Too much is too bad: The effect of media coverage on the price volatility of cryptocurrencies

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ABSTRACT

This study investigates the influence of information excess due to the increased media coverage on the price volatility of cryptocurrencies. News coverages may serve as either signals or noise in cryptocurrency markets characterized by an insufficient understanding of the fundamental value of assets and a high level of strategic complementarity. In a game-theoretic model, we show that the number of news coverages, either related or unrelated to the fundamentals, increases the price volatility of assets in a nascent financial market. We tested our hypotheses using a unique dataset of 358,118 observations of 500 cryptocurrencies and 36,572 media coverages between 2014 and 2017, the early period of cryptocurrency with the rise of public attention. The results show that cryptocurrency price volatility increases in the number of unrelated news for both major and minor coins. The volatility even increases with the number of related news in minor coins. These results have important implications for investors and entrepreneurs about the effect of misinformation in nascent markets.

1. Introduction

Studies conducted across a variety of disciplines on global market behaviors generally assume that the availability of information reduces uncertainty, increases the efficiency of decision making (Grossman, 1981; Raith, 1996; Vives, 1984, 1988), and reinforces the institutionalization and social construction of markets (Zajac and Westphal, 2004). However, not all information is useful for decision making and it is only meaningful when it aligns resource allocation with an evolving set of available information (Klingebiel and De Meyer, 2013).

Selecting correct and relative information when dealing with environmental complexity has become a critical issue in contemporary market behavior (Gavetti et al., 2012), especially during rapid market changes, such as the rise of new markets or market crises. Although uncertainty and ambiguity are still high, contemporary markets are featured by ample or excessive information due to technological advances, making proper information selection and interpretation essential but difficult. Under such circumstances, a key question emerges: does more information enhance decision-making or does it function as noise that should be disregarded (Antweiler and Frank, 2004; Barber and Odean, 2008; Pollock and Rindova, 2003)?

Interestingly, despite its intuitive appeal and practical benefit, the conjecture of information overflow has never attracted much relevant research—especially in relation to market changes. Previous research has either focused on the positive rela-

tionship between market outcomes and the appropriate selection and interpretation of relevant information, or emphasized its scarcity during crises and other disruptions (Greve and Yue, 2017; Pollock et al., 2008; Weick, 1993) while generally overlooking the potential impact of information overflow on market behaviors.

In this study, we investigate the effect of unrelated information's overflow on investment decisions in a nascent and rising market—the cryptocurrency market—where the fundamental value of the asset is highly uncertain and subject to rapid ongoing change. During investment decision-making, being able to judge whether the information provided would function as a useful market signal or as a noise for the valuation of market assets is critical (Chan, 2003; Peress, 2014). We draw on the current literature to model investment behaviors in nascent or rising financial markets that receive substantial media attention and examine the relationship between the availability and irrelevance of information and its market outcomes.

In nascent or rising financial markets, considerable uncertainty may exist on the fundamental value of the assets, as investors often deal with relatively new institutional and technological environments. As previous literature has suggested, the more uncertain the markets are, the more psychologically biased the investors are (Daniel et al., 1998, 2001; Hirshleifer, 2001). For instance, some investors overreact to unrelated information, while others fail to distinguish between related and unrelated information, leading them to form their own heuristics based on the observed actions of others in the market (Pollock et al., 2008).

To examine how the increased unrelated media information influences investment behavior in a nascent and rising market, we revisit the study of Morris and Shin (2002). Morris and Shin studied the roles of publicly available information and strategic complementarity in determining agent decisions (Bulow et al., 1985; Morris and Shin, 2002). Specifically, they assumed that, like in any conventional financial market, investment decisions of agents mutually reinforce each other, motivating coordination of actions - referred to as the coordination motive. Owing to this motive, agents may underweight their private information and overreact to public information. Therefore, as the authors demonstrated, the existence of additional publicly available and even highly accurate information may lead individuals to make bad decisions in terms of social welfare.

Awareness of the possibility of misinterpretation of accurate information or over- or underreaction to it in new or rising markets does not fully grasp its potential critical consequences. Specifically, too much misinformation or unrelated information may not be filtered or properly evaluated in terms of its relatedness or usefulness due to the immaturity of markets lacking reliable professionals or institutional guidelines (Kraaijeveld and De Smedt, 2020; Yarovaya et al., 2021), while nonetheless receiving broad attention from news media.

Our theoretical model considers both related and unrelated news items to provide a comprehensive understanding of these stylized facts in new and emerging markets. The model assumes that some investors may not fully comprehend the underlying characteristics of a market's assets, leading to difficulty in distinguishing related from unrelated news (Barber and Odean, 2008; Bloomfield et al., 2000; De Long et al., 1990; Yan, 2010; Zhang, 2006). Using this theoretical model, we show that a substantial amount of unrelated news items in a market may lead to related news not receiving enough attention of most investors. Based on the observed actions of most investors, even professional and sophisticated investors who fully understand market fundamentals or are able to differentiate related from unrelated news may give insufficient attention to related news due to strategic complementarity (Morris and Shin, 2002), which means that inefficiency in utilizing unrelated market information can be transferred to them. This pattern of market behavior reinforces fluctuations in the project valuation of financial markets—that is, investors pay too much attention to overflowing and unrelated news items, leading to an increase in price volatility. Additionally, we demonstrate that the impact of related news on price volatility is contingent upon investors' understanding of market fundamentals. Specifically, we show that if investors have a considerably low level of understanding, even related news can exacerbate the fluctuation of asset valuation.

We test our hypotheses with a unique dataset of 500 cryptocurrencies from the cryptocurrency market, which is a prominent example of a nascent and rising market. In this market, no clear agreement exists on the fundamental value of cryptocurrencies (coins or token) (Kraaijeveld and De Smedt, 2020; Lee et al., 2020; Mai et al., 2018). Given this uncertainty, amplified by the absence of clear institutional guidelines and the limited number of professionals, we expect most investors to respond to the sizable unrelated news or misinformation, particularly for newly founded projects and products rather than established coins. Following our theoretical framework, we explore the relationship between the volume of related and unrelated news on a given cryptocurrency and its price volatility and test the varying degree of impact of news across major and minor coins.[1] We hypothesize that the price volatility of cryptocurrency projects generally increases with the number of unrelated news items, due to the ambiguity mentioned earlier and the rapid dissemination of unrelated news in cryptocurrency markets. Additionally, we demonstrate that for minor coins, price volatility can even increase with the number of relevant news items.

2. Related literature

Information typically refers to a distinguishable and meaningful feature of an object in the world, usually regardless of context. Garfinkel (2008) emphasized that social and communicative conditions play a crucial role in enabling the creation

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[1] Note that, according to our definition, price volatility is not the same as return volatility, which is usually considered in the literature on financial markets. See Section 3 for details.

of information. When individuals make decisions, they should actively seek relevant and appropriate information from various sources, taking into account social context. Furthermore, the recent advancements in information technology allow access to an overwhelmingly vast amount of information, which has made the decision-making process more dependent on the choice of information within the context rather than the access to it.

Several scholars have examined the process of information selection as part of a decision-making process in situations with limited information, high uncertainty, and ambiguity (Mintzberg, 1979; Simon, 1955; Weick, 1993). From a structural perspective on information processing, it has been suggested that effective communication occurs when formal communication channels are established within an organization or field. (Hutchins, 1991; March 2001; Sperber and Wilson, 1995). From this perspective, these studies focused on the amount of information available and framed the issue of processing or interpreting as a problem of ignorance rather than ambiguity (March 2001). Subsequently, they assumed that the availability of more information within organization channels would lead to a more suitable response to environmental changes. Similarly, Sutter et al. (2012) examined the impact of information about fundamentals on asset market bubbles and found that fundamentals are better reflected in asset prices when investors are better informed.

As Lant (2017) pointed out, though, this approach was not unanimous: a combination of empirical and theoretical works in the late 1970s and 1980s "recognized that assessing and reacting to the organization's environment was not an unambiguous process" (Lant, 2017, P. 346). The observation that organizations in the same environment react remarkably different to the same external event (Meyer, 1982) needed to be explained. Daft and Weick (1984) argued that we can think of organizations as interpretation systems, whereby environmental and organizational characteristics affect the ability of individuals (and consequently organizations) to identify, recognize, and interpret information (Jackson and Dutton, 1988; Milliken, 1990; Thomas et al., 1993; Walsh, 1988). Improved decision-making thus depends not only on the amount of information, but also on the appropriate perception and interpretation of information.

These considerations raise the question of how effectively investors can interpret information in financial markets. If all investors were rational and had complete access to all relevant information, enabling them to accurately interpret it, there would be no disagreement on market prices at least at the aggregate level. (Black, 1986). However, theoretical and empirical evidence suggests that investors often behave irrationally, thereby creating noise in financial markets, especially new and immature markets, such as cryptocurrency markets (Shleifer and Summers, 1990; Yarovaya et al., 2021). Bounded rationality can lead to biased interpretation of available information in financial markets (Barber and Odean, 2008; De Long et al., 1990; Zhang, 2006), and it can do so even at an aggregate level (Yan, 2010). In a laboratory experiment, Bloomfield et al. (2000) showed that prices in financial markets underreact to a reliable piece of information and overreact to an unrelated one.[2]

Biased information processing is more salient in nascent and rising markets due to the lack of institutional investors and guidelines. Traditionally, compared to institutional investors, individual investors are considered relatively naive or irrational as they fail to diversify their portfolio and show herding behavior (Goetzmann and Kumar, 2008; Kaniel et al., 2008; Lease et al., 1974). However, the herding behavior is not limited to nascent markets or naive investors, as previous literature has demonstrated the negative aspects of information in financial markets with fully rational investors. In his seminal book, Keynes discussed an example of beauty contests as an analogy for stock markets (Keynes, 1936) and highlighted why people choose the 'most popular face' when they should select the 'most attractive face' from several candidates. A rational individual would not choose the face they consider the most attractive but would try to guess the opinion of others based on 'what would be the average opinion of the public,' grounding their selection on an inference from their knowledge of public perceptions. In this situation, choice depends on the reasoning of other decision makers, which the picker processes to choose the face 'near the average.' This implies that further information on the face 'near the average' could make their selection further diverge from the 'most attractive face.'.

Building on this idea, Morris and Shin (2002) studied the societal value of publicly shared information and showed that additional public information, even when it is highly accurate, may lead individuals to make bad decisions in terms of social welfare. Suppose a sense of strategic complementarity is at work, whereby individuals with private information make decisions not only based on the fundamentals of valuation but also on an incentive to coordinate their actions with other rational agents; Morris and Shin (2002) showed that publicly available information related to the fundamentals can impair the social welfare of the actions of individuals by inducing them to overreact to the information on account of the coordination motive. We extend Morris and Shin's (2002) basic model by introducing the idea of unrelated news in a nascent market and show that the amount of publicly available media coverage, either related or unrelated to the fundamentals, increases the price volatility of organizational projects in a nascent financial market.

Concerning price volatility, previous literature has widely addressed it both in traditional financial markets (Andersen et al., 2001; Li, 2013; Lux and Marchesi, 1998; Turner and Weigel, 1992) and cryptocurrency markets (Conrad et al., 2018; Katsiampa et al., 2019; Koutmos, 2018; Zhang et al., 2021). In particular, Turner and Weigel (1992) compared the daily return volatility of S&P 500 and the Dow Jones from 1928 to 1989, and Andersen et al. (2001) showed that the unconditional distributions of variances of intraday stock prices are considerably right skewed. By focusing mainly on downside risk in the cryptocurrency market, Zhang et al. (2021) examined the relationship between risk and returns (or prices). The literature both on the traditional and cryptocurrency markets largely shows that the higher risk, represented by higher volatility, is positively correlated with the higher return.

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[2] See also Nelson et al. (2001) and Tetlock (2011).

Another line of research has focused on information or media impact on market volatility (Boudoukh et al., 2019; Ederington and Lee, 1993; Engle et al., 2021; Glasserman and Mamaysky, 2019; Kandel and Pearson, 1995). Earlier works have examined the existence of the relationship between information and volatility. Treating an asset's unexpected return as a news arrival, Engle and Ng (1993) tried to measure its impact of news on the volatility of a financial market. Kandel and Pearson (1995) theoretically and empirically showed that investors do not interpret public information identically. Recent works try to identify the relationship between news information and volatility in traditional financial markets. Using news data from RavenPack News Analytics, Shi et al. (2016) showed that the positive relationship between idiosyncratic volatility and the expected return on portfolios is weakened after accounting for the arrival of related news items. By using textual analysis, Boudoukh et al. (2019) identified the fundamental information in public news, and showed that such information accounts for considerable proportion of return volatility. Focusing on 28 large U.S. stocks, Engle et al. (2021) showed that arrival of public information is related to the changes in volatility: Nine to 65% of firm-specific volatility is explained by the arrival of public information. Glasserman and Mamaysky (2019), in a study based on 360,000 news articles on 50 large U.S. companies, found the evidence that unexpected positive news is associated with low (future) stock market volatility: they also showed that company specific volatility reflects unexpected news faster than general market volatility. By studying forty-one developed and emerging markets worldwide, Lau et al. (2012) showed that countries with better information environments have a lower risk of premium volatility. While previous literature has mainly focused on the relationship between related news and return volatility, we examine the effect of the volume of both related and unrelated news on investing decisions and price volatility, to better understand the impact of information processing in nascent financial markets.

A few studies have focused on volatility or speculative bubbles and public information's role in cryptocurrency markets. Grobys and Junttila (2021) showed the existence of lottery-like demand in cryptocurrency markets.[3] Focusing on the twenty largest cryptocurrency markets, Baur and Dimpfl (2018) showed that, unlike in the other equity markets, the volatility of cryptocurrency prices is more sensitive to positive (rather than negative) information. The authors discussed the effects of the asymmetric behavior of uninformed and informed investors on markets. In recent studies of cryptocurrency market prediction, many employed textual sentiment analyses to study cryptocurrency prices. Most of them used Twitter sentiment analyses and have only, or primarily focused on the properties and/or predictions related to Bitcoin (Chen et al., 2022; Kim et al., 2022). While the results of sentiment analyses had inconsistent findings about its impact on price changes across coins and periods, the volume of media had a consistent relationship with cryptocurrency pricing (Kraaijeveld and De Smedt, 2020). We believe that the audience for information was not sensitive enough to identify sentiments behind each news item, indicating that this might not be a significant factor impacting overall pricing dynamics. Hence, as in our theoretical economic models, we empirically investigate the relationship between price volatility and the amount of related and unrelated news for each cryptocurrency.

The literature on limited or selective attention on information mostly focus on the rational or bounded rational attention decision on the related information regarding the state of nature of the world (Hendershott et al., 2021; Lu et al., 2016; Sims, 2003): Agents with some cognitive or time constraints make decisions on how much information they will acquire, or to which information they will pay attention. The attention decisions may affect the beliefs of the agents. On the other hand, while investigating the nascent financial markets, we focus on the issue of plethora of misinformation: Agents make the investment decisions based on the unrelated news (misinformation) as well as the related news (information).

3. Theoretical model

In this section, we build a theoretical model of a nascent financial market, incorporating two crucial stylized facts common to new markets such as cryptocurrencies. First, these markets exhibit substantial uncertainty in asset fundamentals due to the relatively unfamiliar institutional and technological surroundings for investors. The more uncertainty in markets, the more the cognitive bias in investors (Daniel et al., 1998, 2001; Hirshleifer, 2001). In particular, some investors may not be able to distinguish between related and unrelated information.

Second, these markets receive a significant level of attention from 'new media,' such as online news outlets or social media. For example, in 2018, over eighteen sources of online news media, including Crypto Currency News (CCN), CoinTelegraph, and Cryptopanic, provided daily coverage of blockchains and cryptocurrencies.[4] The problem was that new media covered misinformation or unrelated news on cryptocurrency more often than not. As a result, investors with no clear understanding of market fundamentals could have been exposed to misinformation and increased unrelated news in this nascent financial market.

