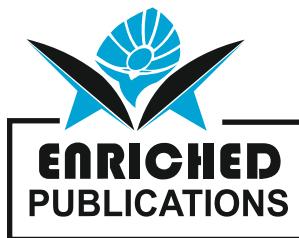


An EP Journal of Behavioural Finance

**Volume No.13
Issue No. 1
January - April 2025**



**JE - 18, Gupta Colony, Khirki Extn,
Malviya Nagar, New Delhi - 110017.
E- Mail: info@enrichedpublication.com
Phone :- +91-8877340707**

An EP Journal of Behavioural Finance

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Contents

Sr. No	Article/ Authors	Pg No
01	Behavioral Finance in Joseph de la Vega's Confusion de Confusiones - <i>Teresa Corzo, Margarita Prat, and Esther Vaquero</i>	1 - 16
02	Behavioural Finance –A study on its Bases and Paradigms - <i>Dhruva Jyoti Sharma1, Dr. Nripendra Narayan Sarma2</i>	17 - 34
03	The Mediating Effect of Trading Volume on the Relationship between Investor Sentiment and the Return of Tech Companies - <i>Jesse Hoekstra and Derya Guler</i>	35 - 60
04	The Price of Happiness: Traders' Experiences of Work in Investment Banks - <i>Daphne Sobolev</i>	61 - 82

Behavioral Finance in Joseph de la Vega's Confusion de Confusiones

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ABSTRACT

*In this paper, we link Joseph de la Vega's work *Confusion de Confusiones*, written in 1688, with current behavioral finance and propose that Vega be considered the first precursor of modern behavioral finance. In addition to describing excessive trading, overreaction and underreaction, and the disposition effect, Vega vividly portrays how investors behaved 300 years ago and includes interesting documentation on investor biases, such as herding, overconfidence, and regret aversion.*

Keywords: Behavioral finance, Investor biases, Stock market history, Overconfidence, Herding, Regret aversion

INTRODUCTION

Research on behavioral finance has seen explosive growth in the last 30 years. However, we can trace evidence of behavioral finance in writings before this period. In this paper, we claim that the work *Confusion de Confusiones* (hereafter CC), written by Joseph de la Vega in 1688, is the first study we have a record of that documents investor biases and thus is a clear precursor of the current behavioral finance literature.

Joseph de la Vega's work has been widely studied from different points of view. He wrote about diverse subjects, primarily philosophy and poetry. His active commercial life began in Amsterdam in 1683. CC was a consequence of his financial experience. This is the first and oldest book about the stock exchange and even today is a good description of financial transactions.

As with every first book of its class, some authors (Neal

[1983]) have conferred on it great importance in the constitution and operations of other markets, such as the London Stock Exchange. This work has been studied not only by economists (Perramon [2011], Leinweber and Mandhavan

[2001]) but also by historians (Gelderblom and Jonjer [2005], Petram [2011]). A sign of the importance of this book is that the European Federation of Stock Exchanges (FESE) offers an annual prize in the name of Josede la Vega to the best study on financial markets.

This book is not a work on stock exchanges or economics, nor is it a legal analysis. It acts more as a description of the beginning of the activities and games of the stock exchange. Nobody by that time had tried to understand and describe this activity. Even in Amsterdam, there was no technical work about this frantic activity.

The style of Vega's book is very rhetorical and makes frequent references to Latin and Greek mythology, rendering it difficult for modern readers to approach. Vega is aware of this difficulty but prefers to be understood by only a few readers.

There will be readers capable of understanding all of what I say. Perhaps there will not be many but there will be some and this is what I want. (para. 142) It is evident from the reading of this book that stock exchange activity is something subject to all sorts of uncertainty. The prices of the two companies then traded in Amsterdam varied wildly due to natural phenomena or to the irrational activity of the traders. In turn, news that was true, false, and invented complicated the formation of prices. Joseph de la Vega detects and colorfully documents some investor behaviors that currently are frequent topics in the behavioral finance field. In addition, he offers several pieces of advice that anticipate the current state of behavioral finance.

Other precursor studies of behavioral finance have been identified, such as the 1896 work by Gustave le Bon, *The Crowd: A study of the Popular Mind*, an influential book on social psychology, and Selden's [1912] *Psychology of the Stock Market: Human Impulses lead to Speculative Disaster*, but all of these studies were written later than CC. Using the taxonomy of applications of behavioral finance described by Barberis and Thaler [2005]—the cross-section of average returns, closed-end funds and comovement, investor behavior, and corporate finance—the work of Joseph de la Vega can be framed in the area of documenting investor behavior. In addition, within this broad field of studies on investor behavior, CC focuses only on some of the main biases. Vega's book, CC, written in Spanish, was translated into Dutch in 1939, and some scripts were translated into English in 1957. In this paper, we will use, where possible, the 1957 English translation, but on several occasions we offer the reader the present authors' translation, as the English translation is not complete. Author's translations are indicated at the end of quotations. The Spanish version used in this paper is the one edited jointly with the Dutch translation in 1939, as it has numbered paragraphs, which facilitates quotation. The paragraph number is specified in brackets.

The paper is organized as follows. In the second section we introduce Joseph de la Vega and his work. In the third section we document the behavioral biases found in CC, and we comment on them. We conclude in the fourth section. At the end of the paper, we include an Appendix, where the original Spanish quotes cited along this paper can be found.

JOSEPHDELAVEGAANDHISWORK

Joseph de la Vega is the author of *Confusion de Confusiones*, but the first confusion concerns his own name and birthplace. His name varies between his works for two reasons. In Spain at that time, a change

of place or kingdom of residence often led to this variation, but also Jews frequently changed their names when they converted to Christianity or emigrated (Torrente [1980]).

His family was from Cordoba, but it is not clear whether he was born in 1650 in Cordoba or in Amsterdam because his parents had immigrated to Amsterdam by that time. CC, published in Amsterdam in 1688, does not pretend to be a treatise on the stock exchange; rather, it is “a set of the experiences of a gambler” (Anes [1986]) that contains references to complex exchange operations, philosophical elements based on classical culture, and a complete description of how the Amsterdam Stock Exchange operated. Joseph de la Vega lived in the collapse of the Oriental Indies Company of the Netherlands, which financially ruined him.

Joseph de la Vega describes the workings of the exchange, in particular those of the “ruedas or coros” (rings), in which everybody could work directly or by means of an agent. For him, the distinction between “bulls” and “bears” is very important. He calls the bulls “liefhebberen” and the bears “contraminores.” He also describes at length the way in which orders are made and formally settled. The book is structured in dialogues, a form very much in vogue in the 17th century. The three protagonists in the dialogues are an erudite shareholder; a cautious merchant, who gradually becomes aware of a new way of making money; and a quick-witted philosopher. The philosopher is initially skeptical but becomes enthusiastic by the end of the work. There is no order in the book, and the subject changes constantly. The first dialogue concerns the origin and etymology of the word “share,” the meaning and use of options (opsies) and the techniques performed by actors in the exchange. In the second dialogue, Vega discusses the volatility of prices and the reasons for this instability, events that cause changes in the behavior of buyers and sellers. The third dialogue considers contracts, specifically how participants agree to prices, when they sign the agreements and how they deliver the shares or merchandise to the buyer. The fourth and final dialogue considers the speculative aspects¹ of this business, which he attributes to the diverse abilities of the actors but also to external influences (rumors or false news). The author defines this business as “enigmatic”:

This enigmatic business which is at once the fairest and most deceitful in Europe. (para. 16)

In addition,

Even as it was the most fair and noble in all Europe, so it was also the falsest and most infamous business in the world. (para. 21) In his initial dedication to D. Duarte Nu~nez de Costa, Vega considers the stock business a game of chance: This unique business is normally called a game. Why? I will personally call it ‘men’ because every man wants to play it. (para. 5, Author translation) In the same dedication, he says that the exchange business has a questionable origin: If in this game the one who most steals most wins, how can I be the best at stealing the humorous thing without giving the game all my time? (para. 5,

Author translation) In the same dedication, he says that the exchange business has a questionable origin: If in this game the one who most steals most wins, how can I be the best at stealing the humorous thing without giving the game all my time? (para. 5, Author translation)

Joseph de la Vega has multiple aims in writing this book: to entertain the reader, to describe the share business, and to tell the truth. This last objective implies telling the reader the risks of the game (Benito [1969], p. 22). It is necessary to paint with the tools of truth the means of deceiving the adversary. (para. 6, Author translation) Although it is clear throughout the book that the exchange occurs in a market, only in the third dialogue is there a clear mention of the premises where trading takes place. However, Vega states that this business can be conducted everywhere:

The business is so constant and incessant that hardly a definite place can be named where it goes on. (para. 203) In the opinion of Vega, the stock exchange has only one role: to earn money (Torrente [1980], p. 91). For this reason, the originality of this book is its technical explanation of aspects that nobody had previously described in detail. Most of the operations and activities that Vega describes remain valid. The author does not consider that the exchange has a social role, a place where companies can find investors and where savers can allocate their savings. In addition, he does not consider the stock exchange the only place where the share business will take place. According to Vega, the stock exchange has no relation to general economic welfare and is of no use for implementing political economic policy. Even if Vega states that this game can be the falsest and most infamous business in the world, he provides some consideration of the range of players' moral sense: Innumerable men earn their living in its shadow. And those who are satisfied with the fruits and do not insist on pulling up the roots...will admit that they do pretty well in such business. (para. 19) This statement implies that depending on the moral sense of the players, trading can be a business of gamblers.

In paragraph 65, he mentions the reasons why shareholders must have information because of their influence on business development: The conditions in India, European politics, and opinion on the stock exchange itself.

In Vega's opinion, the behavior of the shareholder depends in a great way on his overconfidence, although sometimes this overconfidence is derived from the actions of powerful people: There are times in which the powerful investor is followed by many, even at the cost of losing money. (para. 73)

Groups of bull and bear investors drive the behavior of other investors who often lack knowledge or discretion. These uninformed investors follow the tendency of the moment and buy or sell without a clear motivation, trusting in their luck and hoping that the tendency of the markets will favor their position.

BEHAVIORAL FINANCE IN CONFUSION DECONFUSIONES

As Subrahmanyam [2007] asserts, behavioral finance allows for the explanation of financial phenomena on nonrational behavior among investors. Behavioral models are based on how people actually behave and, based on extensive experimental evidence, explain the findings better than classical finance. A pioneer person bridging the gap between psychology and finance is Paul Slovic, especially in his works of late sixties and early seventies.² The development of behavioral finance as we currently know it began with works by Tversky and Kahneman [1973, 1974], who describe heuristics employed when making judgments under uncertainty, and Kahneman and Tversky³ [1979], who propose the revolutionary prospect theory, a descriptive model of decision making under risk, which became an alternative model to expected utility theory. Other early studies in behavioral finance are works by Thaler [1980] and De Bondt and Thaler [1985]. However, Richard Thaler⁴ sets the true origin of behavioral finance on October 19, 1987, when stock prices fell more than 20% without any important news and when many economists began to take behavioral approaches to finance more seriously. In addition, Shiller [2003] highlights that in the 1990s much of the focus of academic discussion shifted away from the econometric analysis of stock prices, dividends, and earnings and moved toward developing models of human psychology as it relates to financial markets. As we noted earlier, in this study we claim that Vega produced the first work available that documents behavioral biases in finance. Specifically, his work focuses on investor biases. Within the broad area of investor bias, we find evidence in CC of three major biases: herding, overconfidence, and regret aversion. In relation to overconfidence bias, there are several examples of excessive trading and overreaction and underreaction. In addition, in relation to the regret aversion bias, we find clear examples of the disposition effect. Next, we detail the quotes where we find these biases and comment on their relationship with actual behavioral finance.

Herding

One of the most common investors' behaviors and the first we find evidence of when reading CC is herding. According to Shiller [2000], herding behavior, although individually

rational, produces group behavior that is, in a well-defined sense, irrational. Herding behavior has frequently been observed in the housing market as well as in the stock market, such as the 1987 stock market crash (e.g., Shiller [1990], Thaler [2005]) and the bursting of the dot-com bubble (Shiller [2005]); see also, for example, the early work by Charles MacKay, *Memoirs of Extraordinary Popular Delusions*.

As Devenow and Welch [1996] write, imitation and mimicry are perhaps among our most basic instincts. Herding can be found in fashion and fads, such as in simple decisions as how best to commute

and what research to pursue. There is an especially prominent belief not only among practitioners but also financial economists (when asked in conversation) that investors are influenced by the decisions of other investors and that this influence is a first-order effect. Some other recent well-known papers on herding are Grinblatt, Titman and Wermers [1995], Wermers [1999], and Welch [2000]. Herding behavior is said to arise from an informational cascade. The idea of informational cascades (Devenow and Welch [1996]) is that agents gain useful information from observing previous agents' decisions to the point where they optimally and rationally completely ignore their own private information. Joseph de la Vega directly presents this same idea:

Merchant: In this chaos of opinions, which one is the most prudent? Shareholder: To go in the direction of the waves and not fight against the powerful currents. (para. 67, Author translation) Despite all these absurdities, this confusion, this madness, these doubts and uncertainties of profit, means are not lacking to recognize what political or business opinions are held by persons of influence. He who makes it his business to watch these things conscientiously, without blind passion and irritating stubbornness, will hit upon the right thing innumerable times, though not always. (para. 79) This observation is related to the paper by Bickchandani,

Hirshleifer and Welch [1998], where we find that learning by observing the past decisions of others can help to explain some otherwise puzzling phenomena about human behavior. For example, why do people tend to converge on similar behavior, in what is known as "herding"? Why is mass behavior prone to error and fads?

Therefore, it is not important that the basic value of the shares be practically nothing as long as there are other people willing to close their eyes and support those contradictions. (para. 81) However, we note here that herding is used by Joseph de la Vega in a different sense than in the actual behavioral literature. In CC, herding helps investors to avoid making the

wrong decision—the decision that will make you lose money—whereas in recent research, herding leads people and even entire populations to make systematic erroneous decisions (Devenow and Welch [1996]).

Nevertheless, both perspectives recognize that herding is linked to imperfect expectations, but Vega argues that this herding behavior, even when actors know that it is not consistent with the right information, will help them to avoid losses and to recognize the irrationality of prices. It is likely that the difference lies in the holding period considered;

Vega does not appear to be adopting a long-term perspective in making these affirmations. In addition, we should consider that Vega wrote his essay before the first bubbles appeared and burst.

Overconfidence

Overconfidence bias is one of the most commonly explored biases in the behavioral finance literature. It is also among the most often observed biases in the financial markets. In fact, there are some authors, such as Plous [1993], who argue that overconfidence is the most dangerous bias. An early trace of this bias can be found in Slovic [1972].

Overconfidence is derived from one's self-perception, so people tend to overestimate their skills and capabilities. In moments when one believes that he can achieve impossibly high targets or when one repeatedly succeeds, the overconfidence phenomenon arises because one does not realize what is actually achievable. Related to this phenomenon, evidence has been found of the undervaluation of other's capabilities. In this paper, we focus on financial markets. In such markets, as Batchelor and Dua [1992] state, investors tend to undervalue investors' community forecasts while simultaneously believing in their own forecasts.

It should be noted that there are a range of approaches complementary to overconfidence. In addition, overconfidence leads to different consequences, which have been widely studied. Among all of these approaches, one of the most interesting is the one that explains that people, when facing a certain event, are prone to overvalue their capabilities instead of undervaluing themselves and underestimating their skills, as reported in Shiller [2000] and Hirschleifer [2001].

Overconfidence can be observed periodically throughout the four dialogues in CC. The authors will focus on the most relevant references to overconfidence. According to the news, the shares should be quoted at 1000, but the actual value is only 500; however, the shares should be quoted at 400, but it happens that they are quoted much more highly. (para. 71, Author translation) As can be observed, the shareholder highlights the difference between the intrinsic stock value and its market value, simply trying to show that such a difference is due to a personal and distorted perception of reality. This

perception may be derived from strong confidence (that is, overconfidence) in one's opinion rather than in what is evident.

According to Griffin and Tversky ([1992], p. 1), "people are often more confident in their judgments than is warranted by the facts"; this statement brings to mind paragraph 74 in CC, which states that transactions are made without any justification:

They will sell without knowing the motive; and they will buy without reason. They will find what is right and they will err for fault of their own. In this paragraph, such strong overconfidence is due to the lack of fundamental reasons supporting what the shareholder does. It could be said that this behavior is a mix of both overconfidence and herding. It happens that an investor continues to make the same investments primarily because in the past he did well, and either he does not worry about whether there have been any changes or, if he knows, he does not take them into account into his forecasts or decision-

making processes. Therefore, it is his instinct and continuing to do what he has always done that explain his behavior. In fact, sometimes there are reasons explaining why a trade no longer exists or has changed; therefore, engaging in such behavior is not rational. However, there are still investors who extrapolate from the past to justify predictions without reconsidering them. In response, Joseph de la Vega makes a definitive statement:

It is contrary to philosophy for contraminors to continue to sell when there is no longer any reason to do so, and in their insistence, the effect persists after the cause has ceased to exist." (para. 120, Author translation) It has been shown that one of the forms taken by overconfidence is trading solely based on how well one does and think he does, which is neither reasonable nor rational. Therefore, as Joseph de la Vega states, these investors will have to find a comprehensive explanation they can provide the investor community that justifies what they are doing: Speculators do not fail to seek protection against such excesses, using even the faintest reasons capable of sustaining their thesis. (para. 77, Author translation)

Overconfidence bias also considers how people hold on to their achievements and past successes, believing that they can continue to succeed forever. De la Vega warns us about this thinking and attempts to make us avoid engaging in such behavior: If fortune is on your side, be grateful, and do not ruin things with unjustified pride. (para. 95, Author translation) Overconfidence not only is related, as stated in the previous paragraph, to holding onto past achievements, but it also leads to the undervaluation of the setbacks traders face and the belief that such events will never recur. In fact, if one faces a bad outcome in trading, the investor should be more tough and rational, as De la Vega reminds us: It is a mistake to say that you are not going to err twice. (para. 172, Author translation)

Another aspect directly linked to overconfidence is the effect that overconfidence bias has on volume. For example, Shefrin [2000] links overconfidence to high trading volume. He is not the only author with this opinion. Among others, Shiller [2000] states that regardless of the mechanism leading to overconfidence, this attitude becomes an important driver of high trading volume in speculative financial markets. He believes that were people not overconfident, trading volumes would be substantially lower. Following Thaler [2005], we can say that one of the clearest predictions of rational models of investing is that there must be limited trading. In a world where rationality is common knowledge, potential buyers are reluctant to buy if potential sellers are reluctant to sell. In contrast to this prediction, the volume of trading is very high. We refer to this fact in behavioral finance as excessive trading.

Excessive Trading

In CC, we find that there was already excessive trading at Vega's time, and it is interesting to note some wise advice that he gave on this subject. Barber and Odean [2000] find that investors would do substantially better if they traded less. Transaction costs are a cause of this underperformance. Vega provides some sensible advice in this respect: I am of the opinion that one should trade little because my philosophers tell me that in order to increase your strength, you should not eat a lot but rather digest your food well. (para. 125, Author translation) He also has an original take on the enthusiasm with which shareholders normally conduct business: A person who is always in action (buying and selling) you will without doubt call a shareholder. (para. 211, Author translation)⁵

In addition, he comments that the interest in shares and in this business is so great that everybody wants to be part of the game: The trade has increased so much over the last five years that everybody is now involved: women, old people, even children. (para. 240, Author translation) As stated earlier, the most prominent behavioral explanation of such excessive trading is overconfidence. One possible explanation for this increase in trading volume is provided by Griffin and Tversky [1992], who describe how more experienced investors are more confident in their predictions and thus about their decisions, leading them to initially tend to trade more than inexperienced investors. However, given the previously mentioned herding effect, inexperienced investors will observe the activities of the experts and tend to copy them, as the experts' overconfidence is contagious.

Overreaction and Underreaction According to De Bondt and Thaler ([1987], p. 1), overreaction occurs when "they [people] overweight recent information and underweight base rate data." That is, such overweighting leads to extreme reactions that drive asset prices substantially above or below their fundamental value. It should be noted that overconfidence usually generates overreactions or underreactions (Kent, Hirschleifer and Subrahmanyam [1998]). This overreaction can be accompanied with the source of speculative bubbles. For this reason, phenomenon of bubbles can be studied from the perspective of overconfidence bias and subsequent overreaction. In CC, there are few clear references to this bias because these statements usually appear alongside references to overconfidence bias. However, Vega makes the following statement concerning overreaction bias: Unexpected news arrives, and shareholders panic. Shares are sold, but shareholders soon feel a sense of despair; they feel mistaken, and after some time they discover

that they were wrong in their dealings. (para. 69, Author translation) There is a clear connection between this statement and a finding made three centuries later by De Bondt and Thaler [1987], who state that vast distances between price and intrinsic value are based on the belief in more recent news (regardless of its truth or the sources' credibility) rather than a company's history and fundamentals. Such a case, as De la Vega says, provokes both extreme upward (overreactions) and extreme downward (underreaction) reactions.

