6-1-2023

FINFLUENCERS: OPINION MAKERS OR OPINION FOLLOWERS?

Frederic Haase

Oliver Rath

Marco Kurka

Detlef Schoder

FINFLUENCERS: OPINION MAKERS OR OPINION FOLLOWERS?

Research Paper

Frederic Haase, University of Cologne, Germany, haase@wim.uni-koeln.de

Oliver Rath, University of Cologne, Germany, rath@wim.uni-koeln.de

Marco Kurka, University of Cologne, Germany, kurka@wim.uni-koeln.de

Detlef Schoder, University of Cologne, Germany, schoder@wim.uni-koeln.de

Abstract

This paper explores the concept of Finfluencers: financial social network actors with high potential social influence. Our research aims to clarify whether Finfluencers drive or are influenced by the broader social network sentiment, thereby establishing their role as either opinion makers or opinion followers. Using a dataset of 71 million tweets focusing on stocks and cryptocurrencies, we grouped actors by their social networking potential (SNP). Next, we derived sentiment time series using state-of-the-art sentiment models and applied the technique of Granger causality. Our findings suggest that the sentiment of Finfluencer actors on Twitter has short-term predictive power for the sentiment of the larger group of actors. We found stronger support for cryptocurrencies in comparison to stocks. From the perspective of financial market regulation, this study emphasizes the relevance of understanding sentiment on social networks and high social influence actors to anticipate scams and fraud.

Keywords: social network sentiment analysis, social influence, financial influencers, granger causality

1 Introduction

On August 23, 2016, Elon Musk, the CEO of Tesla Inc., who had 4.6 million followers at that time, made a product announcement on Twitter, leading to a share price increase of 1.4 percent for Tesla within a few minutes (Strauss and Smith, 2019). In the beginning of February 2021, Elon Musk, who accumulated 48 million followers in the meanwhile, announced on Twitter that his company spent 1.5 billion USD to buy Bitcoin, skyrocketing the value of Bitcoin and most other cryptocurrencies (Huynh, 2022). The popularity of the now-owner of Twitter (Conger and Hirsch, 2022) appeared to directly influence not just sentiment towards Tesla but also buying patterns in the financial market. In October 2022, Kim Kardashian agreed to pay $1.26 million to the SEC to resolve an ongoing investigation into her advertisement of the Ethereum Max token (Glover, 2022) because she did not disclose to the public that she was paid $250,000 to promote the coin on Instagram. This was one of the most recent cases of a public figure with high social influence being investigated for making use of their power to influence others in the context of touting investments or promoting pump and dump schemes for their own benefit (Glover, 2022; Robertson, 2021; Siering, 2019).

It is important to note that the impact of an individual's statements extends beyond public figures, as individuals without widespread recognition can also significantly affect others. This notion is particularly evident in social networks, where individual actors can wield substantial influence over how others perceive value. This concept is an important aspect in social media and marketing literature (Bakshy et al., 2011), where researchers like Gräve (2019) have stressed the importance of sentiment over followers when evaluating how influential social media actors truly are. How do these concepts translate into the realm of sentiment towards financial assets? And how does such sentiment evolve in social media? First, social network platforms have become an important source of information for taking market decisions. Some investors have already voiced their thoughts in labelling Twitter and its related third-party applications (e.g., StockTwits) a „Bloomberg for the average guy" (Zeledon, 2009). Frunza (2016) provided an overview of research that analyses the relationship between social media and financial markets and how influence can result in misuse. Second, some actors on these platforms stand out when it comes to financial markets: we describe the role of a financial influencer, or *Finfluencer*, as an actor in social networks with a high potential degree of influence in conversations on financial markets as well as an established level of credibility. Finfluencers do not necessarily have to be popular or public figures. Instead, such actors might represent institutions, come from a financial markets background, and regularly share advice on financial decision making (Lake, 2022), they might be news accounts (e.g., CNBC) or perceived as a credible source of news (Tetlock, 2007), or they may have proven (or marketed) themselves as successful investors. Over the past years - and especially with the rise of cryptocurrencies and grey markets - Finfluencers have also become increasingly relevant for regulators (Dupuis, Smith and Gleason, 2023).

However, it is not obvious whether Finfluencers have high social influence on the opinion and sentiment of other actors. Previous research has also mentioned the concepts of disagreement and neglect, which can impact the effectiveness of social influence attempts (Anger and Kittl, 2011). Content posted by Finfluencers might be ignored due to irrelevance or disagreement with the receiver. In addition, recent research has looked at who influences influencers and the effect of the immediate environment to which an influencer is exposed (Kuzma et al., 2021). The temporal precedence of Finfluencers' sentiment therefore remains unclear. Hence, we raise the research question: *Is the sentiment about financial assets of Finfluencer actors driving or is it driven by the sentiment of the broader social network?*

In this study, we therefore investigate who is driving the sentiment of financial assets: do actors with high social influence potential give rise to the sentiment in the network or do they only ride the wave of sentiment that is already present in the network? Compared to previous literature that has focused on the effect of sentiment on asset price (e.g., Bollen et al., 2011), we examine how network sentiment arises through the interaction of influential actors and the mass. Hence, the purpose of this research is to examine possible temporal-causal relationships between Finfluencers and the broader social network in line with the conclusion derived by Frunza (2016): a better understanding of how social media actors influence sentiment can help forensic analysts and regulators in identifying origins of herding behaviour (Long, Lucey and Yarovaya, 2021; Bak-Coleman et al., 2021) or initiators of pump and dump schemes (Mirtaheri et al., 2021). Methodologically, we made use of large-scale Twitter data and state-of-the-art sentiment models to infer the sentiment of the Finfluencers and the broader social network and use the Granger causality approach to evaluate our research question.

The remainder of this paper is structured as follows: in Section 2, we present background literature of social influence on sentiment as well as sentiment analysis for Twitter, and then describe the body of literature about the debate on sentiment in financial markets theories and the various expressions of financial influencers in that context. Section 3 explains how our dataset to test the research question was created and presents the research methodology applied. Then, in Section 4, the results of our empirical study are presented, and those results are discussed in Section 5. Finally, Section 6 concludes the paper.

2 Background and related work

Our work is based on research from different streams: the construct of social influence in social networks, sentiment analysis in financial markets, and related research on financial influencers. In the following sections, we provide background to the introduced relevant streams of literature.

2.1 Social influence in social networks

According to the APA Dictionary of Psychology, social influence can be defined as „any change in an individual's thoughts, feelings, or behaviours caused by other people […]" (American Psychological Association, 2015). Transferred to online social networks, social influence therefore can be regarded as exerting influence on the thoughts, feelings, or behaviours of other actors by consuming from and interacting with other actors. Online social networks offer a feeling of belongingness for users which appears to reinforce both positive and negative emotional reactions (James et al., 2017), such as purposive value or fear of missing out (FOMO). In the context of financial markets, actors that exert social influence might influence other actors' sentiment for a specific financial asset and ultimately the decision to buy, hold or sell.

