How Do Large, Sophisticated Cryptocurrency Trades Impact Broader DeFi Market Dynamics?

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Abstract

Using transaction-level on-chain data for Bitcoin (BTC), Ethereum (ETH), and Wrapped Bitcoin (WBTC) matched to public Whale Alert signals (2017–2025), we test whether large "whale" trades change which non-whale investors are active, trigger leader–follower herding, and raise short-term volatility. Whale alerts sharply reshape BTC participation and are followed by same-direction trading by smaller investors; on the Ethereum network, participation stays stable and herding is confined to the largest non-whales. Alerts precede a transitory BTC volatility spike (largest after WBTC alerts) but lower ETH volatility. These asymmetries persist across Ethereum's move from proof-of-work to proof-of-stake.

Introduction

- Crypto market value rose from about $4 billion (2015) to a $4.35 trillion peak (Oct 2025); more than 560 million people now hold crypto.
- On-chain trades are transparent but pseudonymous: anyone can watch large "whale" wallets move funds in near real time.
- Retail investors face information asymmetry and few protections; the GENIUS Act (2025) and proposed CLARITY Act are only starting to address this.
- Large trades can move prices through liquidity, imperfect-substitution and information channels (Kraus & Stoll, 1972; Holthausen et al., 1987).

Research question: Do whale trades change who trades, which way they trade, and how volatile the market is?

Data

- All on-chain BTC (Bitcoin blockchain) and ETH and WBTC (Ethereum network) transfers, 2015–2025, from Google BigQuery; minute-level prices from Tickstory.
- Whale Alert history, Dec 2017–Dec 2025: 20,848 BTC and 12,104 ETH alerts; 6,645 BTC and 5,075 ETH isolated alerts (no other whale trade within ±120 min).
- **Whale** = any single transfer above $50M. Non-whales re-tiered every six months: **Large** (95th pct+), **Medium** (50th–95th), **Small** (<50th) of on-chain non-zero transfer size

	BTC	ETH
On-chain data	Jul 2015–Dec 2025	Aug 2015–Dec 2025
Whale Alerts issued	20,848	12,104
Isolated whale alerts	6,645	5,075
Whale buys / sells	3,471 / 2,413	2,473 / 2,370

Table 1. Sample. WBTC (Bitcoin wrapped as an Ethereum token) covers Jan 2019–Dec 2025.

Methods

Event windows: control = 15 minutes before the alert; outcomes measured in 15-minute windows up to 60 minutes after (volatility: 15 minutes to 24 hours).

H1 – Composition. Do alerts change which non-whales are active?

$$Post\%_{iw} = \beta_0 + \beta_1 Control\%_i + \Sigma\gamma_k Window_{kw} + X_i + \varepsilon_{iw}$$

H_0: $\beta_1 = 1$ (pre-alert mix carries over one-for-one).

H2 – Leader–follower. Do non-whales trade in the whale's direction?

$$\Delta Share_{iw} = \beta_0 + \Sigma\gamma_k Window_{kw} + X_i + \varepsilon_{iw}$$

Estimated separately for whale buys and sells; $\beta_0 > 0$ in both = herding.

H3 – Volatility. Do alerts move short-term volatility?

$$Vol_{i,w} = \alpha + \beta_1 Whale_i + \Sigma\gamma_k Win_k + \Sigma\sigma_k Win_k \times Whale_i + \eta_h + \mu_d + \varepsilon_{i,w}$$

Annualized realized volatility vs. time-matched control windows.

Controls: log alert value, prior 1-hour return, prior 24-hour realized volatility, hour and year fixed effects. Re-estimated before and after the Ethereum Merge (Sept 15, 2022).

Results

BTC: $\beta_1 \approx 0$. Alerts pull in a new set of non-whale investors who were not active beforehand; the share of medium BTC wallets trading jumps from 34% to 58% within 15 minutes. ETH (0.63–0.71) and WBTC (0.27–0.51) stay much closer to one-for-one.

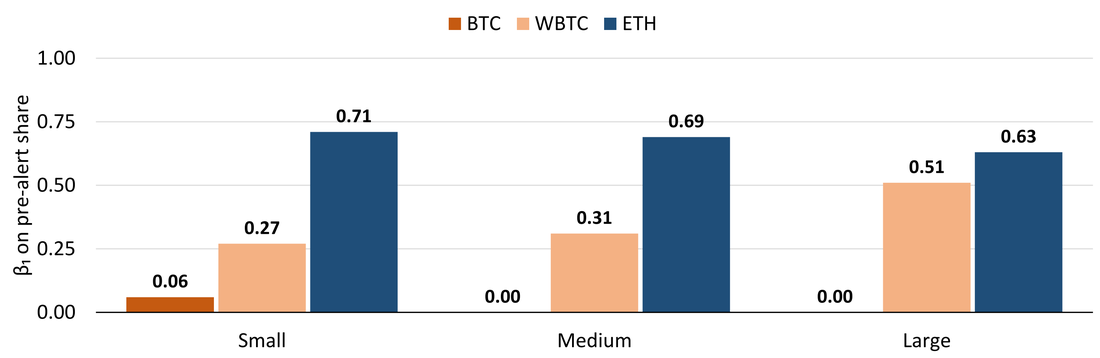


Figure 1. Estimated β_1 on the pre-alert participation share (Eq. 1, full sample). The top of the axis, $\beta_1 = 1$, is the null of no change in composition.

BTC non-whales follow the whale's direction within 15 minutes, most strongly among medium wallets (+23.7 pp after whale buys, +29.5 pp after whale sells). On the Ethereum network, only the largest ETH holders follow whale sells (+0.76 pp).

