

Same Shock, Same Assets, Different Microstructure: A Comparative Analysis of CeFi and DeFi Venue Performance During the October 10, 2025 Cryptocurrency Cascade

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Abstract

On October 10, 2025, a geopolitical shock triggered one of the largest forced deleveraging events in cryptocurrency history, with total liquidations plausibly exceeding \$19 billion across CeFi and DeFi venues within 24 hours. This paper exploits the event as a natural experiment to study how identical assets respond to identical shocks across fundamentally different market architectures. Using sub-second L2 order book data from Hyperliquid and millions of Binance tick-level trades, we document extreme cross-venue dislocations: BTC prices diverged by 7.24% (\$7,387) within a single second, ETH spreads widened 602-fold, and bid depth collapsed by up to 99.8%.

We show that these divergences are not solely driven by liquidity stress, but by structural differences in market design. Using the Hansen–Seo (2002) threshold cointegration framework, we reject linear price linkage and identify regime-dependent adjustment dynamics: under normal conditions, prices converge symmetrically, while during stress, adjustment becomes asymmetric and amplification emerges on centralized venues.

A central contribution of the paper is to demonstrate that market observability is itself an architectural property. Due to exchange-level reporting constraints, publicly observed liquidation volumes on centralized exchanges constitute a structural lower bound on true activity, implying systematic undermeasurement during peak stress.

The findings highlight a new form of market fragmentation—architectural fragmentation—where arbitrage fails not due to information frictions but due to constraints embedded in trading infrastructure. These results have implications for market design, risk measurement, and regulatory reporting standards in increasingly hybrid CeFi–DeFi financial systems.

JEL Classification G01; G10; G14; G23; C32

1 Introduction

At 20:50 UTC on October 10, 2025, U.S. President Donald Trump announced a 100% tariff on all Chinese imports via Truth Social. Within 40 minutes, cryptocurrency derivatives markets entered a cascade that liquidated \$6.93 billion in leveraged positions. By 03:00 UTC the following morning, total liquidations reached \$9.89 billion on centralized exchanges alone, with on-chain venues adding substantially to the total. The event constituted the largest single-day deleveraging in cryptocurrency history, affecting over 1.6 million trader accounts (Amberdata 2026; CoinGlass 2025).

This paper treats the October 10 cascade as a natural experiment in comparative market microstructure. The same exogenous shock hit the same assets (BTC, ETH) simultaneously across venues with fundamentally different architectures: centralized exchanges (Binance, Bybit), on-chain perpetual DEXs (Hyperliquid), AMM-based spot DEXs (Uniswap), and on-chain lending protocols (Aave). The outcomes

diverged radically—not because of different assets or different shocks, but because of architectural design choices that each venue made differently.

This paper makes three contributions. First, it provides high-frequency empirical evidence that identical assets can exhibit substantial and persistent price divergence across venues under stress, even in the presence of nominal arbitrage links. Second, it demonstrates that market observability is an architectural property: while decentralized venues provide complete and verifiable transaction records, centralized exchange reporting mechanisms impose structural constraints that lead to systematically incomplete observation during periods of peak activity. Third, it shows that cross-venue price dynamics are inherently regime-dependent, and that threshold cointegration models provide a more appropriate framework than linear methods for capturing market behavior during extreme events.

1.1 A concept: architectural fragmentation

We introduce the concept of *architectural fragmentation* to describe a specific form of cross-venue price divergence. The existing literature on fragmented markets (Foucault et al. 2013; O'Hara and Ye 2011) studies identical securities trading across multiple venues where arbitrage is assumed to be active; in that setting, price differences are small and mean-reverting. Architectural fragmentation describes conditions under which the arbitrage link is mechanically severed because each venue's internal state machine — its oracle design, liquidation engine, withdrawal availability, and order book persistence — produces different price signals under stress. Three conditions jointly characterize the phenomenon: (i) a friction threshold that arbitrage cannot overcome during stress (transfer delay, withdrawal halts, depth collapse); (ii) regime-dependent error correction that breaks down asymmetrically across venues; and (iii) observability sufficient to detect the breakdown — itself an architectural property, and one that the CeFi stream rate cap constrains. We use this concept as a descriptive framework for the empirical patterns that follow; it is not a formal model, and we identify the development of a structural theoretical treatment as an important direction for future work.

Our work connects to several strands of the market microstructure literature. Hasbrouck (1995, 2007) established the framework for analyzing price discovery across multiple venues trading identical securities; we extend this to the CeFi–DeFi setting where venue architectures differ not just in speed but in fundamental design. Budish et al. (2015) argued that market design choices—not just information—determine microstructure outcomes; our findings strongly support this thesis, showing that oracle sourcing and liquidation engine design produced 7% price divergence on identical assets under identical shocks. Kirilenko et al. (2017) documented venue-specific amplification during the 2010 equity Flash Crash; the October 10 cryptocurrency cascade represents a cross-venue analogue with the added dimension of architectural heterogeneity between CeFi and DeFi. Finally, Easley et al. (2012) showed that flow toxicity predicts liquidity crises; our depth collapse findings (99.8% on ETH) demonstrate that toxicity can be venue-specific even for the same asset, determined by the venue's liquidation engine rather than by information flow alone.

2 Event timeline and data sources

2.1 The cascade sequence

The cascade unfolded in four phases, as reported by Amberdata (2026). Phase 1 (approximately 14:27 UTC): Large whale short positions reportedly totaling approximately \$1.1 billion were established on Hyperliquid; on-chain investigators later linked the wallet to an address associated with former exchange executive Garrett Jin, though this attribution remains under review (Investing.com 2025). Phase 2 (14:57 UTC): The tariff announcement hit markets (Reuters 2025). Phase 3 (14:57–20:50 UTC): A six-hour gradual sell-off during which prices declined slowly but market maker quotes began thinning. Phase 4 (20:50–21:30 UTC): The violent cascade. Amberdata estimated liquidation rates accelerated from \$0.12B/hour to \$10.39B/hour—an 86x acceleration. At 21:15 UTC, an estimated \$3.21 billion was liquidated in a single 60-second window.

2.2 Data sources and observability asymmetry

For DeFi venues, data observability is complete. Every Aave liquidation is recorded on the Ethereum blockchain with full details: collateral seized, debt repaid, liquidator address, transaction hash, and block timestamp. Hyperliquid publishes complete order book snapshots, trade fills, and liquidation records to a public S3 archive (Hyperliquid 2025b). Uniswap trades are individually recorded on-chain with AMM-specific metadata (pool address, tick range, liquidity utilized).

For CeFi venues, data observability is structurally limited. Binance’s public liquidation data stream pushes at most one liquidation order snapshot per symbol per 1,000-millisecond window (Binance 2025a). During peak volatility when hundreds of liquidations occur per second, external observers—including data aggregators like CoinGlass—see only a fraction of actual events. This observability asymmetry is not a data collection failure; it is an architectural property. We develop the formal implications of this architectural constraint in Sect. 3.7, where we establish that publicly reported Binance figures constitute a strict lower bound on true liquidation volumes.

2.3 Observability as an architectural constraint

A key implication of the data structure is that observability differs fundamentally across venue types. On decentralized platforms, all transactions are recorded on-chain and are fully reconstructible. In contrast, centralized exchanges rely on data dissemination systems that are subject to throughput constraints. In the case of Binance, the liquidation stream publishes at most one event per symbol per second.

This implies that during periods of elevated activity, the observed number of liquidation events is mechanically censored. Let the true number of liquidation events in a given interval be N , and the observed number be $\tilde{N}$. Under a binding reporting constraint, $\tilde{N} \leq N$, with equality holding only when activity remains below the reporting threshold. As volatility increases, the probability that this constraint binds rises, introducing a systematic downward bias in observed liquidation counts.

This property is not a data limitation but a feature of exchange architecture. As a result, publicly reported liquidation volumes should be interpreted as lower bounds rather than complete measures of market activity during stress.

3 Five axes of architectural divergence

Table 1
Venue architecture and performance during the October 10, 2025 cascade

Metric	Binance (CeFi)	Hyperliquid (DeFi)	Aave (DeFi)	Uniswap (DeFi)
Reported liq.	\$2.41B	\$10.31B	\$250M+	N/A (spot)
True liq. bound	≥ \$2.41B (see Sect. 3.7)	\$10.31B	\$250M+	N/A
System uptime	Subsystem deg. 21:18–21:51	100%	100%	100%
ADL triggered	Yes (opaque)	Yes (1st in 2y)	No (Umbrella)	N/A
Compensation	>\$328M (by Oct 22)	\$0	\$0	\$0
Oracle type	Internal spot	8-exch. median	Chainlink	AMM-native
USDe nadir	\$0.65	~\$1.00	\$0.97	~\$1.00
Liq. reporting	1/sec cap	Full on-chain	Full on-chain	N/A
Notes. Sources: <i>Binance (2026), Amberdata (2026), Aave (2026), Chaos Labs (2025), CoinDesk (2025), CoinGlass (2025)</i> . True liquidation bound for <i>Binance</i> derived architecturally from stream rate cap (see Sect. 3.7). Compensation per <i>Binance (2026)</i> .				

