Why are cryptocurrencies so volatile?

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Abstract

Cryptocurrencies are five times more volatile than stocks – why? We shed light on this issue by applying a variance decomposition that separates noise and different forms of information in returns. We find that noise plays the dominant role in the price variance, accounting for 40%. The remaining variance is distributed across different types of information: market-wide information contributes 20%, private information accounts for 19%, and public information makes up approximately 21%. Noise share in cryptocurrencies is much higher than in traditional assets, including stocks (21%), currency (18%), and commodities (15%), yet lower than non-fungible tokens (47%) and the less regulated market such as in-game items (63%). We find that the high noise in cryptocurrencies is related to the high participation of retail investors, who are influenced by media and are prone to behaviors like FOMO and HODL. However, we also show that the fundamental information about cryptocurrencies does not improve the market quality. These results suggest that cryptocurrencies are still immature, relatively informationally inefficient, and face larger systemic considerations than unique asset-specific issues.

JEL classification: G12, G14, G15

1. **Introduction**

One of the frequently cited reasons why cryptocurrencies are not viable as a means for payments or as a store of wealth is their persistently high level of volatility. Compared to gold, Bitcoin is about six times more volatile. Compared to fiat currencies, Bitcoin is around ten times more volatile than the major exchange rates. Bitcoin is even five times more volatile than risky assets such as US stocks, further highlighting their limited ability to be used for payments.[1] Further, the volatility of cryptocurrencies has not declined substantially through time, as shown in Figure 1, as the markets for cryptocurrencies become more "mature". This paper investigates why.

[FIGURE 1]

One narrative that has been proposed to explain the volatility is that cryptocurrencies are a highly speculative asset driven by hype, retail traders with limited rationality, and Ponzi-like dynamics with no intrinsic value. Under this conjecture, one would expect a very high share of noise in the volatility and little or no information in cryptocurrency prices. Volatility is likely to be persistent or even increasing as hype cycles unravel. A competing narrative is that cryptocurrencies are based on a very novel and complex technology that takes time to fully appreciate, with considerable uncertainty about emerging regulation, user adoption, and ultimate demand once the asset class reaches maturity. Under this conjecture, one would expect a substantial information content in the volatility, with both market-wide (cryptocurrency "asset class") information and information specific to individual cryptocurrencies. A further feature of this conjecture is that volatility should decline through time as price discovery resolves the uncertainty about the asset value. Supporters of the first narrative argue that the sharp falls in cryptocurrency prices from their peak is evidence of the speculative/Ponzi nature of cryptocurrencies. However, crashes in asset values can occur for informational reasons such as when information about fundamentals changes (e.g., Fama, 1970), so price dynamics alone cannot distinguish between the competing hypotheses.

Our approach to shed light on these competing conjectures is to apply a novel variance decomposition model to separately identify how much of the volatility is "noise," being temporary deviations of prices from their equilibrium levels versus information. Using this approach, we get

[1] We measured the volatility of various assets by calculating the standard deviation of returns for Bitcoin, the S&P 500, gold, and specific currency pairs from 1st January 2013 to 30th June 2024.

insights into what drives cryptocurrency volatility – market-wide information vs. information about specific cryptocurrencies and public information vs. private information that enters the price through trading. We then give these novel estimates context by applying the same decomposition to stocks, fiat currencies, and commodities to better understand why cryptocurrencies are so volatile and whether the volatility is expected to ever subside.

Analyzing daily return data for the 1500 largest cryptocurrencies from January 2015 to June 2024, we find that noise contributes 40.17% to the price variance. Market-wide information explains 19.52% of the variance, with private information accounting for 19.45% and public information for 21.01%. Comparing these estimates to more established traditional assets provide an obvious contrast that illustrates noise plays a disproportionately large role in driving the high volatility of cryptocurrency returns. Specifically, our findings indicate that the noise component share accounts for 21% in the stock market, 18% in fiat currencies, and 15% in commodities. To further examine the impact of noise on cryptocurrencies, we compare them with younger and less regulated markets, such as Non-Fungible Tokens (NFTs)[2] and in-game items[3]. Our findings show that price volatility due to noise share in the cryptocurrency market is lower than in NFTs (47%) and in-game items (63%). This comparison shows that noise share and volatility tend to be greater in markets either in the early stages of development or less regulated compared to traditional markets.

Our component analysis also sheds light on several critical trends about noise in the cryptocurrency market. First, it reveals a significant increase in the noise component share, which escalated from about 21% to more than 42% during Bitcoin's first peak at approximately $20,000 in late 2017 and has since remained high. This surge aligns with several pivotal factors, including heightened media attention, increased adoption, and the proliferation of new cryptocurrencies. Also, our analysis underscores that the noise component tends to spike during crises. For instance,

[2] The term "Non-Fungible Token" (NFT) here differs from the native token of an NFT project. NFTs are unique (or non-fungible) digital tokens representing ownership of a specific asset (artwork, music, collectibles, and even real estate). Native tokens of NFT projects are typically fungible and used to facilitate economic activities within the NFT ecosystem.

[3] Game items are virtual objects within video games, ranging from functional tools that enhance gameplay, such as weapons and armor, to cosmetic items that alter character appearances. These items can be traded on various platforms, including in-game marketplaces controlled by game developers, third-party online platforms where transactions might involve real money, and blockchain-based platforms where items are traded as non-fungible tokens (NFTs). Trading these items is subject to the game's rules and local laws to ensure security and fairness within the game's economy.

the COVID-19 pandemic in early 2020 and the crisis stemming from China's ban on Bitcoin mining in May 2021 contributed to an upsurge in the noise component. Remarkably, the tumultuous events of 2022, including the Russia-Ukraine conflict, the Luna cryptocurrency crash, and the FTX exchange collapse, also contributed to an elevation in the noise component.

We then investigate whether the participation of retail investors contributes to higher noise in the cryptocurrency market. We use the number of small wallets to measure retailer investor activity and find that increased retail investor participation significantly impacts noise in the cryptocurrency market. In contrast, the engagement of large and giant wallets elevates the private information share component. The result shows that the latter groups are more sophisticated than retail traders, characterized as noise traders in the market

We further examine how social media influences the components of return variance. Using the sentiment of positive and negative news on X (formerly Twitter), our findings reveal a marked asymmetry between the effects of good and bad news. Specifically, good news increases market noise and volatility, whereas bad news decreases it. These results are consistent with the "Fear Of Missing Out" (FOMO) and “Hold On for Dear Life” (HODL) phenomenon prevalent among uninformed retail investors, who are dominant in the cryptocurrency market.

Finally, we assess the impact of fundamental information on variance components. Our findings reveal that changes in crypto fundamentals do not improve market quality; instead, they increase noise and volatility and diminish the contribution of public information in explaining price volatility.

We are the first to separate the information components in cryptocurrency return variance and compare them with other markets to shed light on market volatility. We contribute mostly to the literature that explains why the cryptocurrency market is highly volatile. Recent theoretical research indicates that the price volatility of cryptocurrencies, including Bitcoin, stems from intrinsic and non- intrinsic factors. We demonstrate that the high volatility of the cryptocurrency market is primarily due to significant contributions from noise components that lack intrinsic value. Our evidence indicates that this high noise level mainly originates from retail investors, who are unsophisticated and driven by FOMO and HODL. However, we also show that the fundamental information about cryptocurrencies does not improve the market quality.

