論文 / 著書情報
Article / Book Information

Title	Price Transmission from Bitcoin to Altcoins: High-Frequency Evidence and Implications for Trading Strategy
Authors	Tomoki Kurihara, Takuji Matsumoto
Citation	Asia-Pacific Financial Markets
Pub. date	2026, 3
Creative Commons	Information is in the article.

Asia-Pacific Financial Markets
https://doi.org/10.1007/s10690-026-09589-z

ORIGINAL RESEARCH

Price Transmission from Bitcoin to Altcoins: High-Frequency Evidence and Implications for Trading Strategy

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Received: 12 August 2025 / Accepted: 31 December 2025

Abstract

This study investigates the lagged price transmission from Bitcoin (BTC) to altcoins (ALTs) using high-frequency data and empirically validates trading strategies that leverage these market inefficiencies. Our comprehensive analysis across multiple market regimes reveals that small-cap cryptocurrencies exhibit significant delayed responses to BTC price movements. To examine this behavior, we introduce a simple indicator of immediate price responsiveness and find that lower liquidity tends to be associated with slower reactions. Granger causality tests further demonstrate unidirectional Granger-causal relationships from BTC to ALTs. Based on these findings, we develop a lag trading strategy using BTC's preceding returns as a leading indicator. Through machine learning-based trading decisions, our strategy consistently outperforms traditional buy-and-hold approaches across diverse market conditions. This research provides evidence of information transmission frictions in cryptocurrency markets and demonstrates the viability of practical investment strategies that leverage short-term anomalies. Our findings offer value to high-frequency and arbitrage traders while contributing new academic insights to the literature on cryptocurrency market microstructure.

Keywords Cryptocurrency · High-frequency data analysis · Market inefficiency · Machine learning trading strategy

JEL Classification G14 (Information and Market Efficiency, Event Studies, Insider Trading) · G12 (Asset Pricing, Trading Volume, Bond Interest Rates)

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Published online: 10 March 2026

1 Introduction

Bitcoin (BTC) was proposed by Nakamoto (2008) as a new electronic cash system that does not require third-party mediation. One of BTC's key features is its decentralized nature, unlike fiat currencies. For example, while central banks regulate the supply of currencies like the Japanese yen or the US dollar, BTC has a pre-set maximum supply of 21 million units. Although there exists a community involved in maintenance and improvements, this fundamental supply limit cannot be altered. Due to these unique characteristics, BTC gained significant attention during the financial crisis in Cyprus, leading to a sharp rise in its value. However, issues such as high transaction fees and prolonged transaction confirmation times have also emerged. To address these challenges, a variety of cryptocurrencies have been developed, and those other than BTC are collectively referred to as altcoins (ALTs).

While the number of cryptocurrencies, including BTC, is said to exceed 2 million, as of September 23, 2024, BTC accounts for approximately 58% of the total cryptocurrency market capitalization, maintaining firm market dominance. Although cryptocurrencies are interconnected (Corbet et al., 2018), BTC's overwhelming influence remains unshaken. In recent years, the cryptocurrency market has developed rapidly and attracted the attention of many investors and researchers (Wątorek et al., 2021). However, even BTC exhibits high volatility compared to stocks and gold (Meiryani et al., 2023), and its uncertainty and risk are well documented (Hayashi & Routh, 2024). Therefore, under such volatile market conditions, it is valuable to explore profit opportunities while mitigating risk through cryptocurrency price forecasting and investment strategy development.

If Fama's (1965) efficient market hypothesis fully applies to the cryptocurrency market, predicting future returns based on historical data would be challenging. However, if this assumption does not hold, there may be room for investment strategies that exploit market inefficiencies. Many researchers, including Jaquart et al. (2021) and Huang et al. (2019), have proposed prediction models and trading strategies utilizing historical BTC price information, demonstrating considerable effectiveness. Consequently, the efficiency and predictability of the cryptocurrency market remain inconclusive, requiring further empirical verification.

In this study, we examine ALT markets from a short-term, high-frequency perspective (1-min intervals) and assume that market inefficiencies exist. Specifically, we focus on "trade count (liquidity)" as a factor that could significantly contribute to such inefficiencies and formulate the following two hypotheses:

H1: The logarithmic returns of BTC have a lagged effect on certain ALTs.
H2: ALTs with lower trade count are more susceptible to delayed effects from BTC's logarithmic returns.

To test these hypotheses, this study first analyzes the price correlations between BTC and ALTs using statistical methods such as cross-correlation functions, Granger causality tests, and vector autoregression (VAR) models to quantitatively capture the delay structure of influence transmission from BTC to ALTs. Subsequently, we focus on small-cap cryptocurrencies with prominent delay structures and simulate trading strategies triggered by recent BTC price fluctuations to verify whether significant profit improvements can be achieved in practice.

Therefore, this study makes a unique contribution by not only elucidating the dynamics of cryptocurrency markets but also empirically demonstrating the profitability of trading strategies that exploit lagged effects. The remaining sections of this paper are structured as follows: Section 2 reviews the relevant literature, Section 3 outlines the data and methodology, Section 4 presents the empirical results, and Section 5 concludes.

2 Literature Review

Research on the efficiency of the cryptocurrency market is diverse, but opinions are divided, particularly regarding the BTC market. Some studies suggest that information inefficiencies exist in the BTC market and that returns can be predicted to some extent based on past price fluctuations. Zargar and Kumar (2019) used intraday data at 60-min, 30-min, and 15-min intervals and pointed out that BTC consistently deviates from the random walk hypothesis. Takaishi and Adachi (2020) also analyzed daily BTC data from 2011–2018, reporting a trend toward increased efficiency after 2013, while also noting periods where inefficiency resurfaced. Abdul Rahim et al. (2021) classify the entire cryptocurrency market as inefficient but note that there are periods where randomness cannot be ruled out for BTC, suggesting that market efficiency can vary significantly depending on the period and sample. On the other hand, Yi et al. (2023) analyzed BTC using variance ratio tests and quantum harmonic oscillator models and concluded that the market generally functions efficiently. Thus, the efficiency of the BTC market exhibits mixed results, with both inefficient and efficient aspects coexisting.

Several studies report that ALT markets are inefficient. For instance, Abdul Rahim et al. (2021) applied the Ljung–Box test and runs test and concluded that many ALTs exhibit predictable price formation, including autocorrelation. Verma et al. (2022) also strongly rejected the random walk hypothesis for the entire cryptocurrency market based on the results of unit root tests and runs tests conducted on BTC, Ethereum (ETH), Litecoin (LTC), USD Tether (USDT), and Ripple (XRP). One important factor contributing to the inefficiency of ALTs is low liquidity. In stock market research, Fama (1965) stated that rapid actions by many arbitrage traders are the key to stabilizing price fluctuations, and Prasanna and Menon (2012) demonstrated that larger companies and higher trading volumes in the Indian stock market lead to faster information incorporation. In the cryptocurrency market, Takaishi and Adachi (2020) suggested a correlation between illiquidity indicators and the Hurst index, while Abou Tanos and Badr (2024) comprehensively demonstrated that price delays are less significant when liquidity is high and volatility is low.

Furthermore, numerous studies have been conducted on the impact of BTC on ALTs, with many reports indicating that short-term fluctuations in BTC prices have significant spillover effects on ALTs. Demir et al. (2021) pointed out that BTC shocks are transmitted asymmetrically to ALTs over periods ranging from several days to several weeks, with ALTs reacting particularly strongly during downturns.

Zięba et al. (2019) suggest that while BTC maintains its dominance across the market, the influence from other cryptocurrencies remains limited. On the other hand, Ciaian et al. (2018) argue that BTC's influence is prominent in the short term but diminishes over the long term, while Gupta et al. (2024) report that BTC best explains ALTs' price fluctuations when compared to gold prices or the NASDAQ index. However, altcoin-specific factors cannot be ignored.