3.1 Oracle design and the USDe depeg

Binance uses an internal spot price oracle derived primarily from its own order book. When USDe (Ethena’s synthetic dollar) came under selling pressure, its price on Binance fell to \$0.65 while maintaining near-parity on all other venues and on-chain. This venue-specific depeg triggered margin calls and liquidations for all positions collateralized with USDe on Binance—even though the asset had not lost value elsewhere. Notably, the price nadir occurred at 21:20–21:21 UTC, while the severe USDe depegging began at 21:36 UTC—a 15-minute gap distinguishing the initial market crash from subsequent venue-specific amplification (Binance 2026).

Hyperliquid uses a composite oracle drawing from eight exchanges with a weighted median calculation and outlier filtering (Hyperliquid 2025a). This architecture naturally rejects single-venue anomalies. Aave relies on Chainlink’s decentralized oracle network with multiple data sources and built-in circuit breakers. Both DeFi oracles treated USDe as near-par throughout the event.

3.2 Liquidation engine transparency

The contrast between CeFi and DeFi liquidation reporting constitutes a key finding. On DeFi venues, every liquidation is an on-chain transaction with complete metadata. On Binance, the architecture produces an irreducible information loss: when 150 liquidations occur in one second for a single symbol, external observers see exactly one. The resulting observability asymmetry means that the true scale of the cascade on CeFi venues remains partially unknown. We develop a formal lower-bound argument in Sect. 3.7.

3.3 Liquidity provision architecture

Hyperliquid and Binance both operate central limit order books (CLOBs), but with different market maker dynamics. During the cascade, Hyperliquid’s on-chain CLOB saw bid depth collapse from approximately \$5 million to \$8,745 on ETH—a 99.8% decline—as market makers withdrew. Uniswap’s constant-function AMM, by contrast, cannot withdraw in the traditional sense: liquidity remains available at algorithmically determined prices. Uniswap processed approximately 10x its normal volume during the event (Adams 2025).

3.4 Auto-deleveraging mechanics

Hyperliquid triggered auto-deleveraging (ADL) for the first time in two years during the cascade (CoinDesk 2025). ADL forcibly closes profitable counter-positions when the insurance fund is insufficient, potentially removing buy pressure at the worst moment. Aave uses an “Umbrella” safety module that absorbs bad debt without closing any user positions. Binance reportedly used internal ADL but has not disclosed specifics.

3.5 System availability under stress

Binance experienced transfer-subsystem degradation (21:18–21:51 UTC) and abnormal index price deviations for USDe, WBETH, and BNSOL (21:36–22:15 UTC) during peak stress; Binance stated that core matching, risk, and clearing systems remained operational throughout (Binance 2026). The Crypto.com CEO publicly called for regulators to investigate whether trades were priced correctly during the event (CoinDesk 2025).

Hyperliquid maintained 100% uptime, reportedly processing \$50–70 billion in trading volume without any interruption during the cascade. Uniswap processed approximately 10x its normal volume with zero downtime. However, DeFi availability carries a hidden friction cost: Ethereum gas prices spiked to approximately 450 Gwei during the crash, with some users paying \$400–500 per transaction (Liu 2025). This congestion tax effectively creates a wealth-based access barrier during peak stress.

3.6 Empirical price divergence: Binance vs. Hyperliquid

To quantify the divergence implied by the architectural differences documented above, we collected data from three sources at increasing resolution. First, hourly candle data for BTC/USDT and ETH/USDT from both Binance and Hyperliquid public APIs for the crash window (October 10–11, 2025) and a baseline period (October 8–9, 2025). Second, sub-second L2 order book snapshots from Hyperliquid’s public S3

archive (Hyperliquid 2025b; approximately 6,550 snapshots per hour per asset) to reconstruct minute-by-minute mid-price divergence during the cascade window (20:00–23:00 UTC). Third, tick-level BTC trade data from Binance’s public historical data repository (Binance 2025b), comprising 11.4 million individual trades for October 10, aggregated to per-second volume-weighted average price (VWAP) and matched against contemporaneous Hyperliquid L2 snapshots for second-by-second divergence analysis during the 21:10–21:30 UTC peak cascade window.

Table 2
Hourly price divergence: crash day vs. baseline

Metric	BTC Base (Oct 8)	BTC Crash (Oct 10)	ETH Base (Oct 8)	ETH Crash (Oct 10)
Mean div (close)	0.04%	0.07%	0.04%	0.08%
Max div (close)	0.08%	0.27%	0.10%	0.65%
Max div (lows)	—	1.52%	—	5.64%
Max gap (USD)	\$94	\$305	\$4.40	\$194
Peak hour	09:00	21:00	00:00	21:00
<i>Notes. Sources: Binance public API (klines) and Hyperliquid public API (candleSnapshot). Hourly data. Divergence = (Hyperliquid – Binance) / Binance × 100.</i>				

At the hourly level, divergence widened sharply during the crash: BTC close-price divergence peaked at 0.27% (vs. 0.08% baseline), while ETH low divergence reached 5.64% (\$194 gap). However, hourly bars smooth the cascade’s internal dynamics. The minute- and second-level analysis below reveals far more extreme dislocations.

Table 3
Sub-second price divergence during cascade (20:50–21:30 UTC)

Metric	BTC	ETH
Peak divergence	+ 7.24% at 21:24:09 (HL \$109,387 vs Bin \$102,000)	–5.32% at 21:19 (HL \$3,295 vs Bin \$3,480)
Peak USD gap	\$7,387 in one second (HL above Binance)	\$185 (HL below Binance)
Binance trades at peak	26,558 trades in one second (21:24:09)	—
Max spread	160.9 bps at 21:17:42	301 bps at 21:19 (602x baseline)
Min bid depth (HL)	\$56,313 at 21:15	\$8,745 at 21:19
Depth collapse	~\$5M to \$56K (98.9%)	~\$5M to \$9K (99.8%)
Direction reversal	21:18: HL 3.77% below Bin; 21:24: HL 7.24% above (7 min)	HL consistently below Binance
<i>Notes. Sources: Hyperliquid L2 order book snapshots (Hyperliquid 2025b; ~6,550/hr). BTC Binance from tick-level trades (Binance 2025b; 2M+ trades in window). ETH Binance from 1-min kline API.</i>		

Three findings emerge from the sub-second data. First, the magnitude of divergence was far larger than hourly analysis suggested. At 21:24:09 UTC, Binance’s BTC price crashed to \$102,000 while Hyperliquid’s best bid remained at \$109,387—a \$7,387 gap (7.24%) in a single second, with 26,558 Binance trades executing in that one second alone. ETH low divergence peaked at 5.32% (\$185) at 21:19 UTC. These are not rounding errors; they represent materially different execution prices for traders on different venues during the same seconds.

Second, the direction of divergence was asymmetric and dynamic. For BTC, at 21:18:17 UTC Hyperliquid traded 3.77% below Binance (\$105,748 vs \$109,707). Just seven minutes later, at 21:24:09, Hyperliquid was 7.24% above Binance (\$109,387 vs \$102,000)—an 11-percentage-point swing in relative pricing. This reversal coincided precisely with the window when Binance experienced transfer-subsystem degradation and index price deviations: Binance’s BTC price continued falling to a \$102,000 low even as Hyperliquid’s order book had already stabilized above \$109,000. This pattern is consistent with Binance’s internal oracle/collateral cascade amplifying BTC downside beyond fundamental price discovery. For ETH, Hyperliquid traded consistently below Binance throughout the cascade, suggesting Hyperliquid’s on-chain liquidation engine was more aggressive on ETH positions.

Third, the microstructure breakdown was extreme. ETH bid-ask spreads on Hyperliquid widened from a baseline of ~ 0.5 basis points to 301 basis points at 21:19—a 602x widening. ETH bid-side depth collapsed from approximately \$5 million to \$8,745—a 99.8% decline, meaning the entire visible bid side of ETH on Hyperliquid could be swept with under \$9,000 in notional. BTC spreads on Hyperliquid reached 160.9 bps at 21:17:42 and depth fell 98.9%. On the Binance side, the tick data reveals the violence of the

cascade: at the 21:24:09 peak, over 26,000 trades executed in a single second at prices ranging from \$102,000 to \$109,000—a \$7,000 intra-second range on one venue alone.

