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The relevance and influence of social media posts on investment decisions of young and social media-savvy individuals — An experimental approach based on Tweets

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ABSTRACT

We conducted an experiment to examine the role of positive and negative tweets (generated by AI) on investment behavior of young and social media-savvy individuals, comparing them with provided historical and fundamental financials. Through mediator analysis, we discovered that positive tweets have a significantly positive mediating effect on investment amounts, while negative tweets have a negative impact. Importantly, we found that this effect is not primarily driven by the perception of the tweets; rather, positive tweets influence individuals' perception of a company's financials which is the most influencing factor in individuals' investment decision. In this manner our study contributes to the existing literature by (1) proving evidence for a causal effect of social media investor sentiment on investment behavior on capital markets and especially (2) focussing how the influence channels are built.

1. Introduction

Predominantly starting with (Kyle, 1985) and Black (1986) the influence of noise in financial markets has aroused the interest of many researchers in the field of Behavioral Finance. In financial research the role of noise traders has been widely discussed as noise trading is supposed to explain why stock prices could differ from their fundamental value. This idea contradicts the idea of information-efficient markets stated in the EMH by Fama (1970). Fama (1965) himself argues that irrational noise traders would meet rational traders on financial markets who trade against them. This should result in systematic losses for noise traders who will leave the market because of the behavior of rational arbitrageurs. De Long et al. (1990) oppose that there are limits to arbitrage due to risk aversion and short time horizons allowing noise traders to temporarily diverge prices from the fundamental value. Consequently, the development, identification (and prediction) of noise has become a main interest of research in financial research.

Market or investor sentiment defined as market's general, psychological environment is believed to wield considerable influence over noise trading, thereby anticipated to impact stock prices. Given the non-trivial nature of observing investor sentiment, the debate on its influence within financial markets pivots on identifying the most appropriate measure. Over time, three main distinct measurement approaches have emerged: market-based, survey-based, and text-based methodologies.[1]

The approach last mentioned, which has gained and continues to enjoy widespread popularity, aligns with the ascent of social media platforms like Twitter, Facebook, and Instagram. Their expanding user bases, coupled with increasingly accessible textual analysis tools such as BERT with nearly 9,000 trained models on *Huggingface.co*, have propelled this approach. Consequently, researchers have probed the potential impact of a platform's content on stock market performance. Given investors' limited attention spans, their investment decisions often exhibit biases toward assets that consciously or subconsciously grab their attention — such as through framing techniques (Barber and Odean, 2008). As a result, social media platforms may indeed sway individual investment choices (Liu, 2020). Johnson and Tversky (1983) previously noted that sentiment has the power to influence investors' risk perceptions. Kaplanski et al. (2015) corroborate this observation, even detecting the effects of investors' personal happiness on their investment behavior. Additionally, Baker and Wurgler (2007) conclude that the debate no longer revolves around whether sentiment influences

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[1] A comprehensive overview about the three measurements is given for example in Aggarwal (2022).

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market participants but rather focuses on the intensity of its impact and how best to measure it.

Despite empirical findings predominantly suggesting relationships, discussions surrounding causality, particularly the causal direction and channels, have surfaced. This area has been experimentally explored across various papers in economic literature. Hales et al. (2011) contribute to linguistic analysis in financial accounting research (e.g. Tetlock, 2007; Tetlock et al., 2008; Feldman et al., 2010) by demonstrating that investors are more susceptible to the influence of vivid language compared to dull language of the same sentiment in financial reporting. This effect is especially pronounced when the underlying information is preference inconsistent. Studies by Tan et al. (2014) and Rennekamp and Witz (2021) echo these findings, suggesting that text can significantly impact investors' judgments, particularly when the readability of the text is low or when the language used is informal. Moreover, Miller (2010) finds that lengthy and less readable filings lead to reduced trading, prompting small investors to halt trading activities. The chosen information channel also plays a role. Kelton and Pennington (2020) note that investors tend to identify more with a CEO when communication occurs through Twitter compared to the company's website. A recent and comparable study by Boulu-Reshef et al. (2023) specifically examines the influence of emojis in social media posts (tweets) on financial professionals. Their research indicates a significant yet marginal impact of these messages on investment decisions.

Despite the specific experimental findings, there remains a limited understanding of the intricate mechanisms underlying these effects. A deeper examination of the influential channels could significantly enhance our comprehension of individuals' investment behavior. Thus, we aim to contribute to the aforementioned literature by investigating individuals' investment choices and their perceptions of financial and social media sentiment within an experimental setting encompassing various financial and social media information sources. Since the present experiment primarily involved students and young adults, our results specifically focus on the decision-making of young individuals who are socially media-savvy and have relatively little experience in the capital markets.

Through the application of mediation analysis, our study seeks to scrutinize whether and through which channels these distinct information sources exert an influence on perceived sentiment. Subsequently, we aim to explore how these perceptions, in turn, impact investment decisions. We go in line with prior findings, but also find using mediator analysis that the tweets do not have significant influence on investment decision directly as well as over the mediator perceived tweet Sentiment. Moreover, the tweets influence the perceived Financial Sentiment which has a large and significant influence on the investment decision. To assess the relevance and generalizability of our results, this or a similar experiment would need to be repeated in future research with a representative participant group. This would also allow for the investigation of differences in decision-making and the underlying mechanisms among individuals with varying characteristics.

The remainder of this paper is structured as follows: Section 2 provides a detailed description of the methods utilized to gather financial and social media data within the experimental framework, aiming for authenticity. It further delves into the implementation process, concluding with the formulation of hypotheses based on the established setting. Section 4 offers a concise overview of the collected data, leading into the presentation of our findings. This includes a mediation analysis elucidating the impact on investment decisions. Finally, Section 5 serves as the conclusion, where we summarize our observations in light of previous literature, and highlight potential avenues for future research.

2. Experimental design

Our experimental design aims to assess the impact of social media posts, specifically tweets on the platform 'X' (formerly 'Twitter'), on the investment behavior of individuals. Taking into consideration aspects of loss aversion following prospect theory by Kahneman and Tversky (1979), we are also interested in observing this behavior with positive and negative versions of provided financials and tweets. To achieve this, we divided our test subjects into six different groups, as outlined in Table 1.

Table 1
Grouping.

Group	Tag	Financials	Twitter	Size
1	PP	Positive	Positive	45
2	PN	Positive	Negative	42
3	NP	Negative	Positive	42
4	NN	Negative	Negative	43
5	P	Positive	*None*	42
6	N	Negative	*None*	45

In the following subsections, we describe the specified investment setting along with the design of positive and negative financials and tweets. We conclude our introduction to the experimental design by detailing the incentive system. Subsequently, we derive our hypotheses based on our key findings in the introduction and our experimental design.

2.1. Investment setting

Test participants were instructed to gather information about the fictional company 'Glubon AG'[2] of which they already owned 100 stocks, each valued at 10€ (resulting in a total stock capital of 1000€). Based on a brief company description (refer to Fig. A.1 in Appendix A.1.1), stock charts, financial metrics (see Section 2.2) and (for groups 1 to 4) posts on the platform Twitter[3] ('Tweets', see Section 2.3), participants had to decide whether to sell or buy stocks at a rate of 10€ each. Each participant also possessed 1000€ of free capital, and the decision was limited to holding between zero stocks and 2000€ of free capital or holding 200 stocks and 0€ of free capital at the end of the experiment. After all participants made their decisions, a new stock price per group would be calculated, as explained in Section 2.4. This calculation also affected the total capital (and consequently, the number of lottery tickets) of the participants. Therefore, the experimental setting is limited to one period and each participant makes only one decision.

All information was presented on a self-designed, Visual Basic-based information and trading platform, exemplified by the opened (negative) *Financials* tab in Fig. 1. On this platform, our participants could freely navigate between three tabs: *company description*, *Financials*, and *social media*, to gather information for the final decision in the *investment decision* tab. Thanks to the autonomous coding of the platform, we were also able to track all transitions between tabs and monitor the time spent within each tab.

2.2. Financials

The structure of the financials tab is modeled after financial websites such as Yahoo! Finance, presenting charts for different time horizons along with financial figures. The positive and negative cases can be found in Figs. A.2 and A.3 in the appendix.

The stock price development was simulated using a random walk with drift, as described in formulas (1) and (2). To enhance the authenticity of the development, a new drift α was drawn from a normal

[2] AG is the German abbreviation for 'Aktiengesellschaft', which translates to 'stock company'.

[3] Before the conclusion of our experiment, 'Twitter' had unexpectedly been rebranded to 'X'. We chose to keep using the name Twitter, as most participants might not be familiar with the new branding and the name 'Twitter' has been used to provide information to the participants.