Such extreme reactions make lead to two investor profiles: those who tend to overestimate good results and forecasts, and pessimists, who analyze the news under a negative scope, leading them to become even more pessimistic. Joseph de la Vega broadly explains the behavior of these two groups of investors. He calls optimists “liefhebberen” and pessimists “contraminores.” In paragraphs 83 and 86, Joseph de la Vega clearly defines them and observes that regardless of the actual news, both investors continue to follow their instinct and maintain their outlooks. Vega makes the following statement about liefhebberen:

They are not afraid of the fires, nor do they fear the earthquake. (para. 83, Author translation)

He says the following about contraminores:

They exaggerate the risks so much that the onlookers think they are witnessing death, even to the point to preferring death and disaster to anything else. (para. 86, Author translation) We can observe in the descriptions of these liefhebberen and contraminores the precursors of modern bulls and bears.

Regret Aversion

Finally, we find in CC that investors show regret aversion and are somehow prone to a disposition effect. Regret is an emotional reaction, a pain felt when facing negative effects or the lack of positive effects of one's own decision or move (or lack of move). In finance, an investor may suffer such a feeling when his action, or lack thereof, yields a loss or a lost gain. Loomes and Sudgen [1982] developed a theory of regret. According to those authors, regret theory depends on two fundamental assumptions: first, several people experience the sensations we call regret and rejoicing; second, in making decisions under uncertainty, they try to anticipate and consider these sensations. The authors suggest that representing one fundamental factor in people's choices that has been overlooked in conventional theory are people's emotions.

In behavioral finance, this feeling is referred to as regret aversion, defined as the fear of regretting having made bad decisions. There is a large body of evidence of regret feelings in CC: Some people are always unhappy. If they have bought and the prices fall, they are unhappy because they bought; if the prices rise, they are unhappy because they did not buy more. If they have sold they are unhappy because they sold for less than they could have; if they did not buy or sell, they are unhappy because they did not do anything; if they receive a tip and they did not follow it, they are also unhappy. Everything produces unhappiness. (para. 51, Author translation) As Shefrin and Statman [1985] state, regret aversion

represents an important reason for why investors may have difficulties realizing gains as well as losses. The positive counterpart to regret is pride, but as Kahneman, Knetsch and Thaler [1991] argue, regret is stronger, and this asymmetry between the strength of pride and regret leads inaction to be favored over action, which may be an obstacle to rational decisions.

The default option consisting of changing nothing, that is, inaction, may lead a trader to take an even greater risk. Traders may do so because regret is usually less pronounced when a bad result comes from a “decision not to act” rather than from a decision to act (Zeelenberg,

Van den Bos, Dijk and Pieters [2002]). In his book, De la Vega appears to be clearly aware of the effects of regret aversion on investors, offering advice intended to make investors act and take their profits: Take every game without showing any remorse about missed profits... It is wise to enjoy that which is possible without hoping for the continuance of a favorable situation and the persistence of good luck. (para. 73) Regret aversion is one of the causes of the so-called disposition effect (Sheffrin and Statman [1985]), and the advice given by Joseph de la Vega also points to this topic.

Disposition Effect

The finding that investors are prone to sell winners too early and hold losers for too long has been labeled the disposition effect by Shefrin and Statman [1985]. Thaler [2005] proposes two behavioral explanations for these findings: investors may have an irrational belief in mean reversion, or they may rely on prospect theory and narrow their cognitive framing of the situation. Shefrin and Statman find the roots of the disposition effect in four elements: prospect theory, mental accounting, regret aversion and self-control. Without mentioning the psychological causes leading the investor to inactivity (and probably without knowing anything about them), Joseph de la Vega was convinced that shares should be sold quickly when there was money to be made, and he makes this point on several occasions in his book:

A wise man eats right away the fruits found in season without any delay. (para. 97) It is wise to collect some profit without waiting to collect all profit. Profits can be compared to arrows and it is wise to collect the profit of each arrow. (para. 127) ...Miracles should not be expected from the stock exchange and the only ones who will be happy will be the ones who enjoy the initial successes. (para. 128) His advice appears to be confirmed in light of the results described by Odean [1998], who reports that the average performance of stocks that people sell is better than that of stocks they hold on to. The statements in CC may also be closely related to the problem of self-control (Thaler and Shefrin [1981]), which concerns the control of emotions. The investor’s rational impulse may not be strong enough to

prevent the investor's emotional reactions from interfering with her rational decision making. If Vega's advice is followed, an improvement in self-control will be a direct result.

CONCLUSION

In this paper, we link Vega's *Confusion de Confusiones*, written in 1688, with current behavioral finance. We claim that Vega was a pioneer in the depiction of shareholder behavior, as his book contains several examples of investor bias. Vega's work is the first study written about a stock exchange—the Amsterdam Stock Exchange during the 17th century—and its participants, the shareholders. CC was written in Spanish and was translated into Dutch in 1937 and into English in 1957. In 2010, it was also translated into Chinese. Although CC is not the only literary work of Vega, it is the one that has created the most interest and has been studied from several perspectives (i.e., Perramon [2011], Gelderblom and Jonjer [2005], Petram [2011]).

In this paper, we connect Vega's documentation on investor behavior with current investor biases studied in modern behavioral finance. We find evidence of three major biases in CC: herding, overconfidence, and regret aversion. In addition, we identify references to excessive trading, overreaction, and underreaction, as well as the disposition effect. In an old-fashioned and rhetorical Spanish style, Vega vividly portrays 17th century investor behavior, and we find with some satisfaction that what he describes does not differ from the behavior of modern investors.

ACKNOWLEDGMENTS

The authors are grateful to the Servicios de Estudios of Madrid Stock Exchange for facilitating the reading of different editions of *Confusion de Confusiones*. The paper benefited from comments of Antonio Arroyo, Ricardo Gimeno and an anonymous referee.

FUNDING

Teresa Corzo acknowledges financial support from the Spanish Ministerio de Ciencia e Innovacion via project ECO2011-29144.

NOTES

1. See in relation to this point Leinweber and Madhavan [2001].

2. i.e., Slovic [1969, 1972].

3. Amos Tversky and Daniel Kahneman wrote many papers together that have greatly contributed to the development of the behavioral area, but it is not the aim of this paper to cite them all here.

4. Preface to *Advances in Behavioral Finance*, ed. Richard Thaler [2005].

5. This quote in Spanish is a play on words with the word accion. The meaning of this word is both action and share (stock).

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Behavioural Finance –A study on its Bases and Paradigms

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ABSTRACT

Traditionally rational models have been chosen in the field of economics and finance. Experimental psychology has provided the behavioural insights in finance and economics. Behavioural finance is a new field which explains the economic decisions of people. It is a field which combines behavioural and cognitive psychological theories with conventional economics and Finance. In this paper efforts have been made to provide a framework for the concept related to the behavioural finance. Review of literature is carried out so that different dimensions and views regarding behavioural finance can be understood. Theories, models and studies which try to complement behavioural finance studies are also discussed. New frontiers and approaches that can be adopted for further studies are discussed and it may help to provide a conceptual framework for future studies.

Key Words: *Behavioural Finance, Theories, Models, Conceptual Framework*

I. INTRODUCTION

“One of the funny things about the stock market is that every time one person buys, another sells, and both think they are astute.” – William feather. The rationality of investors is the central idea around which the traditional finance paradigm revolves around. According to Nofsinger(2001),the evolution in the field of finance has taken place based on the premise that people make rational decisions and they are unbiased in the forecasting about the future. Rationality of the investors is depended on the premise that they can (i) Update their beliefs correctly on time on the receipt of fresh information. (ii) Choose options those have normative acceptance (Thaler, 2005). According to Jensen and Merckling(1994), the “Rational Man” is the central idea behind the concept of traditional finance, a person who is very different from the individual. Montier(2002), discusses about a construct where assumption is made that investors can make comprehension of complex puzzles and process endless instantaneous optimizations. Such assumptions lead to the conception of market efficiency. According to fama(1965), An efficient market is a market where investors are rational, they can maximize profit by predicting future market values of securities, where they can update their information which is freely available to all the participants. In other words, a market where the actual price of a security is a good estimate of its intrinsic value is an efficient market. The foundations of the world economy were questioned due to the financial crisis of 2008, which resulted in global recession. The traditional economic and financial

theories labeled it as an “anomaly”® Subash, 2012).

Bernstein(1998) discusses about the choices and decision of „Rational Man“ who showcases repeated patterns of irrationality, inconsistency and incompetence when faced with uncertain situations. Nofsinger(2001) discusses about the drubbing of rationality as a central idea and unbiasness of investors.

The theoretical and experimental propositions by psychologists Daniel Kahneman and Amos Tversky in 1970s, served as the foundation for development of new horizons in 1980s called as Behavioural Finance, which elaborates about people’s behavior in any financial setting. Specifically, it elaborates on the impact of psychology on financial decisions, organizations and financial markets. Hirshey and Nofsinger(2008) defines behavioural finance as an analysis of cognitive errors and emotions in financial decisions. It is also characterized by an inquiry which helps to find out the impact of psychology on the financial behavior of incumbents and the market as a whole (Sewell, 2007). Schindler (2007) enumerates the three principal areas of study in behavioural finance. They are:

1. Sociology: It is a structured study of social behavior of individuals and groups and impact of society on attitudes and behavior.
2. Psychology: It is the study of human behaviours and cognitive processes which underlines the behaviours, which are result of human’s physical, cognitive and external surroundings.
3. Finance: It is the subject related with determination of allocation of capital, its accession and distribution.

Pompian(2006) lists two sub topics under behavioural finance:

1. Behavioural finance Micro (BFMI) - It is a study of the behaviours and biases of investors who distinguish themselves from the investors who are seen as rational actors in traditional economic theories.
2. Behavioural Finance Macro (BFMA)- It tries to detect and describe the found anomalies in the EMH(Efficient Market Hypothesis), behavioural models may provide explanation to the found anomalies.

Pillars of Behavioural Finance:

In the 1960’s Kahneman and Tversky were carrying out their individual research on different lines, 1970s was the decade they created the benchmark in the area of behavioural finance. They started with the experiment related with psychology and decision theory and its implication in the real world scenarios. Tversky’s expertise was mathematical work in the area of normative theory and Kahneman’s

„Psychophysical emphasis on the difference between objective stimulus and subjective sensation“ came together perfectly to serve the purpose (Heukelom, 2007). “Belief in the law of small numbers” was the first paper they authored together in 1971, where they reported that “People have erroneous intuitions about the laws of chance. In particular, they regard a sample randomly drawn from a population as highly representative” (Kahneman and Tversky, 1971).

They published a paper titled “ Subjective Probability: A judgement of Representativeness”, where they discussed about the representative bias and then they carried out another publication in 1973 called “On the psychology of prediction “, which discusses about the representativeness and its key role in the predictions of intuitions made by individuals (Kahneman and Tversky,1972,1973). In the year 1974, they published a paper “Judgment under Uncertainty: Heuristics and biases “. In this paper they discussed about three heuristics- Representativeness, Availability and Anchoring. They described that “a better understanding of heuristics and of biases to which they lead could improve judgments and discussions in situations of uncertainty”.

In the year 1979 they published their most important work titled “Prospect theory: An analysis of decisions under risk” which criticized expected utility theory and they developed a model called Prospect theory. Nobel Prize in economics in 2002 was awarded to Kahneman, for his work in Prospect theory. They introduced the effect known as Framing in another paper published in the year 1981. It was illustrated

in this paper that when the same problem was framed in different ways, the choices are influenced with respect to the different wording, settings and situations (Tversky and Kahneman, 1981).

Human Behavioural Theories:

Prospect Theory: This theory is developed by Kahneman and Tversky(1979). According to this theory, there are two distinctive phases in the choice process:

- I. Framing Phase
- ii. Evaluation Phase

They developed this theory and showcased the management of risk and uncertainty by individuals. It tries to explain the irregularity in behavior of humans while they assess risk in uncertain situations (Subash, 2012). Kahneman and Tversky (1979) introduced an effect called as “Certainty effect” which explains how people put less weight on the outcome that are mere probable and place more weight on the outcomes that are considered to be more certain. Heuristics Theory:

This theory states that heuristics are simple and efficient thumb rules which are helpful in explaining

how people can make decisions come to conclusions and solve problems when they face complex problems or face situations of incomplete information. These thumb rules generally work under most circumstances, but in certain cases it induces systematic cognitive biases (Parikh, 2011). Tversky and Kahneman recognized that the decision making process gets influenced by the heuristics. According to Tversky heuristics is a strategy that can be used to solve many complex problems but it does not always result in a correct solution. It is a simple tool to reach easy conclusions (Tversky and Kahneman, 1981). Brabazon(2000) states that heuristics is a decision process in which investors use trial and error method to find things out for themselves, which leads to the evolution of a structure for rules of thumb. This is especially relevant in modern day trading, where there is enormous amount of information and increasing number of instruments. Heuristics speeds up the process of decision making in comparison to rational processing of information. One of the most important aspect of using heuristics is the time that can be saved but the dependence on past experiences is its main drawback while traditional finance models do not have any provisions for using heuristics and decision making is completely based on rational tools(Shefrin,2000).

Johnsson,et al.(2002), proposes following theories under heuristics and prospect theory.

Table: 1 Behavioural Finance theories

Heuristics	Prospect Theory
Anchoring	Self Control and Regret
Overconfidence and Over Under reaction	Loss Aversion
Herd Behaviour	Mental Accounting

Source: Johnsson,et al.(2002)

Behavioural Biases:

Studies in the field of Psychology have identified a variety of behavior regarding decision making called as Biases. The impact of such biases is all pervasive but it has its particular implications in the area of finance particularly in investments. The association of biases is with how does people process information and reach decisions and choices (shefrin, 2000). Specific studies in the particular field try to categorize the biases on the basis of some meaningful framework. Some scholars classify biases along the cognitive and emotional lines, others call biases as heuristics and others refers to them as beliefs, judgments or preferences. The taxonomy of bias is although helpful in carrying out a specific research but there is lack of a theory of investment behavior which is universally accepted. Behavioral finance studies are based on collection of evidences which explains the ineffectiveness of human decision making in economic decision making situations (Pompian, 2006).

Table: 2 Types of Biases

Cognitive Biases	Emotional Biases
1. Hindsight bias	1. Loss Aversion Bias
2. Framing Bias	2. Regret Aversion Bias
3. Availability Bias	3. Status Quo Bias
4. Self Attribution Bias	4. Confirmation Bias
5. Overconfidence Bias	5. Self control bias
6. Representativeness Bias	6. Optimism Bias
7. Illusion of control Bias	7. Endowment Bias
8. Recency Bias	
9. Mental Accounting Bias	
10. Anchoring and Adjustment Bias	
11. Conservatism Bias	
12. Ambiguity Aversion Bias	
13. Cognitive Dissonance Bias	

Source: Pompian(2006)

Individual investors might have inclination towards a wide variety of behavior biases, which leads them to make cognitive errors. Difficult and uncertain situations make people to go for choices which are predictable and non-optimal because of its heuristic simplicity. Behavioural biases are explained in the same manner as systematic errors are in the case of judgment (Chen et al, 2007).

Montier(2002), broadly categorizes biases in three different types.

Table 3: Taxonomy of Biases

Social Interaction	Self Deception(Limits to learning)	Heuristics simplification(Information processing errors)	
cascades	Confirmation Bias	Representativeness	Emotion/Affect
contagion	Overconfidence	Categorization	Ambiguity Aversion
Herding	Self Attribution Bias	Framing	Mood
Imitation	Over optimism, Illusion of control, Illusion of Knowledge	Anchoring/Salience	Self control
	Hindsight Bias, Regret Theory, Cognitive	Availability Bias, Cue competition, Loss Aversion,	
	Dissonance	Prospect theory	

Source: Montier(2002)

Definitions Of Behavioural Finance:

1. Behavioral Finance is an area of research in which human interpretation is studied and how do they act on information with the help of interpretation to make informed investment decision (Linter G, 1998).
2. Behavioral Finance studies are unique area of finance that tries to explain stock market anomalies

with the help of biases rather than simply trying to dismiss them as a chance factor consistent with the market efficiency hypothesis (Fama, 1998).

3. Behavioral finance is a field of finance which tries to depart from traditional assumptions of economics by using observable, systematic and human departures from rationality. The humans tend to be overconfident which cause first bias and human desires to avoid regret which leads to second bias (Barber and Odean, 1999).
4. Behavioral finance is a fast growing field of finance which deals with the psychological influence on the behavior of the practitioners of finance. It is also a study which deals with how psychology affects finance related decision making and financial market as a whole (Shefrin, 2000).
5. Behavioral finance is a close combination of individual behavior and market occurrences and the knowledge which is taken from the field of psychology and finance (Fromlet, 2001)
6. Frankfurter and McGoun (2002) defined behavioral finance as a part of behavioral economics and it gets help from theories of psychology and sociology which tries to discuss occurrences which are inconsistent with the theories of expected utility of wealth and rationality of people. Behavioral economics is generally experimental in nature which uses research methods that are not used in traditional mainstream finance studies.
7. W. Forbes (2009) defines behavioral finance as a scientific study which describes about how psychology affects financial market. This view points out about the affect of psychology and cognitive biases on the decision making abilities rather than the affect of rationality and wealth maximizing behavior of investors.

Table 4: Behavioral Finance Theories and Models

Sl. No	Researcher Name	Year	Theory/Model
1.	Herbert Simon	1955	“Models of bounded rationality”.
2.	Leon Festinger	1957	“Theory of cognitive dissonance”.
3.	Tversky and Kahneman	1973, 1974	“Introduced heuristic biases: availability, representativeness, anchoring, and adjustment”.
4.	Kahneman and Tversky	1979	“The prospect theory introduced loss aversion bias”.
5.	Tversky and Kahneman	1981	“Introduced framing Bias”.
6.	Shefrin and Statman	1985	“Introduced Disposition effect”.
7.	Richard Thaler	1985	“Introduced mental accounting bias”.
8.	De Bondt and Thaler	1985	“Theory of overreaction in stock markets”.
9.	Barberis, Shleifer, and Vishny	1998	“Investor sentiment model for underreaction and overreaction of stock prices”

10.	Meir Statman	1999	“Behavioral asset pricing theory and behavioral portfolio theory”.
11.	Andrei Shleifer	2000	“Linkage of behavioral finance with the Efficient Market Hypothesis to find that stock markets are inefficient”
12.	Barberis, Huang, and Santos	2001	“Incorporation of prospect theory in asset prices”
13.	Grinblatt and Keloharju	2001	“Role of behavioral factors in determining trading behavior”
14.	Hubert Fromlet	2001	“Importance of behavioral finance, emphasis on departure from homoeconomicus’ or traditional paradigm to more realistic paradigm”
15.	Barberis and Thaler	2003	“Survey of behavioral finance”
16.	Coval and Shumway	2005	“Effects of behavioral biases on stock prices. The price reversal for biased investors is quicker than unbiased investors”
17.	Michael M. Pomplian	2008	This model was developed in 2008; it identifies four Behavioral Investor Types (BITs).
18.	R.Subash	2012	In his thesis “Role of behavioral finance in portfolio investment decision –Evidence from India” he found out that behavioral biases affects both the younger and experienced investors in a similar manner but with varying degrees.
19.	Neelakantan .P.R	2015	The study found out that demographic factors and risk taking capacity of the investors are not correlated. Investors having Cognitive bias are likely to give satisfactory outcome while emotional bias will negatively influence and may give negative or least return outcome to an investor.

Source: Jaya Mamta Prosad(2014), R. Subash (2012), Neelakantan .P.R (2015)

Review of Literature:

According to Lord, Ross and Lepper (1979) once investors form their own opinion they would cling to it for long. They would not look for evidences that can contradict their belief and if they somehow find contradicting evidence they would be skeptic about its authenticity. Weinstein (1980) identified that majority of people displayed unrealistic beliefs in their abilities and prospects in the financial market. According to Bell (1982), Loomes and Sugden(1982) the theory of regret aversion discusses about the behavior of people when they face a decision, they might anticipate regret and hence they try to eliminate or reduce the possibility of regret in their choice. Gilovich, Vallone and Tversky(1985) in their study found that many a times representativeness heuristics plays an important role for investors, but sometimes it also proves to be counterproductive as it leads to sample size neglect i.e., when people

are not aware of the data generating process, they come to conclusion very quickly on the basis of few data points.

Shefrin and Statman (1985) found out that investors generally do not want to sell assets at a loss with comparison to the initial price at which it was purchased. This phenomenon is called as “Disposition effect”.

Chopra, Lakonishok and Ritter(1992) and La Porta, Lakonishok, shleifer, and Vishny (1997) provided the evidence that the investors tend to make irrational forecasting of future cash flows.

In the study conducted by Buehler, Griffin & Ross (1994) majority of people, around 90% of them who were surveyed, predicted about the completion of task much sooner than they actually are. Gali J (1994) Studied that investors generally tend to copy the investment decisions of their friends having sound investment knowledge. It has been found out that this tendency of copying friends is generally high among first time and new investors of capital market. According to Chung, Jo, and Statman(1995) Analyst and brokers“ role can be comprehended when we see them as marketing agents for their respective brokerage organization. Jo specifically points out that investors prefer companies which act responsibly in society and analysts plays a role as instruments that help brokers in selling stocks.

