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Keith Hazen
Federal Reserve Bank of Philadelphia and Rutgers University

Julapa Jagtiani
Federal Reserve Bank of Philadelphia Supervision, Regulation, and Credit Department

Loretta J. Mester
Wharton School of Business, University of Pennsylvania, and Griswold Center for Economic Policy Studies, Princeton University

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Keith Hazen
Federal Reserve Bank of Philadelphia and Rutgers University

Julapa Jagtiani*
Federal Reserve Bank of Philadelphia

Loretta J. Mester
Wharton School of Business, University of Pennsylvania and
Griswold Center for Economic Policy Studies, Princeton University

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Abstract

Using transaction-level data for Bitcoin (BTC), Ethereum (ETH), and Wrapped Bitcoin (WBTC) matched to public "Whale Alert" signals, we examine how large-scale cryptocurrency trades shape market microstructure. Specifically, we test whether whale transactions alter the composition of active non-whale participants, trigger leader-follower herd behavior, and elevate short-term return volatility. We document a stark divergence between networks: Whale alerts heavily reshape (native) BTC participation by mobilizing previously inactive retail and institutional investors, whereas ETH and WBTC participant profiles remain highly stable on the Ethereum platform. Furthermore, non-whale investors exhibit strong leader-follower behavior in the BTC market — buying and selling in tandem with whale direction. This pattern is largely absent in the Ethereum ecosystem, except among the largest non-whale tranches. These behavioral dynamics directly mirror market stability: Whale alerts induce a brief 24-hour spike in BTC volatility (most acutely following WBTC alerts) but coincide with compressed volatility on the Ethereum platform. Additionally, these asymmetric market responses persisted across Ethereum's transition from proof-of-work to proof-of-stake. These findings indicate persistent informational and structural asymmetries between large and small digital-asset investors.

Keywords: Cryptocurrency, Ethereum, ETH, Bitcoin, WBTC, crypto whales, DeFi
JEL Classification: G14, G23, G28, G41

*Correspondence to Julapa Jagtiani, Federal Reserve Bank of Philadelphia, Ten Independence Mall, Philadelphia, PA 19106, julapa.jagtiani@phil.frb.org. The authors thank Alan Chernoff, Jon Frost, Leonardo Gambacorta, Bruce Mizrach, and Nathaniel Yoshida for their helpful comments.

I Introduction

Cryptocurrency volumes have risen by a thousandfold in the last decade, rising from about $4 billion (in market capitalization) in 2015 to a peak of about $4.35 trillion in October 2025 before dropping significantly to about $2.12 trillion in June 2026).[1] The overall cryptocurrency market is still small relative to the U.S. stock market, which was valued at about $71 trillion as of October 2025. However, cryptocurrency adoption is growing at an increasingly fast pace. According to CoinLedger, more than 560 million people worldwide currently own cryptocurrency (as of June 2026).[2]

Cryptocurrencies trade 24/7 on decentralized, peer-to-peer blockchain networks, eliminating central governance. Unlike traditional financial transactions, cryptocurrency on-chain transactions are immutable (irreversible). While these decentralized transactions are highly transparent, they are pseudonymous — that is, transaction records are public (exposing wallet identifiers), but user identities remain pseudonymous (displaying wallet addresses without revealing the wallet holders' legal names).

The proliferation of cryptocurrencies has raised issues about investor protection, particularly for retail investors who may lack the resources or knowledge to navigate the market safely. Unlike traditional finance, in which regulatory frameworks aim to ensure the same information is available for all investors, the decentralized and pseudonymous nature of crypto markets exacerbates informational asymmetry. The Guiding and Establishing National Innovation for U.S. Stablecoins (GENIUS) Act, passed by Congress in July 2025, attempts to address some of the issues surrounding consumer protection for stablecoins through reserve requirements, anti-money laundering (AML), and Countering the Financing of Terrorism (CFT) policies. Additionally, the proposed Digital Asset Market Clarity (CLARITY) Act aims to develop a framework that clearly defines regulatory authority between the Securities and Exchange Commission (SEC) and Commodity Futures Trading Commission (CFTC), to create transparent categories (security versus commodity) for tokens, to establish rules for exchanges and custodians, and to give the industry a predictable path for launching, trading, and safeguarding digital assets.

As expected, small, less sophisticated retail investors tend to face higher risks of fraud, scams, and catastrophic losses owing to risks stemming from market volatility and failures of exchanges and cryptocurrencies. Fraud is especially costly in the crypto ecosystem because the irreversibility of transactions gives users no recourse. While fraud and predatory behavior exist in traditional markets, many explicit protections have already been in place in traditional markets to

[1] https://www.statista.com/statistics/730876/cryptocurrency-maket-value/

[2] https://coinledger.io/nl/research/how-many-people-own-crypto-in-the-world

provide protection to investors, while the regulatory environment of crypto markets is only now starting to take shape.

Whale investors are individuals (or entities) who hold exceptionally large amounts of a particular digital asset, often large enough to significantly influence market prices through their trading activity (Chernoff and Jagtiani, 2025). While there is no universally fixed threshold, crypto whales are typically defined as wallets controlling holdings worth tens of millions of dollars of the underlying asset, such as those owning thousands of Bitcoin (BTC) or Ethereum (ETH). Whale investors may include early adopters of a cryptocurrency, institutional funds, hedge funds, or even crypto exchanges holding customer assets. Their influence makes them a central subject of analysis for traders and researchers who monitor blockchain activity to anticipate potential market movements.

There are several reasons the trading activities of crypto whales are impactful. First, crypto whales could affect available liquidity and prices through their control over the large supply of cryptocurrencies. Second, market participants could tend to follow them and assign a large weight on their trading activities if, as sophisticated traders, crypto whales are believed to have better access to relevant or proprietary information.[3] Third, with so much supply often being held for long intervals without circulating, a large transfer made by a crypto whale has the potential to significantly move crypto prices.

Using transaction-level data on the largest two cryptocurrencies, Ethereum (ETH) and Bitcoin (BTC), in conjunction with whale trading signals from the "Whale Alert" telegram group,[4] we analyze the impact of crypto whale transactions on market dynamics, focusing on impacts on non-whale market participants, leader-follower behavior, and crypto market volatility following whale alerts. We find a significant impact of whale-initiated transactions on the composition of market participants among those non-whale retail investors (large, medium, and small). In addition, there is evidence of leader-follower behavior, in which retail investor activity intensifies in response to whale trades. Specifically, we find evidence that non-whale investors buy (sell) the same cryptocurrency following a whale buy (sell) transaction.

The remainder of this paper is organized as follows: Section II reviews the relevant literature. Sections III and IV describe the data and our empirical methodology, respectively. Section V presents the empirical results. Section VI presents the conclusions and policy implications.

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[3] In 2017, 1,000 whales owned 40 percent of the Bitcoin market (Kharif, 2017), whereas in 2023 whales controlled a third of the Ethereum's supply (Young, 2023).

[4] See https://whale-alert.io/

II. Review of the Literature and Our Contribution

Bitcoin (BTC), introduced by Nakamoto (2008) as a peer-to-peer electronic cash system, revolutionized digital transactions by eliminating the need for trusted intermediaries through its decentralized proof-of-work (PoW) consensus mechanism, whereby new transactions are approved in a decentralized fashion by other users on the blockchain network. Despite ongoing concerns about its scalability, privacy, and regulatory integration (Chiu and Keister, 2022), BTC remains the most widely recognized and valuable digital asset, with a market capitalization peaking at approximately $2.5 trillion as of October 2025 (when each BTC was valued at $126,000). While substantial research has examined BTC as a standalone cryptocurrency, relatively little work has been extended to explore BTC in relation to other digital assets.

Ethereum (ETH), the second-largest cryptocurrency by market capitalization, possesses several features that make it a particularly interesting environment to study. Unlike BTC, which positions itself primarily as a currency, ETH serves as the native cryptocurrency of the Ethereum network — a platform that also enables the development of new cryptocurrency tokens, financial instruments such as smart contracts, and other services including trading applications. The Ethereum network is rich in tokens, decentralized organizations, and automatically executing “smart” contracts, which gives it functionally beyond just that of a speculative crypto asset.

Literature on Crypto Whales and Leader-Follower Behavior

The behavior of sophisticated investors and their effects on markets and other participants remains understudied in the context of digital assets. We explore the leader-follower dynamics in cryptocurrency markets, where small retail investors may follow crypto whales’ movements that can be readily observed on blockchains. Central to this paper is the literature on investor sophistication and leader-follower behavior. While investor sophistication lacks a consistent definition, it tends to correlate with several factors, such as the amount of crypto holdings an individual possesses, the organization the investor belongs to or represents, the length of time the investor has been trading cryptocurrencies, and the complexity of instruments and features the investor uses (Liu, Makarov, and Schoar, 2023).

These differences in sophistication manifest in markedly different investment and trading behavior across both traditional and digital assets. Grinblatt and Keloharju (2000) find that sophisticated investors tend to buy past winning stocks and sell past losers, whereas unsophisticated investors tend to sell winners and hold on to losers, demonstrating the reluctance of small retail investors to realize losses. Additionally, the authors find that sophisticated investors tend to place less weight on past returns when deciding whether to buy or sell. Similarly, in their analysis of the Terra-Luna collapse, Liu et al. (2023) find that more sophisticated investors exited their positions sooner and consequently lost a smaller percentage of their holdings.

Feng and Seasholes (2005) explore, among other things, whether a combination of investor sophistication and trading experience could eliminate the tendency for less sophisticated investors to hold on to losing stocks. Related to this, while large investors are less likely to act immediately after a shock in the cryptocurrency market, all investors appear to prioritize news about specific currencies over general market sentiment (Łęt, Sobański, Świder, and Włosik, 2023). In an experimental setting, Victoravich (2010) finds that unsophisticated investors are more likely to be overly optimistic and overvalue favorable financial information. This finding aligns with recognized concepts within behavioral finance, highlighting how limited experience and knowledge among small retail investors can lead to cognitive biases — particularly excessive optimism regarding positive news coupled with insufficient understanding and analytical ability.

Literature on Crypto Returns and Volatility

Cavalheiro et al. (2024) find that investor psychology plays a persistent and significant role in shaping cryptocurrency market dynamics. Specifically, their results suggest that the returns of digital assets are strongly tied to investor sentiments and emotions. Auer et al. (2025) investigate the relationship between BTC price movements and retail investor behavior, finding that rising BTC prices attract retail investors motivated by speculation. This research highlights a dynamic whereby large investors tend to sell during price increases, likely profiting at the expense of smaller, less sophisticated investors who enter the market belatedly.

Kraus and Stoll (1972) and Holthausen et al. (1987) identify three primary explanations for potential price effects from whale-initiated transactions. First, liquidity costs (short-run price pressure): When a large investor wants to buy (or sell) a significant amount of assets, they may exhaust the available supply at the current bid price (or demand at the current ask price). Prices would generally revert to their previous equilibrium levels once the liquidity imbalance resolves. Second, inelastic demand curves (imperfect substitution): Assuming no close substitutes exist for a particular asset, a large purchase or sale by whales could result in a permanent shift in the equilibrium price. Third, information effects: Small investors tend to adjust their beliefs about the asset following whale trades, resulting in permanently lower or higher equilibrium prices. Consistent with these explanations, Chernoff, Jagtiani, and Yoshida (2026) find evidence that a digital currency's function tends to be network-dependent, based on chain-specific liquidity, investor composition (whales, institutional, retail investors), and other unique risk factors specific to blockchain networks.

Holthausen et al. (1987) document differential impacts of seller-initiated versus buyer-initiated transactions. They find that seller-initiated blocks primarily exhibit temporary price effects, while buyer-initiated blocks show permanent price effects, with the magnitude of these effects increasing with block size. Subsequent research expanded on these findings by examining the impact of additional factors such as volatility, market returns, and bid-ask spreads (see Chan and Lakonishok, 1997; Domowitz et al., 2001). Moreover, Frino et al. (2007) further refined the analysis by introducing intraday time dependencies and more precise measures of market returns, finding that liquidity, as proxied by bid-ask spreads, is also a significant determinant of the price impact of block trades. We add to this literature by exploring the impact of whale-initiated sell and whale-initiated buy transactions on cryptocurrency market activity, participants, and volatility.