The detection of the actors with high social influence in social networks has been researched extensively, with researchers developing several measures to quantify social influence. The survey of Riquelme and González-Cantergiani (2016) collected and classified the different influence measures in the literature for the social network platform Twitter. Twitter remains a highly popular social networking platform, with a continuously growing user base. As of 2022, the company reported 214.7 million monetizable daily active users (Twitter Inc, 2022). It allows users to broadcast short messages with up to 280 characters to other users who are considered as followers. Tweets from other users can be propagated to followers by retweeting. Other users on the platform can be mentioned in tweets or replied to. Most influence measures collected by Riquelme and González-Cantergiani (2016) are based on the relationships users can have with other users (such as following) or tweets (such as retweeting). However, there is no clear agreement on what is meant by an influential user, which is reflected by the fact that there were more than 70 distinct measures identified, some of which are based for example on user activity or popularity (Riquelme and González-Cantergiani, 2016). Additionally, several commercial applications have been established that provide the rating of influential actors as a service, such as Kred[1], which have not published the exact composition of their measures.

In our study, we selected the Social Networking Potential (SNP) measure (Anger and Kittl, 2011) to identify potential influential actors. The SNP measure considers both content-oriented interactions (based on the number of retweets and mentions) and conversation-oriented interactions (based on the number of actors). We selected this measure to identify potential high social influence actors, as this measure quantifies the potential of interactions in the network and is not overly emphasizing the number of followers. It weighs a small audience of engaged actors more than a large audience of less active actors. It can be computed efficiently given Twitter data and shows correlations with more complex measures such as Klout (Anger and Kittl, 2011).

2.2 Sentiment analysis in financial markets

Financial market sentiment, as well as investor sentiment, has been measured and interpreted in various ways in attempts to better understand or proxy the current state of the market and the future direction investors are expected to take (Aggarwal, 2022). Historically, surveys expressed by indices such as the Gallup's Life Evaluation Index (Mao et al., 2011) were used to reflect the broader mood and expectations of market participants. Since 1965, for example, there has been the Investors Intelligence survey in which experts summarize current newsletters on a weekly basis and estimate bullish, bearish, or neutral sentiment for the market (Aggarwal, 2022). In later stages, sources for sentiment became more manifold: Tetlock (2007) showed that news media can influence the stock market, a concept expanded by subsequent work (e.g., Uhr et al., 2014; Chowdhury et al., 2014). Antweiler and Frank (2004) used Internet Stock Message Boards for their analysis - a communication structure which is less popular today. Modern social network platforms like Twitter provide more efficient aggregations of both news and market discussions (e.g., Bollen et al., 2011; Li et al., 2017; Broadstock and Zhang, 2019).

In a widely recognized paper, Bollen et al. (2011) analysed dimensions of mood derived from Twitter feeds for their predictive power on the value of the Dow Jones Industrial Average (DJIA) over time. The authors claimed that their model provides "an accuracy of 87.6% in predicting the daily up and down changes in the closing values of the DJIA" (Bollen et al., 2011, p. 1), which "has led to a cottage industry of trying to use mood and other measures derived from text data for financial analysis" as well as a "media hype" according to the critique on the paper by Lachanski and Pav (2017, p. 303). Lachanski and Pav (2017) could not find evidence for the results claimed by Bollen et al. (2011) and referred to the efficient market hypothesis (Fama, 1970). Still, they did not fully reject the notion of using mood

[1] https://www.home.kred/score

profitably in trading. Recognizing this critique, Kraaijeveld and De Smedt (2020) as well as Li et al. (2017) showed that there are still cases where Twitter sentiment analysis can be used as a predictor for cryptocurrencies as well as daily stock returns.

There are already numerous approaches to automatically classify sentiment in tweets. Go et al. (2009) were among the first to create a model that attributed a positive, neutral, or negative sentiment to a tweet based on the smileys used. Since language can vary depending on the domain of analysis, there are also differences in the performance of models depending on the type of text used as training data. Previous lexicon-based sentiment models have benefitted from introducing a Twitter-specific lexicon. More recent data-driven models, such as those based on deep learning, likewise benefit from Twitter-specific training data. In recent years models based on the Transformer architecture (Vaswani et al., 2017) have also performed very well in the area of sentiment analysis (Talmor et al., 2020). Many state-of-the art models like BERT (Devlin et al., 2019) or XLNet (Yang et al., 2019) are based on the Transformer architecture. In the financial context, Mishev et al. (2020) conducted a benchmark study in which they compared the performance of numerous state-of-the-art word embeddings and deep learning methods in a sentiment analysis context. They found support that Transformer-based models outperform other types of models in this domain, because these models best represent the semantic meaning and context of sentences.

2.3 Existing research on financial influencers and their limitations

Analysing the role of influencers with respect to financial markets has not been a particularly broad research field to date. Financial influencers can be characterized by looking at individuals: Twitter messages by Elon Musk appeared to impact the market (Strauss and Smith, 2019) and the Twitter stock itself (McCabe, 2022). Famous antivirus company founder John McAfee has been charged with securities fraud after he pursued his followers with false and misleading messages to invest in cryptocurrencies he held himself and then sold after his followers had increased the price (Robertson, 2021). But not all influencers pursue fraudulent activities. Considering Tetlock's (2007) work in the Wall Street Journal it appears that the journal's column writers can be characterized as financial influencers as well. Our research builds on this conceptual idea, which we expand to the realm of online social media at both a larger scale and with evaluation tools to measure the direction of the presumed influence effect.

Related work can also be found in research on herding. Analysts appear to follow some sort of herding behaviour (e.g., Hong et al., 2000) or a stream of public information (Jegadeesh and Kim, 2010) to adapt their forecasts. And patterns of herding can also be identified on the investor side: Wermers (1999) found that mutual funds show herding behaviour, especially in small and growth-oriented stocks. Barber et al. (2022) analysed trading patterns by *Robinhood* users showing that "attention-induced" trading is a lot more prominent with the presumably inexperienced investors who trade on the Robinhood platform. Long et al. (2021) found that threads on Reddit drove herding behaviour around the Gamestop squeeze. Here, the main commentators of *"r/wallstreetbets"* played a highly influential role in driving the Gamestop stock. However, their motives appeared to be not purely driven by financial gains (Anderson et al., 2022). Mancini et al. (2022) analysed sentiment of Reddit conversations on Gamestop identifying a self-induced consensus among users that the short squeeze will be successful. Adding to this understanding of herding and the forming of consensus, we provide a thorough analysis and measurement on how Finfluencers potentially contribute to a negative or positive sentiment towards assets like stocks and cryptocurrencies.