Shanmugam and Muthusamy (1998) in their article “Decision process of individual investors, Indian capital markets: theories and empirical evidences” identified that demographic factors such as education and occupation has a greater impact on ownership of risky assets. Investment decisions were dependent on decision making tools such as fundamental analysis and technical analysis.

Rajarajan V (1999) in his article “stage in life cycle and investment pattern” observed that the stage in life cycle of retail investor determines their investment size in the financial assets. Law of small numbers is the belief of people that even very small samples of parent population can mirror its properties. This law does generate a fallacy effect known as Gambler“s fallacy where in such situations people knows the data generating process in advance (Rabin, 2002). Diacon S (2002) in his study found out that retail investors are of belief that long term objectives can be fulfilled by equity investment and short term goals can be fulfilled by investing in fixed income bearing shares.. Chan Y and L kogan (2002) concluded that normally friends are the source from where they draw inspiration and motivation, especially in case of investment decision. Investors approach friends to get mental support from them by getting their consent regarding investments which makes them feel that they have taken the right decision. Jay R Ritter (2003) uses the behavioral finance to negate the assumptions made by traditional theories of finance which believed in expected utility maximization by a rational investor.

Discussion on the dimensions of behavioral finance such as cognitive psychology and the limits of arbitrage is carried out. Matthews J (2005) in his article “A situation based decision making process” concludes that investment life cycle of an investor plays a major role in investment decision making

process.

Mittal Manish and Vyas R.K (2007) in their research paper “Demographic and Investment choice among Indian Investors” found out that investment choice made by investors is influenced by demographic factors. People with income less than 1 lakh usually preferred low risk investment for e.g. post office deposit etc, and investors of age around 26-35 years preferred investing in mutual funds and investors aged between 36-45 preferred investing in bonds and debentures. Kannadhasan K & Nandagopal, R (2008) in their research studied behavioral finance and its role in investment decisions. They found that investor decisions are effected by cognitive illusions. They suggested

that an investor has to minimize or mitigate illusions by taking steps which would curb the factors which has influence on their investment decision making process. Dhananjay Rakshit(2008) in his finding “Capital market in India and abroad-A comparative Analysis”, concluded that Indian capital market is one of the preferred markets for foreign investors and their only concern regarding investment is increased volatility. Mittal M and RK Vyas(2008) in their paper “Personality Type and Investment Choice:

An empirical study” found out that decisions regarding investments are effected by cognitive and emotional biases. While processing the information for making a decision, these behavioral errors lead investors to make systematic errors; they also observed that investment decision of an individual is effected by demographic factors like age, income, education and marital status. Kiyilar and Acar (2009) believes that we humans are social creatures and all of us have separate value systems, values are formed by any individual’s behavior and emotions.

Behavioral finance is an extension of traditional finance. It is said that behavior, emotions, and mood plays an important role in decision making process of any individual. According to Wernet DeBondt et. al. (2010), the three important psychological factors that are inseparable components of behavioral finance are the cognitive, the emotional response and the social psychology. Shanmuga Sundaram V & Balakrishnan V (2010) in their study on impact of behavioral dimensions of investors in capital market have found that Psychological factors created by fear of losing money, market crash and lack of confidence in one’s decision making ability influences investors’ decision. Brahmana et. al. (2012) in their research study found out two major psychological biases- affection biases and cognitive biases.

They identified biases which are major determinants of the „Day of the week Anomaly”(DOWA). DOWA contradicts the assumptions of the traditional finance which focuses on rationality of the people. Anomaly of the market is caused by investors and these results into irrational behavior of the investors. Subash R (2012) in his thesis “Role of behavioral finance in portfolio investment decision –Evidence from India “ found out that behavioral biases affects both the younger and experienced investors in a

similar manner but with varying degrees.

Daiva and Olga (2013) found out the correlation between household financial decisions and behavioral finance. They observed that decision of household finance is affected by psychological traits just like corporate finance decisions. It is also found out that the loss aversion bias found in the literate households are same to those set by the experts in behavioral finance while the characteristics like the absence of the market impact are found uniquely only among the households. Bikas et. al. (2013) stated that decision in financial markets are not only based only on the available information from the market but also the psychological factors play a huge role influencing the investment decision making process. Mitroi and Oproiu (2014) in their research found out that emotional intelligence and investment performance are positively correlated. According to them in financial decision making process psychological factors plays more important role than the rational factors. According to Neha Aggarwal(2014) herds seem to form often in those markets where there is inferior aggregation of information and poorer accuracy of the public information. Moreover, it is found that herds exist on the buy side of the market than on the sell side. Buy herding is more intense than the sell herding. The study by Jaya Mamta Prosad(2014), captures the order of prevalence of biases in the Indian equity market. On the basis of ranking, it is seen that overconfidence has the highest prevalence followed by optimism (pessimism) and herding while; the disposition effect has the lowest rank.

Lubis et. al (2015) stated that emotional intelligence, defense mechanism, and personality trait are three major elements that influence the investors' risk-taking behavior. Neelakantan .P.R (2015) found out that demographic factors and risk taking capacity of the investors are not correlated. Investors having Cognitive bias are likely to give satisfactory outcome and while emotional bias will negatively influence and may give negative or least return outcome to an investor. Swati Vishnoi(2015) found the effect of behavioural factors namely Herding, Prospect and Heuristics on investment performance. It revealed that market factors have negative effect, heuristic and herding have positive effect and prospect factor have no impact on investment performance. Yamini Gupta(2016) found that less experienced investors of the market were tend to be less impacted by loss aversion bias, regret aversion bias, anchoring bias and cognitive dissonance bias as compared to more experienced investors. According to Ayaat Fatima(2016) investors are subjected to psychological biases and cognitive biases which impacts decision making process. The results exhibits the absence of overconfidence bias in the individuals of Kashmir and they showcased impression of being underconfident, sensitive to other's reactions and opinions and very hesitant.

Darshita Ganatra(2016) in her study collected responses from sample respondents about their decisions when they are put under fifteen different hypothetical situations so as to measure fifteen types of irrationalities among them. The proportion of responses exhibiting rationality was higher in case of nine

types. It shows that more sample respondents are not irrational in their approach so far as loss aversion, sunk cost fallacy, endowment effect, mental accounting, optimism, overconfidence, gambler's fallacy, herd behavior and representativeness bias are concerned. More sample respondents are irrational in their approach in the context of anchoring, disposition effect, regret of omission and commission, availability bias, confirmation and regret aversion.

According to Amlan Jyoti Sharma(2016) behavioral finance is a descriptive and advisory study of ideas and thoughts which are not exhaustive. To be a good theory it needs to be refined after holding discussions and conducting more studies. Till then it should be accepted as a theoretical framework and rigorous and refined analysis is required to replace a concrete theory like EMH. In the study conducted by A.Pankajam(2017) the behavioural factors such as Locus of Control, Emotional Intelligence, Risk Attitude , Herding, Heuristics and the Prospect factors were analysed with the help of canonical correlation to investigate the relationship between each and every factor of the behavioural factor and the investment decision making factor as a vector analysis. From the analysis it was found that both the sets were having a high correlation to the extent of 85.4% shows a high relation between the behavioural factors and the investment decision making behaviour of the investors.

The correlation between the input variables such as the risk attitude, Emotional Intelligence, Locus of control, Herding, Heuristics and the Prospects and the decision making variables such as the Performance, Satisfaction and the Strategy for Decision Making shows a high correlation between 70 and 92 percent. According to Nidhi Kumari (2017) the combined effect risk tolerance bias, herd behavior bias and overconfidence bias, strongly explains the variation in the extent of investment in the capital market. This reveals that investors are not rational in terms of their investment decisions. They deviate from the theory of rationality and are affected by psychological factors. Therefore, it can be said that capital market investors in Odisha, West Bengal, Jharkhand and Bihar overall reflect the investors' behavior of the Eastern India. Sashikala and Chitramani (2018) stated that the investment intention is the prime factor which influences the investment decision of the investor regarding personal and portfolio management. Short term investment intention was impacted by prospect factors and herding factors and long term investment intention was impacted by prospect factors and market factors.

It was found out that heuristic factors' impact on both long term and short term investment intention was insignificant. Joo and Durri (2018) found in their study that investment decision making is impacted by psychological traits like confirmation biases , herd behavior, pessimism, faith, heuristics and overconfidence and optimism.

faith is considered to be the most important bias that significantly impacts investors decision making . Division of investors“ portfolio can be done into short term and long term portfolios. Psychological traits play the major role in building a short term portfolio and the long term portfolio could be build depending

on the market behavior and the expected returns. According to the study by Kruti P. Bhatt (2018), Anchoring bias has been found to influence 97.4 percent of the total respondents and Overconfidence bias has been found to influence 97.8 percent of the total respondents. So anchoring bias and Overconfidence bias are the most prominent biases among investors under study.

Availability bias, Disposition Effect, Herd Behavior, and Representative bias have been found to influence 70.4 percent, 70.2 percent, 70.4 percent and 56.3 percent of the respondents respectively. So these biases are comparatively less prominent in investors under study. Mental Accounting and Naive Reinforcement Learning have been found to influence 6 percent and 2 percents of the respondents respectively. So, these biases are the least prominent in investors under the study.

New Frontier of Neuroeconomics:

Neuroeconomics is an emerging field of study which could offer insights for private client investment practitioners. Neuroeconomics combines tools from neuroscience such as, Electrophysiology, MRI(Magnetic resonance Imaging), & TCS(Transcranial Cortex Stimulation; from psychology such as Psychophysiology and eye tracking; and from experimental economics to study the neural basis of economic decision making. To understand the choice people make regarding their money the gap between brain science and economic theory is bridged using neuroeconomics. How does emotion affect financial decision making? What about risk and does the risk affect the people“s judgment? How do people perceive uncertainty? All these questions are interesting field of research for both asset manager as well as neuroeconomists. The most prominent work in this field is Paul Glimchers“s Decisions, uncertainty, and the brain: the science of neuroeconomics (Pomian,2006).

Research Gap and Problem Identification:

Although the biases and Heuristics are identified but why people operate under bias and what causes different people to have different biases under same situation is again a subject of empirical evidence research in psychology. If answers to these questions are obtained, then again its implication in the area of behavioural finance will open new vistas of research. Retail investors of stock market are prone to behavioral biases when they are making their investment decisions, evidences could be found from the studies around the world and other parts of India. Criticism of Traditional finance theories has led to a

situation where the rationality of the investor is considered less important and effect of behavioral aspects is given more importance. Some people value possession of physical assets more than investing in stock markets and vice-versa. May be because they are wired differently, different emotions arise and brain juices produced? How to check this aspect? The research and studies in the field of Neuroeconomics can play an important role in unraveling the secrets of brain juices (Pompian, 2006).

Conclusions:

Rationality of investors in case of EMH is interpreted differently by different stake holders. Rationality according to EMH is about following a set of rules while taking decision regarding investment and having information about the market. Principles of Homo-economicus govern the economic decisions by individuals that are a simple model of human economic behavior. So, this is a very basic tenet which is required for being any investor i.e., to have self interest, to be rational and must have perfect information. Evolution of behavioural finance studies have started to add new angle of influence of psychology in finance. Some people value possession of physical assets more than investing in stock markets and viceversa. May be because they are wired differently, different emotions arise and brain juices produced? How to check this aspect?

Relevance:

study about foundations of behavioural finance and its importance in addition to the traditional rational models of finance. It could also be used for studying the Impact of different classes of biases on investment decision making. More literature and studies could be reviewed in the field of neuroeconomics and its recent developments could be traced and hence could be used in empirical research. This study would help create a framework for different kinds of approaches that can be taken as a base for conducting research in the field of behavioural finances. The approaches could be related to literature based

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The Mediating Effect of Trading Volume on the Relationship between Investor Sentiment and the Return of Tech Companies

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ABSTRACT

This paper investigates the mediation effect of trading volume to explore the relationship between investor sentiment, measured as a volatility forecast (VIX), and the return of tech companies based on the mediation analysis. This paper focuses on Tesla, a list of the 30 largest technology companies and the MSCI World Index. It implements this mediation analysis by using an ARMA-EGARCH model for the time series of Tesla stock and the MSCI World Index returns and a Fixed-Effects regression model for stock returns of the list of 30 technology companies. Estimation results show that trading volume mediates the relationship between investor sentiment and stock returns. The mediating effect found in the case of Tesla and the MSCI World Index is much more present than regarding the list of companies. Furthermore, to obtain an all-encompassing analysis and create less dependence on proxy selection, additional mediation analyses are incorporated that include the 10-year Treasury yields, prices of the Swiss franc currency and the Baker-Wurgler index as investor sentiment proxies. The results show that the mediating effect of the trading volume is present also for these proxies providing more evidence that such a mediating effect is the underlying mechanism in stock markets.

KEYWORDS ARMA-EGARCH model; Fixed-effects model; Investor sentiment; Mediation analysis; Panel data; Tech companies; Tesla stocks; Time series

INTRODUCTION

Ritter (2003) showed that people often behave irrationally, and cognitive biases such as heuristics, overconfidence, mental accounting, framing, conservatism, disposition effect and representativeness drive behavior. All-encompassing, this means that human sentiment affects behavior. Translating this to the financial sector means that investor sentiment affects investor behavior. But which specific behavior? Moreover, what are the consequences for the financial market?

These questions have induced many researchers to investigate this particular topic of investor sentiment, especially its effect on stock returns. Fisher and Statman (2000) found that the sentiment of wall street strategists affects future stock returns. Moreover, they found that individual investor sentiment also affects future stock returns, and the same applies to the sentiment of newsletter writers. Schmeling (2009), moreover, found that consumer confidence, as a proxy for investor sentiment, affects expected stock returns internationally in 18 industrialized countries. Previous research studied the direct impact of investor sentiment on asset returns and volatilities especially by making use of trading volume as investor sentiment. Previous research shows a significant impact of investor sentiment on stock returns.

However, one could argue that this is too simply specified, and investors must first act a certain way for the stock returns to change—which has induced this study to investigate the indirect relation between investor sentiment and stock returns through trading volume. The impact of investor sentiment-related investor behavior can be observed in the trading volume. In other words, the concept of investor sentiment influencing trading volume to affect stock returns subsequently. Shepherd (2004) in his book, “Social and Economic Transformation in the Digital Era”, portrays the rapid development of technology in the digital era. He states that this technological growth has increased the speed and range of knowledge turnover in the community

and economy. Consequently, many tech companies have entered the markets in the last few decades and have experienced rapid growth. One company that particularly stands out is Tesla. Tesla was founded in 2003 and is currently worth \$679.10 B; this is arguably mainly due to Tesla’s CEO, Elon Musk, whom most people see as the visionary of the 21st century. Besides that he makes many good decisions businesswise; he is also a master at influencing people. Strauss and Smith (2019) their research illustrates this. They state that Elon Musk’s tweets are valuable market information concerning Tesla stocks. For example, they mention that tweets of Elon Musk related to a new battery raised limited attention in the media. However, investors reacted considerably, and stock prices rose significantly after that

Tesla stock returns seem to be significantly influenced by investor behavior caused by investor sentiment. Although, the question remains whether this phenomenon can be observed when we analyze it more quantitatively through mediation analysis. This study, therefore, undertakes a mediation analysis to test whether trading volume mediates the relationship between investor sentiment and Tesla stock returns. The major contribution of this paper is filling the gap between mediation analysis and investor sentiment because the research on mediation analysis between stock returns and investor sentiment making use of the time series models has not been conducted before. The application of mediation analysis in time series models for the investigation of the indirect relation makes the contribution unique. This respective mediation analysis demands three separate regressions, requiring time series data in the form of Tesla stock returns, trading volume and the volatility forecast as a proxy for investor sentiment. Therefore, to model this mediation analysis depending on time series data, this study utilizes an ARMA-EGARCH model.

Baker and Wurgler (2006) studied how investor sentiment affects the cross-section of stock returns by making the distinction between different stock categories. The results show that when sentiment is high, subsequent returns of small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividendpaying stocks, extreme growth stocks, and distressed stocks are relatively low. When sentiment

is low, subsequent returns of these stocks are relatively high. These findings indicate that focusing on different stock categories are more appropriate when analyzing the investor sentiment impact. One stock category that stands out in the digital area is tech stocks therefore the main focus of this paper is the list of the 30

largest tech firms to observe whether this potential mediation by trading volume is exclusive to Tesla compared to other large tech companies. Broader extension of the research question is the inclusion of the Morgan Stanley Composite Index (MSCI) World Index. The MSCI World Index is included to gain more insight into the broader impact of investor sentiment as an extension of a list of 30 tech companies. Studying the impact of the investor sentiment through trading volume on the returns of the MSCI World Index can explore if the impact is present at a global level as well. Furthermore, this paper uses additional sub-research questions to limit the dependency on the specific proxy selected for investor sentiment-incorporating the most important investor sentiment proxies provides this study with additional confirmation concerning potential mediating effects. These mediation analyses use data from the 30 largest technology firms. Therefore, they use so-called panel data and require different modeling techniques than this study previously used. This study employs the Fixed-Effects regression for these respective analyses.

This paper proceeds as follows: the next section summarizes existing literature. Section three describes the data used in this study. The fourth section discusses the various econometric models, mentioning their advantages and limitations. Subsequently, the fifth section presents the main empirical results. Finally, the sixth section concludes.

Literature review

Gaining more insight into the drivers of stock returns is paramount to many; stakeholders, ranging from private investors to the actual firms. Multiple of these drivers follow traditional finance theories and use the assumption of rational traders. A good example is the homo economicus model, introduced by John Stuart Mill in 1836, which suggests that a person merely makes rational decisions and always seeks to maximize utility (Mill (1836)). However, as Ritter (2003) discusses, behavioral theories have shown that people suffer from many cognitive biases. Such as overconfidence and representativeness, where people are overconfident about their abilities and tend to put too much weight on recent experiences. Therefore, incorporating this would provide a more realistic scenario —this has inspired many researchers to investigate the relationship between investor sentiment and stock prices. Trading volume is widely used in the investor sentiment-related existing literature since the 80s; Tauchen and Pitts (1983) studied the relationship

between the variability of asset price change trading volume on the speculative markets and their results indicate that if the volume of trading is strongly trended over the sample period, then the results of a price variability-volume study can be very misleading. Baker and Stein (2004) investigated that market liquidity which is measured by trading volume could be an indicator of investor sentiment. Moreover, Marschner and Ceretta (2019) studied the short and long-term non-linear and asymmetric connections between investor sentiment and trading volume in the U.S. market. The results show that trading volume reacts rapidly to the presence of lower-confidence investors and that this relationship is deeply asymmetrical in the long run. Their results also show that low liquidity is associated with declining investor confidence and increasing risk aversion, and therefore investors reduce their trading to avoid negative results. These findings indicate that investor sentiment and trading volume are related therefore the main research question is about the validity of the mediating effect of the trading volume.

The effect of investor sentiment on stock prices has been measured with both direct and in-direct methods to try and develop a considerable understanding of this relation. Furthermore, as mentioned by Guler (2021), there is no perfect proxy for investor sentiment, and different proxies could give different results. Therefore, in existing literature, researchers often use numerous different proxies. The most well-known measure of market sentiment is the CBOE Volatility Index (VIX), a 30-day expected volatility of the U.S. stock market. The VIX is called the “investor fear gauge” and it captures investors’ fear of security investment. When the VIX index increases, the stock market tends to decrease because of the high turbulence in the US stock market Whaley (2000). So and Lei (2015) used the VIX as a proxy of investor sentiment in their research concerning the relationship between investor sentiment and trading volume. Moreover, Smales (2017) showed in his research that the VIX is the preferred measure of sentiment in terms of enhancing model fit and adding explanatory power.

Shan and Gong (2012) exploited the Wenchuan Earthquake in China to better understand investor sentiment’s direct effect on stock prices. This research, among other things, used a linear regression model which incorporated a dummy variable for 12months following the earthquake. Shan and Gong (2012) found that stock returns are significantly lower for Chinese- listed firms with headquarters near the epicenter.

One could argue that research regarding the direct effect of investor sentiment on stock prices is unrealistic due to its simple nature. Therefore, a better approach could be to investigate the indirect effect of this relationship. Saunders (1993) provided us with research regarding such an indirect effect. Without explicitly modeling this indirect effect, Saunders (1993) showed that the weather in New York City significantly influences stock returns —implying that, due to existing experimental and survey literature indicating that weather influences mood, this supports the belief that stock returns are causally

affected by investor sentiment. Yi and Xiugang (2018) applied mediation analysis to the relationship between irrational investor sentiment and an enterprise's non-efficient investment, with stock price volatility as a mediating variable. Yi and Xiugang (2018) found that stock price volatility positively mediates the significant effect of irrational investor sentiment on an enterprise's non-efficient investment. Furthermore, Wahba and Elsayed (2015) undertook a mediating analysis and found that financial performance negatively mediates the relationship between social responsibility and institutional investors. Nevertheless, there is no research regarding a mediating effect on the relationship between investor sentiment and stock returns. To fill this gap, the main research question of this paper is formulated in the following hypothesis:

H: Trading volume mediates the relationship between investor sentiment, measured as a volatility forecast, and stock returns especially stock returns of prominent technology companies.