As described above, substantial knowledge has been accumulated regarding BTC's dominance, the inefficiencies of ALTs, differences in liquidity, and delays in price reactions. However, there are only a limited number of empirical studies that have examined these structures using high-frequency data and applied them to investment strategies. This study aims to contribute by clarifying the time lag between BTC price fluctuations and their impact on ALTs, as well as the factors that determine this lag, thereby demonstrating the potential to generate actual trading profits.

3 Data and Methodology

We adopt a comprehensive approach combining multiple statistical methods to quantitatively analyze the delay structure of price transmission from BTC to ALTs. Since the cryptocurrency market exhibits significantly different price fluctuation characteristics depending on the market regime, analyzing a single regime alone is insufficient. Therefore, this study classifies the market into multiple regimes (Bull, Bear, Sideways, and Crash) and conducts individual analyses tailored to the characteristics of each regime. The analytical methods, target market regimes, and analytical objectives are summarized in Table 1.

The analysis is conducted in stages. First, cross-correlations between BTC and ALTs are investigated using cross-correlograms in both Bull and Bear regimes to visually capture the delay relationships. Similarly, in both regimes, hypothesis testing is employed to statistically evaluate the impact of trade count on price responsiveness. Next, Granger causality tests are used to identify causal influences from BTC to ALTs, as well as the reverse relationships.

Table 1 Statistical methods applied to each market regime and their analytical objectives

Analytical method	Market regime(s)	Objective
Cross-correlation Analysis	Bull, Bear	Examining cross-correlations between BTC and ALTs
Hypothesis Testing (Liquidity-Responsiveness Correlation)	Bull, Bear	Assessing how trade count (liquidity) affects price responsiveness
Granger Causality Test	Bull, Bear	Identifying causal influences from BTC to ALTs and vice versa
VAR Model	Bull	Investigating time-series interdependencies among cryptocurrencies
Orthogonalized Impulse Response Function	Bull	Analyzing the BTC shock impacts including contemporaneous effects
Trading Simulation	Bull, Sideways, Crash	Practical backtesting of trading strategies

For more detailed analysis in the Bull regime, VAR models are employed to investigate time-series interdependencies among cryptocurrencies, and orthogonalized impulse response functions are used to analyze the dynamic impacts of BTC shocks on other cryptocurrencies. Finally, we conduct trading simulations across three market regimes (Bull, Sideways, and Crash) and perform practical backtesting of trading strategies that exploit the discovered price transmission patterns.

Through this stepwise, market regime-specific approach, we comprehensively elucidate the price transmission mechanism from BTC to ALTs and verify its practical applicability.

3.1 Data and Sample Period

We used the Binance cryptocurrency exchange API[1] to obtain 1-min closing prices and trade count data. Binance is one of the world's largest cryptocurrency exchanges, providing access to data representative of market activity in terms of liquidity and trading volume.

To test Hypothesis H2 (lower trade counts result in delayed reactions), comprehensive analyses were conducted using all cryptocurrencies traded during the Bull regime (369 securities) and Bear regime (381 securities). Meanwhile, to test H1 (BTC has lagged effects on ALTs) and conduct detailed analyses, representative cryptocurrencies were selected based on market capitalization.

To establish clear causal relationships, we selected specific event periods where BTC played a leading role in the market. As shown in Fig. 1, we analyzed the following four market regimes:

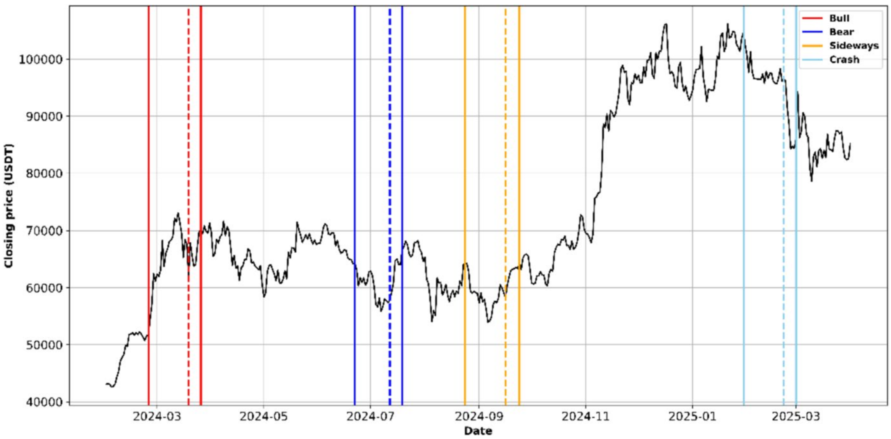

Fig. 1 Data collection period and BTC closing price. Note: Colored lines indicate market regime:Red = Bull, Blue = Bear, Orange = Sideways, Light blue = Crash; The dashed lines indicate the boundary between in-sample and out-of-sample periods, and for Bull and Bear regimes, they also mark the end date of each event. BTC closing price is denominated in USDT, a U.S. dollar-pegged stablecoin, serving as a stable reference unit for the quantitative measurement of BTC price fluctuations. Data source: Binance API

[1] https://www.binance.com/en

- **Bull Regime**: February 25–March 25, 2024 (MicroStrategy's[2] large purchase of approximately 24,245 BTC from February 26 to March 19[3])
- **Bear Regime**: June 22, 2024–July 19, 2024 (Sale period of approximately 49,858 BTC seized by the German government during June 19-July 12[4])
- **Sideways Regime**: August 24–September 24, 2024 (verification period for price transmission patterns in a sideways market)
- **Crash Regime**: January 30–March 1, 2025 (verification period for strategy effectiveness during sharp market declines)

For each market regime, we established periods that included post-event market reactions and designated the final week as an out-of-sample period to verify trading strategy effectiveness.

3.2 Data Description

To gain a comprehensive understanding of the cryptocurrency market, we selected two large-cap cryptocurrencies, one medium-cap cryptocurrency, and five small-cap cryptocurrencies.[5] We chose BTC and ETH as large-cap cryptocurrencies, and LTC as a medium-cap cryptocurrency due to its strong correlation with BTC.

For small-cap cryptocurrencies, we selected assets that ranked in the bottom 50 by total trade count among cryptocurrencies traded during the Bull regime. This selection process corresponds to Fig. 2, which was constructed based on trade count data for each cryptocurrency obtained from Binance. During the selection process, we excluded assets that were pegged to other assets and do not exhibit independent price movements (marked in green in Fig. 2).

Furthermore, we considered technical differences such as the presence or absence of smart contract functionality compatible with multiple cryptocurrencies, and which cryptocurrency system serves as the underlying foundation. After comprehensively evaluating these factors, we ultimately selected Beefy Finance (BIFI), Manchester City Fan Token (CITY), Private Instant Verified Transaction (PIVX), Gnosis (GNO), and QuarkChain (QKC), as indicated in red in Fig. 2.

3.3 Hypothesis Testing (Liquidity-Responsiveness Correlation)

To quantify how quickly ALTs react to BTC price fluctuations, we define the following Immediate Sensitivity Indicator (ISI):

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[2] A US-listed company that regularly purchases large amounts of BTC as part of its financial strategy.

[3] MicroStrategy. (2025, July 29). Purchases. Strategy. https://www.strategy.com/purchases

[4] Pereira, A. P. (2024, July 18). Bitcoin sale nets German government $2.8B. Cointelegraph. https://cointelegraph.com/news/bitcoin-sale-nets-german-government-2-8-billion

[5] Large-cap cryptocurrencies refer to those ranked in the top 10 by market capitalization, medium-cap cryptocurrencies refer to those ranked 11th to 50th, and small-cap cryptocurrencies refer to those ranked 51 st or below.

