencies in place, where home bias is not applicable.

For application of these findings into real life finance, a link to the collection and handling of Know-Your-Client data seems to be a reasonable starting point: Increasing regulatory requirements within the financial industry have led to a collection of Know-Your-Client information in a dimension never seen before. This data reflects the degree of a client's knowledge and experience about certain financial products. Furthermore, information about the client's source of wealth/ funds/ investments are mandatory. Within all this collected data, the assessment of personality traits is omitted. This study showed with an assessment of the dark triad through the dirty dozen questionnaire that for US nationality clients the personality has a significant influence on behavioral biases.

For research, the study revealed that the field of dark personality traits in combination with behavioral biases needs more attention. The differences in sample group on nationality level is interesting besides a more and more globalized investment market. Future research could explore subsequent questions like how do dark triads influence biases for other nationalities in detail.

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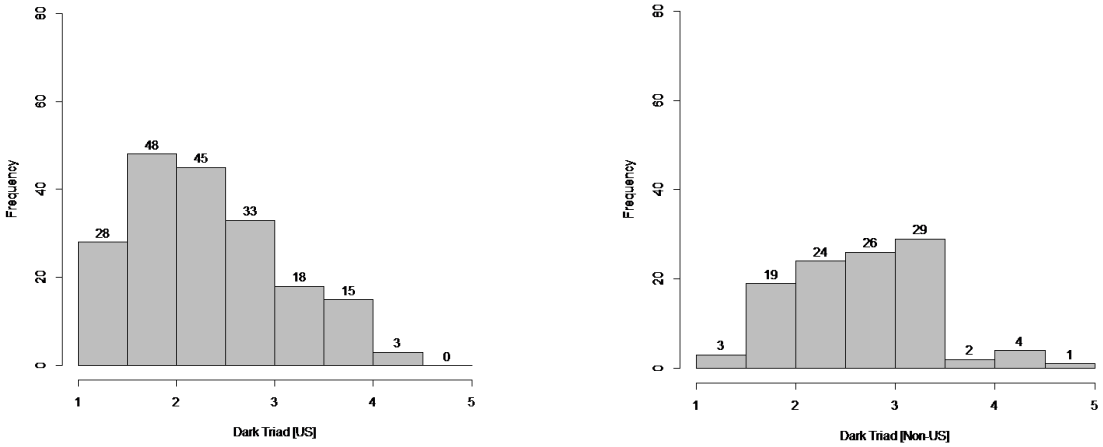

Figure 2.1: Distribution of dark triad across nationalities

Dark triad is measured by taking the average out of three subvariables: machiavellianism, narcissism and psychopathy – each measured with a Likert scale, one to five, consisting out of 4 questions for each variable, also within Likert scales.

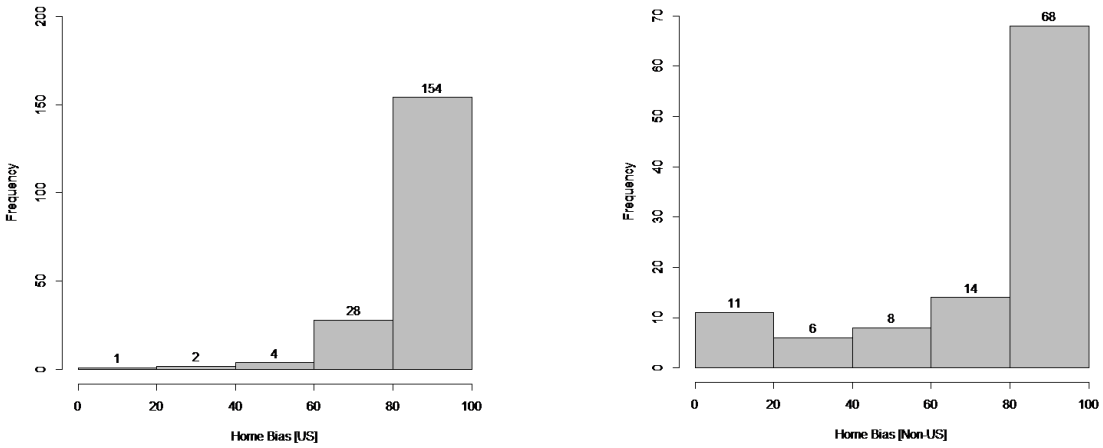

Figure 2.2: Distribution of home bias across nationalities

Home bias is measured with the inverse value of the percentage of how many of the subject's wealth were invested into international shares.

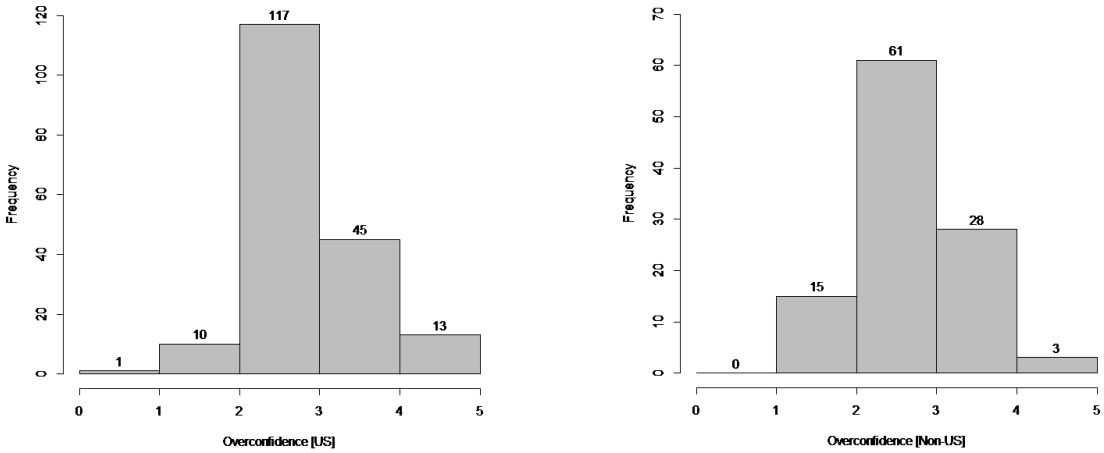

Figure 2.3: Distribution of overconfidence across nationalities

Overconfidence is measured with a Likert scale on how the subject sees the success rate of the investments compared to peers.

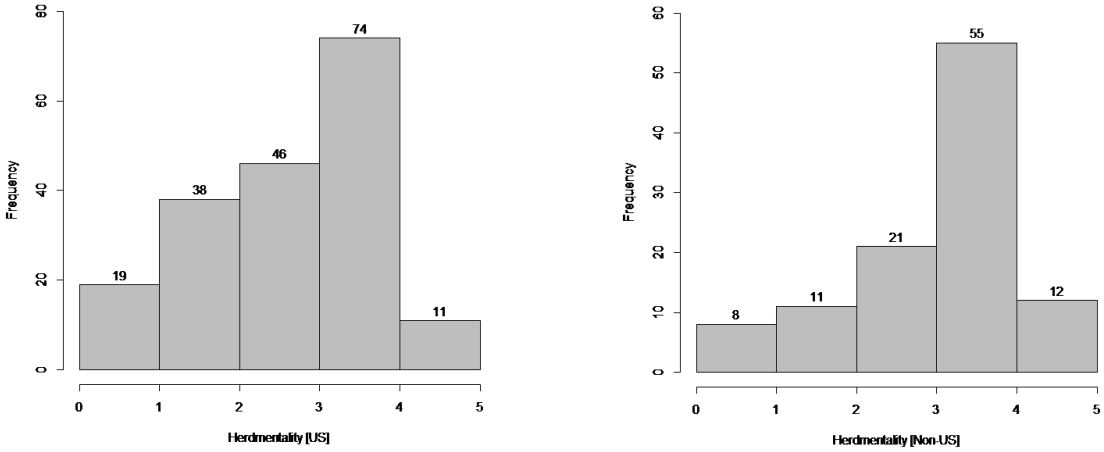

Figure 2.4: Distribution of herd mentality across nationalities

Herd mentality is measured by a Likert scale on how strong rumors in the market affect the subject's decision-making power.

Table 2.1: Cronbach's Alpha for the dark triad and it's components

Raw_alpha	**Std.alpha**	**G6(smc)**	**average_r**	**S/N**	**ase**	**mean**	**sd**	**median_r**
0.85	0.86	1	0.61	6.3	0.015	2.5	0.75	0.66

	raw_alpha	**Std.alpha**	**G6(smc)**	**Average_r**	**S/N**	**ase**	**Var.r**	**med.r**
Dark triad	0.70	0.70	0.65	0.44	2.3	0.030	0.027	0.48
Psychopathy	0.86	0.87	0.91	0.70	7.0	0.016	0.039	0.74
Narcissism	0.88	0.89	0.90	0.73	8.2	0.013	0.023	0.75
Machiavellianism	0.79	0.81	0.92	0.58	4.2	0.024	0.082	0.74

Dark triad is measured by taking the average out of three subvariables: machiavellianism, narcissism and psychopathy – each measured with a Likert scale.

Table 2.2: Correlation of dark triad and the selected biases

	Dark triad	**Home bias**	**Overconfidence**	**Herdmentality**
Dark triad	1.00			
Home bias	-0.15*	1.00		
Overconfidence	0.14*	-0.07	1.00	
Herd mentality	0.20***	-0.03	-0.10*	1.00

$^{**}p < 0.001, "p < 0.01, "p < 0.05$

Dark triad is measured by taking the average out of three sub variables: Machiavellianism, Narcissism and Psychopathy – each measured with a Likert scale, one to five, consisting out of 4 questions for each variable, also within Likert scales. Home bias is measured with the inverse value of the percentage of how many of the subject's wealth were invested into international shares. Overconfidence is measured with a Likert scale on how the subject sees the success rate of the investments compared to peers. Herd mentality is measured by a Likert scale on how strong rumors in the market affect the subject's decision-making power.

Table 2.3: Summary statistics

ALL DATA							
Statistic	**N**	**Mean**	**St. Dev**	**Min**	**Pctl(25)**	**Pctl(75)**	**Max**
Dark triad	291	2.45	0.75	1.00	1.92	3.00	4.83
Machiavellianism	291	2.18	0.97	1.00	1.25	2.75	5.00
Psychopathy	291	2.38	0.89	1.00	1.75	3.00	5.00
Narcissism	291	2.79	0.99	1.00	2.00	3.50	5.00
Gender	288	0.43	0.50	0.00	0.00	1.00	1.00
Age	267	36.04	10.02	20.00	28.00	41.00	71.00
Education	291	4.07	0.90	0.00	4.00	5.00	6.00
Investment horizon	291	4.40	1.70	0.00	3.00	6.00	6.00
Information frequency	289	2.98	1.05	1.00	2.00	4.00	4.00
Herd mentality	291	3.24	1.12	1.00	2.00	4.00	5.00
Home bias	291	86.98	22.06	0.00	84.00	100.00	100.00
Overconfidence	291	3.27	0.70	1.00	3.00	4.00	5.00
US DATA							
Statistic	**N**	**Mean**	**St. Dev**	**Min**	**Pctl(25)**	**Pctl(75)**	**Max**
Dark triad	185	2.33	0.75	1.00	1.83	2.75	4.33
Machiavellianism	185	2.10	0.97	1.00	1.20	2.80	5.00
Psychopathy	185	2.25	0.90	1.00	1.50	2.75	4.75
Narcissism	185	2.64	1.02	1.00	2.00	3.50	5.00
Gender	182	0.48	0.50	0.00	0.00	1.00	1.00
Age	175	36.32	10.14	20.00	28.00	42.50	71.00
Education	185	3.92	0.91	0.00	4.00	4.00	6.00
Investment horizon	185	4.70	1.63	1.00	3.00	6.00	6.00
Information frequency	185	3.07	1.04	1.00	3.00	4.00	4.00
Herd mentality	185	3.11	1.12	1.00	2.00	4.00	5.00
Home bias	185	91.62	13.15	10.00	90.00	100.00	100.00
Overconfidence	185	3.32	0.70	1.00	3.00	4.00	5.00
NON-US DATA							
Statistic	**N**	**Mean**	**St. Dev**	**Min**	**Pctl(25)**	**Pctl(75)**	**Max**
Dark triad	106	2.66	0.70	1.25	2.17	3.17	4.83
Machiavellianism	106	2.34	0.95	1.00	1.50	3.00	4.75
Psychopathy	106	2.60	0.84	1.00	2.00	3.25	5.00
Narcissism	106	3.03	0.87	1.00	2.30	3.75	4.75
Gender	106	0.35	0.48	0.00	0.00	1.00	1.00
Age	92	35.50	9.82	23.00	28.00	40.25	67.00
Education	106	4.32	0.82	1.00	4.00	5.00	6.00
Investment horizon	106	3.91	1.70	1.00	3.00	5.00	6.00
Information frequency	104	2.83	1.05	1.00	2.00	4.00	4.00
Herd mentality	106	3.48	1.07	1.00	3.00	4.00	5.00
Home bias	106	78.88	30.61	0.00	70.00	100.00	100.00
Overconfidence	106	3.16	0.69	2.00	3.00	4.00	5.00

The table shows descriptive statistics of the variables used for regression, separately for all subjects (First segment), for subjects with US nationality (Second segment) and subjects without US nationality (Third Segment). Dark triad is measured by taking the average out of three subvariables: Machiavellianism, Narcissism and Psychopathy – each measured with a Likert scale, one to five, consisting out of 4 questions for each variable, also within Likert scales. Home bias is measured with the inverse value of the percentage of how many of the subject's wealth were invested into international shares. Overconfidence is measured with a Likert scale on how the subject sees the success rate of the investments compared to peers. Herd mentality is measured by a Likert scale on how strong rumors in the market affect the subject's decision-making power. Gender is measured as binary variable. Age is measured as range value. Education is measured from one to six. Investment horizon is measured from one to six. Information frequency is

measured from one to four.

Table 2.4: Basic regression model

ALL DATA				US				NON-US			
	Home bias	Overconfidence	Herd mentality		Home bias	Overconfidence	Herd mentality		Home bias	Overconfidence	Herd mentality
(Intercept)	96.45***	2.94***	2.55***	(Intercept)	99.69***	2.92***	2.45***	(Intercept)	80.43***	2.81***	3.00***
	(4.35)	(0.14)	(0.22)		(3.15)	(0.17)	(0.26)		(11.73)	(0.26)	(0.41)
Dark triad	-3.82*	0.13*	0.28**	Dark triad	-3.53**	0.17*	0.28**	Dark triad	-0.54	0.14	0.18
	(1.69)	(0.05)	(0.09)		(1.28)	(0.07)	(0.11)		(4.24)	(0.10)	(0.15)
R2	0.02	0.02	0.03	R2	0.04	0.03	0.04	R2	0.00	0.02	0.01
Adj. R2	0.01	0.02	0.03	Adj. R2	0.03	0.03	0.03	Adj. R2	-0.01	0.01	0.00
Num. obs.	294	291	293	Num. obs.	189	186	188	Num. obs.	107	107	107
RMSE	21.82	0.70	1.10	RMSE	13.25	0.70	1.09	RMSE	30.78	0.69	1.06
***p <0.001, **p <0.01, *p <0.05				***p <0.001, **p <0.01, *p <0.05				***p <0.001, **p <0.01, *p <0.05			

Dark triad is measured by taking the average out of three subvariables: Machiavellianism, Narcissism and Psychopathy – each measured with a Likert scale, one to five, consisting out of 4 questions for each variable, also within Likert scales. Home bias is measured with the inverse value of the percentage of how many of the subject's wealth were invested into international shares. Overconfidence is measured with a Likert scale on how the subject sees the success rate of the investments compared to peers. Herd mentality is measured by a Likert scale on how strong rumors in the market affect the subject's decision-making power. All data contains the complete data set of 298 subjects, whereas the US and Non-US sample were divided through a question about nationality; Questionnaire can be found in the appendix; standard error is listed in parentheses under the coefficient.

Table 2.5: Basic model enhanced with socio-demographic factors gender, age and education.

	ALL DATA				US				NON-US		
	Home bias	Overconfidence	Herd mentality		Home bias	Overconfidence	Herd mentality		Home bias	Overconfidence	Herd mentality
(Intercept)	113.77***	2.89***	2.76***	(Intercept)	105.89***	2.82***	3.06***	(Intercept)	112.61***	2.49***	2.90**
	(9.21)	(0.33)	(0.50)		(6.70)	(0.39)	(0.59)		(27.46)	(0.67)	(0.99)
Dark triad	-3.94*	0.13*	0.28**	Dark triad	-3.17*	0.16*	0.24*	Dark triad	-2.44	0.16	0.27
	(1.70)	(0.06)	(0.09)		(1.27)	(0.07)	(0.11)		(4.68)	(0.11)	(0.17)
Gender	0.93	-0.11	-0.00	Gender	1.46	-0.11	0.12	Gender	-2.95	-0.17	-0.16
	(2.53)	(0.09)	(0.14)		(1.87)	(0.11)	(0.17)		(6.73)	(0.16)	(0.24)
Age	0.08	0.00	-0.01	Age	0.06	0.00	-0.01	Age	0.18	0.01	-0.01
	(0.13)	(0.00)	(0.01)		(0.09)	(0.01)	(0.01)		(0.33)	(0.01)	(0.01)
Education	-4.83***	0.01	0.00	Education	-2.44*	0.04	-0.08	Education	-7.10	0.01	0.04
	(1.42)	(0.05)	(0.08)		(1.06)	(0.06)	(0.09)		(4.04)	(0.10)	(0.15)
R2	0.08	0.02	0.04	R2	0.09	0.04	0.04	R2	0.04	0.03	0.04
Adj. R2	0.06	0.01	0.03	Adj. R2	0.06	0.02	0.02	Adj. R2	-0.00	-0.01	-0.00
Num. obs.	272	269	271	Num. obs.	179	176	178	Num. obs.	93	93	93
RMSE	20.23	0.71	1.09	RMSE	12.32	0.70	1.09	RMSE	29.74	0.72	1.07
***p <0.001, **p <0.01, *p <0.05				***p <0.001, **p <0.01, *p <0.05				***p <0.001, **p <0.01, *p <0.05			

Dark triad is measured by taking the average out of three sub variables: Machiavellianism, Narcissism and Psychopathy – each measured with a Likert scale, one to five, consisting out of 4 questions for each variable, also within Likert scales. Home bias is measured with the inverse value of the percentage of how many of the subject's wealth were invested into international shares. Overconfidence is measured with a Likert scale on how the subject sees the success rate of the investments compared to peers. Herd mentality is measured by a Likert scale on how strong rumors in the market affect the subject's decision-making power. Gender is measured as binary variable. Age is measured as range value. Education is measured from one to six. All data contains the complete data set of 298 subjects, whereas the US and Non-US sample were divided through a question about nationality; Questionnaire can be found in the appendix; standard error is listed in parentheses under the coefficient.

Table 2.6: Basic model enhanced with socio-demographic factors gender, age and education and financial factors investment horizon and Information

	ALL DATA				US				NON-US		
	Home bias	Overconfidence	Herd mentality		Home bias	Overconfidence	Herd mentality		Home bias	Overconfidence	Herd mentality
(Intercept)	110.31***	2.49***	3.15***	(Intercept)	111.65***	2.66***	3.34***	(Intercept)	107.94***	2.24**	3.05**
	(10.33)	(0.36)	(0.55)		(7.78)	(0.45)	(0.69)		(27.97)	(0.66)	(1.01)
Dark triad	-3.90*	0.17**	0.24*	Dark triad	-3.60**	0.17*	0.22	Dark triad	-3.01	0.19	0.24
	(1.77)	(0.06)	(0.09)		(1.32)	(0.08)	(0.12)		(4.97)	(0.12)	(0.18)
Gender	1.05	-0.10	-0.02	Gender	1.15	-0.10	0.11	Gender	-1.68	-0.12	-0.19
	(2.55)	(0.09)	(0.14)		(1.88)	(0.11)	(0.17)		(6.85)	(0.16)	(0.25)
Age	0.07	0.00	-0.01	Age	0.05	0.00	-0.01	Age	0.08	0.00	-0.00
	(0.13)	(0.00)	(0.01)		(0.09)	(0.01)	(0.01)		(0.34)	(0.01)	(0.01)
Education	-5.12***	-0.00	0.00	Education	-2.44*	0.04	-0.09	Education	-8.13	-0.04	0.08
	(1.46)	(0.05)	(0.08)		(1.08)	(0.06)	(0.10)		(4.19)	(0.10)	(0.15)
Investment horizon	0.14	0.07**	-0.08*	Investment horizon	-1.12	0.04	-0.07	Investment horizon	0.93	0.09	-0.07
	(0.74)	(0.03)	(0.04)		(0.57)	(0.03)	(0.05)		(1.99)	(0.05)	(0.07)
Information frequency	1.42	0.02	0.03	Information frequency	0.31	-0.02	0.05	Information frequency	3.35	0.08	-0.02
	(1.19)	(0.04)	(0.06)		(0.87)	(0.05)	(0.08)		(3.42)	(0.08)	(0.12)
R2	0.08	0.05	0.06	R2	0.11	0.05	0.05	R2	0.06	0.09	0.05
Adj. R2	0.06	0.03	0.04	Adj. R2	0.08	0.01	0.02	Adj. R2	-0.01	0.02	-0.01
Num. obs.	271	269	271	Num. obs.	178	176	178	Num. obs.	93	93	93
RMSE	20.29	0.70	1.09	RMSE	12.28	0.70	1.09	RMSE	29.86	0.71	1.08
***p <0.001, **p <0.01, *p <0.05				***p <0.001, **p <0.01, *p <0.05				***p <0.001, **p <0.01, *p <0.05			

Dark triad is measured by taking the average out of three sub variables: Machiavellianism, Narcissism and Psychopathy – each measured with a Likert scale, one to five, consisting out of 4 questions for each variable, also within Likert scales. Home bias is measured with the inverse value of the percentage of how many of the subject's wealth were invested into international shares. Overconfidence is measured with a Likert scale on how the subject sees the success rate of the investments compared to peers. Herd mentality is measured by a Likert scale on how strong rumors in the market affect the subject's decision-making power. Gender is measured as binary variable. Age is measured as range value. Education is measured from one to six. Investment horizon is measured from one to six. Information frequency is measured from one to four. All data contains the complete data set of 298 subjects, whereas the US and Non-US sample were divided through a question about nationality; Questionnaire can be found in the appendix; standard error is listed in parentheses under the coefficient.

II Appendix

II.1 Questionnaire

Demographic part:

1. Please enter your age in years:	-----
2. Please select your gender:	Male Female
3. Please enter your nationality:	-----
4. Please select your highest educational achievement:	Secondary education Secondary vocational education High school Bachelor Master Doctor
5. Select your current profession:	Non-governmental – Finance Non-governmental – Non – Finance Governmental Unemployed Student
6. Please select your annual salary in USD:	< 40.000 USD 40.000 USD – 59.000 USD 60.000 USD – 79.999 USD 80.000 USD – 99.999 USD 100.000 USD – 124.999 USD 125.000 USD – 149.999 USD 150.000 USD – 199.999 USD 200.000 USD – 499.999 USD > 500.000 USD

Financial part:

7. How many % of your wealth have you invested into international shares? (company not based in your home country	_____ %
8. How often do you update yourself on financial matters? (financial blogs, magazines,etc.)	Daily Weekly Monthly Less than one time in a month

9. How long is your general investment horizon?	$\leq$ 1 year – I speculate on fast gains 1 – 2 years 2 – 3 years 3 – 4 years 5 – 10 years $>$ 10 years – I invest long term related
10. How would you rate the success of your investment decisions compared to your peers (colleagues, the market, etc.)	Very unsuccessful Quite unsuccessful Average Successful Very successful

Personality traits

11. I see myself as someone who is talkative	Disagree strongly Disagree a little Neither agree nor disagree Agree a little Agree strongly
12. I tend to manipulate other to get my way	Disagree strongly Disagree a little Neither agree nor disagree Agree a little Agree strongly
13. I see myself as someone who prefers work that is routine	Disagree strongly Disagree a little Neither agree nor disagree Agree a little Agree strongly
14. I see myself as someone who is easily distracted	Disagree strongly Disagree a little Neither agree nor disagree Agree a little Agree strongly
15. I see myself as someone who tends to be disorganized	Disagree strongly Disagree a little Neither agree nor disagree Agree a little Agree strongly

16. I see myself as someone who is original, comes up with new ideas

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

17. I see myself as someone who has an active imagination:

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

18. I see myself as someone who tends to be quiet:

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

19. I use flattery to get my way

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

20. I tend to seek prestige or status

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

21. I tend to not be too concerned with morality or the morality of my actions

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

22. I have used deceit or lied to get my way

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

23. I tend to be cynical

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

24. I tend to be callous or insensitive

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

25. I tend to want others to admire me

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

26. I tend to exploit others towards my own end

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

27. I tend to want others to pay attention to me

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

28. I tend to lack remorse

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

29. I tend to expect special favors from others

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

30. I see myself as someone who is outgoing or sociable:

Disagree strongly
Disagree a little
Neither agree nor disagree
Agree a little
Agree strongly

3 The disposition effect and admiration seeking

The disposition effect and admiration seeking

Suchanek, Max and Minh-Lỳ, Liêu[1]

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Abstract

This paper examines the relationship between the disposition effect and personality traits and aims to find an additional explanation of this bias in a willingness to pay for admiration. We conduct a personality assessment, a stock trading game and a sealed-bid English auction for 84 individual investors. The gathered data correspond with the literature on a descriptive level; however, even though admiration-seeking behavior is an important part of social interaction, there is no significant willingness to pay for it. Furthermore, we do not see any influence of personality on the disposition effect. Our findings add to the ongoing discussion of personality traits in connection with behavioral biases.

Keywords: admiration, big five, dark triad, disposition effect, personality traits

3.1 Introduction

Personality traits and financial decision making have been widely assessed by current research, e.g., on household finances (Brown & Taylor, 2014) or risk tolerance (Pinjisakikool, 2017). Furthermore, personality traits play an important role in regard to the appearance and strength of behavioral biases. For example, Rzeszutek, Szyszka, and Czerwonka (2015) indicate that individuals with the traits of impulsivity and empathy are more susceptible to all three of the biases included certainty effect, sunk-cost fallacy and mental accounting. Additionally, Lin (2011) finds that individuals high in the trait openness are prone to herding bias. The disposition effect—the tendency to sell winning positions early and keep losing positions in the books (Shefrin & Statman, 1985)—is one of those biases. This effect is independent of asset classes and even occurs among experienced investors (Grinblatt & Keloharju, 2001). It is a very popular behavioral bias experiencing high research coverage (Haryanto, Subroto, & Ulpah, 2020; Von Beschwitz & Massa, 2020) and is specially affected by social settings; Heimer (2016) showed that "*self-image or reputation [...] contributes to the disposition effect*". Introducing an interaction between individuals by allowing access to a social network has a significant influence on individuals' trading behavior, which ultimately increases the disposition effect. By leveraging this argument of reputation (Heimer, 2016), some individuals show a higher disposition effect in a social setting, which could indicate admiration-seeking behavior (see Pelster and Hofmann (2018) for a similar argument).
Based on this argument, a facet of narcissism (Rijsenbilt & Commandeur, 2013) may drive the disposition

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effect. In this case, the reputation power arising from possessions (Belk, 1985) would outrank the plain purchasing function for certain individuals (Pilch & Górnik-Durose, 2016). Individuals might prioritize admiration over the monetary value of trading profits. Therefore, we would expect a trade-off between the social admiration that an individual receives and the monetary payoffs. Explaining this relationship could contribute to a better understanding of preference construction and how much admiration is worth to an individual in a social setting.

In this paper, we concentrate our research on the disposition effect and the measurement of admiration-seeking behavior and aim to test whether investors' personality explains their behaviors. We pose two important research questions. First, we ask whether there is a significant influence of personality traits on the disposition effect. Second, we ask whether there exists a willingness to pay for admiration.

For our analysis, we combine reliable personality assessment inventories, i.e., the dark triad, the honesty-humility dimension of the HEXACO[1] and the big five. We implement a widely used stock trading game to measure the disposition effect and set up a reliable auction design to measure willingness to pay for admiration. In addition to providing insights into the disposition effect of participants, the stock trading game also allows the introduction of a social setting through a leaderboard. Coming out of the trading game, each participant has a certain balance in a virtual currency available depending on the achieved performance. Additionally, the participants know their place on the leaderboard. They have the possibility to take part in a sealed-bid English auction measuring the willingness to pay for admiration. The bidding item of this auction is a unique certificate. Since the certificate owner will have the possibility to post it on social media, it should result in admiration from one's peers. Funding for taking part in this auction is determined by the balance of the stock trading round. Particularly, the maximum bid value that participants can bid is their final balance after the stock trading game.