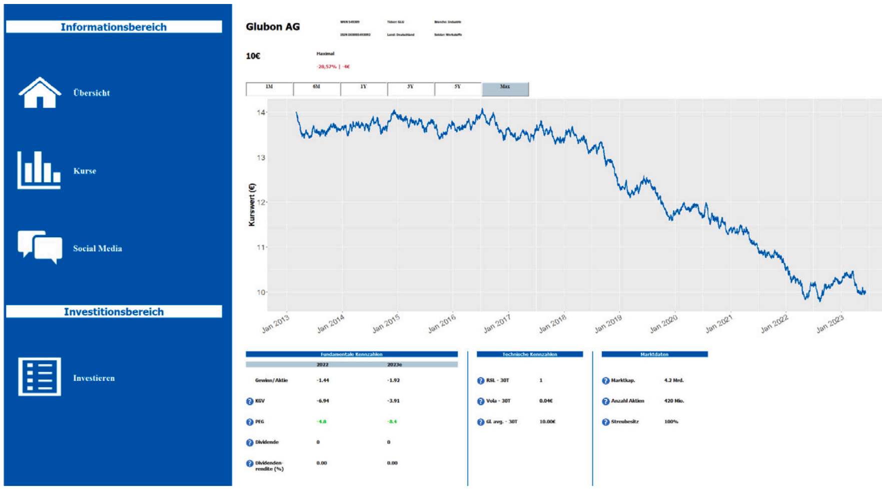

Fig. 1. Platforms interface (*Financials* tab opened, negative version).

distribution with a positive mean for the positive case every 30 days, as detailed in formula (3).

$$P_t = P_{t-1} + \alpha_i + \epsilon_t \tag{1}$$

with

$$\epsilon_t \sim N(0,1) \tag{2}$$

and an every 30 days t changing α_i

$$\alpha_i \sim N(1,25) \tag{3}$$

For the negative case, daily returns were reversed, and both stock price developments were scaled to a price of 10€ on the last day.

Additionally, participants could find financial figures below the charts, designed to appeal to economically educated participants who assumed the market, following Fama (1970), to be semi information-efficient. Even less economically educated participants could benefit from this information, as each figure was explained by clicking the '?' buttons next to the figure. The provided positive (negative) financial figures included positive (negative) profits per share, positive (no) dividends/dividend returns, positive (negative) price-earning ratios for the previous year as well as expected for the current year. Furthermore, figures for low (high) volatilities, relative strength, 30 days moving average, as well as information about the market capitalization, free float, and number of shares, were presented.

Consequently, we are aware of possible biases in the perception of the financials of Glubon as 'positive' and 'negative', especially for the charts, due to prior findings in behavioral finance (in this case, especially the disposition effect empirically introduced by Shefrin and Statman, 1985). Therefore, we ask the participants about their perception as well as their judgment regarding plausibility and trustworthiness of the given financials after the investment decision.

Table 2
Queries and presence of tweet type per group.

Query specification			Occurrences per group		
Sentiment	Colloquial	Max character	1 & 3	2 & 4	5 & 6
Positive		20	5		0
Positive		70	5		0
Positive		140	5	Randomly	0
Positive	X	20	5	picked 3	0
Positive	X	70	5		0
Positive	X	140	5		0
Neutral		20			0
Neutral		70			0
Neutral		140	Randomly	Randomly	0
Neutral	X	20	picked 7	picked 7	0
Neutral	X	70			0
Neutral	X	140			0
Negative		20		5	0
Negative		70		5	0
Negative		140	Randomly	5	0
Negative	X	20	picked 3	5	0
Negative	X	70		5	0
Negative	X	140		5	0
Σ			40	40	0

2.3. Tweets

tweets were presented as the result of a search for the cashtag '$GLU' of the imaginary Glubon AG on the platform Twitter. The content of the tweets was generated using OpenAI's ChatGPT queries mentioned in Appendix A.1.3. Due to different queries, positive, negative, and neutral tweets were created by the AI using varying maximum lengths (20, 70, or 140 characters) as well as in colloquial and non-colloquial language. From the created database of 180 Tweets, we sampled 40 Tweets each for groups 1 & 3 and groups 2 & 4, as stated in Table 2.

The tweets provided on the platform for group 1 & 3 not only contain positive tweets but also a minor number of neutral and negative tweets for authenticity reasons. The same holds true vice versa for the tweets provided to group 2 & 4. To ensure that this does not affect the treatment, participants were asked for their perception of the tweets after the investment decision. To enhance authenticity further, we added ChatGPT-generated German usernames as well as randomly picked profile pictures from the academic dataset delivered by the company 'Generated photos'. The picture dataset, including estimators for gender, race, and the emotion shown in the picture, allowed us to pick a diverse spectrum of mostly happy profile pictures. While we randomly ordered the sampled tweets per group, the order of profile names and pictures is the same in every group. Ultimately, replies, retweets, likes and impressions were drawn from a normal distribution with a higher mean if the tweet sentiment fits the group's social media treatment than for tweets of another sentiment as those factors can also influence investors' perception following Cade (2018) or Rennekamp and Witz (2021). All these operations lead to a social media tab as exemplified in Fig. 2.[4]

Consequently, this operationalization does not mimic a potential 'timeline' of the users and can be more accurately compared to a

[4] A translated example for a tweet of every query type mentioned in Table 2 can be found in of Appendix A.1.3.

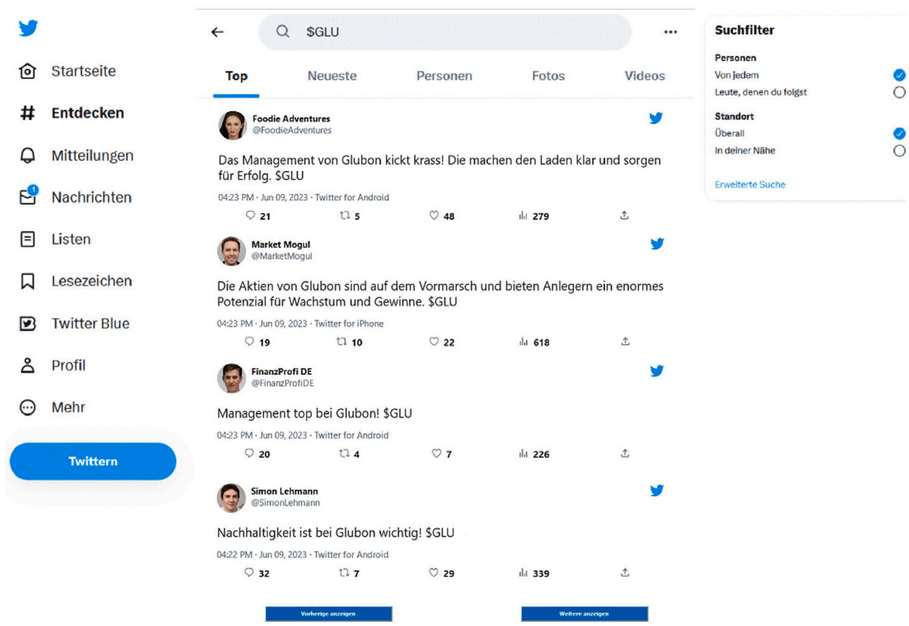

Fig. 2. *Social media* tab, site 1 of 10 opened, positive version.

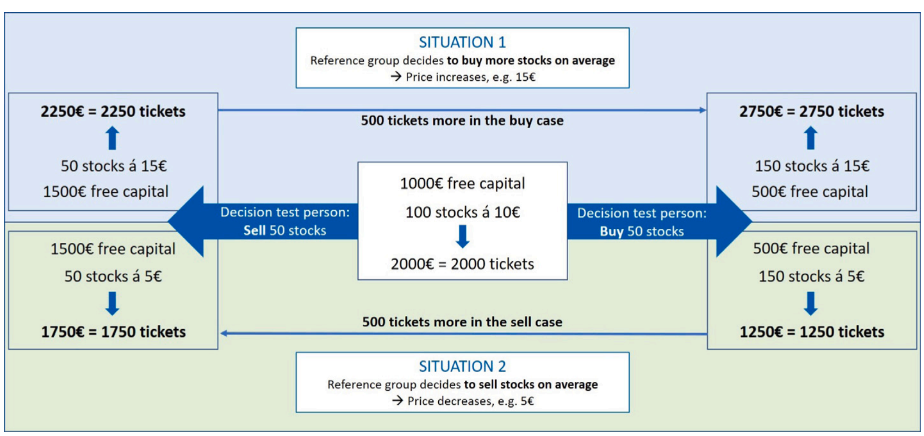

Fig. 3. Ticket outcomes under different situations and decisions.

search for the company's cashtag ($) in the Twitter feed. We assume that potential effects reported in Section 4 would be more pronounced if tweets had been posted by users our test participants would have decided to follow in real life, which would not have been possible to mimic reliably in an experiment. Additionally, the AI-generated content could possibly be recognized by the users. Therefore, we asked the participants for their assessment of the trustworthiness of the tweets.

2.4. Implementation

The experiment took place in a lab at the Heinrich-Heine-University Duesseldorf in July and August 2023 with an open registration for everyone speaking German fluently. Over time we collected data from 300 participants mainly containing economic students but also professionals and students from other disciplines. From the 300 participants we use 259 responses for our dataset excluding 41 participants who failed at answering at least 3 of 4 control questions regarding the given setting and incentive system correctly. This number of responses leads to an ANOVA power of 0.95 (0.86) assuming an medium effect size (0.25) and an error probability (α) of 0.05 (0.01) utilizing the G*power software.

In addition to a fixed compensation of 5€, participants were incentivized by a lottery giving out further 300 (50 per group) times 5€ which ensures conscientious behavior by the participants (Holt and Laury, 2002). Participants have been clearly enlightened about their winning chances (starting with an expected value of winning further 5€) with the following information and also the understanding has been checked within the control questions. Each participant started the experiment with a total capital of 2000€ (1000€ stock capital, 1000€ free capital), which translated into 2000 tickets for the lottery (1€ equals 1 ticket). Depending on the decisions made within each reference group, a new stock price was calculated, affecting the stock capital and total capital of each participant based on their decision. Fig. 3 illustrates how the decision to buy or sell 50 stocks affects the total capital, and consequently, the number of lottery tickets, if the stock price increases to 15€ (blue situation) or decreases to 5€ (green situation).