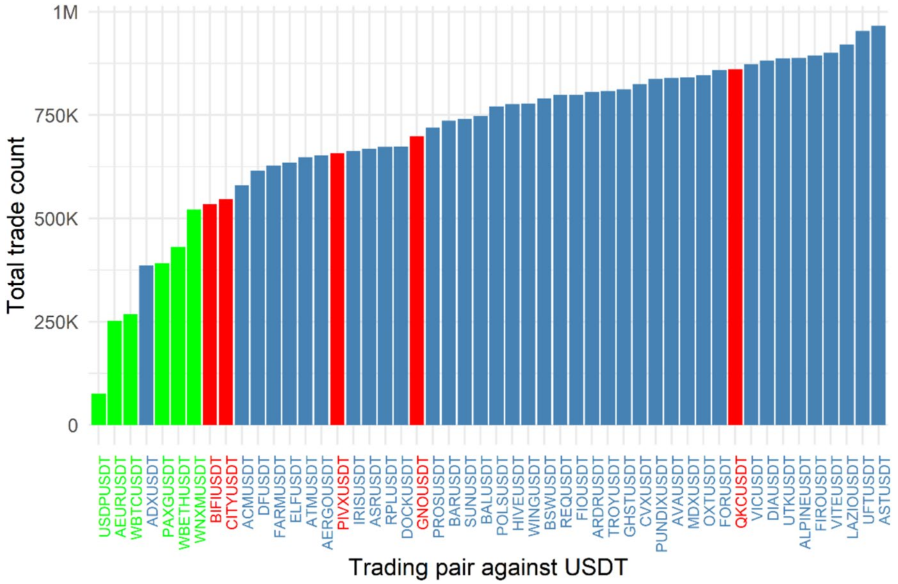


Fig. 2 The least frequently traded 50 cryptocurrency pairs. Note: Green bars represent asset-pegged cryptocurrencies, and red bars indicate the pairs selected for analysis. Data source: Binance API

$$ISI = \rho_0 - \frac{1}{5}\sum_{i=1}^{5} \rho_{-i} \tag{1}$$

where ρ_i is the correlation coefficient between the logarithmic returns of ALTs (at time $t + i$) and the logarithmic returns of BTC (at time t). When $i = 0$, it represents an immediate reaction, and when $i < 0$, it indicates that ALTs react to BTC with a delay.

H2 asserts that ALTs with lower trade count are more susceptible to lagged effects from BTC's logarithmic returns (i.e., the lower the trade count, the more delayed the reaction). The degree of immediate response is reflected inρ_0, while delayed responses are captured by ρ_{-i} (where $i > 0$). Therefore, the relationship between trade count and the speed of ALTs' lagged response to BTC can be quantified using the ISI defined in Eq. (1). The ISI ranges from negative to positive values; a higher ISI implies that ALTs react more promptly to BTC price fluctuations (strong liquidity transmission), while a lower or negative ISI denotes slower, lagged responses (weak transmission).

In our analysis, we construct a scatter plot with the vertical axis representing the ISI and the horizontal axis representing the logarithmic trade count, thereby visualizing the relationship between trade count and ALTs' response speed to BTC. We then conduct a hypothesis test on the correlation coefficient to assess the validity of H2's assertion. Specifically, we set the null hypothesis as "There is no positive correlation between the logarithmic trade count and the ISI indicator" and the alternative hypothesis as "There is a positive correlation between the logarithmic trade count and the ISI indicator," and verify this using a one-sided test at the 5% significance level.

3.4 Granger Causality Test

To statistically confirm the directionality of causal relationships between BTC and ALTs, we conduct Granger causality tests for each pair. This test individually verifies two relationships: whether BTC returns one minute prior contribute to ALT return forecasts, and whether ALT returns one minute prior contribute to BTC return forecasts. For the former, the null hypothesis is that "using BTC returns from one minute prior does not improve the prediction accuracy of ALT returns." For the latter, the null hypothesis is that "using ALT returns from one minute prior does not improve the prediction accuracy of BTC returns." The F-statistic is used as the test statistic, and the null hypothesis is rejected at the 5% significance level.

3.5 Vector Autoregression (VAR)

To analyze dynamic interactions among cryptocurrencies in greater detail, we estimate the following VAR model:

$$\mathrm{y}_t = \mathrm{c} + \Phi_1 \mathrm{y}_{t-1} + \Phi_2 \mathrm{y}_{t-2} + \Phi_3 \mathrm{y}_{t-3} + \varepsilon_t \tag{2}$$

where $\mathbf{y}_t$ is the logarithmic return vector for each cryptocurrency, Φ_i is the coefficient matrix, and ε_t is the error term vector. In this study, we constructed a VAR model with lags from $t-1$ to $t-3$ for each currency, including the target currency, as explanatory variables. The lag order was set to three, based on the results of cross-correlation analysis presented later in this paper, which indicated that significant interactions among cryptocurrencies generally dissipate beyond the third lag. This choice also helps maintain a parsimonious model specification.

Based on the VAR model estimation results, we quantitatively assess the magnitude and direction of impacts that past price fluctuations of each cryptocurrency have on other cryptocurrencies.

3.6 Orthogonalized Impulse Response Function

To quantitatively and dynamically analyze the causal effects from BTC while accounting for the transmission order, we employ orthogonalized impulse response functions.

Based on the VAR model estimated in Eq. (2), we construct orthogonalized disturbance terms (structural shocks) $u_{j,t}$ by removing correlations among disturbance terms and identify unique fluctuations of each variable. The variable ordering (recursive structural order) is determined based on market capitalization and trading volume, and is set as follows: BTC, ETH, LTC, QKC, GNO, PIVX, CITY, and BIFI.

The impulse response function is defined as:

$$IRF_{ij}(h) = \frac{\partial y_{i,t+h}}{\partial u_{j,t}} \tag{3}$$

where $IRF_{ij}(h)$ represents the response of variable i at time $y_{i,t+h}$ following a one-unit shock $u_{j,t}$ to variable j. We analyze spillover effects on other cryptocurrencies when a one-standard-deviation shock is applied to BTC and calculate 95% confidence intervals using bootstrap resampling with 100 iterations.

3.7 Trading Simulation

In this section, based on the findings obtained thus far, we construct a lag trading strategy using BTC as a leading indicator and verify its practicality through simulation. We design a classification model for making decisions based on the future returns of ALTs and aim to maximize cumulative returns through the buy/sell decisions derived from it.

This study hypothesizes that BTC's logarithmic returns have lagged impacts on ALTs. By leveraging recent BTC fluctuations to predict ALT profitability at the next time point, the strategy seeks to exploit market inefficiencies. In trading, decision-making differs between purchasing from a non-holding state and continuing to hold an existing position; therefore, we establish separate classification models for these two scenarios. We set threshold values ϑ_{entry} and ϑ_{hold} to determine the profitability for the entry model and hold model, respectively, with final profits varying based on the selection of these values.