To capture these stylized facts, we introduce the naïve investors and unrelated news into the Morris and Shin's (2002) theoretical model of a financial market with strategic complementarity. Morris and Shin (2002) assumed that, as investment decisions do in any conventional financial market, decisions by agents mutually reinforce one another, motivating them to coordinate their actions, which is known as the coordination motive. We extend Morris and Shin's (2002) basic model by introducing the idea of unrelated news and naïve investors, which are appropriate for nascent markets.[5]

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[3] By modifying Bali et al. (2011) and Bali et al. (2017), they introduce a new statistical test for unknown dependency structures.

[4] Of course, 'old media' (or legacy media), such as Forbes and New York Times, have also covered the news on cryptocurrency. However, they do not cover related events in a timely fashion (Kraaijeveld and De Smedt, 2020), and mostly focus on a few negative news (such as cryptocurrency-related scams).

[5] Technically, in our model, the unrelated news and the naïve investors are related to the parameter values m_t^j and α which will be formally defined later in this section.

The state of nature $\theta_t \in \Theta \equiv \mathbb{R}$ represents the fundamental value of an asset at time t, and it follows a Gaussian random walk, $\mathcal{N}(0, \sigma_0^2)$.[6] All agents are assumed to observe n_t^* related messages $(m_t^k)_{k=1}^{n_t^*}$, which are independently generated by following a normal distribution around the difference between the fundamental values of the asset at time t-1 and t, $\mathcal{N}(\theta_t - \theta_{t-1}, \sigma^2)$.

An unrelated message, m_t^j, may exist that is randomly generated from a normal distribution $m_t^j \sim \mathcal{N}(\mu_m, \sigma_m^2)$ and is observed by all agents. We assume that, at time t, the number of unrelated messages generated is $n_t > 1$. We denote the realized message profile at time t by $m_t = \left((m_t^k)_{k=1}^{n_t^*}, (m_t^j)_{j=1}^{n_t} \right)$. At time t, the information set of an agent is $I_t = (\theta_{t-1}, m_t)$.

The market is represented by the naivete parameter α and the strategic complementarity parameter β. The parameter value α indicates how naively the investors in a market interpret the messages they observe. More specifically, in this game theoretical model, we assume that there are two types of investors in a unit interval $x_i \in [0, 1]$: sophisticated and naive investors. Sophisticated investors (S-types) $x_s \in [\alpha, 1]$ can distinguish m_t^k and m_t^j, while naïve investors (N-types) $x_n \in [0, \alpha)$ simply believe that all messages are relevant to a change in the fundamentals. That is, whenever N-types observe a message, they believe there has been a change in the fundamentals. Therefore, we can claim that the market naivete parameter α represents the proportion of naive investors in a market, or, alternatively, that the representative investors in the market are naive with probability α.

Fig. 1 depicts our theoretical model in a flow chart. S-types are better-informed investors in two ways. First, they are aware that another type of investors (N-types) exists in the market, whereas N-types think that there is no difference in their investment decisions between N-types and S-types.[7] Second, S-types can distinguish between the related news from the unrelated news, while N-types cannot. This information asymmetry could significantly affect the price volatility of an asset in markets with inherent strategic complementarity.

As in the basic model of Morris and Shin (2002), the strategic complementarity parameter β is associated with investor objectives. The payoff function of an investor i, which is realized at the end of time t, is:

$$u_{t,i}(a_{t,i}; \theta_t) = -\left[(1-\beta)(a_{t,i} - \theta_t)^2 + \beta\left(a_{t,i} - \bar{a}_t\right)^2 \right],$$

where $a_{t,i}$ is the action taken by the agent i, $\bar{a}_t$ is the average value of actions taken by all agents $\bar{a}_t = \int a_{t,i} di$, and $1 - \beta$ represents the importance of targeting the fundamental.[8] Hence, β represents the importance of strategic complementarity.

3.1. Equilibrium analysis

Given any information set I_t, an agent maximizes the expected utility of $\mathrm{E}\left[u_{t,i}(a_{t,i}; \theta_t) | I_t \right]$ by choosing $a_{t,i}$.[9] Solving the maximization problem, we get the optimal action of agent i:

$$a_{t,i}^* = (1-\beta)E_i(\theta_t | I_t) + \beta E_i\left(\bar{a}_t | I_t\right).$$

By using the definition of $E_i(\theta_t | I_t)$ and $E_i\left(\bar{a}_t | I_t\right)$, we can derive the optimal actions of S-type investors and N-type investors as follows

$$a_{t,s}^* = \theta_{t-1} + (1-\beta\lambda)\frac{1}{n_t^*}m_t^* + \beta\lambda(m_t^* + \hat{m}_t) \quad \text{and} \quad a_{t,n}^* = \theta_{t-1} + m_t^* + \hat{m}_t,$$

where the parameter $\lambda \equiv \frac{\alpha}{(1-(1-\alpha)\beta)}$, combining the naivete (α) and the strategic complementarity (β) of the asset, represents how speculative the asset is in both informational and behavioral senses. See Appendix A.1 for the detailed analysis.

By definition of $\bar{a}_t$, we get:

$$\bar{a}_t = \theta_{t-1} + (1-\lambda)\frac{1}{n_t^*}m_t^* + \lambda(m_t^* + \hat{m}_t) \sim \mathcal{N}\left(\theta_t + \lambda\left((n_t^*-1)(\theta_t - \theta_{t-1}) + n_t\mu_m\right), (1-\lambda)^2\frac{1}{n_t^*}\sigma^2 + \lambda^2\left(n_t^*\sigma^2 + n_t\sigma_m^2\right) \right),$$

$$Var\left(\bar{a}_t\right) = (1-\lambda)^2\frac{1}{n_t^*}\sigma^2 + \lambda^2\left(n_t^*\sigma^2 + n_t\sigma_m^2\right).$$

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[6] The starting value of the state of nature is zero, $\theta_0 = 0$.

[7] In the real world, naive investors know that there is another type of investor who does not believe that unrelated news items provide relevant information on the fundamentals. However, they may incorrectly believe that the other (sophisticated) type of investors are less sophisticated than themselves and cannot understand the relationship between unrelated news and market fundamentals. Hence, awareness of the existence of another type of investor does not imply an understanding of their nature. For the sake of this study, we simply assume that N-types think there is no difference between N-types and S-types.

[8] In our model, the utility function and the optimal action of an agent are motivated by the Keynesian beauty contest model. Through the island economy model of Lucas (1972), this model effectively represents a market with both supply and demand sides. See Morris and Shin (2005).

[9] Note that the welfare of society only depends on the fundamental and is formally defined by $E\left[\int -(a_{t,i} - \theta_t)^2 di | I_t \right]$.
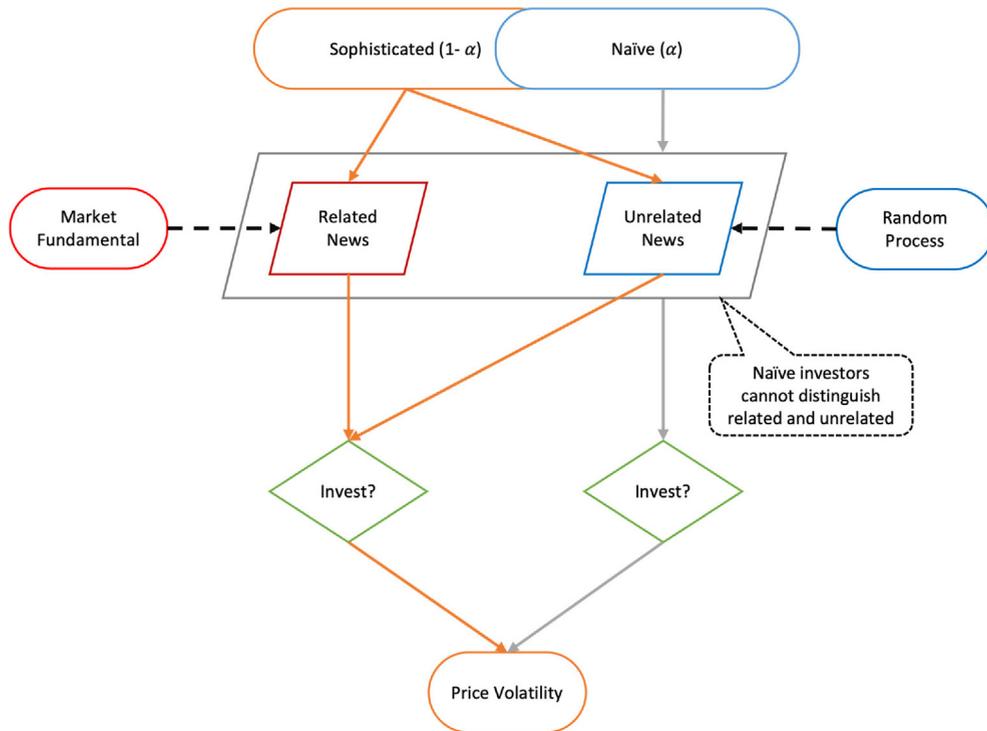
Fig. 1. Flow Chart of Investment Decision-Making in a Nascent Financial Market.

Note that the price volatility of the asset $Var(\bar{a}_t)$ always increases with the number of unrelated news n_t. Furthermore, we can show that volatility also increases with the number of related news n_t^* if and only if $\frac{\lambda}{1-\lambda} > \frac{1}{n_t^*}$.[10] In other words, if the investors of an asset are highly speculative (i.e., if λ is high), then the volatility increases with the number of related news, n_t^*, as well as with the number of unrelated news, n_t. We summarize these results in the following proposition:

Proposition 1 (*News and Price Volatility*).

a) Investors on a specific asset are not perfectly sophisticated if and only if the asset's price volatility increases with the number of unrelated news items: $\alpha > 0 \iff \frac{\partial Var(\bar{a}_t)}{\partial n_t} > 0$.

b) If the investors on a specific asset are relatively less speculative, then the asset's price volatility decreases with the number of related news items: $\exists \lambda^*$ such that for any $\lambda \le \lambda^*$, $\frac{\partial Var(\bar{a}_t)}{\partial n_t^*} \le 0$.

c) If the investors on a specific asset are sufficiently speculative, then the asset's price volatility increases with the number of related news items: $\exists \lambda^*$ such that for any $\lambda > \lambda^*$, $\frac{\partial Var(\bar{a}_t)}{\partial n_t^*} > 0$.

One may wonder whether the ratio of related to unrelated news items affects price volatility. Our theory posits that the effect of the amount of news on price volatility does not depend on the ratio of related to unrelated news. Hence, the lack of unrelated news does not influence the role of related news in increasing the volatility of the asset price. If the asset is speculative enough, N-types act or overreact to related news, which increases volatility.

3.2. Empirical implications

Proposition 1-a) implies that any nascent or newly founded project for which the number of naive investors is not zero will experience situations where price volatility increases with the number of unrelated news items. As stated previously, when β is zero, λ is still positive (that is, λ = α > 0). That is, the strategic complementarity affects market conditions by accelerating price volatility, but it is not a necessary condition of news-driven increased volatility: if naive investors are involved,

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[10] The left-hand side of the condition, $\frac{\lambda}{1-\lambda}$, increases with λ. Additionally, $lim_{\lambda \to 1} \frac{\lambda}{1-\lambda} = \infty$ and $lim_{\lambda \to 0} \frac{\lambda}{1-\lambda} = 0$.

price volatility increases with the number of unrelated news items even when they only care about targeting the fundamentals without any strategic complementarity (Fig. 1).

In Figs. 2 and 3, we provide the numerical examples to elaborate on the model explained above. The Figures depict the price volatility in the number of unrelated news and the number of related news. In this examples, for simplicity, we assume that $\sigma^2 = \sigma_m^2 = 1$ for both figures, and fix $n_t^* = 10$ for Fig. 2 and $n_t = 15$ for Fig. 3. When α is zero, which means there are no naïve investors, so λ is zero, the price volatility does not change in the number of unrelated news as in Fig. 2, while it decreases in the number of related news as in Fig. 3.

Fig. 2 shows that, when α is greater than zero, so there are naïve investors in the market, for any value of β, the price volatility increases in the number of unrelated news. Furthermore, for higher α or β, the price volatility increases faster in the number of unrelated news. This implies that in any nascent market with naïve investors, the number of unrelated news increases the price volatility, and the impact of the unrelated news is higher in more speculative markets.

On the other hand, Fig. 3 illustrates that the price volatility may not increase in the number of related news if the market is not speculative enough. Even when α is greater than zero, if the α is small enough as 1/4 in Fig. 3, then the price volatility decreases or remains almost unchanged in the number of related news. If λ increases further, then the price volatility generally increases in the number of related news too.

It is possible to foresee this kind of scenario in cryptocurrency markets where the fundamental value of each cryptocurrency is vague and the relation or relevance of news is hard to discern owing to the increase of news on media platforms (Kraaijeveld and De Smedt, 2020). Thus, many investors do not understand the relatedness of news for a given cryptocurrency project. At the same time, they are overly sensitive to any news items they encounter. As a result, the price volatility of any cryptocurrency increases with the number of unrelated news items.[11] We thus formulate the following Hypothesis 1 based on Proposition 1-a:

Hypothesis 1. For all cryptocurrency projects, price volatility increases with the number of unrelated news items.

We then anticipate major (i.e., with a larger market cap and longer history) and minor cryptocurrencies (or coins) may have different levels of sensitivity to the number of unrelated and related media coverage, due to differences in coin characteristics (e.g., price range and market shares) and exposures to current and potential investors (e.g., through news coverage) as they attract different types of investors. Zuckerman (2004) highlighted how the efficiency of the market's price-setting process is contingent on the coherence of a stock's position in the industry-based classificatory structure that guides valuation. Thus, this structural distinction between major and minor coins would lead investors to interpret available news differently, which influences the price volatility of cryptocurrencies.

We expect price volatility to decrease with the number of related news items for major coin projects, as investors care more about relatively well-known fundamentals than they do with minor coins (Proposition 1-b). Lastly, we expect investors to be relatively more naive about minor coin projects, such as newly created or small projects, which would lead volatility to increase even with the number of related news items (Proposition 1-c). We thus formulate the following hypotheses:

Hypothesis 2. 1) The price volatility of major cryptocurrencies decreases with the number of related news items.

On the other hand,

2) The price volatility of minor cryptocurrencies increases with the number of related news items.

We further discuss the detailed implications of these hypotheses in our empirical analysis as well as their relationship with the propositions from our theoretical model in Section 4.4.