Many recent studies highlight the intrinsic value of cryptocurrencies, focusing on aspects such as security, transaction benefits and costs, utility, and cash flow. Pagnotta (2022) develops a model linking Bitcoin's security to its price volatility, identifying two primary mechanisms influencing price fluctuations. The first mechanism is fundamental, where shifts in bitcoin demand affect miners' incentives, subsequently impacting security; in this scenario, both price and security are endogenously linked. The second mechanism highlights that volatility stems from market sentiment, independent of fundamentals. Aoyagi and Adachi (2018) also propose a model suggesting that a cryptocurrency's fundamental value is determined by its blockchain platform's security, with its price also influenced by spread, adverse selection, and the cost of transitioning to traditional markets. Biais et al. (2023) find that Bitcoin's intrinsic value, primarily influenced by transaction costs and benefits, accounts for merely 5% of the volatility in Bitcoin returns, with the remaining fluctuations attributed to extrinsic volatility unrelated to fundamental factors. García-Monleón et al. (2021) explain that the intrinsic value of ICO projects lies in the future redeemable value of goods and services based on the held currencies; for single-layer blockchain cryptocurrencies, it is the value of the information transfer network on that layer; and for multi-layer cryptocurrencies, it includes the additional value created by the network for its nodes, alongside the inherent value of the original single layer. Fanti et al. (2021) introduce a Proof-of-Stake (PoS) pricing model and demonstrate that the value of a token is determined by the cash flow accruing to the staker, the monetary policy governing the PoS system, and other external system opportunity costs. Besides, Cong et al. (2021) find that user adoption, which demonstrates network effects, intensifies the influence of platform productivity on prices, leading to "excess volatility."

Empirical research also indicates that non-fundamental factors influence cryptocurrency volatility. For instance, Bhambhwani, Delikouras, and Korniotis (2019) demonstrate that momentum trading can cause Bitcoin returns to diverge from fundamental values. Liu and Tsyvinski (2020) identify that momentum and investor attention affect Bitcoin returns. Makarov and Schoar (2020) also find that capital controls, which limit the movement of arbitrage capital, can distort Bitcoin prices away from their fundamental values. Our research supports the above literature by showing that noise, generally unrelated to fundamental values, contributes 40% to price volatility. The remainder attributed to the volatility is the information about market-wide and specific cryptocurrencies, which are fundamentals in price.

We also contribute to understanding the impact of retail traders on market quality. Retail investors play a crucial role in providing liquidity and counteracting the effects of adverse selection by informed traders on market makers (e.g., Kyle, 1985; Glosten and Milgrom, 1985). However, momentum-chasing and unsophisticated retail traders raise market volatility and negatively affect liquidity, as shown in studies by Ho and Stoll (1981), Grossman and Miller (1988), and Eaton et al. (2022). In the cryptocurrency market, dominated by retail investors (e.g., Dyhrberg et al., 2018; Urquhart, 2018), these participants are prone to momentum trading and exhibit herd behavior (e.g., Ozdamar et al., 2022; Lucey et al., 2022; Almeida and Gonçalves, 2023; Cornelli, 2023). Our research indicates that retail traders contribute significantly to the increased noise share in the market, supporting the fact that cryptocurrency market activity by retail investors is primarily driven by noise trading rather than fundamentals.

Finally, our research is related to studies that decompose information in asset prices. Price returns can be decomposed into information about cash flow and discount rates (e.g., Chen and Zhao, 2009; Chen, Da, and Zhao, 2013; Campbell, 1991) or market-wide and firm-specific information (e.g., Roll, 1988; Morck, Yeung, and Yu, 2000). We employ the method of Brogaard et al. (2021) to decompose variance into four components: market-wide information, private information, public information, and noise. We validate this method by applying it to various markets, allowing us to compare the characteristics of each type. This decomposition provides insights into which types of information or noise primarily drive prices in different markets. In the cryptocurrency market, prices are predominantly driven by noise. Besides, our findings reveal that the noise share in nascent and less regulated markets, such as cryptocurrencies, is significantly higher than in traditional markets.

2. Data and methodology

We use cryptocurrency data from coingekco.com, which includes the 1,500 largest coins by market capitalization. Our dataset encompasses daily prices, trading volume, and market cap from 1 January 2015 to 30 May 2024, totaling 1,270,526 observations. We use the MVIS® CryptoCompare Digital Assets 100 Index (MVDA) from marketvector.com to track the overall market performance. The MVDA is a market cap-weighted index that monitors the performance of the 100 largest digital assets. Besides, onchain and other social network information related to cryptocurrency is extracted from the website intotheblock.com.

We apply the method of Brogaard et al. (2021) to decompose the price variance of each cryptocurrency into four components: market-wide information, private information, public information, and noise for each quarter. Specifically, for each cryptocurrency, we first run the VAR structural equation as outlined below, with approximately 90 observations per quarter, and repeat this process for subsequent quarters for each cryptocurrency.

$$
\begin{aligned}
Rm_t &= \sum_{l=1}^{5} a_{1,l} Rm_{t-l} + \sum_{l=1}^{5} a_{2,l} V_{t-l} + \sum_{l=1}^{5} a_{3,l} R_{t-l} + \varepsilon_{Rm,t} \\
V_t &= \sum_{l=0}^{5} b_{1,l} Rm_{t-l} + \sum_{l=1}^{5} b_{2,l} V_{t-l} + \sum_{l=1}^{5} b_{3,l} R_{t-l} + \varepsilon_{V,t} \\
R_t &= \sum_{l=0}^{5} c_{1,l} Rm_{t-l} + \sum_{l=0}^{5} c_{2,l} V_{t-l} + \sum_{l=1}^{5} c_{3,l} R_{t-l} + \varepsilon_{R,t}
\end{aligned}
\tag{1}
$$

where Rm_t is the daily return (%) of the entire cryptocurrency market, calculated by the logarithmic change of the market index MVDA. V_t is the signed trading volume expressed in dollars, positive if R_t is positive and negative if R_t is negative. R_t represents the daily return (%) of a cryptocurrency, calculated by the logarithmic change. $\varepsilon_{Rm,t}$, $\varepsilon_{V,t}$, and $\varepsilon_{R,t}$ are the innovations in the structural VAR (1).

The subsequent steps follow the methodology outlined in Brogaard et al. (2021). For the sake of brevity, we will only outline the basic steps here. Detailed explanations for each step can be found in Brogaard et al. (2021). We then can calculate the estimated values of the variance components as follows:

$$
\begin{aligned}
MktInfo &= \Theta_{Rm}^2 \, \sigma_{\varepsilon_{Rm}}^2 \\
PrivateInfo &= \Theta_V^2 \, \sigma_{\varepsilon_V}^2 \\
PublicInfo &= \Theta_R^2 \, \sigma_{\varepsilon_R}^2 \\
Noise &= \sigma_S^2
\end{aligned}
\tag{2}
$$

where Θ_{Rm}, Θ_V, and Θ_R represent the cumulative impulse response functions of returns to a unit shock of $\varepsilon_{Rm,t}$, $\varepsilon_{V,t}$, and $\varepsilon_{R,t}$ respectively. $\sigma_{\varepsilon_{Rm}}^2$, $\sigma_{\varepsilon_V}^2$, and $\sigma_{\varepsilon_R}^2$ are the variances of the structural

VAR innovations $\{\varepsilon_{Rm,t}, \varepsilon_{V,t}, \varepsilon_{R,t}\}$, which we can estimate from (1).[4] Besides, σ_S^2 is the variance of $(R_t - \Theta_{Rm}\varepsilon_{Rm,t} - \Theta_V\varepsilon_{V,t} - \Theta_R\varepsilon_{R,t})$. After determining the value of each variance component, we can calculate the relative share value as follows:

$$\begin{aligned}
&MktInfo\ Share = MktInfo/\,(MktInfo + PrivateInfo + PublicInfo + Noise)\\
&PrivateInfo\ Share = PrivateInfo/\,(MktInfo + PrivateInfo + PublicInfo + Noise)\\
&PublicInfo\ Share = PublicInfo/\,(MktInfo + PrivateInfo + PublicInfo + Noise) \quad (3)\\
&Noise\ Share = Noise/\,(MktInfo + PrivateInfo + PublicInfo + Noise)
\end{aligned}$$

We decompose the components for all 1,500 cryptocurrencies and calculate the average for each component to represent the entire cryptocurrency market for each quarter from January 2015 to June 2024. We apply the same steps to other asset markets over the same period to compare with the cryptocurrency market.

