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Information Stress and Trading-Friction Resilience: Evidence from Public Sentiment and News Context in Cryptocurrency Markets

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A B S T R A C T

This paper examines whether information stress affects trading frictions and liquidity resilience in cryptocurrency markets. Using public information proxies and OHLCV-based friction indicators, the analysis applies local projections to trace the response of trading conditions. The results show that information stress mainly affects trading frictions in the short run. Spread-based friction reacts immediately and recovers quickly, while the Amihud-based proxy adjusts more gradually. The cumulative effect is strongest in the early horizons and weaker over longer horizons. Overall, information stress creates temporary trading pressure rather than persistent deterioration in market resilience.

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INTRODUCTION

Cryptocurrency markets respond rapidly to public information. News, online discussion, and investor mood can affect market conditions within a short period. Unlike many traditional asset markets, cryptocurrency markets are often influenced more strongly by investor attention and sentiment. Prior studies show that investor attention is an important driver of cryptocurrency returns, while information releases and word content affect market reactions (Liu & Tsyvinski, 2021; Aysan et al., 2024). This suggests that public information pressure can influence cryptocurrency markets directly and immediately.

Most existing studies focus on return predictability, volatility, jumps, or price efficiency in cryptocurrency markets (Liu & Tsyvinski, 2021; Aysan et al., 2024; Anas et al., 2024). A related question remains underexplored: whether information stress changes trading conditions themselves. When fear rises, attention becomes extreme, or news tone turns negative, the market may become harder and more costly to trade. Therefore, the issue concerns not only price reactions but also the speed at which liquidity returns to normal.

This study focuses on trading frictions and liquidity resilience rather than on price changes alone. Market microstructure theory suggests that transaction costs and price deviations may arise from order-handling costs, inventory risk, asymmetric information, and strategic behavior, while higher uncertainty may reduce trading willingness and weaken market liquidity (Biais et al., 2005; Muranaga & Shimizu, 1999). To capture these effects, several liquidity proxies are employed, including the Amihud illiquidity ratio, the Roll spread proxy, and the high-low spread proxy (Amihud, 2002; Roll, 1984; Corwin & Schultz, 2012). Because liquidity is multidimensional, using multiple indicators is crucial, especially in cryptocurrency markets where low-frequency liquidity measures may behave differently across settings (Gabrielsen et al., 2011; Brauneis et al., 2021; Zhang et al., 2024).

To trace the dynamic response of market frictions to information stress, the empirical analysis applies local projections (Jordà, 2005; Jordà & Taylor, 2024). This approach captures both immediate shock effects and the speed of recovery, consistent with recent cryptocurrency applications (Diop & Chevallier, 2026). The study combines public information measures with market-based friction indicators. Information stress is proxied by attention, sentiment, and news-context variables, while trading-friction measures are constructed from OHLCV data. Multi-source and high-frequency public data can improve the analysis of cryptocurrency market behavior (Anas et al., 2024; Han et al., 2025; Lundin & Seo, 2023; Yang & Malik, 2024).

The main research question is whether information stress raises trading frictions and slows liquidity recovery in cryptocurrency markets. This study contributes by shifting attention from return prediction to trading conditions, linking public information stress with market microstructure and liquidity resilience, and comparing multiple friction proxies within a dynamic empirical framework. The central expectation is that information stress affects trading frictions in the short run, with stronger effects under adverse information conditions.

LITERATURE REVIEW

Prior studies show that public information, investor attention, and sentiment play an important role in cryptocurrency markets. Investor attention helps explain cryptocurrency returns, while information releases, news tone, and high-frequency public data affect jumps, volatility, and short-run market reactions (Liu & Tsyvinski, 2021; Aysan et al., 2024; Anas et al., 2024). This suggests that information stress in cryptocurrency markets should be understood not only in terms of information quantity but also in terms of sentiment, tone, and attention.

A second strand of literature comes from market microstructure and liquidity theory. Trading frictions may arise from order-handling costs, inventory risk, asymmetric information, and strategic behavior, while higher uncertainty may reduce trading willingness and weaken market liquidity (Biais et al., 2005; Muranaga & Shimizu, 1999). The literature also shows that liquidity is multidimensional. Amihud, Roll, and Corwin-Schultz capture different aspects of market friction, and broader surveys as well as cryptocurrency studies confirm that no single proxy is sufficient in all settings (Amihud, 2002; Roll, 1984; Corwin & Schultz, 2012; Gabrielsen et al., 2011; Brauneis et al., 2021; Zhang et al., 2024).