To answer the main research question of this paper, there are six sub-questions as explained in the following paragraphs. Cornell and Damodaran (2014) investigated the role of investor sentiment in the sevenfold run-up of Tesla stock prices in 2013-2014 and found that investor sentiment played an essential role in the enormous price increase of Tesla stocks. Furthermore, Strauss and Smith (2019) found that tweets of Tesla's CEO Elon Musk are helpful for day traders and shareholders to trade at a profit.

Therefore, Tesla stocks are attractive financial assets concerning quantitative research on the potential mediating effect of trading volume on the relationship between investor sentiment and its returns. So the paper puts forward the following sub-question(SQ):

SQ1: Does trading volume mediate the relationship between investor sentiment, measured as a volatility forecast, and Tesla stock returns? Extending this research then, investigating the potential mediating effect of trading volume on the relationship between investor sentiment and the returns of a list of the 30 most prominent technology companies could provide further knowledge into this relationship and how it withstands for different tech companies that is the main focus of this paper. Causing this study to introduce the second sub-question:

SQ2: Does trading volume mediate the relationship between investor sentiment, measured as a volatility forecast, and the stock returns of the 30 largest technology companies?

In a recent study, Huang and Ibragimov(2022; 2022) studied raw text data from Twitter with the keywords “AAPL,” “S&P 500,” “FTSE100” and “NASDAQ” to analyze the relationship between sentiment and the returns on the Apple stock and the S&P 500, FTSE 100 and NASDAQ indices. The findings show the significant relationship and dependence between sentiment measures and the S&P 500 and FTSE 100 indices’ prices and returns. It has not previously been used to investigate the impact of investor sentiment on the MSCI World Index. This research, therefore, applies the E-GARCH approach to explore the influence of investor sentiment on the return rate of the MSCI World Index. The MSCI World Index is the extension of a list of 30 tech companies to gain more insight into the broader impact of investor sentiment. The MSCI World Index is a broad equity index that represents mid-cap and large equity performance across 23 developed countries. It covers approximately 85 percent of the free float-adjusted market capitalization in each country. The MSCI World Index is chosen because the MSCI World Index provides greater diversification: the MSCI World Index includes more than 1,500 mid-cap and large companies from different developed countries whereas the S&P 500 contains the top 500 large-cap companies from the USA and a list of 30 tech companies selected in this paper includes also non-USA companies that makes the MSCI World Index more representative global index for this research. Therefore, this study puts forward the third sub-question:

SQ3: Does the trading volume of the MSCI World Index mediate the relationship between investor sentiment and the stock returns of the MSCI World Index? Many other approaches in choosing the investor sentiment proxy can be explored, limiting dependency on the choice of investor sentiment proxy and creating potentially more evidence concerning the outcomes. One approach is to incorporate so-called safe

havens, indicating classes of assets that possess or increase in value during more perilous times. Tachibana (2022) found that government bonds are the second safest asset overall out of a list of 36 potential safe-haven assets. Moreover, research of Ranaldo and Soderlind (2010) indicated that the Swiss franc appreciates against the U.S. dollar when U.S. stock prices lower and U.S. bonds prices and volatility increase, illustrating the safe haven characteristics of the Swiss franc currency. Furthermore, Cheema, Faff, and Kenneth (2022) investigated how safe, safe-haven assets acted during two crises —namely, the 2008 Global Financial Crisis (GFC) and COVID-19 pandemic. Cheema, Faff, and Kenneth (2022) found that the U.S. Treasuries and the Swiss franc currency acted as strong safe havens during both crises—this has induced this study to put forward the following two sub-questions:

SQ4: Does trading volume mediate the relationship between investor sentiment, measured with the use of 10-year Treasury yields, and the stock returns of the 30 largest technology companies?

SQ5: Does trading volume mediate the relationship between investor sentiment, measured with the use of the Swiss franc currency, and the stock returns of the 30 largest technology companies?

The last proxy is based on the paper of Baker and Wurgler (2006). Baker and Wurgler (2006) generated the most widely-accepted investor sentiment index based on the five financial factors: the number of initial public offerings (IPOs), the average first-day returns of IPOs, the dividend premium, the closed end fund discount, and the equity share in new issues. The Baker-Wurgler sentiment proxy is used as a benchmark for safe heaven investment sentiment proxies. This has induced this study to put forward the last sub-question:

SQ6: Does the Baker-Wurgler index mediate the relationship between investor sentiment, measured with the use of the Baker-Wurgler index, and the stock returns of the 30 largest technology companies?

Data

This section thoroughly analyses all aspects of the data used in this study; this includes descriptive statistics and diagnostic tests for testing normality, stationarity, serial correlation, heteroskedasticity, and heterogeneity. This study applies a mediation analysis, investigating the mediating effect of trading volume in the relationship between investor sentiment and stock

returns. This study will focus on Tesla stock returns, the returns of the 30 largest technology companies, and the MSCI index as dependent variables, more specifically. This study utilizes three different investor sentiment proxies to limit proxy selection dependency. Firstly, the Cboe Volatility Index (VIX), which is an index that measures the market's expectation of future volatility based on the S&P500. Volatility is seen as a measure of market sentiment, inducing this specific forecast to be a good proxy for fear among traders. Moreover, this study employs the 10-year Treasury yields as a proxy for investor sentiment. This variable gives insights into the price level of the respective Treasuries, which, subsequently, gives information on the sentiment of investors. Finally, this study uses the Swiss franc currency as a proxy for investor sentiment. The price of this currency entails information concerning the demand for this asset, and as this currency is known to be, just like Treasuries, a safe haven, this will provide information regarding investor sentiment.

Moreover, the 30 largest companies are selected based on market capitalization, which resulted in the following list of companies: Apple (APPL), Microsoft (MSFT), Alphabet (GOOG), Amazon (AMZN), Tesla (TSLA), Meta (FB), TSMC (TSM), NVIDIA (NVDA), Tencent (TCEHY), Samsung (SAMS), Alibaba (BABA), Broadcom (AVGO), AMSL (ASML), Adobe (ADBE), Oracle (ORCL), Cisco

(CSCO), AMD (AMD), Salesforce (CRM), Intel (INTC), Texas Instruments (TXN), QUALCOMM (QCOM), IBM (IBM), SAP (SAP), Intuit (INTU), Sony (SONY), PayPal (PYPL), Applied Materials (AMAT), ServiceNow (NOW), Keyence (KEY), and Booking.com (BKNG). The adjusted closing stock prices, trading volumes, VIX index, 10-year Treasury yields, and Swiss franc futures were obtained from yahoo finance and span five years, from June 2017 to June 2022, which sums up to 1823 daily observations. The stock returns, trading volatility index, and fear & greed indices are then calculated by applying the following formula:

$$R_t = \log\left(\frac{S_t}{S_{t-1}}\right) \quad (3.1)$$

where P_t indicates the stock price, volume or index value at time t . Furthermore, this study applied the Jarque-Bera test to test whether the data followed a normal distribution. As can be seen in Tables A.II and A.III in Appendix A, the null hypothesis is firmly rejected for all the different variables, indicated by the p-values of zero. According to the Jarque-Bera test, none of the

variables follows a normal distribution; in combination with the occurring positive excess kurtosis for all the variables indicating a fat-tailed distribution, this study applies a student's t-distribution. Moreover, Tables A.II and A.III show the p-value for the Augmented Dickey-Fuller test (ADF). All pvalues are 0.01, indicating that the null hypothesis of a unit root can be rejected, implying that all the variables' processes are stationary.

Besides that, financial time series are often not normal as there are too many observations in the tails; there is also often a correlation among these observations. Significant positive or negative returns are followed by significant positive or negative returns —implying serial correlation. This study tests serial correlation by using the Ljung-Box test. The Tables A.II and A.III, once more, show p-values at a 1% significance level, indicating the serial correlation among the time series. Another characteristic of financial time series is

heteroscedasticity, meaning that the variance of the residuals changes over time. Further, this often signifies a volatility dependence on past values in financial time series —a so-called volatility clustering. This study tests this ARCH effect by using the LagrangeMultiplier test for homoscedasticity. Tables A.II and A.III indicate that all variables are showing heteroskedasticity at a 1% significance level. Serial correlation and heteroskedasticity are vital for the validity of the outcomes and therefore need to be incorporated. This study solves this serial correlation and heteroscedasticity an ARMA(m,n)-EGARCH(p,q). Moreover, this study utilizes the generalized least squares (GLS) method in the case of panel data regression.

All descriptive statistics can be seen in the previously mentioned Tables. A mean close to zero can be observed for all variables. Moreover, besides the positive excess kurtosis for all the variables, a less general notion applies to the skewness. Not much can be said about the skewness of the stock returns and index. However, a positive skewness for the trading volume variables and investor sentiment proxies can be observed.

Finally, this study focused on uncovering whether there might be significant evidence for heterogeneity across companies in the data. Figure A.6 was used to visually investigate whether such heterogeneity occurred in the data. This plot indicates the mean with a 95% confidence interval per company; it shows that, although many confidence intervals overlap, there are still some differences across companies.

Subsequently, to measure this potential heterogeneity across companies more precisely, this study uses a Fligner-Killeen test. The reasoning behind the decision to use this specific test is that it is most robust against deviation from normality. The p-value reveals significant evidence to reject the null hypothesis of homogeneity. Therefore, this study incorporates this heterogeneity across companies using the

Fixed Effects regression model.

Methodology

This research utilizes various econometric models. First, to investigate the mediating effect of trading volume on the relationship between investor sentiment, measured as a volatility forecast, and Tesla stock returns and answer sub-question 1, this paper utilizes the E-GARCH model. Moreover, different econometric models are necessary to test some of the following sub-questions. The second sub-question extends the notion of the main research question by looking at how trading volume mediates the relationship between investor sentiment, measured as a volatility forecast, and the stock returns of the 30 most significant technology firms. Moreover, this study utilizes the MSCI World Index to try and answer sub-question 3, which tests that trading volume mediates the relationship between investor sentiment and the returns of the MSCI. Subsequently, this study investigates the mediating effect of trading volume on the relationship between investor sentiment and the returns of the 30 largest technology companies by using different investor sentiment proxies. The 10-year Treasury yields, the Swiss franc currency, and the Baker-Wurgler index. Most of these sub-research questions utilize panel data. Therefore, this study will incorporate panel data regression as well —more specifically, this research employs a Fixed-Effects model in these cases. This section will elaborate on the econometric models and methods used in this paper, mention the rationale for these choices and discuss their advantages and limitations.

The mediation method

A well-known approach when trying to unveil indirect effects is a mediation analysis (Baron and Kenny (1986)), which approximates the relationship between an independent variable and a dependent variable when a mediator variable is included. The mediation model assumes that the independent variable

influences the mediator which in turn influences the dependent variable. It also allows for an additional effect of the independent variable directly on the dependent variable over and above the effect that goes through the mediator. This method uses multiple regressions. The first step is to regress the dependent variable on the independent variable. If this relationship does not exist, there is nothing to mediate. Subsequently, the analysis requires two additional regressions; the regression of the mediating variable on the independent variable and the regression of the dependent variable on the mediating variable and the independent variable —the changing effect of the independent variable on the dependent variable displays whether there is either no, a partial or full mediation. Namely, these analyses are necessary to research the mediating effect of trading volume on the relationships between investor sentiment and Tesla stock returns, the relationship of investor sentiment on the stock returns of the 30 largest technology companies, and the relationship between investor sentiment and the returns of the MSCI. A mediation analysis focuses on whether another variable, the mediator, is mediating a direct relationship. Therefore, such an analysis can identify whether this direct relationship is maybe too simply specified and could better be explained as an indirect relationship, including a mediating variable that mediates the relationship; this can be clarified more by looking at the following graph:

Investor sentiment can affect the stock returns in two ways, as illustrated in Figure 1. First, by influencing the stock returns directly and secondly by influencing the mediator, trading volume, which influences the stock returns. When, for example, previous research has found that such a direct relationship exists, one could hypothesize that maybe this is not truly the underlying mechanism of the relationship. An indirect effect through a mediating variable, such as trading volume, might better explain the actual characteristics of this relationship- which is precisely the motivation behind this study.

Undertaking such a mediation analysis requires three separate regressions. First is the regression of

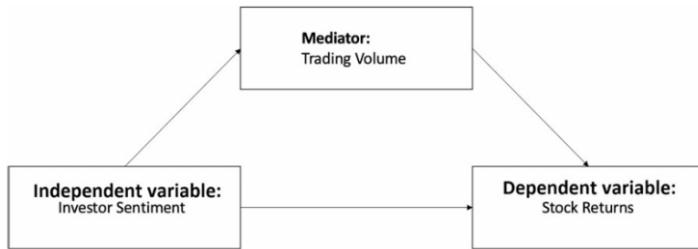


Figure 1. The relationship between investor sentiment, trading volume and stock returns.

the stock returns, so either Tesla stock returns, the stock returns of the 30 largest technology companies or MSCI returns, on the investor sentiment variable. This relation has to exist; otherwise, there is nothing to mediate. Furthermore, the regression of the mediator, trading volume, on the investor sentiment variable and the regression of the stock returns on both the trading volume and investor sentiment variables are necessary. The changing effect of the investor sentiment variable on the stock returns between the first and last regression gives information on whether there is a mediating effect. When this effect wholly or partially disappears in the last regression, while it is significantly present in the first, we speak of full or partial mediation.

The E-GARCH model

Investigating the mediating effect of trading volume on both the relationship between investor sentiment and Tesla stock returns and the relationship between investor sentiment and the MSCI returns require time series data. Testing sub-questions 1 and 3 require time series modeling —this opens the discussion on what model to use. As Chen and Haga (2021) mention, the GARCH(1, 1) model, proposed by Bollerslev (1986), and the E-GARCH model, proposed by Nelson (1991), are the two most widely used models for investigating the relationship between investor sentiment and stock returns.

The exponential GARCH (E-GARCH) model extends the GARCH model- Nelson (1991) proposes the EGARCH model to meet three drawbacks concerning the GARCH model. In particular, the E-GARCH model, by modifying the variance equation, allows for asymmetric effects on the variance provoked by negative and positive return shocks. The fundamental basis of the reasoning for this modification is the finding of Black (1976), namely that there is a negative correlation between past stock returns and their future variance —also known as the leverage effect in financial time series. Furthermore, by taking the natural logarithm of the time- varying variance of the E-GARCH model, we impose a positive variance without restricting the coefficients in the variance equation.

Furthermore, Guler (2021) finds that, concerning bitcoin returns, based on the log-likelihood, AIC and BIC selection criteria, the E-GARCH model outperforms other GARCH models under which the GARCH model. Combining this result with the reasoning from Black (1976) provides this study with the rationale behind using an ARMA-EGARCH model.

The decision to generalize the E-GARCH model to this so-called combined level and variance model allows this study to model serial correlation if present amongst the data. This study undertakes a mediation analysis and therefore will make use of multiple ARMA(m,n)-EGARCH(p, q) models. The explanation of these models are given in the Appendix B ARMA(m,n)-EGARCH(p, q) model explanation.

The fixed-effects model

Moreover, the other research questions use panel data from the stock returns of the 30 most significant technology firms, extending from the mediation analysis focusing only on Tesla stock returns. This extension is necessary for sub-questions 2, 4, 5, and 6 and illuminates whether a potential mediating effect of trading volume withstands when focusing on a list of technology firms and the MSCI World Index. Moreover, it tests the same mediating effect on the same relation but with investor sentiment measured as either the 10-year Treasury yields, the Swiss franc currency price or the Baker-Wurgler index. Furthermore, this type of modeling has many other advantages—the most prominent being that we can control for unobserved heterogeneity. This unobserved dependency of independent variables excluded from the model results in endogeneity. This endogeneity can, in its turn, lead to biased and inconsistent estimators. Some panel data regression methods can guard against these issues and, therefore, be critical. The most widely discussed panel data regression methods consist of Pooled OLS, the Fixed-Effects model and the Random-Effects model. Pooled OLS first pools all the data, ignoring time and individual characteristics, and then performs Ordinary Least Squares (OLS).

However, this method is applied less often on panel data by researchers as this data often violates critical assumptions associated with OLS, such as exogeneity and no autocorrelation. Therefore, this study does not use Pooled OLS. Focusing on the other two panel data regression methods reveals the main difference. Namely, the difference across time in the unobserved effect on the independent variables included in the model. The Fixed-Effects model specifies a constant unobserved effect across time. In contrast, the Random-Effects model specifies this unobserved effect as a random variable across time. Finally, the question remains which of the two to use—a debate ongoing among researchers and dependent on many aspects.

In his book named 'Econometric Analysis on Panel Data', Baltagi (2008) mentions that a Fixed-Effects model is suitable when investigating a specific set of, for example, firms. Moreover, he says that the Random Effects model is more suitable for research with the set of firms following a random draw from a population. Moreover, many researchers investigating similar relationships have argued and applied a Fixed-Effects model. Anusakumar, Ali, and Wooi (2017) performed panel Fixed-Effects regression when examining the connection between investor sentiment and stock returns in emerging Asian markets. Furthermore, Yi and Xiugang (2018) used the Fixed-Effects regression method in a mediation analysis of the relationship between irrational investor sentiment and an enterprise's non-efficient investment. Moreover, Bathia and Bredin (2013) controlled for heterogeneity using firm fixed effects in studying the effect of investor sentiment on G7 stock market returns. Both the underlying theory with the existing literature motivate this study to apply the Fixed-Effects regression model when answering the research questions that include panel data. The explanation of these models are given in the Appendix C Fixed-Effects model explanation.

Results

This section will elaborate on the hypothesis of this study—whether trading volume mediates the relationship between investor sentiment, measured as a volatility forecast, and stock returns especially stock returns of 30 largest technology firms—by answering six sub-questions. The order of the subsections are in line with the order of the sub-questions. The first subsection is about Tesla stock returns. Second subsection gives the results of the panel data of the 30 largest technology firms. Third subsection is about the MSCI World Index. Finally, subsections 4, 5 and 6 concern the results related to investigating whether this potential mediating effect in the case of panel data of the 30 largest technology companies is present when investor sentiment is measured as the 10-year Treasury yields, the Swiss franc currency price or Baker-Wurgler index.

Mediating effect of trading volume on the relationship between investor sentiment, measured as a volatility forecast, and Tesla stock returns

This study uses time series data of Tesla stock returns for the first sub-question; therefore, this study applies time series modeling. The data section indicates

significant serial correlation amongst the data, inducing this study to utilize a mean model in the EGARCH specifications. The parameter values for this combined level and variance model are obtained by looking at the autocorrelation function (acf) and partial autocorrelation function (pacf) of the respective dependent variable, information criteria, and tests for remaining serial correlation and ARCH effects. Figures A.1–A.4 give the ACF and PACF for Tesla stock returns and trading volume, respectively, giving insights into the parameters of the mean model. With the help of these Figures, this study decided to use ARMA(2,2) and ARMA(1,4) specifications for the mean model in the regression with Tesla stock returns and trading volume as the dependent variable, respectively. Moreover, this study utilizes the AIC and BIC information criteria, and the LM-test for remaining ARCH effects to select the best GARCH specifications for the main research question; This resulted in the EGARCH(1,1) model for all three necessary regressions in this mediation analysis. Table 1 indicates the findings.

Firstly, this mediation analysis requires the regression of Tesla stock returns on investor sentiment; this study employs, as mentioned, the ARMA(2,2)-EGARCH(1,1) model. The investor sentiment coefficient k_1 , shown in Table 1, is significant and negative —this indicates that, as the investor sentiment is proxied by a volatility forecast, the investor sentiment positively influences the Tesla stock returns. The p-values of the weighted LjungBox and LM tests show no information to suggest significant serial correlation and remaining ARCH effects. Hereafter, this paper will only mention these tests when there is significant evidence for remaining serial correlation or ARCH effects. Moreover, the coefficient indicated by a_1 follows the reasoning of Black (1976) and indicates the presence of the leverage effect $a_1 < 0 \delta P$; negative shocks will increase the variance more relative to positive shocks. Figure A.5 graphically illustrates the occurring leverage effect.

Subsequently, this study has to consider the regression of trading volume on investor sentiment. The results following this regression are presented in Table 1. The coefficient k_1 obtained in step 2 of the mediation analysis indicates a significant adverse effect of the investor sentiment variable on the trading volume, meaning that the investor sentiment positively affects the trading volume. Finally, this study undertakes the regression of Tesla returns on both the investor sentiment and trading volume variables. The results following this step

Table 1. ARMA-EGARCH regression results focusing on Tesla.