The input for each model is a feature vector composed of the logarithmic returns of BTC and ALTs at time $t-1$:

$$\boldsymbol{x}_{t-1} = \begin{bmatrix} r_{\text{BTC},t-1} \\ r_{\text{ALT},t-1} \end{bmatrix} \tag{4}$$

In our framework, we employ LightGBM (Ke et al., 2017), a gradient boosting decision tree algorithm that effectively captures structural features and excels in interpretability and learning speed. Two binary classifiers, $f_{\text{entry}}(\cdot)$ and $f_{\text{hold}}(\cdot)$ are trained using threshold parameters $\vartheta^*_{\text{entry}}$, $\vartheta^*_{\text{hold}}$,which are described in detail later**.** Specifically, for each ALT, we assign binary labels to the training data based on whether the realized returns exceed the corresponding threshold. That is, the model directly learns to predict whether the next-period return will surpass a predefined profitability threshold, rather than predicting the exact return itself[6]:

$$\widehat{y}_t^{entry} = f_{entry}(x_{t-1}), \widehat{y}_t^{hold} = f_{hold}(x_{t-1}) \tag{5}$$

In executing the strategy, we define a variable $\omega_t \in \{0,1\}$ representing the asset holding status at time t. This is updated based on model outputs and the previous holding status:

[6] Rather than using continuous regression models, we employ binary classifiers as they are more directly related to practical trading decisions.

$$\omega_t = \begin{cases} 1 & \text{if } \left(\widehat{\mathrm{y}}_t^{\mathrm{entry}} = 1 \text{ and } \omega_{t-1} = 0\right) \\ & \text{or } \left(\widehat{\mathrm{y}}_t^{\mathrm{hold}} = 1 \text{ and } \omega_{t-1} = 1\right) \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

Note that the initial state is $\omega_1 = 0$. Here, $\omega_t = 1$ means "held", $\omega_t = 0$ means "not held". In trading, fees are incurred during buying and selling trades. The fee occurrence flag δ_t^{Lag} for the lag trading strategy is defined as:

$$\delta_t^{\mathrm{Lag}} = \begin{cases} 1 & \text{if } \left(\widehat{\mathrm{y}}_t^{\mathrm{entry}} = 1 \text{ and } \omega_{t-1} = 0\right) \\ & \text{or } \left(\widehat{\mathrm{y}}_t^{\mathrm{hold}} = 0 \text{ and } \omega_{t-1} = 1\right) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

According to this definition, fees are applied only when the holding status changes due to a trade. As a comparison, the fee occurrence flag δ_t^{BH} for the buy-and-hold strategy, where ALTs are purchased and held until the end, is defined as:

$$\delta_t^{\mathrm{BH}} = \begin{cases} 1 & \text{if } (t = 1 \text{ or } t = T) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Let the ALT return be r_{ALT}, and the fee rate befee.[7] Then, the cumulative return R^{BH} of the buy-and-hold strategy is:

$$R^{\mathrm{BH}} = \exp\left(\sum_{t=1}^{T} \left(r_{\mathrm{ALT},t} - \delta_t^{\mathrm{BH}} \cdot fee\right)\right) - 1 \tag{9}$$

On the other hand, the cumulative return R^{Lag} of the lag trading strategy, which reflects returns only during holding periods, is defined as:

$$R^{\mathrm{Lag}} = \exp\left(\sum_{t=1}^{T} \left(\omega_t \cdot r_{\mathrm{ALT},t} - \delta_t^{\mathrm{Lag}} \cdot fee\right)\right) - 1 \tag{10}$$

We explore parameters $(\vartheta_{\mathrm{entry}}, \vartheta_{\mathrm{hold}})$ using grid search during the in-sample period to find the optimal combination $\left(\vartheta_{\mathrm{entry}}^*, \vartheta_{\mathrm{hold}}^*\right)$ that maximizes the average return for the ALT set $S = \{\mathrm{QKC}, \mathrm{GNO}, \mathrm{PIVX}, \mathrm{CITY}, \mathrm{BIFI}\}$:

$$\left(\vartheta_{\mathrm{entry}}^*, \vartheta_{\mathrm{hold}}^*\right) = \underset{\vartheta_{\mathrm{entry}}, \vartheta_{\mathrm{hold}}}{\operatorname{argmax}} \frac{1}{|S|} \sum_{i \in S} R_i^{\mathrm{Lag}} (\vartheta_{\mathrm{entry}}, \vartheta_{\mathrm{hold}}) \tag{11}$$

[7] We set trading fees at 0.02%, which exceeds Binance's minimum feasible rate (~0.0175%) to ensure conservative profit estimates.

The search ranges are set to $\vartheta_{\text{entry}} \in \{-0.0001, 0, 0.0001, 0.0002\}$ and $\vartheta_{\text{hold}} \in \{-0.0002, -0.0001, 0, 0.0001\}$, and the optimal combination is applied during the out-of-sample period.

For ETH and LTC, we do not perform separate parameter optimization. Instead, we applied the same parameter settings that were optimized for the small-cap cryptocurrencies, as our primary focus was on evaluating the strategy's effectiveness for low-liquidity assets.

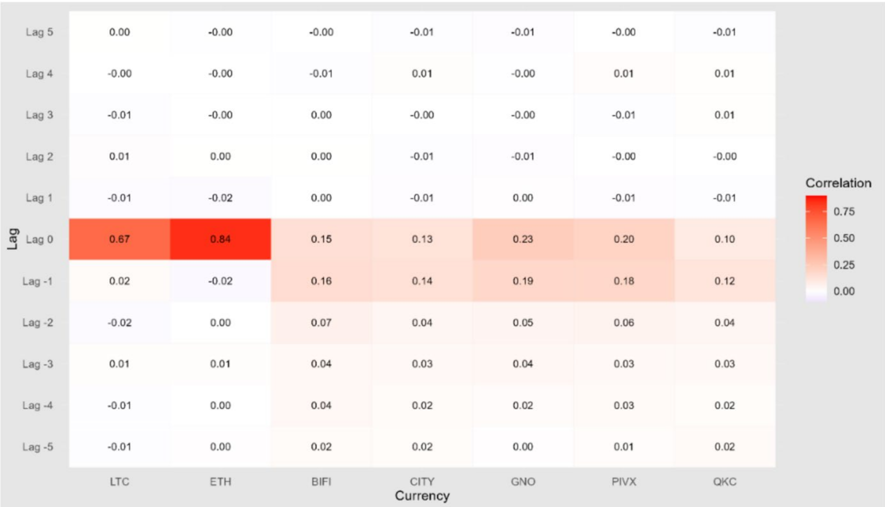
Through this verification, we evaluate the effectiveness of investment strategies that exploit time lags in price transmission from BTC to ALTs and demonstrate the potential for strategically exploiting market inefficiencies.

4 Empirical Results

4.1 Cross-correlation Analysis

To gain an overview of the relationship between BTC and ALTs, we conducted an analysis using cross-correlation functions. Figure 3 shows the cross-correlations between BTC and all cryptocurrencies from lag-5 to lag+5 during the Bull regime. The analysis results confirmed that large and medium-cap ALTs, such as LTC and ETH, exhibited extremely high correlation coefficients at lag0, with no significant reactions observed in subsequent or previous periods.

On the other hand, a different pattern was observed for small-cap cryptocurrencies. QKC, BIFI, and CITY showed slightly higher correlation coefficients at lag-1 than at lag0, indicating a tendency to react to BTC price fluctuations with a one-minute delay. For GNO and PIVX, while the correlation coefficient at lag0 was slightly



Lag	LTC	ETH	BIFI	CITY	GNO	PIVX	QKC
Lag 5	0.00	-0.00	-0.00	-0.01	-0.01	-0.00	-0.01
Lag 4	-0.00	-0.00	-0.01	0.01	-0.00	0.01	0.01
Lag 3	-0.01	-0.00	0.00	-0.00	-0.00	-0.01	0.01
Lag 2	0.01	0.00	0.00	-0.01	-0.01	-0.00	-0.00
Lag 1	-0.01	-0.02	0.00	-0.01	0.00	-0.01	-0.01
Lag 0	0.67	0.84	0.15	0.13	0.23	0.20	0.10
Lag -1	0.02	-0.02	0.16	0.14	0.19	0.18	0.12
Lag -2	-0.02	0.00	0.07	0.04	0.05	0.06	0.04
Lag -3	0.01	0.01	0.04	0.03	0.04	0.03	0.03
Lag -4	-0.01	0.00	0.04	0.02	0.02	0.03	0.02
Lag -5	-0.01	0.00	0.02	0.02	0.00	0.01	0.02