Our results show that the data are in line with existing findings and correlations of personality traits. In regard to the relationship of personality traits on the disposition effect, we observe no statistically significant relationship between the dark triad and big five personality traits and the disposition effect. With this finding, our paper contributes to a growing body of literature on the impact of personality traits on behavioral biases. Importantly, this literature does not yet reach a consensus, as existing studies offer contradictory results. For example, Cecchini, Bajo, Russo, and Sobrero (2019) and Lin (2011) found different explanations for various traits influencing the disposition effect. On the one hand, the results show that extroverts quickly sell their stock to receive an immediate profit realization and a tendency for conscientious individuals to be more patient and not fall for the disposition effect (Cecchini et al., 2019). In addition, high neuroticism counteracts the disposition effect by setting a stop-loss threshold (Lin, 2011). On the other hand, Cecchini et al. (2019) confirm the extraversion and conscientiousness part but lack a similar explanation for neuroticism even though both studies make use of the NEO Revised Personality Inventory from Costa and McCrae (1992). Such differences in results could arise from participant sample selection but also through different methodological approaches. For example, Lin (2011) used hypothetical questions, while Cecchini et al. (2019) applied an experiment.

Regarding the second research question, for the personality trait sincerity in the honesty-humility dimension of the HEXACO assessment, we see no significant influence on the bid amount and therefore willingness to pay for admiration. This result is controversial with the previous result of Kleinlogel, Dietz, and Antonakis (2017); Scigala, Schild, and Zettler (2020), which addresses the relationship between honest humility and predicted cheating behavior. These findings suggest a positive relationship for a low score in honesty-humility personality and the frequency of cheating. Although these specific individuals might perceive the unique certificate as a kind of ploy to gain privileges, our study finds that there is no link between this stimulation and the honesty-humility personality. Our results fuel the ongoing inconclusive discussion about the influence of personality traits on financial decision making.

In addition to our main hypothesis, we were able to analyse overconfidence and its relationship with

personality traits. Embedded questions in the stock trading game tested how sure a participant felt with her trading decision. This allowed us an assessment of overconfidence. Since this elicitation design is directly linked to the experiment, it provides a more believable proxy for overconfidence compared to the existing literature that uses trading frequency (Benos, 1998). Interestingly, we found an association between overconfidence and dark triad traits. These findings add to the literature about the role of personality traits on both overconfidence and cognitive biases.
Our paper proceeds as follows. Section 2 provides background information about the personality traits used. Section 3 develops our hypothesis based on related studies. Section 4 outlines the methodological approach by explaining the different parts and used models and their anchoring within the current literature. Section 5 illustrates the relationship between personality traits and the selected behavioral biases. Section 6 discusses the implications of these findings, shows limitations and opens a door for further research.

3.2 Personality traits

Personality traits are defined as general, internal and comparative dispositions that an individual ascribes to people (McAdams, 2009). The goal of personality traits is to structure a behavioral pattern into categories. Research started exploring personality traits with a linguistic approach looking at the English dictionary and the words describing personality (Allport, 1937). These different dispositional traits can be merged into one of five different categories, i.e., the big five traits. This form of assessment is widely used in psychological research and still counts as a reliable approach to assess personality (McAdams, 2009). In addition to the categorization into five general traits, there are other assessments, such as the dark triad, which focuses on malevolent attitudes of individuals or honesty as the opposite. Scaling these personality traits often ends in an expression of extremes, i.e., extroverts versus introverts, while people in general have some introverted and some extroverted features. The sum of these features then points towards the more extroverted or introverted end (McCrae & Greenberg, 2014). Within this section, we provide background on the personality traits used for this study. The nature of these traits is important to understand, as the next section describes hypothesis creation. Due to popularity and our motivation derived from recent literature, we first start with the dark triad, followed by the honesty-humility dimension and the big five.

3.2.1 Dark triad

The dark triad established by Paulhus and Williams (2002) introduces a method for measuring the malevolent personality traits of narcissism, Machiavellianism and psychopathy, which share a mutual core of callous manipulation (Furnham, Richards, & Paulhus, 2013). The dark triad has become popular in recent years (Lee & Ashton, 2014) and has shown a significant relationship with cognitive biases (Suchanek, 2021) in financial decision making.

- Freud (1914) provided fundamental research on narcissism; the term was originally introduced as referring to an individual who treats their own body as a sexual object to achieve satisfaction. However, as of today, this term still lacks a clear operational definition (Crowe, Lynam, Campbell, & Miller, 2012). Research commonly differentiates between the grandiose and vulnerable narcissism dimensions; definitions for grandiose narcissism highlight a special behavior of individuals in interpersonal relationships that is characterized by self-concentration and conceitedness (Campbell & Baumeister, 2006). The vulnerable dimension, on the other hand, is described with attributes such as low self-esteem or social isolation (Miller & Campbell, 2008). While both dimensions share certain components such as entitlement or egotism (Crowe et al., 2012), our study gives priority to the grandiose dimension because of the underlying admiration aspect.

- Machiavellianism goes back to the work "The Prince" by Niccolo Machiavelli, who was a consultant of the powerful Medici family in the 16th century (Fehr & Paulhus, 2014). The author describes a certain way of ruling as self-serving, malevolent and exploitative. With the research of Christie and Geis (1970), Machiavellianism became popular in psychological research as a measurable individual-difference variable (Fehr & Paulhus, 2014). Today, Machiavellianism determines the degree to which people use traits such as manipulation, flattery and emotional distance to exploit social and interpersonal relationships to reach their goals (Christie & Geis, 1970).

- Psychopathy describes a personality disorder that is characterized by antisocial behavior and a lack of empathy (Patrick, Fowles, & Krueger, 2009). There is a differentiation between the clinical and subclinical spheres of psychopathy (Paulhus & Williams, 2002). For the widely used subclinical definition, individuals show especially high impulsivity and thrill-seeking behavior, which is also validated by looking into noncriminal samples (psychopathy often being related to criminal activities).

3.2.2 Honesty-humility

HEXACO is another concept of categorizing personality traits (Ashton et al., 2004). It covers the six factors honest humility (H), emotionality (E), extraversion (X), agreeableness (A), conscientiousness (C), and openness to experience (O); therefore it also covers three dimensions of the big five. For instance, agreeableness and neuroticism/emotional stability are similar to agreeableness and emotionality. More details on similarities and differences between HEXACO and the big five can be found in Gaughan, Miller, and Lynam (2012). We add the honesty-humility element of the HEXACO personality assessment to describe individual variations in subscales sincerity, fairness, greed avoidance, and modesty. Furthermore, it acts as the opposite for the dark triad explained above. The descriptions of the singular subscales of honest humility below are based on Ashton, Lee, and de Vires (2014):

- Sincerity measures the subject's willingness to be manipulative or dishonest in their interactions with others to achieve a desired outcome. A low score shows dishonesty or manipulative intentions towards others.

- Fairness measures the subject's willingness to cheat or steal with the intention of obtaining an advantage and the tendency to use fraud. A low score is related to treating other parties unfairly.

- Greed avoidance measures the importance put on items such as money, prestige and costly items by an individual. Low-scoring individuals are usually less concerned about wealth and prestige.

- Modesty measures the view of an individual about himself concerning others. High scorers see themselves as equal to others. Low scorers believe in superiority and that they merit special treatment.

3.2.3 Big five

Early research faced several issues in regard to personality assessment, such as the number of different scales or derivations in the formulation of traits (subscales) (John & Srivastava, 1999). This absence of a common language was resolved by consensus on a general taxonomy, namely, the big five. These classifications are also known as the OCEAN model, which contains the traits of openness to experience, conscientiousness, extraversion, agreeableness and neuroticism. The title does not appreciate the greatness of the concept but rather refers to the broadness of the single traits (John & Srivastava, 1999). With this broad but widely agreed structure, the model is one of the most researched assessments for

personality (Cobb-Clark & Stefanie, 2011; John & Srivastava, 1999; McCrae & Costa, 1999). The single traits can be described by following McCrae and Greenberg (2014); McCrae and John (1992):

- Openness to experience describes individuals with fertile imaginations and an awareness of public and private events. While there is a rich vocabulary describing extraversion and agreeableness, only a few words are related to openness (McCrae & Greenberg, 2014). Usually, we can observe explanations such as being more responsive to art and beauty, preferring alternation and trying out new things. It does not surprise that the subscale includes openness to fantasy, aesthetics, feelings, action ideas and values.

- Conscientiousness people are seen as efficient, organized, planful and reliable. The trait is a significant determinant of health, positive aging and human capital according to Roberts, Lejuez, Krueger, Richards, and Hill (2014). The attributes related to high conscientiousness also predict higher achievements, e.g., in case of education or job performance. Furthermore, conscientiousness implies high ethical standards through responsible behavior.

- The term extraversion originated from psychological research but passed on into common usage. It describes active, energetic behavior and an outgoing, talkative attitude of individuals. Extraversion is also associated with endeavoring power and status (Olson & Weber, 2004).

- Agreeableness or "conformity", as labeled in early research (Graziano & Eisenberg, 1997), is linked to adjectives such as appreciative, forgiving, generous, kind and sympathetic. Although this dimension seems to be desirable for most individuals, in many situations, such as career performance, agreeableness can be obstructive (Judge, Livingston, & Hurst, 2012).

- Neuroticism defined by Eysenck (1947) is an alternative term for emotional stability. This implies the calm stable behavior of individuals with low scores in this trait. Those with a high score are often found to be nervous, moody, dissatisfied and sensitive to stress.

3.3 Hypotheses development

The following paragraph outlines our hypothesis development categorized in disposition effect and willingness to pay for admiration. We leverage the existing findings from the literature on common personality traits about financial decision making.

3.3.1 Personality traits and the disposition effect

The disposition effect, known as the cognitive dissonance that appears when investors sell winning stocks too early and realize losses too late (Shefrin & Statman, 1985), has outstanding popularity in regard to behavioral bias research, as shown in Von Beschwitz and Massa (2020) and Haryanto et al. (2020).
To the best of our knowledge, there is no existing literature about the disposition effect and dark personality traits. However, individuals with distinct dark personality traits narcissism, Machiavellianism, and psychopathy (Paulhus & Williams, 2002) decide differently in regard to financial matters. Another argument for including the dark triad in the disposition effect discussion arises from the risk-seeking attitude of individuals. A common explanation for the disposition effect is based on prospect theories asymmetric risk aversion; in this concept, individuals are risk averse when experiencing gains and risk seeking when confronted with losses (Hens & Vlcek, 2011). In particular, individuals scoring high in the dark triad are seen as more risk seeking than other individuals (Grover & Furnham, 2021). Interestingly, narcissists and psychopaths show a propensity for taking investment/gambling risks, while narcissists are involved in real stock investments, Machiavellianism was not related to any aspect of financial risk-taking

(Sekścińska & Rudzinska-Wojciechowska, 2020). Therefore, one would expect individuals with a high score in the dark triads to gamble with losing stocks and not realize these losses, which leads to a higher disposition effect.

Furthermore, individuals with high levels of Machiavellianism will do whatever it takes to achieve their goals due to their manipulative and callousness tendencies. This could lead to a stricter adherence to a trading strategy, meaning holding on to losing positions much longer. In particular, in a social environment, the risk behavior of dark triad individuals could further be triggered by the tendency to protect their personal image and their social standing. Particularly, dark triad individuals use gossip to tune their image (Hartung, Krohn, & Pirschtat, 2019), while narcissists manipulate the others, protecting their social standing and using interaction as a social influence strategy (Lyons & Hughes, 2015). In particular, Crysel et al. (2013) demonstrated that in ego-threat situations, dark triad individuals tend to protect their self-images by engaging in risk taking.

Another argument for this hypothesis can be found in the confirmed correlation between the dark triad and selected big five traits (Jakobwitz & Egan, 2006). Paulhus and Williams (2002) showed these correlations, i.e., agreeableness was negatively correlated with narcissism, Machiavellianism, and psychopathy. Extraversion and openness for experience scores were significantly higher for narcissists and psychopaths. Machiavellists and psychopaths were low on conscientiousness. Finally, psychopaths tended to report lower levels of neuroticism (Paulhus & Williams, 2002). The relationship between the big five and the disposition effect that has been mentioned by Cecchini et al. (2019), and Lin (2011) supports the link between the big five and the disposition effect. These prior studies support the idea that individuals with dark triad traits would be risk taking and take any cost to protect their standing. Thus, we expect that dark triad individuals are prone to the disposition effect by quickly executing gaining positions and holding on to losses.

The literature poses that the big five personality traits can influence the appearance and strength of the disposition effect. As briefly mentioned in the introduction, Lin (2011) assessed this relationship for individual investors from the Taiwan stock market. By using the big five assessment, it was found that neuroticism was positively related to the disposition effect. This means that a higher score led to a higher level of the disposition effect. For conscientiousness, there is a significant positive relationship as well. Cecchini et al. (2019) showed that personality traits can influence the disposition effect in a different way: The authors illustrated a reward system that motivated extroverted individuals to sell their positions rather early. Individuals with high scores in conscientiousness observed a tendency to resist this impulsivity. The individuals hoped patiently for even higher returns in the future. Last, they highlight the importance of openness to experience to acquire more information with thinking of producing higher performance.

Thus, we hypothesize that there exists a significant relationship between the personality traits of the dark triad and the big five and the disposition effect. We therefore put forth the following hypotheses:

- Hypothesis 1a: Dark triad personality traits have a positive relationship with the disposition effect.
- Hypothesis 1b: Extraversion has a positive relationship with the disposition effect.
- Hypothesis 1c: Neuroticism has a positive relationship with the disposition effect.
- Hypothesis 1d: Conscientiousness has a negative relationship with the disposition effect.
- Hypothesis 1e: Openness has a negative relationship with the disposition effect.

3.3.2 Personality traits and admiration-seeking behavior

Financial profits for individuals are associated not only with monetary value but also with admiration that they receive through it (Back et al., 2013; Szücs et al., 2020). This attitude of narcissistic individuals towards money was elaborated in the study of Pilch and Górnik-Durose (2016): Along with the ability to fulfill biologically relevant incentives such as buying food or providing shelter, money also comes with a set of social factors. These factors arise from the symbolic character and can fulfil functions such as social display or protection. This second nature of money, the possible perception as a symbol of power, status or prestige (Pilch & Górnik-Durose, 2016), is a driving factor for individuals with a high level of narcissism. In particular, narcissists have self-enhancement and self-protection strategies. Admiration seeking is a part of the self-enhancing strategy used to help narcissists keep their high rank orders consistent over time (Back et al., 2013). Szücs et al. (2020) also support Back et al. (2013)'s view; the authors find that narcissists demonstrate admiration seeking in social contests. We assume that there is a trade-off between profit and admiration for certain types of individuals. Analyzing this willingness to pay for admiration is important for understanding individuals' trading behavior, especially the appearance of behavioral biases. Admiration as a kind of social profit might be able to mitigate potential underperformance in investments in regard to a comparison with a benchmark. Admiration-seeking behavior is an essential part of narcissism. For individuals with high scores in the dark triad, we expect admiration-seeking behavior to be more dominant than the pure need for monetary reasons. This admiration-seeking behavior could be assessed through an auction with a unique certificate stating success in a trading game.

There are also distinctive behavioral patterns for auctions emerging from a high score in dark triad personalities. These include, e.g., high competitiveness (Fong, Zhao, & Smilie, 2020; Jonason & Webster, 2010) and risk preferences (Hu, Offerman, & Zou, 2011), such as those that influence bidding behavior in an auction. Thus, once an individual has shown the need for admiration by entering the auction, dark triad traits could increase the bid height. A recent contribution from Fong et al. (2020) also showed the relationship between personality and competitiveness for experimental auctions. The authors introduced two settings: a winner-pay auction and an all-pay auction with riskier settings. In these settings, competitions are seen as zero-sum games constructed out of the success of one individual and the failure of the others. High competitiveness leads to higher bidding at auctions. For narcissists, agreeableness is low, and extraversion is high (Cook, Griffiths, & Pontes, 2020). In addition, narcissists are prone to risky decision-making (Yang et al., 2018). This results in greater overconfidence and greater willingness to bet (Campbell, Goodie, & Foster, 2004). We also expect Machiavellians to engage in this auction setting. Individuals with high levels of Machiavellianism will do anything to achieve their goal (Jones & Paulhus, 2009), which should be observable in the bidding height. We see the admiration-seeking behavior of narcissistic individuals as a key driver for taking part in our specific auction. The prize of the auction is the unique participation certificate. Winning the auction by showing superiority can therefore achieve admiration for the owner. With this additional drive in mind, they should out-scale other individuals in the urge to succeed in the auction.

In addition to the dark personality traits, we also included the honesty-humility trait in our analysis. This trait is largely unrelated to markers of the big five, despite the presence of agreeableness; as a facet of the HEXACO assessment, the enhancement of the big five comes with four subscales (Ashton et al., 2014). The subscale of greed avoidance is especially interesting for our setup. Low-scoring individuals who are more concerned with showing prestige could be more likely to bid on the certificate.

Due to this argumentation, we construct the following hypotheses regarding personality traits and admiration-seeking behavior:

- Hypothesis 2a: Dark triad has a positive relationship with the bid value.

- Hypothesis 2b: Honesty-humility has a negative relationship with the bid value.
- Hypothesis 2c: Extraversion has a positive relationship with the bid value.
- Hypothesis 2d: Agreeableness has a negative relationship with the bid value.

3.4 Methodological approach

This study combines three approaches to gain insight into a subject's decision-making behavior. We apply the setting of Weber and Camerer (1998) to create a portfolio management scenario. Afterwards, a personality assessment takes place followed by a sealed-bid English auction. This experiment with all three components is coded in o-Tree, which is an open-source platform software that integrates many advantageous features, such as not requiring installation and having low costs and high scalability (Chen, Schonger, & Wickens, 2016). The implementation is conducted through the online recruitment system Prolific.ac (Palan & Schitter, 2018).

3.4.1 Procedure and experiment design

The following paragraph outlines these three components in detail by explaining their individual relevance to achieving our research goal and by putting them into the literature context. We show that the research methods are commonly used within the current literature and that combining these components is a fitting approach to test our hypothesis.
The complete participation process overall included a demographic questionnaire covering age, gender, risk self-assessment and trading self-assessment. Following that was the round-based trading game; after rounds 7 and 14, the participants guessed the type of stock they wanted to trade and completed a self-assessment about their confidence with their guesses. A loss and risk aversion elicitation task, personality assessment including attention check questions and auction complemented this section. All questions can be found in the appendix, while the following paragraph outlines the more complex settings.

Portfolio management setting

The literature widely uses the experimental design by Weber and Camerer (1998) to investigate the disposition effect in a practical, rather than theoretical, setting. In detail, the setup provides six different stocks (A-F) that participants can trade over a total of 14 rounds. The prices are predetermined by a random process that is independent of the participants' investment decisions. The random movement price process includes two steps. First, we determine the direction of price (increase or decrease) based on the type of stock. This is done by setting fixed probabilities on the different asset classes to give an indication of a price increase or decrease. The type of stocks is summarized in Table 3.1. After the direction of the stock price is determined, the magnitude of the price change is randomly chosen between 1, 3, or 5 Talers, which are the currency to play with. The outcome of this price setting process is communicated to the participants in the way that exactly one asset follows one of the following types: "++", "+", "–", "-", where "++" represents a 65% chance of increasing, similar to "+" being 55%, "0" being 50%, "-" being 45% and "–" being 35%. In the current study, the participants were not informed about which stock had which characteristic. Therefore, we added two guessing sessions, after rounds 7 and 14, to investigate the understanding of players with different types of stocks and confidence with their choices. This framework allowed a reallocation of the current portfolio after a pricing period, in which the assets change their values. In each period, this stage randomly determined the magnitude of the stock price change. The participants received 10,000 thalers as an initial investment and historical stock data about three periods before their investment. Moreover, to ensure that the participants were clear

Stock	Type	Probability of price increase	Probability of price decrease
B	++	65%	35%
F	+	55%	45%
A, C	0	50%	50%
E	-	45%	55%
D	- -	35%	65%

Table 3.1: The stock types with their probabilities of price increases and decreases

about the rules, participants underwent three trial rounds before the experiment started. No lending, borrowing or short selling was allowed during the experiment. Participants could only invest in the six stocks with characteristics described earlier. After 14 rounds, the system automatically liquidated the portfolio, and the result of participants was determined by the value of their portfolio in Talers.
To introduce the impact of social competition, after rounds 5, 10, and 14, the participants were ranked together with other participants who had previously completed the same trading game based on their percentage of the winning trades over the total trades. Winning trade measures the number of trades sold at the price that are higher than the buying prices. To ensure feasibility in an online setting where not all participants take part in the trading game at the same time, the participants were ranked with a random sample of participants who had previously completed the exact same trading game.[2] The top performers of the previous participants were excluded to increase the probability of a high ranking and the motivation to bid in the auction.

Personality assessment

After the trading session, the participants had to finish additional tasks to be eligible for compensation. First, they had to complete an assessment for risk preferences (Eckel & Grossman, 2008; Gächter, Johnson, & Herrmann, 2007; Holt & Laury, 2002). Afterwards, a survey with 39 questions was conducted to assess personality traits. This survey included three measures: the dark triad (Jonason & Webster, 2010), the HEXACO honesty-humility dimension (Ashton et al., 2014) and the big five (Gosling, Rentfrow, & Swann, 2003).

Auction setting

Using an auction to determine willingness to pay for the respective auction price is a commonly used method in research (Noussair, Robin, & Ruffieux, 2004). Particularly, using an auction method to reveal willingness-to-pay information is more effective than the Becker–DeGroot–Marschak method (BDM) (Noussair et al., 2004). It is also more precise compared to, e.g., the use of product cards and gifts. Thus, in this study, we chose the auction as the most suitable method to determine a possible willingness to pay.
We created a social setting in our measurement of the disposition effect. This was done by leveraging the methodology of Weber and Camerer (1998)'s stock trading game by introducing a rating system between the participants.
To trigger admiration-seeking behavior, our auction price had to fulfill three requirements. First, it had to be linked to the participant in a way that personal identification is possible. Second, it had to be immediately available and usable. Third, it had to create a social reaction from related and relevant peers. We assessed that a certificate stating the trading game success of the participant might be the best way to trigger such admiration-seeking behavior. We introduced this at the end of the trading game; after 14 rounds, we offered the participants a possibility to receive the certificate for finishing the trading game. The certificate showed their achieved final ranking. We believed that for some participants with specific dark personality traits, the certificate would more impressive than for others. Each player would

see their real ranking in the ranking list with the past players based on Liêu and Pelster (2020). For the auction itself, the participants first read an explanation of the concept. After confirming to have understood the rules, the current rankings were displayed, as well as the balance from the stock trading game in addition to the field, where the participant could enter the bid amount in thalers.
The winner of the auction was the participant who entered the highest bid among all the participants. Since the setup was a sealed-bid English auction, no participant was able to observe the other bid amounts. Instead, at the end of the auction, and therefore the completion of the experiment, the participants were shown the payout they received from the different experiment categories.

3.4.2 Data collection

The participants were recruited through Prolific.ac. This platform allows participants to be recruited from all around the world and automatically closes the experiment after obtaining the target number of participants. The participants were randomly enrolled from the pool of members in the Prolific platform. The participants had to speak English to participate in the experiment; no other restrictions were put in place.

Each participant was issued a specific Prolific ID, which prevented them from enrolling in the experiment more than once. Finally, the participants were scored on their reliability by the provider. This was done by counting the number of rejections from previous experiments they participated in. Palan and Schitter (2018) indicates that the data quality of Prolific and MTurk are comparable. Moreover, the Prolific's participants had a diverse set of locations and ethnicities. They were also more naive regarding the research tasks (Palan & Schitter, 2018). With those attributes in mind, we believe that Prolific is an appropriate choice for scientific online experiments. This platform is not only user-friendly but also offers many good features for conducting our experiment.
To ensure that participants paid full attention to the experiment, we applied instructional manipulation checks (IMCs). While Ward and Meade (2018) confirm that attention checks help to avoid careless responding, Hauser and Schwarz (2015) indicate that placing the IMCs at the end of the survey could help to eliminate their effect on the ways that participants react during the experiment. We considered attention checks in the instructions and included two attention check questions in the survey at the end of the experiment. Only the participants who passed the attention checks were used for the analysis. The complete questionnaire can be found in the Appendix.
We collected 107 observations from the system through 84 participants who finished the whole experiment and passed the attention checks. On average, the participants took 57.78 minutes to finish the experiment, and they received a range of 12.75 Euro/GBP to 18.40 Euro/ GBP, with an average of 15.63 Euro/GBP in payoff from their trading results. The total payoff for participating was determined by the sum of the value of participants' portfolio at the end of the experiment (including cash and the value of the shares), the earnings of correct guesses, and the earnings from the three additional tasks (the summary statistic of payoff can be found in Table 3.3). This amount was converted into Prolific's standard currency of GBP to pay participants. The personal characteristics of the participants are shown in Table 3.2.

[This is place for Table 3.2]

In cases where the participants won the auction, their payoff was the total payoff deducted from the second-highest bidding price. In our setting, we afterwards converted the thalers back to GBP as an additional dynamic payout for the participants. The experiment was conducted in August 2020.
Our sample contained 84 participants who completed all the tasks and passed the attention checks. Thus, our sample size is similar to previous studies on similar research questions, such as Rzeszutek (2015) with 90 participants or Liêu and Pelster (2020) with 81 participants.

		Percentage
Age		
	$18-34$	76.25
	$35-44$	11.25
	$45-54$	10
	>55	2.5
Gender		
	Female	28.39
	Male	64.19
	Unknown	7.4
Nationality		
	Australia	2.469
	Canada	1.235
	Chile	2.469
	Finland	2.469
	Greece	2.469
	Hungary	1.235
	Italy	3.704
	Kazakhstan	1.235
	Mexico	6.173
	Poland	18.519
	Portugal	7.407
	Slovenia	1.235
	South Africa	2.469
	Spain	3.704
	United Kingdom	20.988
	United States	16.049
	Unknown	6.173

Table 3.2: Personal characteristics of the respondents

3.4.3 Measurement

To measure personality traits and financial decision-making behavior, we use widely established and reliable instruments. The paragraph below describes these instruments and refers to the existing literature to show reliability.

The disposition effect

We measured the disposition effect by following Odean (1998) and Weber and Camerer (1998). Hereby, we relied on two measures. First, we applied the method of Odean (1998), using the proportion of gain realized (PGR) and the proportion of losses realized (PLR). As the definition, the disposition effect is the difference between PLR and PGR. Therefore, we can calculate the disposition effect by the following formula:

$$Disposition\_Effect = PGR - PLR \tag{3.1}$$

With

$$PGR = \frac{Realized\_gains}{Realized\_gains + Paper\_gains} \tag{3.2}$$

$$PGR = \frac{Realized\_losses}{Realized\_losses + Paper\_losses} \tag{3.3}$$

where the *realized_gains (realized_losses)* is counted when the stocks are sold at a profit (loss) position. The paper gain (paper loss) is counted when the current price of the stocks is higher (lower) than the purchasing price. To determine the purchasing price of the stocks, we used the weighted average purchasing price.
The second method calculated the disposition effect based on the method of Weber and Camerer (1998). The α-measure is the percentage between the number of gaining sells and losing sells. Formally:

$$\alpha = \frac{S_+ - S_-}{S_+ + S_-} \tag{3.4}$$

where S_+ and S_- denote the number of sells after the prices increase and decrease, respectively.

Willingness to pay for admiration

An auction is a reliable form to measure someone's willingness to pay for the respective auction item (Chan Y. Tat & Park, 2007; Noussair et al., 2004). For this, we needed to enable the participants of our experiment to engage in the auction for admiration. After the screen showed the ranking of participants, we offered an auction round where they could bid for a unique certificate with their ranking on it. To increase the probability that the participants had an incentive to bid in the auction, we removed the top performers from the previous participants. In this way, we increased the probability of a high ranking and the motivation to bid in the auction. This setting could trigger the need to show off success and to be admired. For anonymity reasons, we use a sealed-bid auction setup, where no participant could see the others' bid. This prevented the participants from feeling observed, and they could bid any value to pay for the certificate within the budget they have. We measured the relative bid amount of a participant compared with their available funds that came together after the trading game finished. The percentage of people participating in the auction accounted for 64.29% (we denoted participants who did not join

the auction as those who had a bid value equal to zero). Specifically, 54 of 84 participants joined the auction.)