Social media also plays a significant role in asset valuation. Min and Cai (2022) note that news, media, and other market signals also play an important role in shaping the market — with larger impacts on the volatile cryptocurrency markets than in traditional asset markets. Moreover, this influence is amplified by the transparency of the blockchain, allowing market leaders' actions to be observed by other market participants (small investors) with minimal delay. Long et al. (2024) use advanced sentiment analysis and time-varying parameter models to demonstrate that social media sentiment is often influenced by whales and significantly drives cryptocurrency volatility. Their findings reveal that whale activities are correlated with heightened market connectedness, particularly during periods of shock transmission. Closely related to social media are "whale alerts." Magner and Sanhueza (2025) use whale alerts to measure contagion on crypto returns post Bitcoin whale transactions.[5] We add to this literature by exploring trading activity among non-whale investors following each of the whale alerts in our sample period.

Ante, Fiedler, and Strehle (2021) estimate the impact of stablecoin transfers on BTC returns and trading volume. Analyzing large stablecoin transactions (exceeding $1 million), they find significant increases in BTC trading volume around these large stablecoin transfers, suggesting that crypto market participants react to on-chain activities, especially large on-chain transactions. Notably, the effects vary depending on specific characteristics of the transactions, showing distinct patterns. Similarly, Chernoff, Jagtiani, and Yoshida (2026) explore flight to safety behavior — transfers from cryptocurrency (BTC and ETH) to stablecoin following a series of shocks. They also

[5] Chernoff and Jagtiani (2025) analyze ETH transactions and pricing, showing that crypto whales, on average (at the segment level), tend to strategically increase their ETH holdings before price surges, while segments of retail investors reduce their ETH holdings, thus exacerbating wealth and return disparities.

find distinct patterns and heterogeneous behavior across blockchains, underscoring a more tailored regulatory approach (rather than a one-size-fits-all framework) that reflects diverse investor behavior, specific network dynamics, and evolving crypto market conditions.

III. The Data

Data on All On-Chain Crypto Transactions

We collect transaction-level data for the two largest cryptocurrencies — Ethereum (ETH), native Bitcoin (BTC), and wrapped Bitcoin (WBTC) using Google's Big Query.

The data set covers all on-chain transactions that involve ETH, BTC, and WBTC on the Ethereum blockchain network, as well as the Bitcoin blockchain during the following periods: ETH on the Ethereum network from August 7, 2015, to December 31, 2025; BTC on the Bitcoin blockchain from July 1, 2015, to December 31, 2025; and WBTC on the Ethereum network from January 7, 2019, to December 31, 2025. All the variables included in the analysis are summarized in **Table 1 Panel A**. The basic summary statistics of the data are presented in **Table 1 Panel B**.

Each crypto transaction contains information about the value being transferred, the timestamp of the transaction (i.e., the time the block was added to the blockchain), the sending and receiving addresses involved, the amount of the native token transferred, information regarding the transaction fees, and other information specific to the transaction such as smart contracts used. We denominate on-chain ETH and BTC transfers to US dollars by matching the transfer timestamp to high-frequency BTC/USD and ETH/USD prices from Tickstory from May 9, 2016, to December 31, 2025.[6] **Table 1A** in the appendix lists all the raw (on-chain) data items (and definitions) collected from Tickstory and other sources.

Data on Whale Alerts

We scrape the complete history of Whale Alert notifications for BTC, ETH, and WBTC from the service's inception on December 14, 2017, through December 31, 2025.[7] These alerts provide precise timestamps of when large transactions are publicly broadcast to Whale Alert's followers, allowing us to identify market responses to the dissemination of information on whale activity rather than to the underlying transactions themselves.

Because of blockchain transparency, investors can directly observe large transactions and the

[6] Tickstory is a database that has been used mostly by traders. It allows users to collect historical market data for traditional and digital assets. See https://tickstory.com/.

[7] For more details about Whale Alerts, see the link https://whale-alert.io/

type of counterparties involved (e.g., individual wallets versus exchanges). However, services such as Whale Alert reduce monitoring costs by aggregating and broadcasting these events in real time, thereby increasing their salience, particularly for less sophisticated investors. Since its inception, in December 2017, to December 2025, Whale Alert has issued 20,848 alerts for BTC transactions and 12,104 alerts for ETH transactions. From this data, we extract transaction timestamps and sizes, which we incorporate into our broader set of whale transactions identified from on-chain analysis.

Data on Investor Size Classification

While "whale investors" are recognized as significant market actors with substantial financial resources capable of influencing market dynamics, a universally accepted definition of their trading behavior does not exist. Because historical wallet-balance data are not available, we define whale investors based on trading activities: We define a whale wallet as a wallet that has conducted a transfer of more than $50 million at least once within our sample period. This threshold aligns with tracking practices used by organizations such as Whale Alert.[8]

We acknowledge that, without off-chain data, this approach may not perfectly link wallets to individual investors, as investors could distribute their holdings across multiple smaller wallets. Given the dramatic growth in digital assets over the last decade, we assert that both the sophistication of the holder (proxied by whale wallet status as described earlier) and the trade size relative to overall supply are crucial in determining market impact.[9] Both factors are incorporated into our analysis. Drawing on Holthausen et al. (1987), who employ metrics such as dollar value, normal volume, and percentage of active supply, and Frino et al. (2007), who examine various definitions of whale traders, our analysis investigates whether crypto whales significantly influence market dynamics.

In addition to exploring whales against non-whales, we further divide non-whale investors into three different size segments (large, medium, and small wallets) based on the largest transaction size that they have made during the relevant sample period. Specific definitions of the large, medium, and small retail investors are described below.

- Large: non-whale wallets with the largest size of transactions in the 95th percentile and above, excluding trades that are associated with exchanges or smart contracts
- Medium: non-whale wallets with the largest size of transactions in the 50th to 95th

[8] Refer to https://whale-alert.io/whales.html for whale definitions.

[9] Note that we have excluded large wallets that belong to a crypto exchange of smart contracts from our analysis.

percentile, excluding addresses that are classified as large

- Small: all remaining wallets with the largest size of transactions being below the 50th percentile

In the process of classifying non-whale wallets into the large, medium, and small segments, we focus on each wallet's activities during each six-month interval (not the entire sample period).[10] In particular, following Natashekara and Sampath (2024), we divide our data set into sub-periods of six-month intervals.[11] For each of these sub-periods, the non-whale wallets are classified into large, medium, or small based on the thresholds of the 95th and 50th percentiles based on all wallet activities during each six-month period. Thus, the pool of large, medium, or small non-whale investors in the analysis for each six-month interval would vary depending on the overall trading activities in each interval. Unlike non-whales, the set of whale investors remains the same (as described earlier) throughout the analysis.

Data on Non-Whale Activities During Relevant Event Windows and Other Control Factors

Given the total number of active wallets in each category in each six-month period (described above), we calculate the percentage of non-whale wallets that transfer ETH within (0, 15), (15, 30), (30,45), and (45, 60) minutes after a whale alert was sent out.[12] We compare these activity levels to a corresponding activities of the same non-whale wallets during the window of "normal" trading period, using the control period being the time interval (−15,0) which is the 15-minute window before each whale alert.

In our analysis of non-whale behaviors in relation to whale transactions, we control for the *type of whale trades*, distinguishing between whale trades that involve a sale versus a purchase. In addition, our analysis also controls for the *type of counterparties*, distinguishing individual wallets from wallets that belong to an exchange (such as Coinbase) and distinguishing transactions that involved smart contracts from others. For example, a large transfer from a whale investor to an

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[10] We choose to classify non-whale wallets into large, medium, and small segments based on a fixed six-month window, rather than a rolling six-month window, to keep the investors' size classification exogeneous to whale alert events. We expect that there would be an influx of non-whale investors entering the market following whale alert events, affecting the thresholds for the control group. In addition, data show that the non-whale tier assignments are highly stable across adjacent windows: about 20 percent (or less) of wallet addresses migrate.

[11] The six-month intervals (windows) are for January-June and July-December of each year. For Ethereum (ETH) data, we have 14 full intervals and two partial intervals. For Bitcoin (BTC) data, we have 11 full intervals and 1 partial interval.

[12] With t=0 being the whale alert event, the time intervals are (0,15), (0,30), (0,45), and (0,60) for ETH transactions that occur within the 15, 30, 45, and 60 minutes following a whale trade, respectively.

exchange may signal potential selling pressure or an impending sell-off and likely result in lower prices, while a transfer from an exchange could indicate accumulation, representing long-term holding strategies that reduce available supply and generally result in higher prices.

Finally, to isolate the effect of one whale transaction from other whale transactions that may occur within 120 minutes of each other, we include only those whale transactions that did not have another whale transaction occurring within plus or minus 120 minutes. This leaves us with the final sample of 6,645 BTC transactions by crypto whales and 5,075 ETH transactions by crypto whales.

Data on Buy versus Sell Activities

In addition to the cryptocurrency-specific analysis, we further differentiate the impact from whale buy versus whale sell transactions. Some of the observed transactions do not have a clear indication whether they were buy or sell transactions. In those cases, the observations are dropped in the buy versus sell analysis, resulting in a loss of about 1,000 whale transactions.[13] The final sample for the analysis for buy/sell transactions includes 3,471 buys and 2,413 sells of BTC (a total of 5,884 buy/sell BTC transactions) and 2,473 buys and 2,370 sells of ETH (a total of 4,843 buy/sell ETH transactions).

IV. Empirical Methodology

We test three hypotheses about the effects of crypto whale trades on the trading activity of non-whale (retail) traders.

Hypothesis I: Crypto whales behave differently than other investors in the cryptocurrency markets and whales' trading activities attract certain types of non-whale investors into the market, thus changing the composition of investors' participation following a whale trade.

Specifically, for each investor size group (small, medium, large) and for each currency (BTC, ETH, WBTC) we estimate Equation (1) to test whether the ratio of active investors to all investors in the size category has changed from pre-alert to post-alerts periods, where we look at four differ post-alert windows: 0 to15 minutes, 15 to 30 minutes, 30 to 45 minutes, and 45 to 60 minutes.[14]

[13] Due to a lack of a buy versus sell indicator for some of the whale alerts, we lost 761 BTC transactions and 232 ETH transactions in the final sample for all the analysis of buy/sell activities.

[14] Note that we consider only whale alerts associated with transactions of a specific cryptocurrency as being relevant for the non-whale participation rates for that cryptocurrency. That is, we use whale alerts on BTC in the analysis of BTC; whale alerts on WBTC in the analysis of WBTC; and whale alerts on ETH in the analysis of ETH.

$$Post\%_{iw} = \beta_0 + \beta_1 \, Control\%_i + \sum_{k=2}^{4} \gamma_k \, Window_{kw} + X_i + \varepsilon_{iw} \quad (1)$$

where:

- $Post\%_{iw}$ is the percent of active investors trading during one of the 15-minute windows following whale alert *i*.
- $Control\%_i$ is the percent of active investors trading during (-15,0) the 15-minute window before whale alert *i*.
- $Window_{kw}$ are dummies for the activity windows from (15, 30), (30, 45), and (45, 60) minutes after the whale alert.
- *Vector* X_i are controls:
  - $ln(Value_i)$ is the standardized natural log of the whale alert transaction (in U.S. dollars)
  - $Return_{1h}$ is the one-hour return preceding the alert (e.g., the return of ETH from 1–2 p.m. for an alert at 2 p.m.)
  - RV_{24h} is the 24-hour realized volatility preceding the alert
  - Hours fixed effect – 23 dummies, one for each hour of the day
  - Year fixed effect – dummy variable for each calendar year

The hour of day and the year fixed effects are included in Equation (1) to absorb systematic temporal patterns in investor activity. We estimate Equation (1) with standard errors clustered at the alert level since investor activity level violates independence across windows within the same alert.