A natural question is whether the observed divergence represented an exploitable arbitrage opportunity. At 21:24:09 UTC, the gross profit from buying BTC on Binance at \$102,000 and simultaneously selling on Hyperliquid at \$109,387 was \$7,387 per BTC (7.24%), against combined taker fees of approximately 0.135% (Binance 0.10%, Hyperliquid 0.035%)—yielding a theoretical net profit of over 7% per unit. However, this arbitrage was practically non-executable for three reasons. First, USDT settlement between venues requires 5–30 minutes depending on chain and confirmation requirements; the divergence reversed within seven minutes, meaning funds could not traverse between venues before the opportunity closed. Second, Binance’s transfer subsystem was degraded from 21:18–21:51 UTC—precisely the arbitrage window—preventing asset transfers off the exchange. Third, Hyperliquid’s BTC bid depth had collapsed to \$56,313 and ETH to \$8,745, meaning only trivial position sizes (approximately 0.5 BTC or 2.5 ETH) could execute before exhausting the visible order book. The non-executability of this arbitrage is itself evidence of genuine venue fragmentation: during the cascade, the two venues were not merely mispriced but effectively disconnected, operating as separate markets for identical assets.

Notes. Upper panel shows hourly close prices. Lower panel shows percentage divergence. Red shading marks the 40-minute cascade window (20:50–21:30 UTC).

Notes. At tick resolution, BTC divergence reached 7.24% (\$7,387) at 21:24:09 UTC in a single second.

Notes. ETH close-price divergence peaked at 4.76% at 21:20 UTC. Hyperliquid consistently printed lower than Binance on ETH.

Notes. ETH low divergence reached 5.32% (\$185) at 21:19 UTC. Bid-ask spreads widened 602x and bid depth collapsed 99.8% to \$8,745.

Notes. Upper panel: per-second divergence. Green = HL above Binance; red = HL below. Direction reversed between 21:18:17 (– 3.77%) and 21:24:09 (+ 7.24%). Middle: Binance trades/sec (peak 26,558). Lower: HL spread (bps).

Notes. Each point = 1 minute. ETH shows expected negative slope (lower depth → larger divergence). BTC positive slope reflects endogeneity during recovery.

Table 4
OLS descriptive regression: |price divergence| on depth and spread

Variable	Model 1	Model 2	Model 3
Constant	0.2574 (4.99)	0.0571 (1.53)	0.2150 (3.10)
Depth (\$M)	0.0245 (3.78)	0.0228 (5.14)	0.0234 (5.34)
Spread (bps)	—	0.0596 (16.49)	0.0561 (14.82)
BTC dummy	—	—	-0.1980 (- 2.69)
R-squared	0.057	0.561	0.574
N	240	240	240
<i>Notes. Dependent variable: Divergence (%). t-statistics in parentheses. See Sect. 3.7 for discussion of endogeneity and the descriptive (non-causal) interpretation of these coefficients.</i>			

3.7 Robustness checks and descriptive regression analysis

This subsection presents OLS regressions of |price divergence| on order book depth and bid-ask spread (Tables 4 and 6), with the important methodological caveat stated at the outset: **these regressions do not identify causal effects**. Depth, spread, and divergence are all endogenous outcomes of the same cascade process — they are three ways of measuring the same microstructural breakdown, not three variables in a causal chain. A proper identification strategy would require either (i) instrumental variables, where a valid instrument for depth must affect divergence only through depth (lagged pre-cascade depth and Ethereum gas-price shocks are candidates, though both have limitations we discuss below), or (ii) a structural vector autoregression that imposes identifying restrictions on the contemporaneous covariance of shocks. We do not implement either here; a formally identified analysis of the cross-sectional relationship between microstructure quality and price divergence during stress is left as a methodological extension.

The OLS coefficients reported in Tables 4–6 should therefore be read as **descriptive co-movement parameters** documenting how the three measures vary together during the cascade, not as causal estimates of depth’s or spread’s effect on divergence. That said, the strength of the associations is informative: spread alone explains 56% of divergence variation (Model 2, $R^2 = 0.561$), and the spread coefficient is statistically distinguishable from zero at conventional levels ($t = 16.49$) even after allowing for simultaneity. The cascade indicator variable (Table 6, Models 4–6) isolates the excess divergence during the 20:50–21:30 UTC window; its significance ($t = 2.09$ – 3.03) confirms that the cascade produced divergence above and beyond what the ambient depth-spread relationship would predict. These descriptive patterns are consistent with the mechanism we propose — that microstructure stress drives venue fragmentation — but cannot establish the direction of causation without further identification.

Table 5

Binance liquidation volume: reported figure and architectural lower bound (October 10, 2025 peak hour)

Source	Estimated Binance liquidation	Basis
Binance forceOrder WebSocket stream (CoinGlass aggregation)	\$2.41B	Subject to 1 snapshot/symbol/second rate cap
Amberdata cross-source estimate, all venues	\$10.39B/hour at peak	Not stream-constrained
Lower bound on true Binance liquidation	$\geq \$2.41B$	Stream-reported figure is architecturally a lower bound
Upper bound	Not publicly identifiable	Constitutes the paper's central observability claim
<i>Notes. The WebSocket forceOrder stream publishes at most one liquidation event per symbol per second (Binance 2025a). External commentators have suggested true volumes could be multiples of the reported figure; we treat these as informed conjecture rather than statistically derived estimates.</i>		

The WebSocket forceOrder stream on Binance Futures publishes at most one liquidation order per symbol per second (Binance 2025a). Binance Futures listed several hundred USDT-margined perpetual contracts as of October 2025. During the peak minute of the cascade (21:15 UTC), Amberdata (2026) estimated cross-venue liquidations of \$3.21 billion in 60 seconds. If a meaningful fraction of that volume executed on Binance and was distributed across active perpetual pairs, the number of liquidation events in that window almost certainly exceeded the stream's maximum observable rate — meaning external observers saw strictly fewer events than occurred.

The reported \$2.41B Binance figure is therefore an architectural lower bound: the true value cannot be less than this, but the true value is not publicly identifiable from stream-based data.

External commentators, including Hyperliquid founder Jeff Yan (Yan 2025), have suggested that true Binance liquidation volumes could be 10x–100x the reported figure. We note this claim for completeness but do not incorporate specific multipliers into our analysis for two reasons. First, the 10x–100x range has not been derived from a formal statistical model; it reflects informed conjecture about the severity of stream-induced information loss rather than an identified estimate. Second, the source operates a competing venue (Hyperliquid) and therefore has a commercial interest in characterizing Binance's reporting as understating the true scale of CeFi liquidations. A rigorous estimate of the true underreporting magnitude would require either (i) access to Binance's internal liquidation logs, which are not public, or (ii) a structural model of the relationship between observable and true event counts given the stream rate, symbol count, and liquidation size distribution — a methodological contribution we identify as an important direction for future research on centralized exchange observability.

Our substantive claim — that CeFi liquidation observability is architecturally limited, not merely imperfectly measured — holds regardless of the precise magnitude of underreporting. The

demonstration that \$2.41B is a strict lower bound, combined with the independent Amberdata estimate that implies true cross-venue liquidations were substantially larger, is sufficient to establish that stream-based reporting cannot faithfully represent CeFi cascade dynamics under peak stress.

A second concern is whether auto-deleveraging (ADL)—triggered by Hyperliquid at approximately 21:15 UTC—slowed price recovery relative to Binance’s internal liquidation engine. Figure 7 compares hourly close prices on both venues, normalized to the 20:00 UTC pre-cascade price. The result is a null finding: both venues reached their nadir at approximately the same depth (BTC: Binance 96.5%, Hyperliquid 96.6% of pre-cascade; ETH: Binance 95.4%, Hyperliquid 95.8%) and both recovered to 95% of pre-cascade within two hours. ADL did not measurably impair Hyperliquid’s recovery speed at hourly resolution.

Notes. Normalized to 20:00 UTC pre-cascade close = 100. Both venues recovered to 95% within 2 hours. ADL did not measurably impair recovery.

Table 6
Extended OLS descriptive regression with cascade-window indicator

Variable	Model 4	Model 5	Model 6
Constant	0.0209 (0.54)	0.1559 (2.16)	0.1829 (2.17)
Depth (\$M)	0.0193 (4.28)	0.0203 (4.51)	0.0202 (4.49)
Spread (bps)	0.0548 (14.10)	0.0526 (13.21)	0.0400 (1.96)
Cascade dummy	0.2227 (3.03)	0.1931 (2.60)	0.1712 (2.09)
Spread × Cascade	—	—	0.0129 (0.63)
BTC dummy	—	−0.1632 (− 2.20)	−0.1762 (− 2.29)
R-squared	0.577	0.586	0.586
N	240	240	240
<i>Notes. Cascade dummy = 1 for 20:50–21:30 UTC window. Cascade positive and significant (t = 2.09–3.03). Spread × Cascade insignificant (t = 0.63): mechanism stable, only intensity changes. Coefficients are descriptive co-movement parameters, not causal estimates (see Sect. 3.7).</i>			

3.8 Price discovery and threshold cointegration

We analyze second-by-second log prices for BTC/USDT on Binance (tick-level VWAP) and Hyperliquid (L2 mid-price) during the 20:00–22:00 UTC window surrounding the cascade (N = 7,050 matched seconds). The extended window allows us to characterize both calm and cascade dynamics within a single sample.