4. Data and empirical setting

We tested our hypotheses with the data of 500 cryptocurrencies and their price changes between 2013 and 2017. We selected the early period of the cryptocurrency market up until the first peak (until 2017) to test our hypotheses in a new and emerging market, where the underlying value of the asset was highly uncertain. Although Bitcoin was invented in 2008 by Satoshi Nakamoto, the monetary value of Bitcoin was relatively inconsequential until 2013. That year, Bitcoin's price rose significantly for the first time, there was a significant increase in transactions, and Bitcoin began to establish itself as both an asset and a currency. By early October 2013, Bitcoin was trading at around $100 and reached $1,120 by the end of November (Booth, 2017). It reached its highest price of $19,783 on December 17, 2017 in only around four years (Salzman, 2019). The surge of the Bitcoin price from 2013 until 2017 laid the foundation for many new coin and token projects. By the end of 2017, there were approximately 4,000 coins and tokens and an estimated 1,500 new projects in development, according to Coinmarketcap.com, CoinGecko, and ICOBench. The market cap of Bitcoin decreased from 85% to 30% as other cryptocurrencies rose by the end of 2017, as reflected by the Coinmarketcap index. Such rapid increases in price and the number of projects caught the attention of the news media, attracting more investors to join the rally. By focusing on the early stages

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[11] Additionally, Proposition 1-a) also implies the presence of naive traders in a financial market if price volatility increases with the number of unrelated news items. Thus, an increase in price volatility when the number of unrelated news items increases would provide evidence that the market is not completely sophisticated.
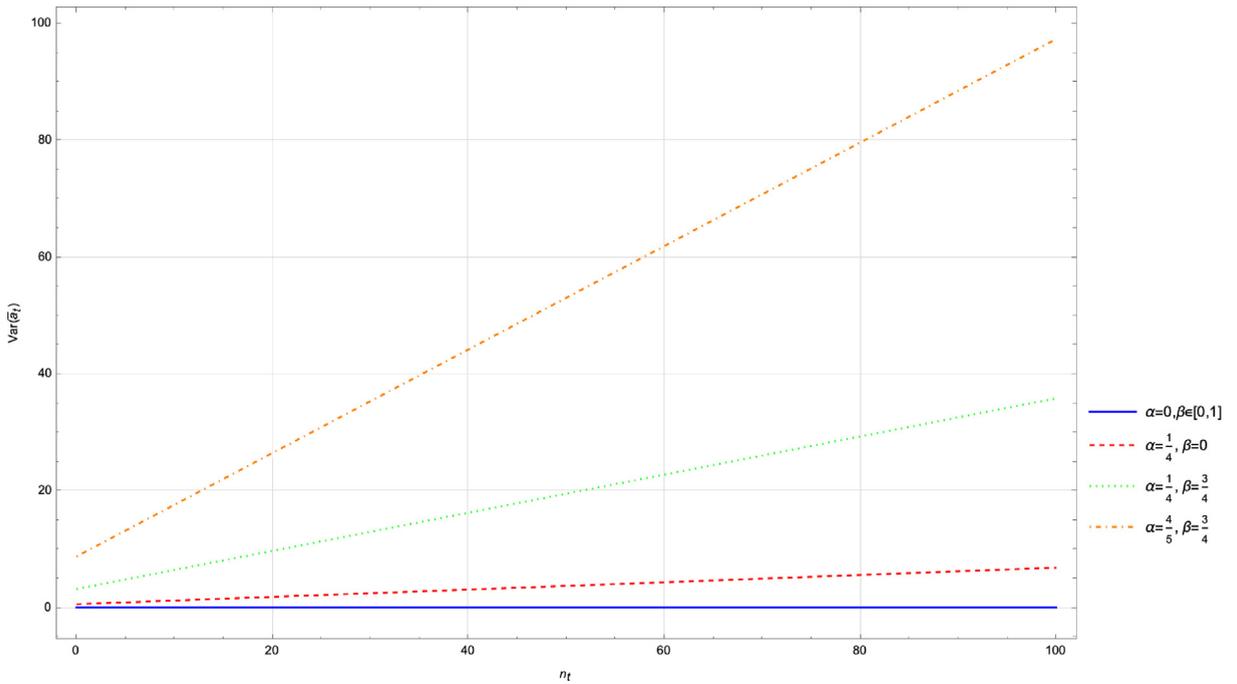
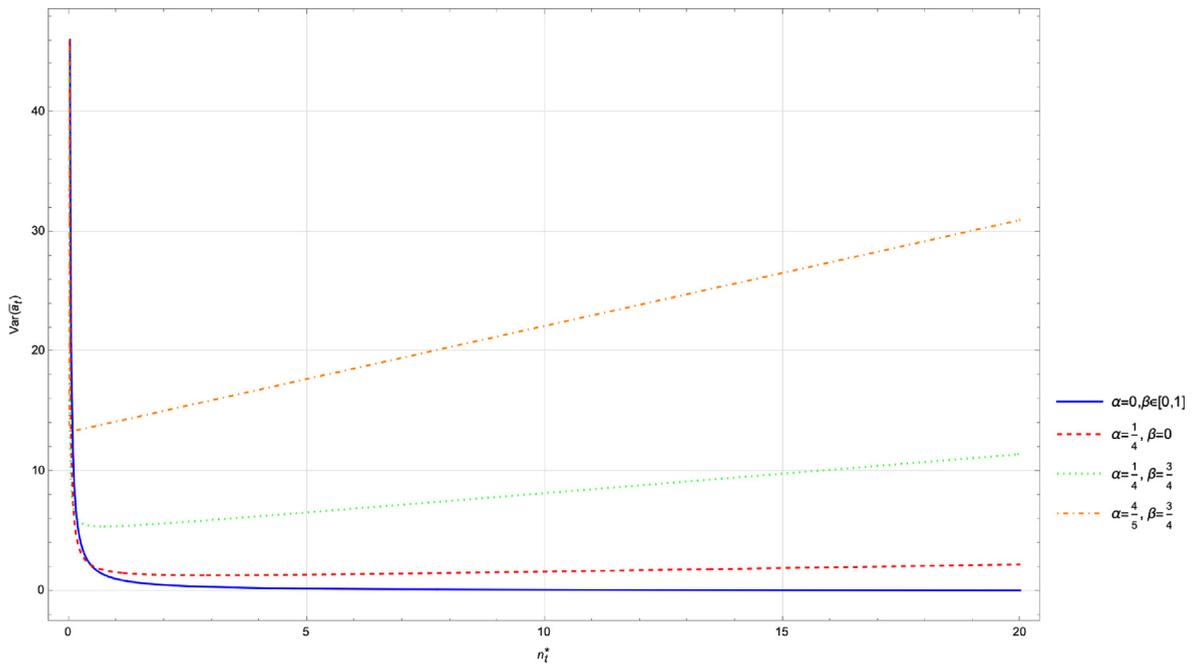**Fig. 2.** Numerical Example - Price Volatility on Unrelated News.

Fig. 3. Numerical Example - Price Volatility on Related News.

of cryptocurrency market change, we aim to extend our theoretical modeling and empirical findings to other emerging markets similar to the cryptocurrency market.

Since ICO presale values are hard to observe transparently, we only included the cryptocurrencies that had undergone an initial coin offering (ICO), equivalent to an initial public offering (IPO) in the stock arena. The selected cryptocurrencies were listed in global coin exchanges, including Coinmarketcap, so that their price changes in markets could be tracked publicly. In general, cryptocurrencies include both coins and tokens as a medium for ventures to raise funds. However, tokens have

specific uses in the cryptocurrency ecosystem and depend on given coin systems. Hence, for our sample selection, we focused on coins that can be used independently to buy and sell both goods and tokens. For example, the most famous coins, Bitcoin and Ethereum, are used to buy and sell tokens (Buterin, 2014; Catalini and Gans, 2019). Moreover, we also excluded coins that discontinued their transactions or whose value became $0 on January 1, 2018. We then came up with a sample of top 500 coins based on their market capitalization ranking in the Coinmarketcap Index.[12]

We collected the prices of cryptocurrencies from December 1st, 2013, to December 31st, 2017 using the Coinmarketcap database. The 500 cryptocurrency projects (i.e., coins) used in our sample covered 95% of the total coin market in 2018. Using transactional data and other exchange-related information, we analyzed weekly coin price volatility (using daily moving window) over the four years up to 358,118 observations, which were then matched with online media coverage of cryptocurrencies during the same period (total of 36,572 news articles).

As noted previously, our research examines general price volatility at the level of individual coins by assessing how unrelated and related news influence coin pricing dynamics. As the cryptocurrency market has not been extensively studied yet, we briefly explain the main features of this rising market in the following section. Specifically, we highlight that the speculative nature of the cryptocurrency market is due to its short history and limited institutional supports and guidelines.

4.1 Cryptocurrency market and its media impact

Cryptocurrencies are digital currencies that do not depend on a centralized system since they are managed through the encryption techniques of blockchain technology that allow for transparent transaction recording without the risk of hacking or manipulation (Scott, 2016). Cryptocurrencies have received much attention due to their disruptive technological potential and unprecedented return on investment (Kraaijeveld and De Smedt, 2020). Specifically, their market attracts many investors owing to the relatively low cost of smart contracts, transparent trading, and lack of oversight due to their independence from central bank systems (Tapscott and Tapscott, 2016). As a result, the cryptocurrency market expanded at an exceptionally fast rate during the early period under study (MarketAndMarket, 2018). Fig. 4 illustrates the spikes in volume since late 2016 among the 500 top-ranked coins; as can be observed, a 300 ~ 700% monthly volume change per year was not uncommon.

The rapid increase of cryptocurrencies in both quantity and price drew the attention of news media, including online media, that repeatedly reported on their remarkable returns (Kraaijeveld and De Smedt, 2020). Eighteen English online news media, including CCN, CoinTelegraph, and Cryptopanic, provided news on blockchains and cryptocurrencies daily in 2017—much of which was translated and redistributed in Chinese, Korean, Spanish, and many other languages through social media such as Telegram and Reddit. The rapid increase of online media and news reposting across different channels reinforced the challenge for investors to investigate the accuracy of information (Kraaijeveld and De Smedt, 2020). Simultaneously, traditional news media giants started to create a news section on cryptocurrency. In 2017, for example, Forbes (one of the main economic media outlets worldwide) introduced a news section called "Crypto & Blockchain." However, news coverage from traditional media was limited to a few critical events and negative news, such as cryptocurrency-related scams, and only seldomly addressed technical or market information related to the fundamentals of crypto projects.

To empirically test the impact of information on the volatility of cryptocurrency prices, we focused on the primary sources of information on cryptocurrency since 2013—namely, CCN, CoinTelegraph, and Coindesk—as our media information sources among the several media outlets available. These three major online media have been translated and distributed worldwide through different online platforms and social media channels, such as Telegram or Reddit, and they were renowned sources for ICO updates, analytics, market changes, regulations across the world, or any news regarding cryptocurrency. Specifically, CCN offers live news shows, real-time prices, and up-to-date, ticker-level information on cryptocurrency. CoinTelegraph is the largest cryptocurrency-focused news source worldwide, offering everything from data-centric articles to opinion pieces; it has the most significant outreach via other media giants, such as Facebook and YouTube. Finally, Coindesk covers a wide range of topics from crypto specialists and provides podcasts and learning tools.

Despite attention from investors and media, institutional authorities haven't reached agreement on cryptocurrency regulation. While there have been many attempts to justify their values and integrate them into preexisting financial markets, such efforts have been unsuccessful and limited due to a lack of consensus on their utility, reliability, and sustainability (Alam et al., 2019; Kraaijeveld and De Smedt, 2020). This resulted in volatile pricing and uncertain valuations. Combined with the rapid increase in media attention without a clear understanding of fundamentals, cryptocurrency mirrored the dot-com bubble (Alam et al., 2019; Leath, 2019; Lieure, 2018). However, cryptocurrency price was not pegged to any existing currency—nor it had a certain standard baseline, which led to fierce arguments and media discussion.

Additionally, its independence from central bank systems and its decentralized data processing mechanisms left the new market decoupled from or loosely coupled to both conventional financial markets (such as the S&P 500 or Gold Index) and international regulatory institutions across different countries (such as the World Bank, the US Securities and Exchange Commission, the Federal Reserve Board, and the Federal Deposit Insurance Corporation). The lack of institutional guidelines

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[12] Extracted from January 1, 2018. Coinmarketcap is one of the first and largest reliable databases providing data on the cryptocurrency market (https://coinmarketcap.com/).
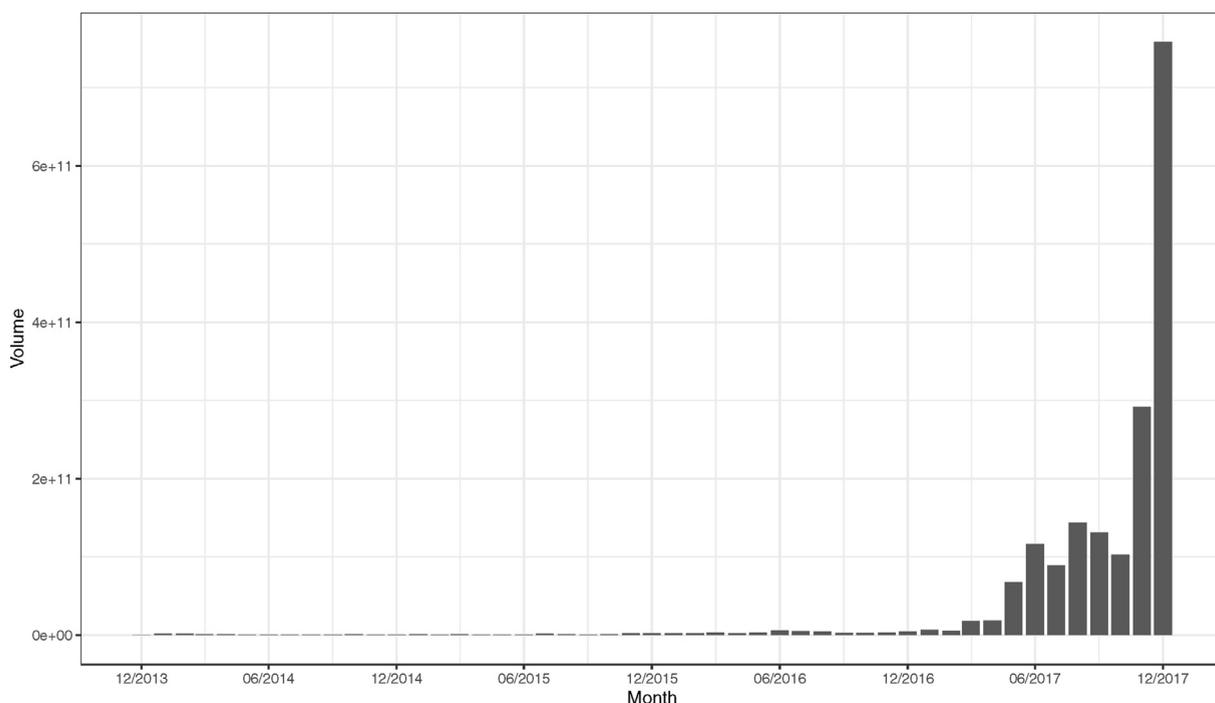
Fig. 4. Monthly Total Market Volume of Transactions for 500 Cryptocurrencies between 2013 and 2017.

for the nascent market not only prevented integration into existing financial markets, but also limited the ability of professionals to analyze it in the early period.

4.2 Empirical specifications

To test our hypotheses about the impact of media information on cryptocurrency price volatility, fixed-effects regression with the first-order autoregressive (AR(1)) models were implemented to resolve the issue of autocorrelation residing in price volatility measurements over time. A recent study (Katsiampa, 2017) on the performance of conditional heteroskedasticity models for Bitcoin's price posits that AR(1) correction is necessary to examine cryptocurrency. While many recent studies have used GARCH or MGARCH models to observe the price movements of Bitcoin and only a few other coins separately (Grobys and Junttila, 2021; Katsiampa et al., 2019), we observed 500 cryptocurrencies together including Bitcoin over time through the fixed-effect model with AR(1) to control both autocorrelation and unobserved heteroskedasticity.