The coefficient of interest is β_1. Under the null hypothesis, $\beta_1 = 1$, suggesting that the pre-alert share of a given investor category carries through to the post-alert window on a one-for-one basis (i.e., there is no change in investor composition from pre- to post-whale alerts). When the coefficient β_1 is significantly different from 1 (below or above unity), the post-alert share during the 15-minute window (0,15) has changed from the pre-alert (-15,0) baseline, implying a significant impact of whale transactions on the investor composition after a whale trade. The coefficients of each window dummy (after the 15-minute window) indicate the level of non-whale activities relative to the base case window period (0,15). A negative coefficient would suggest that the boost in non-whale activity starts to wind down after the first 15-minute window. We also explore whether the results may be affected by the change in infrastructure on the Ethereum network by conducting a separate analysis for the proof-of-work (PoW) and proof-of-stake (PoS) sub-periods defined by the Ethereum Merge of September 15, 2022.

Hypothesis II: There is "leader-follower" behavior in the market, by which non-whale investors perceiving that crypto whales have superior knowledge about the market tend to mimic whale behavior such that non-whale transactions would engage in the same side (buy vs. sell) as the whale.

Specifically, we test whether whales' trading activities, as reported on Whale Alerts, are followed by increased trading activity among non-whale investors, with retail traders selling after whale sells and buying after whale buys, by estimating Equation (2) separately for each currency, investor size group, and whale buy versus sell activities.[15] The intercept captures the average compositional shift attributable to a whale alert. This approach is analogous to event study methodologies, in which the abnormal change relative to a matched benchmark is the quantity of interest (MacKinlay, 1997), with the control period being 15 minutes before each whale alert (−15,0).

$$\Delta Share_{iw} = \beta_0 + \sum_{k=2}^{4} \gamma_k \, Window_{kw} + X_i + \varepsilon_{iw} \qquad (2)$$

where:

- $\Delta Share_{iw} = Post\%_{iw} - Control\%_{iw}$, which is the change in investor size category s share relative to the control period (15,0) window — 15 minutes pre-alert — share from the control window.
    - $Post\%_{iw}$ is the percent of active investors trading during one of the 15-minute windows following whale alert *i*
    - $Control\%_i$ is the percent of active investors trading during the 15-minute window before whale alert *i*
- $Window_{kw}$ are dummies for the activity windows from (15, 30), (30, 45), and (45, 60) minutes after the whale alert — with the base case being (0,15). The intercept β_0 may be considered that of the base case (0,15) relative to the control (-15,0) windows.
- The rest of the control factors are the same as those described earlier from Equation (1).

Hypothesis III: Crypto whales' trading activities have a significant impact on short-term crypto market volatility.

To test this hypothesis, we estimate Equation (3) separately for BTC and ETH transactions to see whether whale transactions are associated with elevated short-term or long-term price volatility after the whale alerts, controlling for time-of-day and day-of-week effect

$$Vol_{i,w} = \alpha + \beta_1 \, Whale_i + \sum_{k=2}^{5} \gamma_k \, Window_{kw} + \sum_{-k=2}^{5} \sigma_k \, Window_{kw} * Whale_i + \eta_h + \mu_d + \varepsilon_{i,w} \qquad (3)$$

where:

- $Vol_{i,w}$ (dependent variable) is the annualized volatility of minute-level returns measured over

[15] Liu, et al. (2023) find that large investors might be the next to follow the whales, especially for large transfers by the whales (probably because the value of their holdings would be more significantly affected by whale trades). In this case, we would expect a larger share of large, non-whale investors to engage in the same buy/sell activities following the whales' transactions.

window $w \in \{15, 30, 60\}$ minutes following (whale alerts) event i. We also explore the impact over longer windows of six, nine, and 24 hours. We compute two measures of the dependent variable as described below:

  - Annualized standard deviation of minute level returns
  - Annualized realized volatility, defined as the square root of the sum of squared returns scaled by the annualization factor

- $Whale_i$ is a dummy indicator equal to 1 for post-whale alert windows and 0 for matched control periods.
- $Window_{kw}$ are dummy indicators for the 15-, 30-, 60-, 360-, and 1,440-minute measurement windows, with the base case being the pre-alert period of the same interval window (15-, 30-, 60-,… minute windows before each alert).
- η_h and μ_d denote dummy indicators for hour of day and day of week fixed effects.
- Standard errors are heteroskedasticity robust (HC1).

The dependent variable in Equation (3) is realized volatility over the post-alert window (t, t+w].[16] The coefficient on each Whale × window term measures the incremental volatility relative to time-matched control periods, with window, hour-of-day, and day-of-week fixed effects and HC3 robust standard errors. We estimate the model for each alert-symbol and price-symbol pair to capture both own-market effects and cross-market spillovers. A positive β_1 indicates that whale alerts are followed by elevated volatility relative to comparable post-non-whale trading periods.

The interaction coefficients test for horizon dependence, where a negative coefficient for later interactive window variables would imply that the whale effect decays at longer windows, consistent with a transitory volatility spike, and an insignificant coefficient of the later interactions would suggest a persistent shift. This approach draws on the event study framework for volatility responses to information arrivals (Ederington and Lee, 1993; Andersen and Bollerslev, 1998).

V. Empirical Results

V.1 Composition of Non-Whale Participation Following Whale Alerts (Hypothesis I)

Before turning to the results based on estimation of Equation (1), we plot the raw mean participation share by investor size in the windows around each whale alert. **Figure 1, Panels A, B, and C** (the full

[16] This variable is computed as the square root of the summed squared one-minute log returns and annualized for comparability across horizons. Minutes without a price carry the previous minute's price forward, so the return is zero rather than missing. We control for realized volatility over a same-length window ending at t, which absorbs the prevailing volatility regime and the persistence that would otherwise carry into the outcome.

sample for BTC, WBTC, and ETH, respectively) show that the share of active non-whale BTC investors rises following a whale alert, with the increase largest for small and medium investors and at the 15-minute window. The corresponding ETH and WBTC plots show movements that are an order of magnitude smaller and less consistent across windows. These raw means point to a pronounced increase in non-whale BTC participation after whale alerts and at most a slight response on the Ethereum network.

Table 2 presents the estimates of Equation (1), which controls for the market environment and other relevant factors. Under the null hypothesis, β1 = 1, i.e., there is no change in the post-alert share compared with the pre-alert share. **Table 2, Panel A** covers the full sample (whale buys and sells pooled); **Table 2, Panels B and C** report the PoW and PoS sub-periods, respectively.

For BTC (columns 1–3, Panel A), β1 is 0.06, 0.00, and 0.00 for small, medium, and large investors, respectively — all far below one. The pre-alert share has little power to predict the post-alert share; post-alert participation is largely independent of which non-whale investors were active beforehand. Viewed together with the increase in the unconditioned means in **Figure 1**, this indicates that whale alerts draw a broad set of non-whale BTC investors into the market who were not active before the alert. These estimates are stable across Ethereum's transition to PoS (**Panels B and C**).

On the Ethereum network, the relationship is much closer to one-for-one. For ETH (columns 7–9), β1 is 0.71, 0.69, and 0.63 for small, medium, and large investors, respectively — below one but near enough to unity that the pre-alert levels of participation largely carry into the post-alert window. WBTC (columns 4–6) is similar, with coefficients (0.27, 0.31, and 0.51) far closer to one than those of native BTC on the Bitcoin blockchain. This shared ETH–WBTC pattern, and its contrast with native BTC, points to a network-dependent response, with whale activity propagating through the Ethereum ecosystem differently than through the Bitcoin blockchain — consistent with Chernoff, Jagtiani, and Yoshida (2026) and Anadu et al. (2024).

Among the control factors in Equation (1), the 24-hour pre-alert realized volatility (RV24h) is negative and significant for the smallest BTC and WBTC investors (−44.20 and −19.26) but not for the smallest ETH investors, and it is positive and significant for WBTC medium investors (50.55) and for the largest BTC and ETH investors (12.80 and 3.97). Recent returns (Return1h) now enter significantly for all three currencies, including BTC (22.61, 34.54, and 6.27 for small, medium, and large, respectively), as well as ETH and WBTC. The coefficients on whale transaction size, ln(Value), are small and mixed in sign.

V.2 Leader–Follower Behavior (Hypothesis II)

Before turning to the results based on estimation of Equation (2), we look at the raw data. **Figure 2** shows the average changes in non-whale trading buy (sell) activities following the whale buy (sell) alerts for the period up to 60 minutes following the relevant whale alerts. The raw data plotted in **Figure 2, Panel A** shows a significant increase in BTC buy activities (BTC sell activities) in response to a whale buy (whale sell) alert in the first 15 minutes. The activities then wane and return to normal within 60 minutes after the whale alerts. This behavior is observed across all investor size categories, where the increased activity is measured by the percentage increase in the ratio of market participants in each of the non-whale size categories.

Figure 2, Panels B and C show the data for WBTC and ETH, respectively. On the Ethereum network, the smallest retail investors reduce their activities in response to any whale activities regardless of whether it is a buy or sell by crypto whales. The largest non-whale investors increase their activities by buying when a whale buys and selling when a whale sells for both WBTC and ETH.

Tables 3 and 4 report estimates of the change model in Equation (2), in which the dependent variable is ΔShare, the post-alert participation share net of the matched control share, estimated separately for whale buys (**Table 3**) and whale sells (**Table 4**). The intercept captures the average abnormal change in participation attributable to the alert, in the spirit of the event-study abnormal response measure. A positive intercept in the buy model, paired with a positive intercept in the sell model, is the signature of leader–follower behavior: Non-whale investors buy after whale buys and sell after whale sells, during the period 15 minutes (base case) following a whale trade. For **Tables 3 and 4, Panel A** is the full sample, and **Panels B and C** are the PoW and PoS sub-periods, respectively. We report results for the full-sample **Panel A** regressions (below) unless stated otherwise.

For BTC, the leader–follower pattern is strong and directional. In the buy model (**Table 3 Panel A**) the intercepts are positive and significant at the 1 percent level — 14.81, 23.72, and 3.50 percentage points for small, medium, and large investors, respectively — so whale buys raise non-whale buy participation, most strongly among medium investors. The sell model (**Table 4, Panel A**) is broadly symmetric: the small, medium, and large sell intercepts are 12.95, 29.52, and 2.95, significant at the 5 percent, 1 percent, and 5 percent levels, respectively.

Among the control factors, we find that recent returns amplify the response. In the sell model, Return1h is positive and significant for BTC across all three sizes (157.19, 236.11, and 42.57 in **Table 4, Panel A**), consistent with non-whale investors trading on the joint signal of a whale transaction and recent momentum. In the buy model (**Table 3, Panel A**), Return1h is positive for all three wallet sizes (67.39, 106.39, and 20.53) but is not statistically significant for any non-whale investors.

On the Ethereum network, an immediate directional response is largely absent, except for the largest investors in the sell model (0.76, **Table 4 Panel A**). For WBTC, the intercepts are almost entirely insignificant; in the buy model, none of the three size categories is significant, and the only marginal exception is small investors in the sell model (7.63, significant at the 10 percent level, **Table 4, Panel A**). This behavior likely reflects how on-chain activity on the Ethereum network is dominated by institutional investors, exchanges, and smart contracts, and often involves transfers between institutions; much of the retail activity is located on exchanges and other layer-2 venues, which ultimately get rolled up into large balance transfers between exchanges.[17]

V.3 Whale Alerts and Short-Term Volatility (Hypothesis III)

Table 5 reports the results based on Equation (3), which relates short-term return volatility to whale alerts.

Whale alerts are associated with elevated BTC volatility at short horizons, and the effect is cross-asset. BTC's own alerts raise BTC realized volatility by 0.11 at 15 minutes, rising to about 0.22 by the six-to-nine-hour period (following the alert) before fading.

The ETH alerts have a near-identical effect on BTC volatility (0.11 rising to 0.21). The WBTC alerts produce the largest impact of all: 0.20 at 15 minutes, rising to 0.33, roughly double the own-Bitcoin effect, despite the much smaller sample. By the 24-hour period following whale alerts, the short-horizon increase has reversed for BTC alerts and ETH alerts (−0.12 and −0.14) and is indistinguishable from zero for WBTC, indicating a transitory volatility burst that dissipates within a day.