A final strand concerns dynamic response analysis. Local projections provide a flexible framework for tracing the effects of shocks over multiple horizons and across market states (Jordà, 2005; Jordà & Taylor, 2024). Recent cryptocurrency evidence shows that this method can also capture short-run liquidity disruption and recovery (Diop & Chevallier, 2026). Related work further suggests that multi-source public data can improve the analysis of cryptocurrency market behavior and trading opportunities (Anas et al., 2024; Han et al., 2025; Lundin & Seo, 2023; Yang & Malik, 2024). However, fewer studies examine whether information stress directly affects trading frictions and liquidity resilience rather than returns, jumps, or volatility. This study addresses that gap by linking public information stress to multiple friction proxies in a dynamic setting.

METHODOLOGY

Data

This study uses daily data for major cryptocurrency markets, with a focus on Bitcoin and Ethereum. These assets are selected because they are the largest and most actively traded cryptocurrencies, receive substantial public attention, and generally provide more reliable market data than smaller coins. The use of major assets also improves comparability across trading-friction measures and information-based indicators.

The empirical design combines two groups of variables: information-stress variables and trading-friction variables. The information-stress variables are drawn from public sources. Market mood is proxied by the Fear and Greed Index. News-based information stress is captured using GDELT variables, especially news volume and news tone. Public attention is measured by Wikipedia pageviews. This choice is consistent with earlier research showing that investor attention, sentiment, and multi-source public data are useful for understanding cryptocurrency market behavior (Liu & Tsyvinski, 2021; Aysan et al., 2024; Anas et al., 2024; Han et al., 2025; Lundin & Seo, 2023; Yang & Malik, 2024).

The trading-friction variables are constructed from OHLCV market data, namely open, high, low, close, and volume. OHLCV-based measures are used because they are public, widely available, and frequently employed in empirical liquidity research. They also make the analysis easier to replicate across assets and sample periods.

All variables are aligned by date and merged into a daily panel dataset. Missing observations are removed or adjusted before estimation. To improve comparability across specifications, the main information-stress variables are standardized before they enter the empirical models.

Variables

The study uses three main dependent variables to capture trading frictions. The first is the Amihud illiquidity ratio, which measures the size of price movement relative to trading volume. A higher value indicates lower liquidity because a given amount of volume is associated with a larger price response (Amihud, 2002):

$$ILLIQ_t = \frac{|R_t|}{VOL_t} \quad (1)$$

where R_t is the daily return and VOL_t is daily trading volume.

The second dependent variable is the Roll spread proxy, an implicit measure of the effective bid-ask spread based on the serial covariance of price changes (Roll, 1984):

$$ROLL_t = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} \quad (2)$$

where ΔP_t is the daily change in price.

The third dependent variable is a high-low spread proxy based on daily price ranges (Corwin & Schultz, 2012):

$$HL_t = f(HIGH_t, LOW_t) \quad (3)$$

where $f(\cdot)$ denotes the range-based spread estimator constructed from daily high and low prices.

The main explanatory variables are the information-stress measures: the Fear and Greed Index, GDELT tone, GDELT volume, and Wikipedia pageviews. These variables capture different dimensions of information pressure. Fear and Greed reflects broad market mood, GDELT tone captures whether the information environment is more negative or positive, GDELT volume measures information intensity, and Wikipedia pageviews proxy public attention.

To make these variables comparable, the study converts them into standardized scores:

$$Shock_t = \frac{X_t - \bar{X}}{\sigma_X} \quad (4)$$

where X_t is the original information variable, $\bar{X}$ is its sample mean, and σ_X is its standard deviation.

The empirical analysis also uses market-state indicators to distinguish between normal and stress periods. Stress states are defined by extreme fear, strongly negative tone, or other extreme information conditions.

Empirical Model

The main empirical method is local projections. This approach is suitable because the objective is to estimate the dynamic effect of information stress on trading frictions over several future horizons rather than at only one point in time (Jordà, 2005; Jordà & Taylor, 2024). It is also consistent with recent cryptocurrency applications of local projections (Diop & Chevallier, 2026).

The baseline specification is:

$$Friction_{t+h} = \alpha_h + \beta_h Shock_t + \gamma_h Controls_t + \varepsilon_{t+h} \quad (5)$$

where $Friction_{t+h}$ is the trading-friction measure at horizon $t+h$, $Shock_t$ is the information-stress variable at time t, and $Controls_t$ is a vector of control variables. The coefficient β_h captures the effect of the information shock at each horizon.

To examine whether market responses differ across states, the analysis also estimates a state-dependent specification:

$$Friction_{t+h} = \alpha_h + \beta_h^N Shock_t \times Normal_t + \beta_h^S Shock_t \times Stress_t + \gamma_h Controls_t + \varepsilon_{t+h} \quad (6)$$

where Normal_t and Stress_t are state indicators. This model allows the effect of information stress to vary depending on whether the market is in a normal or already fragile condition. State-dependent specifications were also estimated as an extended analysis, but the discussion below focuses on the baseline and cumulative results because they provide the most stable evidence.