3. Empirical results

3.1. Variance components in cryptocurrency and other assets

Table 1 presents the variance share of cryptocurrencies from January 2015 to June 2024. Panel A shows the average of each component. The results indicate that noise constitutes the largest portion of cryptocurrency return variance, at approximately 40.17%. The market-wide information component is about 19.52%. The information component specific to individual cryptocurrencies accounts for around 40%, with private information at 19.45% and public information at 21.01%. This pattern demonstrates that the cryptocurrency market is primarily driven by noise rather than information. The primary reason for the high noise share is that the cryptocurrency market is predominantly influenced by the activities of retail investors (e.g., Baur and Dimpfl, 2018; Fink and Johann, 2014).

[TABLE 1]

[4] We estimate the innovations $\{\varepsilon_{Rm,t}, \varepsilon_{V,t}, \varepsilon_{R,t}\}$ of the structural VAR system of equations through the reduced form of the VAR system of equations. Please refer to the Appendix in Brogaard et al. (2021) for more information.

We next explore how the variance components of cryptocurrency have evolved over time. Figure 2 illustrates the four components from 2015 to 2024. Over this period, the shares of noise have been predominant (represented by the red line), while the contributions from market-wide, private and public information remain significantly lower. Notably, the share of noise surged dramatically in late 2017 and early 2018, increasing from about 30% to 43%. This surge coincided with Bitcoin reaching its first price peak of around $20,000, which drew significant attention from retail investors and the media. This pattern reflects a speculative bubble, where the price of an asset inflates rapidly beyond its intrinsic value, primarily driven by investor enthusiasm and market speculation rather than underlying economic fundamentals. The rapid increase was fueled by media hype, speculative trading, and FOMO among new investors drawn to potential quick profits. The subsequent crash illustrated the unsustainable nature of such price increases, as reality set in and many investors rushed to sell off their holdings, leading to a sharp decline in prices. This cycle is a hallmark of 'Irrational Exuberance' in asset markets that Shiller (2016) highlights the psychological and speculative dynamics that temporarily distort cryptocurrency values.

Since 2018, the noise share in the cryptocurrency market has remained elevated. This trend has persisted through various crises, including the COVID-19 pandemic, the China mining ban, the Russia-Ukraine conflict, the Terra Luna crash, and the FTX collapse. Panel B of Table 1 provides annual data for each component's share, while Panel C underscores that during these periods of crisis, the noise share has consistently surpassed the average. This pattern indicates a sustained high level of market speculation and uncertainty during crises.

Figure 2 also illustrates a significant surge in the market-wide component during 2018, coinciding with the "crypto winter" and various government bans on cryptocurrencies, collectively impacting the entire market. Another notable increase in this component occurred in 2022 amid multiple crises, including the Russia-Ukraine conflict, the Luna crash, and the FTX collapse. Generally, the market-wide component spikes during periods of market crises. Panel C of Table 1 further highlights that during quarters marked by crisis events affecting the whole market, the market-wide component significantly exceeds the average. During these turbulent times, the contribution of private and public information components tends to diminish while the noise and market-wide components markedly increase. Overall, the market-wide, private, and public information components each generally contribute around 20% over time, whereas the noise component consistently remains much higher, around 40%.

[FIGURE 2]

We next perform variance decomposition on other traditional markets, including stocks, commodities, and fiat currencies, over the same period from 2015 to 2024 to compare them with cryptocurrencies. The data for these markets are downloaded from Refinitiv. Figure 3 illustrates the variance of returns and the four components of variance, calculated using the values as described in (2), for markets including stocks, technology stocks, commodities, and fiat currencies. Panel A in Figure 3 reveals that the variance in cryptocurrency returns is significantly higher than that of traditional markets. Panel B further breaks down the variance components, showing that each component for cryptocurrencies is also markedly higher than those for other markets. However, comparing these variance components does not provide deep insights into the specific characteristics and how the components drive the variance in each market. To address this, Figure 4 presents the share of each variance component across different markets, with blue columns representing cryptocurrency markets and gray columns representing traditional markets.

Figure 4 indicates that the cryptocurrency market's volatility is predominantly influenced by noise, with a noise share of 40.17%. This figure starkly contrasts other markets: the stock market has a slightly over 20% noise share, commodities are at 14.93%, and fiat currencies are at 18.31%. These comparisons highlight that information components significantly impact volatility in traditional markets more than noise. Specifically, in the fiat currency market, volatility is primarily driven by market-wide components and public information, with market-wide information being the most dominant at 29.36%, closely followed by public information at 28.02%. This dominance is expected as fiat currencies are typically influenced by macroeconomic factors.

In riskier asset classes like stocks, volatility during our research period is primarily driven by private information, accounting for over 30%, and public information, contributing over 35%. Market-wide information has the most negligible impact on volatility in this market, at around 10%, with a noise share of about 23%. This finding contrasts with the results from Broggard et al. (2021) that indicate that the stock market was primarily driven by noise, at about 31%. The difference in findings is attributed to the different sample periods; our data spans from 2015 to the present, whereas Broggard et al. (2021) covers a period before 2015. Nonetheless, our results align with Broggard et al. (2021) in identifying a trend where noise share is decreasing while the share of asset-specific information is increasing.[5] Besides, the commodity market shares similarities with the stock market, with its volatility primarily driven by public information (42.24%) and private information (25.78%). Market-wide information in this market accounts for 17.05%, while noise represents approximately 14.93%.

The findings indicate that the cryptocurrency market is still immature, with return volatility primarily driven by noise. As regulations are continually enhanced and more widely adopted, we can expect a future reduction in this noise component. This evolution will likely align the cryptocurrency market more closely with the patterns in other traditional markets, such as stocks and commodities.[6]

[FIGURE 3]

3.2. Determinants of cryptocurrency variance components

We first examine how retail investors influence each component of variance, particularly noise. We measure retail investor participation using the ratio of small wallets and the change in the number of small wallets in the market. Table 2 shows the panel regression of the component shares with the percentage ratio of the small wallets (Panel A) and with the number of wallets in or out of the market (Panel B). The percentage ratio of the small wallets is the number of wallets holding less than 0.1% relative to the total coin supply. $\Delta\ Small\ wallet_{it}$, $\Delta\ Medium\ wallet_{it}$, $\Delta\ Large\ wallet_{it}$, and $\Delta\ Giant\ wallet_{it}$ are, respectively, the number of wallets in (out) of the small, medium, large, and giant wallets for each cryptocurrency. Our dependent variables include $MktInfo\ Share_{it}$, $PrivateInfo\ Share_{it}$, $PublicInfo\ Share_{it}$, and $Noise\ Share_{it}$, which are

[5] Broggard et al. (2021) find that noise accounts for 31% of the variance in stock returns, private information contributes 24%, public information 37%, and market-wide information 8%.
[6] We also apply the variance decomposition for new, non-traditional, and less regulated markets, such as Non-Fungible Tokens (NFTs) and game items. Our findings reveal that the noise share in these markets is higher than in cryptocurrency. Specifically, noise accounts for 47.23% of the total variance in the NFT market and approximately 61.29% in the game item market. Detailed results are available in the Appendix. These findings indicate that younger and less regulated markets are more strongly driven by noise than traditional asset classes.

respectively the shares of market-wide information, private cryptocurrency-specific information, public cryptocurrency-specific information, and noise.

