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RESEARCH PAPER

The Role of Finfluencers in Shaping Crowd Sentiment

An Empirical Investigation

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Abstract The paper utilizes empirical data to investigate *finfluencers* – key actors in financial social media – and their impact on crowd sentiment. Despite its importance for various stakeholders such as hedge funds and regulators, the antecedents of crowd sentiment remain largely unexplored. The study analyzes 80 million posts on stocks and cryptocurrencies, grouping actors by their social networking potential (SNP) to distinguish between those with potential to influence and the broader crowd. The authors construct sentiment time series employing transformer-based models for both groups and apply panel vector error correction models (PVECMs) to examine their relationship. Drawing on herd theory, the findings confirm that finfluencer sentiment positively predicts crowd sentiment in the short term, without a reciprocal effect. This effect is stronger for cryptocurrency assets than for stocks and is positively moderated by the uncertainty of the crowd. These insights contribute to the fields of information systems (IS) and marketing research by exploring the role of social media influencers (SMIs) in contexts outside traditional consumer marketing. The study's findings have significant implications for regulators, firms, social media platforms, and investors, supporting the development of regulatory frameworks, marketing strategies, platform policies, and investment decisions.

Keywords Finfluencers · Crowd sentiment · Sentiment analysis · Social media influence · Herding · Vector error correction model · Granger causality

1 Introduction

Financial social media have become fundamental for the exchange of information between various stakeholders within the financial ecosystem. Platforms such as *Seeking Alpha*, dedicated exclusively to financial content (Li et al. 2024), along with general-purpose platforms such as *Reddit* or *X* (former *Twitter*), are increasingly used for both dissemination and consumption of financial information (Buz and De Melo 2024). In fact, a recent *Forbes Advisor* survey found that almost 80% of young adults have received financial advice from social media (Egan 2023). Recognizing the growing influence of financial social media, the SEC published an investor bulletin to help inform investors navigating this space (SEC 2022). This expanding influence presents opportunities and challenges to the financial community: on the one hand, it democratizes access to financial information, empowering a broader audience to engage with financial topics and advice (Buz and De Melo 2024); on the other hand, it facilitates potential risks and fraud, such as misinformation (Clarke et al. 2021) and market manipulation (Siering et al. 2021). These risks are amplified by the anonymity of social networks, the lack of regulation, and the social dynamics that cause the rapid spread of information.

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Beyond their role in information exchange, collective social media posts are considered the largest source of data for public opinion (Deng et al. 2018; O'Leary 2011; Yu et al. 2013). One particularly important form of opinion extracted from financial social media is *crowd sentiment*, the collective opinions and emotional state transmitted through social media posts, often reflecting attitudes towards specific assets (Chen et al. 2014; Deng et al. 2018). Widely regarded as an indicator of market sentiment, it is of significant importance to various stakeholders and offers insight to advance theory. Professional investors rely on crowd sentiment of financial assets to anticipate market movements. Research suggests that it correlates with asset prices (Antweiler and Frank 2004; Bollen et al. 2011; Chen et al. 2014; Mai et al. 2018; Xie et al. 2020), making it a valuable signal for strategies in trading systems (Subramanian et al. 2023). With its predictive power, crowd sentiment has also become an important emotional pulse for retail investors (Münster et al. 2024). Meanwhile, policymakers are warning against the risks and frauds of sentiment-driven investing tools (SEC 2019). Firms, on the other hand, need to understand and manage their social media sentiment because it can significantly impact their stock values (Sprenger et al. 2014; Luo et al. 2013). In academic discourse, understanding crowd sentiment provides deeper insight into how collective opinion and information dissemination affect market dynamics.

However, while the predictive value of crowd sentiment on financial market outcomes is well documented, only a few studies have examined its antecedents. These include past market outcomes (Deng et al. 2018; Xie 2022), the sentiment of professional analysts' reports (Eickhoff and Muntermann 2016), and the emotional contagion between crypto vlogger posts and their audience (Meyer et al. 2023). Given the practical importance of crowd sentiment for various stakeholders, including investors, policy makers, and companies, more research is needed to explore the factors that influence it. Without understanding what shapes crowd sentiment, we have a one-sided view, knowing the outcomes it is associated with, but lack insights into the mechanisms that drive it.

One promising area for investigating the antecedents of crowd sentiment is the role of influential actors. A recent theoretical model identified influential actors as key players in financial social media (Pedersen 2022). Often called finfluencers, they share common traits with social media influencers (SMIs) in traditional consumer marketing contexts, who leverage their social influence to shape consumer opinions and decisions and promote firm offerings (Leung et al. 2022). Similarly, finfluencers may impact others' financial perspectives and decisions with their online presence as opinion leaders (De Veirman et al. 2017; Guan 2023a; Ki et al. 2020). However, while traditional influencer marketing is typically intentional and structured, aiming to maximize campaign effectiveness (Hinz et al. 2011), finfluencers tend to be less coordinated and directed and have different motivations (Guan 2023a). Two well-known examples highlight the impact of finfluencers on financial markets. On August 23, 2016, Tesla CEO Elon Musk tweeted about a "product announcement at noon California time today" (Strauss and Smith 2019); that generated significant user engagement from other social network actors (>5,000 retweets,>14,000 likes), but also caused Tesla's share price to rise by 1.4 percent. In 2021, retail investors used Reddit's *r/WallStreetBets* to coordinate the GameStop (GME) short squeeze against hedge funds (Mancini et al. 2022), driven largely by what was found to be a small minority of influential actors (Lucchini et al. 2022).

These examples of influential actors in financial social media demonstrate not only individual reach, but also collective behavioral dynamics. One theoretical lens that helps to explain such collective dynamics is herd theory. Traditionally, herding has explained how individuals mimic the behavior of others, such as investment managers aligning with peers (Scharfstein and Stein 1990) and analysts adjusting forecasts based on public information (Hong et al. 2000; Jegadeesh and Kim 2010). More recently, herding has also been found and investigated in social media contexts; for example, Mattke et al. (2020) showed that strong ties between social media actors can drive herd behavior. The GameStop squeeze herding example (Long et al. 2023) underscores how users follow and amplify cues from influential figures such as opinion leaders.

Taking into account previous theoretical considerations regarding opinion leadership (Ki et al. 2020) and herding (Long et al. 2023; Mattke et al. 2020) as well as example cases of finfluencers, we hypothesize that finfluencers are key players in driving crowd sentiment of financial social media. Although the marketing literature has extensively investigated the role of SMIs in shaping consumer behavior, research has been mostly limited to a firm-level marketing context. The question of whether the influence of SMI extends to financial environments – driven by fundamentals and technical indicators – remains unclear. Furthermore, while theoretical models of influential actors have been proposed (Pedersen 2022) and isolated events such as Musk's tweets affecting Tesla's stock price (Ante 2023; Strauss and Smith 2019) have been investigated, we lack a systematic understanding of the phenomenon. Therefore, we investigate the following research questions:

- *RQ1: Can the sentiment of finfluencers predict crowd sentiment in financial social media?*

- *RQ2: Under what conditions does the sentiment of finfluencers have increased predictive power on crowd sentiment in financial social media?*

Our study develops a theoretical framework that draws on herd theory to address these research questions. We perform a large-scale field analysis using data from *X*, applying transformer-based sentiment analysis to distinguish between the sentiment expressed by influential actors and the broader social network. We employ panel vector error correction models (PVECMs) to assess the relationships between finfluencer sentiment and crowd sentiment through Granger causality and impulse response function (IRFs) analysis. Additionally, we examine moderators that may strengthen this relationship. Our dataset selection includes both stocks and cryptocurrencies from a single social media platform which allows for a comparative analysis of social dynamics between different asset classes. We find that finfluencer sentiment positively predicts crowd sentiment in the short term and is not driven by it. This effect is stronger in certain cryptocurrencies compared to stocks and is positively moderated by crowd uncertainty.

Our research makes several theoretical contributions. Many studies consider financial social media sentiment as a singular construct; we argue that corresponding research models can benefit from a differentiated view by segmenting sentiment into crowd and influencer sentiment. We empirically show how finfluencers can drive herding in financial social media and establish influencer sentiment as an antecedent of crowd sentiment. Therefore, we contribute to the broader marketing and IS literature on SMIs by extending into the financial domain, which differs from traditional firm-level marketing contexts. Marketing studies on influencers often focus on the individual's behavioral intentions such as purchase intentions (Masuda et al. 2022); our study explores how finfluencers can shape collective crowd sentiment through opinion leadership, providing insights into broader social dynamics. Finally, our empirical analysis offers a systematic exploration of the finfluencer phenomenon, addressing a gap in literature which has so far only focused on single events such as Musk's tweets (Ante 2023; Strauss and Smith 2019). Our study empirically investigates the phenomenon using a broader approach based on large-scale field data.

This study offers practical implications for various stakeholders. By identifying the antecedents of crowd sentiment, we contribute to the discussion around regulatory frameworks that address platform responsibility, the enforcement of measures against harmful financial behaviors, and finfluencer activity (Guan 2023b; Stefanou 2022). Beyond regulation, our insights can also draw the attention of social media platforms to finfluencers who amplify extreme sentiment on financial topics. Soft moderation measures, such as warning labels or content disclaimers, could help mitigate misinformation and provide users with context, as seen in political discussions (Zannettou 2021). Our findings are also relevant for investors. Trading strategies and systems that incorporate social media sentiment (Subramanian et al. 2023) can benefit from differentiating between general crowd sentiment and finfluencer sentiment to better model the underlying temporal dynamics. Our research can also raise awareness among retail investors about the potential social influence of influential actors when users are consuming content on financial social media. Finally, our research provides insights that can help firms understand the role of finfluencers in shaping crowd sentiment and their potential impact on stock valuations.

2 Related Literature

Our work bridges and expands research from different disciplines: we draw from the body of research on SMIs in consumer marketing, on works dealing with sentiment analysis in financial markets, and related research on financial influencers. Here, we provide some background information on these relevant streams of literature.

2.1 Social Media Influencers in Marketing Research

Social influence may be defined as "any change in an individual's thoughts, feelings, or behaviors caused by other people [...]" (American Psychological Association 2024). Unlike social or emotional contagion, which involves the involuntary spread and adoption of emotions such as excitement, social influence is characterized as a *mentalizing* mechanism that causes individuals to actively seek conformity, yield to peer pressure, or follow the decision-making processes of others in their social groups (Raafat et al. 2009).

When examined within the context of online social networks, social influence is the capacity to impact the thoughts, emotions, or actions of other participants through engagement and interaction. In marketing research, it serves as a catalyst for promoting new products and services, supported by studies that demonstrate the significant role of (electronic) word-of-mouth in influencing the attitudes and decision-making of potential customers (Cao and Belo 2024; De Veirman et al. 2017; Goldenberg et al. 2024; Han and Balabanis 2024; Probst et al. 2013; Thies et al. 2016; Zhou et al. 2021). Marketers frequently seek to leverage influential individuals (SMIs) to effectively inform and persuade target audiences within defined timeframes and marketing budgets (Hinz et al. 2011).