Resilience Measures

Beyond the immediate friction response, the study evaluates liquidity resilience by examining three response features. The first is the peak effect, defined as the largest increase in the friction measure after the shock. The second is the half-life, or the number of days required for the response to fall to half of its peak value. The third is time-to-baseline, defined as the number of days required for the response to return close to zero. Longer half-life and time-to-baseline values indicate weaker liquidity resilience.

Together, these measures make it possible to evaluate not only whether information stress worsens trading conditions, but also how quickly the market absorbs and recovers from that shock.

RESEARCH RESULT

Baseline Effects

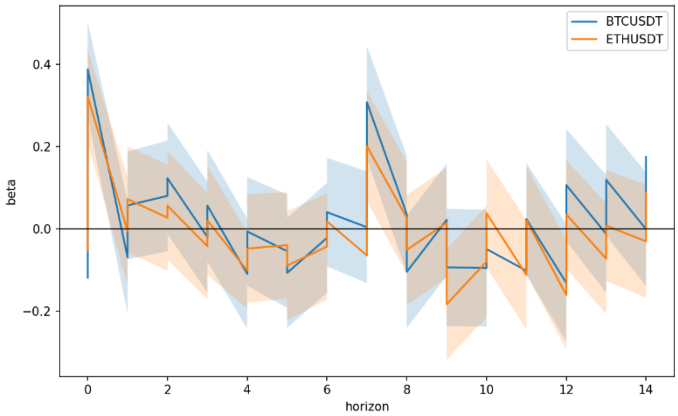
The first step is to examine whether information stress is associated with an average change in trading friction. Table 1 reports the baseline estimates for the Amihud proxy. The pooled estimate is statistically significant at the 5% level, while the BTC estimate is only marginally significant and the ETH estimate is not significant. This suggests that information stress affects trading friction on average, although the response is not uniform across assets. A Roll-based proxy was also computed as a supplementary friction indicator, but the discussion emphasizes the Amihud and high-low spread proxies because they yield the clearest dynamic patterns.

Table 1. Baseline effect of information stress on the Amihud friction proxy

Asset	Beta	Std. Error	t-statistic	p-value	95% CI	N
BTCUSDT	-0.1178	0.0668	-1.7620	0.0781	[-0.2488, 0.0132]	342
ETHUSDT	-0.0686	0.0652	-1.0520	0.2928	[-0.1964, 0.0592]	342
Pooled	-0.0970	0.0470	-2.0643	0.0390	[-0.1890, -0.0049]	684

The baseline evidence therefore supports a cautious version of the main hypothesis. Information stress appears to matter for market quality on average, but the response is not equally strong across individual cryptocurrencies. This is consistent with the broader view that public information can affect crypto markets quickly, while asset-level sensitivity remains heterogeneous.

Figure 1: Baseline impulse responses for BTCUSDT and ETHUSDT



Dynamic Response Across Friction Proxies

The next step is to compare the dynamic response of different friction proxies. This is important because trading friction is multidimensional, and different indicators may capture different parts of market quality.

Table 2 summarizes the peak effect, peak horizon, half-life, and time-to-baseline for the two main friction proxies retained in the final narrative: the Amihud proxy and the high-low spread proxy.

Table 2. Dynamic response metrics across friction proxies

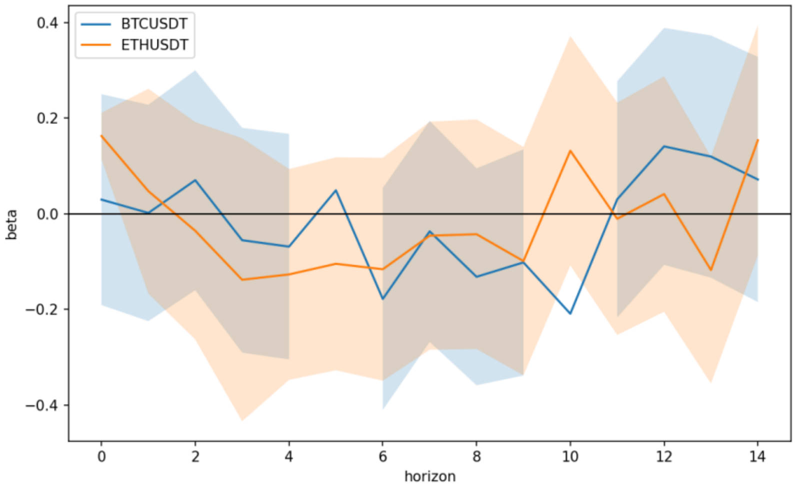
Asset	Friction proxy	Peak effect	Peak horizon	Half-life	Time-to-baseline
BTCUSDT	Amihud (fr_amihud_z)	0.1196	13	14	14
ETHUSDT	Amihud (fr_amihud_z)	0.0383	10	13	11
BTCUSDT	High-low spread (hl_spread_z)	0.3882	0	1	1
ETHUSDT	High-low spread (hl_spread_z)	0.3224	0	1	1