We find that ETH volatility moves in the opposite direction. Alerts of all three types are associated with significantly lower ETH realized volatility at every horizon, and increasingly so as the window lengthens; from roughly −0.21 to −0.23 at a 15-minute period to −0.61 to −0.67 at a 24-hour period following the whale alerts. These results imply that rather than triggering volatility, large Ethereum network transfers tend to occur during periods of declining volatility.

Overall, our results suggest that, following a whale-trading-activity alert, BTC volatility increases but ETH volatility decreases, with the largest effect being that of WBTC alerts on BTC volatility. **Figures 3 and 4** display these dynamics for BTC volatility and ETH volatility, respectively.

[17] Our analysis throughout the paper does not include transactions with crypto exchanges (such as Coinbase).

VI. Summary

This paper provides a comprehensive analysis of how crypto whale transactions shape non-whale market participation, trading direction, and short-term volatility across the Bitcoin (BTC), Ethereum (ETH), and Wrapped Bitcoin (WBTC) markets. Our empirical findings reveal a striking divergence in how retail investors respond to large-scale on-chain movements depending on the underlying network structure.

Whale alerts act as a powerful catalyst on the Bitcoin network, drawing in a broad cohort of previously inactive non-whale participants and triggering distinct leader-follower trading behaviors, but their impact on the Ethereum network is far more muted. In contrast to the Bitcoin network, non-whale market composition on the Ethereum network remains highly stable post-alert, and herd-following behavior is strictly confined to the largest non-whale investors.

Furthermore, our analysis reveals that whale alerts spark a 24-hour surge in BTC return volatility, particularly pronounced following WBTC trading activity by crypto whales, but coincide with a dampening of ETH volatility. Additionally, we find that these distinct behavioral and structural patterns persisted across Ethereum's historic transition from proof-of-work to proof-of-stake, implying that it is the underlying asset class and network culture, rather than the consensus mechanism, that drive non-whale dynamics.

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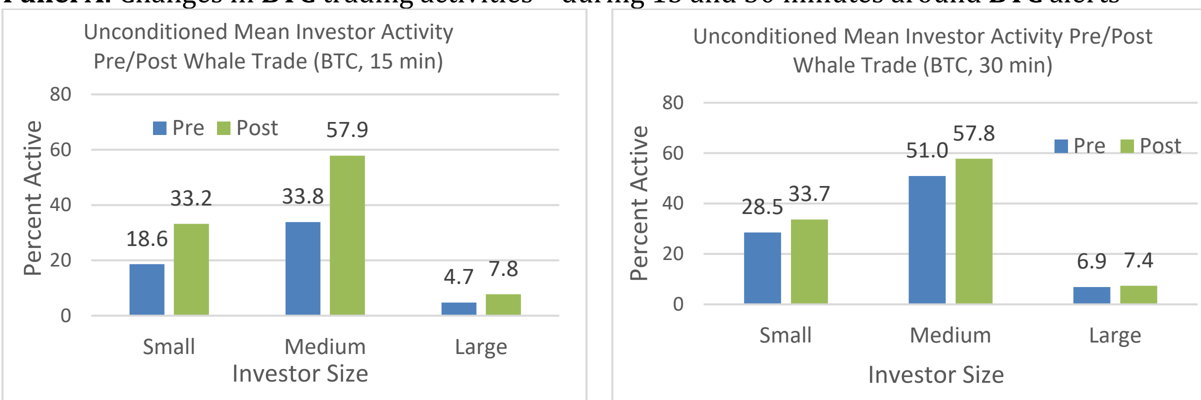
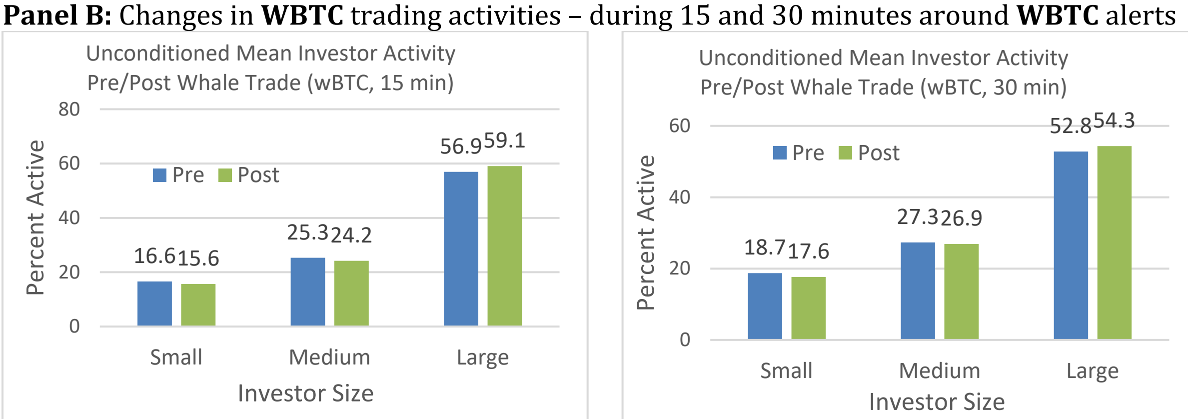
Figure 1: Changes in Non-whale Trading Activities
During 15- and 30-Minute Windows Around Whale Alert Events

The plots below explore activities of non-whale investors during pre- and post-whale alerts — showing average change in trading activities by investor size (changes in the percent of active small to total small; the percent of active medium to total medium; and the percent of active large to total large non-whale investors) during the period pre-alert and period 15 and 30 minutes after whale alert events.

Panel A: Changes in **BTC** trading activities – during 15 and 30 minutes around **BTC** alerts



Panel B: Changes in **WBTC** trading activities – during 15 and 30 minutes around **WBTC** alerts



Panel C: Changes in **ETH** trading activities – during 5 and 30 minutes around **ETH** alerts

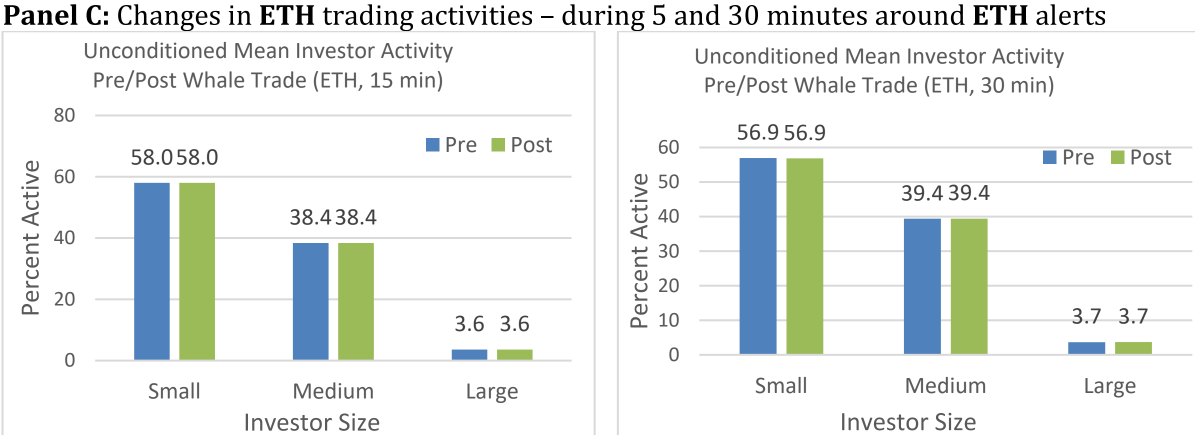
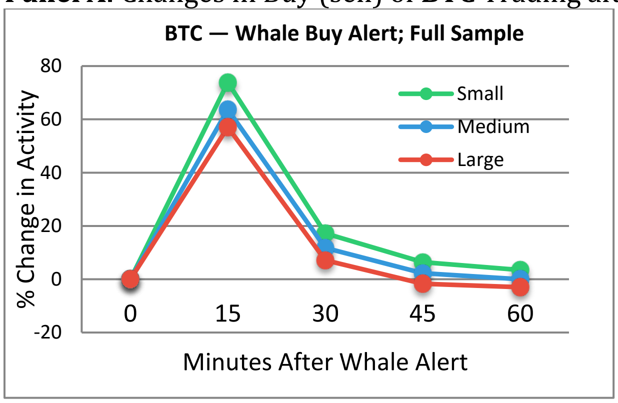
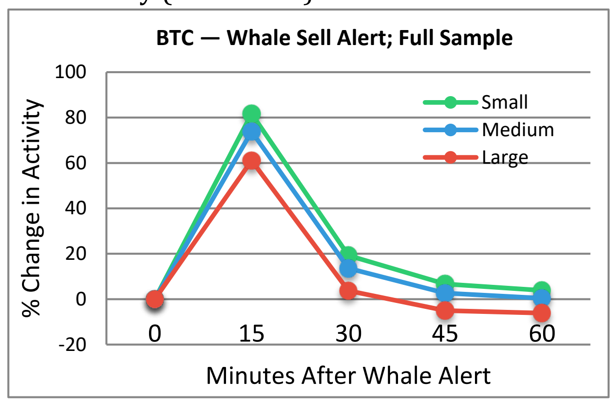


Figure 2: Percentage Change in Ratio of Non-whale Participation Buy (Sell) Following Whale Buy (Whale Sell) Relative to the Control Periods

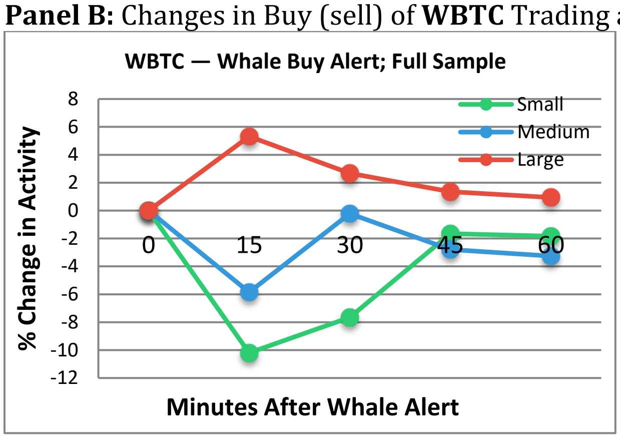
The plots below explore changes in buy (sell) activities of non-whale investors during the periods (windows 15, 30, 45, 60 minutes) after a whale buy (whale sell) alert — showing average change in buy (sell) activities by investor size (changes in the percent of active small to total small; the percent of active medium to total medium; and the percent of active large to total large nonwhale investors) during the period pre-alert and post-alert of whale buy (whale sell).