3.8.1 Linear VECM and the case for threshold methods

The Engle-Granger test fails to reject the null of no cointegration across this window, despite both series being individually $I(1)$ with $I(0)$ first differences. Under normal conditions, prices for the same asset across arbitrage-linked venues should cointegrate with a $(1, -1)$ vector. The failure of linear cointegration is most naturally interpreted not as independent price discovery on each venue but as **misspecification of the linear error-correction model under cascade conditions**. The economic mechanism is well understood: arbitrage is active only when the price gap exceeds a threshold large enough to overcome transfer friction (5–30 minute USDT settlement), subsystem degradation (Binance withdrawals halted 21:18–21:51 UTC), and depth collapse (top-of-book liquidity insufficient to absorb arbitrage size). Below the threshold, the error-correction coefficient is effectively zero; above it, conventional arbitrage dynamics resume but with venue-specific amplification. This is precisely the structure Hansen and Seo (2002) developed the threshold VECM to estimate.

3.8.2 Hansen–Seo test results

We test the null of linear cointegration against the alternative of threshold cointegration using the sup-LM statistic of Hansen and Seo (2002), with threshold γ searched across a 300-point grid and bootstrap critical values from 300 fixed-regressor bootstrap replications. The test decisively rejects linear cointegration (sup-LM = 47.77 vs. 5% critical value = 35.14; bootstrap $p < 0.003$). The estimated threshold lies at $\gamma = 0.00252$ in the error-correction term (log-price units), corresponding to approximately a 0.25% deviation from the cointegrating relationship. Below this threshold lie 95% of the 7,050 observations (the “calm regime”); above it lie 5% (the “cascade regime”) concentrated during the 20:50–21:30 UTC cascade window. The threshold effect is tail-concentrated by design: the cascade minutes themselves constitute the second regime.

3.8.3 Regime-specific error-correction dynamics

Table 7 reports the estimated regime-specific VECM coefficients. In the calm regime, both venues adjust slowly and symmetrically toward the cointegrating equilibrium: Binance $\alpha = -0.0071$ ($p = 0.002$), Hyperliquid $\alpha = +0.0076$ ($p = 0.002$). In the cascade regime, adjustment dynamics change qualitatively. Hyperliquid’s error-correction coefficient jumps to $+0.1068$ ($p < 10^{-33}$) — fourteen times faster than in the calm regime — reflecting rapid on-chain price correction toward Binance as the order book re-populates. Binance’s coefficient reverses sign to $+0.0246$ ($p = 0.0003$) — indicating that during cascade seconds, Binance moves away from the cointegrating relationship rather than toward it, consistent with the internal-oracle and liquidation-cascade amplification documented in Sect. 3.1. **This sign reversal is the quantitative signature of architectural divergence:** Binance’s venue-specific cascade pushes its price further from fundamental value while Hyperliquid’s on-chain book corrects aggressively. The estimated cointegrating coefficient in the threshold VECM is $\beta = -1.000$, notably closer to the theoretical $(1, -1)$ arbitrage vector than the linear VECM’s $\beta = -1.091$; the threshold specification better captures the underlying arbitrage relationship by allowing regime-dependent adjustment.

Table 7
Threshold VECM regime-specific coefficients (BTC, 20:00–22:00 UTC)

Coefficient	Linear VECM	Calm regime (below γ)	Cascade regime (above γ)
α on Binance	-0.0041 ($p = 0.041$)	-0.0071 ($p = 0.002$)	+ 0.0246 ($p = 0.0003$)
α on Hyperliquid	+ 0.0176 ($p < 0.001$)	+ 0.0076 ($p = 0.002$)	+ 0.1068 ($p < 10^{-33}$)
Cointegrating β	-1.091	-1.000	-1.000
Observations	7,050	$\approx 6,697$ (95%)	≈ 353 (5%)
<i>Notes. Error-correction coefficients (α) with p-values. Hansen–Seo threshold VECM estimated with lag = 4, ngridBeta = 50, ngridTh = 50, trim = 0.05. Threshold $\gamma = 0.00252$ (approximately 0.25% deviation in the error-correction term). p-values from the regime-specific regressions. See Table 8 for robustness across alternative tuning parameters.</i>			

3.8.4 Alternative explanations and interpretation

We interpret the cascade-regime sign reversal on Binance as consistent with venue-specific amplification — the internal oracle feeds Binance’s own order book into its liquidation logic, creating positive feedback that is absent on Hyperliquid’s externally-referential oracle. We do not, however, claim to identify this mechanism causally. Several alternative explanations could produce observationally similar dynamics: (i) *liquidity withdrawal* by market makers during stress, which would produce asymmetric price impact without any oracle effect; (ii) *asynchronous timestamps* between Binance tick data and Hyperliquid L2 snapshots at the one-second match tolerance, which could artificially inflate apparent divergence during periods of rapid price movement; (iii) *bid-ask bounce* under thin liquidity (ETH bid depth collapsed to \$8,745), which can generate sign-dependent mean-reversion in VWAP measures; and (iv) *feed latency differences* between public API endpoints, which are difficult to characterize without direct exchange telemetry. The threshold VECM results are **descriptively consistent with architectural fragmentation and the self-referential oracle mechanism, but should be read as suggestive evidence, not causal identification**. Causal identification of the oracle channel would require instrumental variables (e.g., exogenous variation in oracle composition), cross-venue variation across events, or structural estimation — all of which are beyond the scope of this paper and identified in Sect. 4.3 as future research directions.

3.8.5 Robustness

The threshold rejection is robust across lag specification (lag = 2, 6), alternative bootstrap (residual-based rather than fixed-regressor), and alternative trim. At trim = 0.10 (requiring 10% minimum observations in each regime rather than 5%), the sup-LM statistic drops to 34.62 and the rejection becomes marginal at the 5% level ($p = 0.040$, 5% critical value = 33.70). This marginal result is consistent with the paper’s substantive claim: the regime-switching dynamic is concentrated in the cascade tail rather than diffuse across normal cross-venue dynamics. At trim = 0.05, which admits the architecturally

meaningful cascade window as its own regime, the rejection is decisive; at trim = 0.10, which forces the test to find a more balanced regime split, the evidence is narrower but still significant.

Table 8
Hansen–Seo sup-LM test: robustness to tuning parameters

Specification	sup-LM	p-value	5% CV	Decision
Baseline (lag = 4, trim = 0.05, FixedReg)	47.77	< 0.003	35.14	REJECT
Lag = 2	36.48	< 0.003	24.81	REJECT
Lag = 6	58.59	< 0.003	46.06	REJECT
Trim = 0.10	34.62	0.040	33.70	REJECT (marginal)
Residual bootstrap	47.77	< 0.003	—	REJECT

Notes. Tests conducted on N = 7,050 matched seconds, 20:00–22:00 UTC, October 10, 2025. Bootstrap replications: 300. Reported p-values capped at < 0.003 where all 300 bootstrap draws fall below the observed statistic. Residual bootstrap returned compute warnings; baseline and lag-varying specifications should be regarded as the primary evidence.

3.8.6 Comparison to linear price-discovery measures

As a further check, we compute standard Hasbrouck (1995) information shares and Gonzalo-Granger component shares from the linear VECM restricted to the 21:10–21:30 UTC peak-cascade window (N = 1,102 matched seconds). Under this linear approximation, Binance leads price discovery with a Hasbrouck information share of 82.5% (midpoint of [80.2%, 84.8%] bounds) and a Gonzalo-Granger component share of 76.3%. Figure 8 shows rolling Gonzalo-Granger shares over 5-minute windows advanced in 1-minute steps: Binance led price discovery in every single window, with shares ranging from 77.2% to 99.6%. The linear-VECM decomposition is informative as a summary statistic, but the Hansen–Seo results above reveal its incompleteness: the linear model averages across regimes with qualitatively different error-correction dynamics, so its 82.5% share describes an average behavior rather than a regime-invariant structural parameter.

Notes. Each bar = 5-min VECM window, 1-min steps. Binance dominated every window (min 77.2%, max 99.6%). These are linear-VECM shares; the Hansen–Seo threshold VECM estimated in Table 7 reveals regime-specific adjustment dynamics that the linear decomposition averages across.

4 Discussion

4.1 The transparency–protection tradeoff

The event crystallized a novel tradeoff in market design. Binance initially reported approximately \$283 million in compensation to affected users, later stating total compensation exceeded \$328 million by October 22, 2025 (Binance 2026). Hyperliquid compensated nothing—its HLP vault earned

approximately \$40 million in liquidation fees that flowed to liquidity providers. Traditional market microstructure theory assumes venues are transparent and available. The October 10 event shows that in crypto markets, transparency and availability are endogenous to venue architecture.