There are many approaches to identify and characterize SMIs, typically based on their user activity and popularity (Probst et al. 2013; Riquelme and González-Cantergiani 2016). SMIs' capacity to exert influence is founded on a range of distinct qualities, including attractive physical appearance, perceived expertise, prestige, authenticity, and communication style, among others (Ki and Kim 2019; Kim and Kim 2021; Zhou et al. 2021). Notably, SMIs do not need to be traditional celebrities who achieve popularity and success in sports, media, or other fields; rather, their status often derives from the personal brands they cultivate within online social networks (Leung et al. 2022; Mallipeddi et al. 2022).

SMIs are frequently conceptualized as individuals possessing many social network connections or serving as opinion leaders within specific domains (Lanz et al. 2019; Leung et al. 2022; Lou and Yuan 2019). They can be classified into user cohorts, such as categorizing them as low-status or high-status influencers (Beichert et al. 2024; Goldenberg et al. 2024; Hinz et al. 2011; Landherr et al. 2010), or on a scale from micro and nano influencers to celebrity influencers (Campbell and Farrell 2020; Zhou et al. 2021). The various approaches to quantify and assess social influence create challenges in establishing a universal definition. For example, a survey by Riquelme and González-Cantergiani (2016) identified and classified more than 70 different measures of influence used in the literature on platform X. These measures focus on user-user and user-post relationships, such as following and reposting. Graph-based approaches evaluate the positioning of influential accounts within a network, categorizing them as hubs, bridges, or interconnectors based on specific graph and network metrics (Goldenberg et al. 2009, 2024; Hinz et al. 2011; Probst et al. 2013).

Several research streams explore strategic approaches firms can use to leverage SMIs for their campaigns and analyze the nature of influencer-follower relationships (De Veirman et al. 2017; Ki et al. 2020; Leung et al. 2022). Influencer marketing can be seen as a form of *native advertising* (Cao and Belo 2024), with messages integrated into seemingly natural interactions. While it shares characteristics with celebrity endorsements, it generally places a stronger emphasis on content and two-way communication (Masuda et al. 2022). Firms need to consider goals, budgets, domains, and campaign characteristics in their choice of seeding strategies when they decide which influencers to target for a campaign to maximize effectiveness or go *viral* (Beichert et al. 2024; Hinz et al. 2011; Koch and Benlian 2015; Lanz et al. 2019).

Another important dimension of SMIs is how they shape the preferences and decision making of their audience. Ki and Kim (2019) identify two distinct approaches that SMIs use to influence their audience: taste leadership and opinion leadership, depending on whether their attempts rely more on visual or verbal factors. Both types significantly affect the desire of followers to mimic the behavior of SMIs, as well as their participation in word-of-mouth marketing and purchasing intentions (De Veirman et al. 2017). SMIs as opinion leaders build trust through perceived expertise, valuable information, and interaction, and can be seen more as advisers than friends (Hinz et al. 2014; Ki and Kim 2019). This concept of opinion leadership extends beyond influencer marketing and has a long history in fields such as political communication and technology adoption (Katz and Lazarsfeld 1955; Rogers and Cartano 1962). Its influence on people's thinking, information acquisition, decision-making, and purchasing decisions has been widely researched (Li and Du 2011; Lou and Yuan 2019; Lyons and Henderson 2005). On platforms such as X, SMIs can establish themselves as opinion leaders by demonstrating expertise and authenticity, which fosters relational trust and allows them to effectively initiate and participate in information diffusion processes (Kim and Kim 2021; Park 2013; Zhou et al. 2021). The literature suggests that opinion leadership should not be measured solely by the number of followers, which may primarily reflect the popularity of the account, but must consider user interactions and the context and content of posts (De Veirman et al. 2017; Lou and Yuan 2019).

Marketing research provides the foundation for understanding how SMIs are characterized, the strategies they employ, and the dynamics of influencer-follower relationships. However, our work differs from marketing perspectives on SMIs. Marketing research looks at means to leverage SMIs for marketing campaigns; our research on finfluencers describes a diverse group of actors that may or may not be incentivized by their own financial goals or external sources. Although social media's impact on financial decision-making becomes more important (Barber et al. 2022), investors still heavily rely on fundamental data and other outside information on financial assets. Thus, finfluencers may be less typical of the marketing ideal than fashion or travel influencers. Our contribution lies in providing empirical evidence of how SMIs that position themselves as opinion leaders in a specific domain (finance) influence the sentiment of others within the network. We specifically investigate how sentiment forms and diffuses in the network, not in the downstream effects such as asset price effects covered by other researchers.

2.2 Sentiment in Financial Markets

Investor sentiment reflects the overall mood and emotional responses of market participants and has been a focal point of financial market research for decades (O'Leary 2011; Yu et al. 2013; Deng et al. 2018). Early measurement efforts used surveys and indices designed to capture these states. For instance, the Gallup Life Evaluation Index (Mao et al. 2011) was employed as a proxy for investor sentiment; more specialized tools such as the Investors Intelligence survey (since 1965) aggregated financial newsletter views into bullish, bearish, or neutral outlooks for financial assets (Aggarwal 2019). Over time, sentiment analysis evolved to consider new data sources, particularly news media and, later, online social media communication. Tetlock (2007) demonstrated that media content could predict the stock market, contributing to a growing body of research on the impact of financial asset sentiment derived from various text-based sources, including internet message boards (Antweiler and Frank 2004), and traditional news outlets (Chowdhury et al. 2014). Subsequently, social media have become central sources for sentiment analysis, due to their real-time and highly interactive nature. Platforms such as X aggregate investor discussions and opinions, enabling researchers to use this sentiment as a potential predictor of market behavior. Notably, Bollen et al. (2011) found that mood states extracted from Twitter feeds were 87.6% accurate in predicting daily changes in the Dow Jones Industrial Average, findings later challenged because they conflict with the efficient market hypothesis (Lachanski and Pav 2017). As social media's role in financial markets grew, so did research on its predictive power. Kraaijeveld and De Smedt (2020) and Li et al. (2018) found that sentiment derived from platforms such as Twitter could predict stock returns and cryptocurrency movements.

Sentiment about financial assets derived from online social media communication is often treated as singular construct, yet only a few studies have explored more nuanced dimensions. Nofer and Hinz (2015) identified that follower-weighted sentiment – more popular users' opinions carrying more weight – could predict stock returns more effectively than raw sentiment measures. Mai et al. (2018) emphasized the importance of posts from the silent majority (less active users) in predicting Bitcoin's value, arguing that different types of users contribute unequally to social media sentiment's predictive power. Subramanian et al. (2023) developed a more advanced sentiment analysis framework that significantly outperformed traditional benchmarks, incorporating multiple sentiment dimensions such as emotional and factual content into a trading decision support system for Bitcoin. Chen et al. (2014) analyzed different social media post sources – original articles and comments – and found predictive power for both. Similarly, sentiment analysis itself has been varied in methodology. Early studies often relied on lexicon-based sentiment models which classify sentiment based on predefined word lists. More recent approaches have iterated on these methods (Subramanian et al. 2023), incorporating more complex sentiment models such as machine-learning based sentiment analysis (Mishev et al. 2020).

To summarize, numerous studies have analyzed sentiment of financial assets as a predictor for financial market outcomes, advancing the understanding of three influencing factors: which *users* contribute most to predictive power, with several studies indicating that certain user groups may have a stronger influence on market outcomes; which *sources* of sentiment (such as original articles versus comments) differ in their predictive power; and which *sentiment analysis approaches* provide most predictive power. However, few studies have investigated how the sentiment about financial assets itself emerges within financial social media. Xie (2022) found past market outcomes to be a driver for crowd sentiment toward Bitcoin, and Meyer et al. (2023) showed that crypto vloggers exert emotional contagion toward the sentiment of viewer comments. For stocks, professional analysts' sentiment in weblogs, forums, and reviews influence social media sentiment (Eickhoff and Muntermann 2016). Sentiment in forums is largely driven by market movements reciprocally, with stock returns having a stronger influence on negative than positive sentiment (Deng et al. 2018). Our work provides the first investigation of the mutual relationship between finfluencer sentiment and crowd sentiment, analyzing this relation based on independent social media posts rather than comment relations, and analyzing a wide range of assets.

2.3 Existing Research on Financial Influencers

Within the growing field of SMI research (Han and Balabanis 2024), studies that analyze and conceptualize finfluencers are rapidly evolving (Guan 2023b, a; Kakhbod et al. 2023; Merkley et al. 2023; Pedersen 2022). Finfluencers influence "investing decisions through social media" (Guan 2023b, p. 489) and gain visibility in networks through proven expertise, informative content, or traits such as attractiveness and trustworthiness, aligning with the concept of opinion leaders. The literature has identified a broad set of motives for finfluencers, ranging from interest in the field, fame, popularity, opinion leadership, their own financial interests, and external incentives (Guan 2023b; Pedersen 2022).

Looking at various individuals can help identify who is a finfluencer, and these examples also demonstrate the diversity of their motives. Considering the work by Tetlock (2007) on journalists from the *Wall Street Journal*, it appears that the journal's column writers could be characterized as finfluencers. Elon Musk's posts appear to have impacted financial markets (Strauss and Smith 2019), cryptocurrencies (Ante 2023), and Twitter stock itself (McCabe and Banerji 2022). John McAfee, who founded a

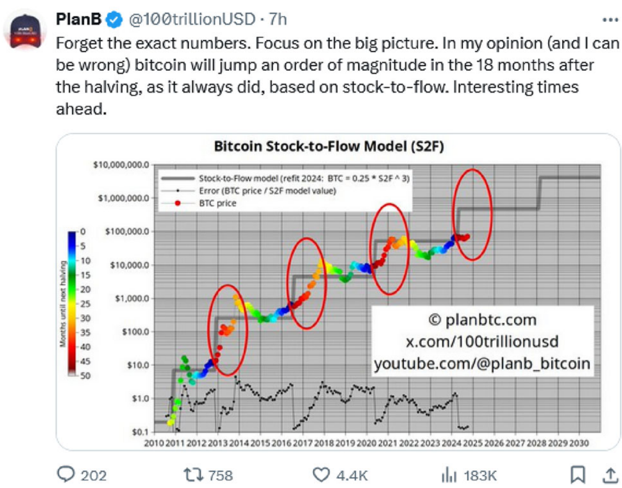

Fig. 1 Example message by X user *@100trillionUSD*

famous antivirus company, was charged with securities fraud after posting false and misleading messages urging his followers to invest in cryptocurrencies he held and then sold after the investments increased the price (Robertson 2021). *PlanB* (*@100trillionUSD* on X, Fig. 1), with 2 million followers, posts as an expert and opinion leader, discusses charts on Bitcoin price indicators, promotes the self-developed Bitcoin stock-to-flow model, and engages with content on cryptocurrency regulation and the monetary systems. The number of followers and other relevant metrics on popularity and activity characterize *PlanB* as an SMI (Riquelme and González-Cantergiani 2016).