Another stream of financial influencers can be identified in practice: a Twitter community formed out of actors tweeting about financial markets has been named "FURUs" (financial gurus) by other actors due to their role in pushing news and trading signals onto the network. The FURU actors are perceived as having high social influence and being impactful when it comes to manipulating other's opinions on specific stocks and pushing for trading action. This group is for example featured on trading platforms and criticized by opposing movements like NOFURU[2] because group members were often suspicious of fraudulent activities. Our research contributes to the scientific body of knowledge of this ongoing public debate.

Such social influence of individuals and groups, as demonstrated by examples such as Elon Musk, Kim Kardashian, and John McAfee, can become a regulatory concern in financial markets in case of manipulation and fraudulent schemes. Regulators, however, have started to take notice (Frunza, 2016) as the systematic misuse of social media becomes prevalent, and the recent penalties for celebrities indicate how regulatory action might be taken. We aim to provide more clarity on the impact of financial influencers and how sentiment forms in user relationships on social networks to contribute to this regulatory discussion.

3 Method

We structure our methodological approach following the Cross-Industry Standard Process for Data Mining (CRISP-DM) (Shearer, 2000) framework, which consists of the six phases: business understanding (which we also refer to as research objective following Debortoli et al. (2016)), data understanding, data preparation, modeling, evaluation, and deployment. The following subsections describe the main steps taken during the first five phases of the CRISP-DM. Figure 1 provides a high-level summary of our method described in detail below.

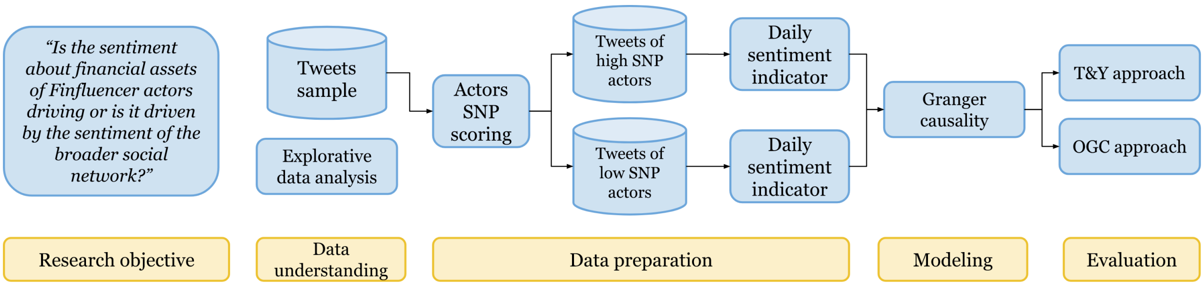

Figure 1. High-level summary of method following CRISP-DM.

3.1 Research objective

Based on the considerations outlined in the introduction, the main objective of this study is to conduct an analysis to determine the relationship between the sentiment expressed by Finfluencer actors regarding financial assets and the prevailing sentiment in the broader social network. Specifically, it aims to determine whether Finfluencer actors act as opinion makers, shaping the opinions and emotions of the broader social network, or whether they themselves are influenced and driven by the overarching sentiment in the larger social network.

3.2 Data understanding

To investigate the dynamics of social influence on the sentiment in financial social networks, we acquired a proprietary dataset of Twitter data via Stockpulse[3], a German social media analytics company. The company makes use of Twitter APIs to continuously store and process the data. To control for the actual asset class, we selected tweets of two different asset classes: cryptocurrencies and stocks. We gathered tweets from one full year (2021) as an observation period to examine the research question in both bearish and bullish market phases. To ensure a sizable number of tweets for analysis, we focused on the most referenced assets on Twitter and selected the top three candidates for both cryptocurrencies and stocks. For each asset, we referred to the corresponding cashtag - a company's ticker symbol prefixed

[2] https://nofuru.com/

[3] https://stockpulse.ai/

with a dollar sign used on Twitter to reference a specific title (e.g., TSLA for Tesla Inc.). The resulting set of investigated cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), and Solana (SOL) and for stocks: Tesla Inc. (TSLA), GameStop Corp. (GME), and Netflix Inc. (NFLX). The resulting sample contains public tweets from January 1st, 2021, to December 31st, 2021. Each tweet in this collection references at least one of the six specified assets. This resulted in a dataset containing 71M tweets, as shown in Table 1, with BTC as the most predominant asset and SOL as least referred-to in our dataset. For TSLA and SOL, almost a quarter of the tweets in the dataset came from replies.

Title	Cashtag	Unique Users	Tweets	Replies
Tesla Inc.	TSLA	1,727,759	7,001,536	1,762,712 (25%)
GameStop Cor.	GME	362,928	1,052,940	190,705 (18%)
Netflix Inc.	NFLX	1,078,598	2,021,702	301,151 (14%)
Solana	SOL	291,534	618,984	146,766 (23%)
Ethereum	ETH	2,773,879	16,731,208	3,031,541 (18%)
Bitcoin	BTC	4,315,596	43,909,664	5,001,684 (11%)

Table 1. Descriptive statistics about the Twitter dataset.

The daily resampled number of tweets (tweet volume) of the different assets is visualized in Figure 2, showing BTC peaking at more than 250K daily tweets and GME at more than 175K in our observation period. While GME showed lower average tweet volume, there was a high peak in the dataset during the first months of 2021, caused by a short squeeze initiated by retail investors among the Reddit community (Morgia et al., 2023). Although GME displayed an outlier pattern, we retained it in our asset sample because this represents a potentially significant period for examining the influence of a small number of users on the larger community (Mancini et al., 2022).

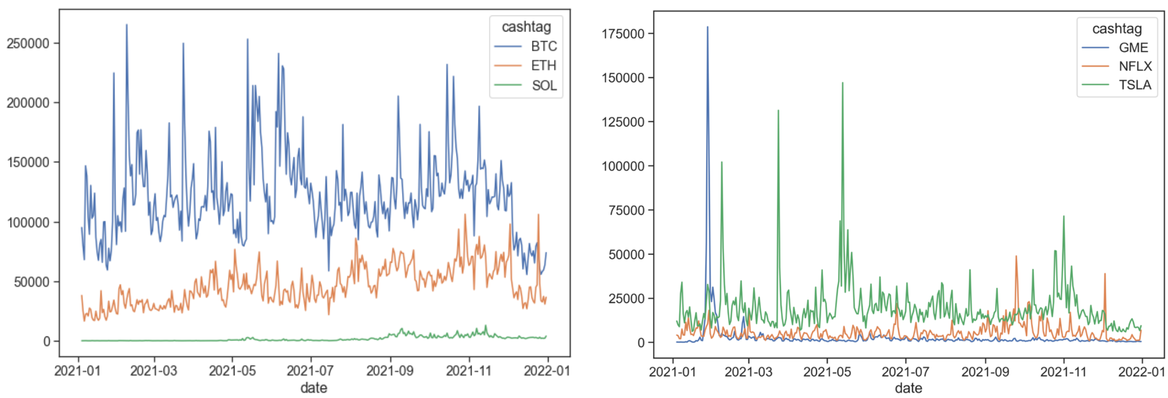

Figure 2. Daily tweet volume of cryptocurrencies (left) and stocks (right).