Dark triad

We assessed the dark triad by using the Dirty Dozen questionnaire from Jonason and Webster (2010). This instrument contains twelve items, i.e., four items per subscale on narcissism, Machiavellianism and psychopathy, which efficiently recover information for dark personality traits (Webster & Jonason, 2013) and shows a consistent factor structure (Kajonius, Persson, Rosenberg, & Garcia, 2016). These items are measured with a Likert scale, ranging from 1 to 5 (1 = Strongly Disagree, 5 = Strongly Agree). Although there is criticism stating the Dirty Dozen is too brief (Jones & Paulhus, 2013), we relinquished introducing the Short Dark Triad (SD3) due to the participation length of the overall experiment.

Honesty-humility

To measure honest humility, we applied the inventory of Ashton et al. (2014). In particular, we added four questions to determine four subscales: sincerity, fairness, greed avoidance, and modesty. The items were measured with a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Big five

Due to time constraints in the survey and the need to assess personality traits, we use the ten-item personal inventory of the big five Dimensions (TIPI-G) by Gosling et al. (2003). We did not contest the funded criticism on short-version measures usage stated by Crede, Harms, Niehorster, and Gaye-Valentine (2012) but rather prioritized the survey length over it. Items were measured with a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Risk aversion

To measure risk aversion, we followed Eckel and Grossman (2008)'s approach due to simplicity and based on the criticism around (Becker, H-DeGroot, & Marschak, 1964). Participants need to pick one of five gambles. One of them is a safe option, while the others consist of 50/50 gambles constructed from a linear function of payoff and risk. With this setup, the expected returns are easy to measure, and the expected payoff is linear in risk.

Loss aversion

To measure the loss aversion level of individuals, we replicated the task of Gächter et al. (2007). In this choice task, individuals have ten lotteries that they can choose to accept or reject. The win value of lotteries is fixed, while the loss value increases. At the end of the experiment, the computer system randomly chooses one lottery and flips the coin. The participants who choose to reject the lotteries will end the task with their endowment. However, those who accept the coin and the outcome of the coin toss will receive the win value of the coin. Through this task, we can determine loss aversion based on prospect theory. The participants who did not make it through consistent choices were excluded from the data.

(Over-)Confidence

As mentioned in Section 3.4.1, after completing the trading section in rounds 7 and 14, the participants were required to guess the type of stocks and were asked afterwards to state the probability that they were confident in their guessing (from 0% to 100%). We used this value to determine the confidence level

of participants. The confidence level of participants is the average of their confidence levels after rounds 7 and 14. In addition to the confidence level, we created a dummy variable for the overconfidence of participants by comparing their confidence levels with the number of correct guesses. The participants whose confidence levels were 20% higher than the percentage of corrected guessing took a value of one, and the value was zero otherwise.

3.5 Results

We divide our results section into four parts. In the first part, we show summary statistics and the correlation between personality traits and overconfidence. The second part explains the relationship between personality traits and the disposition effect. Third, we explain the relationship of personality traits and admiration-seeking behavior through the auction. Due to contradiction with existing literature, the last part provides a description of additional results that were obtained from the data. For our regressions, we make use of a robust regression that may be more appropriate in cases where extreme values exist. Robust regression is also *"...providing a convenient way to control for influential observations and enhance inter-study comparability..."* (Leone, Minutti-Meza, & Wasley, 2019).

3.5.1 Descriptive analysis

The following paragraph outlines the descriptive findings in our data. We provide confirmation that our data are congruent with the existing literature by looking at summary statistics and correlations within the key variables used.

Summary statistics

Table 3.3 provides descriptive statistics among our 84 observations. In general, male and female investors have insignificant differences in their trading experience, preferences and understanding of stocks, except for their willingness to take risks. Indeed, male investors are more willing to take risks compared to female investors ($p\_value = 0.053$). They also show a higher level of psychopathy compared to women, which compliments the study of Jonason and Davis (2018), whereas women seem to be more extroverted than men. This result is consistent with many prior studies (Costa et al., 2001; Schmitt et al., 2008; Weisberg et al., 2011).

[This is place for Table 3.3]

Table 3.3 also provides descriptive statistics among the distribution of the dark triad elements. In comparison with the study of Preotiuc-Pietro, Carpenter, Giorgi, and Ungar (2016), our data correspond with the established literature to some extent. For psychopathy, the data of Preotiuc-Pietro et al. (2016) peak at approximately 1.5, which indicates a concentration of individuals with only mild psychopathy tendencies. For our data, we see that the distribution of psychopathy is slightly positively skewed. For narcissism, we observe a similar distribution as Preotiuc-Pietro et al. (2016) as well, with a peak at approximately 3 on the scale. For our data, we see a more heterogeneous distribution with higher variance in the different scores over the complete set. For Machiavellianism, we find the most similar distribution. Most individuals in the reference data are located between 1 and 2 on both sets. The rest of the distribution on site of the higher scales follows a flattering tendency. In general, prior studies have shown that the distribution of dark triad traits is not normally skewed but negatively skewed (Preotiuc-Pietro et al., 2016). This is fitting with the distributions in our study.
Table 3.3 also provides descriptive statistics among the distribution of the subsets of the big five. We observe similar distributions for the personality traits in the literature (Chapman, Talbot, Tatman, &

	Mean	Std.de	Skew	Kurtosis	N	t-test (Gender)
Trading experience	0.369	1.015	3.25	11.51	84	0.516
Risk self-assessment	5.083	2.218	-0.26	-0.88	84	0.053
Guess	2.869	1.574	0.10	-0.28	84	0.789
Risk aversion (Eckel & Grossman, 2008)	0.534	0.837	-0.54	-0.44	84	0.699
Risk aversion (Holt & Laury, 2002)	0.549	0.641	0.03	-0.25	61	0.745
Loss aversion (Gächter et al., 2007)	2.744	1.355	0.86	-0.44	60	0.281
Hexaco	3.47	0.705	-0.51	0.32	84	0.662
Sincerity	3.702	1.23	-0.70	-0.65	84	0.514
Fairness	3.583	1.282	-0.28	-1.23	84	0.492
Greed avoidance	2.821	1.121	0.30	-0.80	84	0.497
Modesty	3.774	1.034	-0.71	0.06	84	0.592
Extraversion	2.512	0.969	0.43	-0.56	84	0.055
Agreeableness	3.512	0.868	-0.13	-0.54	84	0.072
Conscientiousness	3.774	0.859	-0.28	-0.59	84	0.353
Emotional stability	3.202	1.053	0.00	-0.77	84	0.169
Open experience	3.685	0.842	-0.27	-0.54	84	0.258
Dark triad	2.416	0.674	0.65	-0.24	84	0.341
Machiavellianism	2.188	0.974	0.78	-0.21	84	0.473
Psychopathy	2.429	0.747	0.31	0.15	84	0.098
Narcissism	2.631	0.776	-0.05	-0.53	84	0.991
Narc (Back et al., 2013)	3.085	0.661	0.09	-0.42	84	0.310
Bid value	3.936	3.419	0.00	-1.65	84	0.688
Performance	10,324	523.7	0.67	1.66	84	0.180
Total payoff	15,633	1.266	-0.134	-0.281	84	0.163

Notes: *Trading experience* denotes participant stock trading experience, with a 5-point scale ranging from 1 (<1 year), to 5 (>10 years). *Risk self-assessment* denotes the risk willingness level of participants, with a scale ranging from 1 (not at all willing to take risks) to 10 (very willing to take risks). *Guess* denotes the total amount of correct guesses from the stock types in round 7 and 14. *Risk aversion (Eckel & Grossman, 2008)* denotes the result of the Eckel and Grossman-task; *Risk aversion (Holt & Laury, 2002)* denotes the result of the Holt and Laury task. *Loss aversion (Gächter et al., 2007)* denotes the result of the Gächter-Johnson-Herrmann task. Participants who had no consistent choices with transitivity in the Holt and Laury task and the Gächter-Johnson-Herrmann task, were excluded from the descriptive statistics. *Hexaco* denotes the mean value of the honesty-humility measure (Ashton et al., 2014). *Sincerity*, *Fairness*, *Greed Avoidance*, *Modesty* denotes the result of honesty-humility measure; *Extraversion*, *Agreeableness*, *Conscientiousness*, *Emotional Stability*, and *Open experience* denotes the result of big five factors; *Machiavellian*, *Psychopathy*, *Narcissism* denotes the result of the Dirty Dozen measure. *Bid value* denotes the logarithm of bid value. *Performance* denotes the final returns of participants. *Total payoff* denotes the final earnings of participants included additional tasks bonus. t-test (gender) = p_value for gender difference.

Table 3.3: Descriptive statistics, gender differences for demographics, personality preference, and trading

Britton, 2009; Samek, 2017).

For the honesty–humility dimension of the HEXACO personality assessment, we describe the distribution of the subscales in Table 3.3. We observe a right leaning distribution for sincerity and modesty, whereas greed avoidance is a more left-leaning distribution. Fairness seems to be most evenly distributed, but with a peak at the highest point in scale.

Concerning the disposition effect, the mean value of PLR, PGR, DE, and α of our study can be compared with the treatment results from the study of Liêu and Pelster (2020) because we applied similar settings of ranking (ranking based on the winning trades). In particular, our results regarding the disposition effect (0.043) are lower than the result of Liêu and Pelster (2020) (0.088). We argue that the gap in the study of Liêu and Pelster (2020) and our study may be caused by the difference in the environment of the experiment. Indeed, Liêu and Pelster (2020) is a lab experiment, while our experiments use an online platform.

Interestingly, the average disposition effect and α of our study are higher than the baseline condition from the study reports for the individual investors of Rau (2015). Hence, our result confirms the impact of the frame on the disposition effect, which is in line with Liêu and Pelster (2020). Additionally, this high disposition effect complements prior studies, which indicates the impact of social interaction on the disposition effect (Lukas, Eshraghi, & Danbolt, 2017; Pelster & Hofmann, 2018). Thus, we focus on differences in the trading and auction behavior of investor groups. In Table 3.4, we cannot find a difference in the trading behavior and the auction behavior of investors when comparing the high dark triad or overconfident participants. However, investors who are willing to engage in risky activities have significantly higher bid values than investors who are less willing (0.164 vs 0.0684; t-test, p = 0.0312). This means that the risk-willing participants consider auctions a risky activity and are interested in putting a higher bid, while the others are not.

	PGR	PLR	DE	Alpha	Bid value	Auction on Result	N
Mean	0.154	0.09	0.064	0.241	3.936	0.111	84
Std.de	0.099	0.065	0.098	0.297	3.419	0.203	
Dark triad							
Low	0.149	0.0822	0.0664	0.237	3.55	0.102	41
High	0.159	0.0983	0.0610	0.245	4.33	0.119	43
t-test	0.622	0.259	0.804	0.912	0.318	0.701	
Overconfidence							
Low	0.156	0.0949	0.0607	0.241	4.18	0.0997	55
High	0.151	0.0820	0.0693	0.240	3.48	0.131	29
t-test	0.85	0.389	0.704	0.989	0.375	0.503	
Risk willingness							
Low	0.146	0.0982	0.0479	0.209	3.14	0.0684	47
High	0.164	0.0805	0.0836	0.281	4.95	0.164	37
t-test	0.411	0.216	0.0972	0.273	0.0146	0.0312	

PLR denotes the proportion of losses realized. *PGR* denotes the proportion of gain realized. *DE* denotes the disposition effect. α denotes the α measure followed Weber and Camerer (1998). *Bid value* denotes the logarithm of participants‘ bid value. *Auction on Result* denotes the proportion of bid value over the final asset of participants.

Table 3.4: Trading behavior of participants

Correlation between personality traits and risk attitude

The relationship between the dark triad and other personality traits was summarized in the study of Furnham et al. (2013). In detail, due to the anti-social tendency of people scoring high in the dark triad, the authors found a low relationship with agreeableness. Similarly, prior studies have also indicated that the dark triad is negatively associated with conscientiousness (Furnham et al., 2013). Jakobwitz and

Egan (2006) found that psychopathy and Machiavellianism had a positive relationship with neuroticism. These results are consistent with our correlation in Table 3.5 at some points. In general, we find that the correlation between the dark triad mean and agreeableness is −0.378. Moreover, the results from the partial correlation show that there is no correlation between the disposition effect and the alpha with any traits. Specifically, we find a partial correlation between bid amount and agreeableness (0.509). When focusing on the relationship between personality traits and risk preferences, Table 3.5 shows the association between risk aversion (Eckel and Grossman-task) and loss aversion (0.482), whereas loss aversion has a negative association with confidence (−0.469). In addition, risk aversion (Holt and Laury task) has a negative link to emotional stability (−0.337). Table 3.5 also indicates some connection between personality traits. Particularly agreeableness is negatively related to both dark triad (−0.378) and psychopathy (−0.405). This result is consistent with the prior study of Lee and Ashton (2005) and Jonason et al. (2013). In addition, the other popular measure is the HEXACO honesty-humility trait (Ashton & Lee, 2001), which determines honesty, fairness, greed avoidance, and modesty. These traits reflect high prosocial traits that contradict the antisocial behavior of dark triad traits. Consequently, a negative correlation between HEXACO honestly humility and the dark triad is observed, e.g., Lee et al. (2013) or Hodson et al. (2018), as well as in this study (−0.531). Notably, Table 3.5 applies the partial correlation that helps to observe the relationship between traits when controlling for the influence of the other traits.

[This is place for Table 3.5]

	R_eckel	Lambda_gaechter	R_holt	Confidence	Hexaco	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Open Experience	Dark Triad	Machiavellian	Psychopathy	Narcissism	DE	α
R_eckel																
Lambda_gaechter	0.482*															
R_holt	0.312	-0.275														
Confidence	0.397	-0.469**	-0.334*													
Hexaco	-0.135	0.226	0.198	0.132												
Extraversion	0.133	-0.187	-0.241	-0.394*	0.193											
Agreeableness	-0.167	0.059	0.084	0.045	-0.072	0.107										
Conscientiousness	-0.017	0.181	0.127	0.129	-0.068	0.034	-0.292									
Emotional stability	0.105	-0.355	-0.337*	-0.306	-0.194	-0.166	-0.029	0.262								
Open experience	0.082	-0.037	-0.041	0.093	0.213	0.206	0.253	0.355	0.241							
Dark triad	-0.122	0.240	0.194	0.247	-0.531**	0.256	-0.378*	-0.316	-0.062	0.169						
Machiavellian	-0.230	0.031	0.029	0.202	-0.268	0.280	0.065*	-0.094	0.231	0.1	-0.038					
Psychopathy	0.067	0.084	0.06	-0.121	-0.066	-0.224	-0.405*	-0.095	-0.191	0.053	-0.508**	0.676****				
Narcissism	-0.013	0.165	0.141	0.315	-0.327	0.405	0.058	-0.178	-0.046	0.033	-0.533***	0.008	0.138			
DE	-0.214	0.044	0.269	0.249	-0.036	0.208	0.083	-0.049	0.211	0.128	-0.155	-0.203	0.015	-0.004		
α	0.039	0.189	-0.178	-0.057	-0.086	-0.121	-0.098	-0.032	-0.134	-0.081	0.027	0.095	0.003	-0.0791	0.873****	
Bid value	0.172	0.0009	0.170	0.109	0.094	0.142	0.509*	0.233	0.273	-0.185	0.195	0.034	0.174	-0.053	-0.218	0.213

$^{****}p < 0.0001$ ' $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: *R_eckel* denotes the result of the risk aversion measure of the Eckel and Grossman-task; *R_holt* denotes the result of the risk aversion measure of the Holt and Laury task. *Lambda_gaechter* denotes the result of the loss aversion measure of the Gächter-Johnson-Herrmann task. Participants who have no consistent choices with transitivity in the Holt and Laury task and the Gächter-Johnson-Herrmann task, are excluded from the descriptive statistics. *Confidence* denotes the average self-assessment value of participants about their confidence with their guessing choices, with the 10 scale from 10% to 100%. *Hexaco* denotes the mean value of the honesty-humility measure (Ashton et al., 2014); *Dard triad* denotes the mean value of the dirty dozen measure (Jonason & Webster, 2010); *Extraversion*, *Agreeableness*, *Conscientiousness*, *Emotional stability*, and *Open experience* denote the result of big five factors (Gosling et al., 2003); *DE* denotes the disposition effect. α denotes the α measure followed Weber and Camerer (1998). *Bid value* denotes the logarithm of participants' bid value.

Table 3.5: Spearman Correlation between personal traits and confidence and risk preference

3.5.2 Personality and the disposition effect

The following section explains the regression results for different combinations of personality traits and the disposition effect.

Dark triad and disposition effect

We run robust regression models to explain the disposition effect with the dark triad personality traits. None of the personality traits show any significance even after adding demographic control variables and control variables for loss and risk aversion. Due to missing research on the dark triad and the disposition effect, a comparison with existing results is not possible. We think that the mentioned stock market experience within our sample could be determining a weaker disposition effect for the results overall. Thus, we focus on the relationship between the dark triad and two components of the disposition effect, including PGR and PLR. Similarly, we cannot find a significant relationship between these factors.

[This is place for Table 3.6]

	The disposition effect (DE)								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Narcissism	−0.0072	−0.0006	0.0115						
	(0.0145)	(0.0153)	(0.0196)						
Machiavellian				−0.0168	−0.0140	−0.0122			
				(0.0113)	(0.0118)	(0.0173)			
Psychopathy							−0.0198	−0.0240	−0.0301
							(0.0143)	(0.0156)	(0.0251)
Female		−0.0151	−0.0022		−0.0180	0.0000		−0.0209	−0.0050
		(0.0245)	(0.0289)		(0.0241)	(0.0300)		(0.0248)	(0.0314)
Age		−0.0097	−0.0016		−0.0100	−0.0052		−0.0104	−0.0066
		(0.0107)	(0.0131)		(0.0104)	(0.0135)		(0.0106)	(0.0143)
Trading selfassessment		−0.0220	−0.0012		−0.0197	0.0125		−0.0208	0.0136
		(0.0122)	(0.0321)		(0.0118)	(0.0326)		(0.0117)	(0.0332)
Loss aversion (Gächter et al., 2007)			0.0138			0.0129			0.0174
			(0.0101)			(0.0106)			(0.0112)
Risk aversion (Eckel & Grossman, 2008)			−0.0244			−0.0252			−0.0232
			(0.0161)			(0.0169)			(0.0175)
(Intercept)	0.0816*	0.0973*	0.0224	0.0990**	0.1266	0.0832*	0.1117**	0.1585**	0.1221
	(0.0397)	(0.0486)	(0.0659)	(0.0271)	(0.0371)	(0.0592)	(0.0363)	(0.0488)	(0.0739)
Num. obs.	84	82	59	84	82	59	84	82	59

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: The dependent variable is the participant's disposition effect. *Narcissism* denotes the narcissism value of participants in the Dirty Dozen assessment, with a scale ranging from 1 to 5. *Machiavellian* denotes the Machiavellianism value of the participants in the Dirty Dozen assessment, with a scale ranging from 1 to 5. *Psychopathy* denotes the psychopathy value of the participants in the Dirty Dozen assessment, with a scale ranging from 1 to 5. *Trading selfassessment* denotes participant stock trading experience, with a 5-point scale ranging from 1 (<1 year), to 5 (>10 years). *Female* is a dummy variable that takes a value of one for female participants and zero otherwise. *Age* denotes participants' age in years. *Risk aversion (Eckel & Grossman, 2008)* denotes the result of the Eckel and Grossman-task; *Risk aversion (Holt & Laury, 2002)* denotes the result of the Holt and Laury task. *Loss aversion (Gächter et al., 2007)* denotes the result of the Gächter-Johnson-Herrmann task. Participants who have no consistent choices with transitivity in the Gächter-Johnson-Herrmann task are excluded from this regression.

Table 3.6: Robust regression the disposition effect on narcissism, Machiavellian, psychopathy

Big five and the disposition effect

Table 3.7 shows the regression models with the big five personality traits as exogenous variables and the disposition effect as an endogenous variable. The results show nonsignificant differences for all subscales of the big five.

These results contradict Lin (2011). In particular, Lin (2011) found a significant relationship between conscientiousness and the disposition effect. Similarly, neuroticism has a positively significant relationship with the disposition effect. The difference in results can arise from using different instruments to measure the disposition effect. While Lin (2011) differentiated behavioral biases in the form of latent variables, the study used hypothetical questions rather than a real experiment in the methodology. On the other

hand, De Bortoli, da Costa Jr., Goulart, and Campara (2019) used a laboratory setting similar to Weber and Camerer (1998) to show risk seeking behavior in the choice of investment instruments. With greater risk tolerance according to the investor profile, the individuals also chose to invest in riskier asset classes. This effect is also partially explained by a significant relationship between openness to experience and risk seeking. While the main goal of De Bortoli et al. (2019) was to "*observe whether each participant chooses higher or lower risk assets to invest in, in order to approximate their "real" investor profile*", it did not directly include the disposition effect concerning changes in investments (e.g., holding on to losing stocks/asset classes). Because of the construction of the study variables and a different research goal, the findings are not directly comparable to ours.
While our questionnaire seems rather consistent (with a Cronbach's alpha of .68 concerning the small item scale), we see this as the main source of the diverging results. This idea of overstating demand, which arises from the usage of hypothetical answers, was underlined by Balistreri, Mcclelland, Poe, and Schulze (2001). A more comparable setting, run by Cecchini et al. (2019)), also used the experimental design of Weber and Camerer (1998). There are only small differences in the setup, such as incentivizing high performance in the trading game: Cecchini et al. (2019) reached this goal over a competition-related payout to the participants, with €165 for the winner, €100 for second place, and €50 for third place. In our setting, we showed the participants a leaderboard after certain intervals and trigger competition over the social setting. Payout was also related to the performance in our setting but not in a fixed amount, as in the comparative study. Comparing our data with the summary statistics of Cecchini et al. (2019) shows one additional explanation of the differences; while the authors used a larger sample, the participants were also significantly younger and had less stock market knowledge compared to those in our study. Da Costa Jr, Goulart, Cupertino, Jr, and Silva (2013) confirmed that investing experience mitigates the disposition effect. For two groups (one experienced – 26 investors , the other not – 38 students), the authors found less exposure of the experienced group to the disposition effect.

[This is place for Table 3.7]

3.5.3 Personality and admiration-seeking behavior

The following section explains our results for different combinations of personality traits and admiration seeking. As the relative bid amount represents the willingness to pay for the certificate, it translates to the willingness to pay for admiration, which arises by publishing the certificate on social media.

Dark triad and admiration-seeking behavior

Table 3.8 shows different regression models with the bid amount as an endogenous variable and the dark triad personality traits together with demographic control variables as exogenous factors. Both narcissism and Machiavellianism show no significance for all three models. Even though manipulativeness is a central facet for Machiavellians, they do not show a significant relation with the auction price. This means that these individuals do not use the auction to achieve the unique certificate and certify their uniqueness. In other words, Machiavellians are not interested in the certificate and rate monetary value higher than the possible admiration that might come with the publication of the certificate. Psychopathy was also insignificant in all three models.
These nonresilient findings could suggest that there is no significant willingness to pay for admiration. It could also suggest that dark triad personality traits do not influence auction behavior.

[This is place for Table 3.8]

	The disposition effect									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Extraversion	0.0014	0.0096								
	(0.0115)	(0.0156)								
Agreeableness			0.0083	0.0212						
			(0.0130)	(0.0167)						
Conscientiousness					−0.0186	−0.0169				
					(0.0123)	(0.0160)				
Neuroticism							−0.0062	−0.0069		
							(0.0107)	(0.0140)		
Open experience									0.0099	0.0111
									(0.0134)	(0.0167)
Female		−0.0064		−0.0111		−0.0056		−0.0040		−0.0037
		(0.0304)		(0.0310)		(0.0289)		(0.0293)		(0.0289)
Age		−0.0038		−0.0035		−0.0029		−0.0043		−0.0031
		(0.0130)		(0.0134)		(0.0127)		(0.0128)		(0.0128)
Trading selfassessment		−0.0025		0.0069		0.0075		0.0102		−0.0012
		(0.0327)		(0.0316)		(0.0298)		(0.0311)		(0.0315)
Loss aversion (Gächter et al., 2007)		0.0139		0.0174		0.0143		0.0126		0.0153
		(0.0102)		(0.0110)		(0.0101)		(0.0106)		(0.0103)
Risk aversion (Eckel & Grossman, 2008)		−0.0219		−0.0221		−0.0233		−0.0243		−0.0239
		(0.0166)		(0.0170)		(0.0160)		(0.0162)		(0.0161)
(Intercept)	0.0591	0.0327	0.0328	−0.0259	0.1294*	0.1123*	0.0814*	0.0800	0.0256	0.0093
	(0.0311)	(0.0510)	(0.0471)	(0.0745)	(0.0477)	(0.0685)	(0.0359)	(0.0683)	(0.0506)	(0.0751)
Num. obs.	84	59	84	59	84	59	84	59	84	59

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: The dependent variable is the participant's disposition effect. *Extraversion* denotes the extraversion value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Agreeableness* denotes the agreeableness value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Conscientiousness* denotes the conscientiousness value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Neuroticism* denotes the neuroticism value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Open experience* denotes the openness to experience value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Trading selfassessment* denotes the participant's stock trading experience, with a 5-point scale ranging from 1 (<1 year), to 5 (>10 years). *Female* is a dummy variable that takes a value of one for female participants and zero otherwise. *Age* denotes participants' age in years. *Risk aversion (Eckel & Grossman, 2008)* denotes the result of the Eckel and Grossman-task; *Risk aversion (Holt & Laury, 2002)* denotes the result of the Holt and Laury task. *Loss aversion (Gächter et al., 2007)* denotes the result of the Gächter-Johnson-Herrmann task. Participants who have no consistent choices with transitivity in the Gächter-Johnson-Herrmann task are excluded from this regression.

Table 3.7: Robust regression of subscales of the big five on the disposition effect

	Auction on the result								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Narcissism	0.0034	−0.0057	−0.0160						
	(0.0118)	(0.0122)	(0.0115)						
Machiavellian				0.0102	0.0068	−0.0000			
				(0.0088)	(0.0093)	(0.0083)			
Psychopathy							0.0100	0.0051	−0.0057
							(0.0122)	(0.0120)	(0.0118)
Female		0.0030	0.0353*		0.0036	0.0274		0.0040	0.0264
		(0.0196)	(0.0170)		(0.0191)	(0.0144)		(0.0190)	(0.0148)
Age		−0.0056	−0.0106		−0.0046	−0.0069		−0.0045	−0.0077
		(0.0085)	(0.0077)		(0.0083)	(0.0065)		(0.0081)	(0.0068)
Trading selfassessment		0.0363**	0.0220		0.0292**	0.0120		0.0310	0.0131
		(0.0098)	(0.0189)		(0.0094)	(0.0156)		(0.0090)	(0.0157)
Loss aversion (Gächter et al., 2007)			−0.0102			−0.0086			−0.0081
			(0.0059)			(0.0051)			(0.0053)
Risk aversion (Eckel & Grossman, 2008)			0.0148			0.0126			0.0129
			(0.0095)			(0.0081)			(0.0082)
(Intercept)	0.0395	0.0600	0.0972*	0.0240	0.0281	0.0463	0.0244	0.0296	0.0600
	(0.0323)	(0.0388)	(0.0388)	(0.0210)	(0.0294)	(0.0284)	(0.0311)	(0.0375)	(0.0348)

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: The dependent variable is the participant's proportion of the bid value on the final asset. *Narcissism* denotes the narcissism value of the participants in the Dirty Dozen assessment (Jonason & Webster, 2010), with a scale ranging from 1 to 5. *Machiavellian* denotes the Machiavellianism value of the participants in the Dirty Dozen assessment (Jonason & Webster, 2010), with a scale ranging from 1 to 5. *Psychopathy* denotes the psychopathy value of the participants in the Dirty Dozen assessment (Jonason & Webster, 2010), with a scale ranging from 1 to 5. *Trading selfassessment* denotes the participants' stock trading experience, with a 5-point scale ranging from 1 (<1 year), to 5 (>10 years). *Female* is a dummy variable that takes a value of one for female participants and zero otherwise. *Age* denotes participants' age in years. *Risk aversion (Eckel & Grossman, 2008)* denotes the result of the Eckel and Grossman-task; *Risk aversion (Holt & Laury, 2002)* denotes the result of the Holt and Laury task. *Loss aversion (Gächter et al., 2007)* denotes the result of the Gächter-Johnson-Herrmann task. Participants who have no consistent choices with transitivity in the Gächter-Johnson-Herrmann task are excluded from this regression.

Table 3.8: Robust regression of dark triad personality traits on bid amount

Honesty-humility trait and admiration-seeking behavior

We test the influence of sincerity, fairness, greed avoidance, and modesty on auction behavior. Table 3.9 shows insignificant results with all the subtraits of the honesty-humility trait. Although we are offering a rather unethical choice to manipulate the initial ranking, we cannot confirm our hypothesis.