Fig. 3 Cross-correlations between BTC and ALTs from lag-5 to+5 during the Bull regime. Note: Darker red cells indicate stronger positive correlation. Lag 0 corresponds to simultaneous correlation; negative lags indicate BTC leading ALTs. Data source: Binance API

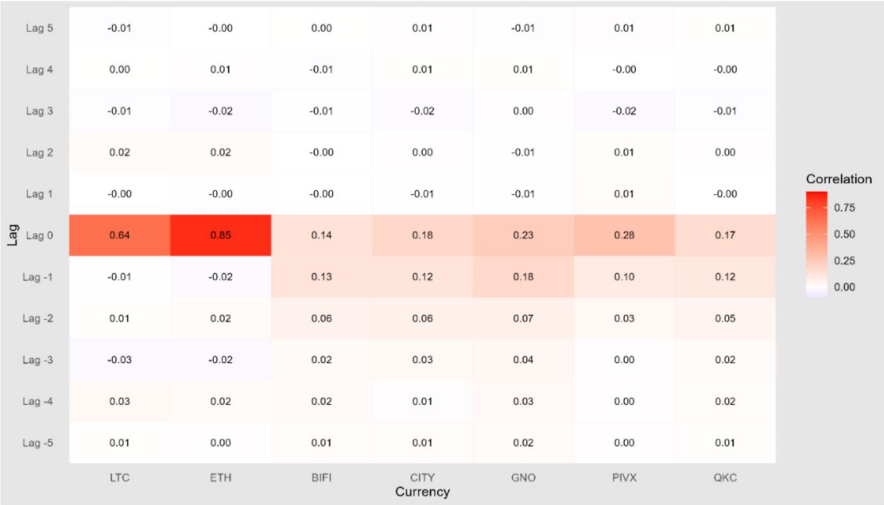


Fig. 4 Cross-correlations between BTC and ALTs from lag-5 to + 5 during the Bear regime. Note: Darker red cells indicate stronger positive correlation. Lag 0 corresponds to simultaneous correlation; negative lags indicate BTC leading ALTs. Data source: Binance API

higher than at lag-1, the correlation coefficient at lag-1 was also at a similar level to lag0, suggesting delayed reactions similar to QKC, BIFI, and CITY.

In the cross-correlation analysis during the Bear regime shown in Fig. 4, large and medium-cap cryptocurrencies consistently showed high lag0 correlation coefficients, similar to the Bull regime, with no reactions observed in subsequent or previous periods. For small-cap cryptocurrencies, similar to the Bull regime, correlation coefficients at lag-1 remained at levels comparable to those at lag0, indicating persistent delayed reactions. However, when compared to the Bull regime, small-cap cryptocurrencies showed relatively higher lag0 correlation coefficients, while values at lag-1 and beyond exhibited a tendency to be slightly smaller.

These results indicate that in both regimes, large and medium-cap cryptocurrencies react simultaneously to BTC returns with strong, unlagged correlations. Simultaneously, small-cap cryptocurrencies react immediately to BTC returns but also tend to exhibit lagged responses over several minutes. Additionally, faster reactions during downturns compared to upturns were observed, which aligns with the general pattern of higher price volatility during downturns and investors' tendency to liquidate positions rapidly. These results suggest that BTC could serve as a reliable leading indicator for small-cap cryptocurrencies.

4.2 Hypothesis Testing (Liquidity-Responsiveness Correlation)

Following the confirmation of time-lagged cross-correlations between BTC returns and small-cap cryptocurrencies, we conducted hypothesis testing to statistically verify H2's assertion. Figure 5(a) shows the analysis results using data from the Bull regime, with the horizontal axis representing the logarithmic trade count and the vertical axis representing the ISI defined in Eq. (1).

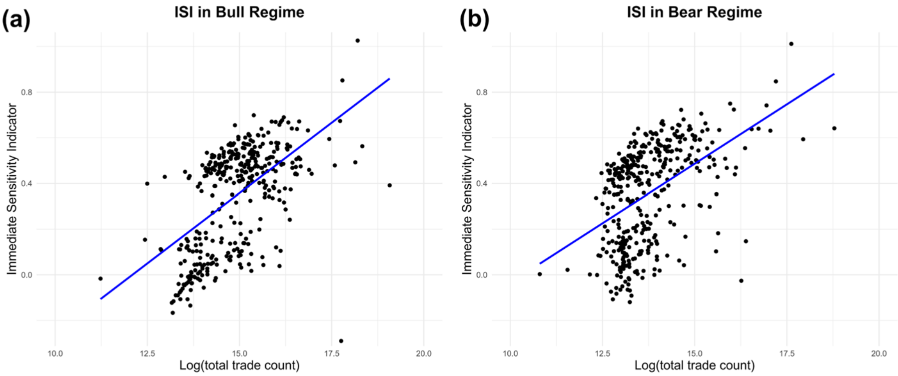


Fig. 5 Regime-wise ISI and logarithmic total trade count. **a** ISI in the bull regime; **b** ISI in the bear regime; data source: Binance API

Table 2 Results of hypothesis testing

Market regime	t-value	Degrees of freedom	p-value	Confidence interval
Bull	12.987	367	$< 1 \times 10^{-16}$	[0.499, 1.000]
Bear	10.740	379	$< 1 \times 10^{-16}$	[0.416, 1.000]

p-values smaller than 1×10^{-16} are reported as $< 1 \times 10^{-16}$ due to numerical precision limits

The correlation coefficient in the Bull regime was 0.561, confirming a clear positive correlation. The hypothesis test results for this correlation coefficient are shown in Table 2. The null hypothesis that no positive correlation exists was statistically rejected, and the alternative hypothesis was accepted. Additionally, the 95% confidence interval for the correlation coefficient was calculated as $[0.499, 1.000]$.

Figure 5(b) shows the analysis results based on data from the Bear regime, with a correlation coefficient of 0.483. In this case as well, a statistically significant positive correlation was confirmed, and the hypothesis test results (Table 2) rejected the null hypothesis and accepted the alternative hypothesis. The 95% confidence interval for the correlation coefficient was $[0.416, 1.000]$.

These results indicate that H2—"ALTs with lower trade count are more susceptible to delayed effects from BTC's logarithmic returns"—is statistically supported in both Bull and Bear regimes. This finding strongly suggests that reaction speed to BTC may vary depending on trade frequency.

4.3 Granger Causality Test

To statistically confirm the directionality of causal relationships between BTC and ALTs, Granger causality tests were conducted. The left side of Table 3 shows the results of testing causal relationships from BTC to ALTs. Based on the p-values, the null hypothesis that "using BTC returns from one minute prior does not improve the prediction accuracy of ALT returns" was rejected at the 5% significance level for all pairs. Therefore, the alternative hypothesis that "using the previous minute's BTC returns improves the predictive accuracy of ALT returns" was statistically supported.