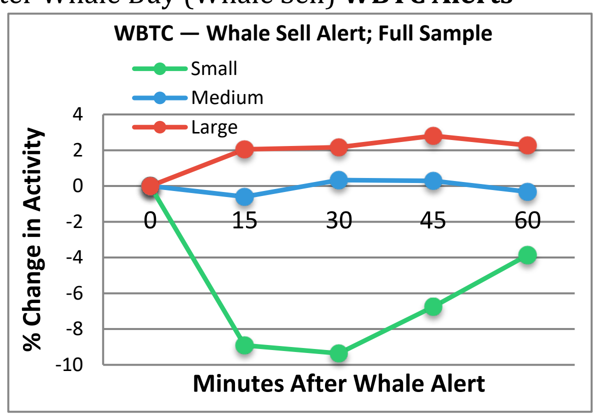
Panel A: Changes in Buy (sell) of **BTC** Trading after Whale Buy (Whale Sell) **BTC Alerts**



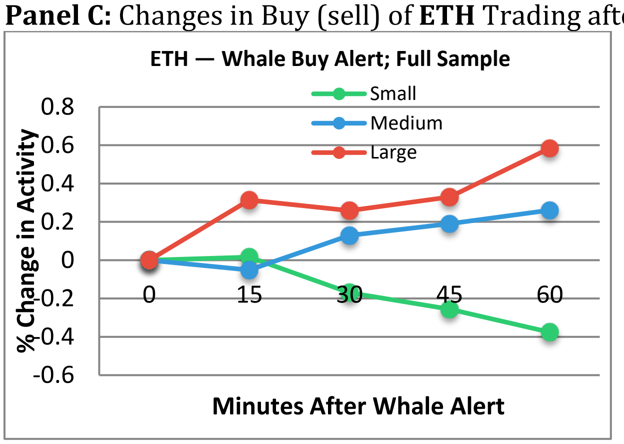


Panel B: Changes in Buy (sell) of **WBTC** Trading after Whale Buy (Whale Sell) **WBTC Alerts**





Panel C: Changes in Buy (sell) of **ETH** Trading after Whale Buy (Whale Sell) **ETH Alerts**



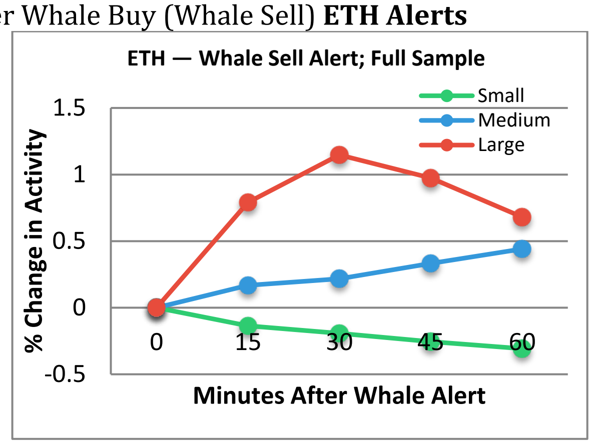
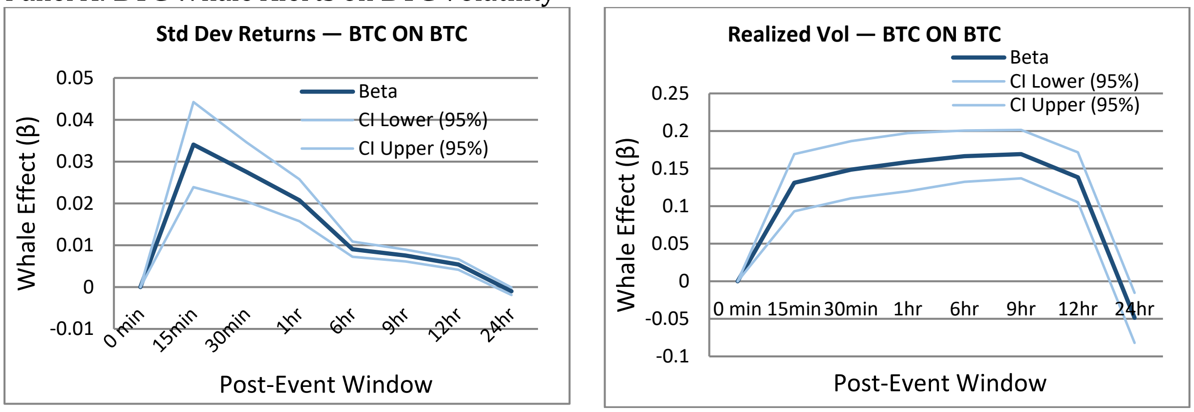
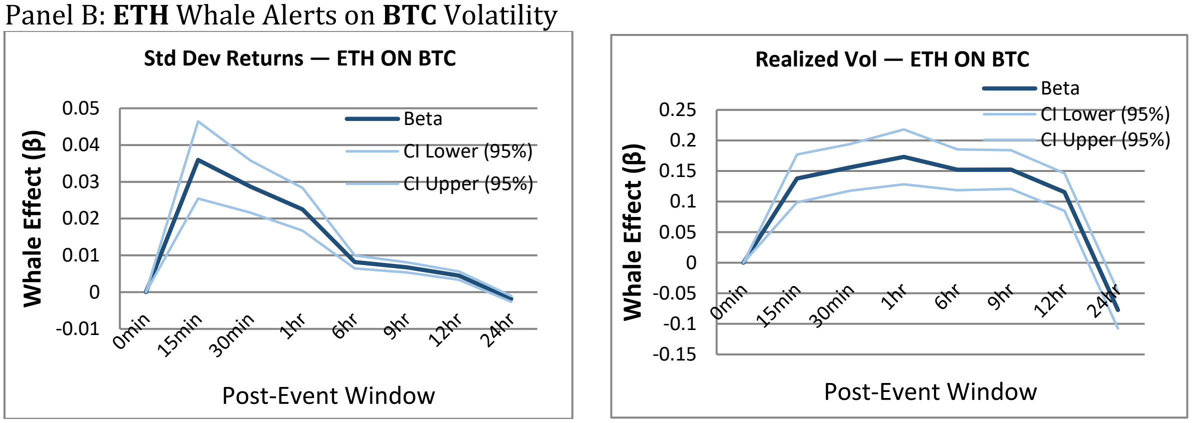


Figure 3: Whale Alert Impact on Bitcoin Price Volatility

Panel A: **BTC** Whale Alerts on **BTC** Volatility



Panel B: **ETH** Whale Alerts on **BTC** Volatility



Panel C: **WBTC** Whale Alerts on **BTC** Volatility

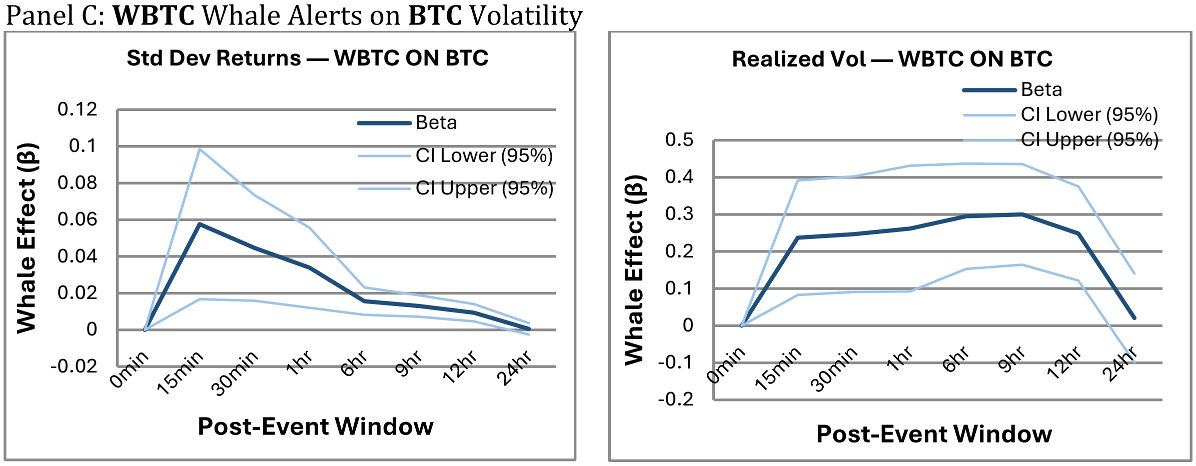
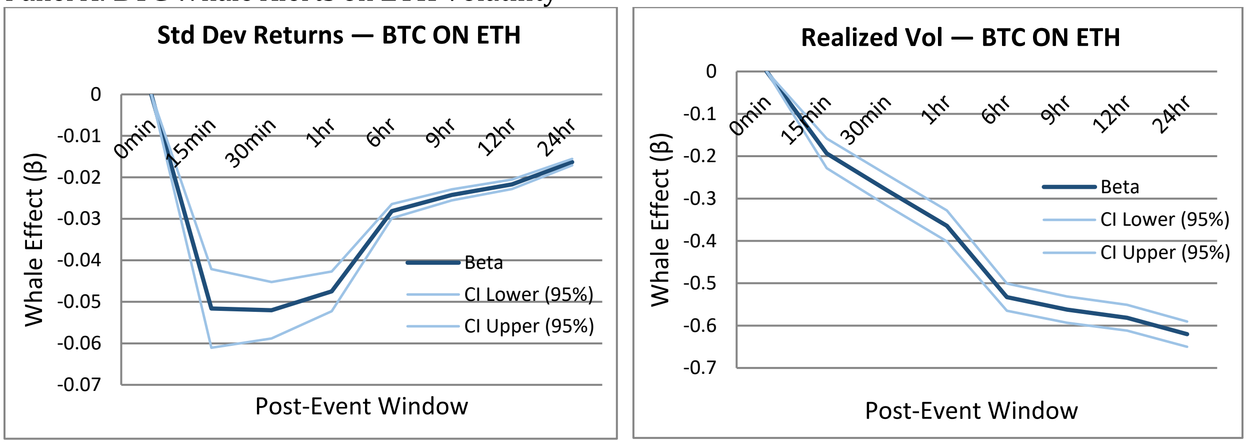
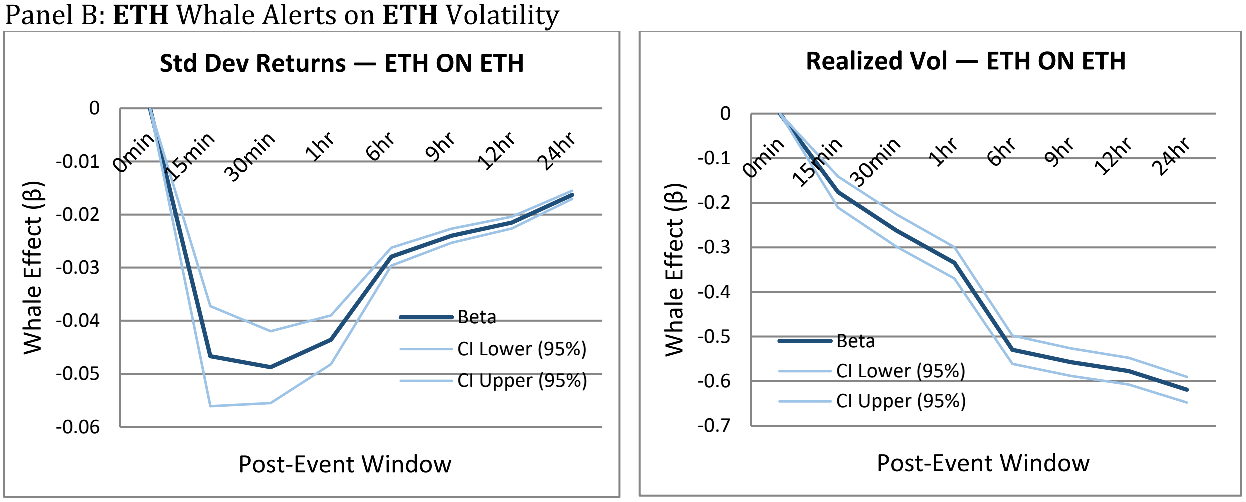


Figure 4: Whale Alert Impact on ETH Price Volatility

Panel A: **BTC** Whale Alerts on **ETH** Volatility



Panel B: **ETH** Whale Alerts on **ETH** Volatility



Panel C: **WBTC** Whale Alerts on **ETH** Volatility

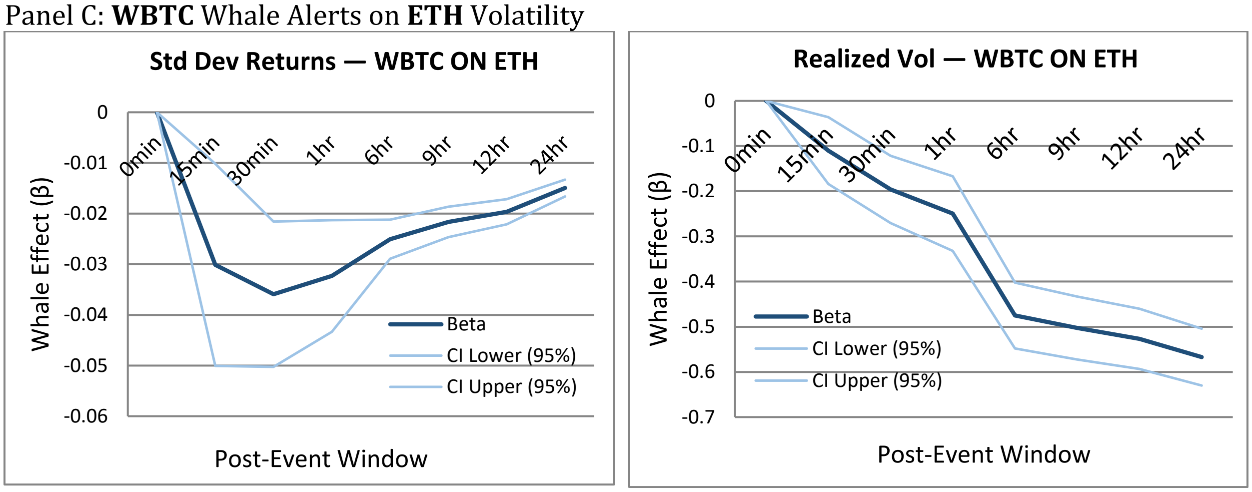


Table 1
List of Variables – with Definitions and Sources

Panel A1: Variables in Equation (1) - Composition Persistence (Levels Model)