[This is place for Table 3.9]

	Auction on the result									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Sincerity	0.0050	−0.0014								
	(0.0092)	(0.0119)								
Fairness			−0.0011	−0.0083						
			(0.0086)	(0.0123)						
Greed avoidance					−0.0056	−0.0102				
					(0.0099)	(0.0121)				
Modesty							0.0167	0.0050		
							(0.0105)	(0.0141)		
Hexaco									0.0080	−0.0135
									(0.0159)	(0.0226)
Female		−0.0010		0.0013		0.0026		0.0004		0.0003
		(0.0286)		(0.0299)		(0.0296)		(0.0291)		(0.0286)
Age		−0.0037		−0.0015		−0.0027		−0.0049		−0.0016
		(0.0127)		(0.0138)		(0.0131)		(0.0132)		(0.0132)
Trading selfassessment		0.0055		−0.0026		0.0049		0.0070		0.0014
		(0.0301)		(0.0337)		(0.0308)		(0.0304)		(0.0308)
Loss aversion (Gächter et al., 2007)		0.0142		0.0163		0.0123		0.0131		0.0155
		(0.0101)		(0.0109)		(0.0103)		(0.0104)		(0.0103)
Risk aversion (Eckel & Grossman, 2008)		−0.0235		−0.0230		−0.0257		−0.0229		−0.0242
		(0.0161)		(0.0167)		(0.0166)		(0.0164)		(0.0160)
(Intercept)	0.0440	0.0575	0.0663*	0.0717	0.0783*	0.0842	0.0006	0.0375	0.0347	0.0924
	(0.0357)	(0.0573)	(0.0329)	(0.0488)	(0.0302)	(0.0520)	(0.0412)	(0.0590)	(0.0562)	(0.0763)
Num. obs.	84	59	84	59	84	59	84	59	84	59

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: The dependent variable is the participant's proportion of the bid value on the final asset. *Sincerity* denotes the sincerity value of the participants in the honesty-humility measure (Ashton et al., 2014), with a scale ranging from 1 to 5. *Fairness* denotes the fairness value of the participants in the honesty-humility measure (Ashton et al., 2014), with a scale ranging from 1 to 5. *Greed avoidance* denotes the greed avoidance value of the participants in the honesty-humility measure (Ashton et al., 2014), with a scale ranging from 1 to 5. *Modesty* denotes the modesty value of the participants in the honesty-humility measure (Ashton et al., 2014), with a scale ranging from 1 to 5. *Hexaco* denotes the mean value of the honesty-humility measure of the participants (Ashton et al., 2014). *Trading selfassessment* denotes the participant stock trading experience, with a 5-point scale ranging from 1 (<1 year), to 5 (>10 years). *Female* is a dummy variable that takes a value of one for female participants and zero otherwise. *Age* denotes participants age in years. *Risk aversion (Eckel & Grossman, 2008)* denotes the result of the Eckel and Grossman-task; *Risk aversion (Holt & Laury, 2002)* denotes the result of the Holt and Laury task. *Loss aversion (Gächter et al., 2007)* denotes the result of the Gächter-Johnson-Herrmann task. Participants who have no consistent choices with transitivity in the Gächter-Johnson-Herrmann task are excluded from this regression.

Table 3.9: Robust regression the honesty-humility on the bid amount

Big five and admiration-seeking behavior

Table 3.10 shows different regression models with the bid amount as an endogenous variable and the big five personality traits together with demographic control variables as exogenous factors. The regressions show an influence on agreeableness after including demographic control variables in the model. This means that agreeable individuals are more likely to pay a higher amount for the certificate. This circumstance could be explained if agreeable people see the bidding as an offer they should take, rather than a competition. We see similar behavior in career choices and salary discussions (Rode, Arthaud-Day, Mooney, Near, & Baldwin, 2008; Seibert & Kraimer, 2001).

The model shows no significance for subscales of the big five, including neuroticism, extraversion, conscientiousness, and openness to experience. Comparing these results to the existing literature, Grebitus, Lusk, and Jr. (2013) showed that "*personality plays a larger role in explaining behavior in choice experiments than in auctions*". Similar to Grebitus et al. (2013), we observed conscientiousness as an irrelevant personality trait for bidding behavior. Furthermore, in the auction model of Grebitus et al. (2013), personality trait agreeableness was significant, which is consistent with our result in Table 3.10. Differences arise in regard to extraversion; Grebitus et al. (2013) found a significant positive influence on the bidding amount. This led them to the conclusion that extraversion increases the willingness to pay. Our results

cannot confirm these findings due to the insignificance of extraversion. Fong et al. (2020) showed in a lab setting that high agreeableness leads to lower auction results. The authors explained this with the less-competitive attitude of agreeable individuals.

[This is place for Table 3.10]

	Auction on the result									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Extraversion	0.0070	0.0059								
	(0.0094)	(0.0077)								
Agreeableness			0.0255	0.0190*						
			(0.0117)	(0.0080)						
Conscientiousness					0.0109	0.0171				
					(0.0121)	(0.0096)				
Neuroticism							0.0082	0.0125		
							(0.0087)	(0.0072)		
Open experience									0.0058	0.0115
									(0.0106)	(0.0091)
Female		0.0248		0.0207		0.0374		0.0365		0.0293
		(0.0150)		(0.0148)		(0.0174)		(0.0150)		(0.0158)
Age		−0.0076		−0.0078		−0.0092		−0.0067		−0.0079
		(0.0064)		(0.0064)		(0.0076)		(0.0066)		(0.0070)
Trading selfassessment		0.0079		0.0108		0.0115		0.0056		0.0063
		(0.0161)		(0.0150)		(0.0179)		(0.0159)		(0.0173)
Loss aversion Gächter et al. (2007)		−0.0088		−0.0060		−0.0115		−0.0066		−0.0084
		(0.0050)		(0.0052)		(0.0060)		(0.0054)		(0.0056)
Risk aversion Eckel and Grossman (2008)		0.0139		0.0147		0.0145		0.0152		0.0143
		(0.0082)		(0.0081)		(0.0096)		(0.0083)		(0.0088)
(Intercept)	0.0309	0.0347	−0.0342	−0.0222	0.0140	−0.0034	0.0234	−0.0014	0.0262	0.0075
	(0.0252)	(0.0251)	(0.0425)	(0.0355)	(0.0469)	(0.0411)	(0.0295)	(0.0349)	(0.0399)	(0.0411)
Num. obs.	84	59	84	59	84	59	84	59	84	59

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: The dependent variable is the participant's proportion of the bid value on the final asset. *Extraversion* denotes the extraversion value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Agreeableness* denotes the agreeableness value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. The dependent variable is the participant's proportion of the bid value on the final asset. *Conscientiousness* denotes the conscientiousness value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Neuroticism* denotes the neuroticism value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Open experience* denotes the openness to experience value of the participants in the big five scale (Gosling et al., 2003), with a scale ranging from 1 to 5. *Trading selfassessment* denotes participant stock trading experience, with a 5-point scale ranging from 1 (<1 year), to 5 (>10 years). *Female* is a dummy variable that takes a value of one for female participants and zero otherwise. *Age* denotes participants' age in years. *Risk aversion (Eckel & Grossman, 2008)* denotes the result of the Eckel and Grossman-task; *Risk aversion (Holt & Laury, 2002)* denotes the result of the Holt and Laury task. *Loss aversion (Gächter et al., 2007)* denotes the result of the Gächter-Johnson-Herrmann task. Participants who have no consistent choices with transitivity in the Gächter-Johnson-Herrmann task are excluded from this regression.

Table 3.10: Robust regression of the big five on bid amount

3.5.4 Personality and (over)confidence

Overconfidence causes many consequences, such as failures of firms (Invernizzi, Menozzi, Passarani, Patton, & Viglia, 2017) and entrepreneurs (Hogarth & Karelaia, 2012) and market bubbles (Glaser & Weber, 2007; Michailova & Schmidt, 2016). There are many reasons that raise overconfidence, and personality traits could be one of the reasons. In this section, we additionally explore the relationship between overconfidence and personality traits. The study of Moore and Healy (2008) mentions three approaches to overconfidence: (a) overestimating the actual performance, (b) overplacing the performance relative to others, and (c) excessively precise beliefs. In a financial context, the most obvious manifestation of overconfidence is overestimation. In this paper, we also define overconfidence based on an overestimation of self-efficacy. By using self-assessment, we can determine the overconfidence in the most direct and accurate way. In particular, the gap between their self-assessment and their performance (guessing the type of stocks) is the highly reliable scale of overconfidence (the details of the overconfidence measure are shown in section 3.4.3).

For the dark triad measured with the dirty dozen scale, Table 3.11 shows significance for all components, i.e., psychopathy, Machiavellianism, and narcissism. High scores in psychopathy, Machiavellianism or narcissism tend to influence overconfidence in a positive way. All exogenous variables remained significant after adding demographic variables, gender, age, and trading experience. This is also valid for the

dark triad as a combined variable. Dark triad individuals are often depicted as being callous, manipulative, and having fetish for their self-image. With these characteristics, dark triad individuals tend to think that they are superior to others and that perception is the cause of overconfidence. Specifically, narcissism has the strongest link to overconfidence. This result supports the description of narcissism as ego satisfaction, a sense of superiority, and grandiosity.

[This is place for Table 3.11]

This result is consistent with the notion that dark triad individuals have an inflated view of themselves and are often shameless about self-promotion. Moreover, the association between (over)confidence and dark triad adds to the literature review an explanation for predicting (over)confidence. Specifically, this result supports the view that personality traits contribute to the formation of (over)confidence and thus further contribute to the results of Schaefer et al. (2004), which focuses on the relationship between overconfidence and the big five. In addition, because of the close relationship between the dark triad and overconfidence, we can infer that the effects of overconfidence also affect dark triad individuals. In particular, dark triad individuals may also have problems with overestimating the outcomes, overpredicting the results, and underestimating the risk.

	Confidence mean							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Machiavellian	0.0700*	0.0629*						
	(0.0262)	(0.0260)						
Psychopathy			0.0892*	0.0767*				
			(0.0316)	(0.0333)				
Narcissism					0.1132**	0.1096**		
					(0.0319)	(0.0320)		
Dark triad							0.1337**	0.1247**
							(0.0367)	(0.0375)
Female		−0.0257		−0.0055		−0.0360		−0.0154
		(0.0532)		(0.0529)		(0.0514)		(0.0524)
Age		−0.0208		−0.0206		−0.0138		−0.0201
		(0.0230)		(0.0226)		(0.0223)		(0.0227)
Trading selfassessment		−0.0057		0.0039		−0.0178		−0.0126
		(0.0261)		(0.0250)		(0.0256)		(0.0258)
(Intercept)	0.3871***	0.4637***	0.3256**	0.4060**	0.2367*	0.2998*	0.2133*	0.2948*
	(0.0626)	(0.0819)	(0.0801)	(0.1041)	(0.0874)	(0.1017)	(0.0920)	(0.1101)
Num. obs.	84	82	84	82	84	82	84	82

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: In Model (1)-(2), the independent variable is the participant's Machiavellian value that was calculated based on the Dirty Dozen scale. In Model (3)-(4), the independent variable is the participant's psychopathy value that was calculated based on the Dirty Dozen scale. In Model (5)-(6), the independent variable is the participant's narcissism value that was calculated based on the Dirty Dozen scale. *Confidence mean* denotes the average self-assessment value of participants about their confidence with their guessing choices, with the 10 scale ranging from 10% to 100%. *Female* is a dummy variable that takes a value of one for female participants and zero otherwise. *Age* denotes participants' age in years. *Trading selfassessment* denotes participants' stock trading experience, with a 5-point scale ranging from 1 (<1 year), to 5 (>10 years).

Table 3.11: Robust regression of the Dirty Dozen on confidence

3.6 Discussion and conclusion

The literature has shown that the disposition effect, as a central research topic in behavioral finance, is influenced by different personality traits. Furthermore, there exists a relationship with special social interactions such as reputation/self-image that could increase this effect as well. We build our paper on the idea of analyzing a potential relationship between personality traits, the disposition effect and admiration-seeking behaviour, also considering that personality traits have shown no significant relationship with behavioral biases in some studies. This also introduces the challenge of reproducibility from a meta-science perspective.

To test our hypothesis, we make use of a well-established methodology; we use a stock trading game setup introduced by Weber and Camerer (1998) to measure the strength of the disposition effect. Furthermore, we introduce a social setting by including a leaderboard and the possibility to take part in a sealed-bid English auction that has a unique certificate as an auction item. Our idea is that admiration-seeking people who score high in the dark triad will be more likely to bid a high price for the certificate. To assess personality traits, we make use of instruments for measuring the dark triad, the honesty-humility dimension of the HEXACO personality assessment and the big five. With robust regression analysis, we combine the data from these approaches to present our results.

In general, we were motivated by explaining investors' preferences in the case of the disposition effect. This should reveal important information about influencing factors that play a role in financial decision making and preference construction. Satisfying admiration-seeking behavior instead of maximizing returns could therefore lead to different market behaviors of investors, especially in social trading settings, which have gained increasing popularity (Oehler, Horn, & Wendt, 2016; Pelster & Hofmann, 2018). This understanding could lead to a stronger link of character assessments to trading activities and result in different regulatory approaches to protect investors from behavioral biases. From a methodological point of view, this paper is important to confirm uprising personality assessments such as the dirty dozen to show interactions between personality dimensions and linking behavioral biases to them.

Our paper results show the relationships of different personality traits; we find a negative correlation between the dark triad and conscientiousness and a positive correlation between the dark triad and (over)confidence. Furthermore, the dark triad is negatively correlated with the honesty-humility dimension of the HEXACO assessment, thereby confirming previous results found in the literature. However, we reveal that there is no significant relationship between popularly used personality trait assessments and the disposition effect. This result comes despite the descriptive analysis agreeing with the previous literature on terms such as distribution and correlation. Furthermore, our data do not show any significant relationship between personality traits and willingness to pay for admiration. These observations add to the inconclusive literature regarding the influence of personality traits on behavioral biases.

The reason for these unexpected findings regarding nonsignificant willingness to pay for admiration may come from a violation of our assumptions regarding the auction price in the form of the certificate. To recap: the item has to be linked to the participant in a way that personal identification is possible. Second, it has to be immediately available and usable. Third, it needs to create a social reaction from related and relevant peers. Participants could have no incentive to identify themselves with the experimental results. Another explanation could be found by taking a deeper look at current research practice and the issue of reproducibility; since psychology is impacted with the problem of weak significance, we see structural difficulties for the field of behavioral finance as well. Differences in the study designs, e.g., hypothetical versus experimental settings (Lin, 2011) or different data compositions in Cecchini et al. (2019), are driving factors that cause study results to end up with different findings (Ionnidis, 2005). Additionally, Dowgwillo and Aaron (2017) indicated that the different measurement instruments for the dark triad could lead to heterogeneity in the findings. We look forward to future research that explicitly tests such

differences. This issue of reproducibility could be addressed over two potential causes. First, there is a potential for priming when a previous stimulus unintentionally affects the individuals' response to another stimulus (Weingarten et al., 2016). This might especially take place in studies where the personality assessment is conducted before the disposition effect is measurement. Second, especially arising from longer personality assessments and experiments, we might see ego depletion, which limits the willingness of an individual to participate (Baumeister, Bratslavsky, Muraven, & Tiee, 1998). Despite not being able to find a significant answer to our main research question, with this study, we overcome publication bias (Song et al., 2010) and contribute to the ongoing discussion about the impact of personality traits on behavioral biases.

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III Appendix: Experimental instructions

Dear study participant,

Thank you for agreeing to participate in our experiment on decision making in financial markets. Below, you will be presented a detailed description of the following experimental setup. Please read these instructions to the experiment carefully.

In the experiment, you will receive an amount of 10,000 Talers of fictional money, which you can use for investment in stocks subsequently presented to you in fourteen investment rounds.

If you complete all investment rounds and fill in all questionnaires you will receive a performance-based compensation for your participation in the experiment. After completing the study, you will receive the account balance of your fictional money divided by 1,000 in real money. Thus, during the experiment you will earn Talers which are converted to Euros by the following exchange-rate:

1,000 Talers = 1 Euro

For example, if your fictional account balances at 10,000 Talers at the end of the study, you will receive 10 Euros in real money.

Description of the experiment

The experiment consists of 14 periods. In every period you have the possibility to buy shares of the firms A, B, C, D, E, and F. Every share has a certain value in Talers in every period. You start the experiment with an endowment of 10,000 Talers.

Performance of shares

The shares A-F will change in prices at the beginning of each of the 14 periods, i.e., in the subsequent period there was no share which will have the same price as in the previous period. The share-price changes have been randomly predetermined before the experiment started. That is, all price changes of all shares are completely independent of all your buying and selling decisions. The same is true for all buying and selling decisions of the other participants of the experiment. Each of the shares A-F is of a certain type. The share types differ regarding their probability of increasing (decreasing) in value at the beginning of the period. The distributions of the types are given in the table below. In the experiment there was exactly one share (of the shares A-F) which follows type "+ +" and the same is true for one share of type "+", "-", and "- -". There was two types (of the shares A-F) which follow type "0". All types are displayed in the below table.

Shares in the market	Type	Probability of price increase	Probability of price decrease
1	++	65%	35%
1	+	55%	45%
2	0	50%	50%
1	-	45%	55%
1	–	35%	65%

Example:

- Assume that share X is of type: "+ +"

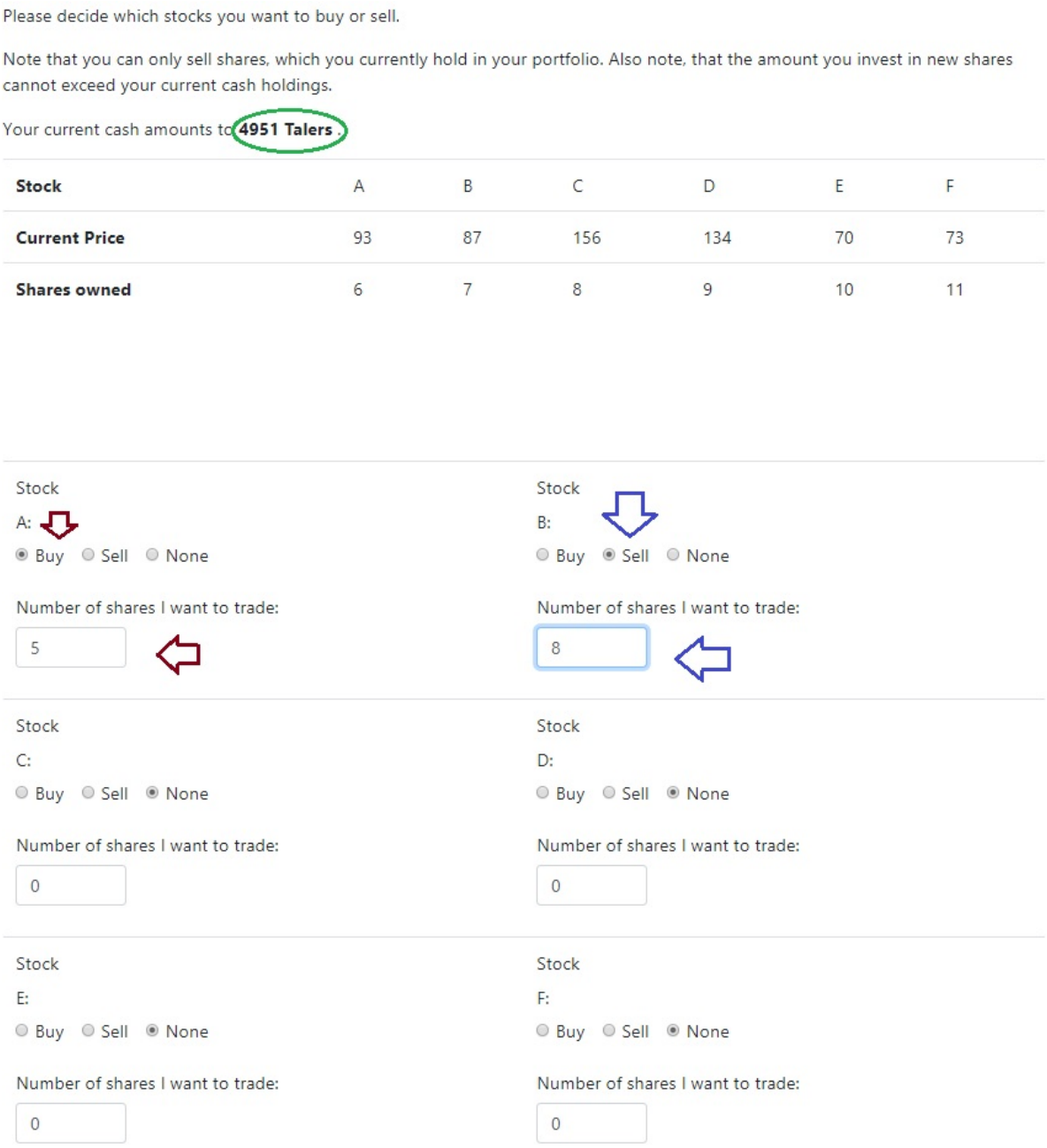
- At the beginning of each period the probability of a price increase of X is: 65%
- At the beginning of each period the probability of a price decrease of X is: 35%

The share price is determined as follows:

1. At the beginning of each period a share either increases (decreases). The probability depends on the share's type (see table).
2. Furthermore, the magnitude of the price movement (increase/decrease) was determined. The magnitude of the price movement can either be of 1, 3 or 5 Talers. Every magnitude (1, 3 or 5 Talers) can happen with the same probability. That is, every magnitude (1, 3 or 5 Talers) can happen with a probability of one-third. This is the same for every share, independent of its type.

Buying and selling actions of shares

In each of the 14 periods you have the possibility to buy and sell shares for your portfolio. You will find a screen shot below which depicts all of your decision possibilities in the course of the experiment.



Possibilities of decisions in the experiment

In the upper part you will find the share price window, displaying shares A-F. The price changes of shares A-F will be displayed here. (not shown in the figure)

Below, the screen displays your current portfolio value, your endowment (cash), and your current portfolio.

- "Current cash" displays your endowment, your cash. If you decide to buy shares of a firm then you have to pay for each share its current price. The sum of your expenditures cannot exceed your actual endowment.
- The array "Current price" depicts the price which has to be paid in order to buy new shares. At the same time you would receive this price for each share sold. For example, in the screen shot share A has a price of 93 Talers.

- The array “Shares owned” displays the current number of shares owned. For example, in the screen shot, you currently own four shares of A.

The window at the bottom is the transaction window. Here, you can decide in each period whether you would like to buy/sell one or more shares of shares A-F. If you decide to buy shares of a firm then you have to pay for each share its current price. The sum of your expenditures cannot exceed your current cash.

Example:

- Share A's current price in period 1 is 110 Talers. You decide to buy five shares of A.
- The expenditures for this transaction are given by: 5 * 110 Talers = 550 Talers and are immediately subtracted from your endowment

If you already own some shares at the beginning of a period, then you have the possibility to sell these shares. You will receive the current price of each share which is sold. Then the revenue is added to your cash. Selling shares follows the same principles as buying shares. However, the numbers of sold shares cannot exceed the total number of shares owned.

Example:

- Share C's current price in period 5 is 90 Talers. Assume, you own a total of four shares C, which you bought for 85 Talers in the previous round, and decide to sell 3 shares C.
- This will lead to a payoff of: 3 * 90 Talers = 270 Talers. This amount will be directly credited to your current cash. Afterwards you will still own one share of C.

The experiment ends after 14 periods. Then you do not have the possibility to buy or sell shares. All shares that you own at this point in time are automatically liquidated. The resulting money amount will automatically credited to your endowment.

Rankings

During the experiment, and at the end of the experiment, you will be presented rankings, which show your success in the experiment compared to other study participants. In this ranking, participants will be ordered according to their percentage of successful (”winning”) trades.

To generate the ranking, you will be asked to enter a ”screen name” at the beginning of the experiment. The screen name will not be saved together with your decision variables, but is only used for the rankings. You are completely free to choose any screen name you want.

In order to calculate your percentage of successful (”winning”) trades, the number of trades you closed at a price, which is higher than the price you paid to purchase the stock, will be counted and divided by the number of trades you initiated (the number of times you buy new shares of a stock).

Note that you have to sell your shares (at a higher price than you paid for the shares) in order for your trade to be successful. Thus, shares, which are currently in your portfolio, do not count towards your successful trades.

Example:

- Share C's current price in period 5 is 90 Talers. Assume, you own a total of four shares C, which you bought for 85 Talers in the previous round, and decide to sell 3 shares C.

- This will count as a successful trade and increase your number of successful trades.
- Share D's current price in period 5 is 60 Talers. Assume, you own a total of three shares D, which you bought for 59 Talers in the previous round.
- This will not count as a successful trade, because you did not sell any of the shares, yet. Thus, the transaction is not ended, yet.

Additional tasks

During the main experiment, you have to submit guesses on the stock types. This happens after the end of period 7 and after the end of period 14. Here, you have to guess which stock A-F followed the types: "+ +", "+", "0", "-" and "- -". You will be credited 200 Talers to your endowment for every correct guess at the end of the main experiment.

After the main experiment ends, you have the possibility to earn additional money by carrying out three short tasks. The instructions for the tasks are displayed on the computer screen, respectively.

Payoff

The total payoff you earn in the experiment is calculated as follows:

Total payoff = cash at the end of the experiment + value of the shares in your portfolio + earnings of your guesses + your earnings from the three additional tasks.

Practice rounds

We will start the experiment with 3 practice rounds of investments (the main experiment), which allows you to get accustomed to making the decisions and to get a feeling for the six different stocks.

After the practice rounds, we will reset your endowment to 10,000 Talers and then start the experiment. Thus, any gains or losses during the practice rounds will not affect your payoff.

III.1 Additional task 1: Eckel and Grossman (2008)

In this part you have to choose one of 9 lotteries which you prefer most. After your decision the computer will perform your selected lottery. Both payoffs arise with a probability of 50%. At the end of the experiment you will be informed of the outcome of the draw.

Lottery	Expected value of the lottery (1)	Payoff A probability 50% (2)	Payoff B probability 50% (3)	Please choose your preferred lottery (4)	Range of constant relative risk aversion if choosing this lottery (5)
1	€2.00	€2.00	€2.00	○	$1.37 \leq r \leq \infty$
2	€2.08	€2.56	€1.59	○	$0.97 < r \leq 1.37$
3	€2.26	€3.28	€1.24	○	$0.68 < r \leq 0.97$
4	€2.46	€4.00	€0.92	○	$0.41 < r \leq 0.68$
5	€2.55	€4.35	€0.74	○	$0.15 < r \leq 0.41$
6	€2.58	€4.59	€0.57	○	$-0.15 < r \leq 0.15$
7	€2.57	€4.65	€0.48	○	$-0.49 < r \leq -0.15$
8	€2.55	€4.67	€0.42	○	$-0.95 < r \leq -0.49$
9	€2.45	€4.68	€0.22	○	$-\infty \leq r \leq -0.95$

Column 5 was not shown. A power utility function of the form $U(x) = \frac{x^{1-r}}{1-r}$ is assumed (Eckel & Grossman, 2008).

Table 3.12: Eckel and Grossman-task

III.2 Additional task 2: Gächter et al. (2007)

For this part, you receive an endowment of 70 cents. In the following, you are faced with 10 lotteries. Assume that for each of the lotteries a fair coin is thrown. The coin can either land on "heads" or "tail". To answer each of the 10 questions you will have to choose "accept" or "reject" for taking part in the respective lottery. After you submit your decision, the computer will randomly draw one of the lotteries. If you reject this specific lottery, you will receive the endowment after the experiment. If you accept the randomly chosen lottery, the computer will flip a coin and the outcome of this coin toss will be added to your endowment. At the end of the experiment you will be informed of the randomly selected lottery and the outcome of the draw.

III.3 Additional task 3: Holt and Laury (2002)

Below you are presented a set of lottery choices. For each of the ten lottery choices you can choose between lottery A and B. Please note that – while the payoffs for both lotteries remain the same across all ten lotteries – the probabilities between the lotteries vary. After you submit your decisions the computer will randomly draw one of the lotteries. Then, the computer will randomly decide the outcome of the chosen lottery. At the end of the experiment you will be informed of the outcome of the draw.

III.4 Additional task 4: personality test

Please answer the following questions. Your participation is completely anonymous and your identity is not known. There are no right or wrong answers. We would, therefore, kindly ask you to be as truthful as possible.

To what extent do the following statements apply to you?