For the calculation of the new stock price, P_1, in each group i with N_i participants, we use a simplified stock pricing formula that interprets the return of the stock, r_i, as the ratio between the change in cumulated stock capital in t_1, $SC_{i,1}$, and the cumulated stock capital in t_0, $SC_{i,0}$:

$$r_i = \frac{SC_{i,1} - SC_{i,0}}{SC_{i,0}} \tag{4}$$

Consequently, the new price per group i ($P_{i,1}$) is calculated as

$$P_{i,1} = P_0 * (1 + r_i) \tag{5}$$

which is limited between

$$\lim_{SC_{i,1} \to 0} P_1 = 0 \tag{6}$$

and

$$\lim_{SC_{i,1} \to 2000N_i} P_1 = 20. \tag{7}$$

Further, we collected variables for controlling purposes regarding participants' demographics (as gender, age, income & risk tolerance following Holt and Laury, 2002), financial experience and social media usage.

Alternatively to the proposed incentive system, where each participant receives a fixed starting capital, it would also be possible to allow participants to earn their starting capital in advance through a performance-based game. This could create a more realistic emotional connection and potential loss aversion regarding the capital. However, in this paper, we deliberately chose to avoid the second method, as we risk that the mentioned effects might overshadow the impact of sentiment, complicating the nuanced measurement of this effect. Repeating our experiment with the outlined incentive system and comparing the results of both studies could be interesting for future research projects, providing deeper insights into investor sentiment.

3. Hypotheses

In the context of the EMH (Fama, 1970), it can be assumed that economic agents process information provided to them appropriately, thereby adjusting their actions to the existing information environment. As indicated by the relevant literature and various economic studies, both social media (see i.a. Antweiler and Frank (2004), Baker and Wurgler (2006), Da et al. (2015), Das and Chen (2007), Renault (2017), Sun et al. (2016), Tetlock (2007)) and financial indicators influence the investment calculus of individuals. However, Tversky and Kahneman (1974), in their highly regarded study considered the starting point of Behavioral Finance, demonstrated that due to behavioral biases, the available information is inadequately processed using experience and heuristics (Ritter, 2003). In this context, differences may arise in the consideration of various information sources and their interpretation leading to departures from rational decision-making calculations, as exemplified by phenomena such as noise trading. Thus, it can be assumed that different economic agents may consider various information sources differently based on their experiences and perceptions. In our specific case, economic agents have access to social media posts in the form of tweets and financials (historical and fundamental) for their investment decisions. The goal of this study is to examine whether the provided information has an impact on individuals' investment decisions.

However, in the context of the presented behavioral biases, it is also necessary to investigate how the tweets and financial information were perceived by each participant (sentiment) and whether this sentiment also influences the investment decision. To address this question, a mediation analysis will be employed, aiming to answer the following main hypotheses:

Hypothesis 1. There is a mediating effect of Financial Sentiment on the investment decisions of the participants.

Hypothesis 2. There is a mediating effect of Tweet Sentiment on the investment decisions of the participants.

In our analysis, we draw insights from Baron and Kenny (1986) and Zhao et al. (2010) to elucidate the intricate mechanism by which provided information and the associated sentiment shape investment decisions. Our approach involves examining both the direct impact of tweets and financials on investment decisions and their indirect effects mediated by two factors: *Tweet Sentiment* and *Financial Sentiment*. Furthermore, we also examine the influence of tweets on Financial Sentiment and the influence of financials on Tweet Sentiment to account for a potential deviation from rational decision-making in the context of Behavioral Finance. Hence, the following sub-hypotheses arise:

Hypothesis 1.1. There is an indirect effect of Tweets via the mediator Tweet Sentiment on the investment decisions of the participants.

Hypothesis 1.2. There is an indirect effect of Tweets via the mediator Financial Sentiment on the investment decisions of the participants.

Hypothesis 1.3. There is a direct effect of Tweets on the investment decisions of the participants.

Hypothesis 2.1. There is an indirect effect of Financials via the mediator Financial Sentiment on the investment decisions of the participants.

Hypothesis 2.2. There is an indirect effect of Financials via the mediator Tweet Sentiment on the investment decisions of the participants.

Hypothesis 2.3. There is a direct effect of Financials on the investment decisions of the participants.

However, it should be noted when considering our results that the participants in this experiment were primarily students with limited experience in capital markets. In light of the previous section, they are media-savvy and may therefore attribute more significance to social media based on their individual experiences than the average population.

4. Results

4.1. Participants' information

Before proceeding with the analysis of the data from the conducted experiment in the next section, we will first delve into the collected information of the participants. To do this, the data is divided into three categories, with the last category further subdivided into three more categories. All information discussed below can be found in Table 3.

The 'Participants' behavior' category encompasses the 'Stocks held' by participants at the end of the experiment, thus reflecting their investment decision. By definition, the values in this category can only be integers in the interval [0, 200], where 0 represents the sale of all initially (100) held stocks, and 200 represents the maximum purchase of 100 additional stocks within the available budget. This interval was utilized, as evident from the maximum and minimum values, with participants acquiring, on median, an additional 10 stocks, while, on average, only 1.6 additional stocks were acquired by a standard deviation of 61.73 stocks.

The second category, 'participants' sentiment', includes the sentiment of the participants regarding the given tweets and financials. After making their investment decisions, participants were tasked with using a Likert scale ranging from 1 to 5 to assess how they perceived the given tweets and financials.

In this context, a value of 1 corresponds to a very negative sentiment, 3 to a neutral one, and 5 to a very positive sentiment. These pieces of information serve in the further development of the work both to validate whether the given treatment was perceived by the participants according to its intention and to highlight whether perception, rather than the actual information, has an impact on investment decisions. The entire possible interval of $[1, 5]$ was also utilized by

Table 3
Participants' information.

		Min	Max	Med	Mean	Sd	Dummy
Participants' behavior							
	Stocks held	0	200	110	101.60	61.73	
Participants' sentiment							
	Tweets	1	5	2	2.63	1.59	
	Financial	1	5	3	3.01	1.43	
Participants' characteristics							
Demographic							
	Age	17	62	23	24.93	7.25	
	Male	0	1	1	0.60	0.49	X
	Risk	0	10	5	4.86	1.79	
	Income	0	10	1	1.77	2.00	
	Student	0	1	1	0.78	0.41	X
Financial							
	Economic	0	1	1	0.61	0.49	X
	Cap market	0	1	1	0.60	0.49	X
Social Media							
	Usage	0	14	2	2.48	1.74	
	Twitter	0	1	0	0.26	0.44	X

the participants for both Social Media and Financial Sentiment, with the Social Media Sentiment being more negative on both average and median compared to the Financial Sentiment.

The last category, 'Participants' characteristics', includes characteristics of the participants regarding their demographic information, financial experience, and social media usage. The category of 'Demographics' includes the age, gender, risk attitude and income of the participating individuals. The youngest participant was 17 years old, and the oldest person was 62 years old. Based on the median (23) and the average age (24.93), it can be observed that, as expected, it is a relatively young participant group since this study was conducted at an university.

The variable 'Male' is a dummy variable, which takes the value 1 for participants who identify as male. To account for the three different gender specifications of the participants and considering that only one observation is labeled as gender-diverse, a dummy variable is used. As indicated by the median and the mean, there is a slight majority of male participants in the present dataset.

The 'Risk' variable measures the risk tolerance of each participant with values ranging from $[0, 10]$, which was determined using the Holt–Laury test (Holt and Laury, 2002).[5] A value of 0 indicates a high risk appetite, while a value of 10 reflects a pronounced risk aversion. In the present dataset, the majority of participants are therefore more risk-averse.

Furthermore, participants were asked about their monthly income, which could be indicated in increments of 500. Thus, the number 0 represents an income of 0–500€, and the number 10 (the maximum in this dataset) represents an income of more than 5000€. Hence, we observe a relatively low income level of 1.77 on average, which again, is to be expected since the experiment was conducted at an university.

Aside from demographic information, additional data was collected on participants' financial background and social media usage to consider their effects in the further analysis. In terms of economic characteristics, there is a dummy variable indicating whether a participant has an economic-related background in form of an university degree or an apprenticeship. The variable 'Cap market' indicates whether a participant has been active in a capital market. In terms of social media characteristics, the dummy variable 'Twitter' differentiates whether a participant uses or has used the social media platform Twitter, as this study focuses primarily on this platform for social media posts. Additionally, the variable 'Usage' indicates how many hours per day a participant uses social media channels.

Overall, the majority of participants have been active in the capital market and are currently or have previously pursued a study with an economic background. However, most participants do not use the social media platform Twitter. Furthermore, participants spend an average of 2.48 h (2 h in median) per day on social media channels. However, it is important to note that one participant with a daily usage of 14 h is a clear outlier, which needs to be critically considered in the subsequent ANOVA analysis.

The collection of the data described above allows, on one hand, drawing conclusions about the characteristics of the participating individuals to assess the generalizability of the results of the present study. On the other hand, these variables serve as control variables in a later section to check the robustness of the results.

After examining participants' behavior, sentiment, and characteristics, the next step is to take a closer look at these factors for each group. Since this study aims to contribute to the explanation of individuals' investment behavior, Figs. 4 and 5 are used to provide an overview of the differences in investment behavior between the individual groups.[6].