4.2 Regulatory implications

Former CFTC regulator Salman Banaei compared the event to the May 2010 equity Flash Crash, calling for formal investigation. Our analysis suggests three regulatory priorities: (1) standardized liquidation reporting, as the current regime where venues self-report creates systemic opacity; (2) oracle resilience standards, as single-venue oracle dependencies create venue-specific amplification risks; and (3) leverage caps, as the dominance of perpetual futures in crypto trading volume represents a misalignment between platform incentives and systemic stability.

4.3 Limitations and future research

The CeFi data gap — with the architectural stream rate cap documented in Sect. 3.7 meaning that \$2.41B is a strict lower bound rather than a census — means our analysis necessarily relies on self-reported CeFi figures as a floor. Several empirical questions remain open: (1) extension of the threshold VECM analysis to ETH, which our BTC results suggest should also exhibit regime-switching dynamics given the parallel cascade patterns documented in Sect. 3.6; (2) minute-by-minute price discovery leadership across venues for ETH and other affected assets; (3) effective depth comparison (dollar cost to move price 1%) across CLOBs and AMMs at matched timestamps; (4) whether venues that triggered ADL experienced slower sub-minute price recovery than our hourly data misses; and (5) a structural model of the relationship between stream-observable and true liquidation event counts, which would convert our architectural lower bound into an identified estimate of true CeFi liquidation volumes. We also identify the development of a formal theoretical model linking the five architectural axes to the estimated regime-specific error-correction coefficients as the highest-priority theoretical extension. All empirical questions above are answerable with existing public data.

It is worth noting that market infrastructure has not remained static since October 10. Binance's January 2026 post-mortem reported that the exchange has since tightened index deviation thresholds, improved cross-exchange reference pricing for collateral assets, and enhanced circuit breakers to reduce recurrence risk (Binance 2026). Whether these measures are sufficient to prevent a similar cascade remains an empirical question that future stress events will test.

5 Conclusion

The October 10, 2025 cryptocurrency cascade provides a unique natural experiment for comparative market microstructure analysis. We document that identical assets experiencing the same exogenous shock produced radically different outcomes across architecturally distinct venues. The divergence traces to five design choices: oracle sourcing, liquidation transparency, liquidity provision architecture, auto-deleveraging mechanics, and system availability under stress.

Empirically, we find that these architectural differences are associated with extreme price divergence under stress. Using tick-level Binance trade data and sub-second Hyperliquid order book snapshots, we document that at 21:24:09 UTC, BTC prices diverged by 7.24% (\$7,387) between Binance and Hyperliquid in a single second – with 26,558 trades executing on Binance at that moment. ETH diverged by 5.32% (\$185), with bid-ask spreads widening 602x and bid depth collapsing 99.8% to under \$9,000. Our central methodological contribution is the estimation of a Hansen–Seo (2002) threshold vector error-correction model on 7,050 matched seconds. We decisively reject linear cointegration (sup-LM = 47.77, bootstrap $p < 0.003$) and identify a threshold at approximately 0.25% separating a calm regime (95% of observations) from a cascade regime (5%) concentrated in the 20:50–21:30 UTC cascade window. In the calm regime both venues adjust symmetrically toward the cointegrating equilibrium. In the cascade regime, Hyperliquid’s adjustment rate rises fourteen-fold while Binance’s error-correction coefficient reverses sign – a pattern consistent with, though not proof of, venue-specific oracle and liquidation-cascade amplification. Robustness across alternative lags, trim levels, and bootstrap methods confirms the rejection of linear cointegration, with the cascade regime emerging as a tail-concentrated feature of the data rather than a diffuse property of cross-venue dynamics.

Our central finding is that market microstructure observability is an architectural property, not a data collection problem. DeFi venues provide complete, verifiable, permissionlessly auditable transaction records. CeFi venues employ liquidation reporting architectures – in Binance’s case, a WebSocket stream constrained to one event per symbol per second – that can produce strictly incomplete observation during peak stress. Our analysis establishes that the publicly reported figure is an architectural lower bound on true liquidation volumes; the true value is not identifiable from stream-based data alone. This asymmetry means the full scale of systemic risk during the cascade remains partially unknown, a condition that itself constitutes a form of market risk that current regulatory frameworks do not adequately capture.

The event revealed a transparency–protection tradeoff with no clear resolution: CeFi venues compensated losers but obscured the true state of the system; DeFi venues exposed every transaction but offered no recourse. As crypto markets continue integrating with traditional finance, resolving this tradeoff – through circuit breakers, standardized reporting, oracle resilience standards, informed regulatory frameworks, and econometric tools suited to regime-switching dynamics under stress – becomes an urgent priority for market designers and regulators alike.

5.1 Limitations

This paper has important limitations that should inform interpretation. First, we do not identify causal effects. The cascade-regime sign reversal on Binance is consistent with multiple mechanisms – oracle feedback, market-maker withdrawal, depth collapse, asynchronous timestamps – that produce observationally similar dynamics. Distinguishing among them would require instrumental variables, cross-venue variation across events, or structural estimation, all beyond the scope of this paper. Second, the cascade regime is estimated from a small tail subsample (approximately 353 observations, or 5% of

the window); inferences about regime-specific coefficients are therefore subject to finite-sample concerns that the robustness table partially, but not fully, addresses. Third, our analysis is restricted to the BTC pair on two venues (Binance spot and Hyperliquid perpetual). Extension to ETH and to other venue pairs is identified as future work. Fourth, the architectural lower bound on CeFi liquidations derives from the stream rate cap alone; a structural model linking observable and true event counts would convert the lower bound into an identified estimate. We view these limitations not as weaknesses to be hidden but as an honest map of what the present paper does and does not establish.

Declarations

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Competing Interests

The author declares no competing financial or personal interests that could have appeared to influence the work reported in this paper.

Author Contribution

B.C.L. conceived the study, collected and analyzed the data, performed the econometric analysis, and wrote the manuscript. The author reviewed and approved the final version of the manuscript.

Data Availability

The data used in this study are derived from publicly available sources, including Binance historical trade data (data.binance.vision), Hyperliquid public order book archives, and on-chain Ethereum transaction records. Supplementary data from Amberdata and CoinGlass were used for contextual analysis. The processed datasets and analysis code supporting the findings of this study are available from the author upon reasonable request.

Declarations of Generative AI Use

During the preparation of this work the author used Anthropic's Claude (a large language model) for literature review, data synthesis, and manuscript drafting. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

References

1. Aave (2026) How Aave liquidations perform under volatile conditions. Aave Blog, 5 February 2026. <https://aave.com/blog>
2. Adams H (2025) Uniswap volume during the October 10 crash [Post]. X, 11 October 2025. <https://x.com/haabordeaux>
3. Amberdata (2026) How \$3.21B vanished in 60 seconds. Amberdata Research Blog, 8 January 2026 (author: M. Marshall). <https://blog.amberdata.io>
4. Binance (2025a) Liquidation order streams. Binance API Documentation. <https://developers.binance.com>
5. Binance (2025b) Daily aggregate trades: BTCUSDT, October 10 [Data set]. Binance Historical Data. <https://data.binance.vision>
6. Binance (2026) The October 10 crypto market flash crash. Binance Blog, 30 January 2026. <https://www.binance.com/en/blog>
7. Budish E, Cramton P, Shim J (2015) The high-frequency trading arms race: frequent batch auctions as a market design response. *Q J Econ* 130(4):1547–1621. <https://doi.org/10.1093/qje/qjv027>
8. Chaos Labs (2025) Risk report: insights from recent market events, 10/11/25. Aave Governance Forum, 11 October 2025. <https://governance.aave.com>
9. CoinDesk (2025) Largest ever crypto liquidation event. CoinDesk Markets, 11 October 2025. <https://www.coindesk.com>
10. CoinGlass (2025) Aggregated liquidation data, October 10–11, 2025 [Data set]. <https://www.coinglass.com>
11. Easley D, López de Prado M, O'Hara M (2012) Flow toxicity and liquidity in a high-frequency world. *Rev Financ Stud* 25(5):1457–1493. <https://doi.org/10.1093/rfs/hhs053>
12. Foucault T, Pagano M, Röell A (2013) Market liquidity: theory, evidence, and policy. Oxford University Press, Oxford
13. Hansen BE, Seo B (2002) Testing for two-regime threshold cointegration in vector error-correction models. *J Econom* 110(2):293–318. [https://doi.org/10.1016/S0304-4076\(02\)00097-0](https://doi.org/10.1016/S0304-4076(02)00097-0)
14. Hasbrouck J (1995) One security, many markets: determining the contributions to price discovery. *J Finance* 50(4):1175–1199. <https://doi.org/10.1111/j.1540-6261.1995.tb04054.x>
15. Hasbrouck J (2007) Empirical market microstructure: the institutions, economics, and econometrics of securities trading. Oxford University Press, New York
16. Hyperliquid (2025a) Oracle documentation. Hyperliquid GitBook. <https://hyperliquid.gitbook.io>
17. Hyperliquid (2025b) Historical L2 order book data [Data set]. S3 archive. Accessed April 2026. <s3://hyperliquid-archive/>
18. Investing.com (2025) The crypto crash and the mystery of the \$1 billion whale. Investing.com, 22 October 2025. <https://www.investing.com>
19. Kirilenko A, Kyle AS, Samadi M, Tuzun T (2017) The flash crash: high-frequency trading in an electronic market. *J Finance* 72(3):967–1013. <https://doi.org/10.1111/jofi.12498>