III.5 Additional task 5: auction

CONGRATULATIONS! YOU ACHIEVED THE RANKING NUMBER 3 IN OUR TRADING GAME!

Lottery		Accept	Reject	Range of loss aversion coefficient (λ) if switching to reject in this row
1		2	3	4
1	If the coin turns up heads, then you lose 12 cents; if the coin turns up tails,you win 60 cents	( )	( )	$5.00 \leq \lambda \leq \infty$
2	If the coin turns up heads, then you lose 15 cents; if the coin turns up tails,you win 60 cents	( )	( )	$4.00 \leq \lambda \leq 5.00$
3	If the coin turns up heads, then you lose 20 cents; if the coin turns up tails,you win 60 cents	( )	( )	$3.00 \leq \lambda \leq 4.00$
4	If the coin turns up heads, then you lose 25 cents; if the coin turns up tails,you win 60 cents	( )	( )	$2.40 \leq \lambda \leq 3.00$
5	If the coin turns up heads, then you lose 30 cents; if the coin turns up tails,you win 60 cents	( )	( )	$2.00 \leq \lambda \leq 2.40$
6	If the coin turns up heads, then you lose 35 cents; if the coin turns up tails,you win 60 cents	( )	( )	$1.71 \leq \lambda \leq 2.00$
7	If the coin turns up heads, then you lose 40 cents; if the coin turns up tails,you win 60 cents	( )	( )	$1.50 \leq \lambda \leq 1.71$
8	If the coin turns up heads, then you lose 50 cents; if the coin turns up tails,you win 60 cents	( )	( )	$1.20 \leq \lambda \leq 1.50$
9	If the coin turns up heads, then you lose 60 cents; if the coin turns up tails,you win 60 cents	( )	( )	$1.00 \leq \lambda \leq 1.20$
10	If the coin turns up heads, then you lose 70 cents; if the coin turns up tails,you win 60 cents	( )	( )	$0.86 \leq \lambda \leq 1.00$

Column 4 was not shown. As in Gächter et al. (2007), equal curvature parameters in the gain and the loss domain are assumed for deriving λ.

Table 3.13: Gächter-Johnson-Herrmann-task

Lottery	Please choose one of the following		Range of relative risk aversion for $U(x) = \frac{x^{1-r}}{1-r}$
	Lottery A	Lottery B	
1	€4 (10% chance) / €3.20 (90% chance)	€7.70 (10% chance) / €0.20 (90% chance)	$r < -0.95$
2	€4 (20% chance) / €3.20 (80% chance)	€7.70 (20% chance) / €0.20 (80% chance)	$-0.95 < r < -0.49$
3	€4 (30% chance) / €3.20 (70% chance)	€7.70 (30% chance) / €0.20 (70% chance)	$-0.49 < r < -0.15$
4	€4 (40% chance) / €3.20 (60% chance)	€7.70 (40% chance) / €0.20 (60% chance)	$-0.15 < r < 0.15$
5	€4 (50% chance) / €3.20 (50% chance)	€7.70 (50% chance) / €0.20 (50% chance)	$0.15 < r < 0.41$
6	€4 (60% chance) / €3.20 (40% chance)	€7.70 (60% chance) / €0.20 (40% chance)	$0.41 < r < 0.68$
7	€4 (70% chance) / €3.20 (30% chance)	€7.70 (70% chance) / €0.20 (30% chance)	$0.68 < r < 0.97$
8	€4 (80% chance) / €3.20 (20% chance)	€7.70 (80% chance) / €0.20 (20% chance)	$0.97 < r < 1.37$
9	€4 (90% chance) / €3.20 (10% chance)	€7.70 (90% chance) / €0.20 (10% chance)	$1.37 < r$

Column 4 was not shown. Ranges of relative risk aversion are as in Holt and Laury (2002).

Table 3.14: Conducted Holt and Laury-task

I consider myself to be dependable or self-disciplined.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to manipulate others to get my way.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I am anxious or easily upset.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I maintain definite standards of performance.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I am disorganized or careless.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I have a desire to be admired.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to lack remorse.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
How seriously do you take this study? Choose 'Disagree strongly' if you read this question.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I enjoy my successes very much.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be extraverted or enthusiastic.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be friendly and polite.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be great.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to be unconcerned with the morality of his/her actions.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to use deceit or lies to get his/her way.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I show others how special I am
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be sympathetic or warm.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be open to new experiences.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
Mostly, I am very adept at dealing with people.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to be callous or insensitive.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly

This survey included the big five measurement (Gosling et al., 2003), The dirty dozen measure (Back et al., 2013), and the honesty-humility part of the HEXACO model (Ashton et al., 2014).

Table 3.15: Personality test - Part 1

I use flattery to get my way.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be reserved or quiet.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
This is a quality check. Please choose 'Agree moderately'.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I keep to myself.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I will someday be famous.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to be critical or quarrelsome.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I am willing to make changes.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be conventional or uncreative.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to seek prestige and status.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to be cynical.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to exploit others towards my own end.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
Being a very special person gives me a lot of strength.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I tend to expect special favors from others.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I want others to pay attention to me.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be calm or emotionally stable.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I consider myself to be confident.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
Most of the time I am able to draw people's attention to myself in conversations.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I manage to be the center of attention with my outstanding contributions.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I wouldn't pretend to like someone just to get that person to do favors for me.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I would never accept a bribe, even if it were very large.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I manage to be the center of attention with my outstanding contributions.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
Having a lot of money is not especially important to me.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly
I wouldn't want people to treat me as though I were superior to them.
○ Disagree strongly ○ Disagree moderately ○ Neither agree nor disagree ○ Agree moderately ○ Agree strongly

This survey included the big five measurement (Gosling et al., 2003), The dirty dozen measure (Back et al., 2013), and the honesty-humility part of the HEXACO model (Ashton et al., 2014).

Table 3.16: Personality test - Part 2

We want to provide you with an official certificate for participating in the trading game that you can share with your friends or on social media. The certificate will show your ranking (see above) amongst all participants that took part in the experiment over the last 24 hours. We will provide a link where you can download the certificate on the next page.

As we believe that the certificate will be more impressive if the certificate is **UNIQUE**, we will issue ONLY 1 certificate. Here you have the opportunity to bid for this certificate.

Auction design:

- In this auction, you will be asked to decide **how much you would be willing to pay for the certificate.**
- The auction is a sealed bid, second price auction. You can bid Talers that you earned during the trading game.
- The winner of the auction is the one with the highest bid among all participants over the last 24 hours. We will compare your bid with all bids from the last 24 hours.
- A second price auction means that the winner of the auction will have to **pay** the **second-highest bidding price.**

For example, if the highest bid was x Talers and the second-highest was 300 Talers, the highest bidder would receive the certificate and must pay 300 Talers.

Only the winner will pay the price and receive the certificate.

If you win the auction, we will deduct the price (the second-highest bidding price from your current balance).

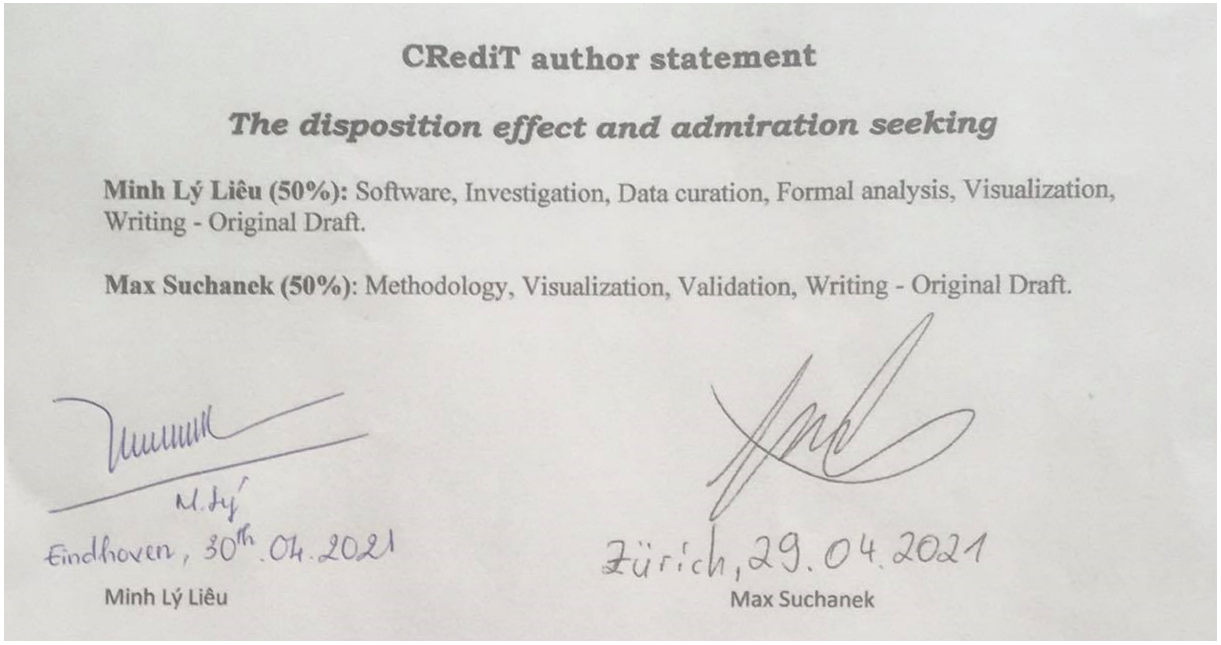
Please answer the following question, which is designed to help you understand the design of the auction.

If your x Taler bid is the highest, and the second-highest bid is 3000 Taler, what price will you pay for the certificate?

_____

Your maximum bid / current balance is: **12.350** Talers.
Please enter your bid for the certificate?

III.6 Author contribution statement



CRediT author statement

The disposition effect and admiration seeking

Minh Lý Liêu (50%): Software, Investigation, Data curation, Formal analysis, Visualization, Writing - Original Draft.

Max Suchanek (50%): Methodology, Visualization, Validation, Writing - Original Draft.

M. Lý

Eindhoven, 30th. 04. 2021

Minh Lý Liêu

Zürich, 29. 04. 2021

Max Suchanek

Author contribution statement

4 Social interactions in short squeeze scenarios

Social interactions in short squeeze scenarios

Suchanek, Max[1]

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Abstract

This paper studies the relationship between the intent dimension of social media postings and stock metrics such as trading volume and returns. Thereby, the paper contributes to the literature that studies the short squeeze phenomenon around GameStop focusing on textual sentiment. I use data from December 2020 to September 2021 and a vector autoregression model framework to study the connection between investor intent, textual sentiment, and stock metrics. I find that strong appeal of potential investors to hold onto investments significantly reduces stock volume in the short term. Higher sentiment lead to an increase in trading volume across several stocks. These findings indicate that observations made on the GameStop stock generalize to other stocks. Investor intent in social media postings can significantly impact stock markets.

Keywords: GameStop; investor behavior; Reddit; sentiment

4.1 Introduction

In January 2021, the GameStop short squeeze - when a group of private investors, predominantly organized on the social news aggregator Reddit, coordinated to drive up the stock price of GameStop corporation - captured the world's attention for three important reasons. First, its duration surpassed that of other short squeezes, which typically last just one or two days. Second, it was not only limited to GameStop but also included other companies. Lastly, the pivotal role of social interactions among investors played a significant role in these market events. These four distinctions provide a unique context to examine the social behavior of private investors in volatile market conditions, including their intent and sentiment, as well as stock performance metrics such as trading volume and returns.

Textual sentiment analysis, which involves assigning a sentiment score, expressed as a numerical value, to each word in a text, is a major focus of research explaining the GameStop short squeeze. Textual sentiment can affect the performance of speculative assets such as cryptocurrencies (Long, Lucey, Xie, & Yarovaya, 2022), lead to euphoria, and contribute to behavioral biases, such as investment overconfidence (Nofsinger, 2005), especially during volatile markets. This can make investors more susceptible to emotions and irrational behavior (Bollen & Mao, 2011). For GameStop, textual sentiment correlated

[1]I am grateful for the excellent comments and suggestions from Arman Eshraghi (the editor) and an anonymous referee from the journal of International Review of Economics and Finance. I also thank Matthias Pelster for valuable comments and suggestions.

significantly with stock performance metrics such as trading volume and returns (Anand & Pathak, 2022; Betzer & Harries, 2022). However, this relationship was only observable during the first peak of the GameStop stock in January and February 2021 and only for that specific stock, leaving room for more research focused on generalizability.

In addition, investors have different motives to participate in social interactions. One of these motives is to convince other investors to hold onto stocks regardless of their market performance, which is characterized by the expression "diamond hands"[2]. However, despite this strong linkage between the expression of investor intent and underlying mechanism of short squeezes, researchers have not yet explored this dimension fully in context of the 2021 events.

With reference to stock performance metrics, while some researchers found that trading volume does not Granger-cause returns over long periods (Lee & Rui, 2002), others have shown evidence that trading volume has a significant positive effect on stock returns and that trading volume Granger-causes returns in certain markets (Al Samman & Al-Jafari, 2015). I add to the literature on the trading-volume-returns relationship by studying the relationship during short squeeze scenarios. Analyzing the relationship in particular market scenarios is important and contributes to our knowledge.

The novelty of this study is twofold. On one side, this study is the first to introduce the intent dimension to examine short squeeze scenarios. An examination of the intent of diamond hand submissions on Reddit can provide valuable insights into investors' intentions. For example, categorizing submissions according to the intended effect on the community could reveal whether the message is to hold onto investments. Including such a dimension in the analysis can therefore provide a more comprehensive understanding of the event, as shown by Bradley, Jr, Jame, and Xiao (2021). In connection with sentiment, it allows for the examination of both the emotional tone expressed in submissions and their underlying message or theme.

Second, I focus on multiple stocks and additionally include AMC; BlackBerry, and Nokia (see also (Lyócsa, Baumöhl, & Vỳrost, 2022)), which allows to examine whether the social media dynamics observed for GameStop can be generalized to other stocks or if they differ by stock and social media discussion group. While many studies discussed the GameStop short squeeze, incorporating additional short squeeze stocks such as BlackBerry, Nokia, and AMC generates a more comprehensive understanding of the underlying social dynamics and collective behavior that drive financial market movements.

The analysis also extends those of previous studies by adopting a longer period, ranging from December 1, 2020 to September 30, 2021[3]. While some studies cover the price increases in March, those from May to June 2021 have only been examined by a few authors and no studies have thus far examined price changes after June 2021 . This suggests that previous studies have focused on explaining the event as a case study and that the longer-term behavior of the community remains an open question.

Further, I use two datasets based on the submissions of two subreddits, namely, /r/wallstreetbets and /r/GME, to cover a variety of short squeeze stocks and a more specialized GameStop community (/r/GME). The intent dimension is derived using Reddit's internal categorization system, called flairs, as well as segregating diamond hand submissions using a combination of keywords. To measure textual sentiment within the communities, the adapted dictionary of Long et al. (2022) is used, as it accounts for the unique language used by the community. The stock data include hourly volume and returns and are obtained from Finnhub.io.

The analysis based on these two datasets uses a time-dependent vector autoregression (VAR) model to

[2]This expression, which was used by the Financial Times (Platt, Smith, Darbyshire, Kantor, & Wigglesworth, 2021) and The Wall Street Journal (Spencer, 2021), refers to investors' intent to hold onto investments regardless of price changes (Andreev, Sermpinis, & Stasinakis, 2022) and trigger a short squeeze by achieving a price increase.

[3]The five largest daily price increases of GameStop occurred on January 27, 2021 (+79%), January 29, 2021 (+44%), February 1, 2021 (+150%), February 3, 2021 (+73%), and March 23, 2021 (+51%). Additionally, smaller price increases were observed on February 8, 2021 (+19%), March 12, 2021 (+20%), June 9, 2021 (+37%), November 22, 2021 (+16%), and December 10, 2021 (+16%)

put the sentiment and intent dimensions into a time-related context following (Aharon, Kizys, Umar, & Zaremba, 2023). To further explain the model, Granger causality tests and impulse response function (IRF) analyses are performed.

First, for the intent dimension, the results show a significant correlation between diamond hand submissions and trading volume because the historical trading volume of GameStop helps explain current diamond hand submissions on the /r/GME and /r/wallstreetbets subreddits. The IRF analysis also shows that a positive reaction to diamond hand submissions on /r/GME leads to a significant decrease in trading volume within 10 hours, but this effect is not observed for /r/wallstreetbets. The study further finds that this effect is not limited to GameStop, but is also observed for AMC, while no significant effect is observed for Nokia and BlackBerry. Hence, this study is the first to examine the combined effects on other short squeeze stocks and stability of the findings beyond GameStop. Moreover, adherence to community advice differs by subreddit: the community on /r/GME follows the diamond hands advice and reduces trading volume, while the broader mass on /r/wallstreetbets does not. This finding suggests a centralization of true believers on more specialized subreddits.

Second, the results show that textual sentiment impacts trading volume for the GameStop stock on both the /r/GME and the /r/wallstreetbets subreddits. Historical trading volume can help explain the sentiment on these subreddits and vice versa. Furthermore, a positive reaction to sentiment leads to an increase in trading volume for the GameStop, AMC, and BlackBerry stocks, but the timing and magnitude of this effect differ by stock. Overall, these results support current evidence on the causal link between sentiment and trading volume. This study thus shows causal inferences about the relationship between social media activity and stock performance metrics, extending previous studies (Betzer & Harries, 2022).

Lastly, from the perspective of stock performance metrics, the model shows no significant relationship between returns and trading volume for GameStop and other stocks besides AMC, in line with the results of Lee and Rui (2002).

The remainder of this paper is organized as follows. Section 4.2 summarizes the related literature and existing gaps. Section 4.3 formulates the hypotheses. Section 4.4 introduces the data and methodology. Section 4.5 presents the results. Section 4.6 concludes, links these findings to practical applications, and provides avenues for further research.

4.2 Literature review

4.2.1 Sentiment-driven literature on the GameStop short squeeze

Textual sentiment analysis, the computational study of people's views, mood and emotions (Cambria, Das, Bandyopadhyay, & Feraco, 2017), refers to the degree of positivity or negativity in written texts (Kearney & Liu, 2014). Textual sentiment is different from the widely used term "investor sentiment," which incorporates beliefs about future cash flows, and "investment risks," which are not justified by the facts at hand (Kaplanski & Levy, 2010).

Anand and Pathak (2022) showed that the textual sentiment of /r/wallstreetbets discussions influences GameStop's future intraday variables. The tone of the subreddit has significant predictive associations with GameStop's daily volatility for three consecutive days ahead. However, the causal relationship between these variables remains unclear. Furthermore, only 462 users have a high impact on GameStop, pointing toward a centralization of power in this community. This might suggest that different communities could behave differently, underlying the need for generalizability. In line with this, Betzer and Harries (2022) showed a significant relationship between Reddit posts and GameStop trading data within a 30-minute window, indicating the informative nature of such posts; however, no one-way causality was

identified.

Long et al. (2022) analyzed the role of sentiment by performing a text-based analysis on Reddit comments. Using the Valence Aware Dictionary and sEntiment Reasoner (VADER) sentiment analysis tool, the authors adapted the default dictionary to cover the community-specific slang of Reddit users. For 1-minute data, the results suggested that GameStop returns Granger-cause both net and average sentiment; however, the 5-, 10-, and 30-minute data did not show significant findings. Their study is important for two reasons. First, as potential investors use specific language on Reddit, the authors adjusted the sentiment dictionary to fit to these discussions. Second, the findings underlined the time-based difference in significance levels, suggesting the need for a time-dependent model.

Mancini, Desiderio, Clemente, and Cimini (2022) characterized the structure and time evolution of Reddit conversation data using a voter model. The findings showed that the occurrence and sentiment of GameStop-related comments increase significantly before the short squeeze occurs. The authors also showed that user engagement can trigger a self-reinforcing mechanism, leading to the emergence of a consensus. Such a drive for consensus could be seen as the goal of potential investors with regard to triggering a short squeeze.

Zheng et al. (2021) examined the evolution of topological structure, discussion topics, and user sentiment polarity by constructing dynamic interaction networks, modeling topics, and analyzing user sentiment. The topological structure of the interaction network evolves in a more efficient direction, the discussed topics become more centralized, and user sentiment tends to be more positive and divergent. The study also found that social media activity, the popularity of the dominant topic, topic cohesiveness, user sentiment, and sentiment divergence between users on the r/wallstreetbets subreddit can partially explain GameStop's stock price. Despite incorporating many variables, this study leaves open the opportunity to study more time horizons and generalize the findings beyond GameStop.

A variation in sentiment was also revealed by Hu, Jones, Zhang, and Zhang (2021), who found higher returns, increased retail order flows, and decreased shorting flows on the next day, as indicated by increased Reddit activity. However, no statement on causality could be made, offering another possibility for enhancing the existing literature.

4.2.2 Attention-driven literature on the GameStop short squeeze

Lyócsa et al. (2022) showed that a rise in activity on the /r/wallstreetbets subreddit compared with Google searches can account for some of GameStop's price variance on the following day. The analysis, using daily financial data on GameStop, AMC, BlackBerry, and Nokia, showed that Google searches, as a measure of attention, also explain the events to some extent. Incorporating this selection of stocks enhances the comprehensiveness of this study's analysis.

Vasileiou, Bartzou, and Tzanakis (2021) focused on the impact of trading volume and Google trends on GameStop's intraday performance. By applying a GARCH model, this study provided empirical evidence that increasing trading volumes and Google searches for GameStop has a positive and significant impact on its prices (and vice versa). The authors also highlighted the importance of considering the speed of information arrival: Redditors must have time to observe the price, process that information, create content, and finally submit the posting. Therefore, lagged effects must be considered.

Klein (2022) examined the demand for education as another facet of investor attention. The author linked financial literacy and autodidacticism to the increased attention of private investors on meme stocks led by GameStop. The short squeeze and related financial concepts are significantly reflected in the keyword searches across multiple platforms. This finding showed a positive result from events that lead to increased financial literacy among private investors. In addition to the danger of potential biases, such events can also benefit a large group of investors. Figure 4.1 summarizes the literature beyond the

above mentioned and additional studies.

Insert Figure 4.1 here

4.3 Hypotheses development

4.3.1 Difference between sentiment and intent

Sentiment refers to the attitude or emotion expressed in a piece of text, while intent refers to the underlying purpose or goal behind the text. For example, a post with a positive sentiment may express admiration for a company, while the intent of the post may be to persuade others to purchase the stock. In this case, sentiment would be positive, but with an ill intent behind it.
While sentiment analysis is an established field in text analysis, identifying intent is more challenging. Researchers are increasingly turning to machine learning techniques to identify intent, using natural language processing algorithms to analyze the structure and content of text (Chen, Zhuo, & Wang, 2019). However, sentiment analysis tools often fail to accurately identify intent, as they result in many false positives and false negatives (Khurana, Koli, Khatter, & Singh, 2023).

4.3.2 Intent dimension

Understanding the intent of the diamond hand submissions of the GameStop short squeeze is crucial not only because they are one of the leading motives of the event covered widely by the media, but also because they contain direct trading advice.

Why might positive returns lead to increased diamond hand submissions

The concept of strategic complementarities suggests that investors' actions are more effective when they are part of a larger group and that the value of their actions increases as more people participate, as described by Hirshleifer and Teoh (2003, 2009). For the GameStop short squeeze, investors who held shares pushed the price upward, forcing short sellers to rebuy their positions at a higher price. Therefore, a single GameStop investor holding their position may not have been sufficient to trigger the short squeeze event. As this mechanism is understood by many investors within the Reddit community, communication within the subreddit became crucial to convince other investors to hold onto their shares.
Since investors discuss market movements with their peers Shiller, Fischer, and Friedman (1984), social desirability can also motivate investors to communicate certain messages. For example, if investors holding onto stocks because of good past performance, they might obtain social benefits by posting their success as diamond hand submissions. Indeed, individuals are more likely to share information about their investments when they expect it to enhance their social standing or reputation (Bastian, Jetten, & Ferris, 2014; Kaustia & Knüpfer, 2012). Han, Hirshleifer, and Walden (2022) showed that investors also tend to report their investment gains more often than their losses, as traders seek to report positively about themselves and dislike having to admit failure to both themselves as well as their peers. Transferring these findings to the short squeeze phenomenon, positive returns can signal knowledge and success to other investors, which may increase that investor's perceived credibility and influence in the community. In this context, Burks, Carpenter, Goette, and Rustichini (2013) proposed that overconfidence may be driven by the desire to send positive signals to others about one's skills. Therefore, closing a losing position may signal a bad investment decision and holding onto it can be driven by the desire to maintain a positive self-image.
Information sharing can also motivate investors to post specific content on Reddit (i.e., to improve others'

decision-making) (Rime, Mesquita, Boca, & Philippot, 1991). For example, investors who have success holding onto a short squeeze stock may post about their returns to inform others of the stock's potential, which can benefit the community as well as motivate others to follow this previously demonstrated successful strategy.

In summary, potential investors may appeal to the Reddit community to hold onto their investments for such reasons as strategic complementarities, self-presentation, and information sharing, as shown by Bastian et al. (2014); Choi and Toma (2014); Kaustia and Knüpfer (2012); Rime et al. (1991). Therefore, the number of diamond hand submissions can be influenced by returns, as increasing returns might signal to investors that the short squeeze is about to occur. For a positive reaction to returns, individuals are expected to hold onto their positions and communicate that they are doing so, which should result in more diamond hand submissions. Therefore,

Hypothesis 1 (H1): *Increasing returns lead to increased diamond hand submissions.*

Why might increased number of diamond hand submissions lead to reduced trading volume

Kaustia and Knüpfer (2012) found that investors tend to follow the trades of highly connected individuals, even when those individuals have a poor track record of investment performance. In other words, individuals follow the trading advice originating from their social networks. Highly connected or credible individuals on Reddit can be described by their score. Every registered user can upvote or downvote submissions, providing an indication of the relevance of the content to the subreddit and therefore promoting credible users. Since most Reddit users only consume content, as Singer, Flöck, Meinhart, and Zeitfogel (2014) pointed out, registered users might seem more credible when posting content, especially if their post has many upvotes. Increased diamond hand submissions, especially by Reddit users perceived as credible and connected as well as those with recognized track records, are expected to encourage the community to adhere to their intent and therefore not sell their stocks, thus reducing its trading volume. The price increase and Reddit activity surrounding short squeeze stocks can also be viewed as a self-fulfilling prophecy for private investors. Following others' actions blindly has been shown to be a successful strategy in the short term. Individuals are also more likely to make investment decisions based on the actions of others rather than their own independent analysis (Hirshleifer & Teoh, 2003; Kaustia & Knüpfer, 2012). Therefore, if members of the Reddit community communicated not to sell the GameStop stock, other investors would likely have held onto their positions, too. This could also have reduced trading volume, as investors stuck to their positions and delayed placing new orders.

Moreover, an increased number of diamond hand submissions can displace all other types of submissions with different intents posted on the subreddit, leaving investors with only one opinion from the community. Such cognitive bias in which information that is brought to mind more easily has a disproportionate influence on outcomes is known as availability heuristics (Taylor, 1982). This absence of other intent-relevant submissions would lead to reduced trading volume. When investors are exposed to a large number of diamond hand submissions, they may perceive that the community is overwhelmingly in favor of holding onto the stock, even if this is not the case.

For the above reasons, investors are likely to follow the advice of community leaders, adhere to herding behavior, or fall for the availability heuristics, leading them not to sell the stock. Hence,

Hypothesis 2 (H2): *An increase in diamond hand submissions lowers trading volume.*

4.3.3 Sentiment dimension

Textual sentiment plays an important role in explaining the GameStop short squeeze (Anand & Pathak, 2022; Betzer & Harries, 2022; Hu et al., 2021; Long et al., 2022; Mancini et al., 2022; Zheng et al.,

2021). In general, when looking into different investor groups, it was shown that novice investors are more prone to being influenced by textual sentiment (Kaniel, Saar, & Titman, 2008). This is relevant because Hasso, Müller, Pelster, and Warkulat (2022) characterized Reddit investors participating in short squeeze scenarios as younger and less experienced. One could therefore expect additional significance in the context of short squeeze scenarios.