Firstly, the cumulative relative frequency of Stocks held for the groups without tweets is examined (Fig. 4). The two groups only differ in the provided financials. It can be seen that the group with positive financials (P), represented in green, holds more stocks throughout the entire distribution compared to the comparison group with negative financials (N). Looking at the density distribution of the other groups (Fig. 5), which were provided with tweets, a similar pattern emerges. The compared groups always differ in the provided tweets, while the financials do not differ in the individual comparisons. It becomes clear that both in the case of positive and negative financials, there is a difference in the held stocks. In both cases, participants who were provided with positive tweets (PP, NP) hold more stocks throughout the entire distribution compared to the groups with negatively connotated tweets (PN, NN).

4.2. Analysis of variance & post-hoc test

Based on these observations, an Analysis of Variance (ANOVA) is conducted subsequently to examine whether the held stocks differ significantly among the individual groups. In addition to differences

[5] Holt and Laury measure individuals' risk aversion by presenting two lotteries. Participants are asked to choose between a less risky and a riskier but potentially more profitable lottery in 10 different scenarios, with the probability of the higher payoff increasing in each iteration. The degree of risk aversion is determined by the switching point from the less risky to the riskier lottery, with the rational switch based on expected value occurring after the fourth iteration. Therefore, values above 4 indicate increased risk aversion. For a more detailed overview, see Holt and Laury (2002).

[6] For an overview of the different groups see Table 1.

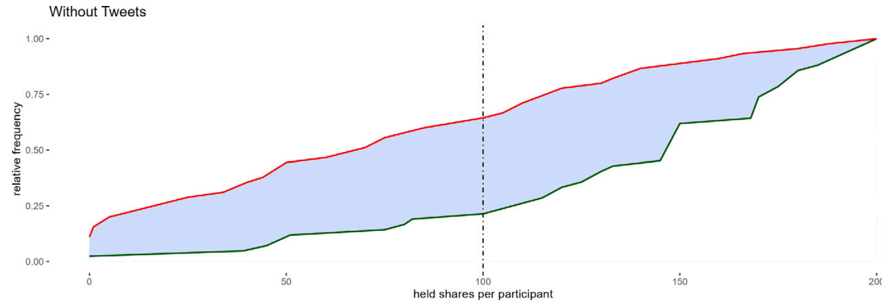

Fig. 4. Cumulative relative frequency of Stocks held (without Tweets).

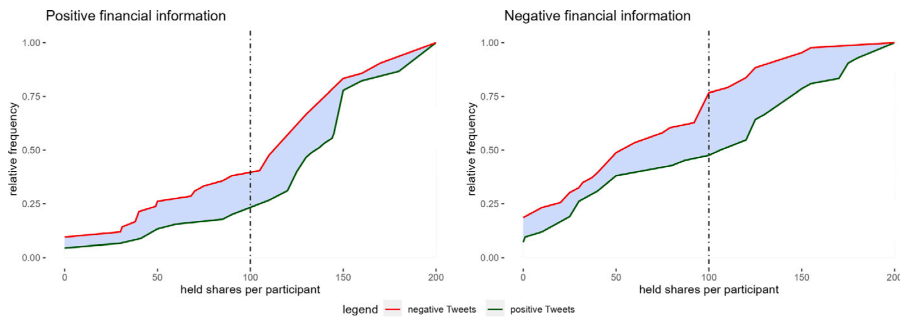

Fig. 5. Cumulative relative frequency of Stocks held (with Tweets).

in participant behavior, an examination will also be conducted to determine whether there are differences in participants' sentiment and characteristics among the individual groups. The ANOVA results and the means for every aspect analyzed are depicted in Table 4.

The F-statistic of the ANOVA clearly indicates that there are significant differences between individual groups regarding the average number of Stocks held at the end of the experiment. On average, groups with positive financials hold more stocks than those with given negative financials. In particular, the control group with positive indicators without social media posts (P) holds the most stocks on average. Furthermore, a difference can be observed between the groups with positive financials and positive or negative social media treatment (PN & PP). Participants in the group with positive social media posts (PP) hold, on average, about 23 more stocks compared to participants with negative posts (PN), which might hint towards an influence of the given social media treatment. A similar pattern emerges when examining the groups with negative financials and different social media treatments (NN & NP). Participants in the group with positive social media posts (NP) hold, on average, about 30 more stocks than the comparison group with negative posts (NN). The NN group also holds the lowest number of stocks on average, even when compared to the control group with negative financials and no social media posts (N).

Moreover, the results of the ANOVA regarding participants' perceptions reveal that the given treatments (social media posts) were perceived by the participants in accordance with their intended sentiment. There are significant differences in the perception of the sentiment of social media posts among the individual groups, as measured on a Likert scale. The groups with positive tweets (PP & NP) perceive these posts significantly more positively on average (deviation of approximately 2.5 units) compared to the groups with negatively formulated tweets. A different perception also exists regarding the financials. The groups with positive financials (PP & PN & P) perceive them on average significantly more positively than the groups with given negative financials (NP & NN & N). These results suggest that the treatments were perceived according to their intended purpose.

Finally, ANOVA was used to compare participant characteristics across the individual groups (for characteristics where such a method

Table 4
ANOVA between the different groups.

	PP	PN	NP	NN	P	N	F-Stat
Participants' behavior							
Stocks held	128.77	105.97	97.35	66.86	136.52	75.15	10.53***
Participants' sentiment							
Tweets	3.91	1.38	3.80	1.37	NA	NA	127.99***
Financial	4.15	4.04	2.23	1.72	4.23	1.68	93.54***
Participants' characteristics							
Demographic							
Age	26.68	25.33	23.28	25.79	23.71	24.62	1.37
Male	0.511	0.38	0.42	0.34	0.35	0.4	0.63
Risk	5.17	4.61	4.73	4.88	4.61	5.06	0.75
Income	2.07	1.93	1.64	1.91	1.36	1.69	1.72
Financial							
Economic	0.60	0.62	0.62	0.49	0.79	0.53	0.00
Cap market	0.53	0.57	0.69	0.58	0.67	0.53	0.07
Social Media							
Usage	2.29	2.21	3.28	2.24	2.57	2.32	0.00
Twitter	0.20	0.21	0.33	0.33	0.26	0.20	0.06

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

is meaningful). The results indicate that there are no significant differences in terms of the participants' characteristics, suggesting a balanced distribution of participants.[7]

Although the results of the ANOVA indicate significant differences between the means of the six groups in terms of participant behavior and perception, such an analysis does not provide insight into the specific nature of these differences. Therefore, a post-hoc test, specifically the Tukey post-hoc test, is employed (Tukey, 1992). This test allows

[7] As previously noted, there is an outlier with 14 h of social media usage. The effect of this outlier is evident in the elevated mean of social media usage for the NP group. However, in this context, this outlier should not pose a problem, as even when considering this outlier, there is no significant difference between the individual groups. Moreover, if the outlier were to be excluded, the average of this group should align even more closely with the lower average of the other groups.

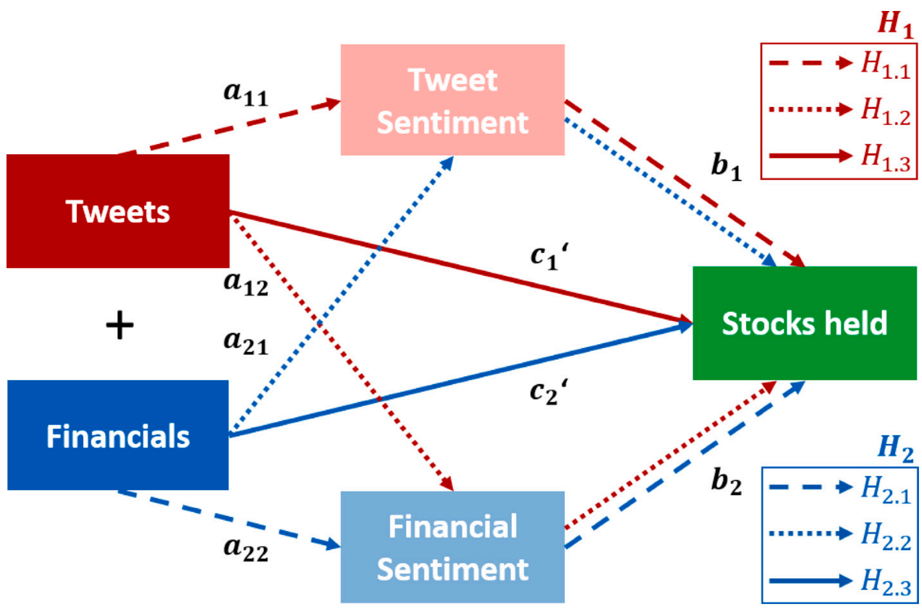

Fig. 6. Mediation analysis.

Table 5
Post-hoc test between each group.