The results in Panel A of Table 2 show that a 1% increase in the proportion of small wallets corresponds to a 6.64% increase in noise share. Panel B indicates that the addition of 1,000 small wallets results in a 0.0013% increase in noise share. These findings suggest that retail investors mainly drive the high noise share. Additionally, the public information component decreases with the increased participation of retail investors. This finding aligns with previous research (e.g., Fink and Johann, 2014; Oyedele, 2017; Baur & Dimpfl, 2018) indicating that these investors tend to be uninformed and unsophisticated, prone to momentum trading and herd behavior (e.g., Ozdamar et al., 2022; Lucey et al., 2022; Almeida and Gonçalves, 2023).

The results also indicate that an increase in the number of large wallets in the market enhances the contribution of the private information component and reduces market noise. According to previous literature, institutional investors improve market quality through their transactions (e.g., Sias and Starks, 1997; Boehmer and Kelley, 2009; Broggard et al., 2021). This result suggests that these large wallets likely belong to informed investors such as institutions, project developers, or cryptocurrency project insiders with privileged information that their trading influences prices. This trend highlights the dichotomy within the crypto market: on one side are highly informed, resource-rich institutional investors who enhance market quality, and on the other are retail investors with limited access to information and analytical capabilities, contributing to market noise. As the cryptocurrency market matures and institutional investor participation increases, we can expect a reduction in noise levels, thereby improving market quality.

[TABLE 2]

We continue to investigate how various factors affect variance components, expecting that the shares will vary with cryptocurrency characteristics. Table 3 presents the panel regression of the component shares, incorporating all variables in the model. Our dependent variables include $MktInfo\ Share_{it}$, $PrivateInfo\ Share_{it}$, $PublicInfo\ Share_{it}$, and $Noise\ Share_{it}$, representing the shares of market-wide information, private cryptocurrency-specific information, public cryptocurrency-specific information, and noise, respectively. $ln\,MC_{it}$ is the natural logarithm of the capitalization of coin i at time t, and $ln\,P_{it}$ is the natural logarithm of the price of coin i at time t. D_t^{2017} is the dummy variable set to one if the observation is after 2017 and zero otherwise.

$D_t^{Luna\ crash}$ is also the dummy variable set to one if the observation is after the Luna crash event in May 2022 and zero otherwise. $ILLIQ_{it}$ is the illiquidity measure proposed by Amihud (2002).

The findings indicate that cryptocurrencies possessing larger market capitalizations exhibit increased shares in the market-wide component. However, the contributions from both private and public components tend to decline notably. These outcomes align with the ongoing trend of incorporating digital assets, particularly Bitcoin, into portfolios that include various other asset classes. This integration enhances the interconnectedness among these asset classes, rendering the cryptocurrency market more reactive to macroeconomic news and global financial events (e.g., Corbet et al., 2020; Nguyen, 2022; Iyer and Popescu, 2023; Karau, 2023). Additionally, our analysis indicates that cryptocurrencies with lower liquidity have a reduced share of the private information component, which shows the discouragement of informed trading. We also confirm the significant trend in market noise: since 2017, the noise share has increased by approximately 17% over previous periods. Moreover, the noise share rose by an additional 2% following the Luna crash.

3.3. FOMO, HODL, and social media

We now explore social media's impact on cryptocurrency volatility and delve deeper into the psychological underpinnings of investor behavior, particularly in response to the dissemination of good and bad news. In Shiller's (2017) paper about narrative economics, he highlights how compelling stories on social media can drive market sentiment, prompting swift reactions from investors. When positive news circulates, such as technological advancements or regulatory approvals, it can generate a wave of optimism, leading to rapid price increases as investors rush to capitalize on potential gains. Conversely, negative news, such as security breaches or governmental crackdowns, can trigger fear and uncertainty, resulting in sudden sell-offs.

In the cryptocurrency market, the phenomena of FOMO (Fear of Missing Out) and HODL (Hold On for Dear Life) are critical in understanding market swings. FOMO can drive investors to make hasty purchases based on rising prices and positive sentiment, fearing they might miss out on potential profits. On the other hand, the HODL mentality, a long-term holding strategy regardless of volatility, reflects a steadfastness in the face of market dips, often influenced by a collective belief in the cryptocurrency's future value propagated through social media narratives. This complex interplay of psychological factors, reinforced by the echo chamber effect of social media, where similar opinions are amplified, leads to pronounced fluctuations in cryptocurrency prices, demonstrating the powerful influence of investor psychology and social narratives in financial markets.

To illustrate the impact of social media sentiment on market volatility, we use the number of positive and negative Twitter posts and investigate their effects on variance and variance components. Table 4 displays the results of a panel regression analyzing the level of variance components ($MktInfo_{it}$, $PrivateInfo_{it}$, $PublicInfo_{it}$, $Noise_{it}$), calculated as specified in (2), and the return variance ($Variance_{it}$) in logarithmic form. The key explanatory variables are the logarithmic counts of positive ($ln\ Positive\ news_{it}$) and negative ($ln\ Negative\ news_{it}$) news posts on Twitter. The findings in Panel A of Table 4 reveal an asymmetry in how positive and negative news affect market volatility. Specifically, positive news heightens market noise and return variance, illustrating how good news can trigger FOMO in investor psychology. This response increases trading activity and heightened price volatility as investors hurry to acquire assets. Conversely, negative news appears to reduce market volatility and noise, reflecting the HODL mentality, where investors are more likely to retain their holdings and wait out the storm, stabilizing price movements during adverse conditions. This dynamic highlights the significant influence of investor sentiment and behavior, shaped by news consumption, on the financial markets.

[TABLE 4]

In Panel B of Table 4, even after controlling historical prices and market capitalization, the impact of positive and negative news on volatility remains consistent. Positive news tends to increase variance and market noise, whereas negative news typically has the opposite effect. Notably, we also observe that higher cryptocurrency prices in dollar terms correlate with increased variance and noise. This finding underscores a distinct behavior in the cryptocurrency market, contrasting with the stock market, where higher-priced stocks usually exhibit lower volatility. This difference highlights a unique "leverage effect" in cryptocurrencies, unlike stocks, where the relationship between high prices and volatility is generally inverse (e.g., Bekaert and Wu, 2000; Shue and Townsend, 2021).

Cryptocurrencies lack conventional debt-equity structures, but the leverage mainly pertains to trading mechanisms like margin trading, futures, and options. As the price of a cryptocurrency rises, often fueled by speculative trading and burgeoning investor interest, more traders are triggered to enter leveraged positions, aiming to amplify their potential returns. This surge in leveraged trading enhances market liquidity and volatility.

Moreover, high prices in the cryptocurrency market tend to attract considerable media coverage, which often highlights record-breaking prices, such as Bitcoin reaching new highs. This media attention brings cryptocurrencies into the limelight and lures more investors and speculators, drawn by the allure of high returns and the fear of missing out on lucrative opportunities. Such coverage intensifies the public's interest and further escalates trading activities, increasing the market's volatility. Our results in Table 4 also indicate that more positive news or a higher dollar value of a cryptocurrency correlates with heightened market noise, suggesting that the activity is predominantly driven by retail and uninformed investors motivated by rising prices and FOMO by positive news in media.

3.4. The effect of fundamental information

In this section, we investigate the impact of fundamental cryptocurrency information on information components, noise, and variance. Given that this information is widely accessible through aggregator websites and blockchain data, we hypothesize whether such public information can help explain cryptocurrency volatility and how this public information contributes to cryptocurrency volatility.

First, we use the fundamental data to predict prices, including fees, supply-side fees, revenue, expenses, token incentives, earnings, circulating supply, number of active users, and core developers (Table 5).[7] This information reveals the cash flow of validators, the accrued value to cryptocurrency holders, network effects, tokenomics, and other key fundamental factors that can predict the price. We then use the absolute values of predicted price changes to measure the

[7] We obtain this data from the website tokenterminal.com. For detailed definitions of these indicators, please refer to the information provided on the website.

changes in fundamental information and investigate how changes in fundamental information affect public information, noise, and variance.