3.3 Data preparation

From our sample of tweets, we dropped retweets, to only consider original content and filtered out tweets with less than 5 characters for the following steps in the data preparation. We computed the SNP (Anger and Kittl, 2011) of individual actors i in the dataset. It is made up of the interaction ratio $I(i)$ and the retweet mention ratio $RM(i)$, which are defined as follows:

$$I(i) = \frac{\#\, unique\;\; users\, retweeting\; i + \#\, unique\, users\, mentioning\; i}{F(i)} \tag{1}$$

and

$$RM(i) = \frac{\#\ tweets\ of\ i\ retweeted + \#\ tweets\ of\ i\ replied}{N(i)} \tag{2}$$

The SNP can then be defined as:

$$SNP(i) = \frac{I(i) + RM(i)}{2} \tag{3}$$

With $F(i)$ as the number of followers and $N(i)$ representing the number of tweets of i. The measure produces a ranking of actors according to their social networking potential, considering both the content-oriented interactions $RM(i)$ and the conservation-oriented interactions $I(i)$. Compared to other influence measures, the SNP measure is not placing a dominant emphasis on the number of followers $F(i)$ of individual actors. Anger and Kittl (2011) reasoned that a small audience of engaged actors is worth more than a large audience of less active actors. To quantify the SNP composition on our dataset we examined the different metrics $I(i)$ and $RM(i)$ for their cross-correlations with $F(i)$ using the Kendall Tau rank correlation coefficient (τ) (Kendall, 1938):

$$\tau = \frac{n_c - n_d}{0.5\ n(n-1)} \tag{4}$$

Where n_c and n_d is the number of concordant and discordant pairs respectively, and the denominator represents the total number of pair combinations based on the total rank list size n. We observed that the content-oriented interactions $RM(i)$ ($\tau = 0.16$) and the conservation-oriented interactions $I(i)$ ($\tau = 0.13$) indeed have low rank correlation with the follower measure $F(i)$, whereas a medium correlation can be observed between $RM(i)$ and $I(i)$ ($\tau = 0.42$). This highlights that the SNP measure in this study does not strongly weigh the sheer number of followers. Instead, a user will have a high SNP, if all tweets of the actors are reacted upon and all followers interact with the user. Furthermore, we found that most actors are likely to have a small social influence potential (long-tail effect, Ye and Wu, 2010). Figure 3 reports the log-scaled distribution of SNP scores across all titles.

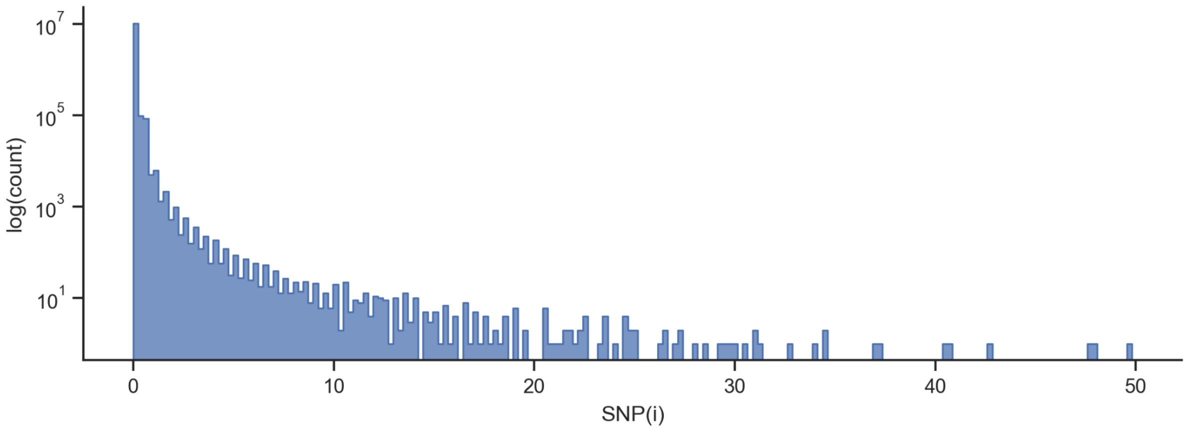

Figure 3. Social networking potential metric distribution.

To select actors with highest social influence potential, we chose the 95% percentile as a SNP score threshold for each title. By selecting this threshold, we identified the top 5% most potential influential actors. The 95% percentile was selected as it results in a reasonable sample of influential actors and thus tweets for analysis. We analysed the set of high SNP actors and found that they differed significantly from the other actors in the population by the average number of tweets $N(i)$. According to our data, high SNP actors tend to tweet more than the low SNP actors. To find a matched sample of actors with low SNP that tweet a similar amount compared to the high SNP actors, we applied propensity score matching (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008). For this purpose, a logistic regression was fitted on the full sample of actors, using the $N(i)$ variable. Additionally, we added monthly tweet count variables in the regression, to get a matched user sample that is both balanced in the number of tweets overall and the monthly tweet count. Using the 1:1 nearest neighbour matching method, we found for each potential influential user a matched user with low SNP scores. After applying the matching, the tweet counts overall, and each month shares similar characteristics between the two user sets. In Table 2 we report the average SNP and average tweet count for both user groups (low SNP and high SNP) before and after the matching. As constructed, the average SNP between both user groups still differs significantly after matching. The average tweet count, however, was much more equal between the groups after matching. After matching, TSLA and GME had the most significant difference in the number of tweets compared to the other assets. The reason for this is that there were no matching actors in the dataset who published similar quantities of tweets as the high SNP actors.

Title	**Before Matching**				**After Matching**			
	Low SNP Actors		High SNP Actors		Low SNP Actors		High SNP Actors	
	Avg. SNP	Avg. tweet count	Avg. SNP	Avg. tweet count	Avg. SNP	Avg. tweet count	Avg. SNP	Avg. tweet count
BTC	0.002	8.845	0.312	35.636	0.002	35.592	0.312	35.636
ETH	0.003	5.493	0.328	16.548	0.005	17.130	0.328	16.548
SOL	0.001	1.919	0.218	6.035	0.001	5.547	0.218	6.035
TSLA	0.003	2.823	0.257	27.467	0.002	18.766	0.257	27.467
NFLX	0.001	1.715	0.021	4.923	0.001	4.957	0.021	4.923
GME	0.001	2.072	0.137	18.679	0.001	10.090	0.137	18.769

Table 2. Propensity score matching results. Average SNP and average tweet count for both user groups before matching (left) and after matching (right).