Group comparison	Stocks held		Tweet Sentiment		Financial Sentiment	
	diff	p adj.	diff	p adj.	diff	p adj.
PN - PP	−22.802	0.420	−2.530	0.000	−0.108	0.992
NP - PP	−31.420	0.105	−0.102	0.991	−1.917	0.000
NN - PP	−61.917	0.000	−2.539	0.000	−2.435	0.000
P - PP	7.746	0.988			0.083	0.998
N - PP	−53.622	0.000			−2.467	0.000
NP - PN	−8.619	0.982	2.429	0.000	−1.810	0.000
NN - PN	−39.116	0.020	−0.009	1.000	−2.327	0.000
P - PN	30.548	0.137			0.190	0.911
N - PN	−30.821	0.118			−2.359	0.000
NN - NP	−30.497	0.134	−2.437	0.000	−0.517	0.063
P - NP	39.167	0.021			2.000	0.000
N - NP	−22.202	0.451			−0.549	0.036
P - NN	69.663	0.000			2.5171	0.000
N - NN	8.295	0.983			−0.032	1.000
N - P	−61.368	0.000			−2.549	0.000

for detailed comparisons between each group and the others, enabling a pairwise comparison across all groups. The results of the post-hoc test can be found in Table 5.

The group-wise comparison of participant behavior (Stocks held) reveals that groups with opposing financials significantly differ in their purchasing behavior (NN-PP, N-PP, NN-PN, P-NP, P-NN, N-P), with groups having negative financials, as expected, holding fewer stocks. Furthermore, the results from the preceding ANOVA analysis is confirmed in the sense that the treatments of sentiment and financials were perceived by the participants according to their intended purpose. Thus, the groups with divergent sentiment in social media posts consistently differ statistically highly significantly in their perception of tweets.

The same applies to the treatment of financials. The metrics are perceived as intended by the authors. However, two group comparisons stand out. Although groups NP, NN, *N* were each provided with the same financial information, these pieces of information were perceived statistically significantly differently. In the N-NP comparison, this difference is significant at a 5% level, and in the NN-NP group comparison, it is still significant at a 10% level.

Since the respective groups all received the same financial information, they differ only in the sentiment of the provided social media posts. In both group comparisons (NN-NP and N-NP), participants received positively connotated tweets. Thus, it can be presumed that the sentiment, especially if the tweets contain positive sentiment, of the given tweets has an influence on individuals' perception of financial information, which in turn might influence an individuals investment decision. To test this hypothesis, a statistical analysis using a mediation analysis will be conducted subsequently.

4.3. Mediation analysis

Mediation analysis (Baron and Kenny, 1986) is used to measure the effect of (an) independent variable(s) on a dependent variable. For this purpose, both the direct influence of the independent variable(s) on the dependent variable and the indirect effect of the independent variable through a mediator are estimated.

In the present analysis, due to the identified group differences, there is reason to believe that the provided tweets and financials have a direct impact on the investment decisions of the participants (H1.3 & H2.3). Thus, these variables are chosen as independent variables to assess their direct influence on the investment decision made. Furthermore, the results of the preceding section provide grounds to assume that the actual manifestations of tweets and financials influence how these variations are perceived by the participants, and in turn, this sentiment has an impact on the investment decision (H1.1 & H2.1). First evidence that tweets (financials) can also frame perceived Financial (Tweet) sentiment (H1.2 & H2.2) can be seen in Table 5 as the perceived Financial Sentiment was significantly more positive when the tweets were of a positive nature. Hence, through the mediation analysis, the model illustrated in Fig. 6 is estimated.

This model uses the provided tweets and financials as dependent variables and the perception of their sentiment as mediators to explain the Stocks held by the participants and test our hypotheses. In the presented base model (A) of a two-mediator model, a total of 4 different regressions need to be estimated to determine the direct and indirect effects of each regressor and takes the following form:

$$Stocks\_held = i_1 + c_1 * Tweets + c_2 * Financials + \epsilon_1 \tag{8}$$

$$\begin{aligned} Stocks\_held = i_2 + c_1' * Tweets + c_2' * Financials \\ + b_1 * Tweet\_Sentiment \\ + b_2 * Financial\_Sentiment + \epsilon_2 \end{aligned} \tag{9}$$

$$Tweet\_Sentiment = i_3 + a_{11} * Tweets + a_{21} * Financials + \epsilon_3 \quad (10)$$

$$Financial\_Sentiment = i_4 + a_{12} * Tweets + a_{22} * Financials + \epsilon_4 \quad (11)$$

To check the robustness of the results of this base model, additional control variables are subsequently added to the estimation. Model (B) includes the demographic information about the participants already presented earlier. In contrast, model (C) has been expanded to include financial and social media characteristics, while model (D) contains both demographic information and financial and social media characteristics.

Please be aware that for assessing the influence of Tweet Sentiment, it is imperative to exclusively consider the groups provided with tweets, given that participants in groups P and N were not exposed to any tweets, thus rendering them incapable of developing any Tweet Sentiment. Consequently, the models are estimated with $N = 172$ observations. The results of these estimation models can be found in Table 6.

The results of model (A) show that the given tweets do not have a direct impact on Stocks held. However, as expected, the given tweets have a strong and highly significant influence (a_{11}) on the first mediator, the Tweet Sentiment (T_Sen). However, this mediator does not have a statistically significant impact (b_1) on Stocks held either, so in this case, we can neither assume a mediating or direct effect, contradicting H1.1 & H1.3. This is also confirmed by the statistically insignificant indirect effect $a_{11} * b_1$. The given financials do not have a statistically significant direct influence on Stocks held, which rejects H2.3. Although the Financial's direct effect does not exert a statistically significant influence (c_2'), there is an indirect impact of the financials on Stocks held through the mediator Financial Sentiment. Stocks held are primarily influenced by the Financial Sentiment and therefore by the perception of the nature of the financial information provided. This indirect effect ($a_{22} * b_2$) is statistically highly significant and substantial, thereby confirming H2.1. In this case, we can speak of full mediation (Baron and Kenny, 1986; Zhao et al., 2010). As suspected from the results of the previous section, the mediator Financial Sentiment is also influenced by the tweets at a 5% significance level (a_{12}). Thus, Financial Sentiment serves as a mediator for both the financials and tweets to explain Stocks held. The indirect effect of tweets on Stocks held through Financial Sentiment ($a_{12} * b_2$) is relatively smaller than the indirect effect $a_{22} * b_2$; however, it is significant and thus provides a first explanation for the group differences with the same financials (NN-NP, N-NP) from Table 5 and confirms H1.2. However, H2.2 must be rejected, as the financials do not exert a significant influence on the perception of tweets.

These effects remain significant even with the gradual inclusion of control variables concerning the participants' demographics, their financial background and social media usage (models (B) to (D)). The direct effect of tweets does not exert a significant influence on Stocks held in any model leading to the continued rejection of hypothesis H1.3. The strength of the significant direct and indirect effects on Stocks held ($a_{12} * b_2$ and $a_{22} * b_2$) in model (A) is slightly increased in models (B) to (D), while most control variables do not exert a significant influence on Stocks held. When all control variables are included in model (D), only the previous experience in capital markets at a 5% significance level has an impact on the Stocks held. In case of existing experience in capital markets more stocks are held by participants.

According to the respective R^2 values for the two mediators, the presented models explain above 60% of the total variance of the perceived Financial Sentiment and the perceived Tweet Sentiment. Also the investment decision of Stocks held can be explained with an R^2 of over 30%.

The measured effect $a_{12} * b_2$ provides an explanation for the group differences in Stocks held, as depicted in Fig. 6, when the financials are the same. However, especially Table 5 provides grounds to assume that tweets primarily affect Financial Sentiment when the financials are of a negative nature (NN-NP, N-NP), as in these cases, there are significant differences in perception at a 10% level for NN-NP and a 5% level for N-NP respectively, which is why a more in-depth analysis of this observation is needed.

Table 6
Results Mediation Analysis models (A)–(D).

	Effect type			(A)	(B)	(C)	(D)
Stocks held	**Direct**						
		Tweets	(c_1')	0.108	0.108	0.087	0.087
				(0.115)	(0.113)	(0.116)	(0.114)
		Financials	(c_2')	−0.142	−0.153	−0.153	−0.157
				(0.106)	(0.107)	(0.099)	(0.100)
		T_Sen	(b_1)	0.059	0.076	0.086	0.096
				(0.115)	(0.111)	(0.113)	(0.110)
		F_Sen	(b_2)	0.560***	0.583***	0.575***	0.590***
				(0.115)	(0.114)	(0.111)	(0.111)
		Age			0.066		0.053
					(0.081)		(0.080)
		Male			0.098		0.046
					(0.064)		(0.067)
		Income			−0.105		−0.120
					(0.089)		(0.084)
		Risk			−0.057		−0.054
					(0.059)		(0.060)
		Economic				−0.045	−0.047
						(0.063)	(0.063)
		Cap Market				0.146*	0.150*
						(0.064)	(0.067)
		Usage				−0.026	−0.035
						(0.075)	(0.080)
		Twitter				−0.070	−0.051
						(0.065)	(0.066)
	Indirect						
		$a_{11} \rightarrow b_1$	($a_{11} * b_1$)	0.046	0.059	0.068	0.075
				(0.090)	(0.087)	(0.089)	(0.086)
		$a_{21} \rightarrow b_1$	($a_{21} * b_1$)	0.001	0.001	0.002	0.002
				(0.004)	(0.004)	(0.005)	(0.005)
		$a_{12} \rightarrow b_2$	($a_{12} * b_2$)	0.063*	0.065*	0.065*	0.066*
				(0.027)	(0.028)	(0.028)	(0.028)
		$a_{22} \rightarrow b_2$	($a_{22} * b_2$)	0.429***	0.447***	0.441***	0.452***
				(0.096)	(0.095)	(0.093)	(0.093)
T_Sen	**Direct**						
		Tweets	(a_{11})	0.784***	0.784***	0.784***	0.784***
				(0.047)	(0.047)	(0.047)	(0.047)
		Financials	(a_{21})	0.018	0.018	0.018	0.018
				(0.048)	(0.048)	(0.048)	(0.048)
F_Sen	**Direct**						
		Tweets	(a_{12})	0.112*	0.112*	0.112*	0.112*
				(0.048)	(0.048)	(0.048)	(0.048)
		Financials	(a_{22})	0.767***	0.767***	0.767***	0.767***
				(0.048)	(0.048)	(0.048)	(0.048)
R^2		Stocks held		0.261	0.285	0.293	0.311
		T_Sen		0.615	0.615	0.615	0.615
		F_Sen		0.605	0.605	0.605	0.605

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$
Regressions estimate Eqs. (8) to (11) for the models (A) to (D) with gradual inclusion of controls and the respective sample size $N = 172$ for each model.