Why sentiment might increase trading volume

While the Granger causality between sentiment and returns was inconclusive in prior studies (Lao, Nie, & Yonghong, 2018), sentiment is significantly correlated with trading volume (Brown, 1999; Cambria et al., 2017; Duz Tan & Tas, 2021) and even Granger-causes it (Canbaş & Kandır, 2009). However, whether these relations hold in volatile market events such as short squeezes remains underexplored. Hence,

Hypothesis 3 (H3): *A more positive sentiment increases trading volume.*

Why sentiment might be higher in diamond hand submissions

Studies using such methods as the text analysis of news articles and social media posts have consistently demonstrated a positive correlation between sentiment and stock returns (Cambria et al., 2017; Hasso et al., 2022). This relationship is significant when sentiment is volatile, particularly for private investors (Kaniel et al., 2008). Owing to confirmation bias, investors also seek out and share information that supports their positive views of stockholdings, while ignoring or downplaying relevant negative information (Klayman, 1995). Such a filtering mechanism in combination with the previously mentioned availability bias means a more positive sentiment can be expected in diamond hand submissions, leading to higher returns.

Another source of more positive sentiment is optimism about the future. Investors posting diamond hand submissions are optimistic about the future prospects of their investments. Optimism and anticipation are closely related to other positive emotions (Deng & Ren, 2021), thus creating a more positive sentiment score.

In summary, rising stock prices influence sentiment positively, as do the short squeeze specifics of confirmation bias and excess optimism about the future. Therefore,

Hypothesis 4 (H4): *Increasing returns increase sentiment.*

4.4 Data and methodology

4.4.1 Data collection

The data used in this study are based on Reddit interactions and stock performance metrics ranging from December 1, 2020 to September 30, 2021. Two datasets on two subreddits are used, as explained next.

/r/GME data

The first dataset contains the submission history of /r/GME. Only GameStop submissions are found on this subreddit, which removes the need for filtering (Long et al., 2022; Lyócsa et al., 2022). It has sufficient coverage, with a daily average of 615 posts as of May 2021 and 289,106 subscribers. The initial data obtained through Pushshift contain 45,623 submissions in the form of Reddit articles.

The analysis excludes comments on Reddit because of their relative insignificance compared with postings. For example, Medvedev et al. (2019) showed that for a sample of 186 Reddit users, 78% of interactions (265,239 of 339,270) were content views, while only 13% (43,982) were views of comments. Furthermore, as

noted earlier, the majority of Reddit users only consume content. Therefore, postings have a much higher influence on the community than comments, which are not displayed on the landing page. Additionally, Reddit only exhibits the top 200 comments, meaning that numerous comments in popular posts go unnoticed (Glenski & Weninger, 2017).

Following traditional VAR approaches, I use linear interpolation to fill in the missing data in the /r/GME subreddit (Bashir & Wei, 2016). The first gap appears in the data over February 5–7, 2021, followed by missing data on March 1, 2021, March 6, 2021, March 18–26, 2021, and April 10–13, 2021, with the March gaps being the most significant. Pushshift is responsible for these gaps, as the data ingest broke during those times according to the Pushshift community.

The /r/GME data contain a unique post ID as well as the title, author, submission date, number of comments, permalink, category of the post, and submission text. They also provide the score received by the submission, calculated through up- and down-voting. I merge the title and submission text into a new variable and use another variable to count the words of the merged string. Owing to several updates, I recategorize the intent categories into 16 classes to ensure no duplication (see the online appendix).

/r/wallstreetbets data

The second dataset contains 1,206,293 threads of the community /r/wallstreetbets. This dataset is consistent with that used by Long et al. (2022), who collected 846,628 threads between January 1, 2021 and February 28, 2021. The dataset, similar to the /r/GME dataset, includes the post's title, score, unique ID, posting URL, number of comments, creation timestamp, and message body. /r/wallstreetbets does not use posting categories/ flairs, which are identifiers that appear in a colored box at the top of a post. Therefore, I combine the title and body text to obtain full information about the post and filter for keywords to identify diamond hands intent.

This study also examines the AMC, BlackBerry, and Nokia stocks to identify any spillover effects arising from the GameStop short squeeze. Stock selection follows Lyócsa et al. (2022), who highlighted that these three stocks were subject to a decentralized short squeeze. These are also popular stock tickers on /r/wallstreetbets. Table 4.1 shows the distribution of these postings for the four stocks on the /r/wallstreetbets subreddit, highlighting its sufficient coverage and that some stocks are more popular than others.

Insert Table 4.1 here

Stock performance metrics

Stock information from the New York Stock Exchange (NYSE), include trading hours; opening, high, low, and closing prices; and trading volume, and were obtained from Finnhub.io on intraday level. I use log returns, as is common practice for analyzing stock price movements due to being a more accurate measure of returns and better reflecting stock price changes.

4.4.2 Variables

Diamond hand submissions

The variable diamond hand submissions reflects one of the 16 intent categories of the /r/GME subreddit. As Figure 4.3 shows, the category system was introduced on February 13, 2021 to allow for intent filtering and has been reworked occasionally since.

Insert Figure 4.3 here

However, after each overhaul, the diamond hand submissions category remained unchanged, highlighting its central role in the community. I remove punctuation and emojis and merge overlapping categories.
To better comprehend the popularity of an intent category in each period, submissions are counted and divided into the relative weights of the category popularity during that hour. For instance, if there are 400 submissions with Flair A and 600 submissions with Flair B between 13:00 and 14:00, Flair A would have a 40% share.
I apply the following rule to identify diamond hand submissions in /r/wallstreetbets: If the submissions contain at least one GameStop identification ("GME," "GameStop," or "GameSt") and at least one holding-related expression ("hold," "holding," "diamond hands"), they are counted as diamond hand submissions. As shown in the literature review, identifying word-based intent is a common research practice used with an awareness of its shortcomings such as including false positives.

Sentiment

Polarity reflects the general mood in a given text and it is derived by assigning a number, called a compound value, to such text. In this method, threshold values are used to categorize texts as positive, negative, or neutral (Elbagir & Yang, 2019).
This study uses the VADER sentiment tool enhanced with a specific dictionary to cover short squeeze-related semantics. VADER includes a lexicon and rule-based approach and is especially suited for social media analysis (Elbagir & Yang, 2019). In VADER, the compound score sums all lexicon ratings, which are normalized between -1 (most extreme negative) and +1 (most extreme positive). The variable "TextandBody" provides a complete picture of any submission and is therefore the basis of textual sentiment analysis. Before usage, the analysis undergoes standard text processing (e.g., removing hyperlinks, user handle mentions, and punctuation as well as replacing emojis).
Wang and Luo (2021) used the tool to examine whether general sentiment on /r/wallstreetbets is correlated with GameStop's price movements. However, they showed that standard VADER sentiment analysis is unsuitable for predicting price movements owing to the specific language used by the community. The comparison of VADER with its human counterpart showed poor quality (Cohen's kappa of 0.078) due to the tendency of VADER to over-predict neutral sentiment, especially for posts labeled "positive" by humans. Therefore, Long et al. (2022) created an updated lexicon incorporating associated valence scores to cover this specific language. These updated dictionary entries are shown in the Appendix and incorporated into the sentiment analysis.
By including these new scores, a sentiment value is assigned for each post on /r/GME and /r/wallstreetbets. Afterwards, as stock data require grouping at the hourly level, the median of all submissions within an hour describes the sentiment during that period.

Stock performance metrics

Returns, defined as relative price changes (Hackethal, Haliassos, & Jappelli, 2012; Linnainmaa, 2010; Tookes, 2008), are calculated as the natural logarithm of the difference in closing prices to account for changes in the variable over time. Trading volume, defined as the number of shares traded for a specified security, is a measure of market activity. It reflects the liquidity provided in a given period. I use log trading volume for the four stocks.

4.4.3 Data synchronization

Assessing the lead-lag relationships in international financial markets raises a pertinent issue related to data synchronization owing to disparities in time zones (Malliaris & Urrutia, 1992). Dealing with this concern is paramount for conducting and interpreting the empirical examinations in this study.

First, as the data from Reddit are in the UTC0 time zone and the stock data from Finnhub.io are shown in NYSE time, the period is matched so that stock prices match the Reddit time using a time-based matching approach. Since the posting times of Reddit content are set at hourly intervals, aligning them with the timestamps of stock market data, I can create a harmonized dataset in which each observation represents a unique hour. As half of Reddit traffic originates from the United States (Wanchoo, Abrams, Merchant, Ungar, & Guntuku, 2023) and the NYSE is the only stock exchange included in the study, no further time zone adaptions are required.
To address non-synchronous trading effects, I consider the hourly nature of the data. While stock markets operate continuously during trading hours, Reddit posts may be published at any time. To mitigate this issue, I aggregate the data at the hourly level, which provides a reasonable compromise between granularity and data synchronization. Moreover, closing prices are extrapolated for Reddit articles posted when the NYSE is closed at weekends. Furthermore, to account for the potential impact of non-synchronous events, robustness tests are conducted to test the Granger causality models under various time intervals.

4.4.4 Descriptive statistics

Reddit users

Anand and Pathak (2022) stated that only 462 Reddit users had a significant influence on the /r/wallstreetbets community, suggesting a concentration of force. The /r/GME dataset shows a similar distribution of submissions. Figure 4.4 indicates that only 58 authors have more than 100 submissions.

Insert Figure 4.4 here

Sentiment and stock performance metrics

Figure 4.5 displays the stock price, textual sentiment, and trading volume data for the four stocks over time.

Insert Figure 4.5 here

For GameStop, before its largest price increase, sentiment rises steadily until the stock price peaks. The following downturn in price is accompanied by a sharp decrease in sentiment, reaching the lowest point during the study period. Although the price after this decline is still higher than that in December and early January, sentiment is at its lowest level. This steadily increasing sentiment followed by a sharp decline once the price drops significantly remains true for the two subsequent major stock price increases. The results indicate that Redditors may be more sensitive to price decreases than increases, as evidenced by the sharp drop in sentiment during periods of falling prices.
For AMC, a similar trend is observable. From early May to the end of July, which corresponds to the stock's highest price, sentiment is approximately 0.5 or higher. These findings suggest a potential relationship between AMC stock prices and positive sentiment among Redditors.
For BlackBerry, when its stock price peaks at almost USD 30 in January, sentiment is also particularly high. Similarly, as the price declines below USD 15, sentiment continues to decrease, falling below 0.5. In particular, from early to mid-May, when the stock price is rising, sentiment increases. However, sentiment decreases in line with the stock price thereafter. Overall, the behavior of the BlackBerry stock is similar to that of GameStop, suggesting that the GameStop short squeeze phenomenon is not an isolated case. Finally, the stock of Nokia shows no specific trends directly attributed to its sentiment or price movements. These findings overall confirm a relationship between negative sentiment and stock prices (Chen et al., 2014; Kearney & Liu, 2014; Tetlock, 2007).

Sentiment in diamond hand submissions

I conduct the Welch two-sample t-test to analyze the textual sentiment particularly for diamond hand submissions. The results indicate a significant difference in mean compound scores between diamond hand and non-diamond hand submissions for the /r/GME subreddit ($p<0.05$). The negative t-value (-3.0792) indicates that the mean compound score of diamond hand submissions is lower than that of non-diamond hand submissions. This implies that diamond hand submissions may be less positively loaded in textual sentiment than non-diamond hand submissions.

To further deepen the examination of the intent dimension, I assess whether the sentiment within diamond hand submissions changes in different market environments. I run separate Pearson's correlation coefficient analyses on each of the four subsamples and find that the relationship between returns and sentiment is not significant for both types of submissions and both datasets. These findings show that overall sentiment remains stable in the intent dimension.

Further, the data show no significant relation between the use of diamond hand submissions and returns for all subreddit and stock combinations, rejecting Hypothesis 1 on a descriptive level.

However, there is a significant negative relationship between diamond hand submissions and trading volume. This relationship exists for the majority of dataset-stock combinations: /r/GME and GameStop ($p<0.05$), /r/wallstreetbets and BlackBerry ($p<0.001$), and /r/wallstreetbets and AMC ($p<0.05$). This provides initial evidence that an increase in diamond hand submissions lowers trading volume, supporting Hypothesis 2.

The data also reveal that the proportion of diamond hand submissions to non-diamond hand submissions is significantly positively related to sentiment for all four stocks in the /r/wallstreetbets dataset ($p<0.001$). Hence, hours with more diamond hand submissions also have more positive sentiment, supporting Hypothesis 3.

Finally, I find a significant relation between returns and trading volume for the /r/wallstreetbets data and AMC stock, in line with previous research (Chen, Firth, & Rui, 2001; Chuang, Liu, & Susmel, 2012; De Medeiros & Doornik, 2006). However, no significant relationships are observed for any other combination.

4.4.5 VAR model estimation

To construct the VAR models, I follow an approach similar to that of Prosad, Kapoor, Sengupta, and Roychoudhary (2017); Statman, Thorley, and Vorkink (2006). First, to identify the order of the lags, I use the Akaike information criterion (AIC), as it "*tends to produce the most accurate structural and semi-structural impulse response estimates for realistic sample sizes*" Ivanov and Kilian (2005). Second, a specified model is estimated. Finally, I use autocorrelation functions, together with the Portmanteau test statistic, to check the adequacy of the model by examining the structure of the residuals. With certain adaptations, the structure of the VAR model of order one is denoted as

$$\begin{aligned}
Dia_{t,1} &= \alpha_1 + \phi_{11} Dia_{-1,1} + \phi_{12} LogRet_{t-1,2} + \phi_{13} LogVol_{t-1,3} + \phi_{14} Com_{t-1,4} + \epsilon_{t,1} \\
LogRet_{t,2} &= \alpha_2 + \phi_{21} Dia_{-1,1} + \phi_{22} LogRet_{t-1,2} + \phi_{23} LogVol_{t-1,3} + \phi_{24} Com_{t-1,4} + \epsilon_{t,2} \\
LogVol_{t,3} &= \alpha_3 + \phi_{31} Dia_{-1,1} + \phi_{32} LogRet_{t-1,2} + \phi_{33} LogVol_{t-1,3} + \phi_{34} Com_{t-1,4} + \epsilon_{t,3} \\
Com_{t,4} &= \alpha_4 + \phi_{41} Dia_{-1,1} + \phi_{42} LogRet_{t-1,2} + \phi_{43} LogVol_{t-1,3} + \phi_{44} Com_{t-1,4} + \epsilon_{t,4}
\end{aligned} \tag{4.1}$$

with *LogRet* representing the hourly log return derived from the hourly closing stock prices and *Dia* representing diamond hand submissions on either /r/GME or /r/wallstreetbets. ϵ_t is an $n * 1$-residual vector. For the spillover analysis, including the different stocks, the respective financials replace the aforementioned ones. As stated by Statman et al. (2006), the VAR methodology allows a covariance

structure to exist in the residual vector e_t, capturing the contemporaneous correlations between variables. Before selecting the final model, an augmented Dickey–Fuller test reveals a test statistic of -7.1025 (p=0.01). This points strongly toward the stationarity of the data. Therefore, no de-trending is necessary and the variables can be included as intended (Cheung & Lai, 1995).
The order of the lags is selected by comparing the performance indicators of the model. AIC, Schwarz's Bayesian information criterion , and Hannan–Quinn information criterion tests are conducted for this purpose. These criteria estimate relative model quality. To emphasize the predictive power of the model, the AIC (Akaike, 1998) is preferred to the Bayesian information criterion (Chakrabarti & Ghosh, 2011). Selecting the lag order of a VAR model based on AIC performance is furthermore common research practice (Ho, 2011; Prosad et al., 2017). Lower lag orders such as those suggested by the Bayesian information criterion would result in autocorrelation in the residual terms. Due to these two reasons, the lag order is set to 12 according to the AIC.
To check the resulting model for autocorrelation, Figures 4.6 and 4.7 show the AFC graphs for /r/GME and /r/wallstreetbets, respectively.

Insert Figure 4.6 here

Insert Figure 4.7 here

In the early lags, diamond hand submissions, sentiment, and the stock performance metrics are all significantly related, most prominently diamond hand submissions; however, after lag 3, these correlations become insignificant. This pattern of positive autocorrelation in low lags is typical for stock price changes (Hasbrouck, 1991). This also suggests that the higher lag order proposed by the AIC prevents autocorrelation. This finding is confirmed by a Portmanteau test, in which the null hypothesis of uncorrelated residuals cannot be rejected for either dataset. Since there is sufficient evidence of an absence of autocorrelation, the VAR model can be used to fulfill the stability condition.
The VAR model can also be used to investigate the dynamic relationships among the variables and conduct the Granger causality tests of whether one variable is useful for forecasting another. Based on predictions, variable x Granger-causes y if a model that uses the current and past values of x and y to predict the future values of y has a smaller forecast error than a model that only uses the current and past values of y to predict y (Granger, 1969).
The IRF analysis, which aggregates the coefficient estimates, shows how the variables relate to one another over time (Hamilton, 2020). Thus, they can trace the effect of a one standard deviation shock (measured within the sample) to one residual of the current and future values of the endogenous variables through the dynamic structure of the VAR (Statman et al., 2006). Figure 4.2 summarizes the data sources, filtering mechanisms, and analysis process.

Insert Figure 4.2 here

4.5 Results

4.5.1 Intent dimension

Table 4.3 summarizes the results of the Granger causality tests for the GameStop stock and /r/GME dataset, showing that trading volume Granger-causes diamond hand submissions, whereas diamond hand submissions do not Granger-cause trading volume.

Insert Table 4.3 here

Table 4.4 summarizes the results of the Granger causality tests for the GameStop stock and /r/wallstreetbets

dataset. The results show the strong influence of GameStop's trading volume on diamond hand submissions and vice versa. This bidirectional causality is similar to the /r/GME data above. By contrast, the returns variable is insignificant in both models.

Insert Table 4.4 here

Overall, the results of the Granger causality tests suggest that the historical trading volume of GameStop helps explain current diamond hand submissions on /r/GME and /r/wallstreetbets. However, for /r/GME, the historical number of diamond hand submissions does not help explain GameStop's trading volume. Panel A of Figure 4.8 shows that a positive reaction to diamond hand submissions on /r/GME leads to a significant change in trading volume but not in the other variables.

Insert Figure 4.8 here

This change is insignificant during the first few hours, meaning that an increase in diamond hand submissions does not lead to an immediate reaction in trading volume. However, when reaching lag 10, the complete confidence interval is below zero, indicating statistical significance at this point. A positive reaction to diamond hand submissions is followed by decreasing trading volume. However, this reaction only lasts approximately 2 hours.
For /r/wallstreetbets, no significant change in volume can be observed for a reaction to diamond hand submissions, as shown in Figure 4.9.

Insert Figure 4.9 here

Hence, potential investors on the /r/GME subreddit may have followed the appeal to hold onto their investments, thereby reducing trading volume, while the broader /r/wallstreetbets community did not.
Figure 4.10 shows that a positive reaction to diamond hand submissions leads to higher trading volume for the AMC stock after some time. This effect is not only more significant than the reverse effect from the /r/GME community toward GameStop, but continues for an even longer time, from lags 6 to 13. Therefore standing in contrast to the hypothesis. For blackberry however, the IRF shows a significant negative relationship between diamond hand submissions and volume on lag 4 similar to the GameStop stock. No significant observations can be made for Nokia.

Insert Figure 4.10 here

In summary, the Granger causality analysis shows that knowing GameStop's historical trading volume helps explain current diamond hand submissions. Furthermore, for the specialized /r/GME community, an increased number of diamond hand submissions is followed by a decreased GameStop volume 10 periods ahead, whereas the effects in the other periods are not significant at the 95% confidence level; this also stands true for blackberry even though the lag orders are slightly different. Hence, Hypothesis 2 is not rejected. Moreover, as neither the Granger causality test nor the IRF analysis shows any significance for returns in that regard, Hypothesis 1 is rejected.
The finding of unidirectional Granger causality between trading volume and diamond hand submissions in the /r/GME data, but bidirectional causality for /r/wallstreetbets might indicate that the /r/GME community followed the appeal to hold onto their investments, thereby reducing trading volume, whereas the broader /r/wallstreetbets community did not, as noted above. For the AMC stock, the IRF analysis shows that a positive reaction to diamond hand submissions leads to an increase in trading volume after some time.
These findings show that the same intent can lead to different behaviors depending on the subreddit and stock combination. In particular, for the GameStop short squeeze event, the findings point toward a centralization of users willing to follow the trading advice of the community.

4.5.2 Sentiment dimension

For the sentiment dimension, the right-hand side of Table 4.3 shows that trading volume Granger-causes sentiment for the GameStop stock. However, this causality is bidirectional, as sentiment also Granger-causes trading volume but with comparatively large standard errors.

Table 4.4 shows the test results for the GameStop stock and /r/wallstreetbets dataset. Sentiment only Granger-causes diamond hand submissions at a weak significance level; however, similar to the GameStop–/r/GME combination, it Granger-causes trading volume. No variable significantly Granger-causes sentiment.

Panel D of Figures 4.8 and 4.9 and Panels D, H, and L of Figure 4.10 show the behavior of the variables when a shock to sentiment occurs. For a positive shock in sentiment in the /r/GME dataset, GameStop's trading volume increases significantly after 3 hours and remains significant for 5 hours before reverting to zero. This result indicates that positive sentiment in the /r/GME subreddit significantly increases GameStop's trading volume. Similar behavior can be observed for AMC and BlackBerry in Figure 4.10, which illustrates the result of the IRF analysis for the non-GameStop stocks and the /r/wallstreetbets dataset. Indeed, similar timing occurs for AMC, showing significance between lags 3 and 7, BlackBerry's trading volume shows a similar significant reaction to sentiment between lags 11 and 15 (i.e., a slight delay). No significant effect is observed for Nokia.

Interestingly, similar to the Granger causality analysis, sentiment has no significant effect on returns for any of the stocks and datasets over time. First, the Granger causality tests show that the historical trading volume can explain the sentiment of GameStop-related submissions and vice versa. The IRF analysis shows that increased sentiment is followed by increased trading volume stock independence, but at various periods. Therefore, these findings support Hypothesis 3.

The results in this section show that for the sentiment dimension, the Granger causality tests provide proof for a relationship between trading volume and sentiment for the GameStop stock on the /r/GME and /r/wallstreetbets subreddits. Additionally, the IRF analysis shows that a positive shock in sentiment leads to an increase in trading volume for the GameStop, AMC, and BlackBerry stocks. However, the timing and magnitude of this effect differ among those stocks. For example, a positive shock to sentiment leads to a significant increase in trading volume for the GameStop stock on /r/GME after 3 hours and remains significant for 5 hours before reverting to zero. Similar behavior can be observed for AMC and BlackBerry. However, no significant effects are observed for Nokia. Overall, these results reinforce the causal link between sentiment and trading volume found in the literature (Checkley et al., 2017).

4.5.3 Stock performance metrics

Additional findings can be observed when looking into the stock performance metrics: The Granger causality tests for /r/wallstreetbets and /r/GME in Tables 4.3 and 4.4 show no significant Granger causality between returns and trading volume. However, the IRF analysis shows that an increased AMC return is followed by an increased trading volume 4 periods later.

4.5.4 Robustness test: Influence of subreddit activity

Following Hu et al. (2021), I also investigate the relationship between subreddit activity, defined here as the total number of submissions excluding visitors and increases in the number of subscribers, and the stocks performance metrics to check the robustness of the results. Hu et al. (2021) showed that increased subreddit activity can explain GameStop's future returns, increased retail order flows, and decreased shorting flows on the next day. I use the log number of submissions for the analysis to check also for other stocks dependency on subreddit activity..

I perform another VAR estimation including subreddit activity for the GameStop stock and the /r/GME and /r/wallstreetbets datasets. The /r/GME subreddit has the highest number of submissions on March 10, 2021, with up to 2021 submissions per hour. This occurs shortly before the stock price peaks. Further, the number of submissions is significantly positively correlated with GameStop's trading volume ($p<0.001$), indicating that higher subreddit activity and higher trading volume appear together. Moreover, the number of submissions is significantly related to diamond hand submissions ($p<0.01$). This indicates a shift in intent for the community. Finally, increasing subreddit activity is also significantly related to an increase in sentiment ($p<0.001$). This result confirms the findings of Hu et al. (2021).
In summary, the Granger causality test in Table 4.5 reveals that diamond hand submissions, trading volume, and returns all Granger-cause subreddit activity.

Insert Table 4.5 here

However, as the number of submissions also Granger-causes returns and trading volume, knowing subreddit activity can help forecast the stock performance metrics of GameStop and vice versa. Furthermore, the previously shown relationship between trading volume and sentiment for the /r/GME data in sections 4.5.1, 4.5.3, and 4.5.2 remains significant.
For the /r/wallstreetbets data, I find a significant negative relationship between the number of submissions and sentiment ($p<0.05$). However, this relationship is weak (-0.034). Hence, sentiment decreases slightly as subreddit activity increases.
Finally, similar to the /r/GME dataset, I find a significant relationship between subreddit activity and diamond hand submissions ($p<0.001$). This relationship is again slightly negative (-0.074), indicating that diamond hand submissions are slightly less prominent in the /r/wallstreetbets subreddit when the total number of submissions increases.
The Granger causality tests in Table 4.6 reveal that knowing GameStop's trading volume and returns is valuable for forecasting future subreddit activity ($p<0.001$). This is opposite the finding for trading volume, but in line with the finding for returns.

Insert Table 4.6 here

The other variables show that the previously outlined relationships remain significant, but at a slightly lower level ($p<0.05$). The results for the sentiment and subreddit activity variables are surprising, as they use the same dictionary and underlying stock information. Nevertheless, I find a positive relationship between sentiment and subreddit activity for the /r/GME data and a negative one for the /r/wallstreetbets data. This reinforces the difference in intent between the subreddits. Furthermore, the robustness test shows that when introducing the subreddit activity variable, the main finding on the relationship between trading volume and sentiment in Sections 4.5.1, 4.5.3, and 4.5.2 remains significant.

4.5.5 Robustness test: Daily intervals

As seen in the existing body of literature, the interval of social interactions can be set differently: while many studies look on daily leveled data, Betzer and Harries (2022) looked at 30min intervals, Long et al. (2022) even looked at minutes.
As Reddit users also undergo a daily- routine, have the tendency of habits by opening Reddit during specific hours, they also need time to post their content. A fitting interval is therefore hard to set. To account for a larger interval, I conducted additional IRFs on a daily level after aggregating the data.
The results, displayed in Figure 4.11 highlight the IRFs for /r/GME and /r/wallstreetbets both for GameStop. 2 effects are observable: On the one side, a shock in returns leads to a significant positive reaction on volume for GameStop after 4 days. Furthermore, a shock in compound leads to a signficiant

reaction on volume after 2 days lasting for about 1 day.

Insert Figure 4.11 here

This shows, that the significant influence on the intent dimension cannot sustain when controlling for daily data. However the sentiment as well as the stock performance metrics dimension remain stable.

4.6 Discussion

The GameStop short squeeze in January 2021 was a highly publicized event in which private investors coordinated on social media to significantly increase GameStop's stock price. The use of diamond hand submissions on Reddit, an appeal to hold onto investments regardless of price developments, is closely linked to the narrative of short squeezes in the media. However, scientific analysis of this linkage is missing. To bridge this gap in the literature, this study examines the relationship between the use of diamond hand submissions and stock performance metrics such as returns and trading volume. It also includes the sentiment dimension and extends the analysis to different stocks and subreddits to improve the generalizability of the findings. For the analysis, I use the time-dependent VAR model as well as Granger causality tests and IRF analysis.

The results of this study provide evidence of a causal relationship between the use of diamond hand submissions and stock performance metrics. The motive of strategic complementarities, namely, triggering a short squeeze by convincing other investors not to sell their positions, could lead all involved investors to profit from the short squeeze-induced rising returns. Diamond hand submissions can also be driven by social motives such as social desirability.

I find that such submissions - when originating from the specialized GameStop community /r/GME - lower GameStop's trading volume after approximately 10 hours. However, they have no such impact on returns. This effect is also present for the AMC stock but not for the Nokia and BlackBerry stocks.

These findings suggest that the user bases of /r/wallstreetbets and /r/GME differ. As Anand and Pathak (2022) pointed out, 462 users of /r/wallstreetbets have the highest influence (for /r/GME, I identify 58 highly influential users, measured by the number of submissions). In addition, the rising popularity of /r/wallstreetbets has been shown to decrease the quality of due diligence research articles (Bradley et al., 2021). Therefore, /r/GME could be seen as a closer circle of specialists, derived from the mainstream subreddit, but with even more adherence to social networking guidelines. In this circle, appeals to hold onto GameStop stocks may have had a stronger influence on the community. Furthermore, this shows that the intent of Reddit submissions is indeed an important determinant of GameStop's variables and should be included in further research.

Further, the IRF analysis reveals that increased sentiment on /r/GME and /r/wallstreetbets is followed by increased trading volume for GameStop after 3 periods and increased trading volume for AMC 4 periods ahead. This finding corresponds with those of previous studies (Liu, 2015) but additionally provides a statement of causality. These findings also reveal that sentiment and returns are unrelated, following Long et al. (2022), who found that positive comments and encouragement to hold onto the GameStop stock on Reddit could not stop or prevent its price falling.