Table 6 presents the results of a panel regression analyzing the levels of public information, noise, and return variance ($PublicInfo_{it}$, $Noise_{it}$, $Variance_{it}$) in logarithmic form with the changes in fundamental information ($|\Delta\ Predicted\ value|_{it}$). We control for price and market capitalization ($ln\ P_{it}$, $ln\ MC_{it}$). Our findings indicate that changes in fundamental values increase market variance and noise; ironically, these changes also reduce public information's contribution to volatility. Although fundamental data effectively predict prices,[8] this available information does not contribute significantly to explaining cryptocurrency volatility but raises the noise level in the market. Besides, we use changes in earnings ($|\Delta\ Earning|_{it}$) as a measure of fundamental information. Our results indicate that changes in earnings also lead to increased noise levels and market variance in the cryptocurrency market.

[TABLE 5]

[TABLE 6]

Our results show that the complexity of fundamental information based on blockchain data in the cryptocurrency market makes it challenging for investors to interpret and react to data adequately. For investors in the cryptocurrency market, predominantly unsophisticated retail investors, interpreting fundamental information is particularly challenging. Instead, news and social media often influence them, leading to FOMO and momentum-driven trading phenomena. Social media hype causes impulsive buying and selling, driving prices based on sentiment rather than fundamental values. Consequently, despite the availability of extensive fundamental information, the market experiences high levels of noise and volatility.

[8] Our regression shows that fundamental factors explain more than 85% of the price change (see appendix for more details)

4. Conclusion

This study comprehensively analyzes what drives cryptocurrency price volatility, mainly focusing on the roles of different information types and noise. We find that noise accounts for a significant 40% of the price variance, markedly higher than in traditional assets like stocks (21%), fiat currencies (18%), and commodities (15%). However, cryptocurrency markets exhibit lower noise share compared to younger, less regulated markets like Non-Fungible Tokens (47%) and in-game items (63%). This comparison shows that noise share and volatility tend to be greater in markets either in the early stages of development or less regulated compared to traditional markets.

Our component analysis highlights critical trends, notably the significant increase in the noise component, which surged during Bitcoin's peak at approximately $20,000 in late 2017 and has remained elevated. This increase correlates with increased media attention, broader adoption, and the proliferation of new cryptocurrencies. Additionally, the noise component tends to spike during crises, as evidenced during the COVID-19 pandemic, China's ban on Bitcoin mining, and major disruptive events in 2022 such as the Russia-Ukraine conflict, the Luna crash, and the FTX collapse.

We then explore whether retail investor participation increases cryptocurrency market noise. By analyzing the activity of small wallets as a proxy for retail investor engagement, we discover that their increased participation correlates significantly with heightened market noise. Conversely, the involvement of large and giant wallets tends to enhance the private information share component, indicating that these groups are more sophisticated than retail traders, who are often characterized as noise traders.

Furthermore, we investigate the impact of social media on return variance components. Using sentiment analysis of positive and negative news on X (formerly Twitter), our results uncover a pronounced asymmetry in the effects of good versus bad news. Specifically, positive news amplifies market noise and volatility, while negative news reduces it. These findings align with the FOMO and HODL phenomena, which are prevalent among the uninformed retail investors who dominate the cryptocurrency market.

Finally, we assess the impact of fundamental information, such as earnings, token incentives, fees, and revenue, on variance components and variance. Our findings reveal that changes in crypto fundamentals do not improve market quality; instead, they increase noise and volatility and diminish the contribution of public information in explaining price volatility.

We demonstrate that the cryptocurrency market is primarily driven by noise resulting from non-fundamental factors, such as media coverage and the investment psychology of retail/noise investors, rather than the fundamental information. We anticipate that as the market matures—with improvements in regulatory frameworks, mass adoption, and increased participation from institutional investors—the volatility and noise components will gradually decrease, aligning more closely with traditional markets like stocks and commodities.

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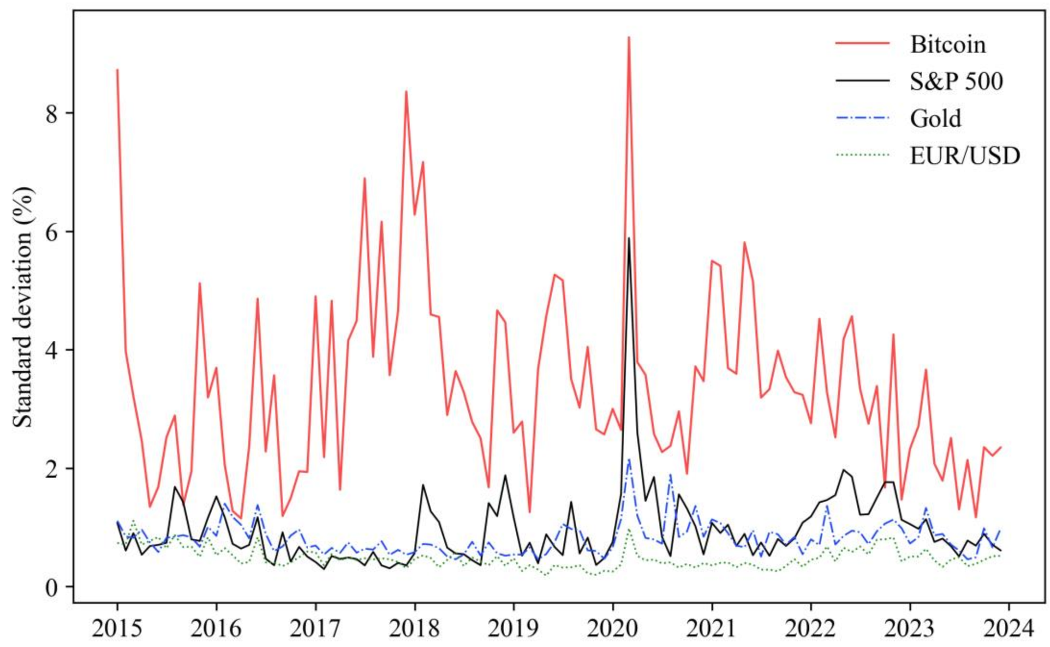

Figure 1. The volatility of assets through time

This figure depicts the volatility of various asset classes (Bitcoin, Gold, S&P 500, and EUR/USD) over time from 2015 to 2024, measured by the annual standard deviation of their daily returns.