	Step 1		Step 2		Step 3	
	ARMA(2,2)-EGARCH(1,1)	ARMA(1,4)-EGARCH(1,1)	ARMA(1,4)-EGARCH(1,1)	ARMA(2,2)-EGARCH(1,1)	ARMA(2,2)-EGARCH(1,1)	ARMA(2,2)-EGARCH(1,1)
M	0.0004	-0.0007	-0.0230	(0.0042)***	0.0001	-0.0007
θ_1	1.0741	(0.0536)***	0.5961	(0.0275)***	1.0191	(0.1022)***
θ_2	-0.3622	(0.0372)***			-0.3181	(0.0336)***
ϕ_1	-0.8264	(0.0511)***	-0.4604	(0.0268)***	-0.7351	(0.1081)***
ϕ_2	0.2374	(0.0469)***	-0.0659	(0.0108)***	0.1800	(0.0314)***
ϕ_3			-0.0954	(0.0105)***		
ϕ_4			-0.0513	(0.0093)***		
λ_1	-0.0134	(0.0066)*	-0.1320	(0.0620)*	-0.0040	-0.0063
λ_2					-0.0042	(0.0018)*
ω	-1.7817	(0.5487)**	-1.1352	(0.1443)***	-1.7110	(0.4297)***
α_1	-0.0936	(0.0367)*	0.0300	-0.0358	-0.0909	(0.0353)*
β_1	0.7304	(0.0835)***	0.4695	(0.0663)***	0.7400	(0.0656)***
γ_1	0.6408	(0.0975)***	0.6078	(0.0624)***	0.5559	(0.0804)***
λ_3	-0.15	-0.4965	0.2696	-0.4234	0.3337	-0.4101
λ_4					0.3730	(0.0985)***
shape	3.0878	(0.2569)***	7.5145	(1.1500)***	3.0576	(0.2538)***
Log likelihood	3,752.93		-619.16		3,763.25	
AIC	-4.1087		0.6943		-4.1178	
BIC	-4.0724		0.7336		-4.0755	
Weighted Ljung-Box (p-value)	0.35		0.65		0.12	
Weighted ARCH LM (p-value)	0.36		0.94		0.26	

***p < 0.001; **p < 0.01; *p < 0.05.

Step 1: Regressing Tesla stock returns on investor sentiment.

Step 2: Regressing trading volume on investor sentiment.

Step 3: Regressing Tesla stock returns on trading volume and investor sentiment.

Table 2. Fixed effects regression results focusing on the 30 largest technology companies.

	Step 1	Step 2	Step 3	
λ_1	-0.0229	(0.0002)***	0.1068	(0.0007)***
λ_2			-0.0133	(0.0002)***
R ²	0.0076	0.0021	-0.0016	(0.0000)***
Balanced panel (n, T, N)	(30, 1821, 54630)	(30, 1821, 54630)	0.0036	(30, 1821, 54630)

***p < 0.001; **p < 0.01; *p < 0.05.

Step 1: Regressing returns of 30 largest technology companies on investor sentiment.

Step 2: Regressing trading volume on investor sentiment.

Step 3: Regressing returns of 30 largest technology companies on trading volume and investor sentiment.

indicate that the effect of investor sentiment on Tesla stock returns entirely vanishes and becomes insignificant. Nonetheless, the negative effect of trading volume on Tesla stock returns is significant—we can therefore speak of full mediation. Therefore, the answer to the first sub-question is that the trading volume mediates the relationship between investor sentiment, measured as a volatility forecast, and Tesla stock returns.

Mediating effect of trading volume on the relationship between investor sentiment, measured as a volatility forecast, and the returns of the 30 largest technology companies

For the second sub-question, we shift our focus to panel data. This study analyses the potential mediating effect of the trading volumes of the 30 largest technology companies on the relationship between investor sentiment, measured as a volatility forecast, and the stock returns of these respective companies.

The data shows no significant evidence to reject the null hypothesis of homogeneity across companies. Therefore, broadening the mediation analysis to a list of large technology companies instead of only Tesla stock returns requires different modeling techniques. Such as the Fixed-Effects method, which models the problem of heterogeneity across companies in the data. The results of this mediation analysis are shown in Table 2. The coefficient k_1 , obtained from the first step of the mediation analysis, shows that there is indeed a significant relationship between investor sentiment and the stock returns of the list of companies. Using the VIX index's definition, these results indicate that stock returns tend to go upward when investor sentiment is better. Furthermore, the second column in Table

2 displays that there is also a significant relationship between the trading volume of the 30 largest technology companies and investor sentiment. More specifically, when investor sentiment rises, the trading volumes decrease.

Table 3. ARMA-EGARCH regression results focusing on the MSCI world index.

	Step 1		Step 2		Step 3	
	ARMA(1,4)-EGARCH(1,1)		ARMA(3,5)-EGARCH(1,1)		ARMA(1,4)-EGARCH(1,1)	
μ	0.0024	(0.0003)***	-0.0135	(0.0000)***	0.0025	(0.0003)***
θ_1	0.0162	-0.0111	1.2559	(0.0001)***	0.0043	-0.0158
θ_2			-0.0151	(0.0000)***		
θ_3			-0.2431	(0.0000)***		
ϕ_1	0.2273	(0.0223)***	-1.2220	(0.0000)***	0.2541	(0.0231)***
ϕ_2	0.1536	(0.0211)***	-0.0236	(0.0000)***	0.1559	(0.0154)***
ϕ_3	-0.0066	-0.0089	0.1614	(0.0000)***	-0.0009	-0.0026
ϕ_4	-0.0103	-0.0085	0.0259	(0.0000)***	-0.0102	-0.0248
ϕ_5			0.0568	(0.0000)***		
λ_1	-0.0070	(0.0029)*	0.0434	(0.0033)***	-0.0010	-0.0018
λ_2					-0.0005	(0.0002)*
ω	-0.3652	(0.1211)**	-1.0744	(0.1294)***	-0.3810	(0.1210)**
α_1	0.0041	-0.0242	-0.0045	-0.0033	-0.0094	-0.0234
β_1	0.9549	(0.0147)***	0.4881	(0.0620)***	0.9531	(0.0147)***
γ_1	0.3634	(0.0618)***	0.7521	(0.0544)***	0.3631	(0.0611)***
λ_3	0.7627	(0.2676)**	-0.1404	(0.0605)*	0.4407	-0.2722
λ_4					0.1530	(0.0608)*
shape	5.2321	(0.7024)***	15.9699	(0.0001)***	5.2931	(0.7109)***
Log likelihood	4,959.47		-690.61		4,959.94	
AIC	-5.4327		0.7761		-5.4310	
BIC	-5.3934		0.8245		-5.3856	
Weighted Ljung-Box (p-value)	0.06		0.48		0.09	
Weighted ARCH LM (p-value)	0.10		0.57		0.13	

***p < 0.001; **p < 0.01; *p < 0.05.

Step 1: Regressing the MSCI world index returns on investor sentiment.

Step 2: Regressing trading volume on investor sentiment.

Step 3: Regressing the MSCI world index returns on trading volume and investor sentiment.

The question remains whether there is a mediating effect of the respective trading volumes in the relationship between investor sentiment and the returns of the list of technology companies. The coefficients k_1 , k_2 from the last Fixed Effects regression display no full mediation was found in the case of Tesla stock returns—that is, the impact of investor sentiment on the list of stock returns stays significant. However, the impact of investor sentiment on the stock returns of the 30 companies does decrease, indicating a partial mediation by trading volume in the case of the 30 largest technology companies. So, although the mediation effect is only partial, the answer to the first sub-question is that the trading volume mediates. The results obtained from the panel-data regressions regarding a list of the 30 largest technology companies do not entirely overlap with results found by the time series regressions regarding Tesla stock returns. In the case of Tesla stock returns, a full mediating effect by trading volume was found. However, when looking at the 30 largest technology companies, only a partial mediating effect was found.

Mediating effect of trading volume on the relationship between investor sentiment, measured as a volatility forecast, and the stock returns of the MSCI world index

After extending the findings that trading volume mediates the relationship between investor sentiment

and the stock returns of Tesla with a list of the 30 largest technology companies, this section discusses the results of an even more general notion. This study utilizes the MSCI World Index as the dependent variable to gain more insight into the broader impact of investor sentiment. Therefore, this section discusses whether trading volume mediates the relationship between investor sentiment and the MSCI World Index's stock returns. Table 3 shows the coefficients for each step in the mediation analysis. The coefficient of the first step in the mediation analysis, k_1 , shows that investor sentiment has a significant adverse effect on the returns of the MSCI index. Moreover, the coefficient k_1 in step 2 of this mediation analysis shows that a significant positive effect occurs for the relationship between investor sentiment and the MSCI trading volume variable. At last, the column on the right indicates the critical coefficients obtained from the final regression of this mediation analysis. This regression includes both the investor sentiment and trading volume variables and regresses these on the returns of the MSCI World Index. Table 3 indicates that the significance of k_1 from the last step in comparison with the coefficient in the first regression completely disappears while the coefficient of MSCI's trading volume variable in the last step, k_2 , stays significant. These results, therefore, indicate a complete mediation by the trading volume.

Table 4. Fixed effects regression results focusing on the 30 largest technology companies and investor sentiment measured as 10 year treasury yields.

	Step 1		Step 2		Step 3	
λ_1	-0.0158	(0.0002)***	-0.2685	(0.0000)***	0.0116	(0.0002)***
λ_2					-0.0016	(0.0000)***
R^2	0.0011		0.0023		0.0016	
Balanced panel (n, T, N)	(30, 1821, 54630)		(30, 1821, 54630)		(30, 1821, 54630)	

***p < 0.001; **p < 0.01; *p < 0.05.

Step 1: Regressing returns of 30 largest technology companies on investor sentiment.

Step 2: Regressing trading volume on investor sentiment.

Step 3: Regressing returns of 30 largest technology companies on trading volume and investor sentiment.

variable of the MSCI onto the relationship between investor sentiment and the returns of the MSCI World Index. Therefore, the answer to the third sub question is that the trading volume mediates the relationship between investor sentiment and the MSCI returns.

Mediating effect of trading volume on the relationship between investor sentiment, measured with the use of 10-year treasury yields, and the returns of the 30 largest technology companies

This section uses the 10-year Treasury yields as a proxy for investor sentiment and utilizes how they relate to Treasury prices; when Treasury yields go up, the prices will fall and vice versa. Subsequently, these prices will lighten the demand for these Treasuries. 10-year Treasuries are known to be a so-called 'safe haven', meaning they maintain or rise in value during treacherous times. Therefore, the demand for these Treasuries provides this research with knowledge regarding investor sentiment. Namely, when investor sentiment is low, investors are more willing to invest in 10-year Treasuries, increasing their demand and boosting the price, reflecting lower Treasury yields. Using multiple proxies for investor sentiment will supply this research with more evidence regarding the results. This section, therefore, tests whether the mediating effect found concerning the VIX index as an investor sentiment proxy withstands for the proxy of 10-year Treasury yields. Table 4 displays all the coefficients per step of the mediation analysis. k_1 for the first step of the mediation analysis indicates the coefficient of the investor sentiment variable obtained from regressing the 30 stock returns on this investor sentiment proxy. This coefficient displays that investor sentiment significantly affects the stock returns of the 30 largest technology companies. Moreover, the second step of the mediation analysis indicates that the list of 30 trading volumes is also significantly impacted by the investor sentiment variable.

Finally, the last regression, including both the investor sentiment variable and the trading volumes of the 30 largest technology companies, displays that the impact of investor sentiment on the list of stock returns decreases whilst the list of trading volumes still significantly affects the list of stock returns. This result suggests that trading volume partially mediates the relationship between investor sentiment, measured with the 10-year Treasury yields, and the stock returns of the 30 largest technology companies.

Mediating effect of trading volume on the relationship between investor sentiment, measured with the use of the Swiss franc currency, and the returns of the 30 largest technology companies

This study has provided evidence for the mediating effect of trading volume on the relationship between investor sentiment and the stock returns of the 30 largest technology companies in both cases where investor sentiment was proxied with the VIX index and with 10-year Treasury yields. This section continues this notion and analyses whether this mediating effect remains when employing a currency as an investor sentiment proxy. More specifically, the Swiss franc. The Swiss franc is a currency with the characteristics of a safe haven and can, therefore, be utilized as an investor sentiment proxy. Following the same reasoning as before: when investor sentiment is low, investor's demand for safe-haven assets grows, which subsequently pushes the prices of these assets upward. Therefore, high prices concerning the Swiss franc reflect low investor sentiment.

Table 5 indicates the vital coefficients for each regression of the mediation analysis. The coefficient of the first step, k_1 , shows that the investor sentiment variable significantly affects the stock returns of the 30 largest technology companies. Moreover, the significant coefficient in the middle column indicates the impact of the investor sentiment variable on the trading volumes of the 30 largest technology companies

Table 5. Fixed effects regression results focusing on the 30 largest technology companies and investor sentiment measured as Swiss Franc currency.

	Step 1	Step 2	Step 3
λ_1	0.0057	(0.0001)***	2.4319
λ_2			(0.0000)***
R^2	0.0005	0.0023	-0.0017
Balanced panel (n, T, N)	(30, 1821, 54630)	(30, 1821, 54630)	0.0012
			(30, 1821, 54630)

***p < 0.001; **p < 0.01; *p < 0.05.

Step 1: Regressing returns of 30 largest technology companies on investor sentiment.

Step 2: Regressing trading volume on investor sentiment.

Step 3: Regressing returns of 30 largest technology companies on trading volume and investor sentiment.

Table 6. Fixed effects regression results focusing on the 30 largest technology companies and investor sentiment measured as Baker-Wurgler index.

	Step 1	Step 2	Step 3
λ_1	0.0641	(0.0046)***	-0.2516
λ_2			(0.0134)***
R^2	0.0016	0.0013	-0.0015
Balanced panel (n, T, N)	(30, 1571, 47130)	E	0.0021
		(30, 1571, 47130)	(30, 1571, 47130)

***p < 0.001; **p < 0.01; *p < 0.05.

Step 1: Regressing returns of 30 largest technology companies on investor sentiment.

Step 2: Regressing trading volume on investor sentiment.

Step 3: Regressing returns of 30 largest technology companies on trading volume and investor sentiment.

At last, the right column provides the necessary coefficients obtained from the last regression of the mediation analysis. The last regression extends on the first and adds the list of 30 trading volumes as an additional independent variable. A significant difference concerning the value of k_1 between the first and last step is visible. The value of k_1 decreases by a factor of four and tells this study that when proxying investor sentiment with the price of the Swiss franc currency, a mediating effect of trading volume on the relationship between investor sentiment and the stock returns of the 30 largest technology companies can be observed. Mediating effect of trading volume on the relationship between investor sentiment, measured with the use of the Baker-Wurgler index, and the returns of the 30 largest technology companies. In the previous subsections, the evidence is provided for the mediating effect

based on important investor sentiment proxies selected in this study. This subsection analyses whether this mediating effect remains when employing the Baker-Wurgler index as a benchmark. The Baker-Wurgler index is a monthly index. This index is converted from monthly to daily data to be consistent with the daily variables of this study and moreover, daily data is more efficient and reliable, has better forecasting power, and fits better especially when using financial data.

Table 6 gives the overview of the important coefficients for each regression of the mediation analysis.

The coefficient of the first step, k_1 , shows that the investor sentiment variable significantly affects the stock returns of the 30 largest technology companies. Moreover, the significant coefficient from the second step indicates the impact of the investor sentiment variable on the trading volumes of the 30 largest technology companies. Step 3 column provides coefficients obtained from the last regression of the mediation analysis. The mediating effect of trading volume on the relationship between investor sentiment and the stock returns of the 30 largest technology companies can be observed also when using the Baker-Wurgler index. The answer to sub-questions 4, 5, and 6 is that the trading volume mediates (partially) the relationship between investor sentiment and the stock returns of the 30 largest technology companies—verifying the hypothesis of this study.

Conclusion

This study aims to investigate the potential mediating effect of trading volume in the relationship between investor sentiment, measured as a volatility forecast (VIX), and the stock returns of technology companies. This paper focused, more specifically, on Tesla stock returns and the stock returns of the 30 most prominent technology firms. Furthermore, this study used the MSCI World Index as a dependent variable. The MSCI World Index is a broad equity index that represents mid-cap and large equity performance across 23 developed countries. Therefore, by focusing on this index, this study analyses whether a potential

mediating effect of trading volume withstands when incorporating a broader range of companies. At last, this study used the 10-year Treasury yields, the Swiss franc currency price, and the Baker-Wurgler index to observe any potential differences in outcomes compared to the analyses using the VIX index as an investor sentiment proxy. By undertaking these additional analyses, this study limits the dependency on the investor sentiment proxy.

The first mediation analysis concerned the stock returns of Tesla; by employing an ARMA(2, 2)EGARCH(1, 1) and ARMA(1, 4)-EGARCH(1, 1) model for the regression with Tesla stock returns and trading volumes as dependent variables, respectively. Subsequently, this paper found a significant positive total effect of investor sentiment on the stock returns of Tesla. Moreover, such a significant positive effect was also found regarding the relationship between investor sentiment and the trading volume of Tesla stocks. After further analyzing the total effect of investor sentiment on the stock returns of Tesla, this study found that this total effect is being mediated by the trading volume of Tesla stocks. Namely, in the regression where the mediating variable is included with the investor sentiment variable, the impact of investor sentiment on the Tesla stock returns ultimately vanishes—indicating complete mediation by Tesla's trading volume.

When shifting focus toward a list of companies, namely the 30 most prominent technology firms, this study employed the Fixed-Effects regression method; this analysis aimed to investigate whether this mediating effect of trading volume persisted for a list of companies. Similar to the research regarding Tesla stock returns, investor sentiment again had a significant positive impact on the stock returns of the

30 largest technology companies. A significant adverse effect was found in the regression of the trading volume of the list of companies on investor sentiment, which differs from the results found in the analysis regarding Tesla stock returns. The final regression includes investor sentiment and trading volume variables and depicts a declining impact of investor sentiment. These results indicate a partial mediation of the trading volume variables in the relationship between investor sentiment and the stock returns of the 30 most prominent technology firms.

Thereafter, to broaden the scope of research even further, this study utilized the MSCI World Index. By investigating whether the mediating effect of trading volume prevailed when focusing on the relationship between investor sentiment and the MSCI World

Index's stock returns, this study gains insights into whether a mediating effect of trading volume withstands a broader range of companies. The results of the first two regressions indicate that investor sentiment significantly affects the stock returns of the MSCI and that investor sentiment significantly affects the MSCI's trading volume variable. The final regression of the mediation analysis, which includes both the investor sentiment and trading volume variables, shows that the significance of the investor sentiment coefficient completely disappears. In contrast, the coefficient of the trading volume variable stays significant—suggesting a complete mediation by the MSCI trading volume variable.

This study subsequently investigated the potential mediating effect of trading volume on the relationship between investor sentiment and the stock returns concerning the 30 most significant technology firms by incorporating different investor sentiment proxies. Doing so adds insights into whether a mediating effect by trading volume persists for more proxy variables and is not dependent on a specific data set. This study utilizes the 10-year Treasury yields first. By applying the Fixed-Effects regression technique, this paper found that investor sentiment had a significant adverse effect on the list of stock returns. Moreover, such a significant negative effect of investor sentiment also occurred concerning the list of trading volumes. The final regression findings, including investor sentiment and trading volume variables, indicate a partial mediating effect. The decline in the investor sentiment proxy's impact on the list of stock returns suggests this partial mediating effect by the list of trading volumes.

This study uses the price of the Swiss franc currency for investor sentiment. The first regression of the mediation analysis indicates that investor sentiment adversely affects the stock returns of the 30 most prominent technology firms. Furthermore, this effect can also be observed in the second step of this analysis, meaning that investor sentiment negatively affects the list of trading volumes. The last regression, including both the investor sentiment and list of trading volume variables, indicates that the impact of investor sentiment on the list of stock returns declines by a factor of four. This result implies a partial mediating effect of the list of trading volumes on the relationship between investor sentiment, measured with the use of the Swiss franc currency, and the list of stock returns. Moreover, this study uses the Baker-Wurgler index for benchmark investor sentiment. The first regression

of the mediation analysis indicates that investor sentiment adversely affects the stock returns of the 30 most prominent technology firms. A significant negative effect of investor sentiment occurred concerning the list of trading volumes in the second regression. The final regression findings, including investor sentiment and trading volume variables, indicate a partial mediating effect. This result implies a partial mediating effect of the list of trading volumes on the relationship between investor sentiment, measured with the use of the Baker-Wurgler index, and the list of stock returns. Therefore, the mediating effect of the list of trading volumes on the relationship between investor sentiment and the stock returns of the 30 largest technology companies withstands whilst using prominent investor sentiment proxies. This result provides this study with more evidence that such a mediating effect is the underlying mechanism and is not particularly dependent on the choice of the investor sentiment proxy. Overall, the results indicate a mediating effect of trading volume in the relationship between investor sentiment and stock returns in all cases: when focusing on Tesla, a list of the 30 most prominent technology firms, and the MSCI World Index. However, when measuring investor sentiment as a volatility forecast, the mediating effect found in the case of Tesla is much more present than regarding the list of companies. These results indicate that Tesla stocks behave differently than other large technology firms. Tesla stocks are more prominently mediated by trading volume in the relationship between volatility forecasts and stock returns. Strauss and Smith (2019) show in their research that Elon Musk's Twitter account is valuable market information for investors concerned with Tesla stocks. Cornell and Damodaran (2014) found that the run-up in the price of Tesla stocks in 2013-2014 cannot be explained by rational decisions on essential information, implying that Tesla traders are not continually trading rationally and are more likely to anticipate the news. In previous research, Tesla stocks are, therefore, especially highlighted concerning irrationality and news impact, compared to other technology stocks. This previous research provides the reasoning for this study's findings that investors concerning Tesla stocks are more heavily affected by a volatility forecast, making them trade more/less, inducing the returns to change. When diverting from merely focusing on technology companies and broadening the scope of businesses, this study utilizes the MSCI World Index. The results indicate that a mediating effect of the MSCI

trading volume variable on the relationship between investor sentiment and the stock returns of the MSCI does occur. These results imply that a mediating effect of trading volume does not merely happen in the case of technology companies; a broader view, incorporating more diverse companies worldwide, also provides significant evidence for such an effect. When shifting this study's focus to the analyses concerning the additional investor sentiment proxies, this study finds that the stocks of the 30 largest technology firms show similar behaviour as was found in the case of the analysis concerning the volatility forecast proxy. With the use of multiple investor sentiment proxies, this study makes the results more tangible and can provide the results, concerning a partial mediation by the list of trading volumes on the relationship between investor sentiment and the list of stock returns, with more evidence. In conclusion, these findings give substantive evidence that the trading volume is a mediating variable between investor sentiment and stock returns; implying the impact of investor behavior on stock returns through changes in trading volumes. The findings of this paper underline the impact of investor behavior and sentiment making use of a more realistic and new approach: the indirect relation between investor sentiment and stock returns through a mediation variable for a complete understanding of stock market dynamics. A complete understanding can help investors and firms in making more rational investment decisions taking into account market dynamics and can help regulators when they are supervising and making policy. However, this study merely uses data concerning the 2017-2022 time interval, which should be considered when using this study's findings. Therefore, these results cannot directly be generalized to other periods. Although, it gives a good insight into what behavior could be expected. Moreover, the reasoning provided by this study for the results found is an excellent first step; however, many other potential rationales can be uncovered in further research. Moreover, this study did not go into much depth concerning the type of investors. Identifying the actual investors affected by investor sentiment causing the trading volume to change could be interesting. Further research could distinguish between smaller and bigger investors and observe potential differences.