Regarding the stock performance metrics, no significant relationship between returns and trading volume for three of the four stocks is found through the Granger causality tests and IRF analysis, aligning with the existing literature (Lee & Rui, 2002, 2000).

While this study uses a robust model with stationary data and without autocorrelation issues, it has certain limitations and makes some assumptions. First, despite this study using a dataset that allows reliable intent filtering, challenges remain when using social interaction data. Individuals might have an ill intent to convince others not to sell a particular stock. For instance, the significance of the findings

might vary for the /r/wallstreetbets community if false positive diamond hand submissions are included in the dataset. This is especially true for stocks outside the focus of the community, as the dataset is smaller.

Second, following the differentiation by Umar, Gubareva, Yousaf, and Ali (2021a), I assume that Reddit is used by media-savvy investors. Umar et al. (2021a) also showed that the GameStop short squeeze phenomenon was not only limited to Reddit. Therefore, another step to establish the generalizability of the findings would be to include additional social media sources.

Third, as in the literature, this study does not incorporate the options market. Further research that accounts for this distinct asset class could yield additional insights and increase the generalizability of the findings.

Fourth, as actual trades cannot be definitively linked to Reddit users, this risks including individuals who may not be investors in the analysis and potentially excluding investors who have not engaged on Reddit. Therefore, further research could examine more specialized communities on Reddit to better understand intent-driven investor behavior or narrow the intent dimensions by focusing on hashtags on Twitter. Furthermore, it might be interesting to observe the use of diamond hand submissions for other non-short squeeze-related stocks.

By way of practical applications, this study proposes a framework for the inclusion of social interactions in investment decisions. As Gurdgiev and O'Loughlin (2020) stated, professional investors are increasingly adopting public information from social interactions, such as sentiment, into their investment strategies. With these findings in mind, investors can better understand social interactions in financial contexts.

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Table 4.1: Summary of Submissions in /r/wallstreetbets and Related Stocks

Subreddit	**Total Submissions**	**Stock**	**Submissions Mentioning Stock (%)**	**Diamond Hands (%)**
/r/wallstreetbets	1'206'293	GameStop	190'893 (15.82%)	30'749 (2.55%)
/r/wallstreetbets	1'206'293	AMC	95'294 (7.90%)	15'941 (1.32%)
/r/wallstreetbets	1'206'293	BlackBerry	48'237 (4.00%)	7'708 (0.64%)
/r/wallstreetbets	1'206'293	NOK	29'532 (2.45%)	3'547 (0.29%)
/r/GME	203'576	GameStop	203'576 (100%)	42'553 (20.94%)

Notes: The table provides a summary of submissions in the /r/wallstreetbets subreddit related to specific stocks, including GameStop, AMC, BlackBerry, and NOK. The data includes the total number of submissions, the percentage of submissions mentioning each stock, and the percentage of submissions expressing a "Diamond Hands" intent.

Table 4.2: /r/GME and /r/wallstreetbets term document matrix extract

/r/GME		/r/GME (Diamond hands only)		/r/wallstreetbets		/r/wallstreetbets (Diamond hands only)	
n = 9'172 (N= 203'576)		n = 7'836 (N= 42'553)		n = 9'528 (N = 1'206'293)		n = 2'071 (N=15'043)	
Word	Wordcount	Word	Wordcount	Word	Wordcount	Word	Wordcount
gme	2,816	gme	2,346	gme	1,573	gme	3,399
will	2,087	will	1,599	buy	937	will	1,848
just	1,808	just	1,512	will	865	shares	1,596
shares	1,602	can	1,312	**amc**	824	stock	1,428
can	1,501	shares	1,310	just	804	**hold**	1,331
like	1,337	like	1,009	stock	794	short	1,234
price	1,194	**price**	965	like	682	can	1,166
buy	1,181	**know**	937	can	668	**price**	1,117
stock	1,088	buy	873	**hold**	656	buy	1,085
apes	1,080	get	837	now	655	just	1,078
know	1,066	stock	817	shares	650	like	1,020
now	1,031	**apes**	798	market	565	**holding**	994
get	1,024	now	781	short	528	amc	982
money	983	short	701	get	525	now	973
short	941	market	677	**moon**	499	market	970
one	840	**people**	647	going	488	**money**	798
market	827	**time**	645	**time**	462	**people**	756
time	824	going	643	**robinhood**	424	get	732
people	807	**money**	640	**one**	422	**squeeze**	716
going	771	**one**	632	**deleted**	415	going	670

Notes: This table presents a selection of the top 20 most frequently mentioned words in the term document matrix for the respective (sub-) data sets. Four samples were created for each of the /r/GME and /r/wallstreetbets Subreddits: one sample of the general submission count (N), and one sample of the diamond hands population only (n). The samples were chosen in a way that would allow for a 1% difference between the sample results and the actual population results, with a probability of 95%. Bold words are not included in the top 20 of every sample.

Table 4.3: GME - Granger-causality test outcome

	F	df1	df2	p		$\chi 2$	df	p	
Diamond.Hands ← LogVolume	5.60	12	2443	<.001	***	67.18	12	<.001	***
Diamond.Hands ← LogReturn	0.09	12	2443	1.000		1.09	12	1.000	
Diamond.Hands ← Compound	1.17	12	2443	.298		14.05	12	.297	
Diamond.Hands ← ALL	2.30	36	2443	<.001	***	82.75	36	<.001	***
LogVolume ← Diamond.Hands	1.44	12	2443	.141		17.26	12	.140	
LogVolume ← LogReturn	0.70	12	2443	.750		8.43	12	.751	
LogVolume ← Compound	2.22	12	2443	.009	**	26.62	12	.009	**
LogVolume ← ALL	1.54	36	2443	.021	*	55.45	36	.020	*
LogReturn ← Diamond.Hands	0.19	12	2443	.999		2.33	12	.999	
LogReturn ← LogVolume	0.64	12	2443	.812		7.64	12	.812	
LogReturn ← Compound	1.33	12	2443	.192		16.01	12	.191	
LogReturn ← ALL	0.69	36	2443	.919		24.82	36	.920	
Compound ← Diamond.Hands	1.11	12	2443	.348		13.31	12	.347	
Compound ← LogVolume	5.13	12	2443	<.001	***	61.61	12	<.001	***
Compound ← LogReturn	1.94	12	2443	.026	*	23.33	12	.025	*
Compound ← ALL	3.22	36	2443	<.001	***	115.98	36	<.001	***

Notes: This table reports results form the different Granger-causality constellations.
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4.4: /r/wallstreetbets - Granger-causality test outcome

	F	**df1**	**df2**	**p**		χ**2**	**df**	p	
Diamond.Hands ← LogVolume	5.66	12	2901	<.001	***	67.97	12	<.001	***
Diamond.Hands ← LogReturn	0.33	12	2901	.985		3.93	12	.985	
Diamond.Hands ← Compound	1.68	12	2901	.066	.	20.12	12	.065	.
Diamond.Hands ← ALL	2.50	36	2901	<.001	***	90.16	36	<.001	***
LogVolume ← Diamond.Hands	5.47	12	2901	<.001	***	65.59	12	<.001	***
LogVolume ← LogReturn	1.50	12	2901	.118		17.95	12	.117	
LogVolume ← Compound	2.23	12	2901	.009	**	26.76	12	.008	**
LogVolume ← ALL	2.64	36	2901	<.001	***	95.04	36	<.001	***
LogReturn ← Diamond.Hands	0.38	12	2901	.972		4.50	12	.973	
LogReturn ← LogVolume	0.26	12	2901	.994		3.13	12	.995	
LogReturn ← Compound	0.89	12	2901	.551		10.74	12	.551	
LogReturn ← ALL	0.52	36	2901	.992		18.77	36	.992	
Compound ← Diamond.Hands	0.46	12	2901	.936		5.58	12	.936	
Compound ← LogVolume	1.44	12	2901	.141		17.25	12	.140	
Compound ← LogReturn	1.15	12	2901	.312		13.83	12	.311	
Compound ← ALL	1.06	36	2901	.367		38.30	36	.366	

Notes: This table reports results form the different Granger-causality constellations.
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4.5: r/GME and GME - Granger-causality subreddit activity

	F	df1	df2	p		χ**2**	df	p	
Diamond.Hands ← LogVolume	3.45	12	2431	<.001	***	41.35	12	<.001	***
Diamond.Hands ← LogReturn	0.18	12	2431	.999		2.15	12	.999	
Diamond.Hands ← Compound	1.50	12	2431	.116		18.03	12	.115	
Diamond.Hands ← Activity	2.11	12	2431	.014	*	25.37	12	.013	*
Diamond.Hands ← ALL	2.26	48	2431	<.001	***	108.57	48	<.001	***
LogVolume ← Diamond.Hands	1.45	12	2431	.137		17.39	12	.136	
LogVolume ← LogReturn	0.82	12	2431	.631		9.83	12	.631	
LogVolume ← Compound	1.63	12	2431	.078	.	19.51	12	.077	.
LogVolume ← Activity	10.12	12	2431	<.001	***	121.49	12	<.001	***
LogVolume ← ALL	3.74	48	2431	<.001	***	179.43	48	<.001	***
LogReturn ← Diamond.Hands	0.24	12	2431	.997		2.85	12	.997	
LogReturn ← LogVolume	0.85	12	2431	.603		10.14	12	.603	
LogReturn ← Compound	1.29	12	2431	.219		15.45	12	.218	
LogReturn ← Activity	3.27	12	2431	<.001	***	39.20	12	<.001	***
LogReturn ← ALL	1.34	48	2431	.060	.	64.30	48	.058	.
Compound ← Diamond.Hands	1.83	12	2431	.038	*	21.97	12	.038	*
Compound ← LogVolume	3.14	12	2431	<.001	***	37.72	12	<.001	***
Compound ← LogReturn	2.34	12	2431	.006	**	28.06	12	.005	**
Compound ← Activity	2.80	12	2431	<.001	***	33.60	12	<.001	***
Compound ← ALL	3.14	48	2431	<.001	***	150.60	48	<.001	***
Activity ← Diamond.Hands	1.62	12	2431	.078	.	19.49	12	.077	.
Activity ← LogVolume	43.15	12	2431	<.001	***	517.75	12	<.001	***
Activity ← LogReturn	3.05	12	2431	<.001	***	36.56	12	<.001	***
Activity ← Compound	1.48	12	2431	.122		17.82	12	.121	
Activity ← ALL	12.81	48	2431	<.001	***	615.07	48	<.001	***

Notes: This table reports results form the different Granger-causality constellations.
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4.6: /r/wallstreetbets and GME - Granger-causality subreddit activity

	F	df1	df2	p		χ**2**	df	p	
Diamond.Hands ← LogVolume	1.46	12	2597	.134		17.47	12	.133	
Diamond.Hands ← LogReturn	0.49	12	2597	.925		5.82	12	.925	
Diamond.Hands ← Compound	2.21	12	2597	.009	**	26.48	12	.009	**
Diamond.Hands ← Activity	2.14	12	2597	.012	*	25.63	12	.012	*
Diamond.Hands ← ALL	1.69	48	2597	.002	**	81.21	48	.002	**
LogVolume ← Diamond.Hands	1.77	12	2597	.048	*	21.19	12	.048	*
LogVolume ← LogReturn	0.73	12	2597	.720		8.80	12	.720	
LogVolume ← Compound	1.36	12	2597	.179		16.29	12	.178	
LogVolume ← Activity	21.01	12	2597	<.001	***	252.11	12	<.001	***
LogVolume ← ALL	6.49	48	2597	<.001	***	311.72	48	<.001	***
LogReturn ← Diamond.Hands	0.23	12	2597	.997		2.75	12	.997	
LogReturn ← LogVolume	0.59	12	2597	.850		7.11	12	.850	
LogReturn ← Compound	0.24	12	2597	.996		2.88	12	.996	
LogReturn ← Activity	1.44	12	2597	.141		17.27	12	.140	
LogReturn ← ALL	0.51	48	2597	.998		24.59	48	.998	
Compound ← Diamond.Hands	1.64	12	2597	.073	.	19.72	12	.072	.
Compound ← LogVolume	1.70	12	2597	.061	.	20.39	12	.060	.
Compound ← LogReturn	0.71	12	2597	.748		8.46	12	.748	
Compound ← Activity	0.97	12	2597	.473		11.67	12	.473	
Compound ← ALL	1.36	48	2597	.051	.	65.24	48	.049	*
Activity ← Diamond.Hands	0.97	12	2597	.474		11.65	12	.474	
Activity ← LogVolume	16.38	12	2597	<.001	***	196.51	12	<.001	***
Activity ← LogReturn	3.89	12	2597	<.001	***	46.66	12	<.001	***
Activity ← Compound	1.37	12	2597	.175		16.39	12	.174	
Activity ← ALL	5.45	48	2597	<.001	***	261.77	48	<.001	***

Notes: This table reports results form the different Granger-causality constellations.
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4.7: /r/wallstreetbets and GME - Granger-causality daily data

	F	**df1**	**df2**	**p**		χ**2**	**df**	**p**	
Diamond.Hands ← LogVolume	0.10	2	184	.905		0.20	2	.905	
Diamond.Hands ← LogReturn	0.65	2	184	.521		1.31	2	.520	
Diamond.Hands ← Compound	1.25	2	184	.289		2.50	2	.287	
Diamond.Hands ← ALL	0.69	6	184	.661		4.12	6	.661	
LogVolume ← Diamond.Hands	1.90	2	184	.153		3.80	2	.150	
LogVolume ← LogReturn	0.81	2	184	.444		1.63	2	.443	
LogVolume ← Compound	2.95	2	184	.055	.	5.89	2	.052	.
LogVolume ← ALL	2.07	6	184	.059	.	12.39	6	.054	.
LogReturn ← Diamond.Hands	1.32	2	184	.270		2.64	2	.267	
LogReturn ← LogVolume	0.21	2	184	.810		0.42	2	.810	
LogReturn ← Compound	0.81	2	184	.449		1.61	2	.447	
LogReturn ← ALL	0.68	6	184	.670		4.05	6	.670	
Compound ← Diamond.Hands	0.29	2	184	.746		0.59	2	.746	
Compound ← LogVolume	3.46	2	184	.034	*	6.92	2	.031	*
Compound ← LogReturn	0.16	2	184	.848		0.33	2	.848	
Compound ← ALL	1.22	6	184	.297		7.33	6	.291	

Notes: This table reports results from the different Granger-causality constellations.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.8: /r/GME and GME - Granger-causality daily data

	F	**df1**	**df2**	**p**		χ**2**	**df**	**p**	
Diamond.Hands ← LogVolume	3.32	3	169	.021	*	9.95	3	.019	**
Diamond.Hands ← LogReturn	0.54	3	169	.653		1.63	3	.652	
Diamond.Hands ← Compound	0.12	3	169	.948		0.36	3	.948	
Diamond.Hands ← ALL	1.58	9	169	.125		14.20	9	.115	
LogVolume ← Diamond.Hands	3.22	3	169	.024	*	9.66	3	.022	*
LogVolume ← LogReturn	1.15	3	169	.333		3.44	3	.329	
LogVolume ← Compound	2.78	3	169	.043	*	8.34	3	.040	*
LogVolume ← ALL	2.76	9	169	.005	**	24.84	9	.003	**
LogReturn ← Diamond.Hands	0.66	3	169	.580		1.97	3	.579	
LogReturn ← LogVolume	0.31	3	169	.816		0.94	3	.816	
LogReturn ← Compound	0.71	3	169	.546		2.14	3	.545	
LogReturn ← ALL	0.57	9	169	.824		5.09	9	.826	
Compound ← Diamond.Hands	3.93	3	169	.010	**	11.79	3	.008	**
Compound ← LogVolume	3.30	3	169	.022	*	9.91	3	.019	*
Compound ← LogReturn	1.45	3	169	.232		4.34	3	.227	
Compound ← ALL	2.98	9	169	.003	**	26.83	9	.001	**

Notes: This table reports results from the different Granger-causality constellations.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

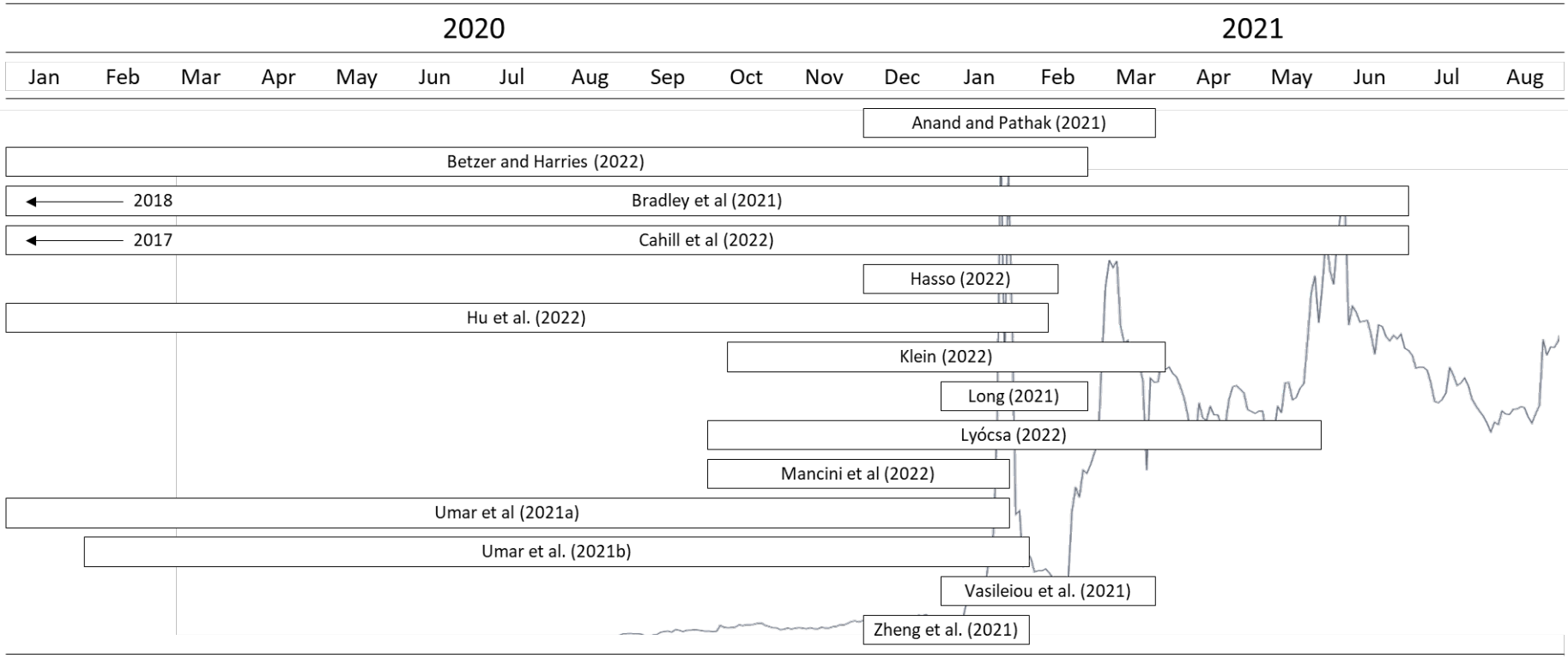

Figure 4.1: Data ranges and sources in existing literature

Notes: This figure shows the data frames of related GameStop short squeeze literature in combination with the GameStop stock return.

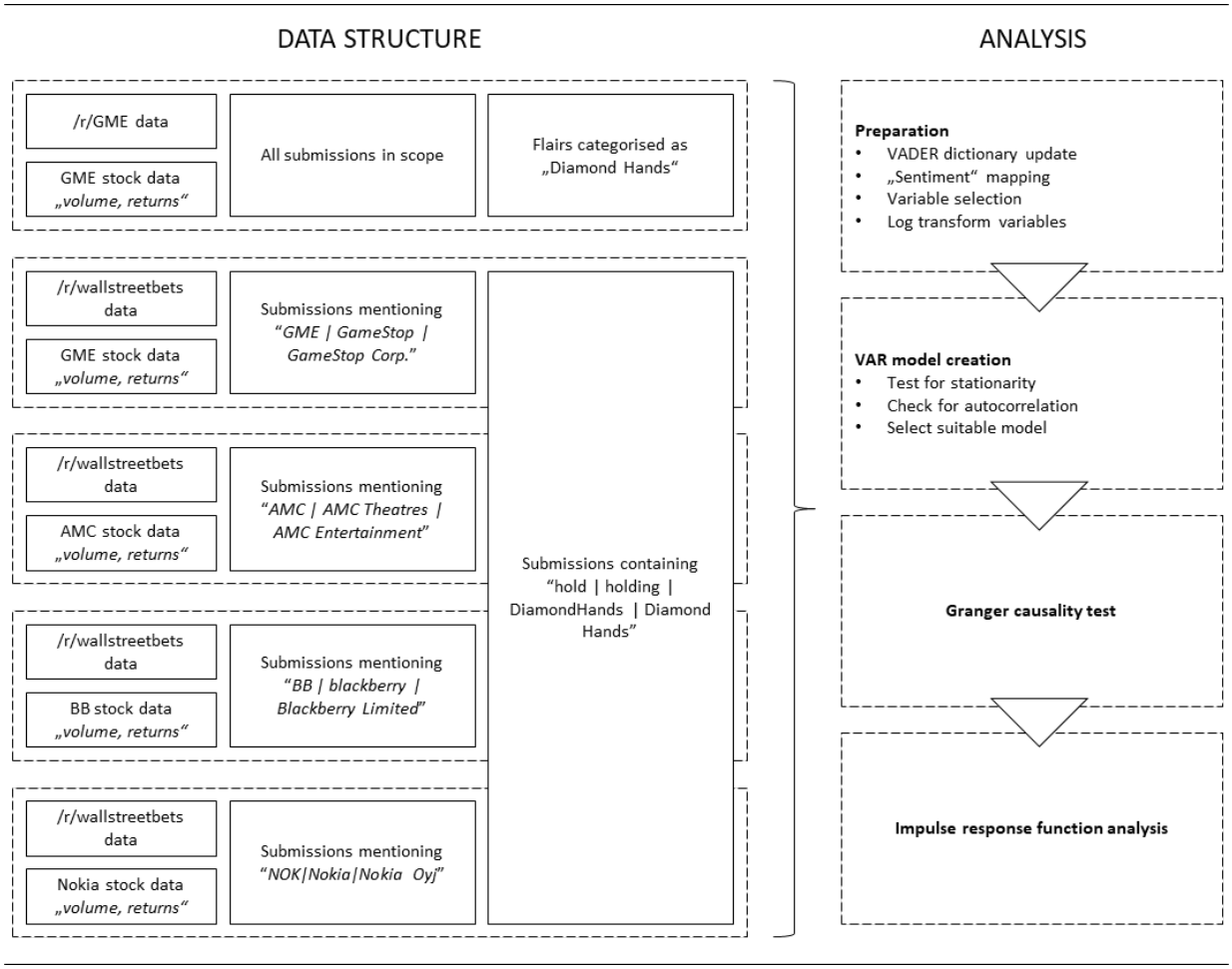

Figure 4.2: Data sourcing and methodology

Notes: This figure shows the used data sources and filtering mechanisms and applied methodology.

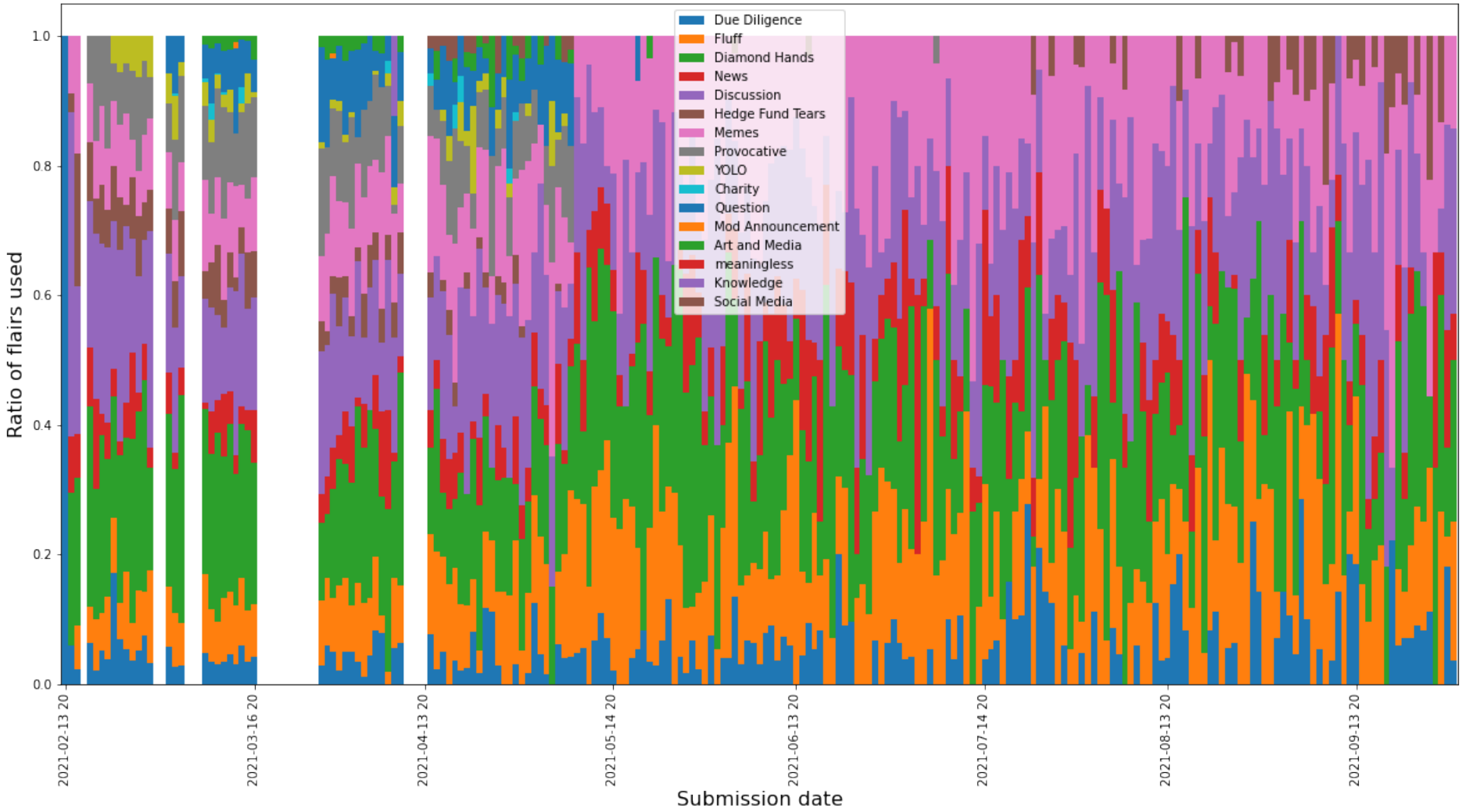

Figure 4.3: Ratio of flairs used in the /r/GME Subreddit

Notes: Flairs display the submission topic and are set by the users. Ratio calculated on daily level.

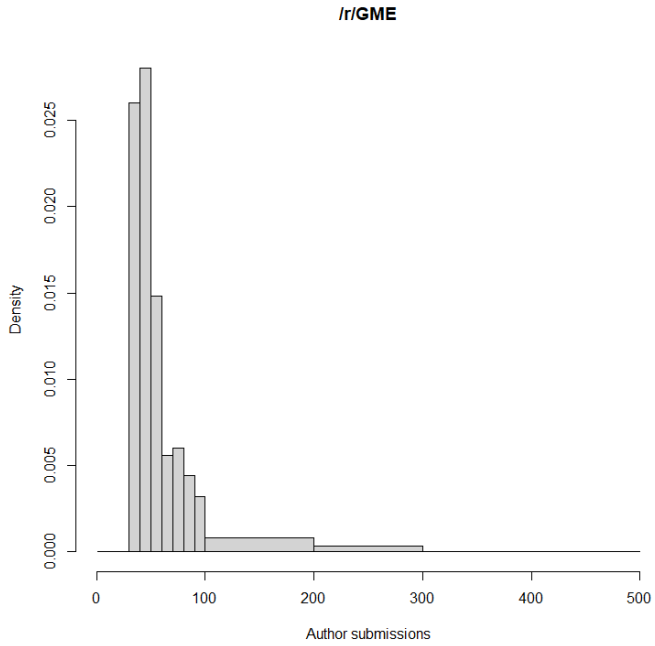

Figure 4.4: Histogram of /r/GME submissions on author level

Notes: Graphical representation of the frequency distribution of submission count among /r/GME authors.