As predicted in Hypothesis 2, major and minor coins evidence different levels of sensitivity to news media coverage, thus creating distinct price volatility patterns. To address these questions, we move to our next set of models to test Hypotheses 2.1) and 2.2), which use the same set of variables linked to two samples, major coins (the top ten coins) and minor coins (the rest 488 coins) separately. Aside from Bitcoin and Etherium, which are controlled in the models, the ten major coins most frequently mentioned in the three media sources during the observation period include Litecoin, Bitcoin Cash, Bitcoin Gold, Cardano, Stellar, Zcash, Monero, IOTA, Ethereum classic, and NEO. Fig. 5 describes monthly total market volume changes and the mean prices of the ten major coins from 2013 to 2017.[13]

The fixed effects regressions with AR(1) that we ran to evaluate whether unrelated or related news influence price volatility are of the form:

$$Y_{jt} = \alpha_j + \boldsymbol{\beta}'_1 \boldsymbol{IV_{jt}} + \boldsymbol{\beta}'_2 \boldsymbol{CV_{jt}} + u_{jt},$$

with the coins $j = 1, \cdots, n$ and the time period $t = 1, \cdots, T$; Y_{jt} are the dependent variables, α_j are coin-specific intercepts that capture the heterogeneities across coins, $\boldsymbol{IV_{jt}}$ is the vector of independent variables, and $\boldsymbol{CV_{jt}}$ is the vector of control variables.

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[13] We ran analyses both with and without Bitcoin and Ethereum in our major coins analyses, and the results stayed robust.
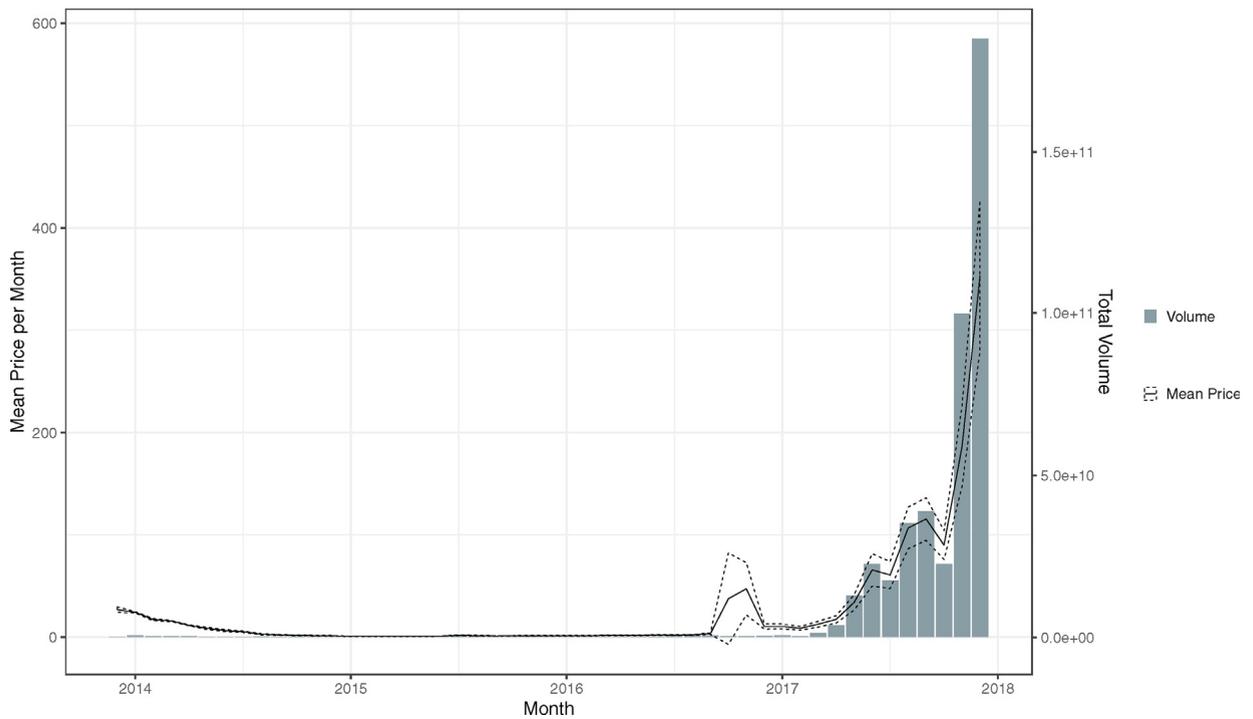
Fig. 5. Monthly Total Market Volume of Transactions and Mean Price for Ten Major Coins between 2013 and 2017.

4.3. Dependent variable

Given our theoretical framework, we focus on the **price volatility** of a cryptocurrency as our dependent variable based on a prior seven-day variance with a daily moving window.[14] Our definition of price volatility is not the same as that of return volatility, which is normally used in the literature on financial markets. While the literature is mainly interested in market risk and its determinants, we concentrate on the trading behavior in a nascent market, with particular reference to the effect of unrelated news. In our model, the action $a_{t,i}$ can be interpreted as an investor position (sell/buy price), and the average value of actions taken by all investors $\bar{a}_t = \int a_{t,i} di$ is the market price at time t.[15] The formal definition is as follows:

$$Y_{jt} = Price\ Volatility_{jt} = \frac{\sum_{l \in L_t} \left(\left(\frac{\sum_{l \in L_t} \left(p_{jl}^o + p_{jl}^c \right)}{2n} - p_{jl}^o \right)^2 + \left(\frac{\sum_{l \in L_t} \left(p_{jl}^o + p_{jl}^c \right)}{2n} - p_{jl}^c \right)^2 \right)}{2n},$$

where L_t is the set of days in the week t, n is the number of elements of the set L_t, p_{jl}^o is the opening price of the day l at 00:00 am (GMT), and p_{jl}^c is the closing price of the day l at 11:59 pm (GMT). We decided the opening and closing time as described to capture the daily change since cryptocurrency exchanges run 24/7.

4.4. Independent variables

To test the impact of the news information on coin market investments, we collected a previously unparalleled dataset of news articles from the selected coin-related media outlets. As we theorized above, we expect our independent variables to show the relationship between the impact of media coverage and price volatility in cryptocurrencies. As mentioned above, we focused on three major cryptocurrency-specific media outlets (CCN, Coindesk, and Coin Telegraph) and their output between 2013 and 2017. A total of 36,572 published articles were collected. The articles were original and covered topics

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[14] In addition, we ran the same models with different durations for price volatility and media count—namely, for three days and five days, respectively. While most results stayed the same, showing stable and robust findings, a shortened duration proved to potentially entail a higher chance of reverse causality, as we could not unquestionably determine whether the news count impacted price volatility or whether they in fact increased due to price volatility. Therefore, we decided to use findings relative to seven days with a daily moving window to measure duration sensitivity.

[15] In the basic model of Morris and Shin (2002), an investor's action $a_{t,i}$ is naturally interpreted as a price at t set by the investor i. See also Morris and Shin (2005) and Allen, Morris, and Shin (2006).

not only on Bitcoin and other cryptocurrencies, but also on related markets and regulations. Fig. 6 depicts the overall news coverage trend of the three media platforms across the observation period.

After collecting news articles, we created our independent variables regarding related and unrelated news at two levels: project-based and country-based levels. The articles were coded based on news-item tags and topics provided by the news provider into the following categories: project-based related news, project-based unrelated news, country-based related news, and country-based unrelated news. The detailed operationalization is described below.

Project-based related news: The media coverage of project-based related news was determined by the number of articles that specifically mentioned each cryptocurrency name or ticker in the news tags or topics. To validate their relatedness or relevance and check whether cryptocurrency names or tickers were mentioned, we reviewed both the news tags of articles and the topic keywords provided by news media. The articles had four to five tags on average, and the coin name was used as a tag whenever the article focused primarily on that coin. To mitigate reverse causality, the number of relevant articles was counted for the seven days preceding the first date of the price that was later included in the calculation of price volatility with a daily moving window.

Project-based unrelated news: To define unrelatedness, we identified all project-related articles on the 500 coins during the same period. Then, we counted the number of articles that are not specific project-related news for each coin. We measured the unrelatedness of news about other cryptocurrencies in order to gauge the observed attention of another investors on other cryptocurrencies, but not necessarily that of totally out-of-context news, such as news about the gold or scam, which we controlled separately.[16] Hence, our measurement did not capture any general market-related news or policy change news if it was not connected to a specific cryptocurrency, although many cryptocurrencies were mentioned in policy change news such as Bitcoins, Etherium, or Ripple. We controlled the other types of news about market changes and policy changes in control variables. The number of unrelated news items during the seven days varied from 16 to 531. Fig. 7 illustrates the trends in related and unrelated news over time: their respective patterns are not significantly dissimilar, but unrelated news items fluctuate more during periods of increased media attention.

In our empirical analysis, we focus mainly on these independent variables to test our hypotheses in Section 3.2 (see also Appendix A.2). In Hypothesis 1, we hypothesize that the coefficient of project-based unrelated news is positive in any market. Additionally, in Hypothesis 2, we hypothesize that the coefficient of project-based related news for the major markets is negative (Hypothesis 2-1), while the coefficient for the minor markets is positive (Hypothesis 2-2).

4.5. Control variables

The growing body of research on volatility suggests a variety of factors that may influence the outcomes under consideration in this study. Hence, in addition to the related and unrelated media measures mentioned above, we included an extensive set of variables to control for these effects, as well as for factors that could offer alternative explanations of our results.

We first controlled country-level related and unrelated news. While cryptocurrency markets emphasize their non-geopolitical presence as a sign of strength and stability, many country-specific investments and projects still highlight the nationality of CEOs and major investors or the origin of projects. In order to control whether country-level news related to a specific cryptocurrency influences its price volatility, we created the following measures. For **country-based related news**, the country of the project was coded based on where the CEO was from and where their head office was located. Then, we counted the number of specific country-related news items by checking for the appearance of the country name in tags and topics during the same project-related news period. The countries included China, India, Japan, South Korea, Singapore, the United States, Canada, Venezuela, Russia, the United Kingdom, Switzerland, South Africa, Australia, and others. "Others" are 13 countries produced less than fifty articles during four years (around 0.01%) that were covered in the three media source. Fig. 8 shows the media coverage of the top five most mentioned countries relative to the cryptocurrencies in our data: China, Japan, Korea, the UK, and the US. In general, their media coverage pattern follows the overall media coverage pattern shown in Fig. 8. But each country shows unique spikes in the trend, which could impact the price volatility of that country's cryptocurrencies.

The variable **country-based unrelated news** indicates the number of news articles mentioning other countries in their coverage and was assessed similarly to project-based unrelated news. We summed news articles from 2013 to 2017 that mentioned any country as the total country-covered news items, and we deducted the number of country-based related news items to assess the impact of the increased number of all other country news items except specific coin-country news.

Then, we controlled for the impact of overall market development using **total market capitalization**, **market volume**, and a specific **year**. Market capitalization is the total dollar market value of a company's outstanding shares of stock—in this case, coins. The total market cap is the aggregated market "cap" for each coin during the observation period and was used to measure the market's rapid growth. The market volume measured the total transaction volume during the observation period and was used to control the level of the trading activity and its impact on price volatility. We also created dummy variables for the years 2013 to 2017 to control for the impact of unexplained year-specific exogenous factors on market volatility.

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[16] Alternatively, we could have included all news items except the directly coin-related news, but their number would have been highly correlated with the total number of articles we would have had to control to understand the explanatory power of related versus unrelated news on price volatility.
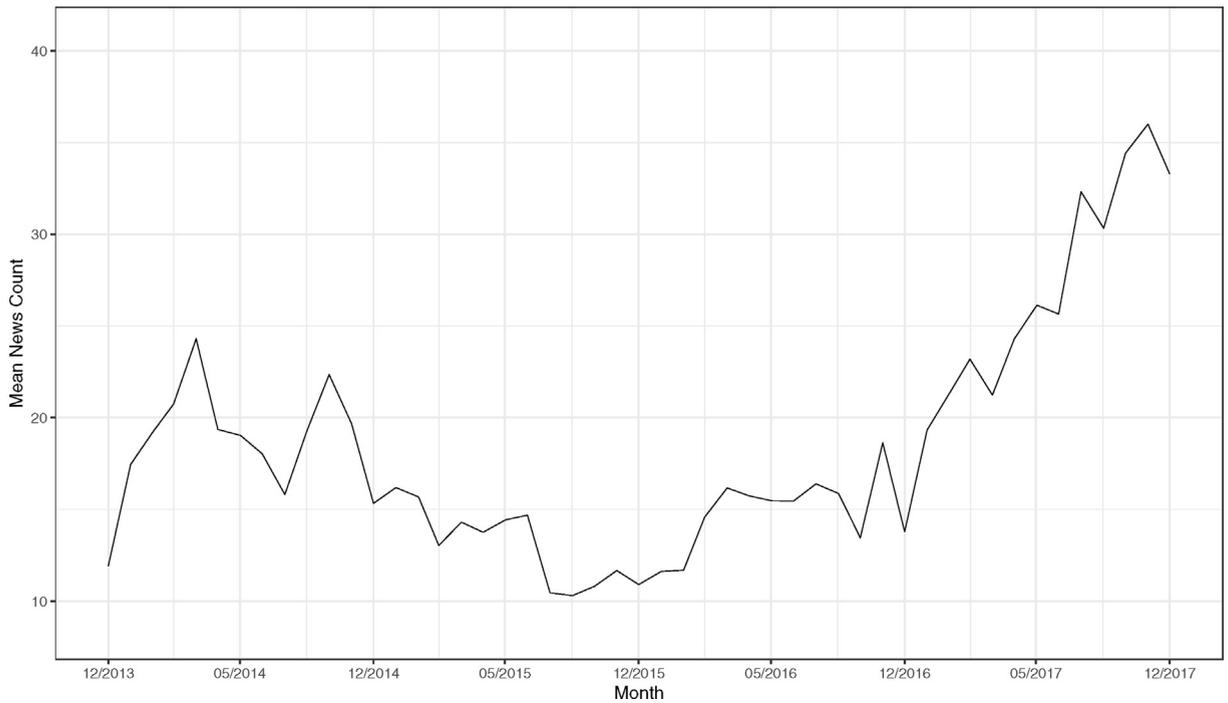
Fig. 6. Mean Number of Daily News Articles from Three Media Sources between 2013 and 2017.
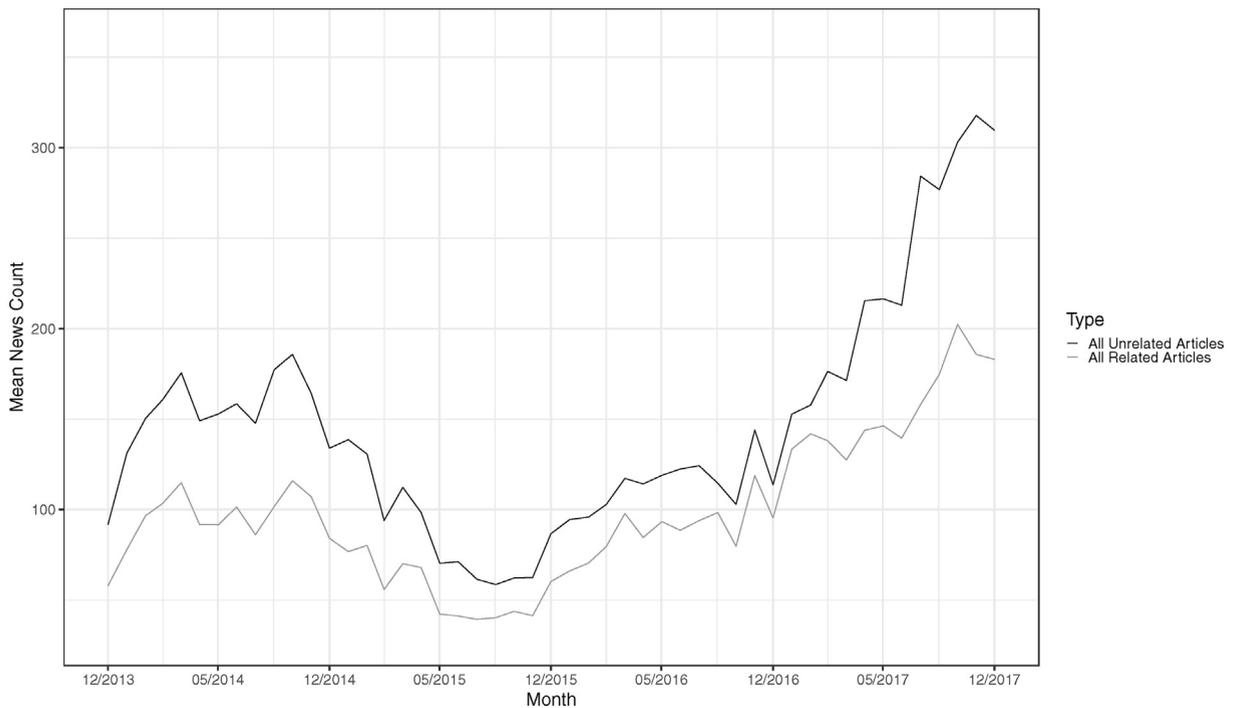
Fig. 7. Mean Number of Related and Unrelated News Items between 2013 and 2017.