20. Liu J-H (2025) The October 11, 2025 crypto black swan crash: an academic analysis. Medium, 11 October 2025. <https://medium.com>

21. O'Hara M, Ye M (2011) Is market fragmentation harming market quality? J Financ Econ 100(3):459–474. <https://doi.org/10.1016/j.jfineco.2011.02.006>

22. Reuters (2025) US will impose additional 100% tariff on Chinese imports. Reuters, 10 October 2025. <https://www.reuters.com>

23. Yan J (2025) Liquidation reporting critique [Post]. X, 13 October 2025. https://x.com/chameleon_jeff

Figures

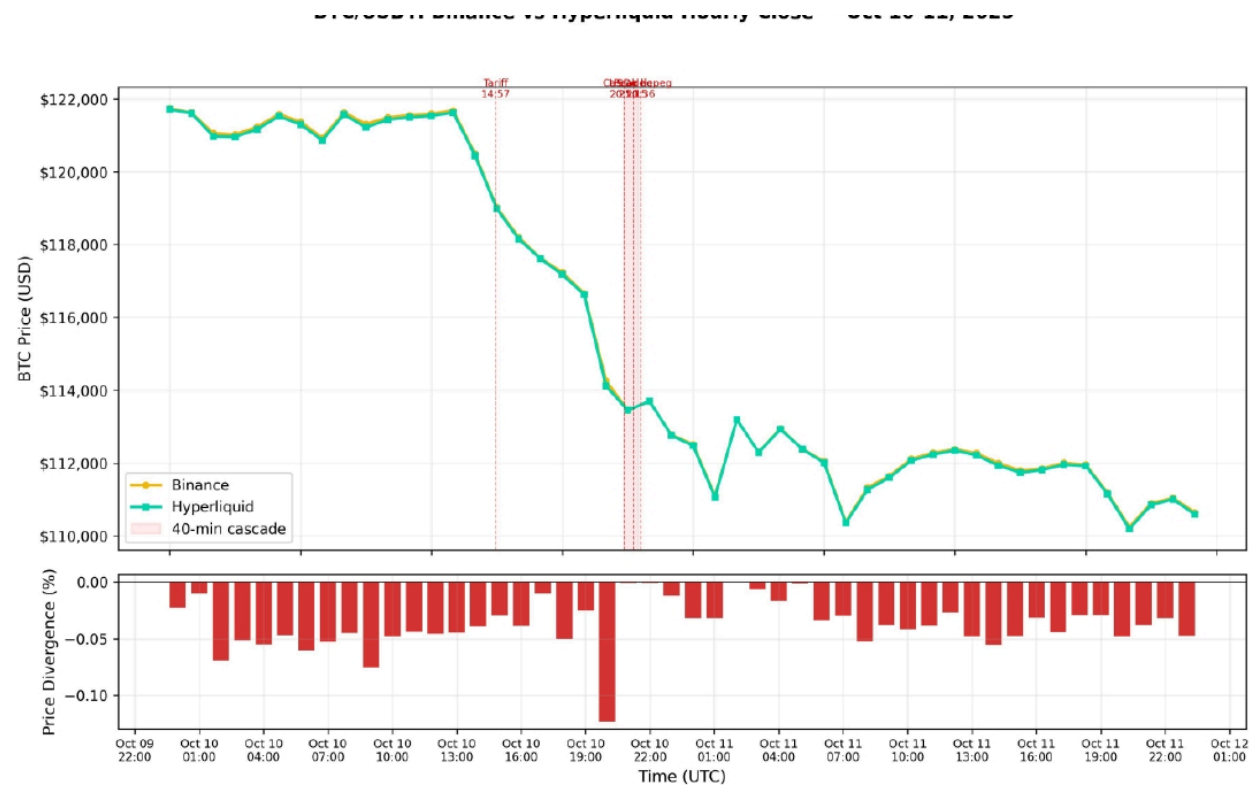


Figure 1

BTC/USDT hourly close: Binance vs. Hyperliquid, October 10–11, 2025

Notes. Upper panel shows hourly close prices. Lower panel shows percentage divergence. Red shading marks the 40-minute cascade window (20:50–21:30 UTC).

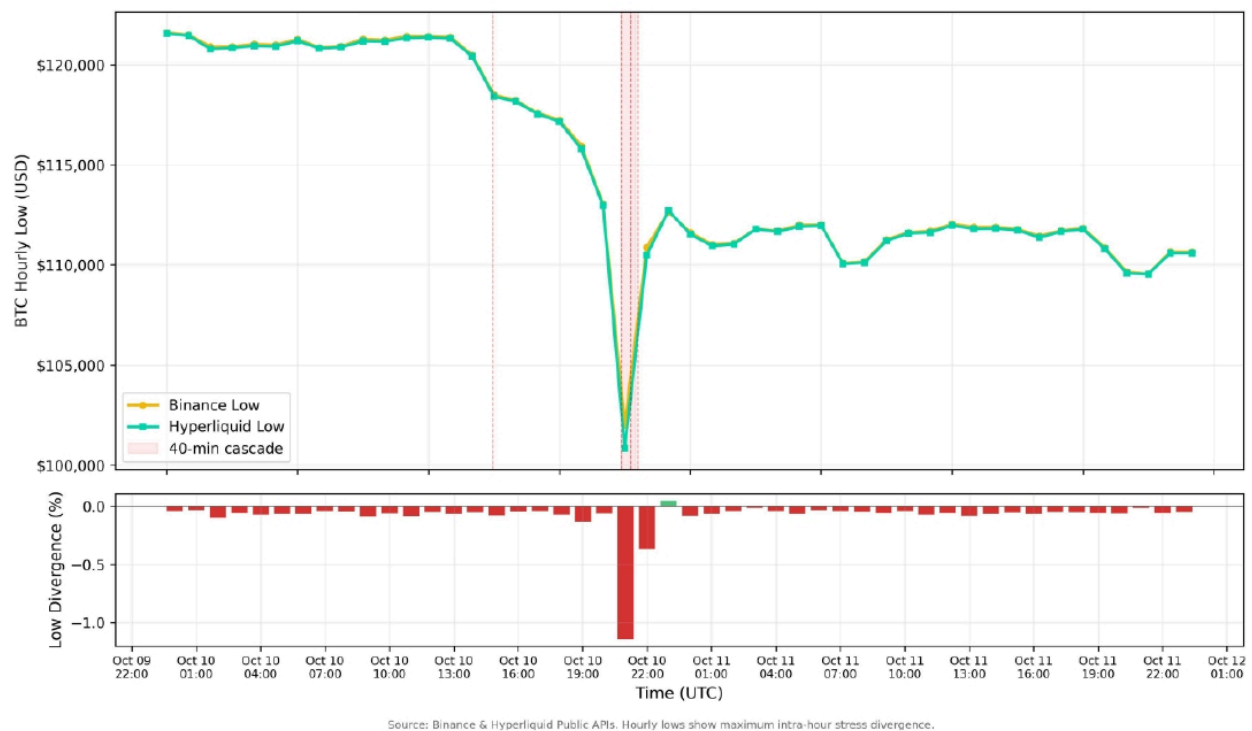


Figure 2

BTC/USDT hourly lows: maximum intra-hour stress divergence

Notes. At tick resolution, BTC divergence reached 7.24% (\$7,387) at 21:24:09 UTC in a single second.