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Appendix A. Graphs, tests and descriptive statistics

ACF of the Tesla Stock Returns

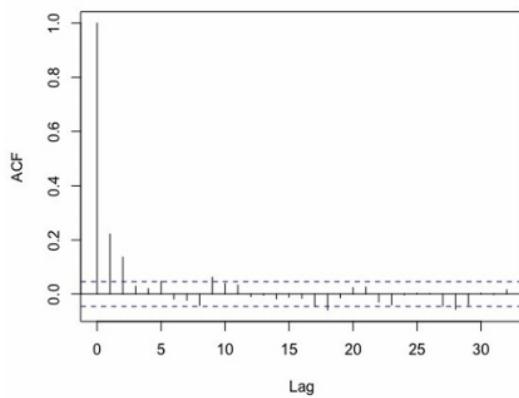


Figure A.1. ACF of the Tesla stock returns.

ACF of the Trading Volume

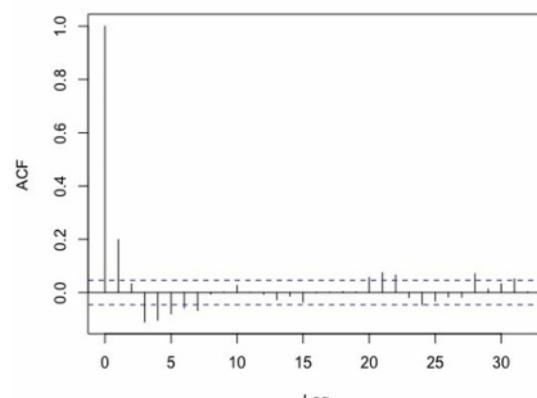


Figure A.3. ACF of the trading volume.

PACF of the Tesla Stock Returns

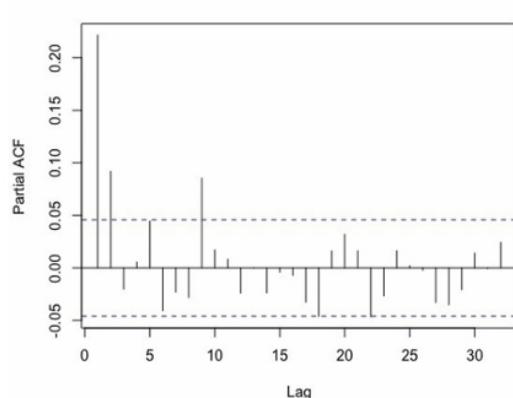


Figure A.2. PACF of the Tesla stock returns.

PACF of the Trading Volume

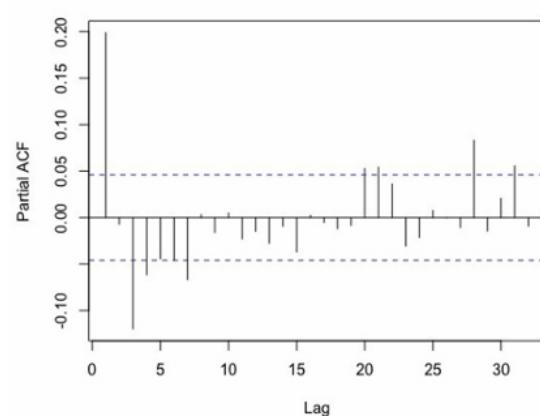


Figure A.4. PACF of the trading volume.

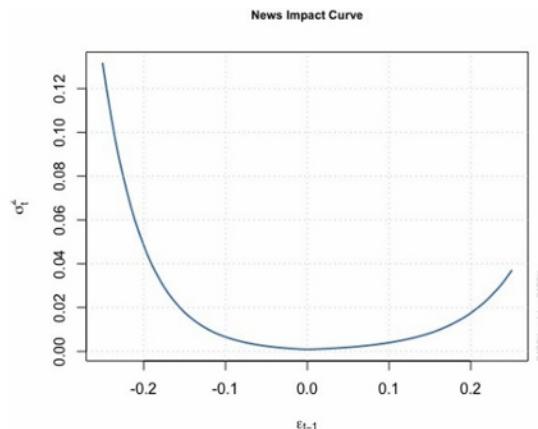


Figure A.5. News impact curve.

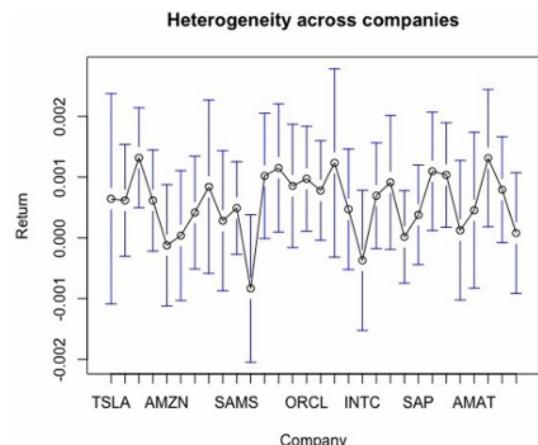


Figure A.6. Heterogeneity across companies.

Table A.I. Fligner-Killeen test of homogeneity of variances.

Fligner-Killeen:med chi-squared	df	p-value
2710.7	29	0.00

Table A.II. Descriptive statistics of the different investor sentiment proxies including Jarque-Bera, Ljung-box, LM-test and ADF test p-values.

Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis	J-B p-value	L-B p-value	LM-test p-value	ADF p-value
VIX	1823	-0.005	0.085	-0.266	0.768	1.389	9.936	0	0	0	0.01
10-year TY	1823	0	0.036	-0.271	0.405	0.188	23.749	0	0	0	0.01
Swiss franc	1823	0	0.004	-0.017	0.017	0.079	3.733	0	0	0	0.01

Table A.III. Descriptive statistics of returns and trading volumes of the 30 largest technology firms and MSCI index including Jarque-Bera, Ljung-box, LM-test and ADF test p-values.

Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis	J-B p-value	L-B p-value	LM-test p-value	ADF p-value
MSCI	1823	0.002	0.021	-0.14	0.166	-0.095	9.808	0	0	0	0.01
MSCI_VOL	1823	-0.01	0.396	-2.196	2.981	0.17	5.444	0	0.001	0	0.01
TSLA_RETURN	1823	0.001	0.038	-0.237	0.181	-0.23	7.44	0	0	0	0.01
TSLA_VOL	1823	-0.011	0.378	-1.342	1.882	0.798	4.968	0	0	0	0.01
AAPL_RETURN	1823	0.001	0.02	-0.138	0.113	0.022	8.72	0	0	0	0.01
AAPL_VOL	1823	0.016	0.314	-1.246	1.289	0.494	4.482	0	0	0	0.01
MSFT_RETURN	1823	0.001	0.018	-0.159	0.133	0.128	12.933	0	0	0	0.01
MSFT_VOL	1823	0.009	0.297	-1.105	1.1	0.185	3.928	0	0	0	0.01
GOOG_RETURN	1823	0.001	0.018	-0.118	0.099	0.082	7.769	0	0	0	0.01
GOOG_VOL	1823	0.021	0.343	-1.323	1.39	0.291	3.984	0	0	0	0.01
AMZN_RETURN	1823	0	0.022	-0.151	0.127	-0.154	11.432	0	0	0	0.01
AMZN_VOL	1823	0.011	0.319	-1.089	1.919	0.537	4.533	0	0	0	0.01
FB_RETURN	1823	0	0.023	-0.306	0.162	-1.605	26.4	0	0	0.005	0.01
FB_VOL	1823	-0.01	0.373	-1.039	2.09	0.742	5.709	0	0	0	0.01
TSM_RETURN	1823	0	0.02	-0.151	0.119	0.027	6.805	0	0	0	0.01
TSM_VOL	1823	-0.022	0.353	-1.106	1.697	0.463	4.156	0	0	0	0.01
NVDA_RETURN	1823	0.001	0.031	-0.208	0.158	-0.628	8.297	0	0	0	0.01
NVDA_VOL	1823	0.005	0.327	-1.011	1.57	0.49	4.126	0	0	0	0.01
TCEHY_RETURN	1823	0	0.025	-0.113	0.288	0.701	13.361	0	0	0	0.01
TCEHY_VOL	1823	-0.019	0.439	-1.691	2.236	0.269	4.421	0	0.001	0	0.01
SAMS_RETURN	1823	0	0.017	-0.066	0.1	0.248	4.772	0	0	0	0.01
SAMS_VOL	1823	-0.021	0.357	-1.583	1.661	0.282	4.477	0	0	0	0.01
BABA_RETURN	1823	-0.001	0.026	-0.143	0.313	0.708	16.821	0	0	0	0.01
BABA_VOL	1823	-0.008	0.389	-1.043	2.582	0.992	7.553	0	0	0	0.01
AVGO_RETURN	1823	0.001	0.022	-0.222	0.147	-0.793	13.422	0	0	0	0.01
AVGO_VOL	1823	0.014	0.376	-1.277	2.499	0.288	4.678	0	0	0	0.01
ASML_RETURN	1823	0.001	0.023	-0.191	0.11	-0.478	7.341	0	0	0	0.01
ASML_VOL	1823	-0.027	0.439	-1.726	1.623	0.126	3.759	0	0.038	0	0.01
ADBE_RETURN	1823	0.001	0.022	-0.16	0.163	0.112	11.473	0	0	0	0.01
ADBE_VOL	1823	0.001	0.349	-1.149	1.148	0.046	3.418	0.001	0	0	0.01
ORCL_RETURN	1823	0.001	0.019	-0.117	0.186	1.727	27.258	0	0	0	0.01
ORCL_VOL	1823	0.008	0.36	-1.457	1.671	0.413	6.104	0	0	0	0.01
CSCO_RETURN	1823	0.001	0.018	-0.148	0.126	-0.266	14.025	0	0	0	0.01
CSCO_VOL	1823	0	0.37	-1.499	1.722	0.298	5.339	0	0	0	0.01
AMD_RETURN	1823	0.001	0.034	-0.168	0.182	0.112	6.184	0	0	0	0.01
AMD_VOL	1823	-0.017	0.31	-1.194	1.503	0.547	4.694	0	0	0	0.01
CRM_RETURN	1823	0	0.022	-0.173	0.231	0.136	14.492	0	0	0	0.01
CRM_VOL	1823	-0.009	0.374	-1.282	1.559	0.339	4.645	0	0	0	0.01
INTC_RETURN	1823	0	0.025	-0.199	0.178	-0.688	16.182	0	0	0	0.01
INTC_VOL	1823	0.024	0.367	-1.318	1.606	0.456	4.437	0	0	0	0.01
TXN_RETURN	1823	0.001	0.019	-0.126	0.127	-0.264	7.522	0	0.001	0	0.01
TXN_VOL	1823	-0.001	0.357	-1.151	1.327	0.192	3.771	0	0	0	0.01
QCOM_RETURN	1823	0.001	0.024	-0.162	0.209	0.531	11.706	0	0	0	0.01
QCOM_VOL	1823	-0.004	0.437	-1.53	2.092	0.403	4.198	0	0	0	0.01
IBM_RETURN	1823	0	0.017	-0.138	0.107	-0.858	13.024	0	0	0	0.01
IBM_VOL	1823	-0.003	0.387	-1.543	2.195	0.483	5.407	0	0	0	0.01
SAP_RETURN	1823	0	0.018	-0.263	0.117	-1.713	33.329	0	0	0	0.01
SAP_VOL	1823	-0.028	0.453	-1.765	2.294	0.376	4.538	0	0	0	0.01
INTU_RETURN	1823	0.001	0.021	-0.156	0.183	0.078	9.903	0	0	0	0.01
INTU_VOL	1823	0.01	0.353	-1.303	1.704	0.27	4.586	0	0	0	0.01
SONY_RETURN	1823	0.001	0.019	-0.098	0.115	-0.199	7.675	0	0	0	0.01
SONY_VOL	1823	-0.016	0.467	-1.791	1.928	0.28	3.976	0	0.004	0	0.01
PYPL_RETURN	1823	0	0.025	-0.282	0.132	-0.685	15.755	0	0	0	0.01
PYPL_VOL	1823	-0.019	0.352	-1.151	2.06	0.318	4.784	0	0	0	0.01
AMAT_RETURN	1823	0	0.028	-0.228	0.121	-0.39	7.267	0	0	0	0.01
AMAT_VOL	1823	0	0.355	-1.28	1.343	0.161	4.118	0	0	0	0.01
NOW_RETURN	1823	0.001	0.025	-0.103	0.126	-0.069	5.259	0	0	0	0.01
NOW_VOL	1823	-0.025	0.399	-2.261	1.623	-0.031	4.352	0	0	0	0.01
KEY_RETURN	1823	0.001	0.019	-0.082	0.107	0.327	5.966	0	0	0	0.01
KEY_VOL	1823	0.01	0.358	-1.393	1.385	0.103	3.903	0	0	0	0.01
BKNG_RETURN	1823	0	0.022	-0.145	0.172	-0.198	11.211	0	0	0	0.01
BKNG_VOL	1823	-0.003	0.339	-1.087	1.575	0.081	3.729	0	0	0	0.01

AppendixB. ExplanationoftheARMA(M,N)EGARCH(P,Q)modelsusedinthisresearch

The three necessary regression can be indicated by:

$$r_t = \mu + \sum_{i=1}^m \theta_i r_{t-i} + \sum_{i=1}^n \phi_i \varepsilon_{t-i} + \lambda S_{t-1} + \varepsilon_t, \quad (B.1)$$

$$TV_{t-1} = \mu + \sum_{i=1}^m \theta_i TV_{t-1-i} + \sum_{i=1}^n \phi_i \varepsilon_{t-i} + \lambda S_{t-2} + \varepsilon_t, \quad (B.2)$$

$$r_t = \mu + \sum_{i=1}^m \theta_i r_{t-i} + \sum_{i=1}^n \phi_i \varepsilon_{t-i} + \lambda_1 S_{t-2} + \lambda_2 TV_{t-1} + \varepsilon_t, \quad (B.3)$$

where ε_t is the error term, assumed to follow a student's t distribution with degrees of freedom and μ is denoted as the constant in each regression.

Equation (B.1) illustrates the regression of the dependent variable on the independent variable. More specifically, the regression of Tesla stock returns (r_t) on the one-day lagged investor sentiment variable (S_{t-1}). The subsequent regression (B.2) indicates the regression of the mediating variable, Trading Volume (TV_{t-1}), on the independent one-day lagged investor sentiment variable. Finally, the last regression (B.3) indicates the dependent variable on both the mediating and the independent variable. More precisely, the regression of Tesla stock returns on the one-day lagged variable of trading volume and the two-day lagged variable of investor sentiment (S_{t-2}). Taking lagged terms is often necessary to observe a potential effect of time $t-1$ on time t . As this study undertakes a mediation analysis, it investigates an indirect effect. Therefore, in regression (B.3) this study includes trading volume at time $t-1$ and investor sentiment at time $t-2$ (Wahba and Elsayed (2015)). The variance equation of the E-GARCH(p, q) models can be given by:

can be given by:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^q (\alpha_i z_{t-i} + \gamma_i (|z_{t-i}| - \mathbb{E}|z_{t-i}|)) + \sum_{i=1}^p \beta_i \ln(\sigma_{t-i}^2) + \sum_{i=3}^r \lambda_i X_t. \quad (B.4)$$

Where ω is defined to be a constant, X_t are the independent variables at time t included in the regression with $r \in \{3, 4\}$, and $z_t \in \mathbb{R}$. Moreover,

$$r = \{3, 4\}, \text{ and } z_t = \frac{\varepsilon_t}{\sigma_t}. \text{ Moreover,}$$

$$\mathbb{E}|z_t| = \frac{2\sqrt{\nu - 2\Gamma(\frac{\nu+1}{2})}}{(\nu - 1)\Gamma(\frac{\nu}{2})\sqrt{\pi}}$$

Since ε_t is assumed to follow a student's t-distribution. The parameters of the ARMA(m, n)-EGARCH(p, q) models

are then estimated by using Maximum Likelihood Estimation(MLE).

For this model, the coefficients associated with a negative and positive shock are α_1 α_1 and $\alpha_1 \beta_1 \alpha_1$ respectively — which illustrates that the model is perfectly symmetric when $\alpha_1 = 0$: Furthermore, adverse shocks will increase the variance more than positive shocks when $\alpha_1 < 0$, and vice versa. The leverage effect, discussed by Black (1976), would therefore induce this study to expect negative constants for α_1 :

Appendix C. Explanation of the fixed-effects regression models used in this research

The panel data regressions needed for this study are given by:

$$r_{it} = \alpha + \lambda_1 S_{i(t-1)} + u_{it}, \quad (C.1)$$

$$TV_{i(t-1)} = \alpha + \lambda_1 S_{i(t-2)} + u_{it}, \quad (C.2)$$

$$r_{it} = \alpha + \lambda_1 S_{i(t-2)} + \lambda_2 TV_{i(t-1)} + u_{it}, \quad (C.3)$$

with $i \in 1, \dots, N$; $t \in 1, \dots, T$. Where α is denoted as the constant in each regression 1. The subscript i refers to each firm, and the subscript t to the point in time. Moreover, the error term can be decomposed into two components: a unobservable effect u_{it} and the remaining error u_{it} . In the Fixed-Effects model, the unobservable effect will be fixed across time and, therefore, the error term can be decomposed as follows: $u_{it} = u_{it} + \beta_{it}$. This unobservable effect can subsequently be eliminated when taking the difference from the mean. For ease of explanation, let us focus on the regressions with the list of stock returns as dependent variables and define a vector X_{it} with dimensions $(K \times 1)$ which is the i th observation of K independent variables at time t , where K differs per regression and is either 1 or 2. By using this vector, we can write:

$r_{it} = \alpha + \beta_{it} X_{it} + u_{it}, \quad (C.4)$ Now, as explained above, the error term in a Fixed Effects model can be decomposed as $u_{it} = u_{it} + \beta_{it}$. Therefore, as β_{it} is fixed across time, this would result in:

$$r_{it} = \alpha + \beta_{it} X_{it} + u_{it}, \quad (C.5)$$

$$\text{Which can be rewritten as: } \sim r_{it} = \alpha + \beta_{it} X_{it} + \sim u_{it}, \quad (C.6)$$

Finally, the Fixed-Effects estimator $\hat{\alpha}_{kFE}$ can be obtained by performing a linear regression parameter estimation method, such as OLS or GLS, on regression (C.6).

The Price of Happiness: Traders' Experiences of Work in Investment Banks

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ABSTRACT

formance. Therefore, it is essential for investment banks to understand the determinants of traders' work experience. Analyzing traders' reviews of major investment banks, this study shows that traders' attitudes depend on the banks' culture, traders' career opportunities, and, to a lesser extent, their pay perceptions. Furthermore, traders are often happy with their coworkers but dissatisfied with their banks' technology, bureaucracy, ethics, and their work-life balance. Hence, this study identifies non-monetary determinants of traders' work attitudes, extends behavioral finance research, and offers applications for investment banks as well as their shareholders.