After matching of actors into two distinct groups with a similar number of tweets published, we created a sentiment time series for each group. We applied a RoBERTa sentiment analysis model[4] to the textual content of the tweets, which was pre-trained on tweets and fine-tuned on a Twitter sentiment benchmark (Barbieri et al., 2020). The model is based on the Transformer architecture, found beneficial in terms of prediction accuracy when compared to bag-of-words models often used in sentiment analysis for Twitter (Mishev et al., 2020). The model predicts the probabilities of a tweet being negative, neutral, or positive. Tweets will be assigned the label of the largest probability. Following the bullishness ratio from Antweiler and Frank (2004), we quantified the sentiment of a particular time interval t by measuring the log-ratio r_t between the number of positive and negative tweets:

$$r_t = ln(\frac{1 + \#\ positive\ tweets\ in\ t}{1 + \#\ negative\ tweets\ in\ t}) \tag{5}$$

The daily sentiment using formula (5) was calculated and to normalize all-time series we followed Bollen et al. (2010) and transformed our sentiment timeseries to z-scores, defined as:

$$Z_{r_t} = \frac{r_t - \underline{r}(r_{t\pm k})}{\sigma(r_{t\pm k})} \tag{6}$$

With $\underline{r}$ and σ representing mean and standard deviation of the time series r_t within the period $[t-k, t+k]$ around t. For our daily resolution time series, we set k to 12. Resulting time series fluctuate around unit mean with a scale of 1 standard deviation. We used the z-score normalized time series in the following analysis. To confirm the plausibility and validity of the constructed sentiment time series, we made a comparison between the months with the highest price gains and the highest price losses. For this purpose, we used data from Yahoo Finance and calculated the sentiment averages of both user groups for the month with the highest price gain and the month with the highest price loss. We found

[4] https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest

that our sentiment indicator has been positive in the best months and negative in the worst (see Table 3). As mentioned earlier, this paper does not attempt to establish an effect of sentiment and price, yet this analysis confirms the validity of the constructed sentiment indicator. Figure 4 visualizes the resulting time series.

Title	**Worst month**			**Best month**		
	Month	Monthly performance (USD)	Avg. sentiment (z-score)	Month	Monthly performance (USD)	Avg. sentiment (z-score)
BTC	5	-20,381	-0.195	10	+17,502	0.437
ETH	12	-941	-0.283	10	+1,286	0.272
SOL	12	-38	-0.194	8	+72	0.392
TSLA	2	-46	-0.191	10	+112	0.273
NFLX	11	-47	-0.053	10	+86	0.011
GME	2	-54	-0.550	1	+77	0.128

Table 3. Average sentiment of both user groups in worst month and best month of 2021.

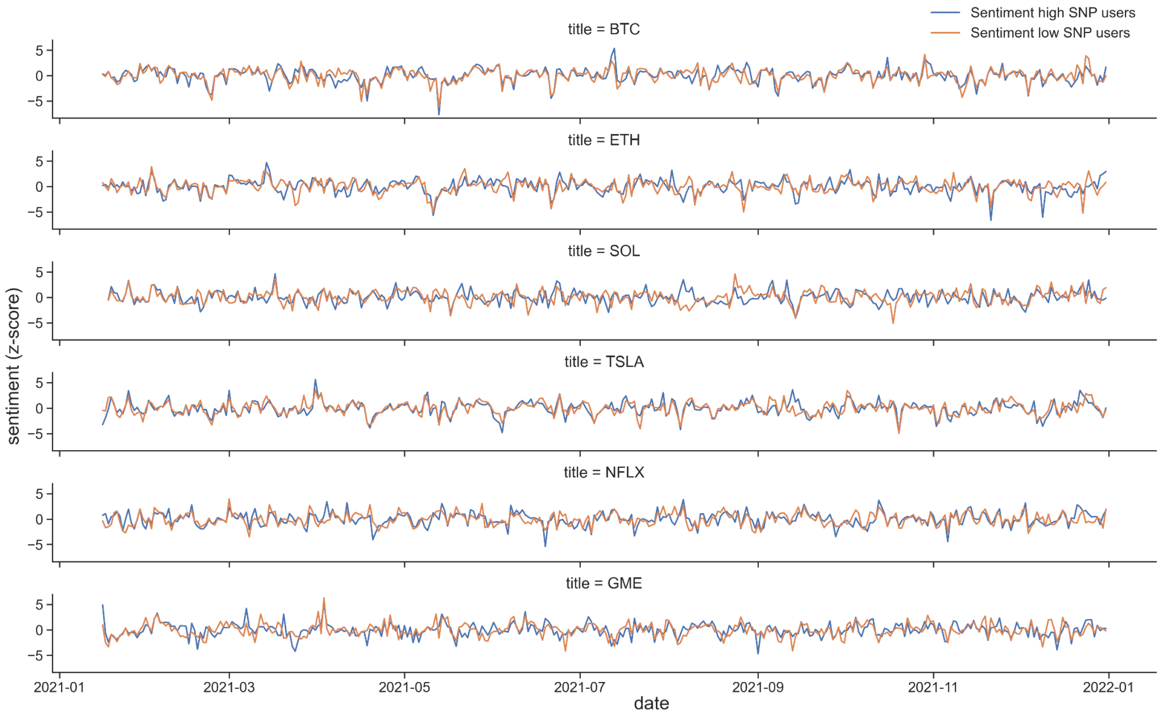

Figure 4. Sentiment time series.

3.4 Modeling

To formally test the relationship between the previously formed sentiment time series, we applied the econometric technique of Granger causality (Granger, 1969). Granger causality is a statistical hypothesis test to determine whether a time series X_t is useful for forecasting time series Y_t by attempting to reject the null hypothesis that X_t does not help to predict Y_t (Mao et al., 2011). Granger causality does not test for actual causality, but it tests for a statistically significant pattern between lagged versions of two time series X_t and Y_t and vice versa. There are several assumptions of the original Granger causality test (OGC), such as stationary data, which can lead to spurious relations when not handled correctly. To mitigate the aforementioned problem, we applied the Granger causality test approach outlined by Toda and Yamamoto (1995) (T&Y) and followed Kraaijeveld and De Smedt (2020) by reporting results for both approaches. The T&Y approach does not require differencing and co-integration testing.

The first step in the T&Y approach is to establish the maximum order of integration D_{max} for each time series. We ran an Augmented Dickey-Fuller (ADF) (Dickey and Wayne, 1979) test and a Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) test for stationarity and establish the maximum order of integration for each of the time series. For the ADF the null is non-stationary, whilst for the KPSS test the null is that of stationarity. For ADF, the number of lags selected was based on the Akaike Information criterion (AIC). For KPSS, the number of lags was selected using the data-dependent method of Hobijn et al. (2004). As the next step in the T&Y approach, the lag length k needs to be determined for setting up a $VAR(k)$ model in the levels of the data. For this, we made use of the Schwarz Criterion (SC) and conducted the Breusch-Godfrey LM test to check for autocorrelation in the residuals. We set up individual $VAR(k)$ models for every title separately. After establishing the maximum orders of integration and the optimal lag length, the T&Y procedure requires the estimation of the $VAR(k + D_{max})$ model:

$$X_t = \mu + \sum_{i=1}^{k+D_{max}} \alpha_t Y_{t-i} + \sum_{i=1}^{k+D_{max}} \beta_t X_{t-i} \tag{7}$$

$$Y_t = \mu + \sum_{i=1}^{k+D_{max}} \gamma_t X_{t-i} + \sum_{i=1}^{k+D_{max}} \delta_t Y_{t-i} \tag{8}$$

Here, μ represents the error terms, and α, β, γ and δ define the autoregressive coefficients.