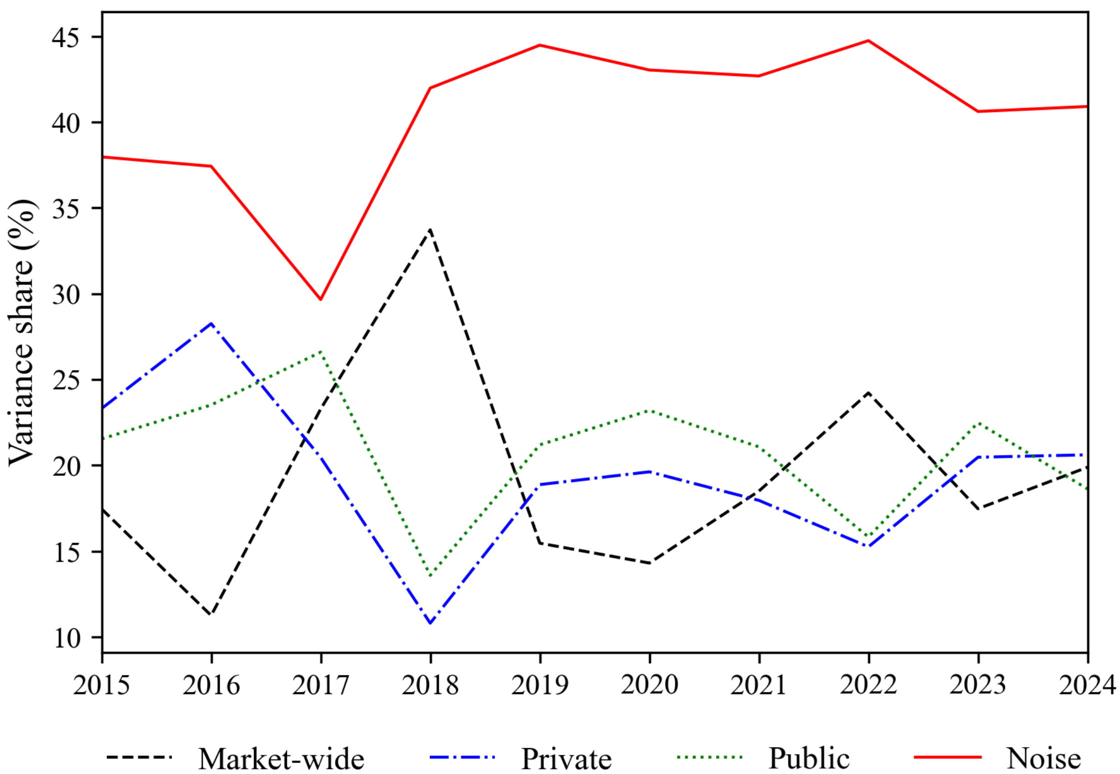

Figure 2. The variance component shares of cryptocurrency return through time.
This figure plots the average shares of four components, including market-wide information ($Market-wide$), private cryptocurrency-specific information ($Private$), public cryptocurrency-specific information ($Public$), and noise ($Noise$) over time from 1st January 2015, to 30th June 2024. We calculate the variance shares for each coin in each quarter using the VAR model for daily observations and take the average. Our sample includes the 1500 largest cryptocurrencies in market capitalization during the above period.

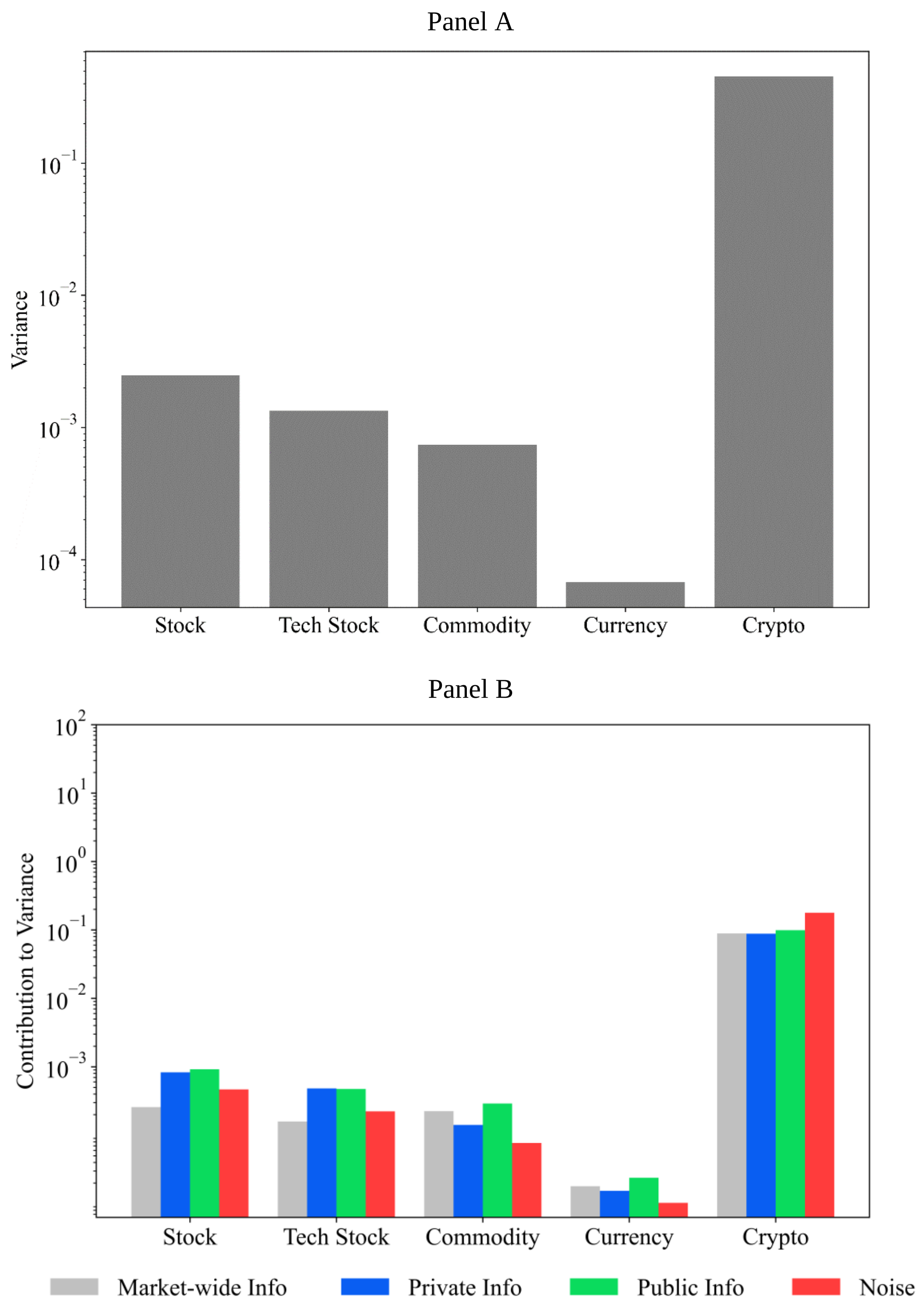

Figure 3. Total variance and variance components of different asset classes
This figure depicts the total variance and its decomposed components (market-wide information, private information, public information, and noise) for various asset classes, including stock, technology stock, commodity, fiat currency, and cryptocurrency. The variance values and their components are calculated using a weighted average for each market from 2015 to 2024. The chart is plotted on a logarithmic scale.