Beyond these individual cases, previous research has examined how finfluencers shape financial markets. Pedersen (2022) introduced a game theoretical model illustrating the mechanisms of consensus building on asset prices with finfluencers as opinion leaders or radicals whose actions may shift consensus prices away from rational prices. The model demonstrates how finfluencers, in shaping investor beliefs, drove speculation and bubble building in the 2021 GameStop squeeze. In work closely related to our research, Mai et al. (2018) analyzed the effect of social media sentiment on Bitcoin value. They classified social media users by posting volume into a vocal minority, a group of community leaders that can be considered finfluencers, and a silent majority, a diverse crowd less engaged in social media activities. The researchers found that social media sentiment has predictive power for the value of Bitcoin and that even though the vocal minority was much more active and visual, the sentiment of the silent majority showed a stronger effect on prices.

Based on our literature review, we conceptualize the diverse group of finfluencers as follows: a) finfluencers individually and as a group actively exert social influence (Raafat et al. 2009) on other actors in the network; b) they have obtained prominent network positions as opinion leaders in their domain and gained trust based primarily on verbal factors (Ki and Kim 2019). While prior research has characterized finfluencers, our work systematically investigates their effect on crowd sentiment. Rather than focusing on their individual characteristics or their potential impact on financial markets, we examine how their sentiment influences the general crowd sentiment.

3 Theory and Hypotheses

3.1 Herding Behavior and Relational Herding

Herd theory provides a fundamental framework for understanding how individuals conform to the behavior of others in decision-making environments. It describes how individuals are influenced by the actions of others, leading to collective patterns that may deviate from purely rational decision-making (Banerjee 1992; Bikhchandani et al. 1992). The alignment of individuals' actions within a herd occurs through local interactions, without reliance on centralized coordination (Raafat et al. 2009). This phenomenon has been observed in a variety of domains, including financial markets and economics (Raafat et al. 2009). In financial contexts, herding occurs when investors, analysts, or other market participants base their decisions not solely on private information but on the actions of others, potentially disregarding their own independent assessments (Hong et al. 2000; Jegadeesh and Kim 2010; Scharfstein and Stein 1990). For example, Barber et al. (2022) found that attention-driven herding among retail investors significantly influences market activity.

Herding is inherently a mass phenomenon, driven by the collective dynamics of a large number of individuals responding to the actions and opinion of predecessors, such as market bubbles or mass hysteria (Raafat et al. 2009). Unlike isolated decision-making processes, herding effects manifest at large scales that can influence collective actions. One of the core mechanisms behind herding lies in *social learning*, where individuals learn information from the actions of others rather than relying solely on private knowledge (Banerjee 1992; Bikhchandani et al. 1992). As a result, individual actions aggregate into crowd dynamics. Within social learning, two key mechanisms contribute to herding: *imitation behavior* and *information discounting* (Sun 2013). Imitation occurs when individuals observe and replicate the actions of predecessors, assuming that those individuals possess superior knowledge or insight. Information discounting, on the other hand, occurs when individuals refrain from their own independent judgment in favor of the perceived expertise of others.

Herd behavior can also be observed in social media contexts, where the visibility and accessibility of individual actions play a central role in exerting social influence (Mattke et al. 2020). While traditional herd theory focuses on observable actions such as investment decisions, recent work has argued that sentiment expression on social media can serve a similar function. Specifically, Matook et al. (2022) draw on herd behavior by conceptualizing social media posts as observable actions that others can observe, imitate, or discount. Building on this perspective, we view sentiment expressed in posts as a form of observable action that can trigger herding dynamics, driven by the same underlying mechanisms as in traditional herding contexts.

Traditional herding research also assumes that individuals follow prior actions without considering social connections between decision-makers. However, in online social platforms, *relational herding* occurs when individuals are influenced by the actions of those within their social network rather than by anonymous actors (Liu et al. 2015). Unlike anonymous interactions, relational herding is shaped by direct ties between individuals and their social relations. For example, individuals are more likely to follow decisions made by their friends or followees they actively engage with, rather than by random actors. This distinction is important in social media platforms, which are centered around social relations, where decision-makers can directly interact and engage with predecessors. This relational aspect is further characterized in the context of SMIs as *parasocial*, primarily one-sided and non-reciprocal. However, social media platforms facilitate more two-sided dynamic interactions and social interactions through features like comments or likes (Lou 2022; Masuda et al. 2022; Meyer et al. 2023).

3.2 Hypothesis Development

In financial social media, herding mechanisms are particularly relevant in understanding the role of finfluencers, who act as opinion leaders within the social network. In the context of relational herding, the crowd of financial social media can be considered as the herd, whose interaction on social media platforms is strongly determined by relational ties to finfluencers. While herding typically refers to the convergence of actions, in financial social media, this process can manifest through the formation and diffusion of sentiment from posts (Matook et al. 2022).

Unlike traditional financial analysts, finfluencers present market discussions and opinions about financial assets in a more accessible and engaging way (Guan 2023b). Their content spreads quickly through social media platforms, reaching a large audience. As users observe the strong engagement that finfluencer posts receive, such as likes, shares, and comments, they may interpret this as a signal of opinion leadership, leading to imitation behavior, where they adopt similar sentiment. Simultaneously, information discounting may occur when users override their own independent assessments, such as evaluations on financial fundamentals, in favor of the finfluencer's view, especially when they perceive the influencer as knowledgeable or when their own expertise is limited.

Beyond these mechanisms, relational herding may further amplify the role of finfluencers. Similar to SMIs in other contexts, finfluencers occupy central positions within social networks. Users who frequently engage with a finfluencer's content may develop trust in their opinions, making them more likely to adopt similar sentiment. Platform algorithms further reinforce this process by amplifying highly engaged posts, ensuring that finfluencer content reaches a wider audience. Given the social ties to the crowd, this increases the likelihood that finfluencer sentiment drives crowd sentiment.

Although studies suggest differences in how sentiment is associated to market outcomes in different asset classes such as stocks and cryptocurrencies (Aysan et al. 2024; Kraaijeveld and De Smedt 2020; Liu et al. 2022; Mai et al. 2018), we posit that the mechanism of social influence from finfluencers to the crowd is likely to hold across both asset classes, even if its strength may vary. This assumption builds on the broader behavioral mechanisms outlined in herd theory, which emphasize social learning processes that apply across different asset classes, including both stocks and cryptocurrencies. However, contextual factors such as asset maturity may influence the degree to which individuals rely on external cues. For example, cryptocurrency markets often attract a higher proportion of retail investors who generally rely more on social media for investment decision-making and often lack access to fundamental valuation research (Kraaijeveld and De Smedt 2020; Meyer et al. 2023). As a result, information discounting based on finfluencers may be more likely in these settings. Therefore, we explicitly test the effect separately for cryptocurrencies and stocks to assess whether the strength of this influence differs across asset types.

To summarize, we expect that crowd sentiment is preceded by influencer sentiment and there exists a positive association given imitation and discounting information of the crowd. We expect this relation to be parasocial and non-reciprocal, and to hold across both stocks and cryptocurrencies. While crowd sentiment is preceded by multiple factors, including market outcomes, we propose that finfluencer sentiment may serve as an additional driver that introduces social influence dynamics beyond those explained by market performance alone. This leads to our first hypothesis:

H1 Finfluencer sentiment positively influences crowd sentiment towards financial assets (i.e., stocks and cryptocurrencies).

Herding behavior is more pronounced when individuals experience uncertainty, as it increases their reliance on external cues rather than independent reasoning (Bikhchandani et al. 1992; Liu et al. 2015; Sun 2013). In our research context, this uncertainty can take multiple forms, potentially affecting the extent to which individuals adopt finfluencer sentiment. Specifically, we conceptualize two facets of crowd uncertainty: uncertainty within the crowd sentiment itself and uncertainty about the asset's value.

The first facet of uncertainty arises from the divergence of sentiment within the crowd, a concept identified in prior research as sentiment dispersion (See-To and Yang 2017). When individuals observe a strong sentiment consensus on financial social media, they are less susceptible to external influence from finfluencers, given the reduced ambiguity in forming their own sentiment. However, when sentiment dispersion is high, indicating significant disagreement within the crowd, individuals experience greater uncertainty in deciding which sentiment to adopt. Under these uncertain conditions, we argue that individuals increasingly rely on external sources to guide their sentiment formation. Rather than following the broader crowd, individuals tend to herd toward finfluencers, who are seen as experts and opinion leaders. Their visibility, engagement levels, and perceived expertise position them as *sentiment anchors* in such environments. A similar mechanism was observed by Dao et al. (2024) in equity crowdfunding, where higher uncertainty driven by increased discussions among investors amplified herding behavior. As a result, we expect finfluencer sentiment to exert a stronger influence on crowd sentiment under conditions of high sentiment dispersion in the crowd. Thus, we hypothesize:

H2a: Crowd sentiment dispersion positively moderates the effect of finfluencer sentiment on crowd sentiment.

A second facet of uncertainty arises from ambiguity in an asset's value, which is closely linked to price volatility in financial markets (Mai et al. 2018). During periods of high volatility, uncertainty about asset values increases. Under such market conditions, individuals become more likely to imitate the actions or opinions of others rather than relying exclusively on their own assessments. Similar patterns occur in related contexts such as social media firestorms, where high uncertainty leads to users quickly imitating the sentiment of earlier comments (Matook et al. 2022). Under these conditions, individuals specifically herd toward finfluencers rather than the broader crowd because finfluencers are perceived as opinion leaders with superior expertise. Thus, we hypothesize:

H2b Asset value volatility positively moderates the effect of finfluencer sentiment on crowd sentiment.

Several studies on herding behavior suggest that the activity of predecessors serves as a moderator for herding effects. The argument is that imitation is a condition that fosters herding behavior (Sun 2013) and depends on the visibility of actions and opinions of predecessors. Given increased activity of predecessors, individuals are more exposed to a particular action or opinion and thus more likely to adopt it. For example, Lee et al. (2015) find that herd behavior in online movie ratings is stronger when user rating activity is high, particularly when individuals see ratings from trusted friends. Similarly, in the context of technology adoption and usage, Sun (2013) and Feng et al. (2022) argue that the strength of herding behavior is influenced by the number of observed adopters in a person's environment. Importantly, Sun (2013) highlights that individuals do not just consider the quantity of observed actions, but also the types of individuals expressing them—such as IT experts or other authoritative figures who may be perceived as better informed.