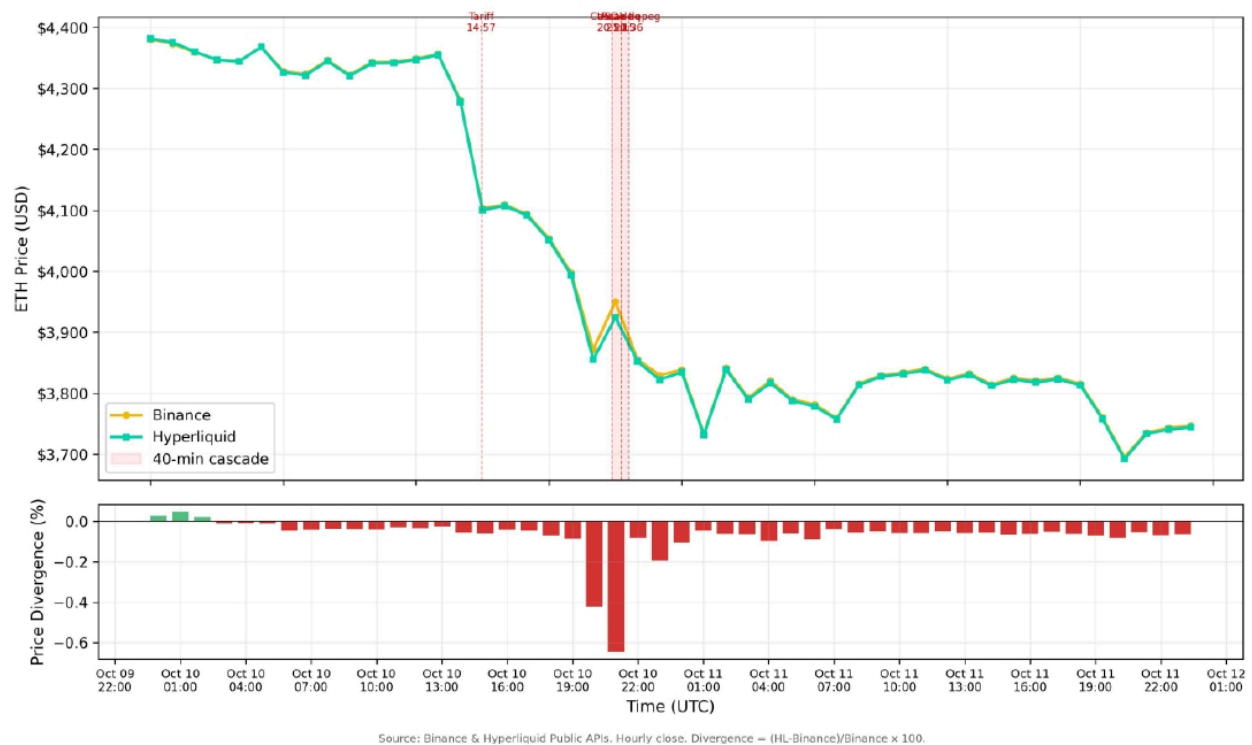


Figure 3

ETH/USDT hourly close: Binance vs. Hyperliquid, October 10–11, 2025

Notes. ETH close-price divergence peaked at 4.76% at 21:20 UTC. Hyperliquid consistently printed lower than Binance on ETH.

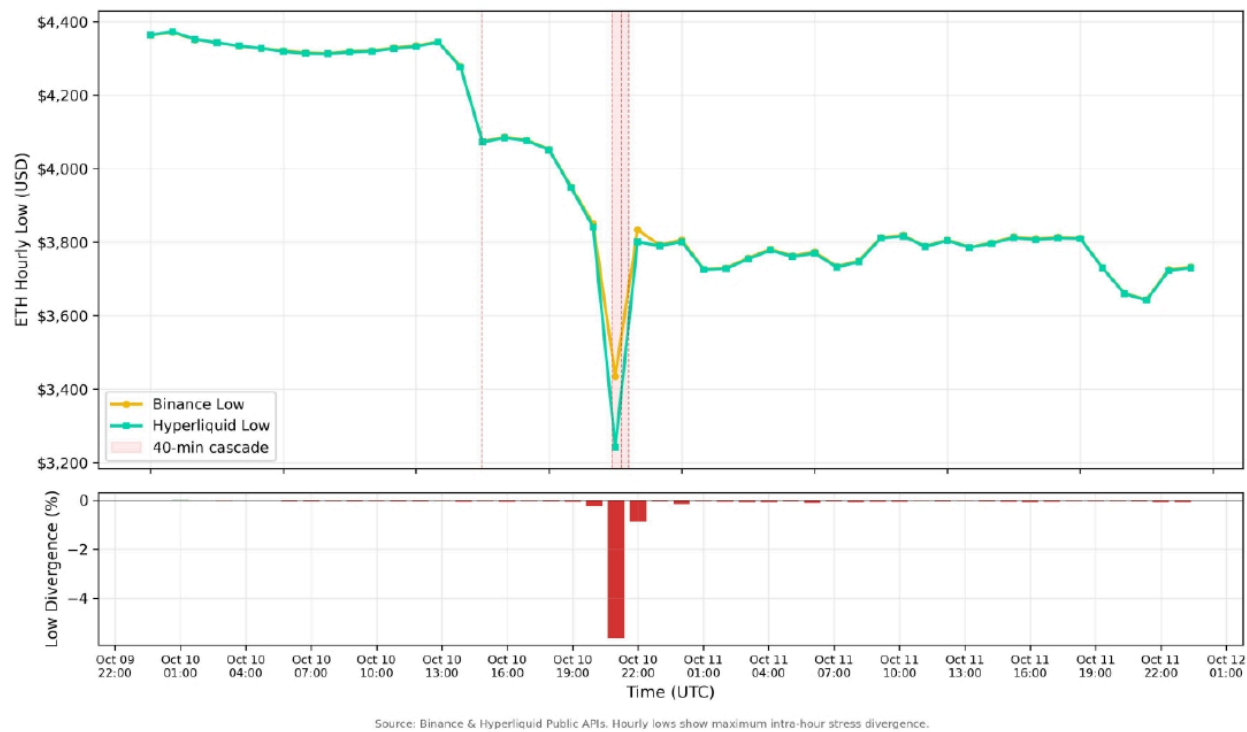
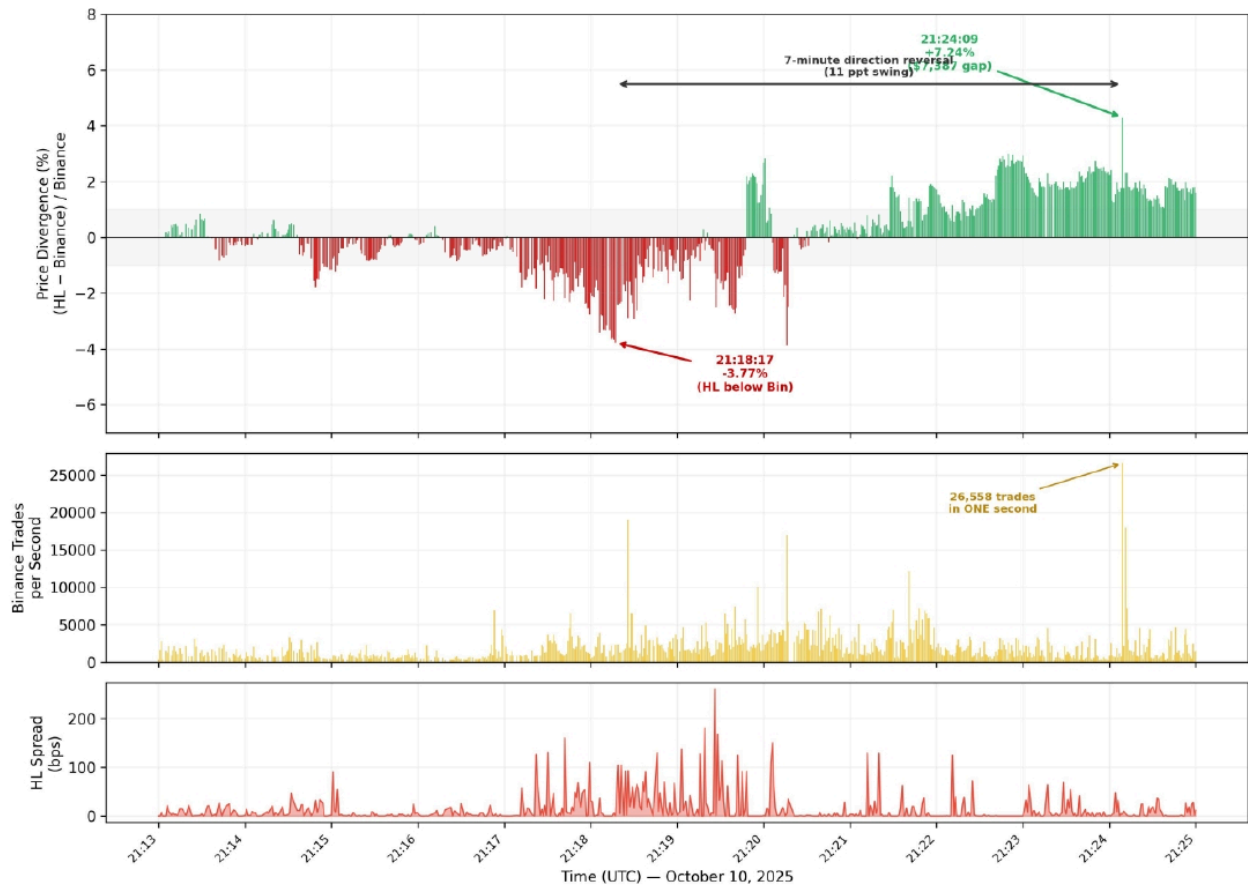


Figure 4

ETH/USDT hourly lows: maximum intra-hour stress divergence

Notes. ETH low divergence reached 5.32% (\$185) at 21:19 UTC. Bid-ask spreads widened 602x and bid depth collapsed 99.8% to \$8,745.