Therefore, in the next step, we divide our overall dataset into participants who received positive financials and participants who were given negative financials for their investment decision. Subsequently, we estimate further separate mediator models for both groups. The base models for positive and negative financials (E) and (F) without control variables take the following form:

$$Stocks\_held = i_1 + c_1 * Tweets + \epsilon_1 \quad (12)$$

$$\begin{aligned} Stocks\_held = i_2 + c_1' * Tweets& \\ + b_1 * Tweet\_Sentiment& \quad (13) \\ + b_2 * Financial\_Sentiment + \epsilon_2& \end{aligned}$$

$$Tweet\_Sentiment = i_3 + a_{11} * Tweets + \epsilon_3 \tag{14}$$

$$Financial\_Sentiment = i_4 + a_{12} * Tweets + \epsilon_4 \tag{15}$$

Both basic models are consequently expanded with the demographic, financial, and social media characteristics to check the robustness of the estimations. The results of the estimation of these models (G) and (H) are depicted in Table 7.

The results of the estimations (E) and (F) confirm, on the one hand, the highly significant direct effect of Financial Sentiment on Stocks held (b_2) and, as expected, the highly significant influence of tweets on Tweet Sentiment. However, on the other hand by dividing the overall dataset, differences in the impact of positive and negative tweets become evident. In the case of positive financials (E), unlike the estimation with negative financials (F) and the previously estimated models (A) and (B), tweets do not exert a significant influence on the Financial Sentiment (a_{12}) and, consequently, exert no indirect effect ($a_{12} * b_2$) on the Stocks held, either. Therefore, the observable variance of Financial Sentiment, which has the dominant influence on Stocks held, can be explained to a significantly lesser extent in the model with positive financials (E) in comparison to the model with negative financials (F) since the nature of the given financials does exert an influence on the investment decision of individuals. As a result, the Financial Sentiment can be explained to a slightly but higher extent in model (F) than in model (E).

All results remain robust for both models even when control variables are included, where model (G) represents the model with control variables and positive financials, and model (H) includes control variables and negative financials. Overall, our observations align with the initial assumptions and indicate that the Financial Sentiment is particularly influenced when the available financials are negative, and the tweets contradict them in their statements. In addition, it can be seen that individuals tend to have a loss aversion as b_2 is considerable higher for negative (models (F) and (H)) than positive (models (E) and (G)) financials.

Transferring this idea of loss aversion to the given Tweets we also divide the dataset by the nature of Tweets in Table 8 estimating the following equations:

$$Stocks\_held = i_1 + c_2 * Financials + \epsilon_1 \tag{16}$$

$$\begin{aligned} Stocks\_held = i_2 + c_2' * Financials \\ + b_1 * Tweet\_Sentiment \\ + b_2 * Financial\_Sentiment + \epsilon_2 \end{aligned} \tag{17}$$

$$Tweet\_Sentiment = i_3 + a_{21} * Financials + \epsilon_3 \tag{18}$$

$$Financial\_Sentiment = i_4 + a_{22} * Financials + \epsilon_4 \tag{19}$$

In the case of negative tweets the effect of perceived Tweet Sentiment (b_1) remains insignificant. Nevertheless, it might be noteworthy that the b_1 coefficients in the negative models (J) and (L) of 0.129 and 0.167 are higher than in the positive models (I) and (K) and also show smaller standard errors leading to p-values decreasing from 95% to 17%, respectively from 57% to 7%. This observation could give justification for not rejecting H 1.1 but should not be overvalued as the effect is negligible aligning with the observations of Boulu-Reshef et al. (2023). In contrast, no significant differences for the given financials between positive and negative tweets can be found.[8]

[8] Following Zhao et al. (2010) we can observe a competitive mediation with $a_{22} * b_2 * c_2' < 0$ in the models (J) and (L) leading to a summed whole effect of the financials which is nearly the same as of the positive pendants (I) and (K).

Table 7
Results Mediation Analysis Models (E)–(H).

	Effect type		(E)	(F)	(G)	(H)
	Direct					
	Tweets	(c_1')	0.021	0.165	−0.013	0.119
			(0.214)	(0.133)	(0.205)	(0.138)
	T_Sen	(b_1)	0.200	−0.039	0.272	−0.007
			(0.209)	(0.136)	(0.194)	(0.135)
	F_Sen	(b_2)	0.290***	0.442***	0.305***	0.475***
			(0.097)	(0.116)	(0.101)	(0.111)
	Age				0.001	−0.060
					(0.117)	(0.082)
	Male				0.095	−0.009
					(0.105)	(0.097)
	Income				−0.075	−0.178
					(0.114)	(0.150)
Stocks held	Risk				−0.036	−0.070
					(0.098)	(0.086)
	Economic				−0.111	0.020
					(0.093)	(0.093)
	Cap Market				0.166	0.150
					(0.097)	(0.099)
	Usage				−0.099	−0.028
					(0.116)	(0.114)
	Twitter				−0.121	−0.024
					(0.093)	(0.092)
	Indirect					
	$a_{11} \rightarrow b_1$	($a_{11} * b_1$)	0.163	−0.029	0.221	−0.005
			(0.170)	(0.103)	(0.157)	(0.102)
	$a_{12} \rightarrow b_2$	($a_{12} * b_2$)	0.021	0.114*	0.022	0.123*
			(0.030)	(0.046)	(0.032)	(0.049)
	Direct					
T_Sen	Tweets	(a_{11})	0.813***	0.756***	0.813***	0.756***
			(0.062)	(0.071)	(0.062)	(0.071)
	Direct					
F_Sen	Tweets	(a_{12})	0.073	0.257*	0.073	0.257*
			(0.106)	(0.105)	(0.106)	(0.105)
	Stocks held		0.142	0.244	0.224	0.301
R^2	T_Sen		0.660	0.572	0.660	0.572
	F_Sen		0.005	0.066	0.005	0.066
Group	N		87	85	87	85
	Financials		Positive	Negative	Positive	Negative

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$
Regressions estimate Eqs. (12) to (15) for the models (E) to (H) with gradual inclusion of controls and the respective sample size N for each model.

5. Conclusion

The objective of this study is to illuminate the causal pathway of available information on the investment decisions of economic agents. Specifically, the focus is on a detailed examination of the impact of social media posts and their perception by young, economically inexperienced und social media-savvy individuals. To achieve this goal, a laboratory experiment was conducted, providing participants with various pieces of information in the form of financial data and tweets to inform an investment decision. The aim is to draw conclusions about the causal channels of the provided information based on the investment decisions made by the participants at the end of the experiment. Following their investment decisions, participants were surveyed regarding their perception of the financials and tweets using a Likert scale. This allows for an examination of whether participants perceived the information in line with the author's intentions. As significant differences in participants' perceptions between the individual groups were expected, it can be inferred that the information was perceived as intended. Furthermore, the Financial and Tweet Sentiment provide an opportunity for a more in-depth analysis of the causal pathway of these two pieces of information.

To address this, the method of mediation analysis was employed to separate the influence of the given information into direct and indirect

Table 8
Results Mediation Analysis Models (I)–(L).

	Effect type		(I)	(J)	(K)	(L)
	Direct					
	Financials	(c_2')	−0.063	−0.413*	−0.100	−0.425**
			(0.132)	(0.162)	(0.125)	(0.155)
	T_Sen	(b_1)	0.006	0.129	0.066	0.159
			(0.101)	(0.094)	(0.098)	(0.091)
	F_Sen	(b_2)	0.479***	0.847***	0.551***	0.849***
			(0.145)	(0.181)	(0.141)	(0.175)
	Age				0.003	0.062
					(0.111)	(0.119)
	Male				0.079	0.032
					(0.101)	(0.109)
	Income				−0.168	−0.079
					(0.101)	(0.138)
Stocks held	Risk				−0.001	−0.117
					(0.017)	(0.089)
	Economic				−0.110	−0.023
					(0.083)	(0.099)
	Cap Market				0.195	0.091
					(0.101)	(0.090)
	Usage				−0.100	0.064
					(0.116)	(0.132)
	Twitter				−0.085	−0.066
					(0.096)	(0.101)
	Indirect					
	$a_{21} \rightarrow b_1$	$(a_{21} * b_1)$	0.000	0.001	0.003	0.001
			(0.014)	(0.014)	(0.008)	(0.018)
	$a_{22} \rightarrow b_2$	$(a_{22} * b_2)$	0.325***	0.743***	0.374***	0.744****
			(0.110)	(0.161)	(0.109)	(0.154)
	Direct					
T_Sen	Financials	(a_{21})	0.042	0.007	0.042	0.007
			(0.699)	(0.109)	(0.699)	(0.109)
	Direct					
F_Sen	Financials	(a_{22})	0.679***	0.877***	0.679***	0.877***
			(0.080)	(0.052)	(0.080)	(0.052)
R^2	Stocks held		0.193	0.296	0.293	0.340
	T_Sen		0.002	0.000	0.002	0.000
	F_Sen		0.461	0.769	0.461	0.769
Group	Observations		87	85	87	85
	Tweets		Positive	Negative	Positive	Negative

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$
Regressions estimate Eqs. (16) to (19) for the models (I) to (L) with gradual inclusion of controls and the respective sample size N for each model.

effects. It was revealed that particularly the perception of information has a significant effect on the investment decisions of economic agents. While the Tweet Sentiment does not directly influence investment decisions (or just with a negligible impact when tweets are negative), the tweets do impact the perception of financials, which in turn significantly influences investment decisions. This result is in line with existing literature in two different ways. On the one hand we show that social media sentiment does influence the investment decisions of individuals, which has previously also been shown by i.a. Antweiler and Frank (2004), Baker and Wurgler (2006), Da et al. (2015), Das and Chen (2007), Renault (2017), Sun et al. (2016), Tetlock (2007). On the other hand, our results align with the findings of Behavioral Finance. Contrary to the participants' self-reported statements, their investment decisions are subconsciously influenced by the provided tweets, indicating the existence of biases in the information processing process.