3.5 Evaluation approach

For evaluation of the Granger causality, the T&Y approach conducts a WALD test for the first k variables, ignoring the last lagged D_{max} coefficients and reports the p-values. Like Kraaijeveld and De Smedt (2020), we also reported results from the OGC approach for evaluation of the models and reported $[k - 2, k + 2]$ lags around the optimal lag length k, to check our results for robustness. For drawing conclusions, we referred only to the results of the T&Y approach.

4 Results

To test our research question given the constructed time series, we conducted the Granger causality analysis as outlined in Sections 3.4 and 3.5. We report the results of the ADF and KPSS tests in Table 4 and the result of both the OGC approach and the T&Y approach in Table 5. Both ADF and KPSS were first run on the data in the levels, then we differentiated the data and ran both tests again. The combination of the results of both tests on the differenced data let us conclude that the time series all have $I(0)$ order of integrations, so we identified D_{max} as 0. In Table 5, we reported the selected k using the SIC criterion and the Breusch-Godfrey LM test, in addition to D_{max} for each title. We obtained consistent results for the OGC and the T&Y approach about the direction of the Granger causality.

For the cryptocurrencies BTC ($p < 0.01$), ETH ($p < 0.1$) and SOL ($p < 0.01$), the sentiment of high SNP actors granger-causes the sentiment of actors with low SNP. The T&Y approach and the OGC approaches tested with different lags both support this direction of Granger causality. For BTC and SOL the effect existed for almost every lag using the OGC approach. For ETH, however, the effect was not significant ($p < 0.1$) for some of the lags under the OGC approach. For the stocks, only NFLX showed a significant ($p < 0.1$) uni-directional Granger causality: sentiment of high SNP actors has predictive power for sentiment of low SNP actors. There was no evidence for significant Granger causality ($p < 0.1$) for TSLA, not for the T&Y approach nor for the OGC approach. For GME, there was no Granger causality for the T&Y approach. For lag 1 using the OGC approach, there is a significant Granger causality in the reverse direction as compared to the previous titles. However, for lags larger than 1, the effect became insignificant.

It is notable that we found evidence for both investigated asset classes (cryptocurrencies and stocks), which states that the sentiment of actors with high levels of potential social influence is driving the sentiment of actors with lower potential levels of social influence. We find stronger support for cryptocurrencies in comparison to stocks. In addition, the results suggest that this effect only holds for smaller lag numbers.

Title	Timeseries		ADF		KPSS		I(d)
			Levels	1st Difference	Levels	1st Difference	
BTC	Low SNP	C	-8.167***	-8.032***	0.031	0.033	
		TC	-8.157***	-8.033***	0.028	0.033	I(0)
BTC	High SNP	C	-12.450***	-11.163***	0.059	0.498**	
		TC	-12.440***	-11.146***	0.050	0.500***	I(0)
ETH	Low SNP	C	-7.923***	-8.814***	0.047	0.312	
		TC	-7.966***	-8.800***	0.021	0.271***	I(0)
ETH	High SNP	C	-12.961***	-10.748***	0.110	0.122	
		TC	-12.966***	-10.742***	0.043	0.077	I(0)
SOL	Low SNP	C	-13.888***	-8.245***	0.068	0.152	
		TC	-13.870***	-8.235***	0.067	0.134*	I(0)
SOL	High SNP	C	-12.367***	-8.876***	0.048	0.096	
		TC	-12.349***	-8.617***	0.039	0.092	I(0)
TSLA	Low SNP	C	-11.554***	-8.647***	0.022	0.111	
		TC	-11.537***	-8.623***	0.022	0.103	I(0)
TSLA	High SNP	C	-12.604***	-7.936***	0.021	0.145	
		TC	-12.583***	-7.928***	0.021	0.090	I(0)
NFLX	Low SNP	C	-8.430***	-9.738***	0.047	0.126	
		TC	-8.411***	-9.722***	0.032	0.101	I(0)
NFLX	High SNP	C	-14.520***	-7.652***	0.040	0.137	
		TC	-14.502***	-7.652***	0.037	0.086	I(0)
GME	Low SNP	C	-10.021***	-8.840***	0.034	0.070	
		TC	-10.006***	-8.820***	0.033	0.064	I(0)
GME	High SNP	C	-10.558***	-7.768***	0.026	0.272	
		TC	-10.543***	-7.750***	0.024	0.131*	I(0)

C = Constant, TC = Trend, Constant.
***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

Table 4. Tests for unit roots.

	T&Y Approach				OGC Approach
Title	H_0	D_{max}	**k**	p**-value**	**Lags &** p**-values**
BTC	(1)	0	3	**0.001*** **	1 (0.111), 2 **(0.001)*****, 3 **(0.000)*****, 4 **(0.000)*****, 5 **(0.001)*****
	(2)			0.900	1 (0.546), 2 (0.741), 3 (0.904), 4 (0.936), 5 (0.656)
ETH	(1)	0	3	**0.073***	1 **(0.097)***, 2 (0.149), 3 **(0.074)***, 4 (0.130), 5 (0.143)
	(2)			0.680	1 (0.582), 2 (0.789), 3 (0.676), 4 (0.751), 5 (0.785)
SOL	(1)	0	2	**0.001*** **	1 (0.110), 2 **(0.001)*****, 3 **(0.001)*****, 4 **(0.001)*****
	(2)			0.740	1 (0.546), 2 (0.741), 3 (0.904), 4 (0.936)
TSLA	(1)	0	4	0.390	2 (0.539), 3 (0.431), 4 (0.387), 5 (0.474), 6 (0.605)
	(2)			0.240	2 (0.115), 3 (0.185), 4 (0.245), 5 (0.355), 6 (0.235)
NFLX	(1)	0	3	**0.091***	1 **(0.047)****, 2 (0.164), 3 **(0.092)***, 4 **(0.082)***, 5 **(0.057)***
	(2)			0.340	1 (0.166), 2 (0.347), 3 (0.337), 4 (0.326), 5 (0.354)
GME	(1)	0	3	0.530	1 (0.319), 2 (0.363), 3 (0.535), 4 (0.670), 5(0.734)
	(2)			0.140	1 **(0.049)****, 2 (0.105), 3 (0.143), 4 (0.199), 5 (0.657)

(1) H_0: Sentiment of high SNP actors does not granger-cause sentiment of low SNP actors.
(2) H_0: Sentiment of low SNP actors does not granger-cause sentiment of high SNP actors.
***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

Table 5. Granger causality results (T&Y approach left, OGC approach right).