At the project level, we controlled for **_the closing price_** of cryptocurrencies. Daily or weekly price volatility may be influenced by the closing price when the price drops or increases at a surprising level. Cryptocurrency exchanges are open 24/7; hence, the market never actually closes. Therefore, we used the closing price measured and provided for every 24 h by Coinmarketcap for the date. Lastly, we controlled for media-level factors that could influence the relationship between related or

Fig. 8. Mean Number of Country-Related News Items between 2013 and 2017.
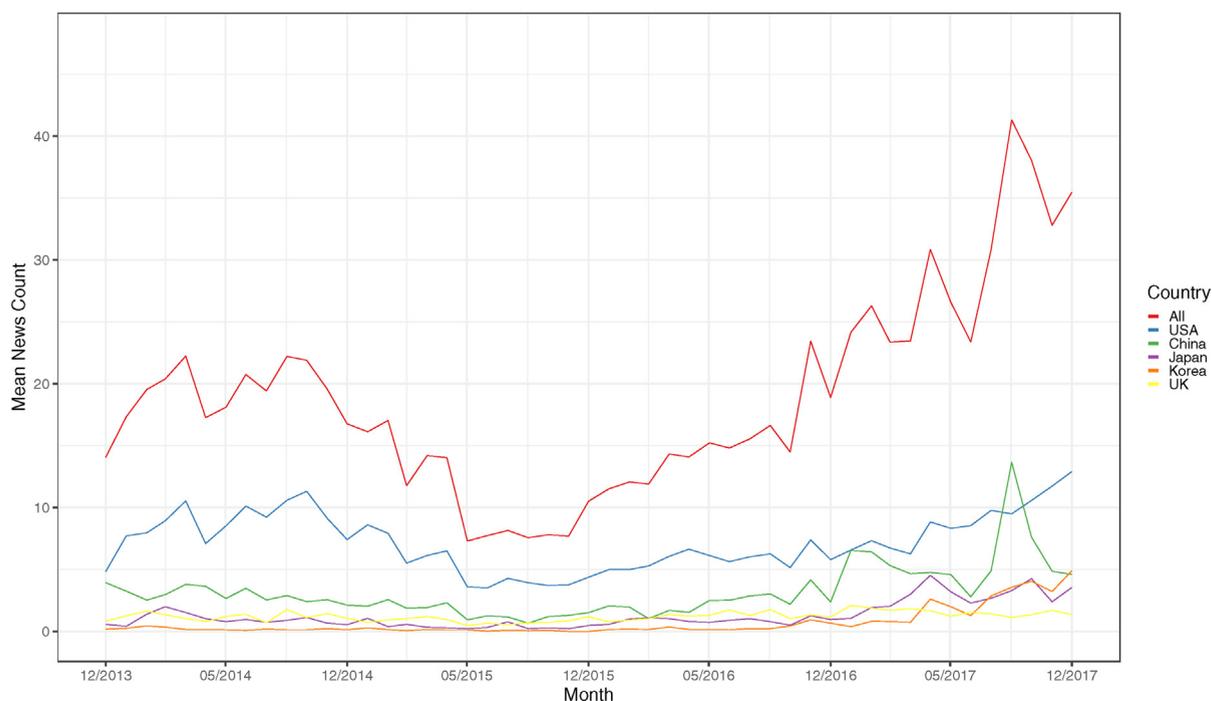
unrelated news and price volatility. Specifically, we included **the number of media items** for the same period as the count of related or unrelated news items and price volatility levels. The number of total media items may impact the visibility of related news and increase the buzz of unrelated news. The amount of media coverage was thus calculated using the average coverage within a seven-day period.

Although we focused on the effects of related and unrelated media coverage for each cryptocurrency, we also controlled for the impact of other topics of media coverage on overall price changes in the cryptocurrency market. To this aim, we collected news items based on five different topics from the same media sources: **Bitcoin- and Etherium-related, bank-related, gold-related, legal issues**, and **negative or scam issues** during the same timeframe. Fig. 9 shows the news media coverage of these topics between 2013 and 2017.

Bitcoin and Ethereum coverage is the number of news items that included references to Bitcoin or Ethereum, such as "Bitcoin," "bitcoin," "bitcoins," "BTC," "Ethereum," "ether," "ethereums," and "ETH." As explained previously, Bitcoin and Ethereum are not simply coins themselves. They also function as exchange currencies for other coins and tokens. The media sometimes use the term "Bitcoin" to represent the cryptocurrency market in general. Thus, we aimed to control the media coverage of Bitcoin and Ethereum separately from other project-based related news to explore project-level price volatility more clearly.

As cryptocurrency is not yet officially defined as either a currency or an asset, there have been many attempts to fold it into conventional financial markets. The media have paid attention to how banks and financial institutions treat cryptocurrencies and their use of these instruments. Accordingly, in order to control for the matters regarding regulation by banks and financial sectors, we also controlled the **bank-related news**, that is, items that included the following keywords: "JPMorgan," "Goldman Sachs," "Wall Street," "Smart Contracts," "FinTech," "Federal Reserve," "Central Bank," and "Bank." Incorporating cryptocurrency into the conventional financial market concerns not only major financial institutions, but also legal, regulatory, tax, and governance issues. These matters are associated with market fluctuations and volatility, as they represent the fundamental process of legitimizing markets. **Legal news** was associated with the news items that included the following keywords: "regulation," "government," "law," "legislation," "SEC (the US Securities and Exchange Commission)," "CFTC (the Commodity Futures Trading Commission)," "taxes," and "IRS (the US Internal Revenue Service)."

We also selected gold-related news that included the keyword "gold." Cryptocurrency has often been compared with gold as a safe asset, and the media have adopted the terminology of Bitcoin or Ethereum mining to draw parallels with gold and emphasize its scarcity. Hence, we controlled for **gold-based news** to check whether any similarity exists between the issues of the gold market and the price volatility of a cryptocurrency. Furthermore, we included **negative or scam news** in the control variables. This is because cryptocurrency tends to receive greater media attention for negative reasons, such as accusations of money laundering and financial fraud by corrupt companies or governments. For our search, we used the following keywords: "scam," "fraud," "crime," "corruption," and "FinCEN (Financial Crimes Enforcement Network)."
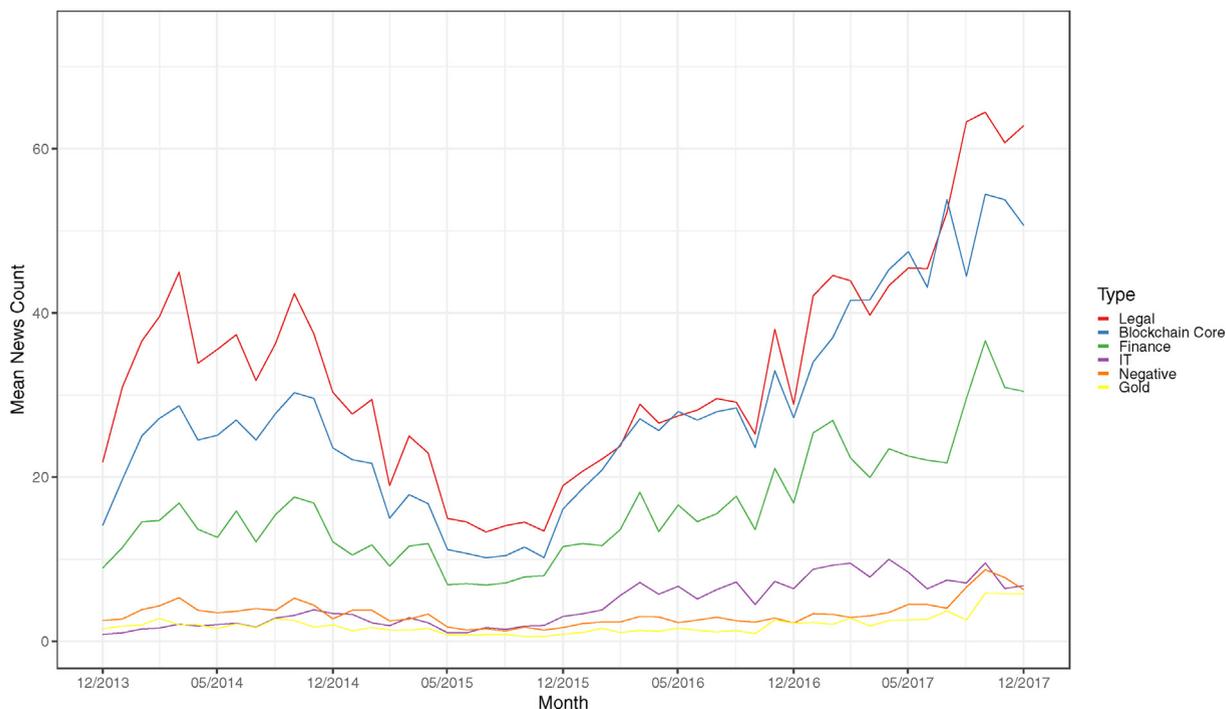
Fig. 9. Number of Topics Covered by the News Media between 2013 and 2017

Lastly, while we controlled the five topics listed above to correctly measure the impact of the other related news, we acknowledged that a broad spectrum of issues might influence perceptions about unrelated information. We thus paid attention to the number of topics covered during the same period. Specifically, we controlled for the ***topic breadth of news***, which covered the average unique number of topics (i.e., tags plus keywords) across three news media (CCN, CoinDesk, and Coin Telegraph) during the same period. Every news article had its own tags; the greater the number of topic tags on the article, the greater the breadth and scope of its content. As shown in Fig. 10, the mean topic breadth stayed at a similar level (aside from the downturn in 2015).

5. Results

Table 1 presents the descriptive statistics for all the variables, and we checked necessary correlations. We found that there is an overall low correlation between coin price volatility and media coverage (see Appendix A.3 for the full correlation table). Most of the control variables, such as the year dummy variables and other topic-related media coverage like Bitcoin- and Ethereum-related, bank-related, gold-related, and legal issues, as well as negative or scam issues, do not have a correlation with price volatility. However, they have a high correlation with market capitalization and volume, as we expected, which helps control overall trends and fluctuations in the models.

Table 2 shows the results of the fixed effects regressions with AR (1) for the total sample (Model 1), the major coins (Model 2), and the nonmajor coins (Model 3). Then, Figs. 11–13 provide standardized estimates to interpret the impact of related and unrelated news on coin price volatility.

The result from Model 1 of our first multivariate model is illustrated in Fig. 11, which shows standardized estimates of the relationship between the volatility in cryptocurrency prices and media coverage volumes of both related and unrelated news. If a confidence interval overlaps with the zero value, it indicates that it is not significant at the 95% level. The actual coefficients and standard error values are detailed in Table 2. We found that higher numbers of unrelated project news led to greater volatility for all coins, as we anticipated in Hypothesis 1. The results from these models demonstrate that, net of other controlling factors, such as market activities, media coverage trends, and closing prices, unrelated news volumes are systematically associated with price volatility. Among the controls, bank-based news items also increase volatility significantly, which links to the debate on how banks and conventional markets treated cryptocurrencies in the past.

Hypothesis 2.1) and 2.2) were tested in Model 2 and 3. As regards major coins, Fig. 12 shows the standardized estimates for the relationship between price volatility and the same set of variables of major coins. Unlike the results for all coins, depicted in Fig. 11, the volume of project-unrelated news is not significantly associated with the volatility of major coins, whereas the volumes of project-related news lead to less volatility, supporting Hypothesis 2.1). For major coins, the degree
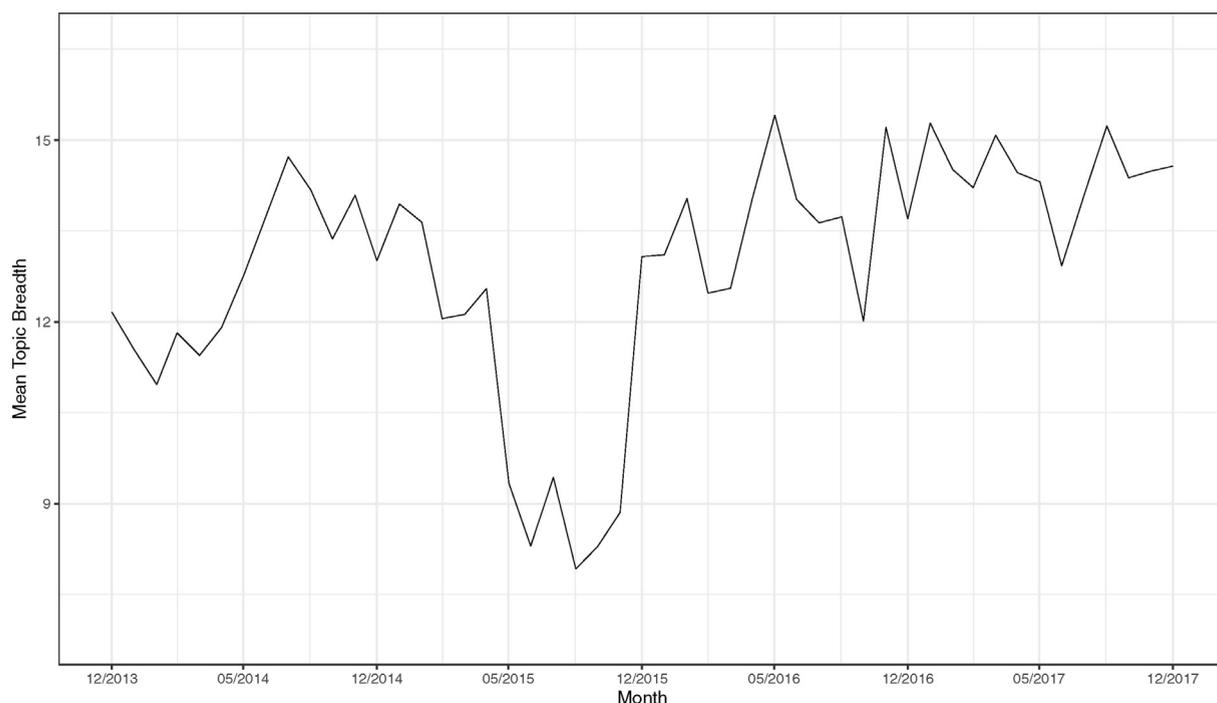
Fig. 10. Breadth of News Topics between 2014 and 2018.

of misinterpretation of unrelated news among crypto market investors decreases. Related news brings attention to a directional price change, either increasing or decreasing, and thus reduces volatility.