KEYWORDS *Trader; Investment bank; Pay; Ethics; Job satisfaction*

1.1 INTRODUCTION

Wall Street's leading banks increased pay by nearly 15 per cent last year as they fought a war for talent [...] JPMorgan Chase, Citigroup, Goldman Sachs, Morgan Stanley and Bank of America disclosed in recent days that they had handed out \$142bn in pay and benefits in 2021, up from \$124bn in 2020, in an effort to keep their top bankers satisfied (Franklin and Moise 2022). Investment banks are known to pay financial practitioners well. For instance, the typical yearly salary of traders working at J.P. Morgan is \$94,522, and traders' salaries can reach \$270,000. Similarly, the average yearly salary of traders working at Goldman Sachs is \$92,150, and traders' salaries can reach \$366,000 (Glassdoor 2022). On top of that, investment banks offer practitioners generous bonuses. These large salaries and bonuses aim to enhance practitioner performance and retention. But how do these monetary rewards impact financial practitioners' overall attitudes toward their banks? Which factors motivate them to work at their banks? And with which work characteristics are they dissatisfied? Understanding the determinants of financial practitioners' work experiences, motivators and job satisfaction could have applications for decision-makers in investment banks and their shareholders. This is because practitioners' work experiences influence their

performance (Judge et al. 2001) and turnover intent. In fact, in nurses (Lum et al. 1998) and USA federal employees (Pitts, Marvel, and Fernandez 2011), turnover intent has been found to depend more on job satisfaction than on pay perceptions. However, the factors affecting work experience and job satisfaction are context- and industry-dependent (Judge et al. 2010). The case of the financial industry is unique, because unlike many other industries, the financial industry is often perceived to be

predominantly motivated by greed (e.g., Murdoch 2021). To date, research has not systematically investigated job satisfaction in the financial industry. Hence, a-priori—before examining the financial industry—the determinants of financial practitioners’ work experiences were unclear. To address this issue, this study explores financial practitioners’ work experiences. Research has conceptualized the experience of work through several aspects, including work attitudes, job satisfaction, work moods and emotions (George and Jones 1996). Of these aspects, this study focuses on practitioners’ attitudes toward their banks. In addition, it examines the factors that motivate practitioners to work at the banks and the work characteristics with which they are dissatisfied. Because traders’ decision-making is central to markets behavior (Coval and Shumway 2005), it focuses on traders. To provide a comprehensive and updated picture of influential investment banks, it investigates all traders’ Glassdoor reviews written between 2012 and 2021 on ten major investment banks (<https://www.glassdoor.co.uk>). Specifically, it quantitatively and qualitatively examines the banks which had the greatest returns in 2020, including J.P. Morgan, Goldman Sachs, Bank of America, Morgan Stanley, Citi, Credit Suisse, Barclays, Deutsche Bank, Jefferies, and UBS (Norrestad 2021).

Quantitatively analyzing traders’ reviews of these banks, this study shows that traders’ overall attitudes toward their banks significantly depend on their pay satisfaction. However, they depend on the banks’ culture more strongly than on traders’ pay perceptions, and this result is robust when the analysis controls for the bank itself and the occurrence of COVID-19. Traders’ bank attitudes significantly depend also on their career opportunities, work-life balance and senior management. Qualitatively analyzing the reviews, this study identifies additional factors that serve as work motivators in investment banks, including satisfaction with coworkers and learning opportunities. Moreover, it shows that a proportion of traders are dissatisfied with their work-life balance, stress level, the banks’ technology, bureaucracy, management and a wide range of ethics-related issues, such as their reward fairness and the bank’s internal politics. Finally, this paper establishes that although traders’ perceptions of their banks and work are diverse, most traders are happy with their pay and career opportunities. This study makes two major theoretical contributions and an empirical contribution to the literature on practitioners’ work experience within behavioral finance. First, it complements previous research by systematically identifying non-financial factors that influence traders’ experience. Previous research has contributed important insights into practitioners’ experience by showing that certain experiential aspects—emotions—impact financial performance (Rubaltelli et al. 2010; Wynes 2021). However, it has focused on the dependence of practitioners’ experience on financial factors, such as returns (Merkle, Egan, and Davies 2015) or return patterns (Grosshans and Zeisberger 2018). Only few, separated studies have examined how organizational factors impact practitioners’ experience (Deng and Gao 2017; Mahmood et al. 2019; Sobolev 2020), and these studies have provided disjointed and partial

descriptions of it. For instance, they have disregarded traders' perceptions of their coworkers, pay fairness, and bank politics. Elucidating the effects of a system of organizational factors, this study provides a comprehensive picture of the determinants of traders' experience.

Furthermore, some of the identified factors challenge common perceptions of investment banks. For instance, although investment banks are perceived to be highly advanced technologically (Shevlin 2019), this study suggests that many practitioners consider their banks technologically underdeveloped. Second, this study is the first to suggest that traders' experience at the banks is, overall, positive. Relating practitioners' emotions to volatile market parameters, the literature about traders' experience has often portrayed it as highly unstable, ranging between the highs of gains and the lows of losses (Fenton-O'Creevy et al. 2011; Lo and Repin 2002). In particular, it has emphasized that professionals often feel extreme emotions such as anxiety, fear, stress, burnout, and euphoria (Fairchild 2014; Peterson 2007; Shefrin 2002). Revealing that most traders in large investment banks are satisfied with many aspects of their work, including their pay and coworkers, this study extends the understanding of traders' experience and highlights its positive facets.

Third, this paper contributes to the literature by empirically investigating traders' experiences in ten influential investment banks. Quantitatively and qualitatively analyzing their reviews, it provides a personal account of their work perceptions.

Theoretical background and research questions Behavioral finance research on practitioners' work experience

Behavioral finance research on financial agents' experience has aimed to characterize their reactions to financial events. Hence, it has conceptualized happiness as practitioners' satisfaction with their financial performance. Using this definition, research has established that happiness depends on realized returns and relative performance (Merkle, Egan, and Davies 2015) and that satisfaction with stock performance depends on stock price patterns (Grosshans and Zeisberger 2018). Furthermore, a study has shown that traders often experience significant mood swings due to their gains and losses. These depressive or euphoric moods could persist for a long time (Fenton-O'Creevy et al. 2011). Both inexperienced and experienced practitioners could feel intense fear during the trading day, and many agents experience short-term stress episodes as well as chronic stress. The anticipation of negative events is especially painful (Peterson 2007). In fact, a study has demonstrated that practitioners exhibit also physiological responses to market volatility (Lo and Repin 2002). Thus, highlighting practitioners' extreme highs and lows, behavioral finance research has portrayed agents' experience as a series of positive and negative

episodes, which are correlated with financial parameters.

Organizational behavior research on job satisfaction, motivators, and dissatisfaction factors

Organizational behavior research has developed several conceptualizations of the notion of job satisfaction. In particular, a classical study has defined job satisfaction to be the pleasurable emotional experience, resulting from the appraisal of one's job (Locke 1976). Another early study has defined job satisfaction to be the extent to which a person expresses satisfaction with the features of the job (Warr, Cook, and Wall 1979). Additional definitions conceptualized job satisfaction as a type of work attitude or work experience (George and Jones 1996). Research has suggested that job satisfaction comprises many aspects, including satisfaction with pay, coworkers, supervisors, the characteristics of the work itself, promotion and career opportunities, as well as autonomy (the freedom to choose the method of work), recognition for good work, and the amount of responsibility that the work involves (Warr, Cook, and Wall 1979). Modern job satisfaction theories often conceptualize job satisfaction through the system of the first five factors on this list (Kinicki et al. 2002). The aspects appearing in conceptualizations of job satisfaction have been termed "motivators." A fundamental study has theorized that motivators, which positively affect job satisfaction (e.g., the work itself, recognition for achievement and responsibility) are different from the factors which lead to job dissatisfaction (originally termed "hygiene factors"; e.g., supervision and company administration; Herzberg 1974). In line with this classification, throughout this study, I refer by "motivators" to factors that increase job satisfaction and by "dissatisfaction factors" to factors that decrease it.

Research questions

Organizational behavior research has related work experience and job satisfaction to a large number of outcomes, including turnover intent (Pitts, Marvel, and Fernandez 2011), employee performance (Judge et al. 2001), and firm financial performance (Kessler et al. 2020). However, research investigating work experience and job satisfaction in the financial industry has been sparse. Moreover, it has often referred to narrow aspects of the conceptualization of the terms. For instance, a study has examined whether workfamily conflicts affect job satisfaction of employees in Shanghai banking industry. That study has found that this effect is significant (Deng and Gao 2017), but has not explored the effects of any other job motivator or dissatisfaction factor. A more recent study has explored the effects of salary, job stability, and job enrichment on job satisfaction of commercial bank employees in Pakistan (Mahmood et al. 2019).

The results revealed significant relationship between these variables but the study has not embedded them in a complete system of job satisfaction motivators. Therefore, neither of these studies has enabled the evaluation of the relative importance of these variables. Furthermore, neither of these studies has provided details about the positions of the participants in their banks and hence it was unclear whether traders were included in their samples. A third study has shown that perceptions of work ethicality influence the well-being of practitioners in the high frequency trading industry (Sobolev 2020). However, it has not examined the effects of other work motivators either. Therefore, this study explores the following research questions:

Research question 1: Which factors determine traders' overall work attitudes?

Research question 2: Which factors motivate traders to work at large investment banks?

Research question 3: With which work characteristics are traders working at large investment banks dissatisfied?

Materials and methods

I chose to focus on the ten investment banks, which had the greatest revenues in 2020 worldwide. Data about the banks' revenues was obtained from Norrestad (2021). Thus, the study sample included J. P. Morgan, Goldman Sachs, Bank of America, Morgan Stanley, Citi, Credit Suisse, Barclays, Deutsche Bank, Jefferies, and UBS. Bank revenues ranged between \$1.78 billion (UBS) and \$8.50 billion (J. P. Morgan; Norrestad 2021). All banks, except for Jefferies, employed more than 10,000 people. Additional details about the bank sample are presented in Table A in the supplementary material file. The analyzed data set consisted of all traders' reviews of the ten investment banks, which were

written on Glassdoor (<https://www.glassdoor.co.uk>) between June 2012 and December 2021. Glassdoor is considered a leading firm-review platform (Campbell and Shang 2021). Its overall rating has been validated as an overall job satisfaction measure. For instance, overall Glassdoor ratings have been shown to be significantly correlated with the results of independent job satisfaction surveys of US federal agencies (Landers, Brusso, and Auer 2019). Furthermore, in the banking industry, Glassdoor reviews of financial analysts fitted theory-based predictions of the relation between perceived work-life balance and analyst performance (Hope et al. 2021).

In addition, research has demonstrated that Glassdoor reviews contain valid information about organizational behavior (Campbell and Shang 2021). Traders' reviews were identified by searching for the keyword "trader" on the Glassdoor review page of each of the banks. However, trading in investment banks involves many tasks and hence the search led to a wide range of job titles. To obtain a

comprehensive understanding of traders' perceptions of leading investment banks, I included in the analyzed sample the reviews of traders who had diverse titles. Thus, for example, I included in the sample the reviews of employees whose job titles were "trader," "junior trader," "senior trader," "fixed-income trader," "derivatives trader," "equity trader," "senior equity trader," "senior FX options trader," and "vice president trader." However, I excluded from the sample reviews of employees whose professions did not involve trading, e.g., "trade support associate" and "trade surveillance analyst." Traders' locations were diverse, too, and included, among others, New York, Chicago, London, Paris, Moscow, and Tokyo. Additional review sample characteristics are presented in Table B in the supplementary material file. In total, the analyzed data set consisted of 372 reviews.

Glassdoor's review instructions required the reviewers to provide an overall rating of their company on the scale ranging between 1 and 5 stars. I used this overall company rating as a measure of traders' overall attitudes toward their banks. Reviewers were also required to specify the "pros" and the "cons" of their work. The "pros" review instructions were "share some of the best reasons to work at [your company]." Because motivation has been defined to be the set of reasons, explaining a person's action (LeducCummings, Milyavskaya, and Peetz 2017), I used the "pros" to explore traders' work motivators. The "cons" review instructions were "share some of the downsides of working at [your company]." I used the "cons" to investigate traders' job dissatisfaction factors.

In addition, Glassdoor enabled reviewers to rate five factors, including the career opportunities that their banks offered them, the banks' culture and values, their senior management, the traders' compensation and benefits, and their work/life balance. These five factors were measured using a 1–5 star scale. As this five-factor set overlapped with that of the job descriptive index (JDI; Kinicki et al. 2002), I used it to measure the corresponding aspects of traders' job satisfaction. In addition, reviewers were asked to report whether they would recommend the job to a friend by choosing between the thumb up icon (yes) and the thumb down icon (no). However, differently from the overall ratings, "pros" and "cons," the rating of the five-factor set and the recommendations were not compulsory and hence not all reviewers completed them. Glassdoor enabled reviewers to provide additional data. In particular, since 2021, reviewers were asked to rate their firms' diversity and inclusion. However, as these ratings were limited to 2021, I did not include them in the quantitative analysis. The review instructions informed the website users that their reviews would help others make work decisions. They required the reviewers to avoid using aggressive language and disclosing trade secrets or confidential information. Examples of traders' reviews, Glassdoor review instructions and Glassdoor review panels are presented in Figures A, B, and C (respectively) in the supplementary material file.

Results

The factors determining traders' overall attitudes toward their banks

To answer research question 1 (which factors determine traders' overall work attitudes?), I used quantitative methods. In particular, I regressed traders' overall bank ratings and recommendations to friends over their ratings of the career opportunities that the bank offered them, their compensation and benefits, the banks' culture and values, their senior management, and traders' work/life balance. The first showed that traders' overall work attitudes significantly depended on all factors (culture: $b/40.34$, $p<0.01$; career opportunities: $b/40.25$, $p<0.01$; compensation and benefits: $b/40.22$, $p<0.01$; senior management: $b/40.14$, $p/40.01$; work-life balance: $b/40.11$, $p/40.01$). However, traders' overall work attitudes depended more strongly on the banks' culture and career opportunities than on compensation and benefits. The second regression revealed that traders' recommendations to friends significantly depended on career opportunities ($b/40.22$, $p/40.004$) and the banks' management ($b/40.30$, $p/40.001$). However, they did not significantly depend on any of the other variables, including compensation and benefits.

Traders' motivators and dissatisfaction factors

Qualitative analysis methods have been used in behavioral finance research (e.g., Foster and Warren 2016; Sobolev 2020; Wu 2022). Hence, to answer research question 2 (which factors motivate traders to work at large investment banks?) and research question 3 (with which work characteristics are traders working at large investment banks dissatisfied?), I used qualitative analysis methods. Specifically, to explore traders' work motivators, I conducted content analysis of the "pros" parts of their reviews, and to explore the factors with which they were dissatisfied, I conducted content analysis of the "cons" parts of their reviews. In line with content analysis methodologies (Corbin and Strauss 2008), I coded the "pros" and "cons" parts of the reviews according to the ideas that the traders expressed in them and generalized the codes into work motivators and dissatisfaction factors. Then, I grouped the factors into dimensions. The content analysis yielded the same eight dimensions for the work motivators and dissatisfaction factors: compensation and benefits, professional development, work characteristics, bank characteristics, management characteristics, coworkers, ethics, and culture. However, these dimensions were linked to different and often contradictory themes in the "pros" and "cons," thus highlighting the large variance in traders' perceptions of their banks and work. Below, I describe traders' perceptions of each of these dimensions and exemplify them by quoting corresponding reviews. The number of traders' reviews, referring to each motivator and dissatisfaction factor in the "pros" and "cons" answers, and additional exemplifying quotations are presented in Table C in the supplementary material file.

Compensation and benefits

Work motivators (“pros”). A relatively large proportion of the reviews referred to monetary work outcomes (78/372/420.97%) or other benefits (26/372/46.99%) as reasons to work at the banks. Traders often described their pay as good or better than the pay given in other banks. For instance, traders wrote as reasons to work at the banks: “good pay” (option trader, J. P. Morgan, 2020), “canmakeatonofmoney” (equity trader, Goldman Sachs, 2020), and “massive salary” (junior trader, City, 2016). Similarly, many traders expressed satisfaction with the benefits that they received. Smaller proportions of reviews mentioned the food and drinks that the banks provided and the location of the banks as work motivators. Job dissatisfaction factors (“cons”). Fifty reviews (13.44%) expressed traders’ dissatisfaction with the monetary outcomes of their work. For instance, traders wrote: “slightly below market pay” (trader, Goldman Sachs, 2021) and “total comp is poor” (equity trader, Morgan Stanley, 2021). Smaller proportions of traders (3/372/40.081% or less) expressed dissatisfaction with their benefits, pay growth, the food and drink that the banks provided, or their locations.

Professional development

Work motivators (“pros”). Forty-one reviews (11.02%) mentioned learning opportunities as reasons to work at the banks. For example, a vice president trader who worked at the Bank of America emphasized that there were “plenty of resources available for those willing to learn” (vice president trader, Bank of America, 2015), and a trader who worked at City wrote “excellent place to learn and grow” (trader, City, 2021). Traders mentioned in their “pros” also that their bank was a good place to be trained, and that they had a “huge learning curve” (trader, Morgan Stanley, 2017). Fewer reviews referred to developmental aspects of the jobs or noted that traders worked in diverse professional areas (e.g., that they enjoyed the exposure to different asset classes or different types of strategies). Thirty-six traders (9.68%) mentioned the career opportunities that their banks offered as reasons to work at the banks. Job dissatisfaction factors (“cons”). Small proportions of traders (11/372/42.96%) expressed dissatisfaction with the learning or training opportunities of their banks, and yet smaller proportions expressed dissatisfaction with their development, task diversity, and interest. However, 30 reviews (8.06%) reflected dissatisfaction with traders’ career opportunities. For instance, traders wrote that it was “difficult to navigate further on in career” (fixed income trader- vice president, Goldman Sachs, 2019), “not great for advancement of career” (equity trader, Barclays, 2021), and “not the fastest career growth” (credit trader, Deutsche Bank, 2021).

Work characteristics

Work motivators (“pros”). Twenty reviews (5.38%) described positive overall work perceptions. For instance, traders wrote: “enjoyed my time” (junior trader, Goldman Sachs, 2019), “fun place to work on a day to day basis” (trader, Barclays, 2012), and “being on the trading floor is certainly one of the most exciting roles—seeing market moves in action and discussing the global economy” (trader, Morgan Stanley, 2016). Twenty-five traders (6.72%) considered the worklife balance at the bank to be good or satisfactory. For instance, a trader suggested “good work life balance” (trader, City, 2015) as a reason to work at the bank. Ten reviews (2.69%) suggested that having a challenging work environment was another reason to work at the banks.

Only nine reviews (2.42%) referred to the financial characteristics of the traders’ work. These reviewers highlighted that “large risk taking for trading” (equity trader, Goldman Sachs, 2016) and “trading in niche products” (institutional sales trader, Deutsche Bank, 2021) were reasons to work at their bank (among other reasons). Few traders considered their work efficient. That is, they wrote that it involved little bureaucracy and that decision-making processes were fast. A few traders mentioned that it was secure. Job dissatisfaction factors (“cons”). Whereas only six reviews (1.61%) described negative overall work perceptions (e.g., not fun, not interesting, or repetitive work), 57 reviews (15.32%) expressed negative worklife balance perceptions. For instance, traders wrote: “long hours” (fixed income trader, Morgan Stanley, 2021), “the hours can be brutal even if you love what you do” (institutional sales trader, Goldman Sachs, 2019), and “long working hours with 10 to 13 hours per day” (junior quant trader, UBS, 2021). In fact, more reviews expressed dissatisfaction with work-life balance (57) than dissatisfaction with pay (50). Furthermore, 20 reviews (5.38%) expressed traders’ dissatisfaction with their stress level and 12 reviews (3.23%) reflected dissatisfaction with the level of difficulty of their work. For example, traders wrote: “it can be pretty stressful” (trader, Morgan Stanley, 2013), “hard work” (senior trader, Barclays, 2021), and “high pressured, cutthroat, unfriendly, stressful” (junior trader, UBS, 2014).

Thirty-two reviews (8.60%) revealed that some traders were dissatisfied with their work efficiency. In particular, they were unhappy with the banks’ bureaucracy and slow decision-making processes. For instance, traders wrote: “lots of red tape” (trader, Morgan Stanley, 2012), “can be extremely bureaucratic reducing nimbleness” (trader, Goldman Sachs, 2017), “Tends to be bureaucratic and slow-moving” (trader, Barclays, 2017), and “overly complex processes slow down decision making” (trader, Deutsche Bank, 2020).

Twenty-four reviews (6.45%) expressed traders' sense of job insecurity. For instance, reviewers referred to the "massive employee turnover, low employee morale" (equity trader, Bank of America, 2020) at the bank and emphasized that their "firm tends to do a lot of layoffs. Not many people ever feel secure with a job here" (block trader, City, 2014).

Bank characteristics

Work motivators ("pros"). Fifty-three reviews (14.25%) suggested that traders were often happy with their banks' environment or atmosphere. These reviews described the banks' environment as nice, good, great, amazing, cool, friendly, collaborative, professional, or fast-paced. Twenty-six reviews (6.99%) suggested that prestige motivated traders to work at their banks. For example, traders described their banks as "a well-respected investment bank" (equity trader, J. P. Morgan, 2020) and "prestigious" (trader, Goldman Sachs, 2014). Twenty-four reviews (6.45%) described other positive bank perceptions, such as "overall impressive and ideal organization to work for" (trader, City, 2021) and "good place to work" (trader, Credit Suisse, 2016).