Variable	Description	Source
$Post\%_{i,s,w}$	Percentage share of investor size category $s \in$ {Small, Medium, Large} in on-chain activity during the w-minute window following whale alert i	Google BigQuery
$Control\%_{i,s,w}$	Percentage share of investor size category s in on chain activity during the w-minute window before whale alert i	Google BigQuery
$\ln(Value_i)$	Natural log of the USD value of the whale alert transaction	Whale Alert
$Return_{1h}$	One hour same symbol return preceding the alert (e.g., the return of ETH from 1–2 p.m. for an alert at 2 p.m.)	Tickstory
RV_{24h}	24-hour same-symbol realized volatility preceding the alert	Tickstory
Hour FE	Hour of day fixed effects (23 dummies)	—
Year FE	Calendar year fixed effects	—
Window dummies	Indicator variables for measurement windows (15, 30, 45, 60 minutes); observations pooled across windows	—

Panel A2: Variables in Equation (2): Change in Investor Composition

Variable	Description	Source
$\Delta Share_{i,s,w}$	Post% minus Control%: the change in investor size category s share relative to the matched pre-alert control window	Google BigQuery
$\ln(Value_i)$	Natural log of the USD value of the whale alert transaction	Whale Alert
$Return_{1h}$	One-hour same-symbol return preceding the alert	Tickstory
RV_{24h}	24-hour same-symbol realized volatility preceding the alert	Tickstory
Hour FE	Hour of day fixed effects (23 dummies)	—
Year FE	Calendar year fixed effects	—
Window dummies	Indicator variables for measurement windows (15, 30, 45, 60 minutes)	—

Panel A3: Variables in Equation (3): Volatility Impact

Variable	Description	Source
$Vol_{i,w}$	Annualized volatility of minute level returns over window $w \in$ {15, 30, 60} minutes following event i. Two measures: annualized standard deviation and annualized realized volatility (square root of summed squared returns)	Tickstory
$Whale_i$	Indicator equal to 1 for post–whale alert windows and 0 for matched control periods. Whale sample restricted to isolated trades (±1 hour of no other whale activity)	Whale Alert
$Win30_i$	Indicator for the 30-minute measurement window (15 minute = baseline)	—

$Win60_i$	Indicator for the 60-minute measurement window	—
$Whale_i \times Win30_i$	Interaction: tests whether the whale volatility effect at 30 minutes differs from the 15-minute baseline	—
$Whale_i \times Win60_i$	Interaction: tests whether the whale volatility effect at 60 minutes differs from the 15-minute baseline	—
Hour FE	Hour of day fixed effects (23 dummies)	—
DoW FE	Day of week fixed effects (six dummies)	—

Panel B: Whale Sophistication Metrics: BTC vs. ETH

Mean and median values by chain (BTC N=82,352; ETH N=11,955). Value/flow figures are in native units (BTC or ETH)

Variable	BTC Mean	BTC Median	ETH Mean	ETH Median
Activity Metrics				
Days Active	54.28	0.00	320.29	87.00
Total Transactions	239.59	2.00	3,189.33	12.00
Transactions per Day	1.95	2.00	9.82	0.55
Transaction Value				
Mean Transaction Value	4,692.39	3,275.96	7,924.87	2,500.00
Median Transaction Value	4,652.31	3,263.87	6,416.62	580.47
Total Value Transferred	67,134.22	6,993.16	163,728.50	37,497.64
Smart Contract Usage (ETH only)				
Contract Interactions (%)	-	-	0.196	0.000
Unique Contracts	-	-	16.60	0.00
Contract Calls (%)	-	-	0.148	0.000
Success Rate	-	-	0.994	1.000
Gas/Fee Optimization				
Mean Gas Price (Gwei)/Fee	-	-	129.58	80.62
Gas Price CV	-	-	0.662	0.596
Gas Efficiency	-	-	0.806	0.880
Nonce Efficiency	-	-	0.337	0.004
Inflow/Outflow				
Total Incoming	33,568.01	3,494.98	74,250.68	17,295.57
Total Outgoing	33,566.21	3,495.10	89,515.79	18,949.97
Net Flow	1.79	0.00	−15,265.10	0.08
Net Flow (after fees/gas)	1.17	−0.00	−15,269.95	0.00
Network Effects				
Unique Counterparties	51.76	2.00	415.09	5.00
Top 5 Concentration	0.974	1.000	0.788	1.000
Herfindahl Index	0.478	0.500	0.294	0.250

Notes: Bitcoin does not have smart contract data nor gas/fee data.

Table 2: Level of Participation by Non-Whale Investors – in response to any Whale Alerts (both buy and sell) – Test of Composition Persistence (H_0: β1 = 1)

The analysis is based on Equation (1). The dependent *Post%*$_{i,s,w}$ is the ratio of all investors in each specific size category (small, medium, large) that have any trading activity during the observation windows. Independent variable *Control%*$_{i,s,w}$ is the ratio of all investors in each size category that have any trading activity during the control window period; *ln(Value$_i$)* is natural log of the whale alert transaction (in U.S. dollars); *Vector* X_i are measures of returns and volatility, which includes: Return_{1h} (one-hour return preceding the alert); RV_{24h} (24-hour realized volatility preceding the alert); Hours fixed-effect (23 dummies; one for each hour of the day); Year fixed-effect (dummy variable for each calendar year); Window dummies (indicating the whether the variables are measured during a 15-, 30-, 45-, or 60-minute window).

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10.

Sample period: August 2015 to December 2025. PoW sub-period is the period before September 15, 2022. PoS sub-period starts on September 16, 2022.

Note: β1 = coefficient on Control %. t(β1 = 1): stars indicate β1 ≠ 1. β1 < 1: mixing (whale alert homogenizes composition). β1 > 1: amplification.

$$Post\%_{iw} = \beta_0 + \beta_1\, Control\%_i + \sum_{k=2}^{4} \gamma_k\, Window_{kw} + X_i + \varepsilon_{iw} \qquad (1)$$

Panel 2A: Entire Sample Period

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Control %	0.06*** (0.01)	0.00 (0.00)	0.00 (0.01)	0.27*** (0.02)	0.31*** (0.03)	0.51*** (0.02)	0.71*** (0.01)	0.69*** (0.01)	0.63*** (0.01)
win 15	30.98*** (1.78)	52.30*** (2.84)	5.90*** (0.45)	8.03** (3.63)	16.81*** (3.69)	17.70*** (4.68)	14.72*** (0.59)	14.58*** (0.59)	0.97*** (0.11)
win 30	-7.13*** (0.25)	-12.38*** (0.40)	-1.60*** (0.06)	0.33 (0.50)	0.97* (0.50)	-1.32** (0.63)	0.04 (0.08)	-0.01 (0.08)	-0.03* (0.02)
win 45	-7.29*** (0.25)	-12.68*** (0.40)	-1.62*** (0.06)	0.63 (0.50)	1.01** (0.50)	-1.59** (0.63)	-0.02 (0.08)	0.05 (0.08)	-0.03** (0.02)
win 60	-7.29*** (0.25)	-12.70*** (0.40)	-1.65*** (0.06)	0.55 (0.50)	1.24** (0.50)	-1.79*** (0.63)	-0.09 (0.08)	0.13 (0.08)	-0.04** (0.02)
ln(Value)	0.20** (0.10)	0.01 (0.15)	0.00 (0.02)	0.13 (0.22)	-0.04 (0.22)	0.36 (0.28)	0.00 (0.03)	-0.03 (0.03)	0.02*** (0.01)
Return1h	22.61* (12.16)	34.54* (19.40)	6.27** (3.09)	40.46* (21.03)	-45.79** (21.23)	21.29 (26.70)	7.97*** (3.07)	-6.17** (3.02)	-1.99*** (0.61)
RV24h	-44.20*** (5.37)	0.13 (8.56)	12.80*** (1.36)	-19.26** (9.43)	50.55*** (9.69)	-16.62 (11.99)	-1.90 (1.39)	-0.80 (1.36)	3.97*** (0.29)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.18	0.10	0.18	0.15	0.26	0.37	0.59	0.57	0.54
N	24,408	24,408	24,408	1,572	1,572	1,572	19,940	19,940	19,940

Panel 2B: PoW Period Subsample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Control %	0.04*** (0.01)	0.00 (0.01)	-0.01* (0.01)	0.25*** (0.03)	0.31*** (0.03)	0.56*** (0.03)	0.67*** (0.01)	0.65*** (0.01)	0.60*** (0.01)
win 15	30.39*** (2.61)	51.13*** (3.54)	6.47*** (0.55)	6.74 (4.21)	14.13*** (4.40)	15.15*** (5.46)	17.76*** (0.83)	15.60*** (0.82)	1.09*** (0.14)
win 30	-8.08*** (0.36)	-11.51*** (0.49)	-1.44*** (0.08)	0.45 (0.62)	0.88 (0.64)	-1.36* (0.79)	0.04 (0.14)	0.02 (0.13)	-0.07*** (0.02)
win 45	-8.45*** (0.36)	-12.02*** (0.49)	-1.44*** (0.08)	0.76 (0.62)	0.91 (0.64)	-1.66** (0.79)	-0.05 (0.14)	0.11 (0.13)	-0.06** (0.02)
win 60	-8.41*** (0.36)	-11.85*** (0.49)	-1.42*** (0.08)	0.59 (0.62)	1.58** (0.64)	-2.18*** (0.79)	-0.14 (0.14)	0.22 (0.13)	-0.08*** (0.02)
ln(Value)	0.31** (0.15)	0.04 (0.20)	-0.01 (0.03)	0.17 (0.25)	0.05 (0.26)	0.29 (0.33)	-0.04 (0.04)	0.01 (0.04)	0.03*** (0.01)
Return1h	16.81 (15.42)	36.14* (20.92)	3.55 (3.24)	24.05 (24.47)	-44.80* (25.24)	43.10 (31.41)	8.85** (4.22)	-5.60 (4.15)	-3.38*** (0.76)
RV24h	-44.95*** (6.53)	0.98 (8.85)	10.15*** (1.37)	-15.98 (10.49)	48.52*** (10.95)	-12.38 (13.49)	-1.12 (1.82)	-2.03 (1.79)	4.10*** (0.35)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.08	0.07	0.08	0.14	0.26	0.40	0.55	0.54	0.46
N	13,692	13,692	13,692	1,048	1,048	1,048	10,508	10,508	10,508