Table 3 Granger causality test results between BTC and ALT across market regimes

Market regime	Causal direction	F-statistic	*p*-value	Market regime	Causal direction	F-statistic	*p*-value
Bull	BTC → ETH	30.354	3.619×10^{-8}	Bull	ETH → BTC	0.350	0.553
Bull	BTC → LTC	42.910	5.795×10^{-11}	Bull	LTC → BTC	0.224	0.636
Bull	BTC → QKC	706.515	$< 1 \times 10^{-16}$	Bull	QKC → BTC	1.473	0.224
Bull	BTC → GNO	2109.444	$< 1 \times 10^{-16}$	Bull	GNO → BTC	4.112	0.042
Bull	BTC → PIVX	2003.931	$< 1 \times 10^{-16}$	Bull	PIVX → BTC	1.405	0.235
Bull	BTC → CITY	961.256	$< 1 \times 10^{-16}$	Bull	CITY → BTC	1.882	0.170
Bull	BTC → BIFI	1334.347	$< 1 \times 10^{-16}$	Bull	BIFI → BTC	0.970	0.342
Bear	BTC → ETH	36.903	1.252×10^{-9}	Bear	ETH → BTC	3.948	0.046
Bear	BTC → LTC	37.294	1.025×10^{-11}	Bear	LTC → BTC	0.145	0.703
Bear	BTC → QKC	976.647	$< 1 \times 10^{-16}$	Bear	QKC → BTC	0.004	0.948
Bear	BTC → GNO	1857.091	$< 1 \times 10^{-16}$	Bear	GNO → BTC	1.131	0.287
Bear	BTC → PIVX	1032.265	$< 1 \times 10^{-16}$	Bear	PIVX → BTC	6.547	0.010
Bear	BTC → CITY	980.972	$< 1 \times 10^{-16}$	Bear	CITY → BTC	1.321	0.250
Bear	BTC → BIFI	887.425	$< 1 \times 10^{-16}$	Bear	BIFI → BTC	0.308	0.580

p-values smaller than 1×10^{-16} are reported as $< 1 \times 10^{-16}$ due to numerical precision limits

On the other hand, regarding reverse causal relationships from ALTs to BTC shown on the right side of Table 3, most pairs failed to reject the null hypothesis that “using the previous minute's ALT returns does not improve the predictive accuracy of BTC returns” at the 5% significance level. As exceptions, the null hypothesis was rejected at the 5% significance level for GNO in the Bull regime and ETH and PIVX in the Bear regime, with the alternative hypothesis being accepted. However, while ETH may influence BTC due to its market size, GNO and PIVX have extremely low liquidity, so price fluctuations caused by specific trades or temporary liquidity shortages may have incidentally affected BTC price prediction accuracy. These are considered temporary events within the data period rather than structural causal relationships.

Overall, the Granger causality test results confirmed unidirectional relationships from BTC to ALTs one minute prior, while reverse relationships were generally not observed. This finding empirically demonstrates that BTC plays a central role in the cryptocurrency market and serves as an important leading indicator for other cryptocurrencies.

4.4 Vector Autoregression (VAR)

As a preliminary step to estimating the VAR model, we analyzed correlations among error terms of each cryptocurrency. As shown in Fig. 6(a), the correlation matrix revealed that error terms of large and medium-cap cryptocurrencies with high trade counts were strongly correlated with each other. In contrast, those of small-cap cryptocurrencies with low trade counts were relatively weakly correlated with error terms of other cryptocurrencies. These results suggest that while large and medium-cap cryptocurrencies share common factors that the VAR model cannot remove, the VAR model can individually explain the movements of each currency series for small-cap cryptocurrencies.

Figure 6(b) shows a heatmap of the VAR model illustrating the impact of explanatory variables (horizontal axis) at time $t-1$ on each cryptocurrency. First, when comparing autoregressive coefficients between time t and $t-1$ for all cryptocurrencies, small autoregressive coefficients were observed for large and medium-cap cryptocurrencies. In contrast, relatively large negative autoregressive coefficients were observed for small-cap cryptocurrencies. In particular, GNO's autoregressive coefficient is notably negative (−0.22). This pattern is consistent with, though not definitive evidence of, temporary price distortions that tend to be corrected quickly in thinly traded markets.

Focusing on the impact of BTC at time $t-1$, PIVX and QKC showed positive regression coefficients of 0.1 or higher. In contrast, regression coefficients of other cryptocurrencies remained relatively small at 0.05 or lower. These results may be related to the technical characteristics of each cryptocurrency. Both QKC and PIVX share strong technical similarities with BTC. QKC adopts a mechanism called PoSW (Proof of Staked Work), which incorporates advantages of PoS (Proof of Stake) while essentially conforming to PoW (Proof of Work). PIVX, on the other hand, is based on DASH, which was developed with BTC as a reference, further reinforcing its technical ties to Bitcoin. Considering these technical backgrounds, it is natural that

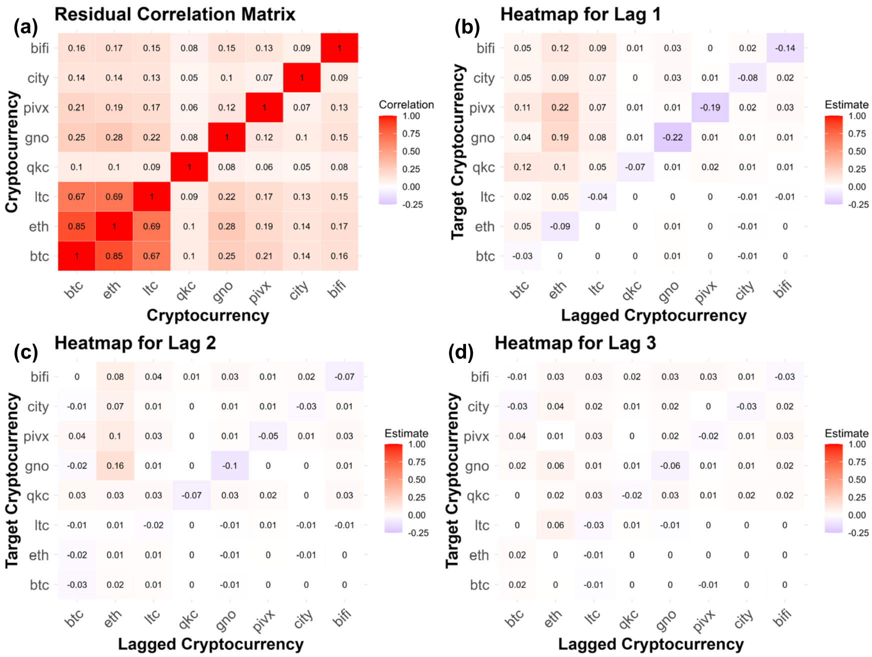


Fig. 6 Heatmaps of VAR model capturing inter-cryptocurrency linkages. **a** Residual correlation matrix indicating contemporaneous relationships among innovations; **b** Coefficient matrix showing one-period lagged effects; **c** Coefficient matrix for two-period lag; **d** Coefficient matrix for three-period lag; Data source: Binance API

both assets exhibit strong correlations with BTC. Finally, for large and medium-cap cryptocurrencies such as BTC, LTC, and ETH, little influence from each other's historical data was confirmed.[8]

The impact analysis at time $t-2$ shown in Fig. 6(c) revealed that, with a two-minute lag, almost none of the cryptocurrencies exhibited any significant impact, except for ETH. Similarly, the analysis results at time $t-3$ shown in Fig. 6(d) confirmed that effects of cryptocurrency returns three minutes earlier on any cryptocurrency were extremely small. Among these, the impact of ETH at $t-3$ was relatively significant compared to others, showing a small but consistent effect of 0.06 on GNO and LTC.[9] When these analysis results are combined, they strongly suggest that small-cap cryptocurrencies have autoregressive properties indicating short-term price corrections, while large-cap cryptocurrencies such as BTC and ETH may serve as effective leading indicators for small-cap cryptocurrencies.

[8] Furthermore, ETH shows remarkably positive coefficients (>0.19) for both GNO and PIVX at t-1. Although noteworthy, this is beyond our current scope.

[9] Given LTC's sufficient liquidity, the ETH impact at $$t-3$$ is likely limited and may represent statistical noise.