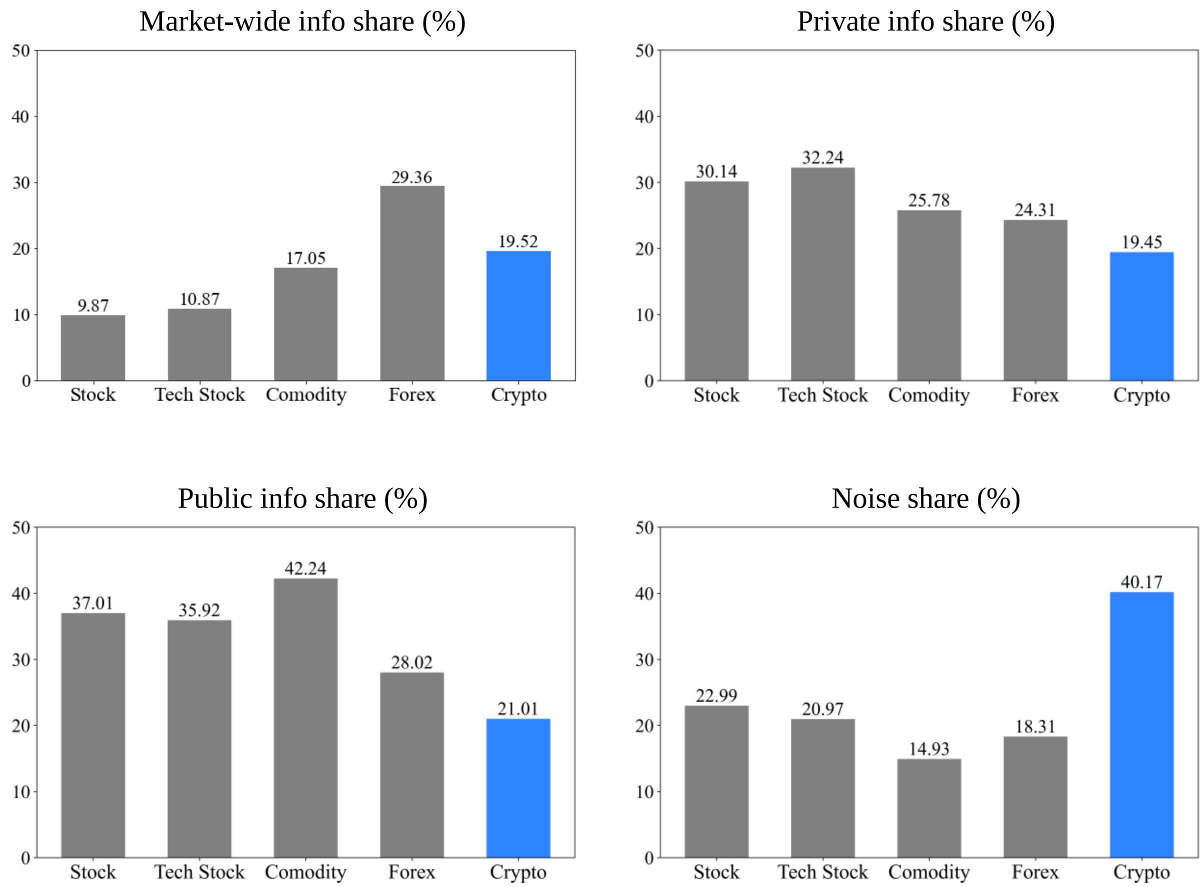

Figure 4. Variance components shares of cryptocurrency and traditional asset classes
This figure displays the attribution (%) of market-wide information, private information, public information, and noise to the return variance of each type of asset, including cryptocurrency, stock, technology stock, fiat- currency, and commodity, over time from January 2015 to June 2024. We also use the same method to decompose components for other asset classes for comparison. We use the VAR model with daily observations to compute the variance components for each type within every quarter, then take the average.

Table 1. Cryptocurrency return variance components.

This table shows the average variance shares (%) of four components, including market-wide information ($Market - wide$), private cryptocurrency-specific information ($Private$), public cryptocurrency-specific information ($Public$), and noise ($Noise$) over time from January 2015, to June 2024. We calculate the variance component shares separately for each cryptocurrency in each quarter based on VAR model and take the mean across coins within a group. Panel A represents the average for our total sample. Panel B shows the components for each year. Panel C presents the four components shares in historical crises that have substantially impacted the cryptocurrency market. Panel D presents these components by quartile of market capitalization. Panel E gives details based on categories, including Infrastructure, Currency, DeFi, NFT& Gaming, and Others.

	MktInfo Share	PrivateInfo Share	PublicInfo Share	Noise Share
Panel A: Total	19.52	19.45	21.01	40.17
Panel B: Year				
2015	17.47	23.31	21.54	37.97
2016	11.26	28.25	23.52	37.42
2017	23.29	20.46	26.60	29.66
2018	33.72	10.81	13.60	41.98
2019	15.47	18.88	21.20	44.48
2020	14.31	19.63	23.20	43.03
2021	18.50	17.96	21.08	42.68
2022	24.22	15.26	15.83	44.74
2023	17.48	20.48	22.49	40.61
2024	19.89	20.62	18.63	40.90
Panel C: Crisis				
Covid-19 pandemic	31.59	6.95	8.29	53.17
China crypto mining ban	23.49	10.65	16.95	49.07
Russia- Ukraine war	27.73	16.32	14.64	41.39
Luna crash	33.14	11.99	10.07	44.87
FTX collapse	20.54	12.19	16.88	50.42
Panel D: Quartiles by market cap				
Q1 = low	18.15	16.36	20.48	44.98
Q2	20.95	17.21	18.32	43.50
Q3	22.91	16.58	17.88	42.60
Q4 = high	26.59	14.21	14.84	44.34
Panel E: Categories				
Infrastructure	24.34	16.57	17.14	41.96
Currency	27.51	11.81	15.02	45.67
DeFi	23.25	16.42	18.26	42.08
Blockchain service	22.76	15.87	18.13	43.24
NFT& Gaming	23.30	17.76	18.24	40.70

Table 2. Component shares and the retail traders

This table shows the panel regression of the component shares with the percentage ratio of the small wallets (Panel A) and with the number of wallets in or out of the market (Panel B). The percentage ratio of the small wallets is the number of wallets holding less than 0.1% relative to the total coin supply. $\Delta\ Small\ wallet_{it}$, $\Delta\ Medium\ wallet_{it}$, $\Delta\ Large\ wallet_{it}$, and $\Delta\ Giant\ wallet_{it}$ are, respectively, the number of wallets in (out) of the small, medium, large, and giant wallets for each cryptocurrency. Our dependent variable $Share_{it}$ includes market-wide information ($MktInfo\ Share_{it}$), private cryptocurrency-specific information ($PrivateInfo\ Share_{it}$), public cryptocurrency-specific information ($PublicInfo\ Share_{it}$), and noise ($Noise\ Share_{it}$), respectively. Our regression includes fixed effects for categories and control variables. Our observations are from January 2015 to June 2024. The t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

Variable	$MktInfo\ Share_{it}$	$PrivateInfo\ Share_{it}$	$PublicInfo\ Share_{it}$	$Noise\ Share_{it}$
$\%\ of\ small\ wallets_{it}$	7.0083**	-5.4978*	-9.0587***	6.6420***
	(2.35)	(-1.87)	(-2.64)	(2.60)
Control variables	Yes	Yes	Yes	Yes
Categories FE	Yes	Yes	Yes	Yes
R^2 (%)	14.54	5.76	10.94	9.76
Observations	1038	1038	1038	1038

Panel B

Variable	$MktInfo\ Share_{it}$	$PrivateInfo\ Share_{it}$	$PublicInfo\ Share_{it}$	$Noise\ Share_{it}$
$\Delta\ Small\ wallet_{it}$	0.0012***	-0.0004	-0.0015***	0.0013***
	(3.04)	(-1.21)	(-4.83)	(2.94)
$\Delta\ Medium\ wallet_{it}$	0.3989***	-0.1594**	0.0013	-0.3023
	(4.92)	(-2.00)	(0.01)	(-1.37)
$\Delta\ Large\ wallet_{it}$	-1.6358***	1.2974***	-0.2055	0.4891
	(-12.36)	(14.97)	(-1.05)	(1.32)
$\Delta\ Giant\ wallet_{it}$	0.4685*	1.3979***	0.1151	-1.4602***
	(1.72)	(2.63)	(0.30)	(-6.69)
Control variables	Yes	Yes	Yes	Yes
Categories FE	Yes	Yes	Yes	Yes
R^2 (%)	18.89	8.04	11.59	10.17
Observations	1003	1003	1003	1003