5 Discussion

The results of this paper indicate that the sentiment about certain financial assets of the long tail of social network actors is influenced by only a small number of actors with high social influence potential. Cryptocurrencies have been discussed a considerable amount on social networks lately compared to stocks (see Figure 2). Despite this difference in volume pattern and the assets' diversity in nature, we have found weak evidence that the observed direction of Granger causality could apply for both asset classes. However, we find stronger support for cryptocurrencies than for stocks.

The following limitations apply to this work. Although we analysed two different asset classes, the selection of six assets offered only a glimpse at the huge amount of social network data and the choice of assets was a trade-off between dataset size, variability, and computational effort. Additionally, we only focused on one year of data (2021) due to computational limitations, possibly introducing time series bias in addition to the inherent noise of social network data. The analysis was conducted at a fixed daily resolution of the time series, providing only one perspective on the data. Similarly, the approach of dividing actors into high social influence and low social influence groups required the selection of a percentile threshold, which may affect the transferability of the results. A possible disturbance factor for TSLA and GME could have resulted from the propensity score matching. It did not perform as well for these two assets as for the other assets, resulting in spurious effects on the time series. Other reasons might be that there is no causality, or there is a nonlinear causality that cannot be established using the Granger causality. Moreover, the assumption made by Granger causality models that predictive information between variables is linear may not hold true for the variables under study. However, we accepted this assumption because we were primarily interested in testing the direction of Granger causality rather than achieving optimal modeling.

As future work, the analysis could be extended to larger data sets with multiple assets. More diverse data sources could also be considered, as much of the financial discussion shifts to new types of social network platforms such as Discord or Telegram. Furthermore, sensitivity analyses can be performed with respect to the sentiment model or social influence measures used. Especially sentiment models pre-trained on financial domain texts remain open for future work. In our work, we have decided to use Transformer-based sentiment models, due to their found superiority in prediction accuracy in the financial domain (Mishev et al., 2020). However, their lack of interpretability might raise the need for lexicon-based approaches for more interpretable results. In this work, we have excluded the impact of sentiment on price entirely, but we plan to build and validate a full research model including price to provide further insights. It is widely known that a sizable proportion of social media actors are bots, and although these actors influence sentiment, we have treated them as part of the effect and have not explicitly accounted for them. More detailed analysis of the effect of bots on social network sentiment encourages future work. This work also gives rise to considerations about the relevance of financial regulation and monitoring of high influence actors since their influence on other actors can be profound. The derivation of practical suggestions for regulators is necessary. Ultimately, more advanced approaches for detecting influential actors can be explored, for example, based on supervised learning techniques considering not only user characteristics but also published content.

6 Conclusion

Social network sentiment has recently attracted increased attention in the financial world as increasingly more is known about its influence on user behaviour. In this paper, we investigated the extent to which the sentiment of a few actors with high social influence - Finfluencers - has predictive power for the sentiment of the broader financial community. By applying Granger causality, we found support for our hypothesis, which, despite some limitations, provides insights into the mechanism described: The sentiment of high influence actors has the potential to be an antecedent of the sentiment of low influence actors. Our study contributes to the existing finance literature by exploring and further unravelling the concept of sentiment in social networks. The practical relevance of our work results from the elaborated function of influencers in the social network and their role as opinion makers on the general financial community. From the perspective of financial market regulation, this study stresses the relevance of monitoring sentiment on social networks and high social influence actors with the goal to anticipate scams and fraud. Nonetheless, social network sentiment, especially in finance, is still a new area of research and needs further investigation.

7 Acknowledgements

This work is part of the research project AFFIN funded by the German Federal Ministry of Education and Research (Grant no.: 01IS21045B).

References

Aggarwal, D. (2022). Defining and measuring market sentiments: A review of the literature. *Qualitative Research in Financial Markets* 14 (2), 270-288.

American Psychological Association. (2015). *APA Dictionary of Psychology*, 2nd Edition. American Psychological Association (APA).

Anderson, J. P., Kidd, J., and Mocsary, G. A. (2021). Social Media, Securities Markets, and the Phenomenon of Expressive Trading. *Lewis & Clark L. Rev.* 25 (4), 1223-1246.

Anger, I., and Kittl, C. (2011). Measuring influence on Twitter. In *Proceedings of the 11th international conference on knowledge management and knowledge technologies* (pp. 1-4).

Antweiler, W., and Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance* 59 (3), 1259–1294.

Bakshy, E., Hofman, J., Mason, W., and Watts, D. (2011). Everyone's an Influencer: Quantifying Influence on Twitter. In: *Proceedings of the 4th ACM International Conference on Web Search and Data Mining 2011*, (pp. 65-74).

Bak-Coleman, J. B., Alfano, M., Barfuss, W., Bergstrom, C. T., Centeno, M. A., Couzin, I. D., ... & Weber, E. U. (2021). Stewardship of global collective behavior. *Proceedings of the National Academy of Sciences, 118(27)*, e2025764118.

Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-Induced Trading and Returns: Evidence from Robinhood Users. *The Journal of Finance*, 77(6), 3141-3190.

Barbieri, F., Camacho-Collados, J., Neves, L., and Espinosa-Anke, L. (2020). Tweeteval: Unified benchmark and comparative evaluation for tweet classification. *arXiv preprint*, arXiv:2010.12421.

Bollen, J., Mao, H., and Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science 2* (1), 1–8.

Broadstock, D. C., and Zhang, D. (2019). Social-media and intraday stock returns: The pricing power of sentiment. *Finance Research Letters* 30, 116-123.

Caliendo, M., and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys* 22 (1), 31-72.

Chowdhury, S. G., Routh, S., and Chakrabarti, S. (2014). News analytics and sentiment analysis to predict stock price trends. *International Journal of Computer Science and Information Technologies* 5 (3), 3595-3604.

Conger, K., and Hirsch, L. (2022). *Elon Musk Completes $44 Billion Deal to Own Twitter*. URL: https://www.nytimes.com/2022/10/27/technology/elon-musk-twitter-deal-complete.html (visited on November 8, 2022).

Debortoli, S., Müller, O., Junglas, I., & Vom Brocke, J. (2016). Text mining for information systems researchers: An annotated topic modeling tutorial. *Communications of the Association for Information Systems (CAIS)*, 39(1), 7.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)* (pp. 4171-4186).

Dickey, D. and Fuller, W. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association* 74 (366), 427-431.

Dupuis, D., Smith, D., & Gleason, K. (2023). Old frauds with a new sauce: digital assets and space transition. *Journal of Financial Crime*, 30(1), 205-220.

Fama, E. F. (1970). “Efficient capital markets: A review of theory and empirical work” *The Journal of Finance* 25 (2), 383-417.