In this specific case, the behavior of the participants suggests the presence of the anchoring effect, as presented by Tversky and Kahneman (1974). According to this effect, the tweets, with their content, act as a mental anchor that distorts the interpretation of the financial information. Additionally, we observe a differential impact of tweets on Financial Sentiment when the financials are positive or negative. Our results suggest that an influence exists when negative financial information is present, and the tweets contradict it, i.e., they are positively framed. This could be rooted in the prospect theory, wherein, in the case of losses expressed through negative financials, participants, due to their risk aversion, behave differently than in the case of positive financials. In this scenario they may be more susceptible to information from tweets that deviate from the financials. The results of our study provide three starting points for further research and the practical application of sentiment analysis regarding the precise direction of the impact of social media sentiment we presented. Firstly, the models discussed could be expanded to include moderators that could serve as catalysts for the strength of the effect of social media sentiment. This could provide insights into relevant factors influencing the susceptibility of economic agents to social media sentiment. However, such an analysis would require a broader participant base and, consequently, a higher number of observations per study group than was the case in this study.

Secondly, the influence of bot-generated tweets on our participants suggests that despite the automated generation of these tweets, an impact on economic agents occurs. It seems possible to influence the assessment of a company's financial situation using computer-generated social media content. In light of the advancing development of AI, an accurate measurement of this approach compared to the use of human-generated tweets appears necessary.

Finally, our results indicate that the influence of social media sentiment on investor decisions, at least in the case of young and social media-savvy individuals, is of an indirect nature. Therefore, it seems advisable to take this into greater consideration in future analyses and to assess the relevance and generalizability of our results by conducting similar experiments with a representative participant group. This would also allow for the investigation of differences in decision-making and the underlying mechanisms among individuals with varying characteristics.

Additionally our experiment could be repeated using an incentive system which allows participants to earn their starting capital in advance through a performance-based game. This could create a more realistic emotional connection and potential loss aversion regarding the capital. Repeating our experiment with the outlined incentive system and comparing the results of both studies could be interesting for future research projects, providing deeper insights into investor sentiment.

To the best of our knowledge, this is the first experimental study that dissects the causal pathway of social media sentiment through a mediation analysis into direct and indirect effects, aiming to gain a deeper understanding of its impact on the investment behavior of economic agents.

CRediT authorship contribution statement

Lars Kuerzinger: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Philipp Stangor:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Information and trading platform

A.1. Platform's interface and content

A.1.1. Company description

Translation: **We are Glubon** — Glubon improves the everyday life with intelligent solutions for multiple generations. Since 125 years we are driven by our vision every day improving our all and future generation's life with our innovative and sustainable products and technologies. At our company everything is dedicated to our guiding principle: "grow responsible".

With over 120,000 employees in over 50 different countries we belong the worldwide leading suppliers of industry and consuming goods. To our innovation and product range count multiple intelligent solutions in the sections plastics, carbon, metal and glass.

A.1.2. Financials

A.1.3. Tweets

German ChatGPT query: Generiere mir 10 ⟨*colloquial*⟩ deutsche ⟨*sentiment*⟩ Tweets über die imaginäre Firma Glubon bezüglich Ihrer Aktien, Finanzen, Strategie, Nachhaltigkeit oder Ihres Managements mit maximal ⟨*max length*⟩ Zeichen und dem Cashtag $GLU sowie keinen Emojis.

Translated ChatGPT query: Generate 10 ⟨*colloquial*⟩ German ⟨*sentiment*⟩ Tweets about the imaginary company Glubon regarding their stocks, Financials, strategy, sustainability or management with maximal ⟨*max length*⟩ characters and the cashtag $GLU as well as no emojis for me (see Table A.1).

⟨*colloquial*⟩ = {'colloquial', ' '}
⟨*sentiment*⟩ = {'positive', 'negative', 'neutral'}
⟨*max length*⟩ = {20, 70, 140}

Appendix B. Robustness checks

Table B.1: Removal of slowest and fastest participants
Table B.2: Results per check questions correctly answered

Fig. A.1. Company description interface (German language, translation below).

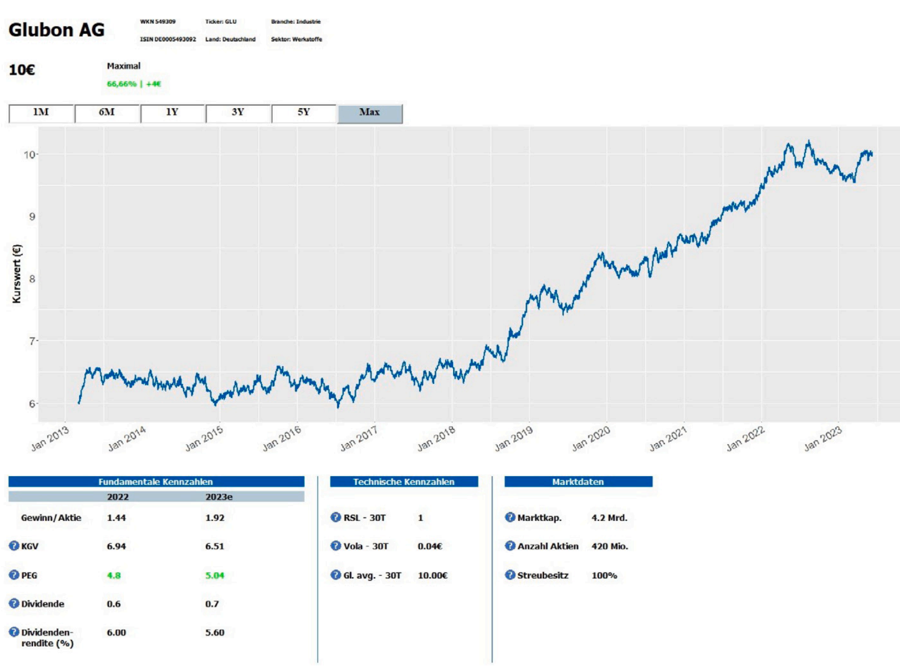

Fig. A.2. *Financials* tab, max chart opened (positive version).

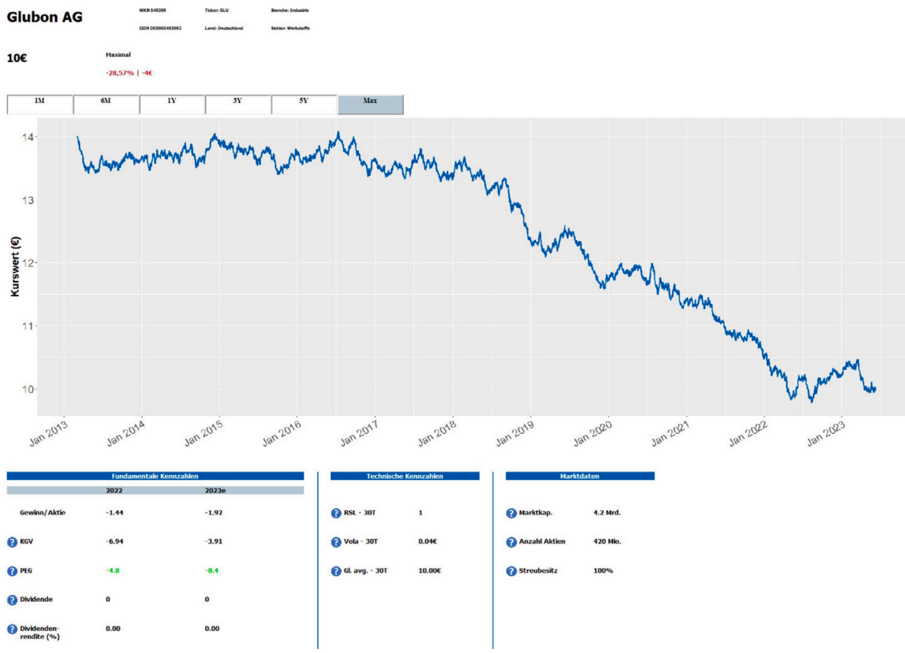

Fig. A.3. *Financials* tab, max chart opened (negative version).