Two patterns stand out. First, the high-low spread proxy reacts immediately. For both BTC and ETH, the peak effect occurs on impact, and both the half-life and the time-to-baseline are only one day. This indicates a short-lived deterioration in spread-based trading conditions followed by rapid recovery.

Second, the Amihud proxy adjusts much more slowly. The peak response appears later in the horizon, and both half-life and time-to-baseline are substantially longer. For BTC, the peak occurs at horizon 13, with a half-life and time-to-baseline of 14 days. For ETH, the peak occurs at horizon 10, with a half-life of 13 days and a time-to-baseline of 11 days. This suggests that the price-impact dimension of illiquidity adjusts more gradually than the spread-based dimension.

These results show that information stress does not affect all dimensions of trading friction in the same way. Spread-type frictions react immediately and normalize quickly, whereas Amihud-type illiquidity adjusts more slowly.

Figure 2: Impulse responses of the main friction proxies



Cumulative Effects

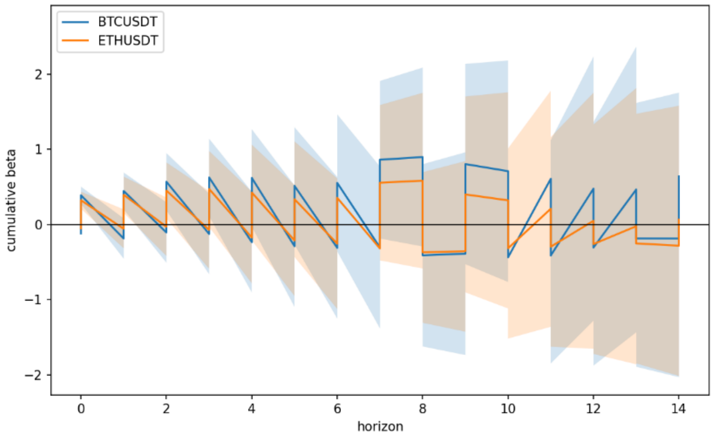
The cumulative response analysis is used to evaluate whether short-run disruption develops into a more persistent deterioration in trading conditions. Table 3 reports the horizons at which cumulative responses remain statistically distinguishable from zero.

Table 3. Summary of cumulative-response significance

Friction proxy	Asset	Significant single-horizon effects	Significant cumulative horizons
Amihud (fr_amihud_z)	BTCUSDT	none	none
Amihud (fr_amihud_z)	ETHUSDT	h = 4	none
High-low spread (hl_spread_z)	BTCUSDT	h = 0, 7, 14	h = 0, 1, 2, 3
High-low spread (hl_spread_z)	ETHUSDT	h = 0, 7, 9, 12	h = 0, 1, 2

The cumulative results show that statistically meaningful effects are concentrated in the earliest horizons. For the Amihud proxy, cumulative effects are generally not significant. For the high-low spread proxy, cumulative significance appears only in the early horizons and disappears as confidence intervals widen over time. Overall, the cumulative evidence supports short-run trading pressure, but not a stable long-run deterioration in market friction.

Figure 3: Cumulative impulse responses



The chart shows that cumulative responses deviate from zero mainly in the early horizons, while uncertainty increases substantially at longer horizons. This visual pattern is fully consistent with the statistical summary in Table 3.

DISCUSSION

Information stress mainly affects trading frictions in the short run. Spread-based friction reacts immediately and recovers quickly, while Amihud-based illiquidity adjusts more gradually. Cumulative effects are strongest early and weaken over time, indicating temporary disruption rather than persistent deterioration in market resilience.

CONCLUSIONS AND RECOMMENDATIONS

Public information pressure creates short-term trading friction without causing lasting market deterioration. Traders should anticipate temporarily higher execution risk during intense information pressure. Exchanges and market makers may monitor sentiment and attention indicators to detect short-term liquidity stress.

ADVANCED RESEARCH

This study uses daily data for Bitcoin and Ethereum and OHLCV-based friction measures. Future research could use intraday data, more cryptocurrencies, and direct order-book liquidity metrics to capture faster and broader market dynamics.

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