Table 3. Determinants of component shares

This table shows the panel regression of the component shares with the characterisitc of cryptocurrency. Our dependent variables include market-wide information ($MktInfo\,Share_{it}$), private cryptocurrency-specific information ($PrivateInfo\,Share_{it}$), public cryptocurrency-specific information ($PublicInfo\,Share_{it}$), and noise ($Noise\,Share_{it}$), respectively. $ln\,MC_{it}$ is the natural logarithm of the capitalization of coin i at time t. $ln\,P_{it}$ is the natural logarithm of the price of coin i at time t. $ILLIQ_{it}$ is the illiquidity measure of Amihud (2002). D_t^{2017} is the dummy variable set to one if the observation is after 2017 and zero otherwise. $D_t^{Luna\ crash}$ is also the dummy variable set to one if the observation is after the Luna crash event in May 2022 and zero otherwise. Our observations are from January 2015 to June 2024. The t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Variable	$MktInfo\ Share\ _{it}$	$PrivateInfo\ Share_{it}$	$PublicInfo\ Share_{it}$	$Noise\ Share_{it}$
$\Delta\ Small\ wallet_{it}$	0.0012***	-0.0004	-0.0015***	0.0013***
	(3.04)	(-1.21)	(-4.83)	(2.94)
$\Delta\ Medium\ wallet_{it}$	0.3989***	-0.1594**	0.0013	-0.3023
	(4.92)	(-2.00)	(0.01)	(-1.37)
$\Delta\ Large\ wallet_{it}$	-1.6358***	1.2974***	-0.2055	0.4891
	(-12.36)	(14.97)	(-1.05)	(1.32)
$\Delta\ Giant\ wallet_{it}$	0.4685*	1.3979***	0.1151	-1.4602***
	(1.72)	(2.63)	(0.30)	(-6.69)
$ln\ MC_{it}$	1.174***	-0.754***	-0.766**	0.356
	(3.649)	(-2.754)	(-2.199)	(1.525)
$ln\ P_{it}$	0.149	0.066	-0.033	-0.174
	(0.890)	(0.436)	(-0.232)	(-1.495)
$ILLIQ_{it}$	0.003	-0.144**	-0.103	0.262
	(0.103)	(-2.086)	(-0.687)	(1.190)
$D_t^{Luna\ crash}$	9.793***	-6.378***	-6.144***	2.570***
	(10.296)	(-7.175)	(-5.269)	(2.725)
D_t^{2017}	5.126*	-7.917***	-4.430	17.089***
	(1.893)	(-3.216)	(-1.451)	(4.148)
Categories FE	Yes	Yes	Yes	Yes
R^2 (%)	10.55	3.10	5.03	6.23
Observations	2682	2682	2682	2682

Table 4. The effect of media

This table displays the results of a panel regression analyzing the level of variance components ($MktInfo_{it}$, $PrivateInfo_{it}$, $PublicInfo_{it}$, $Noise_{it}$), and the return variance ($Variance_{it}$) in logarithmic form. The key explanatory variables are the logarithmic counts of positive ($ln\ Positive\ news_{it}$) and negative ($ln\ Negative\ news_{it}$) news posts on Twitter, presented in Panel A. Panel B displays the above results with the control variables, including price ($ln\ P_{it-1}$) and market capitalization ($ln\ MC_{it-1}$), expressed in logarithmic form. Our observations are from January 2015 to June 2024. The t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

Variable	$MktInfo_{it}$	$PrivateInfo_{it}$	$PublicInfo_{it}$	$Noise_{it}$	$Variance_{it}$
$ln\ Positive\ news_{it}$	0.231***	0.181**	0.243***	0.146***	0.120***
	(3.401)	(2.560)	(3.522)	(4.051)	(3.962)
$ln\ Negative\ news_{it}$	-0.125*	-0.304***	-0.433***	-0.159***	-0.154***
	(-1.740)	(-3.993)	(-5.843)	(-3.916)	(-4.743)
$Constant$	2.053***	1.172***	1.297***	3.233***	3.472***
	(14.199)	(7.640)	(8.988)	(44.548)	(53.946)
Categories FE	Yes	Yes	Yes	Yes	Yes
Observation	1129	1129	1129	1129	1129
R^2 (%)	1.38	1.37	3.58	1.69	2.85

Panel B

Variable	$MktInfo_{it}$	$PrivateInfo_{it}$	$PublicInfo_{it}$	$Noise_{it}$	$Variance_{it}$
$ln\ Positive\ news_{it-1}$	0.042	0.310***	0.351***	0.078**	0.101***
	(0.615)	(3.848)	(4.909)	(1.967)	(2.699)
$ln\ Negative\ news_{it-1}$	-0.179**	-0.267***	-0.392***	-0.176***	-0.153***
	(-2.538)	(-3.494)	(-5.230)	(-4.364)	(-5.097)
$ln\ P_{it-1}$	0.506***	0.244	0.454***	0.394***	0.359***
	(2.809)	(1.261)	(3.139)	(4.259)	(3.946)
$ln\ MC_{it-1}$	-0.001	-0.482**	-0.661***	-0.191**	-0.277**
	(-0.009)	(-2.535)	(-4.227)	(-2.150)	(-3.182)
$Constant$	2.718***	0.125	0.085	3.235***	3.191***
	(10.054)	(0.367)	(0.285)	(20.274)	(20.989)
Categories FE	Yes	Yes	Yes	Yes	Yes
Observation	1109	1109	1109	1109	1109
R^2 (%)	8.73	2.41	5.24	6.76	7.24

Table 5. Definition of fundamental metrics

Metric	Definition
Fees	The total transaction fees paid by users.
Supply-side fees	The portion of transaction fees that go to validators.
Revenue	The share of transaction fees that are burned, which accrue to cryptocurrency holders.
Expenses	The total on-chain expenses for the protocol, currently only including token incentives.
Token incentives	The total block rewards, uncle rewards, and uncle inclusion rewards distributed to miners, plus the staking rewards given to validators.
Earnings	Revenue minus token incentives.
Circulating supply	The number of tokens that are available in the market and freely tradable.
Active users	The number of unique sender addresses active on a monthly basis, based on a 30-day rolling window.
Core developers	The number of distinct GitHub users who made at least one commit to the project's public GitHub repositories in the past 30 days.

Table 6. The effect of fundamental information

This table displays the results of a panel regression analyzing the level of public information, noise, and the return variance ($PublicInfo_{it}$, $Noise_{it}$,$Variance_{it}$) in logarithmic form with the fundamental information. The key explanatory variable is $|\Delta\ Predicted\ value|_{it}$, which is the change in the absolute value of the predicted price estimated from fundamental information, including fees, supply-side fees, revenue, expenses, token incentives, earnings, circulating supply, number of active users, and core developers. We also use the variable $|\Delta\ Earning|_{it}$, which is the absolute value of the change in earnings, as a proxy for fundamental information. Earning measures the total economic value that token holders receive from token burn and token incentives. The control variables include price ($ln\ P_{it}$), and market capitalization ($ln\ MC_{it}$), expressed in logarithmic form. Our observations are from January 2015 to June 2024. The t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively

Variable	$PublicInfo_{it}$	$Noise_{it}$	$Variance_{it}$	$PublicInfo_{it}$	$Noise_{it}$	$Variance_{it}$
$\|\Delta\ Predicted\ value\|_{it}$	-0.007**	0.002**	0.002**			
	(-2.348)	(2.288)	(2.474)			
$\|\Delta\ Earning\|_{it}$				-0.022	0.566***	0.486***
				(-0.036)	(3.672)	(3.559)
$ln\ P_{it}$	0.018	0.121***	0.144***	0.014	0.116**	0.138***
	(0.543)	(2.642)	(2.861)	(0.417)	(2.529)	(2.765)
$ln\ MC_{it}$	-0.125***	-0.045	-0.081*	-0.135***	-0.049	-0.083*
	(-2.737)	(-1.080)	(-1.833)	(-2.969)	(-1.171)	(-1.893)
$Constant$	-4.793***	-5.123***	-3.999***	-4.623***	-5.064***	-3.964***
	(-5.639)	(-6.535)	(-4.913)	(-5.468)	(-6.527)	(-4.911)
Categories FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1336	1336	1336	1336	1336	1336
R^2 (%)	10.71	0.26	2.19	7.64	0.10	0.30