Results for the rest of the coins (i.e., non-major coins) are presented in Table 2 and Fig. 13 to support both Hypothesis 1 and Hypothesis 2.2. Specifically, the volumes of both project-related and unrelated news led to higher volatility. In particular, the results of project-based news presented thus far provide strong evidence that the volume of news items of certain projects-related and unrelated news is significantly correlated with the price volatility of cryptocurrencies, which supports the strategic complementarity mechanism that we modeled for nascent markets. Hence, the price volatility of cryptocurrencies tends to increase with higher volumes of unrelated news. Furthermore, volatility increases with the number of related news items when we separate the samples into major and minor coins, especially for lesser-known and small projects.

Additionally, among controls in every model, country-based news control variables did not significantly impact price volatility among either related or unrelated news. This could be due to the innate nongeographical nature of cryptocurrencies, and we will speculate more on this null finding in the discussion section.

To verify the robustness of our results, we conducted three additional tests using alternative measures of volatility during the same period, in addition to our dependent measure of price volatility: 1) Sample variance with the average daily price, 2) the squared difference between starting price of first day and closing price of the last day of observation period, and 3) the squared difference between the maximum price and minimum price during the observation period. Our findings remained consistent and robust. See Appendix A.4 for the result of 1) the sample variance with the average daily price.

6. Discussion

We developed a theoretical model to understand how increased media information influences investment behavior in a nascent and rising market. Our theory assumes that, given strategic complementarity, in the absence of a clear consensus among investors on the fundamental value in a nascent market, they react to both unrelated and related news for their investment decisions; consequently, other investors cannot but follow these behaviors. Empirically, we found that an increase in the number of unrelated news items tends to amplify the price volatility of cryptocurrencies in general, with varying effects on major and minor coins.

Herding behaviors are more salient in minor coins, whereas major coins reduce their volatility with related news. Owing to the differences in coin characteristics (e.g., price ranges and market shares) and exposure to potential investors, major and minor coins showed different sensitivity to news media coverage. Specifically, price volatility decreases for major coins as the amount of project-related news increases, indicating that, when investors are relatively better informed on a cryptocurrency's fundamentals, the relationship between media coverage and price volatility works similar to what shown in previous studies on the choice of correct and relative information. Conversely, for non-major coins (such as Mediblock, Iota, and Main-

Table 1
Descriptive Statistics.

	Variables	For Total				For Major				For Non-Major			
		MEAN	SD	MIN	MAX	MEAN	SD	MIN	MAX	MEAN	SD	MIN	MAX
1	Coin Price Volatily	376204.8	99,300,000	0	4.42E + 10	1123.675	18826.6	7.32E-11	872271.3	387510.9	101,000,000	0	4.42E + 10
2	Market Capitalization	381,000	667,000	20,700	3,720,000	437,000	719,000	20,700	3,720,000	382,000	668,000	20,700	3,720,000
3	Market Volume	5,067,890	155,000,000	0	2.22E + 10	74,600,000	349,000,000	156	1.19E + 10	430382.5	10.7	0	2,430,000,000
4	Closing Price	55.841	3253.422	0.000	793273.000	51.774	205.164	0.001	3923.070	50.545	3297.695	0.000	793273.000
	Years												
5	2014	0.113	0.317	0.000	1.000	0.123	0.329	0.000	1.000	0.113	0.316	0.000	1.000
6	2015	0.204	0.403	0.000	1.000	0.183	0.387	0.000	1.000	0.204	0.403	0.000	1.000
7	2016	0.272	0.445	0.000	1.000	0.240	0.427	0.000	1.000	0.272	0.445	0.000	1.000
8	2017	0.411	0.492	0.000	1.000	0.453	0.498	0.000	1.000	0.412	0.492	0.000	1.000
9	The Number of Media Coverage	142.551	56.067	38.000	302.000	148.432	57.853	38.000	302.000	142.626	56.097	38.000	302.000
10	Bitcoin and Etherium Coverage	136.423	53.370	38.000	316.000	146.299	58.380	38.000	313.000	136.408	53.317	38.000	316.000
11	Bank related news	90.849	37.153	17.000	204.000	94.679	37.789	17.000	204.000	90.888	37.164	17.000	204.000
12	Gold related news	16.054	11.470	1.000	63.000	17.297	12.120	1.000	63.000	16.064	11.478	1.000	63.000
13	Legal issues related news	256.590	112.060	57.000	552.000	268.968	113.839	57.000	552.000	256.718	112.106	57.000	552.000
14	Negative issues related news	25.576	13.897	4.000	81.000	26.970	14.503	4.000	81.000	25.587	13.903	4.000	81.000
15	Topic breadth of news	54.802	10.401	21.333	73.333	55.258	10.184	23.667	73.333	54.808	10.400	21.333	73.333
16	Project-based related news	0.741	7.441	0.000	237.000	4.769	7.448	0.000	64.000	0.147	0.920	0.000	36.000
17	Project-based unrelated news	236.742	113.969	16.000	531.000	244.838	114.374	52.000	531.000	237.485	113.917	52.000	531.000
18	Country-based related news	9.043	19.971	0.000	128.000	20.330	27.124	0.000	128.000	8.758	19.675	0.000	128.000
19	Country-based unrelated news	5.822	16.592	0.000	216.000	10.425	19.920	0.000	123.000	5.654	16.294	0.000	216.000

Table 2
Results of the Fixed-Effects Regression with First-Order Autoregressive (AR(1)) Model.

Variables	Model 1 (Total)			Model 2 (Major)			Model 3 (Non-majors)		
	Coefficient	SE		Coefficient	SE		Coefficient	SE	
Market Capitalization	0.000	(0.000)		−5.98E-09	(0.000)	***	0.000	(0.000)	
Market Volume	−0.003	(0.001)	**	−8.84E-06	(0.000)	***	−0.001	(0.007)	
Closing Price	37815.250	(99.108)	***	89.330	(2.930)	***	37822.920	(100.674)	***
Years									
2014	−13100000	(2762538.000)	***	−3230.039	(3572.239)		−13800000	(2845554.000)	***
2015	50121.820	(2097164.000)		−2525.390	(2970.674)		10764.540	(2156954.000)	
2016	−242131.800	(1963871.000)		−3861.558	(3007.531)		−188113.600	(2019490.000)	
2017	−1400672.000	(2362870.000)		−773.825	(3759.345)		−1186832.000	(2430275.000)	
The Number of Media Coverage	200.364	(18499.140)		6.355	(39.953)		2675.084	(19067.320)	
Bitcoin and Etherium Coverage	−24490.270	(16066.780)		−17.413	(35.846)		−28277.000	(16559.770)	†
Bank related news	25957.120	(10738.320)	*	−43.279	(24.500)	†	27616.340	(11062.070)	*
Gold related news	−25758.670	(21360.290)		4.656	(46.498)		−25728.110	(22002.130)	
Legal issues related news	−3866.246	(6586.271)		24.126	(14.782)		−4103.481	(6783.722)	
Negative issues related news	−3352.699	(18108.430)		31.368	(40.759)		−4037.051	(18653.670)	
Topic breadth of news	4656.134	(8774.417)		−1.584	(20.942)		4806.075	(9041.204)	
Project-based related news	−52056.950	(89116.090)		−430.543	(90.894)	***	944642.500	(223983.400)	***
Project-based unrelated news	12979.120	(6316.500)	*	5.871	(14.618)		12772.020	(6500.006)	*
Country-based related news	7583.951	(24033.420)		28.177	(33.330)		6306.929	(25138.810)	
Country-based unrelated news	2705.210	(27694.190)		29.665	(44.144)		1560.809	(29014.390)	
CONSTANT	−890570.100	(70978.770)	***	−954.454	(268.059)	***	−919205.700	(73181.320)	***
N	3,58,118			5,981			3,47,443		

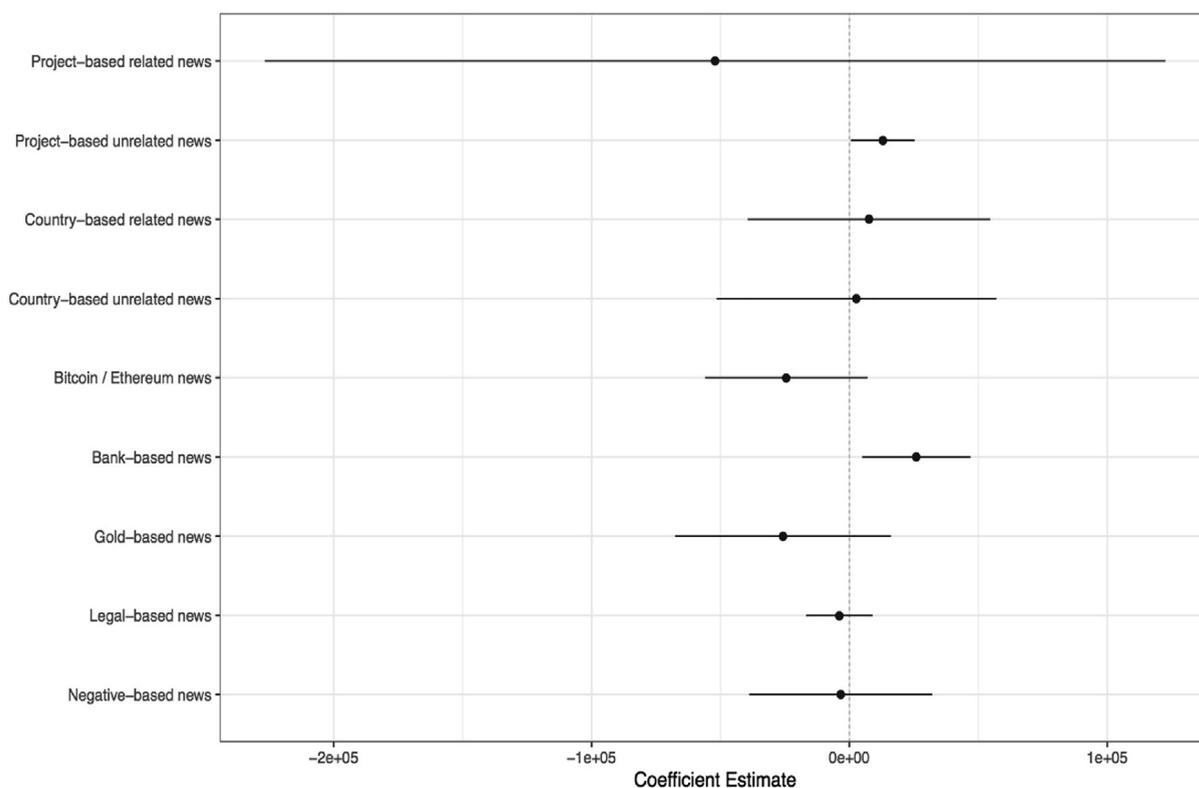Note: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$.

Fig. 11. Results of the Fixed-Effect Regression with First-Order Autoregressive (AR(1)) Model for 500 Cryptocurrencies.

frame), price volatility increases as the amount of both project-related and unrelated news increases. This is because those who invest in these coins are generally less informed than those who invest in major coins. Hence, increased volatility following both related and unrelated news provides evidence of herding behavior in newly created coin markets.
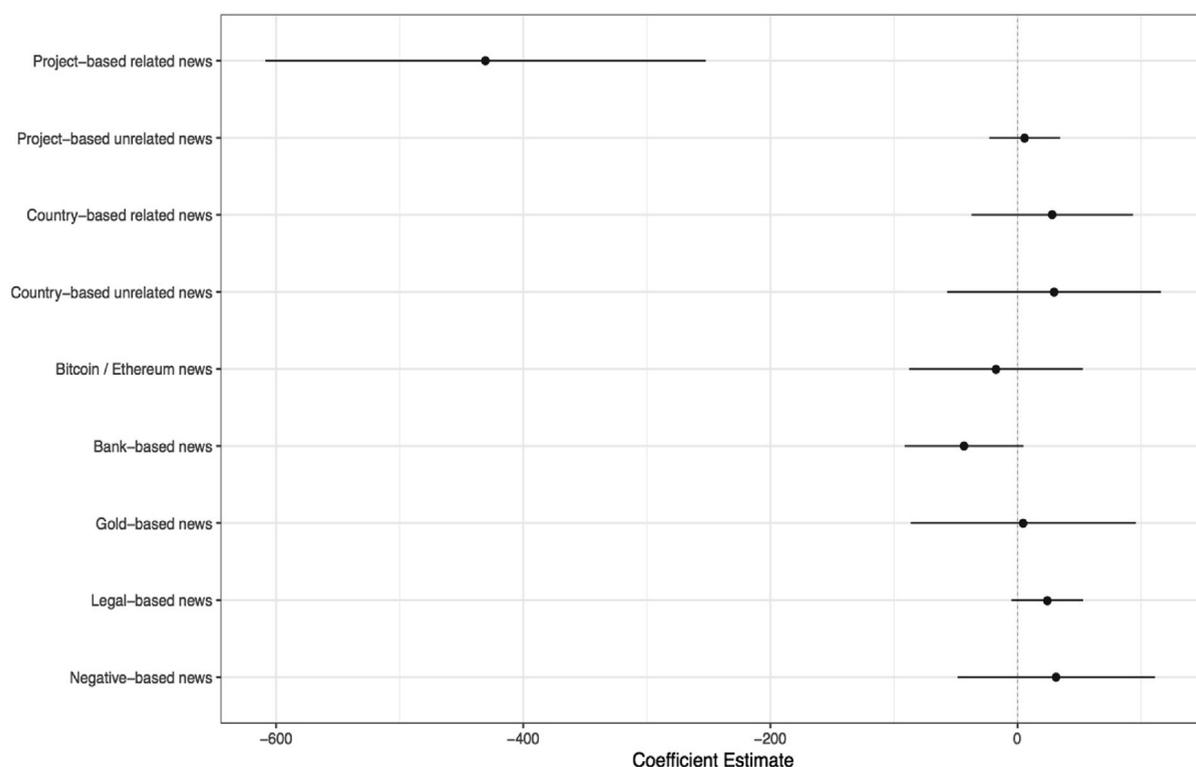
Fig. 12. Results of the Fixed-Effect Regression with First-Order Autoregressive (AR(1)) Model for Major Cryptocurrencies.

This study has important implications for the subject of media information and market interactions in nascent or highly uncertain markets witnessing information overflow. First, the findings shed a light on the effect of the volume of both related and unrelated news on nascent financial markets—specifically, cryptocurrency markets. The latter have received significant media attention due to their unprecedented return, which was compared with lottery payoffs (Grobys and Junttila, 2021) and triggered a vast influx of media coverage, leading to the reproduction of unverified information (Kraaijeveld and De Smedt, 2020). The impact of excessive information on market behaviors has become a common condition in contemporary markets, thus representing a recurrent trope in research on market dynamics featured by uncertainty and ambiguity since excessive information often increases the number of unsophisticated actors in markets due to bounded rationality. We contributed to this debate by explaining how investors in new and rising markets interpret media information to make investment decisions in the presence of strategic complementarity. Specifically, we introduced the notion of strategic complementarity to explain the role of media in shaping financial price dynamics, particularly in markets characterized by increased information and rapid change, which are becoming increasingly common.

Secondly, our study represents one of the first to encompass a broad range of cryptocurrencies beyond Bitcoin and examine their price movements in relation to media coverage. Previous research on cryptocurrencies primarily centered around Bitcoin or a few dominant altcoins. However, with the decline of Bitcoin's dominance and the rise of various coins, the cryptocurrency landscape has changed. With its unprecedented sample size, our study showed the overall relationship between price volatility and media coverage and its variation between major and minor coins due to their differing market dominance and popularity. Our findings, similar to the work of Ciaian et al. (2018) on the interdependence between Bitcoin and a few major altcoins, suggest that coin price volatility driven by the amount of new information creates herding not just among major coins but also minor coins, reinforcing the coins' co-movements. Nevertheless, these co-movements will decrease as investors gain better understanding of each coin, as observed in the case of major coin markets.