Applied to our research context, these mechanisms suggest that finfluencer activity positively moderates the relationship between finfluencer sentiment and crowd sentiment. Higher activity (i.e., post volume) increases the visibility and prominence of finfluencer sentiment, making it more easily observable and reinforcing its influence on the crowd. As a result, the likelihood of imitation among the crowd may increase. Therefore, we hypothesize:

H3 Finfluencer posting volume positively moderates the effect of finfluencer sentiment on crowd sentiment.

Figure 2 illustrates our research model, summarizing the theoretical relationships explored in this study.

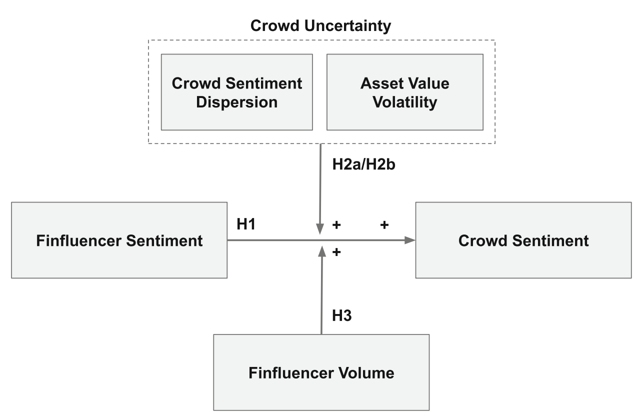

Fig. 2 Research model

4 Data and Methodology

Building on our theoretical framework, this study explores the social dynamics between influential actors and the crowd within financial social media. Our methodology involves collecting a comprehensive dataset of social media posts, processing it to identify potentially influential actors and the crowd, and applying sentiment analysis to both groups. We construct several key variables in daily temporal resolution from the dataset and employ PVECMs, Granger causality tests, and IRFs analysis to empirically test our hypotheses. The following sections outline the steps in detail.

4.1 Collection of Financial Social Media Dataset

We acquired a proprietary dataset of X data via Stockpulse, a German social media analytics company, which utilizes programmatic interfaces of social media platforms to continuously store and process financial social media data. We chose X data for three reasons: first, it has been used extensively in financial social media research (e.g., Bollen et al. (2011); Nofer and Hinz (2015)), given its prominence in financial discussions; second, it is a common platform used by finfluencers (Guan 2023a), making it well-suited for studying their impact on crowd sentiment; and third, it provides the ability to estimate social influence in comparison to other platforms such as forums (Mai et al. 2018) due to its network-based features. The dataset consists of original posts, retweets (shared posts from other users), and replies (responses to original posts of other users). We selected posts in an observation period from January 1, 2022, to January 1, 2023, to conduct our empirical study in various market phases. Since we hypothesize that sentiment contagion from finfluencers to the crowd follows common mechanisms across financial social media, we included both asset classes of stocks and cryptocurrencies. Using the most referenced assets on X in 2022, we chose the top four for each asset class. We chose the criterion of most referenced assets based on three considerations. First, analyzing the most referenced assets on X ensures that our study captures relevant market discussions. Highly discussed assets reflect investor attention, making them a relevant set of assets to investigate (Barber et al. 2022). Second, we selected assets with a high volume of social media posts to enhance the statistical power of our analysis. A sufficient number of posts is required to ensure accurate daily sentiment estimation and econometric modeling, given the inherent noise of social media sentiment (Deng et al. 2018; Subramanian et al. 2023). Following prior research on social media sentiment and financial markets (Mai et al. 2018), our selection ensures that each selected asset has a substantial number of posts per day. Third, selecting the most referenced assets ensures we capture large-scale sentiment dynamics essential for studying herding effects, which rely on widespread social interactions. The limitations and implications of this selection are discussed later in the paper.

For each asset, we refer to the corresponding cashtag, a company's ticker symbol prefixed with a dollar sign used on X to reference a specific title (e.g., $TSLA for Tesla Inc.). The resulting set of cryptocurrencies investigated are Bitcoin ($BTC), Ethereum ($ETH), Solana ($SOL) and Binance Coin ($BNB); and Tesla Inc. ($TSLA), GameStop Corp. ($GME), Netflix Inc. ($NFLX) and Amyris Inc. ($AMRSQ) for stocks. Our final dataset contains 80 million posts (Table 1), with BTC the most predominant asset and GME the least referred-to in our dataset. Nearly 40% of posts are replies to other posts, indicating high levels of interactions among users.

4.2 Identification of Potentially Influential Actors and the Crowd

We used the social networking potential (SNP) (Anger and Kittl 2011; Riquelme and González-Cantergiani 2016) as a measure to identify potentially influential actors for the following reasons. Unlike popularity-based metrics such as follower count that primarily reflect reach, the SNP score aligns with our conceptualization of finfluencers as opinion leaders who actively engage within their network (De Veirman et al. 2017; Lou and Yuan 2019). The SNP score captures both content-oriented interactions (based on replies and retweets) and conversation-oriented interactions (based on the number of distinct actors involved), covering multiple aspects of interactions beyond just popularity-based metrics. Further, SNP can be computed efficiently given our dataset and correlates with more complex influence metrics such as the Klout score (Anger and Kittl 2011). We incorporated replies and retweets by actors for calculating the SNP score; however, we excluded them in our later analysis of sentiment because they primarily indicate endorsement of unique posts. We computed the SNP for each individual actor i in the dataset. It is made up of the interaction ratio $I(i)$ and the reply mention ratio $RM(i)$, defined as follows:

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

and

Table 1 Descriptive statistics about the X dataset

Title	Cashtag	Unique users	Unique posts	Retweets	Replies
Tesla Inc	$TSLA	1,055,293	1,021,800	1,884,818	1,815,840
GameStop Cor	$GME	58,250	39,490	109,814	74,134
Netflix Inc	$NFLX	1,057,430	180,033	1,661,803	491,180
Amyris Inc	$AMRSQ	534,837	93,522	907,164	587.264
Solana	$SOL	948,294	728,176	4,943,423	557,615
Ethereum	$ETH	2,956,788	7,565,675	10,864,492	4,862,928
Bitcoin	$BTC	3,113,846	9,269,055	17,951,455	3,978,847
Binance Coin	$BNB	599,957	147,750	1,314,422	574,443

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

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 $N(i)$ the number of posts of i. The measure produces a ranking of actors according to their SNP, considering both content-oriented interactions $RM(i)$ and conservation-oriented interactions $I(i)$. Our findings show that most actors tend to have a low SNP score, indicating a long-tail distribution. This finding is consistent with prior research on social media networks (Mai et al. 2018; Ye and Wu 2010). Figure 3 reports the log-scaled distribution of SNP scores across all users in the dataset.

To identify actors with the highest social influence potential, we set a threshold at the 95th percentile of SNP scores, following the threshold of Mai et al. (2018). Actors below the 50th percentile were classified as the crowd. We excluded actors between the 50th and 95th percentiles to ensure a clear distinction between finfluencers and the crowd, while maintaining sufficiently large sample sizes for robust analysis. Based on these classifications, we split the tweets into two groups: those posted by finfluencers and those posted by the crowd.

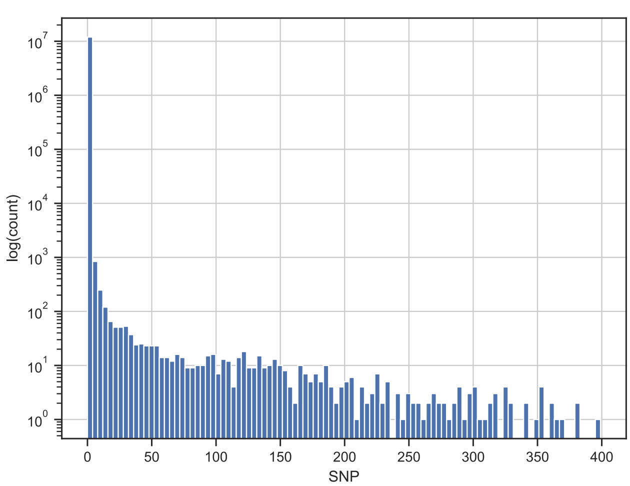

Fig. 3 Distribution of SNP for all users in dataset

4.3 Definition of Variables

After dividing the actors and their corresponding tweets into two distinct groups, we derived sentiment time series for each group of tweets. We included only original tweets and removed replies and retweets at this step, as they primarily indicate endorsement of unique posts. Furthermore, we included only actors who have contributed at least five posts to our dataset to ensure sufficient activity levels for meaningful analysis. The sample results in 17,302 finfluencers and 173,013 crowd users, with 2,284,939 finfluencer tweets and 3,415,390 crowd tweets.

We employed a transformer-based model (Twitter-RoBERTa[1]) to the tweets that was trained on 124 million tweets and finetuned for sentiment analysis (Barbieri et al. 2020; Camacho-Collados et al. 2022). We chose this model due to recent advances in sentiment analysis based on machine learning compared to lexicon-based models (Barbieri et al. 2020; Mishev et al. 2020; Stieglitz et al. 2014). In terms of performance and quality of sentiment estimation, transformer-based models have exceeded lexicon-based approaches on various benchmarks (Mishev et al. 2020). The RoBERTa model outputs a probability of posts being positive to negative. For each tweet, we compiled a compound score ranging from -1 (most negative) to +1 (most positive) by subtracting the probability of a post being negative from the probability of being positive. We then measured sentiment in each time interval t by calculating the average compound score computed as:

$$s_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \text{compound\_score}(i) \tag{4}$$

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

where N_t is the total number of posts in time interval t and compound_score(i) is the compound sentiment score of post i in time interval t.

In addition to sentiment for finfluencers and the crowd, we derived sentiment dispersion for both groups following See-To and Yang (2017), which measures the standard deviation of compound scores for all tweets per time step (daily). This captures the variation in sentiment within the posts and aims to be a proxy for polarity or lack of consensus among the crowd. Additionally, we determined the number of posts per day (volume) as a measure of activity.

For each asset, we included several market variables to control for the asset value and other market indicators. We determined the logarithm of price and trading volume (USD) for each asset retrieved from *YahooFinance*. We further included a measure of volatility following Mai et al. (2018) by applying the exponentially weighted moving average model, which estimates volatility σ with the formula: $\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)r_{t-1}^2$. The volatility on day t is calculated from the previous day volatility and the most recent daily percentage change in price. The parameter λ determines the speed of adjustment to the most recent daily percentage change. We chose $\lambda = 0.94$ in line with (Mai et al. 2018). Table 2 summarizes the resulting variables including standard statistics.