4.5 Orthogonalized Impulse Response Function

To dynamically analyze the causal impacts from BTC, we conducted an analysis using orthogonalized impulse response functions. Figure 7 shows the results when a one-standard-deviation shock was applied to BTC, with the vertical axis representing

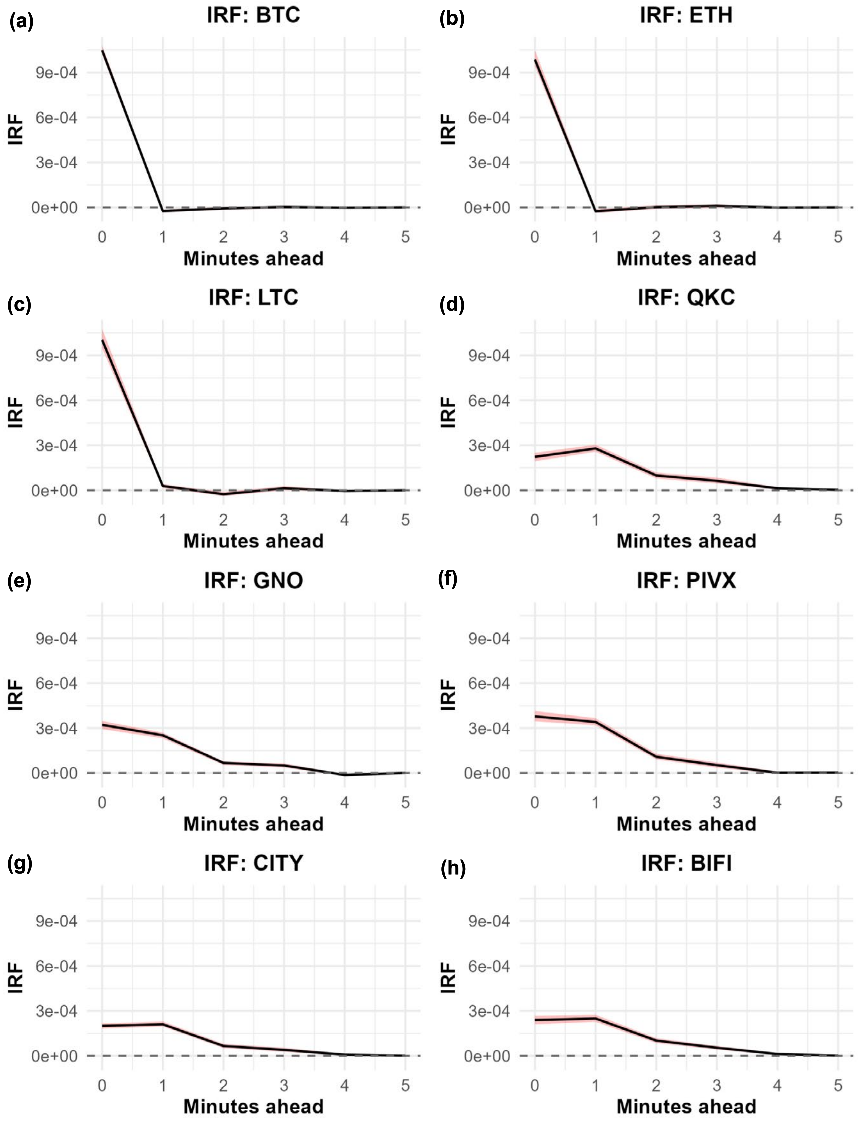


Fig. 7 Orthogonalized impulse response functions to BTC shocks. **a** BTC, **b** ETH, **c** LTC, **d** QKC, **e** GNO, **f** PIVX, **g** CITY, **h** BIFI; Data source: Binance API

the magnitude of each cryptocurrency's response and the horizontal axis representing time elapsed (in minutes). The red dashed lines indicate 95% confidence intervals.

The analysis results confirm that large and medium-cap cryptocurrencies react almost simultaneously to BTC shocks, with impacts nearly disappearing after one minute (see Fig. 7(b) and (c)). Conversely, while small-cap cryptocurrencies also exhibit weak but nearly simultaneous reactions, time-delayed responses were also observed (see Fig. 7(d)-(h)).

Notably, while most cryptocurrencies exhibited positive impacts from BTC shocks that gradually decayed over time, QKC and CITY demonstrated a phenomenon where the response at time t was smaller than the response at time $t-1$ (see Fig. 7(d) and (g)). This result is consistent with the cross-correlation analysis results in Fig. 3, supporting the tendency of these small-cap cryptocurrencies to exhibit delayed reactions to BTC price fluctuations.

The significant BTC-related event (MicroStrategy's large-scale purchase) during the data period and BTC's position at the forefront of the recursive structure likely enhanced the model's accuracy. These results generally align with those from VAR models and Granger causality tests, confirming consistency across analytical methods.

4.6 Trading Simulation

We conducted trading simulations to verify the practicality of applying the characteristics revealed in our analysis to actual trading strategies. For each market regime, the in-sample period corresponds to the first three weeks of the month, while the out-of-sample period corresponds to the final week that follows. The grid search results for optimal decision thresholds, shown in Table 4, revealed interesting strategic patterns.

First, regarding hold thresholds, a negative value of −0.0001 was selected for all market regimes. This indicates that, considering transaction fees incurred with each trade, continuing to hold even in situations with slight unrealized losses leads to overall profitability improvement. In other words, once an asset is held, a strategy of making relatively cautious selling decisions to avoid transaction fees is optimal.

On the other hand, for entry thresholds, values close to zero were selected: 0 for Bull and Crash regimes, and 0.0001 for the Sideways regime. This indicates a tendency to set relatively lenient conditions for new purchase decisions and actively pursue trading opportunities. The slightly stricter threshold for the Sideways regime is likely due to limited price fluctuations shown in Fig. 1, where overly frequent trading could undermine profitability.

These results suggest that an asymmetric strategy of relatively easy entry and cautious exit is optimal, as hold thresholds are negative while entry thresholds are generally zero. In other words, the tendency to initiate trades extensively while carefully timing exits represents a practical strategy that accounts for transaction fees.

Table 4 Threshold grid search results

Market regime	Entry threshold	Hold threshold
Bull	0.0000	−0.0001
Crash	0.0000	−0.0001
Sideways	0.0001	−0.0001

Figure 8 shows comparisons of cumulative returns between buy-and-hold and lag trading strategies across each market regime. The horizontal axis represents cumulative returns (%), and the vertical axis represents dates during the out-of-sample period. Figure 8(a), (c), and (e) show buy-and-hold strategy results, while Fig. 8(b), (d), and (f) show lag trading strategy results, arranged from top to bottom as Bull, Sideways, and Crash regimes.