Lastly, we present an empirical framework for studying the cryptocurrency market, which has garnered ongoing attention. Our framework, which provides information on 500 cryptocurrencies, offers insights into their speculative qualities and can be applied to recent surges in new cryptocurrencies, such as the Dogecoin or NFT (Non-Fungible Token) markets. We believe our findings can be extended to recent cryptocurrency market fluctuations after 2020 or the growth of NFT markets, as both have seen a rapid increase in new investors but with unclear fundamental validation (Griffith, 2021). As a result, the strategic complementarity and excessive media information dynamics would likely operate in a similar manner.

However, both the theoretical model and empirical validation may require further modification based on the different external factors involved in recent crypto-related market fluctuations. The recent cryptocurrency surge was reinforced by COVID-19 and followed cash flow into the financial markets (Sarkodie et al., 2022), which may have interfered with the
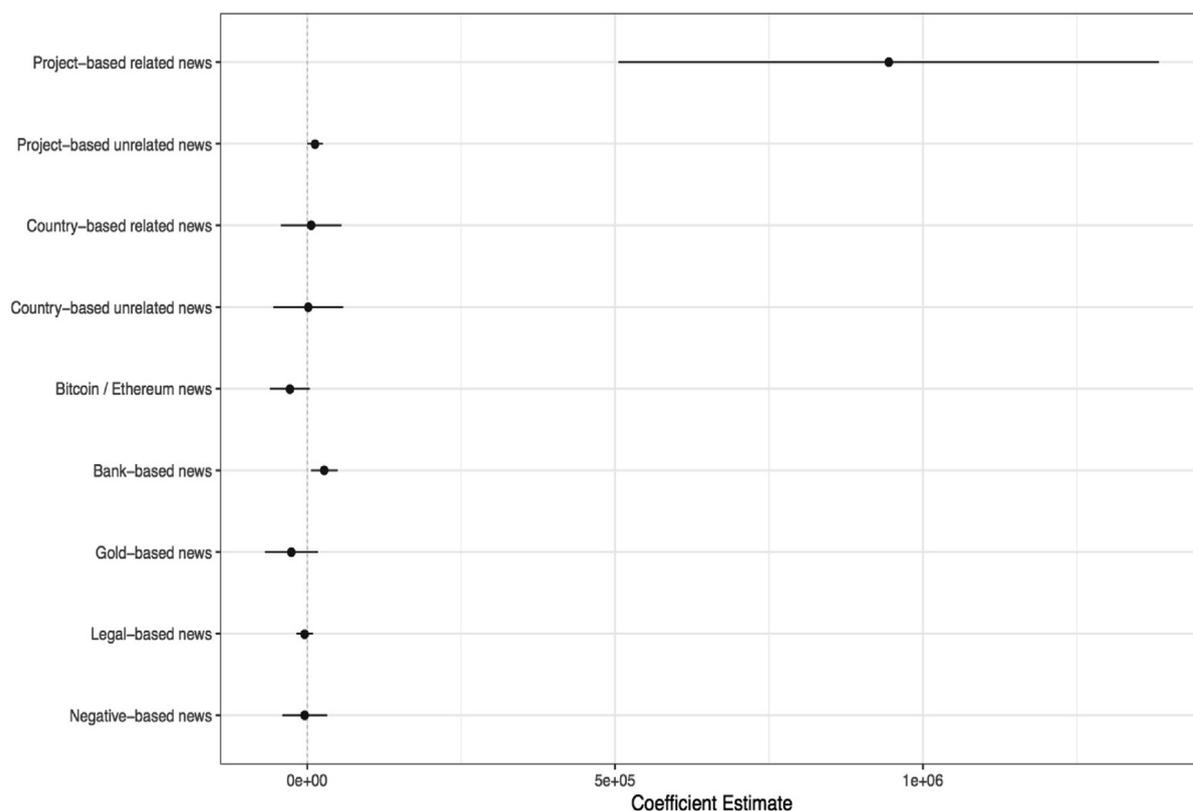
Fig. 13. Results of the Fixed-Effect Regression with First-Order Autoregressive (AR(1)) Model for Non-major Cryptocurrencies.

strategic complementarity differently, thus increasing simple herding behaviors. Additionally, unlike in the early period, diverse institutional actors are now more involved in the cryptocurrency market, particularly when a large cryptocurrency exchange (i.e., CoinBase) lists its shares on the stock market or when a major financial scam like the FTX fraud attracts the attention of the SEC. These external factors could be considered in future studies to extend the current models.

Notwithstanding the contributions of this study, there are some limitations to note. Contrary to expectations, some control variables (of country-based related and unrelated news) did not have any significant relationship with price volatility. Although there were some country-specific spikes and patterns of news coverage, as observed in Fig. 8, country-based related news did not work either as noise or as a signal yet here. This outcome may be owing to two factors: first, the CEO's country or location of headquarters was relatively less known to investors due to the nongeographical nature and anonymity of cryptocurrencies. Specifically, blockchain technology allows transactions to be traced to an individual's specific account, but individual anonymity can be maintained throughout (Tapscott and Tapscott, 2016). Furthermore, it is not just cryptocurrency user anonymity that has gained popularity; the use of pseudonyms for team members in cryptocurrency projects has also increased, with members hoping to become the next "Satoshi Nakamoto," the founder of Bitcoin. Accordingly, we posit that the country of origin for a cryptocurrency may not be easily connected to specific coins or blockchain projects due to the culture of anonymity in the cryptocurrency market.

Second, country-based news items tend to overlap with other relevant issues that we also controlled in our analyses, such as legislation (policy and regulations), finance (banking), or industry (information technologies or IT). The effect of country-based news is an essential element of specific market dynamics, but it may not be ample enough to create the sort of buzz that influences investment decisions independently of other factors. Hence, we recommend further investigation of the sensitivity of global cryptocurrency markets to country-based effects or news.

Lastly, other forms or categories of unrelated information may also play a yet-unexplored impact. Although we defined irrelevance broadly within cryptocurrency media, other researchers may argue that different types of noise can have different effects. In future studies, we aim to examine how the content of news, rather than its relevance, affects investors' behavior. For instance, it would be interesting to study how potential investors properly select and interpret media coverage based on its positive, negative, or analytical content, and the impact this has on market outcomes regardless of direct correlation. Additionally, as news contents update audience perceptions of asset value in specific ways, individuals may have different reactions to positive and negative news. Through a content analysis of news coverage, we plan to explore further how and when the mechanism of strategic complementarity is strengthened or weakened as the market receives more attention.

CRediT authorship contribution statement

Declaration of Competing Interest

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

Acknowledgement

Appendix A

A.1. Equilibrium analysis

Given any information set I_t, an agent maximizes the expected utility of $E[u_{t,i}(a_{t,i};\theta_t)|I_t]$ by choosing $a_{t,i}$.[17] Solving the maximization problem, we get the optimal action of agent i:

$$a_{t,i}^* = (1-\beta)E_i(\theta_t|I_t) + \beta E_i(\bar{a}_t|I_t).$$

Write $m_t^* = \sum_{k=1}^{n_t^*} m_t^k$, and $\widehat{m}_t \equiv \sum_{j=1}^{n_t} m_t^j$. From the definition of $\bar{a}_t$, we get:

$$E_s(\bar{a}_t|I_t) = (1-\alpha)\left((1-\beta)\cdot\left(\theta_{t-1} + \frac{1}{n_t^*}m_t^*\right) + \beta E_s(\bar{a}_t|I_t)\right)$$

$$+ \alpha\left((1-\beta)\cdot(\theta_{t-1} + m_t^* + \widehat{m}_t) + \beta E_s\left(E_n(\bar{a}_t|I_t)|I_t\right)\right) \text{ and} \tag{1}$$

$$E_n(\bar{a}_t|I_t) = (1-\beta)\cdot(\theta_{t-1} + m_t^* + \widehat{m}_t) + \beta E_n(\bar{a}|I_t). \tag{2}$$

Rearranging Eq. (2) gives us $E_n(\bar{a}|I_t) = \theta_{t-1} + m_t^* + \widehat{m}_t$. When this is put into Eq. (1), we get the following:

$$E_s(\bar{a}_t|I_t) = (1-\alpha)\left((1-\beta)\cdot\left(\theta_{t-1} + \frac{1}{n_t^*}m_t^*\right) + \beta E_s(\bar{a}_t|I_t)\right) + \alpha((1-\beta)\cdot(\theta_{t-1} + m_t^* + \widehat{m}_t) + \beta E_s(\theta_{t-1} + m_t^* + \widehat{m}_t|I_t)),$$

$$E_s(\bar{a}_t|I_t) = (1-\alpha)\beta E_s(\bar{a}_t|I_t) + (1-\alpha)(1-\beta)\cdot\left(\theta_{t-1} + \frac{1}{n_t^*}m_t^*\right) + \alpha(\theta_{t-1} + m_t^* + \widehat{m}_t)$$

$$= (1-\alpha)\beta E_s(\bar{a}_t|I_t) + (1-(1-\alpha)\beta)\theta_{t-1} + (1-\alpha)(1-\beta)\frac{1}{n_t^*}m_t^* + \alpha(m_t^* + \widehat{m}_t), and E_s(\bar{a}_t|I_t)$$

$$= \theta_{t-1} + \frac{(1-\alpha)(1-\beta)}{(1-(1-\alpha)\beta)}\frac{1}{n_t^*}m_t^* + \frac{\alpha}{(1-(1-\alpha)\beta)}(m_t^* + \widehat{m}_t)$$

Let us define $\lambda \equiv \frac{\alpha}{(1-(1-\alpha)\beta)}$; this parameter, combining the naivete (α) and the strategic complementarity (β) of the asset, represents how speculative the asset is in both informational and behavioral senses. Note that λ increases in both α and β.[18] Then,

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[17] Note that the welfare of society only depends on the fundamental and is formally defined by $E\left[\int -(a_{t,i}-\theta_t)^2 di|I_t\right]$.

[18] Moreover, even when β is zero, λ is still positive if N-types are present in a market, $\lambda = \alpha$. Of course, the conventional meaning of speculative asset is closely related to the parameter β: investors in a speculative market pay little attention to the market fundamental and focus more on the movement of the asset price. But in our framework, the naivete of a market, α, makes investors focus on news that is unrelated to market fundamentals and decide based on guesses or misinformation. Hence, the naivete of a market also leads investors away from information on market fundamentals. In conclusion, parameter λ captures the informational and behavioral speculativeness of an asset.

$E_s\left(\bar{a}_t|I_t\right) = \theta_{t-1} + (1-\lambda)\frac{1}{n_t^*}m_t^* + \lambda(m_t^* + \widehat{m}_t).$

Therefore, the optimal actions of S-type investors and N-type investors are:

$$a_{t,s}^* = \theta_{t-1} + (1-\beta\lambda)\frac{1}{n_t^*}m_t^* + \beta\lambda(m_t^* + \widehat{m}_t) and$$

$$a_{t,n}^* = \theta_{t-1} + m_t^* + \widehat{m}_t.$$

A.2. Relationship between Proposition and Hypotheses

Proposition	Comparative Statics	Hypothesis	Empirical Proxy
1-a)	$\alpha > 0 \iff \frac{\partial Var(a_t)}{\partial n_t} > 0$	1	For all markets, the coefficient of project-based unrelated news > 0
1-b)	for any $\lambda \leq \lambda^*, \frac{\partial Var(\bar{a}_t)}{\partial n_t^*} \leq 0.$	2–1	For the major markets, the coefficient of project-based related news < 0
1-c)	for any $\lambda > \lambda^*, \frac{\partial Var(\bar{a}_t)}{\partial n_t^*} > 0.$	2–2	For the minor markets, the coefficient of project-based related news > 0

A.3. Pearson correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Coin Price Volatily	1.000																		
2	Market Capitalization	0.015	1.000																	
3	Market Volume	−3.E-04	0.058 *	1.000																
4	Closing Price	0.620 *	0.023 *	0.021 *	1.000															
5	2014	−0.002	−0.220 *	−0.012 *	0.003 *	1.000														
6	2015	−0.003	−0.316 *	−0.017 *	−0.010 *	−0.137 *	1.000													
7	2016	−0.004	−0.357 *	−0.020 *	−0.013 *	−0.164 *	−0.230 *	1.000												
8	2017	0.008	0.059 *	0.007	0.009 *	−0.226 *	−0.316 *	−0.380 *	1.000											
9	The Number of Media Coverage	0.007	0.788 *	0.042 *	0.017 *	−0.145 *	−0.483 *	−0.468 *	0.339 *	1.000										
10	Bitcoin and Etherium Coverage	0.010	0.754 *	0.046 *	0.019 *	−0.108 *	−0.504 *	−0.476 *	0.492 *	0.946 *	1.000									
11	Bank related news	0.004	0.717 *	0.037 *	0.013 *	−0.126 *	−0.549 *	−0.373 *	0.298 *	0.919 *	0.845 *	1.000								
12	Gold related news	0.007	0.698 *	0.041 *	0.014 *	−0.107 *	−0.413 *	−0.368 *	0.368 *	0.805 *	0.834 *	0.735 *	1.000							
13	Legal issues related news	0.005	0.786 *	0.041 *	0.015 *	−0.119 *	−0.519 *	−0.411 *	0.230 *	0.965 *	0.871 *	0.953 *	0.737 *	1.000						
14	Negative issues related news	0.003	0.728 *	0.037 *	0.013 *	−0.074 *	−0.395 *	−0.401 *	0.128 *	0.900 *	0.796 *	0.872 *	0.705 *	0.917 *	1.000					
15	Topic breadth of news	−3.E-04 *	0.333 *	0.018 *	0.005 *	−0.078 *	−0.439 *	−0.008	0.157 *	0.396 *	0.395 *	0.439 *	0.319 *	0.442 *	0.372 *	1.000				
16	Project-based related news	−7.E-04 *	0.005	0.519 *	0.014 *	0.035 *	−0.011	−0.017	−1.E-04	0.013	0.025 *	0.010	0.011	0.011	0.012	0.003	1.000			
17	Project-based unrelated news	0.009	0.818 *	0.017 *	0.019 *	−0.115 *	−0.461 *	−0.495 *	0.361 *	0.970 *	0.966 *	0.860 *	0.816 *	0.916 *	0.858 *	0.389 *	−0.040 *	1.000		
18	Country-based related news	−0.003	0.123 *	−0.001	−0.010 *	0.012 *	−0.075 *	−0.067 *	0.005	0.153 *	0.137 *	0.153 *	0.118 *	0.161 *	0.154 *	0.072 *	−0.010	0.145 *	1.000	
19	Country-based unrelated news	−0.003	0.162 *	6.E-04	−0.009 *	−0.033 *	−0.103 *	−0.079 *	0.038 *	0.190 *	0.169 *	0.191 *	0.143 *	0.199 *	0.181 *	0.091 *	−0.017 *	0.180 *	0.227 *	1

note: * $p < .05$

A.4. Robustness check

Here, we test alternative volatility proxies and its robustness for the better empirical specification. We ran three additional volatility measures of the same period in addition to the current dependent price volatility: 1) Sample variance with the average daily price, 2) the squared difference between starting price of first day and closing price of the last day of observation period, and 3) the squared difference between the maximum price and minimum price during the observation period. All main results stayed same as our original findings. We provide the results of 1) the sample variance with the average daily price here. We can provide the results of 2) and 3) upon request.