4.4 Empirical Methodology

We employ PVECMs utilizing EViews to investigate the social dynamics within financial social media and capture the interdependencies between time series across multiple cross-sectional units. VECM is an extension of the widely used vector autoregression (VAR) model, sharing many of its advantages, including its ability to model bidirectional causality, account for autocorrelation, and handle endogenous relationships across multiple variables (Mai et al. 2018; Lütkepohl 2005). VECMs go beyond the capabilities of a traditional VAR by addressing situations where cointegration exists, that is, long-term equilibrium relationships between variables that move together over time. This allows the model to capture both short-term dynamics and long-term dependencies. Unlike models that distinguish between endogenous and exogenous variables, VECM treats all variables as jointly endogenous, which is particularly useful in systems where feedback loops and mutual influences are possible. Furthermore, VECM allows for formal testing of Granger causality between sentiment time series (Granger and Newbold 1974). Granger causality is a statistical method used to assess whether one time series can provide predictive information about another time series by testing whether past values of, say, X_t significantly improve the forecast of Y_t. Granger causality does not imply a direct causal relationship, however, but identifies statistically significant patterns of association based on lagged values of the variables. Formally, a PVECM for cross-sectional unit i with lag order k is expressed as:

$$\Delta \mathbf{y}_{it} = \Pi_i \mathbf{y}_{i,t-1} + \sum_{j=1}^{k-1} \Gamma_{ij} \Delta \mathbf{y}_{i,t-j} + \mathbf{u}_{it} \tag{5}$$

where $\mathbf{y}_{it}$ is the vector of endogenous variables for unit i, $\Delta \mathbf{y}_{it}$ denotes first differences, and $\Pi_i \mathbf{y}_{i,t-1}$ captures the long-run equilibrium relationships. The matrix Π_i contains information about the cointegration relationships among the variables, while the Γ_{ij} terms account for short-term adjustments. The term $\mathbf{u}_{it}$ represents the error term. While individual asset-specific VECMs could be estimated separately, we adopt a panel approach to capture shared dynamics across time series.

Another benefit of using VECMs is their ability to compute IRFs, which estimate the impact of a one-time shock to one variable on the entire system (Lütkepohl 2005). The impulse responses are derived from the moving average (MA) representation of the VAR process. These impulse responses are crucial in understanding the magnitude and persistence of the effects of shocks and supplement the analysis of the short-term effect of lagged variables. In a VECM, the IRFs are derived by first transforming the model into its MA representation, which expresses each variable as a function of past shocks:

$$\mathbf{y}_{it} = \sum_{j=0}^{\infty} \Phi_j \mathbf{u}_{i,t-j} \tag{6}$$

where Φ_j are the impulse response matrices that describe how shocks propagate over time, and $\mathbf{u}_{it}$ are the residuals or innovations (shocks) to the system at time t. The index j represents the time horizon, indicating how far into the future the initial shock's impact is measured. By calculating these matrices, we can analyze how a shock to one variable affects other variables in the system over future periods.

5 Results

5.1 Relation Between Finfluencer Sentiment and Crowd Sentiment

To test the main finfluencer effect hypothesis (H1), we examine the sentiment variables of finfluencers and the crowd in a PVECM model. To account for various endogenous factors, we incorporate market variables and several control variables in this model. As a first step, we report a set of model specification tests. Specifically, we test the stationarity of the variables involved, as Table 3

Table 2 Summary statistics of key variables for daily time series

Variable	Description	Mean	Median	SD	Min	Max
Sentiment variables						
S_c	Crowd sentiment	0.0746	0.0623	0.0889	−0.5544	0.8779
S_i	Finfluencer sentiment	0.0849	0.0640	0.1266	−0.7124	0.8481
Market controls						
σ	Asset return volatility	0.0436	0.0390	0.0193	0.0174	0.1584
$\ln(P)$	Log asset price	5.3578	5.5041	2.6015	0.4121	10.7724
$\ln(V)$	Log asset trading volume	19.3614	18.9622	3.2519	13.9312	25.5023
Other controls						
SD_c	Crowd sentiment dispersion	0.2404	0.2475	0.0780	0.0000	0.6839
SD_i	Finfluencer sentiment dispersion	0.2210	0.2481	0.1211	0.0000	0.9329
$\ln(N_c)$	Log post volume of crowd	4.9924	5.0845	2.1329	0.0000	11.0107
$\ln(N_i)$	Log post volume of finfluencers	4.2752	4.2627	2.7486	0.0000	9.2602

Table 3 Fisher-Chi-Square unit root test results for variables

Variable	Description	Test statistics	p-value	Order of integration
Sentiment variables				
S_c	Crowd sentiment	−5.749	< 0.0001	I(0)
S_i	Finfluencer sentiment	−5.503	< 0.0001	I(0)
Market controls				
σ	Asset return volatility	−3.647	0.0300	I(1)
$\ln(P)$	Log asset price	−1.135	0.5158	I(1)
$\ln(V)$	Log asset trading volume	−10.543	< 0.0001	I(0)
Other controls				
SD_c	Crowd sentiment dispersion	−9.755	< 0.0001	I(0)
SD_i	Finfluencer sentiment dispersion	−3.847	< 0.0001	I(0)
$\ln(N_c)$	Log post volume of crowd	−2.941	0.1611	I(1)
$\ln(N_i)$	Log post volume of finfluencers	−3.484	0.0591	I(1)

Table 4 Johansen trace test results for cointegration (Fisher statistics)

No. of CE(s)	Fisher statistic (trace test)	Probability
0	148.3	0.0000
1	85.73	0.0000
2	47.46	0.0001
3*	**25.14**	**0.0673**
4	15.77	0.4691

reports via an panel-based Fisher Chi-Square unit root test (Lütkepohl 2005). The results indicate that while some variables are stationary at level, others exhibit non-stationarity and require first-order differencing to achieve stationarity. Given non-stationary variables, we could model their relationship with VAR via integration, however, this approach can suffer misspecification bias if cointegration between variables is present (Lütkepohl 2005; Mai et al. 2018). Therefore, we test for cointegration using a Johansen trace test (Johansen and Juselius 1990) and confirm the presence of cointegration in our variables (see Table 4). The test evaluates the presence of cointegration by sequentially testing for additional cointegration relationships and stops when the null hypothesis of no further cointegration is not rejected at the chosen significance level. Based on these findings, we determine the model's cointegration rank to be 3 (Lütkepohl 2005).

Since cointegration is present, we conclude that PVECM is the appropriate model. We determine the appropriate lag length k in our PVECM model using the Akaike information criterion (AIC), which is widely used in econometrics (Lütkepohl 2005). Selecting the correct number of lags ensures that the model adequately captures the dynamic interdependencies between variables in the data. A model with too many lags can overfit the sample data, capturing noise rather than meaningful relationships; one with too few lags might fail to capture the relevant dynamics. The AIC for a VECM is defined as $AIC = -2L + 2(k + 2kp)$, where L is the normalized log-likelihood, k is the number of coefficients dependent on the number of endogenous

Table 5 VECM order selection based on AIC

Lag	Log-Likelihood	AIC
1	21796.93	−17.04284
2	22230.91	−17.36852
3	22519.20	−17.58069
4	22794.36	−17.78362
5	23133.51	−18.03861
6	23398.17	−18.23557
7	23463.75	−18.27431
8*	**23514.87**	**−18.30166**
9	23514.50	−18.28772

variables, and p is the lag length. Since AIC penalizes model complexity (number of lags and coefficients) while favoring better fit (log-likelihood), we select the lag length that minimizes its value. Based on the results in Table 5, we determine the optimal lag length for the VECM with $k = 8$, as indicated by the lowest value of the AIC.

Based on our model specification tests, we proceed to estimate PVECM models with a lag length of $k = 8$ on our variables (see Table 6). We report results for three different model specifications: one that includes all assets (cross-sectional units), one that focuses only on stocks, and one that includes only cryptocurrencies. The estimated coefficients determine the short-term relationship between the variables. We report only the first lag estimates and investigate Granger causality and IRFs for long-term effects.

The model estimated on all assets reveals several short-term relationships among the variables. First, we observe a strong negative autoregressive relation of the sentiment variables. Days with low sentiment of crowd and finfluencers tend to precede days of high sentiment and vice versa, indicating that spikes in sentiment tend to correct quickly. Second, we find support for a significant relationship in the short-term between finfluencer sentiment and crowd sentiment. A rise in finfluencer sentiment precedes a decline in crowd sentiment tomorrow. Conversely, we find no statistically significant effect of crowd sentiment on the finfluencer sentiment. This short-term asymmetry suggests that finfluencers may impact crowd sentiment, but the reverse effect does not hold. Third, we observe that price increases in assets are associated with higher sentiment of the crowd on the next day, while past trading volume increases are associated with lower sentiment of finfluencers. Fourth, we find that days with higher sentiment dispersion in the crowd precede days with low crowd sentiment, meaning that polarization in the crowd leads to lower crowd sentiment short-term. Interestingly,

Table 6 PVECM estimates for sentiment variables and controls for three model specifications (all assets, only stock assets, and only cryptocurrency assets)

	Dependent variables					
	All		Stocks		Cryptocurrencies	
Independent Var.	$S_c(t)$	$S_i(t)$	$S_c(t)$	$S_i(t)$	$S_c(t)$	$S_i(t)$
$S_c(t-1)$	−0.130***	0.051	−0.205***	0.121	−0.105**	0.054
	(0.043)	(0.055)	(0.060)	(0.105)	(0.051)	(0.030)
$S_i(t-1)$	−0.081**	−0.383***	−0.014	−0.122**	−0.176**	−0.515***
	(0.037)	(0.048)	(0.042)	(0.072)	(0.076)	(0.044)
$\sigma\ (t-1)$	0.117	0.729	0.587	−0.035	−0.036	−0.165
	(0.457)	(0.586)	(0.634)	(1.095)	(0.673)	(0.388)
$\ln P(t-1)$	0.095***	0.045	0.079	0.012	0.026	0.065***
	(0.033)	(0.042)	(0.051)	(0.089)	(0.040)	(0.023)
$\ln V(t-1)$	−0.005	−0.032***	0.012	−0.028*	0.014*	0.002
	(0.006)	(0.008)	(0.009)	(0.016)	(0.007)	(0.004)
$SD_c(t-1)$	−0.180***	−0.036	−0.110***	−0.323***	−0.247***	−0.034
	(0.044)	(0.057)	(0.040)	(0.067)	(0.045)	(0.026)
$SD_i(t-1)$	0.028	−0.019	−0.049	−0.001	0.475***	−0.281***
	(0.028)	(0.036)	(0.050)	(0.086)	(0.101)	(0.058)
$\ln N_c(t-1)$	0.016***	0.007*	0.019***	0.021***	0.007**	0.005**
	(0.003)	(0.004)	(0.005)	(0.008)	(0.004)	(0.002)
$\ln N_i(t-1)$	0.002	0.008	0.014***	−0.002	0.019**	0.022***
	(0.005)	(0.006)	(0.005)	(0.009)	(0.009)	(0.005)
R-Squared	0.399	0.516	0.450	0.521	0.380	0.454
Adj. R-Squared	0.381	0.501	0.419	0.494	0.346	0.424

The first lag estimates are displayed. Only sentiment variables are shown among the dependent variables. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

this effect does not hold for sentiment dispersion of finfluencers. Lastly, a greater number of crowd posts is positively associated with crowd sentiment and finfluencer sentiment on the next day. Again, this effect does not transfer to the number of finfluencer posts.