Frunza, M.-C. (2016). *Solving Modern Crime in Financial Markets*, 1st Edition. Pittsburgh: Academic Press.

Glover, G. (2022). *Kim Kardashian agreed to pay the SEC $1.3 million - a warning shot from the watchdog to crypto-promoting celebrities.* URL: https://markets.businessinsider.com/news/currencies/kim-kardashian-crypto-fine-sec-warning-celebrities-jake-paul-mayweather-2022-10 (visited on November 8, 2022).

Go, A., Bhayani, R., and Huang, L. (2009). *Twitter sentiment classification using distant supervision*. CS224N project report, The Stanford NLP Group.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society* (37) 3, 424-438.

Gräve, Jan-Frederik. (2019). What KPIs Are Key? Evaluating Performance Metrics for Social Media Influencers. *Social Media + Society* 5 (3), 1-9.

Hobijn, B., Franses, P. H., and Ooms, M. (2004). Generalizations of the KPSS-test for stationarity. *Statistica Neerlandica* 58 (4), 483-502.

Hong, H., Kubik, J. D., and Solomon, A. (2000). Security analysts' career concerns and herding of earnings forecasts. *The RAND Journal of Economics* 31 (1), 121-144.

Huynh, T. L. D. (2022). When Elon Musk Changes his Tone, Does Bitcoin Adjust Its Tune? *Computational Economics*, 1-23.

James, T. L., Lowry, P. B., Wallace, L., & Warkentin, M. (2017). The effect of belongingness on obsessive-compulsive disorder in the use of online social networks. *Journal of Management Information Systems*, 34(2), 560-596.

Jegadeesh, N., and Kim, W. (2010). Do analysts herd? An analysis of recommendations and market reactions. *The Review of Financial Studies* 23 (2), 901-937.

Kendall, M. G. (1938). A new measure of rank correlation. *Biometrika, 30(1/2)*, 81-93.

Kraaijeveld, O., and De Smedt, J. (2020). The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. *Journal of International Financial Markets, Institutions and Money* 65, 1-65.

Kuzma, R., Cruickshank, I. J., and Carley, K. M. (2021). Influencing the Influencers: Evaluating Person-to-Person Influence on Social Networks Using Granger Causality. In: *Proceedings of the Tenth International Conference on Complex Networks and Their Applications* (pp. 89-99).

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics* 54 (1-3), 159-178.

Lachanski, M., and Pav, S. (2017). Shy of the character limit: "Twitter mood predicts the stock market" revisited. *Econ Journal Watch* 14 (3), 302.

Lake, R. (2022). *Personal Finance Influencers You Should Know*. URL: https://www.investopedia.com/financial-influencers-to-know-5217608 (visited on November 8, 2022).

Li, T., van Dalen, J., and van Rees, P. J. (2018). More than just noise? Examining the information content of stock microblogs on financial markets. *Journal of Information Technology* 33 (1), 50-69.

Long, C., Lucey, B., and Yarovaya, L. (2021). "I Just Like the Stock" versus "Fear and Loathing on Main Street": The Role of Reddit Sentiment in the GameStop Short Squeeze. *SSRN Electronic Journal* 31, 1-37.

Mancini, A., Desiderio, A., Di Clemente, R., & Cimini, G. (2022). Self-induced consensus of Reddit users to characterise the GameStop short squeeze. *Scientific reports, 12(1), 13780.*

Mao, H., Counts, S., and Bollen, J. (2011). Predicting financial markets: Comparing survey, news, twitter and search engine data. *arXiv preprint* arXiv:1112.1051.

McCabe, C. (2022). *Twitter Stock Falls After Elon Musk Says Deal Is 'On Hold'*. URL: https://www.wsj.com/articles/twitter-stock-tumbles-premarket-after-elon-musk-says-deal-is-on-hold-11652445126 (visited on November 8, 2022).

Mirtaheri, M., Abu-El-Haija, S., Morstatter, F., Ver Steeg, G., and Galstyan, A. (2021). Identifying and analyzing cryptocurrency manipulations in social media. *IEEE Transactions on Computational Social Systems* 8 (3), 607-617.

Mishev, K., Gjorgjevikj, A., Vodenska, I., Chitkushev, L. T., and Trajanov, D. (2020). Evaluation of sentiment analysis in finance: from lexicons to transformers. *IEEE access* 8, 131662-131682.

La Morgia, M., Mei, A., Sassi, F., & Stefa, J. (2023). The doge of wall street: Analysis and detection of pump and dump cryptocurrency manipulations. *ACM Transactions on Internet Technology*, 23(1), 1-28.

Riquelme, F., and González-Cantergiani, P. (2016). "Measuring user influence on Twitter: A survey" *Information processing & management* 52 (5), 949-975.

Robertson, A. (2021). *John McAfee charged with securities fraud for 'pump and dump' cryptocurrency scheme*. URL: https://www.theverge.com/2021/3/5/22315494/john-mcafee-fraud-securities-scheme-charges-cryptocurrency (visited on November 8, 2022).

Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70 (1), 41-55.

Shearer, C. (2000). The CRISP-DM model: the new blueprint for data mining. *Journal of Data Warehousing*, 5(4), 13–22.

Siering, M. (2019). The economics of stock touting during Internet-based pump and dump campaigns. *Information Systems Journal* 29 (2), 456-483.

Strauss, N., and Smith, C. H. (2019). Buying on rumors: how financial news flows affect the share price of Tesla. *Corporate Communications: An International Journal* 24 (4), 593-607.

Talmor, A., Elazar, Y., Goldberg, Y., and Berant, J. (2020). oLMpics-on what language model pre-training captures. *Transactions of the Association for Computational Linguistics* 8, 743-758.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance* 62 (3), 1139-1168.

Toda, H. Y., and Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics* 66 (1-2), 225-250.

Twitter, Inc. (2022, April 28). *Quarterly results: first quarter 2022*. URL: https://s22.q4cdn.com/826641620/files/doc_financials/2022/q1/Final-Q1%E2%80%9922-earnings-release.pdf (visited on November 8, 2022).

Uhr, P., Zenkert, J., and Fathi, M. (2014). Sentiment analysis in financial markets - A framework to utilize the human ability of word association for analyzing stock market news reports. In: *Conference Proceedings - IEEE International Conference on Systems, Man, and Cybernetics* (pp. 912-917). IEEE.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... and Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems* 30, 1-11.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *The Journal of Finance* 54 (2), 581-622.

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., and Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. *Advances in Neural Information Processing Systems* 32, 1-11.

Ye, S., and Wu, S. F. (2010). Measuring message propagation and social influence on Twitter.com. *SocInfo*, 10, 216-231.

Zeledon, M. (2009). *StockTwits may change how you trade*. URL: https://www.bloomberg.com/news/articles/2009-02-10/stocktwits-may-change-how-you-trade (visited on November 8, 2022).