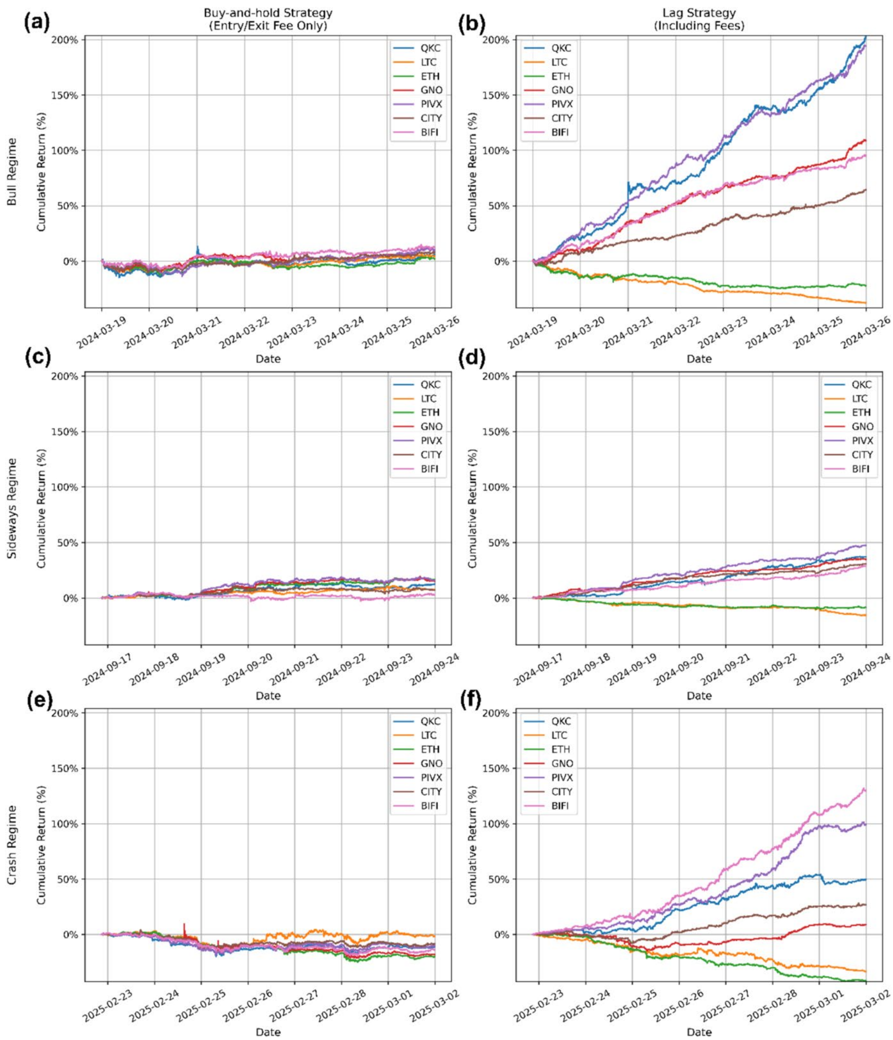


Fig. 8 Comparison of cumulative returns during the out-of-sample periods. **a** Buy-and-hold strategy in Bull regime; **b** Lag strategy in Bull regime; **c** Buy-and-hold strategy in Sideways regime; **d** Lag strategy in Sideways regime; **e** Buy-and-hold strategy in Crash regime; **f** Lag strategy in crash regime; Data source: Binance API

The analysis yielded essential insights. First, cumulative returns for ETH and LTC remained relatively low across all regimes. This is reasonable given that thresholds optimized for small-cap cryptocurrencies were used in Eq. (11), suggesting that BTC functions as an effective leading indicator, particularly for small-cap cryptocurrencies.

Second, PIVX and QKC achieved relatively high cumulative returns across all regimes. As mentioned in Section 4.4, PIVX and QKC have technical structural similarities with BTC, and due to their strong connections with BTC, it is considered that BTC functioned strongly as an explanatory variable across all regimes. These results are consistent with analysis results in Figs. 3 and 7.

Third, cumulative returns of the lag trading strategy were lowest during the Sideways regime (see Fig. 8(d)). This can be attributed to inconsistent trends between in-sample and out-of-sample periods and gradual price fluctuations. Further detailed verification is warranted in this regard.

When evaluating these results comprehensively, it was confirmed that the lag trading strategy outperformed the buy-and-hold strategy in terms of final cumulative returns for small-cap cryptocurrencies across each regime. Furthermore, similar results were obtained in an additional subsample analysis using different time periods (see Appendix 1). Since good performance was confirmed even during out-of-sample periods, the strategy's effectiveness likely does not depend on specific periods or datasets but possesses a certain degree of out-of-sample robustness.

5 Conclusion

In this study, we focused on the price formation mechanism in cryptocurrency markets, particularly the temporal structure of price transmission from BTC to ALTs. We verified whether delays exist in price fluctuation transmission and whether ALT liquidity (trade count) is related to such delays based on high-frequency data. The analysis established two hypotheses: whether BTC returns affect ALTs with a delay (H1), and whether this effect becomes more pronounced as trade counts decrease (H2). These hypotheses were empirically examined using one-minute data. Using multiple statistical methods, results showed that large and medium-cap ALTs react immediately to BTC, while small-cap ALTs with lower trade count tend to respond to BTC price fluctuations with delays of several minutes—a trend that was statistically confirmed. This supports both H1 and H2, suggesting that liquidity differences within cryptocurrency markets may contribute to variations in information transmission speed.

Furthermore, by simulating a simple lag trading strategy for trading ALTs using BTC returns and ALT returns as leading indicators, we confirmed that this strategy significantly improves returns of small-cap cryptocurrencies compared to buy-and-hold strategies. This suggests that not only does inefficient price formation exist in cryptocurrency markets, but there may also be inherent short-term arbitrage opportunities.

These results demonstrate that BTC continues to exert strong influence on markets as a whole, while highlighting the asymmetry of cryptocurrency markets, where information reflection is not necessarily immediate and varies considerably depending on asset characteristics. In particular, our findings are likely useful for investors engaged in short-term high-frequency trading or arbitrage trading. However, if our findings are applied in practice and market participation increases, the low trade frequency that underlies market inefficiency may be resolved in the future, necessitating continued monitoring of cryptocurrency markets.

As for potential limitations, this study analyzed a limited number of cryptocurrency assets, and there is room to enhance result generalizability by conducting analyses targeting broader token ranges. Additionally, although this study focused on BTC, some analysis results suggest that ETH may have influence on ALTs equal to or greater than that of BTC (see footnote 8); therefore, developing strategies based on ETH as a leading indicator represents an important future research direction. Furthermore, this study employed data from Binance, the cryptocurrency exchange with the largest global market share. If the same analysis were conducted using data from other exchanges, the relatively lower trading volume might reduce trading opportunities for small-cap cryptocurrencies, potentially diminishing the effectiveness of the constructed models. However, we expect that similar results would hold for exchanges with sufficient trading activity. Further validation using data from other exchanges remains an important avenue for future research.

Overall, this study contributes to both understanding and practical application of cryptocurrency markets by focusing on delay mechanisms in price formation and the relationship between liquidity and impact speed, while presenting pathways for utilizing these insights in investment strategies. In the future, by expanding this study's framework in response to market structure changes and emerging technologies, we expect to contribute to the development of more effective strategies and market forecasting approaches.

Appendix 1

As a subsample analysis, the model was tested over two market regimes: Bull (October 24–November 22, 2024) and Bear (April 2-May 1, 2024), as shown in Tables 5 and 6. In both regimes, the in-sample period corresponds to the first three weeks, while the out-of-sample period corresponds to the remaining one week. Consistent with the results of the main sample analysis presented in the main text, the Lag Strategy outperformed the Buy-and-Hold Strategy for all cryptocurrencies except LTC and ETH (Table 7).

In both tables, all percentage values are truncated to the integer part (i.e., decimal places are omitted).

Table 5 Threshold grid search results

Market regime	Entry threshold	Hold threshold
Bull	0.0002	-0.0001
Bear	0.0001	-0.0001

Table 6 Comparison of cumulative returns under the bear market regime

Cryptocurrency	Cumulative return (Buy-and-hold Strategy)	Cumulative return (Lag Strategy)
QKC	-9%	116%
LTC	-3%	-20%
ETH	-5%	-17%
GNO	-6%	41%
PIVX	-12%	69%
CITY	-10%	23%
BIFI	-6%	96%

Table 7 Comparison of cumulative returns under the bull market regime

Cryptocurrency	Cumulative return (Buy-and-hold Strategy)	Cumulative return (Lag Strategy)
QKC	7%	59%
LTC	10%	-9%
ETH	7%	-15%
GNO	6%	6%
PIVX	7%	81%
CITY	0%	7%
BIFI	1%	49%

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