Our model estimations also demonstrate significant differences in the relationships between the variables for stocks compared to cryptocurrency assets. The short-term relationship between finfluencer sentiment and crowd sentiment is much stronger in cryptocurrencies compared to stocks. For stocks the relationship is not statistically significant. In cryptocurrencies, the crowd sentiment dispersion is stronger associated with lower future crowd sentiment compared to stocks, indicating that polarization among the crowd has a stronger effect on crowd sentiment in cryptocurrencies. We additionally observe that finfluencer sentiment dispersion has a stronger relationship with both crowd sentiment and finfluencer sentiment in cryptocurrencies, indicating again a stronger association of polarization in cryptocurrencies with sentiment variables. Crowd sentiment of stock assets is more sensitive to increases in crowd posting volume than in cryptocurrencies. This means that a vocal crowd in stock assets has a stronger positive effect on next day crowd sentiment.

Given that the first lag estimates provide limited insights into long-term relationships between variables, we perform a Granger causality test to confirm the predictive relationship between finfluencer and crowd sentiment. The Granger causality test confirms a directional influence of finfluencer sentiment on crowd sentiment (see Table 7). Specifically, we find that finfluencer sentiment *granger-causes* crowd sentiment at the 5% significance level ($\chi^2 = 18.690$, p-value = 0.017). This suggests that past changes in finfluencer sentiment significantly predict future changes in crowd sentiment. Conversely, we do not find significant evidence for Granger causality in the opposite direction ($\chi^2 = 6.131$, p-value = 0.633), indicating that changes in crowd sentiment do not predict future shifts in finfluencer sentiment. Additionally, we investigate both asset classes separately and find that the results align with the PVECM coefficient estimates. The effect is highly significant for the cryptocurrency assets in our sample, where finfluencer sentiment strongly precedes crowd sentiment. Conversely, no statistical significance is found in the stock market.

While the Granger causality test identifies whether one variable can predict another, it does not capture the magnitude or duration of the dynamic responses to shocks. To gain a comprehensive understanding of the dynamic relationship between crowd and finfluencer sentiment, we examine the IRFs (Fig. 4). We report IRFs with 1000 Monte Carlo replications (Lütkepohl 2005). While the PVECM coefficients suggest a short-term inverse relationship between current sentiment levels and their past values, the IRFs provide a view on how sentiment responds to shocks, including long-term effects and cointegration relationships. We determine the IRFs across a 20-day period after a shock. The IRF for the effect of finfluencer sentiment on crowd sentiment ($S_i \rightarrow S_c$) reveals an immediate positive response, peaking around day 2–3 and reaching approximately 0.05 for all assets. In the cryptocurrency market, this effect is stronger, peaking at around 0.08. In contrast, the stock market shows a relatively weak response, remaining below 0.03 throughout the observed period. Economically, this suggests that a one-unit positive shock in finfluencer sentiment leads to an immediate increase in crowd sentiment, with the strongest period-specific response reaching 0.08 units around day 2–3 for cryptocurrencies. The effect gradually declines but remains positive and significant for the horizon length investigated. The IRFs for the effect of crowd sentiment on finfluencer sentiment ($S_c \rightarrow S_i$) are more ambiguous and substantially weaker, fluctuating around 0. This holds for both stocks and cryptocurrencies. The results suggest a lack of sustained impact after shocks, supporting the findings of the Granger causality analysis.

To summarize, while the PVECM lag coefficients suggest a short-term inverse relationship between finfluencer and crowd sentiment, the IRF analysis complements this by revealing a positive relationship of finfluencer sentiment on crowd sentiment over time. Conversely, the effect of crowd sentiment on finfluencer sentiment remains close to zero and lacks statistical confidence. These findings highlight an asymmetry in the relationship, consistent with the Granger causality test results, and collectively support H1.

Table 7 Granger causality test results for three model specifications (all assets, only stock assets, and only cryptocurrency assets)

Direction	All		Stocks		Cryptocurrencies	
	Chi-squared	p-value	Chi-squared	p-value	Chi-squared	p-value
$S_i \rightarrow S_c$	18.690	0.017	6.765	0.562	33.269	0.000
$S_c \rightarrow S_i$	6.131	0.633	7.719	0.461	12.385	0.146

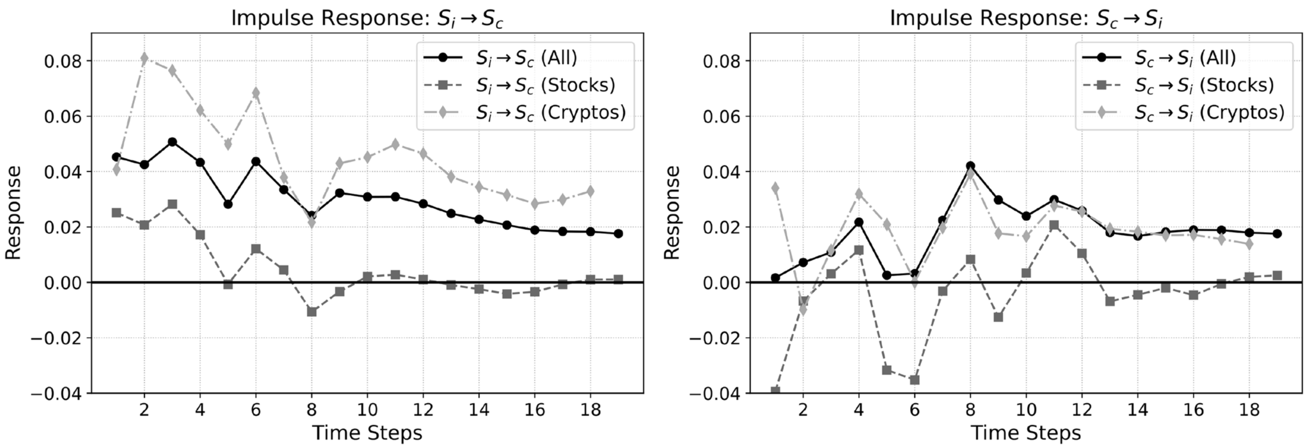

Fig. 4 Impulse response functions for $S_i \rightarrow S_c$ and $S_c \rightarrow S_i$

Table 8 PVECM estimates for sentiment variables and moderators for four model specifications: uncertainty (asset price and sentiment dispersion), influencer volume, and a combined model

	Dependent variables			
Independent Var.	Uncertainty (asset price) $S_c(t)$	Uncertainty (dispersion) $S_c(t)$	Volume $S_c(t)$	Combined $S_c(t)$
$S_c(t-1)$	−0.097**	−0.131***	−0.141***	−0.103**
	(0.043)	(0.043)	(0.043)	(0.043)
$S_i(t-1)$	−0.302***	−0.185**	−0.178**	−0.351***
	(0.085)	(0.058)	(0.053)	(0.098)
$\sigma\ (t-1)$	−0.236	0.269	0.157	−0.219
	(0.464)	(0.456)	(0.458)	(0.458)
$\ln P(t-1)$	0.092***	0.089***	0.084**	0.081***
	(0.033)	(0.043)	(0.003)	(0.033)
$\ln V(t-1)$	−0.003	−0.005	−0.004	−0.003
	(0.006)	(0.006)	(0.006)	(0.006)
$SD_c(t-1)$	−0.250***	−0.227***	−0.169***	−0.256***
	(0.030)	(0.030)	(0.044)	(0.030)
$SD_i(t-1)$	0.069**	0.015	0.021	0.039
	(0.028)	(0.035)	(0.024)	(0.031)
$\ln N_c(t-1)$	0.013***	0.016***	0.016***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
$\ln N_i(t-1)$	0.005	0.005	0.002	0.006
	(0.004)	(0.005)	(0.005)	(0.005)
$S_i \times \sigma\ (t-1)$	3.793***			4.668***
	(1.218)			(1.133)
$S_i \times SD_c\ (t-1)$		0.359*		0.354*
		(0.219)		(0.227)
$S_i \times \ln N_i\ (t-1)$			−0.008	−0.019
			(0.018)	(0.017)
R-Squared	0.419	0.411	0.405	0.431
Adj. R-Squared	0.399	0.390	0.385	0.407

The first lag estimates are displayed. Only crowd sentiment variable is shown among the dependent variables. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

5.2 Moderation Effect of Crowd Uncertainty and Finfluencer Volume

Having established the relationship between finfluencer sentiment on crowd sentiment, we now study how uncertainty and post volume moderate the influence. For this analysis, we estimate various PVECM models, introducing interaction terms for crowd uncertainty based on the volatility of asset prices (σ), crowd uncertainty via sentiment dispersion (SD_c), and the post volume of finfluencers ($\ln N_i$). We estimate three individual PVECM models for each moderator separately, and one model combining all moderators jointly. Table 8 shows the coefficients of the resulting PVECM models.

First, we analyze how uncertainty moderates the effect in the short-term by investigating the coefficients of the estimated PVECM model. The results indicate that higher asset price volatility strongly amplifies the effect of finfluencer sentiment on crowd sentiment. Specifically, the interaction term $S_i \times \sigma$ is positive and significant ($p < 0.01$) in both the individual model and the combined model. In other words, this implies that in days of market turbulence, finfluencer sentiment is strongly associated to crowd sentiment the next day. Similarly, crowd sentiment dispersion (SD_c) also plays a role in moderating this relationship, though to a lesser extent. The interaction term $S_i \times SD_c$ is positive and significant in both the individual model and the combined model ($p < 0.1$). Higher disagreement in crowd sentiment results in a greater association between finfluencer sentiment and crowd sentiment. Lastly, we investigate the role of finfluencer post volume ($\ln N_i$) as a moderator of the sentiment contagion effect. However, in contrast to uncertainty, we do not find strong evidence that finfluencer post volume significantly moderates the relationship between finfluencer and crowd sentiment in the short-term. The interaction term $S_i \times \ln N_i$ is negative but statistically insignificant in both the individual model and the combined model.