Seventeen reviews (4.57%) referred to positive aspects of the size or strength of the banks. Thus, a trader who worked at the Bank of America wrote "safety in size" (trader, Bank of America, 2020). Only a small proportion of reviews (12/ 372/3.23%) referred to the financial qualities of the banks. For instance, UBS was described as having "substantial market size in FX trading" (assistant FX trader, UBS, 2017) and Credit Suisse—as a "great platform with trading risk appetite" (senior trader, Credit Suisse, 2020). Ten reviews (2.69%) described positive aspects of the banks' technology, IT and infrastructure qualities. Smaller proportions of reviews expressed satisfaction with the banks' competitiveness (using expressions such as "ahead of the game", "cutting edge," and "pioneering"), the banks' drive (e.g., "excellence" and "PnL driven"), and the international nature of the banks.

Job dissatisfaction factors ("cons"). Twenty-one reviews (5.65%) expressed traders' dissatisfaction with the environment or atmosphere of the bank. For instance, traders described the environment at their banks as "toxic environment at times" (options trader, J. P. Morgan, 2020) and the atmosphere on the floor as "very dog-eat-dog whereby people will step on their own team members for personal gain" (junior trader, Barclays, 2019).

Thirty-three reviews (8.87%) referred to the banks' technology, IT, systems, and infrastructure problems. For instance, traders wrote in the "cons" field "in house technology is too ancient" (junior trader, Credit Suisse, 2021), "bad tech here, legacy systems" (trader, Goldman Sachs, 2020), and "bad technology" (trader, City, 2020).

Eighteen reviews (4.84%) referred to the financial qualities of the banks. In particular, several traders were unhappy with the risk propensity of their banks. Hence, they suggested that their banks were “conservative in risk taking” (equity derivatives trader, Bank of America, 2021) and had “low risk tolerance” (trader, UBS, 2018).

Seventeen reviews (4.57%) expressed dissatisfaction with a range of aspects of the size or strength of the banks. For example, a quantitative trader reported that the bank was “a bit too slow to change as every big company” (quantitative trader, City, 2021) and an equity trader reported the feeling of “a small cog in a big, political machine” (equity trader, UBS, 2018). Smaller percentages of reviews referred to the banks’ competitiveness or to other negative aspects of the banks (e.g., lack of innovation, agility, or insufficient prestige).

Management characteristics

Work motivators (“pros”). Twelve reviews (3.23%) described positive perceptions of the management, suggesting that it was supportive, considerate, and accessible. For instance, traders wrote: “senior management are very accessible and laid back” (trader, Barclays, 2013) and “superiors don’t micromanage or create undue stress” (trader, Jefferies, 2021). Few reviews reflected positive perceptions of the management structure (e.g., “lean hierarchy”; trader, J. P. Morgan, 2020) and vision. Additional 12 reviews expressed other general positive perceptions. Job dissatisfaction factors (“cons”). Fourteen reviews (3.76%) suggested that some of the traders were dissatisfied with the extent to which the management respected them, supported them, or communicated with them. Thus, traders wrote: “managers treat staff without respect [...]. They will pounce on any member of staff for any small misdemeanor [...] and dock pay” (institutional sales trader, Credit Suisse, 2021) and “new management brought a different feeling...just a number. Keep your head down...” (trader, Jefferies, 2014). Twenty-two reviews (5.91%) suggested that some of the traders were unhappy with the management structure. For instance, traders wrote as “cons”:

“hierarchical structure prevalent in most divisions” (trader, Goldman Sachs, 2020) and “too many directors and managing directors only giving orders and doing nothing” (vice president trader, City, 2014). Twenty reviews (5.38%) expressed traders’ dissatisfaction with the management vision. For instance, traders wrote: “management is focused on short term as they all think they will get fired in a year max

imum. So no long term projects” (senior trader, Bank of America, 2014) and “poor vision of the management” (equity trader, Barclays, 2016). Finally, 25 reviews (6.72%) referred to other negative perceptions of the management, including, e.g., “poor,” “inept,” “sloppy,” “strict,” “pain,” “terrible,” “rotten,” and “avaricious.” Thus, a trader wrote: “absolute dictatorship, where the leader works toward a goal of destroying individual confidence and self-worth, creating an environment where the trader loses confidence in their abilities, resulting in fear of losing money” (power trader, City, 2013).

Coworkers

Work motivators (“pros”). A large number of reviews (110, 29.57%) suggested that many traders considered their coworkers to be their reason to work at the banks. In particular, reviewers described their coworkers as agreeable people (e.g., nice, friendly, and social), professional (e.g., professional, motivated, brilliant), or positive in general (e.g., good, excellent, and amazing). For example, traders described their colleagues as “great people” (trader, Credit Suisse, 2021) and “supportive people” (trader, Deutsche Bank, 2021). Thus, the percentage of reviews in which coworkers were described as a central motivating factor (29.57%) was greater than the percentage of reviews that mentioned monetary work outcomes (20.97%) or other benefits (6.99%) as reasons to work at the banks. Twenty-two reviews (5.91%) emphasized that traders considered team work to be a central motivator, too. For instance, answering the “pros” question, traders wrote: “team collaboration” (trader, Goldman Sachs, 2021), “good teamwork” (equity trader, City, 2020), and “good team spirit” (vice president trader, Credit Suisse, 2017). Job dissatisfaction factors (“cons”). Fourteen reviews (3.76%) described negative perceptions of traders’ coworkers. Few additional reviews referred to inadequate team work.

Ethics-related issues

Work motivators (“pros”). Reviews referred to a wide range of aspects of ethics. Sixteen reviews (4.30%) highlighted fairness in pay or other rewards as a central work motivator. In particular, traders considered meritocracy to be fair. Hence, a vice president trader answered the “pros” question by: “meritocratic environment. Will pick winners to move forward quickly. Career support with honest feedback—the honest feedback is sometimes that the firm is not for you, but I’d take that over political agenda any day” (vice president trader, Credit Suisse, 2020).

Smaller proportions of reviews referred to voice, transparency, and general ethical conduct, the encouragement of charity, diversity and inclusion. For example, a trader, who worked at the Bank of America wrote: “opportunities to be involved with volunteering/ charity work” (trader, Bank of America, 2017). Few reviews suggested that there was only little politics in the bank (e.g.: “not much politics”; trader, UBS, 2019). Two reviews suggested that some traders might have been involved in illegal conduct. In particular, one of the traders mentioned as an answer to the “pros” question: “insider trading information” (trader, Goldman Sachs, 2021; see Figure A in the supplementary material file).

Job dissatisfaction factors (“cons”). Twenty reviews (5.38%) revealed that traders did not always consider their rewards fair. For instance, traders wrote: “some favoritism—a lot of people there that shouldn’t be. Ability and contribution aren’t the main factors with progression at the firm” (trader, Bank of America, 2016) and “perpetually depleted bonus pools which are raided by the well-connected leaving nothing for the rest of the company” (trader, Deutsche Bank, 2018). A trader, who worked at Barclays, wrote: “I was [...] making the kind of money my AVP wasn’t and he was paid double what I was. That’s just not the right way to treat people, especially a woman [...] I worked 12þ hour work days all the time; it went completely unnoticed despite my book absolutely killing it” (trader, Barclays, 2020).

Small proportions of reviews referred to ethical issues such as the lack of transparency, accountability, or diversity. For instance, a trader expressed the perception that “the board go and lose billions of dollars to people like Greensill and Archegos and do not take any responsibility until major news outlets publish something critical” (institutional sales trader, Credit Suisse, 2021). Other traders reported that the management “makes no real effort to improve diversity, a slew of female managers left or [got] fired” (junior trader, Barclays, 2021) and that “treatment of women leadership is terrible” (assistant trader, Morgan Stanley, 2021).

Twenty-eight reviews (7.53%) suggested that a proportion of traders were unhappy with the internal politics at their banks. Thus, traders wrote as “cons”: “very political place as you go up the ranks” (trader, Goldman Sachs, 2016), and “it is a large firm so you will have to deal with a lot of politics” (trader, Morgan Stanley, 2013). Five reviews (1.34%) suggested that some of the traders engaged in unethical or illegal conduct. For instance, traders wrote: “I always [...] manipulate some markets” (quantitative trader, Goldman Sachs, 2021) and “many parts of the business have unethical practices. Customer abuse, collusion with competitors, problems dealing with confidential information” (senior trader, City, 2018). In addition, nine reviews (2.42%) expressed dissatisfaction with the bank’s reaction to regulation. For instance, a derivatives trader, who worked at UBS, wrote: “more focus on compliance than making money” (derivatives trader, UBS, 2019).

Culture

Work motivators (“pros”). Forty-four reviews (11.83%) described positive perceptions of the banks’ culture (e.g., “good,” “great,” “amazing,” “awesome,” “innovative,” “entrepreneurial,” and “friendly”). For example, a senior trader who worked at J. P. Morgan wrote “good friendly culture” (senior trader, J. P. Morgan, 2018) and a trader who worked at Barclays wrote: “innovative culture that lets you go after profit” (trader, Barclays, 2012). Four reviews (1.08%) expressed positive perceptions of the banks’ risk taking and hard work culture. Job dissatisfaction factors (“cons”). Twenty reviews (5.38%) expressed negative banks’ culture perceptions. Thus, traders wrote: “work culture is terrible. No collaboration” (power trader, Bank of America, 2013), “not a good culture that fosters growth and development. Survival of the fittest” (trader, Barclays, 2014), and “zero culture. When you take people from deceased firms—Bear, Leh, Mer, GCM—and throw them into an eat what you kill pool and no management from the top you get a toxic stew” (senior sales trader, Jefferies, 2013).

Additional analysis

Traders’ job satisfaction in large investment banks

One-sample t-tests, comparing traders’ overall attitudes toward their banks and ratings of the banks’ culture, career opportunities, compensation and benefits, senior management, work-life balance, and recommendation to friends, to the scales’ midpoint

Table1. Descriptivestatisticsof traders’ ratingsandthe resultsof t-tests, comparingthemtothescale midpointvalue.

Variable	Number of reviews	Mean (std. dev.)	T-test results
Overall attitudes toward the bank	372	3.80 (1.11)	t (371) = 13.97***
Culture	261	3.42 (1.30)	t (260) = 5.24***
Career opportunities	262	3.61 (1.20)	t (261) = 8.18***
Compensation and benefits	263	3.51 (1.71)	t (262) = 7.11***
Senior management	262	3.17 (1.34)	t (261) = 2.07*
Work-life balance	261	3.26 (1.27)	t (260) = 3.37**
Recommendations	243	0.37 (0.93)	t (242) = 6.12***

The scales of all ratings apart from the “recommendation to friends” scale ranged between 1 and 5 stars and their midpoint value was 3. The recommendation scale included the answers “do not recommend to a friend” (-1) and “recommend to a friend” (1). Hence, the scale midpoint value was 0. Notations: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table2. Correlationsandpartial correlations (inbrackets)betweenreviewers’ jobsatisfactionfactor ratings.

Variable	Culture	Career opportunities	Senior management	Work-life balance
Career opportunities	0.64** (0.51**)			
Senior management	0.75** (0.68**)	0.68** (0.51**)		
Work-life balance	0.66** (0.60**)	0.44** (0.32**)	0.57** (0.49**)	
Compensation and benefits	0.44**	0.63**	0.55**	0.34**

The partial correlations were calculated by controlling for reviewers’ compensation and benefits ratings. Notations: ** $p < 0.01$.

values revealed that all traders' ratings were significantly greater than the midpoint values. Thus, I concluded that most traders were happy with major aspects of their work. In particular, more than 79% of traders rated their compensation and benefits as average (3) or better. Descriptive statistics of traders' ratings and the results of t-tests, comparing them to the scales' midpoint values, are represented in Table 1.

Relationship between the job satisfaction components

To characterize the relationship between the different facets of traders' job satisfaction, I calculated the correlations between them. The correlation matrix is presented in Table 2. The results showed that reviewers, who rated their compensation and benefits higher, considered their work-life balance ($r=0.34$, $p<0.01$) and career opportunities ($r=0.63$, $p<0.01$) to be better. They also perceived the management ($r=0.55$, $p<0.01$) and the organizational culture ($r=0.44$, $p<0.01$) to be better. Reviewers strongly associated between the banks' culture and senior management ($r=0.75$, $p<0.01$), as well as the bank's culture and their career opportunities ($r=0.64$, $p<0.01$). All these correlations remained statistically significant when I controlled for reviewers' compensation and benefits ratings (see Table 2), suggesting that individual reviewers had coherent perceptions of their banks.

Bank effects

To assess the extent to which the banks themselves impacted traders' ratings of their overall attitudes and job satisfaction factors, I conducted one-way ANOVAs on these variables, using bank number (e.g., J. P. Morgan 1, Goldman Sachs 2, Bank of America 3, see Table A in the supplementary material file) as an independent (nominal) variable. The results showed that the banks themselves significantly affected reviewers' overall bank ratings ($F(9,362)=3.004$, $p=0.002$), career opportunities ($F(9,252)=2.78$, $p=0.004$), compensation and benefits ($F(9,253)=2.16$, $p=0.03$), and senior management ($F(9,252)=2.21$, $p=0.02$). However, the banks did not significantly affect reviewers' work-life balance and culture ratings.

Additional independent-samples t-tests revealed that the significant effect of the bank itself on reviewers' overall attitudes toward the banks arose due to differences between reviewers' ratings of some of the banks, but not all banks. For instance, a t-test comparing reviewers' overall ratings of Goldman Sachs to those of J. P. Morgan yielded insignificant results. However, a t-test comparing the overall ratings of Goldman Sachs to those of Deutsche Bank showed that reviewers' attitudes toward Goldman Sachs (mean: 4.32, std: 0.83) were significantly more positive than toward Deutsche Bank (mean: 3.40, std: 1.35, $t(85)=3.9$, $p<0.001$).

In line with these results, to assess the effect of the bank itself on the relationship between traders' job satisfaction ratings and overall attitudes toward the banks, I focused on the bank which had the greatest overall ratings in my sample—Goldman Sachs, and the bank which had the lowest overall ratings—Deutsche Bank (see Table B in the supplementary material file). Defining "Bank" to be a dummy variable, which equaled 0 for Goldman Sachs and 1 for Deutsche Bank, I regressed reviewers' overall ratings of these two banks on the five job satisfaction factors and "Bank." The results showed that culture ($b/40.35$, $p/40.002$) and compensation and benefits ($b/40.29$, $p/40.003$) significantly affected reviewers' overall attitudes toward their banks. However, none of the other variables, including "Bank," significantly affected reviewers' overall attitudes. In particular, the effect of the bank itself was weaker than the effects of the other variables.

COVID-19 effects

The COVID-19 outbreak in December 2019 in China had major effects on the world's financial markets (Zhang, Hu, and Ji 2020). To explore the possibility that it impacted traders' job satisfaction, I conducted t-tests on traders' reviews, using the occurrence of COVID-19 as the independent variable. I chose January 2020 as the cutoff date for the occurrence of the pandemic because in January 2020, the World Health Organization named the virus (World Health Organization 2020). The analysis showed that traders' overall attitudes toward their banks were better after the outbreak (overall ratings before January 2020: mean: 3.49, std: 1.21; overall ratings after January 2020: mean: 4.02, std: 1.05; $t(370) \approx 4.61$, $p < 0.001$). However, controlling for the five job-satisfaction factors, regression of traders' overall attitudes on the occurrence of COVID-19 showed an insignificant COVID-19 effect. For the job satisfaction factors, regression results were similar to the ones obtained before (culture: $b/40.34$, $p < 0.01$; career opportunities: $b/40.24$, $p < 0.01$; compensation and benefits: $b/40.22$, $p < 0.01$; senior management: $b/40.13$, $p/40.02$; work-life balance: $b/40.11$, $p/40.01$). Hence, the results suggested that at the same period, cooccurring events improved traders' attitudes.

Analysis of theme co-occurrence

To investigate the co-occurrence of job satisfaction factors in traders' reviews, I coded the occurrence of each job satisfaction factor in each "pro" and "con" part of each review. Thus, for each of the five job satisfaction factors, I defined a dummy variable, which equaled 1 if the factor appeared in a "pro" comment and 0 otherwise, and a dummy variable, which equaled 1 if the factor appeared in a "con" comment and 0 otherwise. Correlations of these ten dummy variables showed that traders who referred to compensation and benefits themes in the "con" part of their reviews tended to refer to work-life

balance in the “pros” part of their reviews ($r^2=0.16$, $p<0.001$). Traders who referred to work-life balance themes in the “con” part of their reviews tended to refer to compensation and benefits themes in the “pros” part of their reviews ($r^2=0.23$, $p<0.001$). Several additional themes co-occurred in the reviews, but most themes were independent of each other (see Table D in the supplementary material file).

Discussion

Research has acknowledged that financial practitioners have wide range of psychological and social motivators including, for instance, career concerns (Brown, Wei, and Wermers 2014) and ethics (Riedl and Smeets 2017). It has also suggested that financial practitioners are aware that well-being comprises aspects (Statman 2020). However, research examining practitioners’ job satisfaction has been limited (Deng and Gao 2017; Mahmood et al. 2019).

Drawing on organizational behavior research, this study investigates the factors that motivate traders to work at major investment banks, the job characteristics with which they are dissatisfied, and the determinants of their overall attitudes toward their banks. In line with research on financial practitioners’ experience (Mahmood et al. 2019), this study shows that pay serves as a motivator, improving traders’ attitudes toward their banks. However, extending previous practitioners’ experience research (Deng and Gao 2017; Mahmood et al. 2019; Sobolev 2020), it reveals that traders’ attitudes depend on their banks’ culture and career opportunities more than on their compensation and benefits. Traders’ attitudes depend also on their management, technology, bureaucracy, internal politics, and traders’ work-life balance.

Furthermore, this study suggests that overall, most traders are happy with central aspects of their work. Traders are especially happy with their coworkers and learning opportunities. These findings complement research on financial practitioners’ experience, that focused on the volatile, market-dependent aspects of practitioners’ experience (Fairchild 2014; Fent onO’Creevy et al. 2011; Lo and Repin 2002; Peterson 2007; Shefrin 2002). However, they also emphasize that traders’ work perceptions are highly diverse. For instance, whereas some traders consider their banks ethical, others judge their rewards unfair and attribute this unfairness to diversity issues or organizational politics. To summarize, this paper shows that a large number of factors, other than pay, determine traders’ satisfaction with their banks. Hence, it suggests that the price of happiness in the financial industry is not merely monetary.

Applications for investment banks

Traders' job satisfaction and retention

As this study highlights that pay is not the only factor motivating traders' work in large investment banks, it suggests that banks could increase traders' job satisfaction and retention by addressing the issues with which they are dissatisfied. In particular, this study suggests that reducing traders' work hours and stress, providing them with more career opportunities, improving the technological systems of the banks, limiting their bureaucracy and internal politics, and addressing ethics-related issues such as reward fairness, could enhance traders' job satisfaction. Job satisfaction has been shown to be positively related to employees' performance (Judge et al. 2010) and retention (Lum et al. 1998; Pitts, Marvel, and Fernandez 2011).

Shareholders' outcomes

As paying practitioners greater shares of the revenues decreases the financial outcomes of the shareholders, practitioners' pay increase has implications on shareholders (Franklin and Moise 2022). Increasing practitioner retention using efficient methods, which are less expensive, could therefore have positive outcomes for shareholders.

Banks' public image

Substantial bonuses and pay increase detrimentally influence the public image of investment banks. For instance, critics of practitioners' bonus increase said that "these sky-high banker bonuses are a kick in the teeth for everyone suffering with the cost of living crisis" (Neate 2022). Attempts to improve financial practitioners' job satisfaction and retention using nonfinancial measures could help banks avoid criticism of this type.

Limitations and topics for future research

This study's limitations offer paths for future research. First, this study analyses Glassdoor reviews to understand traders' perceptions of their banks. Although Glassdoor has been acknowledged as a valid and insightful data source (Hope et al. 2021; Landers, Brusso, and Auer 2019), it could be beneficial to explore the research questions using complementary research methods, such as interviews. It would be also helpful to extend this study by investigating additional groups of financial practitioners (e.g., financial analysts). Second, this study suggests that a proportion of financial practitioners experience

dissatisfaction with the banks' technology, bureaucracy, internal politics, or relationship with the management. However, research has established that emotions, such as fear and anger could influence practitioners' financial information processing and decision-making (Wynes 2021). Dissatisfaction is likely to elicit negative emotions of this type. Hence, I hypothesize that these organizational factors could impact traders' returns beyond their effect on the banks' efficiency. Testing this hypothesis could have important theoretical and practical implications. Future research could also investigate how traders' satisfaction and financial outcomes depend on the interactions between their individual performance, pay, and overall firm performance. Finally, the results of this study portray traders as people who often value their banks' ethics, learning opportunities, and coworkers. Research has not examined the effects of these values on trading outcomes. However, it has shown that personality traits such as extraversion and neuroticism impact trading decisions and risk preferences (Oehler et al. 2018). As personality traits influence trading outcomes, I hypothesize that ethics, learning, and social values could influence trading outcomes, too. Future research could test this hypothesis.

Disclosure statement

The author reports that there are no competing interests to declare.

Data availability statement

The data is available from the sources identified in this paper.

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