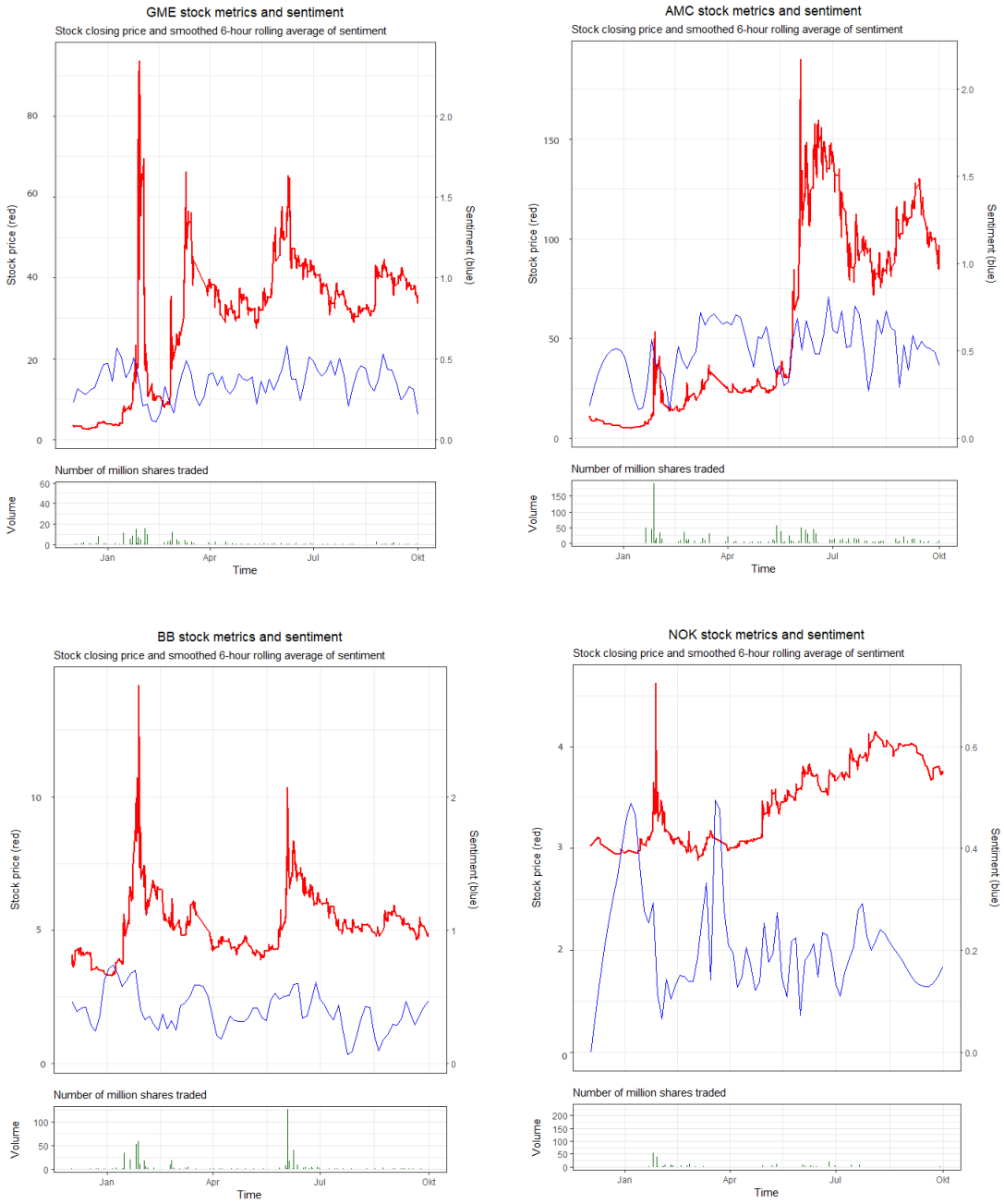

Figure 4.5: Stock metrics and sentiment score

Notes: Graphical representation of the stock price and volume and the sentiment score. A 6-hour rolling average smooths the sentiment and overlaps the stock price to visualise a possible relationship between the two. The figure also shows the traded volume with the number of shares traded as a separate plot.

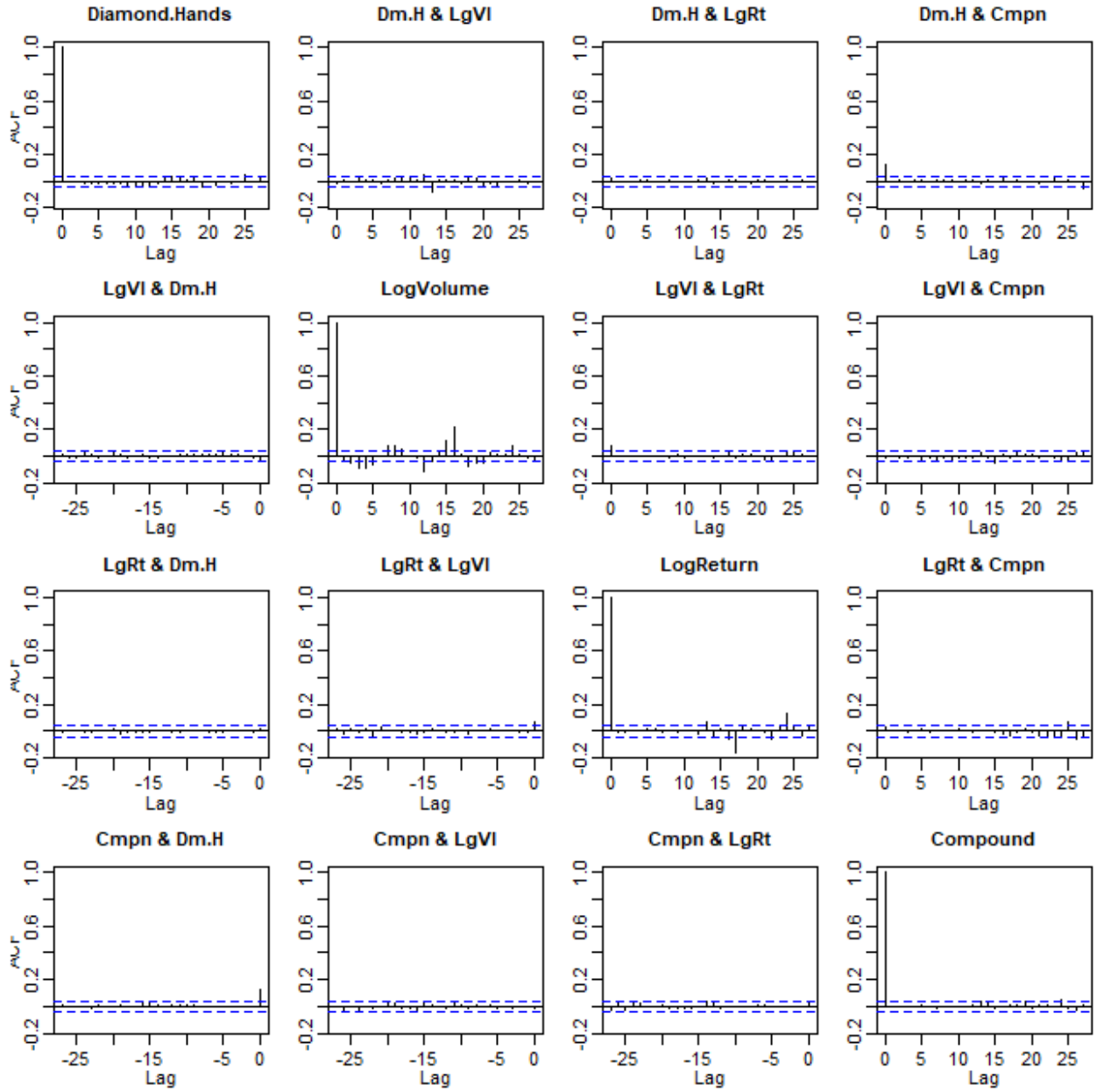

Figure 4.6: GME - Auto and Cross-correlation between VAR model residuals for different dependent and independent variables

Notes: The matrix of plots shows the cross-correlation between the residuals of different VAR models, with different dependent and independent variables. The plots show the cross-correlation at different lags and the spikes outside of the blue line indicate that the correlation for that lag is significantly different from zero. The presence of significant cross-correlation in the residuals suggests that the model is not capturing all of the dependencies between the variables.

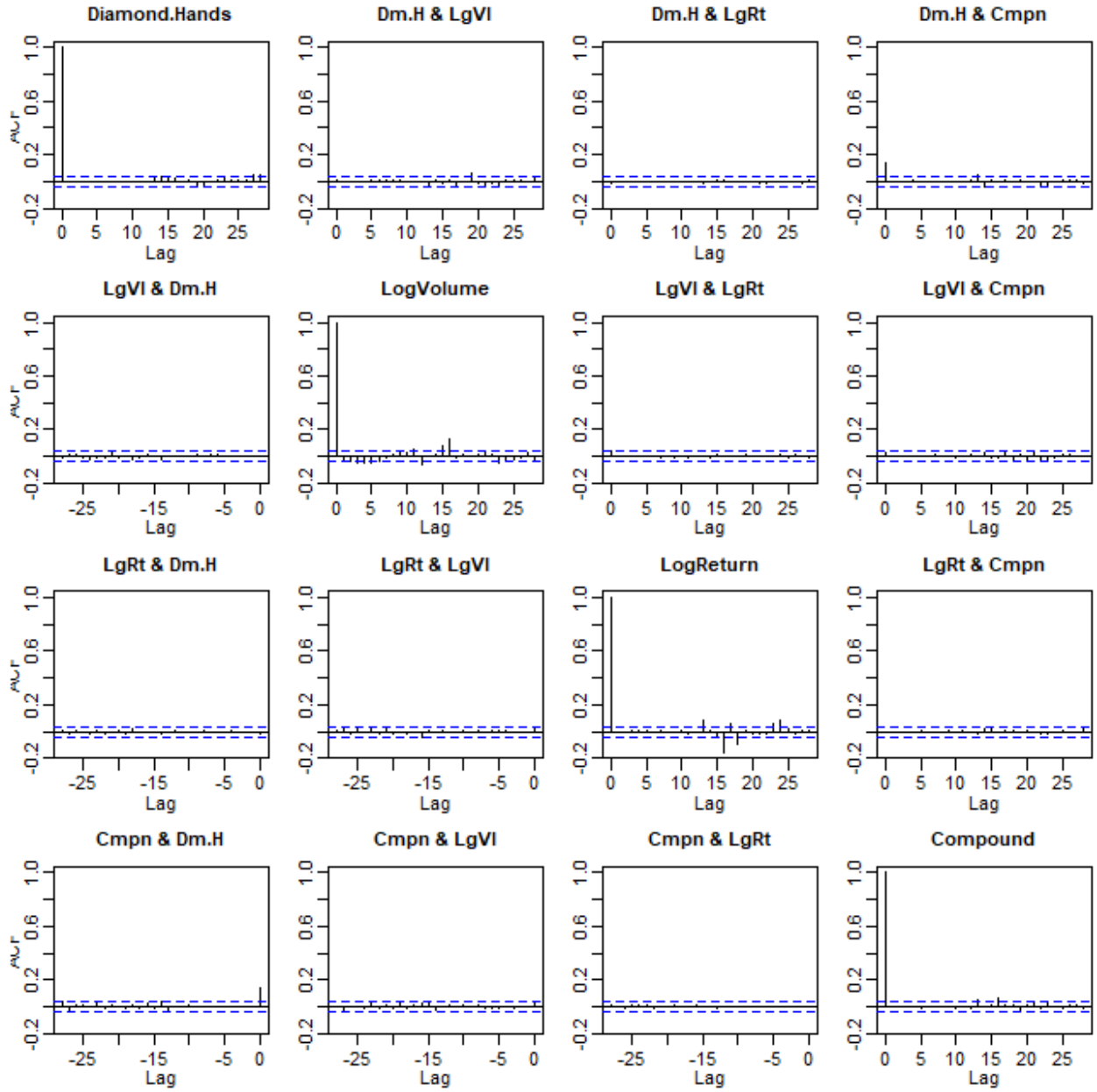

Figure 4.7: /r/wallstreetbets - Auto and Cross-correlation between VAR model residuals for different dependent and independent variables

Notes: The matrix of plots shows the cross-correlation between the residuals of different VAR models, with different dependent and independent variables. The plots show the cross-correlation at different lags and the spikes outside of the blue line indicate that the correlation for that lag is significantly different from zero. The presence of significant cross-correlation in the residuals suggests that the model is not capturing all of the dependencies between the variables.

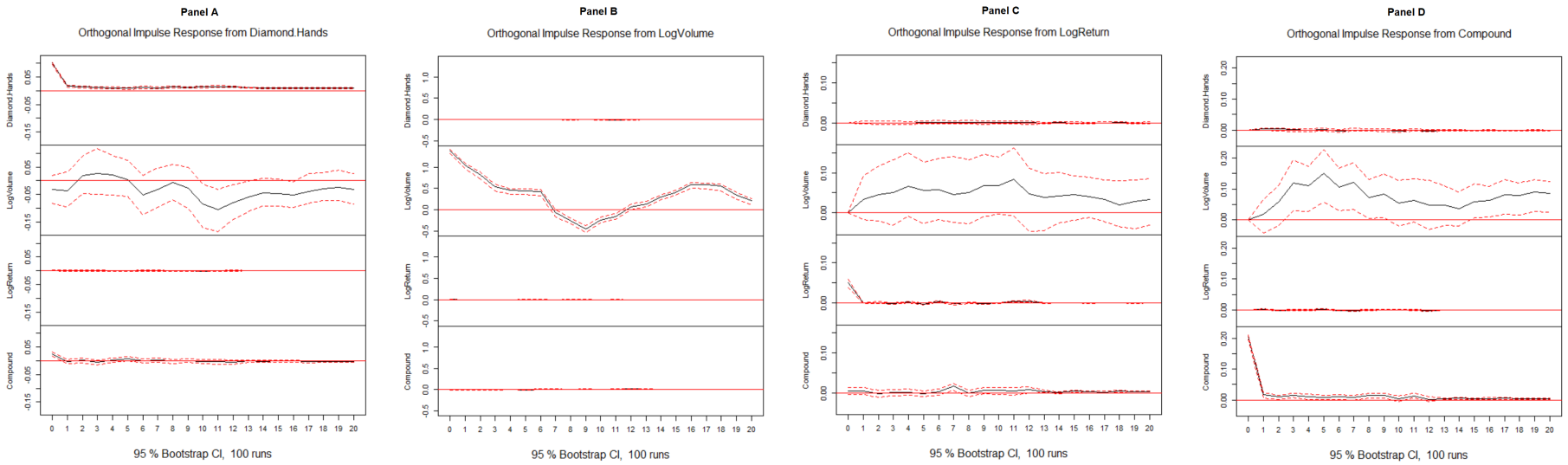

Figure 4.8: /r/GME - Impulse Response Functions (IRF)

Notes: This figure shows the Impulse Response Function for each VAR model's variables. The horizontal axis for each graph is the lag determined in hours. The vertical axis shows the change in percentage. Red dotted line shows the 95% confidence interval.

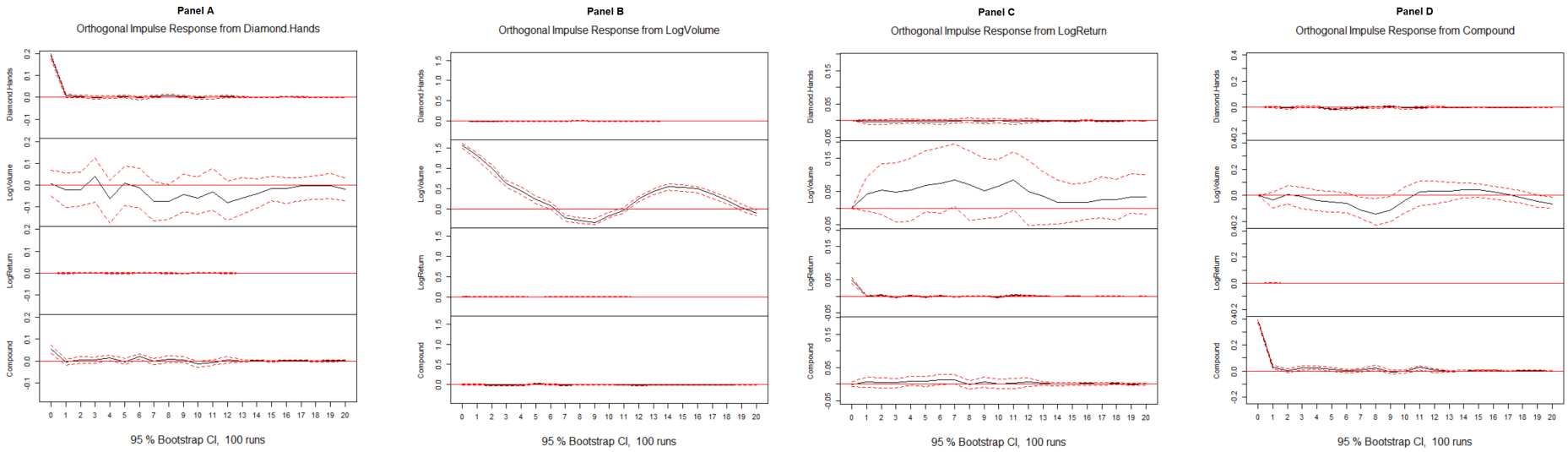

Figure 4.9: /r/wallstreetbets and GME - Impulse Response Functions (IRF)

Notes: This figure shows the Impulse Response Function for each VAR model's variables. The horizontal axis for each graph is the lag determined in hours. The vertical axis shows the change in percentage. Red dotted line shows the 95% confidence interval.

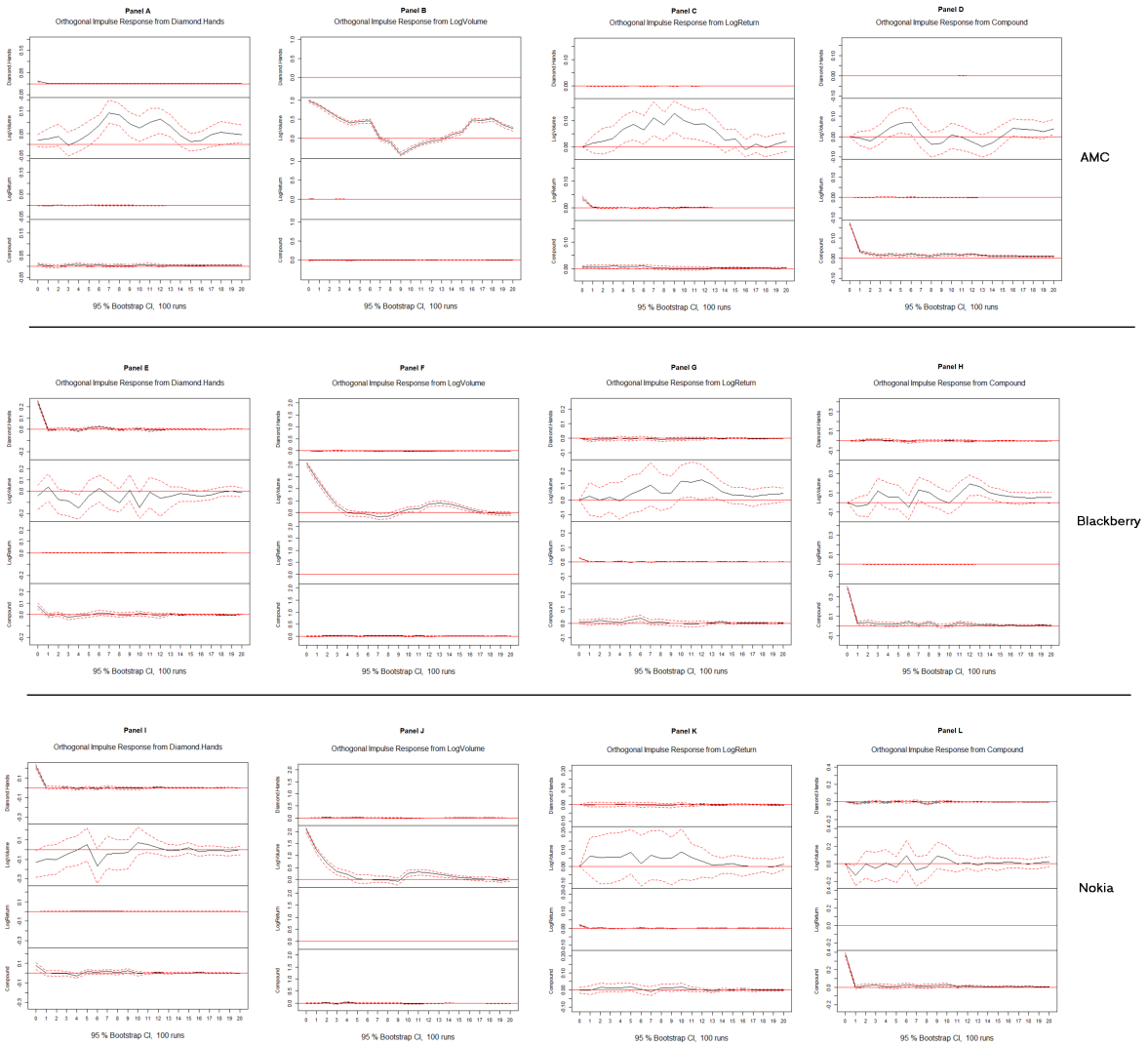

Figure 4.10: Other stocks - Impulse Response Functions (IRF)

Notes: This figure shows the Impulse Response Function for each VAR model's variables. The horizontal axis for each graph is the lag determined in hours. The vertical axis shows the change in percentage. Red dotted line shows the 95% confidence interval.

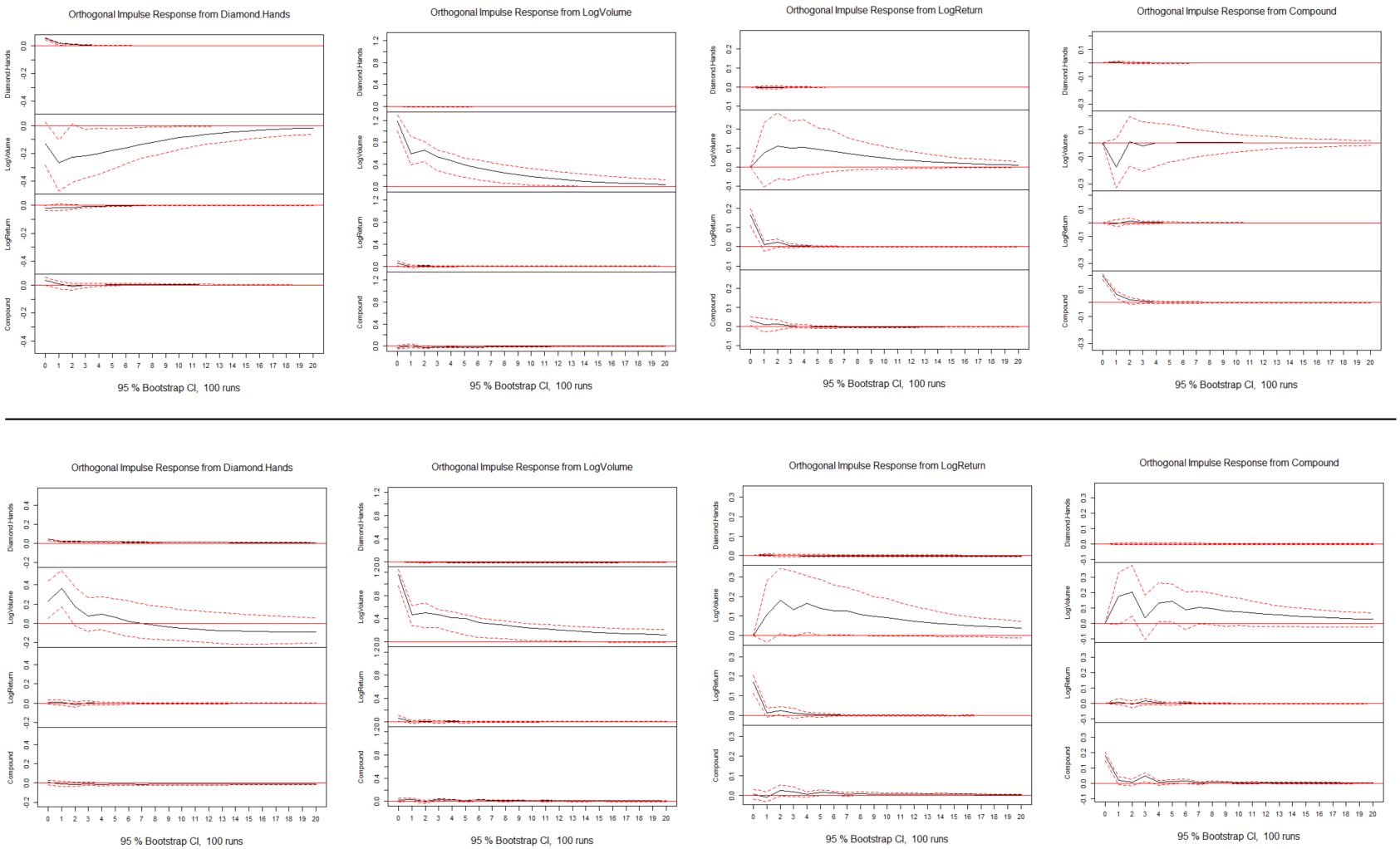

Figure 4.11: /r/wallstreetbets and /r/GME - Impulse Response Functions (IRF) Daily data

Notes: This figure shows the Impulse Response Function for the VAR model's variables of the GameStop stock and different subreddits. The horizontal axis for each graph is the lag determined in hours. The vertical axis shows the change in percentage. Red dotted line shows the 95% confidence interval.

IV Appendix

Table 4.9: Updated sentiment analysis dictionary (VADER)

Word	Score	Word	Score	Word	Score	Word	Score
available	0.8	diamond_hand	3	cash	0.6	advice	1.3
awesome	3.7	dip	-0.4	concern	-1.3	alternative	0.9
baby	1.2	dumb	-1.9	crash	-3.2	amazing	3.2
bad	-2.7	earning	1.8	crazy	0.7	ass	-1.9
ball	0.4	easy	1.6	crypto	0.5	attack	-1.9
bull	2.8	end	-0.8	damn	-1.7	capital	1
bullshit	-2.4	enough	0.1	diamond	2.9	fact	0.3
buy	1.9	hype	1.2	hard	-1.1	fake	-2.3
call	0.9	idiot	-2.6	hedge	0.5	fight	-1.2
future	1.1	illegal	-3.2	hell	-2.5	fine	1.3
gain	2.2	interest	1.1	high	2.4	flair	1.4
gamme	0	issue	-1.1	hodl	2.8	fuck	-2.8
gang	-0.3	joke	-0.5	hold	1.5	fucking	-2.7
gold	2	jump	1.4	holding	1.6	fun	1.9
good	2.5	least	-0.4	hope	1.5	funny	1.9
great	3.1	legal	1.9	limit	-0.4	problem	-2.3
green	2	manipulation	-2.3	lmao	2.6	profit	2.5
hand	0.1	margin	-0.1	lol	1	proud	2.1
party	0.8	moment	0.7	long	1.8	pump	-0.5
penny	-0.2	moon	2.1	loss	-2.5	purchase	1.3
poor	-1.9	movement	0.9	love	2.3	push	0.5
possible	0.8	naked	-1.1	low	-1.7	quick	0.8
potential	1.4	nice	2	luck	2.1	retard	-2.2
power	2.2	order	0.4	revolution	2	share	0.8
pretty	2.3	panic	-3	rich	2.5	shit	-2.6
probably	0.4	straight	1	ride	1	short	-1.8
top	2.4	strong	2.1	rocket	2.8	silver	-0.2
trade	0.6	stupid	-2.1	sale	-0.7	small	-0.3
value	1.3	support	2.2	scare	-2.3	squeeze	-1.6
win	2.7	target	1.3	scared	-2.6	star	2.4
worth	1.9	tendie	1.7	sell	-1.8	stonk	1.5
wrong	-1.8	to_the_moon	3.5	seller	-1.3	stop	-0.8
yolo	2.4			selling	-1.9		

Notes: This table shows the customisation of the sentiment analysis dictionary by Long et al. (2022). 10 annotators manually ranked the sentiment valence of each of the 130 most commonly used words. This human-centered approach to sentiment valence ranking is particularly helpful in providing scores for jargon terms in the GameStop communities.

Erklärungen gem. § 10 Abs. 6 der Promotionsordnung 2012 der Mercator School of Management

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