To further investigate the role of uncertainty and volume in the relationship between finfluencer sentiment and crowd sentiment considering all lags, we conduct the Granger causality tests incorporating interaction terms. Table 9 presents the results for each moderator separately, as well as the combined model including all moderators. The results confirm that finfluencer sentiment (S_i) granger-causes crowd sentiment (S_c) across all models. This effect remains significant in the presence of moderators, particularly when accounting for asset price uncertainty ($\chi^2 = 45.189, p = 0.000$) and sentiment dispersion ($\chi^2 = 28.060, p = 0.001$). However, the reverse relationship – crowd sentiment predicting finfluencer sentiment – is not supported in any specification, consistent with prior findings.

Examining the moderation effects, we find that uncertainty in asset prices strongly amplifies the influence of finfluencer sentiment on crowd sentiment. The interaction between finfluencer sentiment and asset price volatility is highly significant in both the individual ($\chi^2 = 54.452, p = 0.000$) and combined ($\chi^2 = 62.652, p = 0.000$) models. Similarly, crowd sentiment dispersion also plays a significant moderating role, although to a lesser extent ($\chi^2 = 20.388, p = 0.009$). In contrast, the moderating role of finfluencer post volume is weaker. While the interaction term $S_i \times \ln N_i$ is significant in the volume-only model ($\chi^2 = 17.191, p = 0.028$), it becomes insignificant in the combined model ($\chi^2 = 9.009, p = 0.342$), suggesting that volume is not a strong moderator. Furthermore, estimating the IRFs supports the positive direction of the uncertainty moderators identified in the PVECM results, whereas the post volume moderator does not show a clear effect, fluctuating around zero.

Taken together, these results highlight that crowd uncertainty significantly moderates the effect of finfluencers on crowd sentiment. Therefore, we find support for H2a and H2b. The volume of finfluencer posts does not

Table 9 Granger causality test results for four model specifications: uncertainty (asset price and sentiment dispersion), influencer volume, and a combined model

Direction	Uncertainty (asset price)		Uncertainty (dispersion)		Volume		Combined	
	Chi-squared	p-value	Chi-squared	p-value	Chi-squared	p-value	Chi-squared	p-value
$S_i \rightarrow S_c$	45.189	0.000	28.060	0.001	19.47	0.013	45.015	0.000
$S_c \rightarrow S_i$	7.659	0.467	8.425	0.393	8.128	0.421	11.453	0.170
$S_i \times \sigma \rightarrow S_c$	54.452	0.000					62.652	0.000
$S_i \times SD_c \rightarrow S_c$			20.388	0.009			18.591	0.017
$S_i \times \ln N_i \rightarrow S_c$					17.191	0.028	9.009	0.342

appear to play a strong moderating role, as its interaction effect is not consistently significant. While the negative coefficient of the first lag is insignificant, weak evidence for Granger-causality emerges in the model where post volume is considered alone, indicating a possible saturation effect to high volumes of finfluencer posts. However, this effect does not hold in the combined model. This suggests that any potential moderation may occur with a delay (after lag 1). These results lead to the rejection of H3.

5.3 Robustness Checks

To check the reliability of our results, we report several robustness checks. As a first check, we validate our results with alternative sentiment measures and re-estimate our models (all other parameters the same as model reported in Table 6). This is essential to ensure that our findings are not driven by specific choices in sentiment estimation. In our main analysis, we relied on a transformer-based sentiment model due to its superior accuracy compared to traditional lexicon-based approaches. Transformer models leverage deep learning and contextual embeddings, allowing for a more nuanced understanding of sentiment (Barbieri et al. 2020; Camacho-Collados et al. 2022; Mishev et al. 2020). However, to ensure that our results are not contingent on the use of a high-quality sentiment model, we also test our models with lexicon-based sentiment measures. Specifically, we apply the Valence Aware Dictionary and Sentiment Reasoner (VADER) sentiment analysis model, which has been widely applied in academic research, particularly in social media contexts (Hutto and Gilbert 2014). VADER is a lexicon-based model that relies on a predefined dictionary of words and their associated sentiment scores. VADER's open-source lexicon incorporates a dictionary for social media context (including slang and emoticons), that can be extended to specific subdomains such as finance (Kraaijeveld and De Smedt 2020; Meyer et al. 2023). We added the positive and negative dictionary from the Loughran and McDonald financial corpus (Loughran and Mcdonald 2011) and adapted the pre-processing of Kraaijeveld and De Smedt (2020) of the textual data with steps such as case-folding, expanding contradictions and removing stop words. Our final VADER dictionary contains 8616 words (3793 positive and 4823 negative). We define one sentiment measure based on the average compound score as in our main results but utilize the VADER predictions. Additionally, we define one sentiment measure based on the bullishness-ratio as specified by Antweiler and Frank (2004). It is defined as the log-ratio s_t between the number of positive (positive compound score) and negative posts (negative compound score):

$$s_t = \ln\left(\frac{1 + \#\text{ positive posts in } t}{1 + \#\text{ negative posts in } t}\right) \tag{7}$$

Additionally, we apply a different financial lexicon to VADER based on a combined dictionary of SentiBignomics (Barbaglia et al. 2023) and Henry's word list (Henry 2008) as defined by FinVADER,[2] resulting in 3804 positive and 3601 negative words. We then again use the compound score as the sentiment measure. Appendix A (available online via http://link.springer.com) presents the PVECM coefficients of these robustness checks. We present only the coefficients for the relevant crowd sentiment variable. Across all approaches, the coefficients remain consistent with our primary findings, confirming that the original model results are robust to variations in sentiment measurement.

As an additional robustness check, we investigate the sensitivity of our results to alternative definitions of the crowd and the finfluencers. Since these definitions directly determine the selection of tweets, they have a strong impact on the sentiment variables. First, we vary the thresholds for selection of social influence. For the crowd, we define cutoff levels at the 40th and 60th percentiles (compared to the original 50th percentile); we set cutoffs for finfluencers at the 92.5th and 97.5th percentiles (compared to the original 95th percentile). Second, we vary our definition of social influence and use a simple metric based solely on follower count rather than the SNP. The score was adopted in prior literature, for example, to derive high-status finfluencers and other actors (Goldenberg et al. 2024). We split users into high-status finfluencers (more than 10,000 followers) and low-status actors (less than 100 followers) which results in 1,772,074 finfluencer tweets and 3,813,420 crowd tweets. We then derive sentiment variables and re-estimate our models using this alternative definition of influential actors and crowd. The results in Online Appendix B, indicate that the main effects remain consistent across these alternative definitions. Again, we display only the coefficients for the relevant dependent variable crowd sentiment. Similar to our main findings, sentiment of influential actors predicts the crowd sentiment in all variations of thresholds. However, we observe weaker significance ($p < 0.1$) when using a lower crowd threshold (40th percentile) and when defining finfluencers based on follower count rather than SNP.

Since our analysis focuses on assets with high post volume, it remains uncertain whether our methodology is applicable to assets with inherently lower social media activity. To address this limitation, we simulate the effect of lower post volume by randomly sampling a subset of tweets from our full dataset, recalculating sentiment

[2] https://github.com/PetrKorab/FinVADER.

variables, and re-estimating our models. The results of this robustness check are presented in Online Appendix C. We observe that for slightly smaller samples (80%, 60%), the main effects on sentiment variables remain consistent with the full sample. However, as the sample size is further reduced (40%, 20%), effects begin to disappear. Through this simulation, we are unable to determine whether the observed effects also apply to assets with inherently lower posting volumes. However, our results indicate that as post volume declines, the relationship between finfluencer sentiment and crowd sentiment weakens. We observe increased noise in sentiment variables due to fewer messages per day in the daily sentiment measure, which may disrupt meaningful sentiment patterns.

Lastly, there is a possibility that users form stronger attachments to individuals than to business or news accounts, which could influence sentiment dynamics. To ensure that our dataset is not dominated by posts from news channels or business accounts, we compiled a list of 449 popular financial accounts from publicly available sources, including MediaCloud and verified business lists. We identified only 929 matching posts from these sources, representing 17 unique accounts, such as Bloomberg, Forbes, Morgan Stanley, New York Times, Barron's, and The Verge. Given the low number of posts, we conclude that our sample mainly consists of individuals and such actors have not significantly influenced our results.

6 Discussion

Crowd sentiment in the financial context derived from online social media communication has drawn considerable attention in recent decades. Academic explanatory models have shown the usefulness of crowd sentiment in predicting market outcomes (Antweiler and Frank 2004; Bollen et al. 2011; Chen et al. 2014; Deng et al. 2018; Mai et al. 2018; Xie et al. 2020). As a result, finance practitioners, such as hedge funds, have adopted crowd sentiment in predictive models and trading strategies (Deng et al. 2018). Other stakeholders, including policymakers, are also attentive to its potential influence on market behavior. Cases such as the GME short squeeze (Lucchini et al. 2022; Mancini et al. 2022) illustrate how collective dynamics and social influence can drive market movements. However, few antecedents of crowd sentiment have been investigated in previous literature; ours is the first empirical study to systematically investigate the role of finfluencers in shaping crowd sentiment in stocks and cryptocurrency assets.

Our analysis supports our understanding of finfluencers as opinion leaders and aligns with the propositions of herd theory. We find support for our main hypothesis in cryptocurrencies that finfluencer sentiment predicts crowd sentiment (H1) and that it is not predicted by crowd sentiment reciprocally. This supports the concept of a parasocial relationship as a unidirectional bond where the broader network picks up on the sentiment driven by finfluencers. Importantly, our findings confirm that there exist conditions under which finfluencers achieve a similar impact as SMIs in consumer marketing contexts. By conducting a comparative analysis between stocks and cryptocurrencies within a single platform, we can examine potential differences in the effect. We find strong evidence in cryptocurrencies compared to stocks. This may be due to unique communication patterns and cultures prevalent in the cryptocurrency field (Mackenzie 2022). These distinctive characteristics likely influence how finfluencer credibility is assessed, with perceived success and presumed expertise playing a more prominent role than traditional markers of credibility such as authenticity and trustworthiness, as seen in consumer marketing contexts (Kakhbod et al. 2023; Guan 2023a). Importantly, the strength of this effect also varies depending on how social influence is measured. Our analysis shows that the effect of influencer sentiment on crowd sentiment is lower when identifying finfluencers based on follower count compared to using the SNP metric. This difference may arise because follower count primarily reflects popularity rather than engagement or interaction. Opinion leadership, however, is not merely about reach, it requires active participation and interaction within a network. The SNP metric, which more specifically captures engagement dynamics, appears to better capture the potential influence of finfluencers.