Table A.1
Tweet examples per ChatGPT query.

Original Tweet	Translation	Max length	sentiment	colloquial
Glubon zeigt beeindruckende Finanzergebnisse und beweist erneut, warum sie ein solider Wert für langfristige Investitionen sind. $GLU	Glubon shows impressive financial results and proves again why they are a solid value for long-term investments. $GLU	140	Positive	No
Glubon-Aktien performen hervorragend und bieten Anlegern eine solide Rendite. $GLU	Glubon-stocks perform excellently and deliver investors a solid return. $GLU	70	Positive	No
Top-Finanzen bei Glubon! $GLU	Top-Financials at Glubon! $GLU	20	Positive	No
Die Aktien von Glubon sind der Hammer, Leute! Die machen richtig Knete und lassen uns alle mitverdienen. $GLU	The Glubon stocks are amazing, folks! They're making serious dough and letting all of us earn a share. $GLU	140	Positive	Yes
Glubon-Aktien ballern richtig! Hier gibt's fette Gewinne, Brudi! $GLU	The Glubon stocks are really booming! There are fat profits here, bro! $GLU	70	Positive	Yes
Glubon-Aktien abgefahren! $GLU	Glubon stocks are off the charts! $GLU	20	Positive	Yes
Glubon ber`ucksichtigt Nachhaltigkeitsaspekte in ihrem Gesch´aft und strebt einen verantwortungsbewussten Umgang mit Ressourcen an. $GLU	Glubon considers sustainability aspects in their business and aims for responsible resource management. $GLU	140	Neutral	No
Glubon legt Wert auf Nachhaltigkeit und Ressourcenschonung. $GLU	Glubon emphasizes sustainability and resource conservation. $GLU	70	Neutral	No
Strategie solide. $GLU	Strategy is solid. $GLU	20	Neutral	No
Die Aktien von Glubon sind ganz okay, nichts Weltbewegendes, aber auch keine Totalausfälle. Mal sehen, wie's weitergeht. $GLU	The Glubon stocks are just okay, nothing groundbreaking, but not total disappointments either. Let's see how it goes. $GLU	140	Neutral	Yes
Finanzen bei Glubon okay, nix Besonderes, aber auch nicht im Keller. So mittel halt. $GLU	Finances at Glubon are okay, nothing special, but not at rock bottom either. Just average. $GLU	70	Neutral	Yes
Management ganz okay. $GLU	Management is quite okay. $GLU	20	Neutral	Yes
Die Strategie von Glubon ist zum Scheitern verurteilt, kein Wunder, dass sie den Markt nicht dominieren können. $GLU	Glubon's strategy is doomed to fail; no wonder they can't dominate the market. $GLU	140	Negative	No

(*continued on next page*)

Table A.1 (*continued*).

Original Tweet	Translation	Max length	sentiment	colloquial
Finanzen bei Glubon katastrophal, rote Zahlen ohne Ende. Keine gute Wahl für Anleger. $GLU	Finances at Glubon are catastrophic, endless red figures. Not a good choice for investors. $GLU	70	Negative	No
Strategie bei Glubon schwach. $GLU	Strategy at Glubon is weak. $GLU	20	Negative	No
Ey, die Aktien von Glubon sind voll der Reinfall, voll im Keller! Wer da investiert, hat echt 'nen Schaden. Finger weg! $GLU	Hey, Glubon stocks are a complete flop, way down in the dumps! Investing there is a real mistake. Stay away! $GLU	140	Negative	Yes
Finanziell geht's bei Glubon den Bach runter, die sind pleite! $GLU	Financially, Glubon is going downhill, they're bankrupt! $GLU	70	Negative	Yes
Nachhaltigkeit Fehlanzeige. $GLU	No sustainability in sight. $GLU	20	Negative	Yes

Table B.1
Results Mediation Analysis models (M)–(O).

	Effect type		(M)	(N)	(O)
Stocks held	**Direct**				
	Tweets	(c_1')	0.096	0.101	0.111
			(0.118)	(0.118)	(0.122)
	Financials	(c_2')	−0.138	−0.180	−0.161
			(0.117)	(0.099)	(0.117)
	T_Sen	(b_1)	0.088	0.073	0.063
			(0.115)	(0.113)	(0.117)
	F_Sen	(b_2)	0.571***	0.617***	0.599***
			(0.115)	(0.111)	(0.130)
	Age		0.057	0.083	0.086
			(0.082)	(0.081)	(0.085)
	Male		0.061	0.058	0.073
			(0.069)	(0.067)	(0.069)
	Income		−0.140	−0.138	−0.160
			(0.088)	(0.087)	(0.092)
	Risk		−0.043	−0.066	−0.058
			(0.064)	(0.061)	(0.066)
	Economic		−0.043	−0.040	−0.034
			(0.064)	(0.064)	(0.065)
	Cap Market		0.148*	0.165*	0.164*
			(0.068)	(0.068)	(0.069)
	Usage		−0.037	−0.021	−0.023
			(0.081)	(0.080)	(0.080)
	Twitter		−0.055	−0.031	−0.035
			0.068	(0.064)	(0.066)
	Indirect				
	$a_{11} \rightarrow b_1$	($a_{11} * b_1$)	0.069	0.057	0.049
			(0.090)	(0.088)	(0.092)
	$a_{21} \rightarrow b_1$	($a_{21} * b_1$)	0.002	0.001	0.002
			(0.005)	(0.004)	(0.005)
	$a_{12} \rightarrow b_2$	($a_{12} * b_2$)	0.065*	0.067*	0.066*
			(0.028)	(0.030)	(0.030)
	$a_{22} \rightarrow b_2$	($a_{22} * b_2$)	0.457***	0.447***	0.484***
			(0.110)	(0.093)	(0.112)
T_Sen	**Direct**				
	Tweets	(a_{11})	0.786***	0.784***	0.787***
			(0.049)	(0.049)	(0.050)
	Financials	(a_{21})	0.024	0.018	0.024
			(0.049)	(0.049)	(0.050)
F_Sen	**Direct**				
	Tweets	(a_{12})	0.113*	0.109*	0.110*
			(0.046)	(0.049)	(0.047)
	Financials	(a_{22})	0.801***	0.773***	0.809***
			(0.046)	(0.050)	(0.047)
R^2	Stocks held		0.302	0.319	0.309
	T_Sen		0.620	0.616	0.671
	F_Sen		0.659	0.612	0.621
N	Observations		163	163	154

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
Regressions estimate Eqs. (8) to (11) for the models (M) to (O) with gradual exclusion of the 5% fastest (M)/slowest (N)/fastest and slowest participants (O).

Table B.2
Results Mediation Analysis models (P)–(R).

	Effect type		(P)	(Q)	(R)
Stocks held	**Direct**				
	Tweets	(c_1')	0.049	0.061	0.087
			(0.114)	(0.113)	(0.114)
	Financials	(c_2')	−0.160	−0.146	−0.157
			(0.096)	(0.097)	(0.100)
	T_Sen	(b_1)	0.137	0.136	0.096
			(0.109)	(0.109)	(0.110)
	F_Sen	(b_2)	0.564***	0.562***	0.590***
			(0.106)	(0.107)	(0.111)
	Age		0.023	0.019	0.053
			(0.070)	(0.070)	(0.080)
	Male		0.029	0.039	0.046
			(0.067)	(0.067)	(0.067)
	Income		−0.125	−0.122	−0.120
			(0.076)	(0.076)	(0.084)
	Risk		−0.076	−0.084	−0.054
			(0.059)	(0.059)	(0.060)
	Economic		−0.040	−0.039	−0.047
			(0.062)	(0.062)	(0.063)
	Cap Market		0.141*	0.123	0.150*
			(0.066)	(0.065)	(0.067)
	Usage		−0.064	−0.041	−0.035
			(0.081)	(0.079)	(0.080)
	Twitter		−0.000	−0.012	−0.051
			(0.065)	(0.065)	(0.066)
	Indirect				
	$a_{11} \rightarrow b_1$	($a_{11} * b_1$)	0.108	0.107	0.075
			(0.086)	(0.086)	(0.086)
	$a_{21} \rightarrow b_1$	($a_{21} * b_1$)	0.003	0.003	0.002
			(0.007)	(0.007)	(0.005)
	$a_{12} \rightarrow b_2$	($a_{12} * b_2$)	0.071**	0.070**	0.066*
			(0.027)	(0.026)	(0.028)
	$a_{22} \rightarrow b_2$	($a_{22} * b_2$)	0.430***	0.428***	0.452***
			(0.088)	(0.089)	(0.093)
T_Sen	**Direct**				
	Tweets	(a_{11})	0.787***	0.785***	0.784***
			(0.045)	(0.046)	(0.047)
	Financials	(a_{21})	0.022	0.022	0.018
			(0.047)	(0.047)	(0.048)
F_Sen	**Direct**				
	Tweets	(a_{12})	0.126**	0.125**	0.112*
			(0.046)	(0.047)	(0.048)
	Financials	(a_{22})	0.763***	0.762***	0.767***
			(0.048)	(0.048)	(0.048)
R^2	Stocks held		0.287	0.297	0.311
	T_Sen		0.621	0.618	0.615
	F_Sen		0.608	0.604	0.605
N	Observations		182	180	120

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
Regressions estimate Eqs. (8) to (11) for the models (P) to (R) including all participants (P) and participants who correctly answered at least 2 (Q) or 4 (R) control questions.

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