Table 2C: PoS Period Subsample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Control %	0.09*** (0.01)	0.00 (0.01)	0.02** (0.01)	0.32*** (0.04)	0.25*** (0.05)	0.23*** (0.05)	0.74*** (0.01)	0.73*** (0.01)	0.65*** (0.01)
win 15	33.48*** (2.31)	57.70*** (4.60)	4.88*** (0.75)	11.93 (8.26)	17.07** (8.04)	45.47*** (10.42)	15.94*** (0.85)	9.62*** (0.75)	0.93*** (0.19)
win 30	-5.90*** (0.33)	-13.50*** (0.65)	-1.80*** (0.11)	0.08 (0.82)	1.15 (0.81)	-1.24 (0.99)	0.04 (0.09)	-0.05 (0.09)	0.01 (0.02)
win 45	-5.82*** (0.33)	-13.51*** (0.65)	-1.85*** (0.11)	0.36 (0.82)	1.22 (0.81)	-1.46 (0.99)	0.02 (0.09)	-0.01 (0.09)	-0.01 (0.02)
win 60	-5.85*** (0.33)	-13.78*** (0.65)	-1.93*** (0.11)	0.48 (0.82)	0.56 (0.81)	-1.00 (0.99)	-0.04 (0.09)	0.03 (0.09)	0.00 (0.02)
ln(Value)	0.10 (0.12)	-0.09 (0.24)	0.00 (0.04)	-0.06 (0.45)	-0.17 (0.45)	0.23 (0.55)	-0.01 (0.04)	0.00 (0.04)	0.00 (0.01)
Return1h	49.52** (20.68)	33.79 (41.26)	14.34** (6.71)	131.11*** (49.59)	-54.04 (49.02)	-87.26 (59.66)	1.98 (4.27)	-2.80 (4.13)	1.07 (1.07)
RV24h	-38.91*** (10.70)	3.46 (21.33)	25.36*** (3.47)	-18.49 (26.00)	83.31*** (26.96)	-50.37 (30.95)	-1.96 (2.29)	-1.66 (2.22)	5.11*** (0.59)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.07	0.15	0.25	0.17	0.19	0.69	0.67	0.61
N	10,716	10,716	10,716	524	524	524	9,432	9,432	9,432

Table 3: Change in Participation by Non-Whale Investors – in response to Whale Alerts BUY

The analysis is based on Equation (2). The dependent variable $\Delta Share_{i,s,w} = Post\%_{i,s,w} - Control\%_{i,s,}$, which is the change in investor size category s share relative to the matched pre-alert share from the control window. $Post\%_{i,s,w}$ is the ratio of all investors in each specific size category that have any trading activity during the observation windows. $Control\%_{i,s,}$ is the ratio of all investors in each size category that have any trading activity during the control window period; *ln(Value$_i$)* is natural log of the whale alert transaction (in US dollars); *Vector X_i* are measures of returns and volatility, which include: $Return_{1h}$ (the one-hour return preceding the alert); RV_{24h} (24-hour realized volatility preceding the alert); Hours fixed-effect (23 dummies one for each hour of the day); Year fixed-effect (a dummy variable for each calendar year); D_win = window-length dummies (15, 30, 45, or 60 minutes) — with baseline observation window being 15 minutes. Intercept: one-sided (H_1: positive).

Clustered standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10.
DV = Post % − Control %. Separate OLS estimated for each investor size category.

Sample period: August 2015 to December 2025. PoW sub-period is the period before September 15, 2022. PoS sub-period starts on September 16, 2022.

$$\Delta Share_{iw} = \beta_0 + \sum_{k=2}^{4} \gamma_k \, Window_{kw} + X_i + \varepsilon_{iw} \qquad (2)$$

Panel 3A: Changes in Investor Participation After Whale Alerts BUY – Full Sample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
DWin_15	14.81*** (3.01)	23.72*** (5.13)	3.50*** (0.82)	-3.85 (4.55)	0.06 (3.77)	3.56 (3.35)	0.66 (1.02)	-0.81 (1.05)	0.18 (0.16)
Dwin_30	-6.86*** (0.27)	-12.17*** (0.46)	-1.72*** (0.08)	0.76 (0.72)	1.15 (0.83)	-1.94* (1.01)	-0.07 (0.11)	0.08 (0.12)	-0.02 (0.03)
Dwin_45	-7.00*** (0.28)	-12.42*** (0.47)	-1.75*** (0.08)	1.94** (0.85)	0.99 (0.75)	-2.88*** (0.97)	-0.07 (0.13)	0.09 (0.13)	-0.03 (0.03)
Dwin_60	-7.26*** (0.28)	-12.57*** (0.47)	-1.79*** (0.08)	0.30 (0.79)	1.31 (0.85)	-1.58 (1.04)	-0.11 (0.14)	0.10 (0.14)	-0.00 (0.03)
ln(Value)	0.56 (0.52)	0.49 (0.86)	0.08 (0.14)	-0.59 (0.83)	0.57 (0.66)	-0.04 (0.81)	-0.04 (0.15)	0.02 (0.15)	0.03 (0.02)
Return1h	67.39 (46.46)	106.39 (85.78)	20.53 (14.61)	84.14 (93.01)	-111.44 (77.56)	25.17 (87.49)	6.94 (11.69)	-6.56 (11.64)	0.67 (2.69)
RV24hr	-15.97 (20.92)	3.09 (36.60)	5.59 (6.26)	-20.12 (31.74)	-8.97 (27.53)	28.37 (38.07)	-3.29 (4.59)	4.29 (4.65)	-0.95 (0.84)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.03	0.03	0.06	0.07	0.10	0.05	0.05	0.03
N	11,152	11,152	11,152	752	752	752	7,856	7,856	7,856

Panel 3B: Changes in Investor Participation After Whale Alerts BUY – PoW Period Subsample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
DWin_15	16.02*** (3.79)	26.97*** (5.68)	3.93*** (0.88)	-4.50 (4.35)	0.28 (3.98)	3.94 (3.42)	0.59 (1.15)	-0.76 (1.17)	0.20 (0.17)
Dwin_30	-8.07*** (0.42)	-11.40*** (0.60)	-1.52*** (0.10)	0.81 (0.82)	1.27 (0.97)	-2.15* (1.16)	-0.03 (0.16)	0.04 (0.16)	-0.02 (0.03)
Dwin_45	-8.37*** (0.44)	-11.79*** (0.60)	-1.47*** (0.11)	2.41** (0.99)	0.66 (0.87)	-3.04*** (1.07)	-0.04 (0.18)	0.06 (0.18)	-0.05 (0.03)
Dwin_60	-8.52*** (0.43)	-11.62*** (0.60)	-1.49*** (0.10)	-0.14 (0.88)	1.88* (0.97)	-1.72 (1.24)	-0.12 (0.19)	0.12 (0.20)	-0.02 (0.03)
ln(Value)	0.44 (0.70)	0.13 (1.02)	0.01 (0.16)	-0.80 (0.91)	0.39 (0.80)	0.34 (0.88)	-0.01 (0.16)	-0.03 (0.16)	0.04* (0.03)
Return1h	81.54 (58.61)	86.87 (98.44)	18.96 (16.31)	158.87 (98.33)	-124.78 (86.11)	-34.26 (95.20)	8.45 (14.15)	-7.56 (14.08)	0.40 (2.55)
RV24hr	-20.52 (24.57)	-11.53 (40.73)	3.65 (7.14)	-54.54 (35.33)	2.30 (23.80)	51.53 (38.64)	-2.37 (5.38)	3.27 (5.46)	-0.85 (0.90)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.04	0.04	0.11	0.08	0.11	0.07	0.07	0.04
N	5,820	5,820	5,820	564	564	564	5,404	5,404	5,404

Panel 3C: Changes in Investor Participation After Whale Alerts BUY – PoS Period Subsample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Dwin_15	8.64*** (2.98)	10.22** (5.97)	1.25* (0.88)	0.19 (5.87)	8.32** (4.71)	-8.53 (7.03)	0.92** (0.48)	-1.01 (0.51)	0.09 (0.15)
Dwin_30	-5.54*** (0.34)	-13.00*** (0.72)	-1.94*** (0.13)	0.61 (1.69)	0.81 (1.74)	-1.32 (2.28)	-0.16 (0.11)	0.18* (0.11)	-0.02 (0.06)
Dwin_45	-5.52*** (0.34)	-13.11*** (0.73)	-2.05*** (0.13)	0.54 (1.81)	2.01 (1.55)	-2.41 (2.39)	-0.15 (0.12)	0.14 (0.12)	0.01 (0.06)
Dwin_60	-5.88*** (0.36)	-13.61*** (0.74)	-2.11*** (0.13)	1.60 (1.88)	-0.38 (1.87)	-1.18 (2.08)	-0.09 (0.13)	0.06 (0.13)	0.03 (0.07)
ln(Value)	1.04 (0.70)	1.60 (1.67)	0.23 (0.28)	1.18 (1.60)	3.86*** (1.43)	-4.91** (1.96)	-0.26 (0.22)	0.40* (0.21)	-0.14** (0.07)
Return1h	35.23 (72.46)	166.07 (180.68)	29.70 (31.97)	- 851.59*** (236.66)	-494.73** (214.40)	1302.21*** (233.67)	0.15 (13.48)	-1.24 (13.13)	1.10 (8.76)
RV24hr	-12.21 (41.53)	68.59 (83.64)	16.63 (14.42)	113.44 (78.58)	-140.59* (83.29)	26.39 (99.91)	-6.71 (5.67)	8.03 (5.64)	-1.33 (2.13)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.04	0.35	0.38	0.39	0.04	0.04	0.04
N	5,332	5,332	5,332	188	188	188	2,452	2,452	2,452

Table 4: Change in Participation by Non-Whale Investors – in response to Whale Alerts SELL

The analysis is based on Equation (2). The dependent variable $\Delta Share_{i,s,w}$ = $Post\%_{i,s,w}$ – $Control\%_{i,s}$, which is the change in investor size category s share relative to the matched pre-alert share from the control window. $Post\%_{i,s,w}$ is the ratio of all investors in each specific size category that have any trading activity during the observation windows. $Control\%_{i,s,}$ is the ratio of all investors in each size category that have any trading activity during the control window period. *ln(Value$_i$)* is natural log of the whale alert transaction (in U.S. dollars); *Vector X_i* are measures of returns and volatility, which include: $Return_{1h}$ (the one-hour return preceding the alert); RV_{24h} (the 24-hour realized volatility preceding the alert); Hours fixed-effect (23 dummies; one for each hour of the day); Year fixed-effect (a dummy variable for each calendar year); D_win = window-length dummies (15, 30, 45, or 60 minutes) — with the baseline observation window being 15 minutes. Intercept: one-sided (H_1: positive).

Clustered standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10.

DV = Post % − Control %. Separate OLS estimated for each investor size category.

Sample period: August 2015 to December 2025. PoW sub-period is the period before September 15, 2022. PoS sub-period starts on September 16, 2022.

$$\Delta Share_{iw} = \beta_0 + \sum_{k=2}^{4} \gamma_k \, Window_{kw} + X_i + \varepsilon_{iw} \qquad (2)$$

Panel 4A: Changes in Investor Participation After Whale Alerts SELL – Full Sample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Dwin_15	12.95** (5.81)	29.52*** (7.91)	2.95** (1.72)	7.63* (4.93)	-11.27 (4.45)	3.56 (7.27)	-2.61 (1.35)	2.00* (1.25)	0.76*** (0.27)
Dwin_30	-7.45*** (0.42)	-13.47*** (0.63)	-1.92*** (0.12)	-0.84 (0.92)	1.19 (1.04)	-0.40 (1.41)	0.08 (0.09)	-0.06 (0.08)	-0.02 (0.03)
Dwin_45	-7.45*** (0.43)	-12.21*** (0.62)	-1.57*** (0.13)	-0.84 (0.98)	-0.17 (0.88)	1.00 (1.13)	0.06 (0.10)	0.01 (0.09)	-0.07*** (0.03)
Dwin_60	-7.59*** (0.44)	-12.79*** (0.63)	-1.68*** (0.13)	-1.17 (0.86)	-0.07 (0.99)	1.24 (1.11)	-0.02 (0.11)	0.11 (0.10)	-0.09*** (0.03)
ln(Value)	-0.20 (0.76)	1.07 (1.29)	0.32 (0.25)	0.23 (2.03)	-0.79 (1.62)	0.52 (2.72)	-0.16 (0.15)	0.09 (0.15)	0.05 (0.03)
Return1h	157.19*** (50.80)	236.11*** (89.39)	42.57** (16.95)	67.44 (52.56)	32.65 (68.34)	-99.63 (70.83)	6.05 (9.63)	-5.17 (9.35)	-0.62 (2.12)
RV24hr	14.48 (23.89)	20.91 (38.20)	9.23 (7.39)	46.11 (28.07)	45.64 (28.24)	-91.49** (39.76)	-3.06 (4.05)	5.00 (3.86)	-2.04 (1.43)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.03	0.03	0.29	0.17	0.24	0.02	0.02	0.06
N	7,180	7,180	7,180	432	432	432	8,052	8,052	8,052