Our findings also indicate that both crowd and influencer sentiment is associated with changes in asset value, with a predominantly positive relationship. This aligns with previous literature on Bitcoin and stocks, which has shown that asset price precedes crowd sentiment (Xie 2022; Deng et al. 2018). Rising asset values tend to be accompanied by more positive sentiment, whereas declining values often correlate with increased negativity. While this study did not focus on the reverse effect of sentiment on asset prices, our results emphasize the importance of considering different user groups when analyzing financial market outcomes. Given that sentiment dynamics differ between finfluencers and the broader crowd, it becomes particularly relevant to examine whether sentiment from finfluencers has a distinct association with financial markets compared to sentiment from the crowd.

Our second set of hypotheses propose that crowd uncertainty, operationalized as asset price volatility (H2a) and crowd sentiment dispersion (H2b), positively moderates the relationship between finfluencer sentiment and crowd sentiment. Our results support both hypotheses, showing that finfluencer sentiment exerts a stronger influence on crowd sentiment under conditions of higher uncertainty, whether due to greater sentiment dispersion within the crowd or increased asset price volatility. When crowd sentiment is more dispersed, implying a lack of consensus, finfluencer sentiment plays a more prominent role in shaping the overall sentiment of the network. This aligns with herd theory, which suggests that individuals in uncertain environments tend to look to opinion leaders for guidance, using their expressed views as an anchor to reduce ambiguity (Liu et al. 2015). Similarly, when asset price volatility is high, finfluencer sentiment has a stronger influence. Investors facing more uncertainty about fundamental values may rely more on social signals instead of conducting their own analysis. Both uncertainty factors may also help explain the stronger effect observed in cryptocurrency assets, where market participants often exhibit an increased dependence on social cues due to the sector's price volatility, lack of access to fundamental valuation research, and the relative novelty of these financial assets (Aysan et al. 2024).

Although our results lead to the rejection of H3, they are not entirely conclusive. We do not find consistent significance for the moderating role of finfluencer post volume, as the moderation effect is weakly present in the volume-only model and disappears in the combined model. However, the negative but insignificant coefficient of the first lag suggests a potential saturation effect, where a high volume of influencer posts may reduce the marginal impact of additional posts on crowd sentiment. This could suggest that beyond a certain threshold of activity, the impact of finfluencer sentiment weakens as users become oversaturated or less responsive to the increasing volume of content.

While our main explanation for the finfluencer effect is grounded in herd theory and opinion leadership, another contributing factor may be the speed at which finfluencers disseminate financial information. As highly engaged participants in market discussions (Guan 2023a), finfluencers may often be earlier to share information before the broader crowd reacts. Their access to better data, analytical tools, or simply their ability to respond quickly could partially explain why their sentiment appears to precede crowd sentiment. This does not contradict the role of opinion leadership and herding but rather suggests that timing may also play a role in shaping the observed relationship. Finfluencers might not only influence sentiment through social dynamics but also act as early posters who amplify and spread information before they reach the broader crowd.

6.1 Theoretical Contributions

Our paper makes several theoretical contributions to understanding social influence in financial markets. First, we empirically reveal herding mechanisms in social media crowds as collective dynamics of users in financial social media that respond to the sentiment expressed by finfluencers. Unlike previous research that shows emotional contagion of posts from crypto vloggers with their direct comments (Meyer et al. 2023), we find that influencer sentiment is associated with crowd sentiment across independent posts, suggesting that influencers set broader sentiment trends. Thereby, we extend previous work and demonstrate the reach of finfluencers within social media environments beyond direct interactions. This shows the effects of social influence and social learning as proposed by herd theory, driven by characterizations associated with opinion leadership.

Second, we argue that studies incorporating financial social media sentiment can benefit from segmenting sentiment into crowd sentiment and influencer sentiment rather than treating it as a singular measure. Some studies have already differentiated sentiment based on factors such as post volume (Mai et al. 2018); we suggest that social influence offers an alternative and meaningful perspective. Segmenting sentiment based on social influence can provide a deeper understanding of which social media actors are associated with certain market outcomes.

Third, our research extends marketing literature by investigating SMIs in a high-stakes context, financial environments, known to be driven by fundamentals and technical indicators. Unlike SMIs in orchestrated marketing campaigns, many finfluencers are self-driven and may operate without structured support or collaboration with firms (Guan 2023b). Consequently, our research expands on the contexts and conditions under which SMIs are effective (Han and Balabanis 2024) and provides a foundation for further studies, such as exploring seeding strategies for finfluencers.

Finally, our empirical analysis provides a systematic exploration of the finfluencer phenomenon, addressing a literature gap that has often focused on single events such as Elon Musk's tweets (Ante 2023; Strauss and Smith 2019). Our broader approach investigates this phenomenon using large-scale field data, offering a more comprehensive empirical foundation. Rather than viewing finfluencer impact as isolated cases, our findings support the conceptualization of finfluencers as opinion leaders who gain influence through perceived expertise and engagement with their followers (Ki and Kim 2019). Additionally, by conducting a comparative analysis between stocks and cryptocurrencies within a single platform, we contribute to a deeper understanding of potential intra-platform differences. Investigating posts from the same platform allows us to systematically explore variations in sentiment dynamics across asset classes, complementing existing research on the distinct characteristics of cryptocurrency markets (e.g., Xie et al. (2020)).

6.2 Practical Implications

From a practical perspective, investors such as hedge funds that incorporate social media sentiment in their trading strategies (Deng et al. 2018; Subramanian et al. 2023) can benefit from distinguishing between finfluencer and crowd sentiment. The observed Granger causality provides valuable insights for developing more accurate predictive models. Integrating the observed dynamics and temporal dependencies of sentiment variables allows for a more refined modeling approach in predictive systems. Beyond its implications for institutional investors, our findings also highlight potential risks for retail investors. Our results suggest that they should be cautious when consuming social media content from influential actors, as it can shape opinions and potentially influence decisions.

At the same time, the ability of finfluencers to shape crowd sentiment presents an opportunity for firms to better understand and manage how their stock is perceived. As firms increasingly utilize social media for information disclosure and stakeholder engagement (Kim and Youm 2017), finfluencers offer a unique opportunity to actively shape crowd sentiment, which is often assumed to be largely uncontrollable and unmanageable. Although the strength of the effect can vary across asset classes, influencer marketing can nevertheless serve as a tool to engage, inform, and shape the decision-making of potential shareholders as a form of native advertising (Cao and Belo 2024). However, it is essential that firms ensure compliance with legal guidelines for financial advice (Law and Zuo 2021) and consider the potential effect of content saturation that we observed.

Our findings can also inform ongoing discussions about extending regulatory frameworks to cover finfluencer activity and the spread of information by influential actors (Guan 2023b; Stefanou 2022). Regulation could specifically address greater protection for those giving and receiving this new type of financial advice (Stefanou 2022). For example, regulators could establish thresholds that classify certain financial posts as regulated advice, using a data-driven approach to identify cases where social influence has historically played a significant role. Our research also highlights the benefits of monitoring sentiment among influential actors and incorporating a segmented view of social media sentiment into market surveillance tools (Sio 2024).

Our research also has implications for social media platforms. To the best of our knowledge, no general-purpose social media platform currently employs soft moderation interventions for financial content, such as warning labels or content disclaimers. However, similar measures have been effectively implemented in political discussions, where providing users with context before engaging with content has helped mitigate misinformation and improve content awareness (Zannettou 2021). Given the moderating role of crowd uncertainty, such measures could be applied in, for example, phases of high sentiment dispersion or volatile market phases.

6.3 Limitations and Directions for Future Research

Our study has some limitations. Although we included several controls for changes in asset value, one limitation is that we do not account for all possible endogenous and exogenous factors that may shape sentiment on X. Events such as bot activity or viral misinformation campaigns (Tardelli et al. 2020) could influence crowd sentiment independently of finfluencer activity. Another limitation relates to the dataset selection process, which introduces several restrictions on the generalizability of our findings. First, the dataset covers one calendar year (2022), a period characterized by specific market conditions, namely, the transition from the end of COVID-related economic disruptions to rising global inflation concerns. Sentiment dynamics identified in this period may thus differ from other economic cycles. Second, our analysis relies exclusively on data from a single platform, limiting the extent to which our findings can be generalized to other social media platforms that may have distinct user dynamics or network structures.

A further limitation is the focus on highly referenced assets, which were chosen to ensure sufficient data volume for analysis, among other reasons. While this approach allows for a large-scale examination of sentiment formation in high-attention assets, it may not fully capture how sentiment spreads in less-referenced assets. Sentiment dynamics in these assets might differ, as they may experience weaker social influence effects or a greater reliance on fundamental analysis rather than finfluencer sentiment. From a methodological perspective, daily sentiment variables require a high number of posts to be meaningfully included in econometric modeling. Lower referenced assets generate fewer social media posts, making it difficult to extract reliable sentiment measures at a daily frequency. Our subsampling results (Online Appendix C) reinforce this concern, as the sentiment contagion effect weakens when post volume is significantly reduced. However, since our analysis focuses on assets with high social media activity, it remains uncertain whether the observed effect extends to assets with inherently low posting volumes. To address this limitation, a different approach – for example controlled experiments – would be needed to study how sentiment spreads in those cases.

Future research could address these limitations by extending our methodology across diverse market conditions and assets to validate and broaden our conclusions. Investigating inter-platform differences presents a valuable extension to our work, as financial discussion is shifting to newer social media platforms such as Discord, Telegram, and TikTok (de Regt et al. 2023). Further differentiation into finfluencer-types like fanatics and thought leaders (Pedersen 2022) or businesses and individual actors could allow for more nuanced results and tailored use of the findings, such as with respect to influencer monetization or prosecution. Guan (2023a) suggests a differentiation into celebrity, identity, and ordinary finfluencers types, based on how a finfluencer became successful and how the user communicates. However, such distinctions still require operationalization to systematically analyze their impact on sentiment formation and market influence. Overall, finfluencers form a heterogeneous group with varying motivations, and future research could investigate how these different incentives shape their role in influencing crowd sentiment and financial markets. At the same time, not all actors contributing to financial discussions on social media are genuine individuals. It is widely known that bots comprise a sizable proportion of financial social media actors (Kraaijeveld and De Smedt 2020). We treated them as part of the effect without explicitly accounting for them. A more detailed analysis of their effect on social network sentiment encourages future work. Ultimately, future research can develop more advanced approaches for detecting finfluencers, such as supervised learning techniques that consider user characteristics and published content.

7 Conclusion

Social network sentiment is attracting greater attention in the financial world as increasingly more is known about its relationship with market outcomes. 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. Using panel vector error correction models, we found support for our hypothesis that the sentiment of finfluencer actors, despite some limitations, has the potential to be an antecedent of the sentiment of crowd actors. Our study contributes to the literature on herding in financial markets, social media influencers in non-consumer marketing contexts, and helps further unravel the concept of sentiment in social networks. The study's insights have important implications for regulators, firms, social media platforms, and investors, aiding in the development of regulatory frameworks, marketing strategies, platform policies, and investment decisions.

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