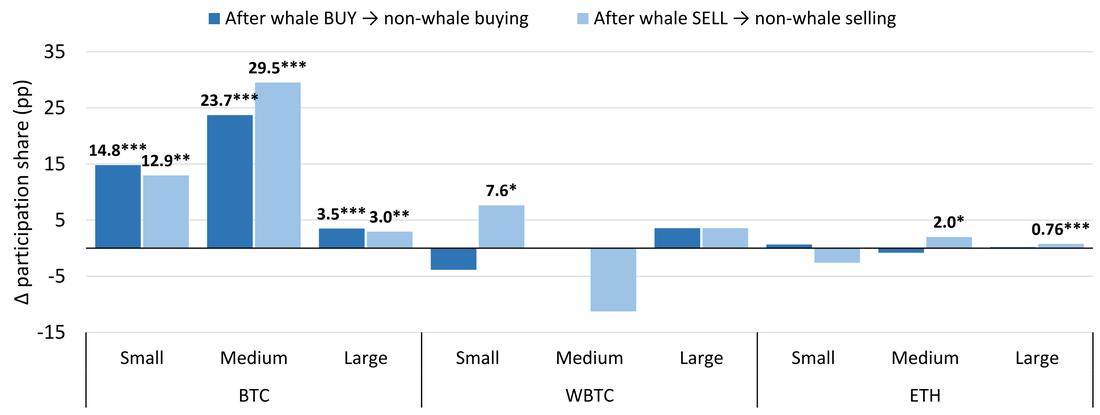


Figure 2. Abnormal change in non-whale participation share in the first 15 minutes after a whale buy or sell alert (Eq. 2, intercepts). Labels shown for estimates significant at 10% or better; *** p<0.01, ** p<0.05, * p<0.10.

BTC volatility rises after every alert type (+0.11 at 15 minutes, peaking near +0.22 at 6–9 hours) and reverses by 24 hours; WBTC alerts have the largest effect (up to +0.33). **ETH volatility falls at every horizon**, to about −0.6 at 24 hours.

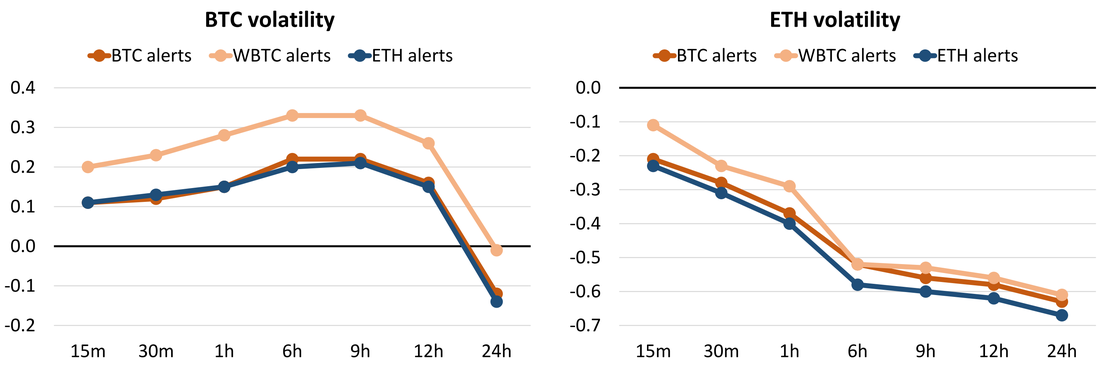


Figure 3. Whale × window coefficients on annualized realized volatility (Eq. 3), by alert type. All significant at 1% except WBTC alerts on BTC at 24 hours.

Conclusions

- **Whale alerts boost Bitcoin:** they draw in previously inactive investors and trigger same-direction herding.
- **Ethereum is different:** investor composition is stable and herding is limited to the largest non-whales, consistent with activity dominated by institutions, exchanges and smart contracts.
- **Volatility diverges:** a transitory BTC spike (largest after WBTC alerts) versus lower ETH volatility.
- **Robust to the Merge:** results hold under proof-of-work and proof-of-stake, so network structure and investor base, not the consensus mechanism, drive the response.
- **Policy:** persistent information gaps between large and small investors argue for network-specific rather than one-size-fits-all investor protection.

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Full paper: Federal Reserve Bank of Philadelphia Banking and Financial Market Working Paper 26-42 (September 2026) and Griswold Center for Economic Policy Studies Working Paper No. 358 (September 2026)

The views expressed are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

References

- Chernoff, A., and Jagtiani, J. (2025). Beneath the crypto currents: The hidden effect of crypto "whales." Journal of Credit Risk 21(2), 61–87.
- Chernoff, A., Jagtiani, J., and Yoshida, N. (2026). Flight to safety: Evaluating stablecoin's role as a safe-haven asset in DeFi markets. FRB Philadelphia WP 26-24.
- Holthausen, R. W., Leftwich, R., and Mayers, D. (1987). The effect of large block transactions on security prices. Journal of Financial Economics 19(2), 237–267.
- Kraus, A., and Stoll, H. R. (1972). Price impacts of block trading on the New York Stock Exchange. Journal of Finance 27(3), 560–599.
- Liu, J., Makarov, I., and Schoar, A. (2023). Anatomy of a run: The Terra Luna crash. NBER Working Paper 31160.
- Magner, N., and Sanhueza, A. (2025). The Moby Dick effect: Contagious Bitcoin whales in the crypto market. Finance Research Letters 85, 107906.