Panel 4B: Changes in Investor Participation After Whale Alerts SELL – PoW Period Subsample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Dwin_15	19.48*** (6.57)	37.13*** (8.68)	4.24*** (1.75)	-3.26 (4.43)	-15.96 (6.44)	19.22*** (6.45)	-1.82 (1.36)	1.26 (1.23)	0.98*** (0.38)
Dwin_30	-7.73*** (0.57)	-12.42*** (0.76)	-1.64*** (0.14)	-0.46 (1.55)	0.95 (1.53)	-0.49 (2.12)	0.13 (0.16)	-0.02 (0.15)	-0.11** (0.05)
Dwin_45	-7.78*** (0.57)	-10.87*** (0.75)	-1.18*** (0.15)	-0.31 (1.60)	0.51 (1.21)	-0.20 (1.86)	0.00 (0.17)	0.12 (0.16)	-0.13** (0.05)
Dwin_60	-8.44*** (0.60)	-12.36*** (0.77)	-1.36*** (0.15)	-0.16 (1.41)	-0.37 (1.51)	0.53 (1.62)	0.06 (0.18)	0.14 (0.18)	-0.21*** (0.05)
ln(Value)	0.75 (1.09)	2.03 (1.73)	0.72** (0.28)	-2.69 (2.43)	-2.84 (2.30)	5.52** (2.65)	-0.22 (0.22)	0.11 (0.20)	0.08* (0.05)
Return1h	150.30** (58.83)	294.13*** (94.34)	56.31*** (17.52)	-78.75 (174.63)	65.25 (152.18)	13.50 (137.03)	4.68 (11.02)	-0.92 (10.64)	-3.36 (2.71)
RV24hr	6.89 (26.91)	30.02 (39.82)	7.80 (7.74)	72.30** (34.39)	49.45 (41.66)	-121.75** (49.18)	-4.32 (4.75)	7.34* (4.38)	-3.03* (1.80)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	0.04	0.04	0.04	0.37	0.36	0.42	0.04	0.04	0.03
N	4,296	4,296	4,296	212	212	212	3,232	3,232	3,232

Panel 4C: Changes in Investor Participation After Whale Alerts SELL – PoS Period Subsample

Variables	BTC			WBTC			ETH		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Dwin_15	14.01*** (4.49)	21.23*** (7.91)	2.81** (1.29)	10.67** (5.32)	-1.15 (4.89)	-9.51 (6.70)	-0.88 (0.85)	0.64 (0.81)	0.25** (0.14)
Dwin_30	-7.03*** (0.61)	-15.04*** (1.07)	-2.34*** (0.23)	-1.21 (1.13)	1.42 (1.51)	-0.30 (2.00)	0.05 (0.10)	-0.09 (0.09)	0.04 (0.03)
Dwin_45	-6.97*** (0.64)	-14.21*** (1.08)	-2.14*** (0.23)	-1.35 (1.27)	-0.82 (1.35)	2.17 (1.43)	0.09 (0.11)	-0.07 (0.11)	-0.03 (0.02)
Dwin_60	-6.33*** (0.64)	-13.44*** (1.06)	-2.15*** (0.22)	-2.14** (1.07)	0.21 (1.40)	1.92 (1.62)	-0.08 (0.13)	0.09 (0.13)	-0.02 (0.03)
ln(Value)	-1.05 (1.03)	0.61 (1.96)	-0.02 (0.42)	4.98* (2.98)	-4.16** (2.10)	-0.90 (4.08)	-0.04 (0.22)	0.01 (0.21)	0.03 (0.04)
Return1h	215.53** (99.23)	62.09 (211.56)	5.92 (43.02)	38.07 (124.33)	-115.03 (159.47)	73.63 (160.16)	7.25 (19.78)	-13.10 (20.04)	5.94 (4.04)
RV24hr	26.37 (52.95)	-65.21 (114.21)	7.19 (21.77)	221.28* (120.62)	-63.16 (112.68)	-158.20 (157.63)	2.90 (8.48)	-2.70 (8.21)	-0.30 (1.82)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	0.06	0.05	0.05	0.50	0.34	0.36	0.02	0.02	0.11
N	2,884	2,884	2,884	220	220	220	4,820	4,820	4,820

Table 5: Whale Alert Impacts on Crypto Realized Volatility

We test whether whale transactions are associated with elevated short-term price volatility after whale alerts, based on Equation (3). Dependent variable $Vol_{i,w}$ is the annualized volatility of minute-level returns measured over window $w \in \{15, 30, 60\}$ minutes following (whale alerts) event *i*. We also explore the impact over longer windows of six, 24, and 48 hours. We compute two measures of the dependent variable as described below: 1) Std Dev, which is the annualized standard deviation of minute-level returns; 2) Volatility, which is annualized realized volatility, defined as the square root of the sum of squared returns scaled by the annualization factor. Independent variable $Whale_i$ is a dummy indicator equal to 1 for post-whale alert windows and 0 for matched control periods; $Win15_i$, $Win30_i$, and $Win60_i$ are dummy indicators for the 15-, 30-, and 60-minute measurement windows, with the base case being the pre-alert window.

The significant levels: *** is p<0.01, ** is p<0.05, and * is p<0.10.

OLS stacked interaction model. DV=Realized Volatility pooled across all windows.

Each coefficient β̂_w from v_{i,w} = Σ_w β_w (Whale_i × W_w) + γ_w + γ_h + δ_d + ε_{i,w}, where γ_w, γ_h, δ_d are window, hour, and day-of-week fixed effects. HC3.

	Impact on BTC Realized Volatility			Impact on ETH Realized Volatility		
	BTC Alert on BTC	ETH Alert on BTC	WBTC Alert on BTC	BTC Alert on ETH	ETH Alert on ETH	WBTC Alert on ETH
D_15min	0.11*** (0.02)	0.11*** (0.02)	0.20*** (0.07)	-0.21*** (0.02)	-0.23*** (0.02)	-0.11*** (0.04)
D_30min	0.12*** (0.02)	0.13*** (0.02)	0.23*** (0.06)	-0.28*** (0.02)	-0.31*** (0.02)	-0.23*** (0.04)
D_1hr	0.15*** (0.02)	0.15*** (0.02)	0.28*** (0.06)	-0.37*** (0.02)	-0.40*** (0.02)	-0.29*** (0.04)
D_6hr	0.22*** (0.02)	0.20*** (0.02)	0.33*** (0.06)	-0.52*** (0.02)	-0.58*** (0.02)	-0.52*** (0.04)
D_9hr	0.22*** (0.02)	0.21*** (0.02)	0.33*** (0.06)	-0.56*** (0.02)	-0.60*** (0.02)	-0.53*** (0.04)
D_12hr	0.16*** (0.02)	0.15*** (0.02)	0.26*** (0.06)	-0.58*** (0.02)	-0.62*** (0.02)	-0.56*** (0.03)
D_24hr	-0.12*** (0.02)	-0.14*** (0.02)	-0.01 (0.06)	-0.63*** (0.02)	-0.67*** (0.02)	-0.61*** (0.03)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.05	0.21	0.06	0.06	0.03
Observations	38,419	29,542	2,913	97,960	87,748	48,378

Appendix: Table 1A
List of On-Chain Data (Raw Data Items and Sources)

Data Sources	Data Items	Description of Data Items
Tickstory[1] 5/9/2016 to 12/31/2025	price	Price ticks of assets at second/minute/day frequency
Whale Alert[2] 11/17/2017 to 12/31/2025	timestamp symbol amount value_usd text	Timestamp of whale transaction Symbol of token transferred (eg. USDT) Quantity in native tokens Value of transfer in USD Description of transfer (eg "transferred from unknown wallet to #Okex")
BigQuery 8/7/2015 to 12/31/2025 Ethereum Transactions	hash nonce transaction_index from_address to_address value gas gas_price input receipt_cumulative_gas_used receipt_gas_used receipt_contract_address receipt_root receipt_status block_timestamp block_number block_hash max_fee_per_gas max_priority_fee_per_gas transaction_type receipt_effective_gas_price max_fee_per_blob_gas blob_versioned_hashes receipt_blob_gas_price receipt_blob_gas_used	Hash of the transaction The number of transactions made by the sender prior to this one Integer of the transactions index position in the block Address of the sender Address of the receiver (null when it is a contract creation transaction) Value transferred in Wei Gas provided by the sender Gas price provided by the sender in Wei The data sent along with the transaction The total amount of gas used when this transaction was executed in the block The amount of gas used by this specific transaction alone The contract address created, if the transaction was a contract creation, otherwise null 32 bytes of post-transaction stateroot (pre Byzantium) Value=1 (success) or 0 (failure) (post Byzantium) Timestamp of the block where this transaction was in Block number where this transaction was in Hash of the block where this transaction was in Total fee that covers both base and priority fees Fee given to miners to incentivize them to include the transaction Transaction type The actual value per gas deducted from the senders account. Replacement of gas_price after EIP-1559 The maximum fee a user is willing to pay per blob gas A list of hashed outputs from kzg_to_versioned_hash Blob gas price Blob gas used
BigQuery 8/7/2015 to 12/31/2025 Bitcoin Transactions	hash size virtual_size version lock_time	The hash of this transaction The size of the transaction in bytes The virtual transaction size (differs from size for witness transactions) Protocol version specified in block which contained this transaction Earliest time that miners can include the transaction in a block

	block_hash block_number block_timestamp block_timestamp_month in- put_count output_count input_value output_value is_coinbase fee	Hash of the block which contains this transaction Number of the block which contains this transaction Timestamp of the block which contains this transaction Month of the block which contains this transactionThe num- ber of inputs in the transaction The number of outputs in the transaction Total value of inputs in the transaction Total value of outputs in the transaction True if this transaction is a coinbase transaction The fee paid by this transaction
BigQuery 8/7/2015 to 12/31/2025 Inputs (repeated record)	index spent_ transaction_hash spent_output_index script_asm script_hex sequence required_signatures type addresses value	0-indexed number of an input within a transaction The hash of the transaction containing the output that this input spends The index of the output this input spends Symbolic representation of Bitcoin script op-codes Hexadecimal representation of Bitcoin script op-codes Number used for transaction replacement or locktime disa- bling Number of signatures required to authorize the spent output Address type of the spent output Addresses which own the spent output Value attached to the spent output
BigQuery 8/7/2015 to 12/31/2025 Outputs (repeated record)	Index script_asm script_hex required_signatures type addresses value	0-indexed number of an output within a transaction Symbolic representation of Bitcoin script op-codes Hexadecimal representation of Bitcoin script op-codes Number of signatures required to spend this output Address type of the output Addresses which own this output Value attached to this output
BigQuery 8/7/2015 to 12/31/2025 Contracts	address bytecode function_sighashes is_erc20 is_erc721 block_timestamp block_number block_hash	Address of the contract Bytecode of the contract 4-byte function signature hashes Whether this contract is an ERC20 contract Whether this contract is an ERC721 contract Timestamp of the block where this contract was created Block number where this contract was created Hash of the block where this contract was created
BigQuery 8/7/2015 to 12/31/2025 Token_Transfers	token_address from_address to_address value transaction_hash log_index block_timestamp block_number block_hash	ERC20 token address Address of the sender Address of the receiver Amount of tokens transferred (ERC20) or id of the token transferred (ERC721). Use safe_cast for casting to NUMERIC or FLOAT64 Transaction hash Log index in the transaction receipt Timestamp of the block where this transfer was in Block number where this transfer was in Hash of the block where this transfer was in
Note 1: Tickstory is a database that has been used mostly by traders. It allows users to collect historical market data for traditional and digital assets. See https://tickstory.com/.		