A.4.1. Results of the Fixed-Effects Regression with First-Order Autoregressive (AR(1)) model (with sample variance with the average daily price)

Variables	Model 1 (Total)			Model 2 (Major)			Model 3 (Non-majors)		
	Coefficient	SE		Coefficient	SE		Coefficient	SE	
Market Capitalization	0.000	(0.000)		−4.96E-09	(0.000)	***	0.000	(0.000)	
Market Volume	−0.002	(0.001)	**	−8.49E-06	(0.000)	***	−0.001	(0.007)	
Closing Price	38954.430	(88.118)	***	71.323	(2.353)	***	38972.7	(89.5)	***
Years									
2014	−12700000.0	(2762538.0)	***	−3009.9	(2838.9)		−13400000.0	(2852413.0)	***
2015	−9937.2	(2097164.0)		−2132.6	(2364.2)		−46241.0	(2155389.0)	
2016	−247819.2	(1963871.0)		−3051.1	(2398.9)		−193965.9	(1993082.0)	
2017	−1341073.0	(2362870.0)		−1263.4	(2998.4)		−1100240.0	(2340436.0)	
The Number of Media Coverage	836.7	(16693.3)		−1.2	(32.1)		2800.6	(17205.8)	
Bitcoin and Etherium Coverage	−23783.8	(14467.8)		−1.5	(28.8)		−26914.0	(14909.9)	†
Bank related news	23658.0	(9663.1)	*	−34.5	(19.7)	†	25217.6	(9954.4)	*
Gold related news	−24800.2	(19249.1)		14.6	(37.4)		−24749.0	(19827.6)	
Legal issues related news	−3429.2	(5932.9)		21.2	(11.9)	†	−3634.0	(6110.8)	
Negative issues related news	−4423.2	(16294.4)		18.8	(32.8)		−5128.1	(16785.0)	
Topic breadth of news	4103.4	(7880.7)		−1.4	(16.9)		4228.7	(8120.2)	
Project-based related news	−46327.8	(83386.5)		−310.5	(73.0)	***	779721.3	(202129.0)	***
Project-based unrelated news	12163.7	(5684.7)	*	1.3	(11.8)		11976.2	(5849.8)	*
Country-based related news	6408.1	(22046.9)		15.4	(26.7)		5356.1	(23062.9)	
Country-based unrelated news	2162.8	(25427.5)		21.7	(35.4)		1182.5	(26636.0)	
CONSTANT	−658069.2	(61975.3)	***	−734.6	(221.5)	***	−673161.4	(63888.0)	***
N	3,58,118			5,981			3,47,443		

Note: *** p < .001, ** p < .01, * p < .05, † p < .10.

References

Alam, N., Gupta, L., Zameni, A., 2019. Cryptocurrency and Islamic Finance. In: Alam, N., Gupta, L., Zameni, A. (Eds.), Fintech and Islamic Finance: Digitalization, Development and Disruption. Palgrave MacMillan, pp. 99–118.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Ebens, H., 2001. The distribution of realized stock return volatility. J. Financ. Econ. 61, 43–76.

Antweiler, W., Frank, M.Z., 2004. Is all that talk just noise? The information content of internet stock message boards. J. Financ. 59, 1259–1294.

Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. J. Financ. Econ. 99, 427–446.

Bali, T.G., Brown, S.J., Murray, S., Tang, Y., 2017. A lottery-demand-based explanation of the beta anomaly. J. Financ. Quant. Anal. 52, 2369–2397.

Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21, 785–818.

Baur, D.G., Dimpfl, T., 2018. Asymmetric volatility in cryptocurrencies. Econ. Lett. 173, 148–151.

Black, F., 1986. Noise. J. Finance 41, 528–543.

Bloomfield, R., Libby, R., Nelson, M.W., 2000. Underreactions, overreactions and moderated confidence. J. Financ. Mark. 3, 113–137.

Booth, N., 2017. Is bitcoin a bubble waiting to burst? Planet of Finance.

Boudoukh, J., Feldman, R., Kogan, S., Richardson, M., 2019. Information, trading, and volatility: evidence from firm-specific news. Rev. Financ. Stud. 32, 992–1033.

Bulow, J.I., Geanakoplos, J.D., Klemperer, P.D., 1985. Multimarket oligopoly: strategic substitutes and complements. J. Polit. Econ. 93, 488–511.

Buterin, V., 2014. A next-generation smart contract and decentralized application platform. White Paper 3.

Catalini, C., Gans, J.S., 2019. Some Simple Economics of the Blockchain. MIT Sloan Research Paper.

Chan, W.S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. J. Financ. Econ. 70, 223–260.

Chen, M., Qin, C., Zhang, X., 2022. Cryptocurrency price discrepancies under uncertainty: evidence from COVID-19 and lockdown nexus. J. Int. Money Financ. 124, 102633.

Ciaian, P., Rajcaniova, M., Kancs, D.A., 2018. Virtual relationships: short- and long-run evidence from BitCoin and altcoin markets. J. Int. Finan. Markets. Inst. Money 52, 173–195.

Conrad, C., Custovic, A., Ghysels, E., 2018. Long- and short-term cryptocurrency volatility components: a GARCH-MIDAS analysis. J. Risk Financ. Manage. 11, 1–12.

Daft, R.L., Weick, K.E., 1984. Toward a model of organizations as interpretation systems. Acad. Manag. Rev. 9, 284–295.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor Psychology and Security Market under- and Overreactions. J. Financ. 53, 1839–1885.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 2001. Overconfidence, Arbitrage, and Equilibrium Asset Pricing. J. Financ. 56, 921–965.

De Long, J.B., Andrei, S., Lawrence, H.S., Robert, J.W., 1990. Noise Trader Risk in Financial Markets. J. Polit. Econ. 98, 703–738.

Ederington, L.H., Lee, J.H., 1993. How markets process information: news releases and volatility. J. Financ. 48, 1161–1191.

Engle, R.F., Hansen, M.K., Karagozoglu, A.K., Lunde, A., 2021. News and idiosyncratic volatility: the public information processing hypothesis. J. Financ. Economet. 19, 1–38.

Engle, R.F., Ng, V.K., 1993. Measuring and Testing the Impact of News on Volatility. J. Financ. 48, 1749–1778.

Garfinkel, H., 2008. Toward a sociological theory of information. Paradigm Publishers, Boulder.

Gavetti, G., Greve, H.R., Levinthal, D.A., Ocasio, W., 2012. The behavioral theory of the firm: assessment and prospects. Acad. Manag. Ann. 6, 1–40.

Glasserman, P., Mamaysky, H., 2019. Does unusual news forecast market stress? J. Financ. Quant. Anal. 54, 1937–1974.

Goetzmann, W.N., Kumar, A., 2008. Equity Portfolio Diversification*. Eur. Finan. Rev. 12, 433–463.

Greve, H.R., Yue, L.Q., 2017. Hereafter: how crises shape communities through learning and institutional legacies. Organ. Sci. 28, 1098–1114.

Griffith, E., 2021. We're all crypto people now, for better or worse. N.Y. Times 170, 1–2.

Grobys, K., Junttila, J., 2021. Speculation and lottery-like demand in cryptocurrency markets. J. Int. Finan. Markets. Inst. Money 71, 101289.

Grossman, S.J., 1981. The Informational Role of Warranties and Private Disclosure about Product Quality. J. Law Econ. 24, 461–483.

Hendershott, T., Menkveld, A.J., Praz, R., Seasholes, M., 2021. Asset Price Dynamics with Limited Attention. Rev. Financ. Stud. 35, 962–1008.

Hirshleifer, D., 2001. Investor Psychology and Asset Pricing. The Journal of finance (New York) 56, 1533–1597.

Hutchins, E., 1991. The social organization of distributed cognition. In: Resnick, L.B.L., John, M., Teasley, S.D. (Eds.), Perspectives on Socially Shared Cognition. American Psychological Association.

Jackson, S.E., Dutton, J.E., 1988. Discerning Threats and Opportunities. The Johnson Graduate School, Cornell University, pp. 370–387.

Kandel, E., Pearson, N.D., 1995. Differential interpretation of public signals and trade in speculative markets. J. Polit. Econ. 103, 831–872.

Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. J. Financ. 63, 273–310.

Katsiampa, P., 2017. Volatility estimation for Bitcoin: a comparison of GARCH models. Econ. Lett. 158, 3–6.

Katsiampa, P., Corbet, S., Lucey, B., 2019. High frequency volatility co-movements in cryptocurrency markets. J. Int. Finan. Markets. Inst. Money 62, 35–52.

Keynes, J.M., 1936. The General Theory of Employment, Interest, and Money. Macmillan, London.

Kim, K., Lee, S.-Y.-T., Assar, S., 2022. The dynamics of cryptocurrency market behavior: sentiment analysis using Markov chains. Ind. Manag. Data Syst. 122, 365–395.

Klingebiel, R., De Meyer, A., 2013. Becoming aware of the unknown: decision making during the implementation of a strategic initiative. Organ. Sci. 24, 133–153.

Koutmos, D., 2018. Return and volatility spillovers among cryptocurrencies. Econ. Lett. 173, 122–127.

Kraaijeveld, O., De Smedt, J., 2020. The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. J. Int. Finan. Markets. Inst. Money 65, 101188.

Lant, T.K., 2017. Organizational Cognition and Interpretation. Blackwell Compan. Organiz., 344–362

Lau, S.T., Ng, L., Zhang, B., 2012. Information environment and equity risk premium volatility around the World. Manag. Sci. 58, 1322–1340.

Lease, R.C., Lewellen, W.G., Schlarbaum, G.G., 1974. The individual investor: attributes and attitudes. J. Financ. 29, 413–433.

Leath, J.L., 2019. Is Bitcoin Reminiscent of Past Bubbles? The Finance Department. The University of Tennessee at Chattanooga.

Lee, A.D., Li, M., Zheng, H., 2020. Bitcoin: speculative asset or innovative technology? J. Int. Financ. Markets Inst. Money 67, 101209.

Li, T., 2013. Investors' heterogeneity and implied volatility smiles. Manag. Sci. 59, 2392–2412.

Lieure, A., 2018. Herd Behaviour and Information Uncertainty: Insights from the Cryptocurrency Market. School of Slavonic and East European Studies. University College London.

Lu, Y., Ray, S., Teo, M., 2016. Limited attention, marital events and hedge funds. J. Financ. Econ. 122, 607–624.

Lucas Jr R.E., 1972. Expectations and the neutrality of money. J. Econ. Theory 4, 103–124.

Lux, T., Marchesi, M., 1998. Volatility clustering in financial markets: a micro-simulation of interacting agents. IFAC Proc. Vol. 31, 7–10.

Mai, F., Shan, Z., Bai, Q., Wang, X., Chiang, R.H.L., 2018. How does social media impact bitcoin value? A test of the silent majority hypothesis. J. Manag. Inf. Syst. 35, 19–52.

March, J.G., 2001. The search for intelligence in organizations. In: Lant, T.K., Shapira, Z. (Eds.), Organizational Cognition. Lawrence Erlbaum Associates Publishers, Mahwah, NJ, pp. 61–72.

MarketAndMarket, 2018. Cryptocurrency Market by Offering (Hardware: GPU, FPGA, ASIC, & Wallet, and Software), Process (Mining and Transaction), Type, Application (Trading, Remittance, Payment: Peer-to-Peer Payment, Ecommerce, and Retail), and Geography - Global Forecast to 2024. MrketsAndMarkets.

Meyer, A.D., 1982. Adapting to environmental jolts. Adm. Sci. Q. 27, 515–537.

Milliken, F.J., 1990. Perceiving and interpreting environmental change: an examination of college administrators' interpretation of changing demographics. Acad. Manag. J. 33, 42–63.

Mintzberg, H., 1979. Patterns in strategy formation. Int. Stud. Manag. Organ. 9, 67–86.

Morris, S., Shin, H.S., 2002. Social value of public information. Am. Econ. Rev. 92, 1521–1534.

Morris, S., Shin, H.S., 2005. Central bank transparency and the signal value of prices. Brook. Pap. Econ. Act. 2005, 1–66.

Nelson, M.W., Bloomfield, R., Hales, J.W., Libby, R., 2001. The effect of information strength and weight on behavior in financial markets. Organ. Behav. Hum. Decis. Process. 86, 168–196.

Peress, J., 2014. The media and the diffusion of information in financial markets: evidence from newspaper strikes. J. Financ. 69, 2007–2043.

Pollock, T.G., Rindova, V.P., 2003. Media legitimation effects in the market for initial public offerings. Acad. Manag. J. 46, 631–642.

Pollock, T.G., Rindova, V.P., Maggitti, P.G., 2008. Market watch: information and availability cascades among the media and investors in the U.S. IPO Market. Acad. Manage. J. 51, 335–358.

Raith, M., 1996. A General Model of Information Sharing in Oligopoly. J. Econ. Theory 71, 260–288.

Salzman, A., 2019. Bitcoin Peaked 2 Years Ago. New Compeition Is on the Way. Barron's.

Sarkodie, S.A., Ahmed, M.Y., Owusu, P.A., 2022. COVID-19 pandemic improves market signals of cryptocurrencies–evidence from Bitcoin, Bitcoin Cash, Ethereum, and Litecoin. Financ. Res. Lett. 44, 102049.

Scott, B., 2016. How can Cryptocurrency and Blockchain Technology Play a Role in Building Social and Solidarity Finance? United Nations Research Institute for Social Development, Geneva.

Shi, Y., Liu, W.-M., Ho, K.-Y., 2016. Public news arrival and the idiosyncratic volatility puzzle. J. Empir. Financ. 37, 159–172.

Shleifer, A., Summers, L.H., 1990. The noise trader approach to finance. J. Econ. Perspect. 4, 19–33.

Simon, H.A., 1955. A behavioral model of rational choice. Q. J. Econ. 69, 99–118.

Sims, C.A., 2003. Implications of rational inattention. J. Monet. Econ. 50, 665–690.

Sperber, D., Wilson, D., 1995. Relevance: Communication and Cognition. Blackwell, Oxford, UK; Cambridge, Mass.

Sutter, M., Huber, J., Kirchler, M., 2012. Bubbles and information: an experiment. Manag. Sci. 58, 384–393.

Tapscott, D., Tapscott, A., 2016. How blockchain will change organizations. MIT Sloan Manage. Rev.

Tetlock, P.C., 2011. All the news that's fit to reprint: do investors react to stale information? Rev. Financ. Stud. 24, 1481–1512.

Thomas, J.B., Clark, S., Gioia, D., 1993. Strategic sensemaking and organizational performance: linkages among scanning, interpretation, action, and outcomes. Acad. Manag. J. 36, 239–270.

Turner, A.L., Weigel, E.J., 1992. Daily stock market volatility: 1928–1989. Manag. Sci. 38, 1586–1609.

Vives, X., 1984. Duopoly information equilibrium: cournot and bertrand. J. Econ. Theory 34, 71–94.

Vives, X., 1988. Aggregation of Information in Large Cournot Markets. Econometrica 56, 851–876.

Walsh, J.P., 1988. Top management turnover following mergers and acquisitions. Strateg. Manag. J. 9, 173–183.

Weick, K.E., 1993. The collapse of sensemaking in organizations: the Mann Gulch disaster. Adm. Sci. Q. 38, 628–652.

Yan, H., 2010. Is noise trading cancelled out by aggregation? Manag. Sci. 56, 1047–1059.

Yarovaya, L., Matkovskyy, R., Jalan, A., 2021. The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets. J. Int. Finan. Markets. Inst. Money 101321.

Zajac, E.J., Westphal, J.D., 2004. The social construction of market value: institutionalization and learning perspectives on stock market reactions. Am. Sociol. Rev. 69, 433–457.

Zhang, X.F., 2006. Information Uncertainty and Stock Returns. J. Finance (Wiley-Blackwell) 61, 105.

Zhang, W., Li, Y., Xiong, X., Wang, P., 2021. Downside risk and the cross-section of cryptocurrency returns. J. Bank. Financ. 133, 106246.

Zuckerman, E.W., 2004. Structural incoherence and stock market activity. Am. Sociol. Rev. 69, 405–432.