Source: Binance tick-level trade data (data.binance.vision, 2M+ trades in window) merged with Hyperliquid L2 order book snapshots (53 archive, sub-second). Divergence = (HL mid - Binance VWAP) / Binance VWAP x 100.

Notes: Upper panel: per-second divergence. Green = HL above Binance; red = HL below. Direction reversed between 21:18:17 (-3.77%) and 21:24:09 (+7.24%). Middle: Binance trades/sec (peak 26,558). Lower: HL spread (bps).

Figure 5

BTC/USDT second-by-second price divergence during cascade (21:13–21:25 UTC)

Notes. Upper panel: per-second divergence. Green = HL above Binance; red = HL below. Direction reversed between 21:18:17 (-3.77%) and 21:24:09 (+7.24%). Middle: Binance trades/sec (peak 26,558). Lower: HL spread (bps).

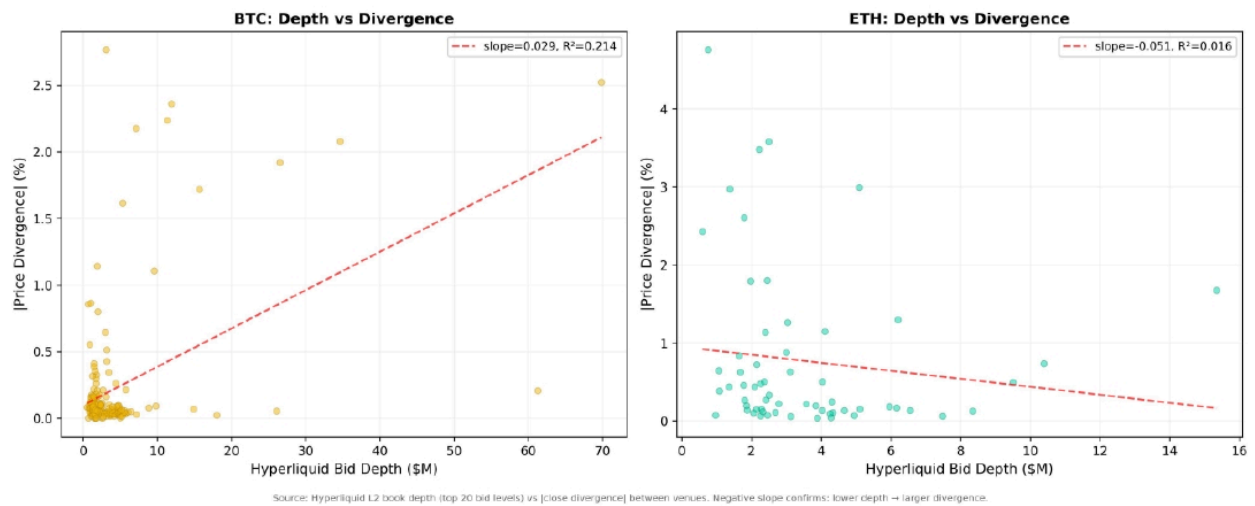
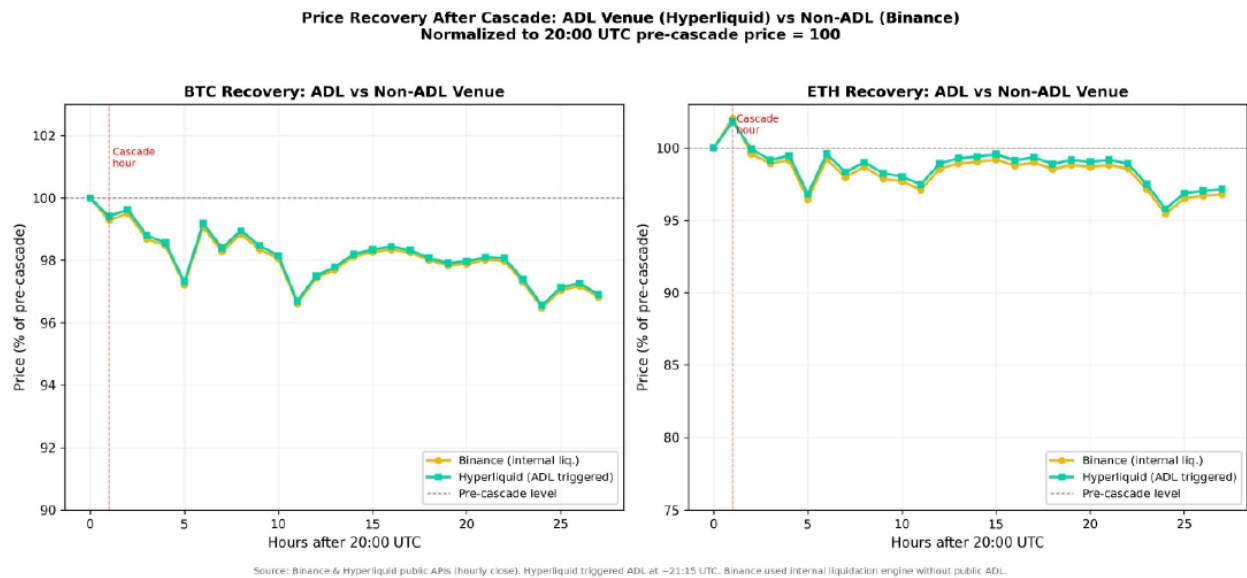


Figure 6

Order book depth vs. price divergence (mechanism test)

Notes. Each point = 1 minute. ETH shows expected negative slope (lower depth → larger divergence). BTC positive slope reflects endogeneity during recovery.



Notes: Normalized to 20:00 UTC pre-cascade close = 100. Both venues recovered to 95% within 2 hours. ADL did not

Figure 7

Price recovery after cascade: ADL venue (Hyperliquid) vs non-ADL (Binance)

Notes. Normalized to 20:00 UTC pre-cascade close = 100. Both venues recovered to 95% within 2 hours. ADL did not measurably impair recovery.

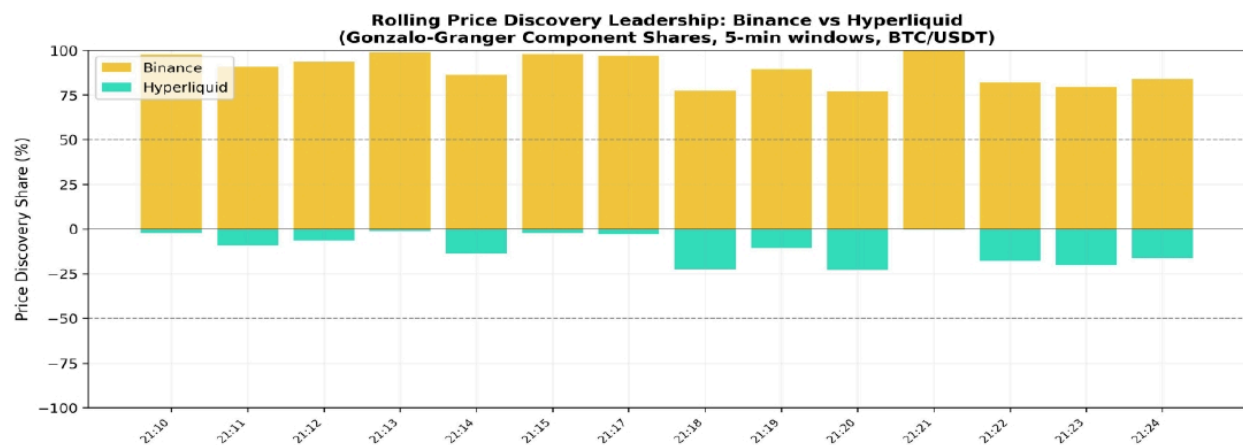


Figure 8

Rolling price discovery leadership: Gonzalo-Granger shares (5-min windows, BTC)

Notes. Each bar = 5-min VECM window, 1-min steps. Binance dominated every window (min 77.2%, max 99.6%). These are linear-VECM shares; the Hansen–Seo threshold VECM estimated in Table 7 reveals regime-specific adjustment dynamics that the linear decomposition averages across.