

Discussion of
“Who Loses and Why? Market Microstructure
of Perpetual Futures”

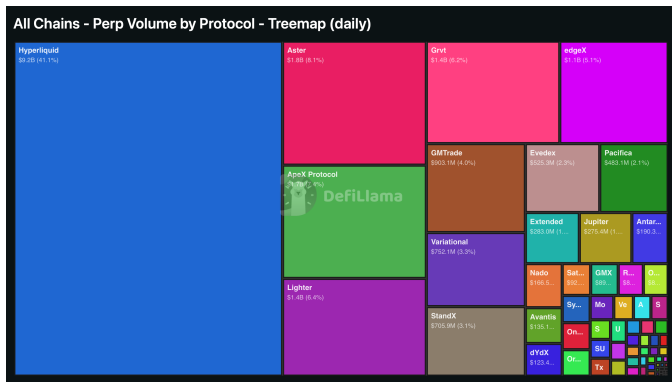
by Jia, Moallemi, Wang, and Zeng.

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OMI-SBS Conference on FinTech and Blockchain Economics

Why care? (1) Hyperliquid is *the* DEX perp market

Perps are now the dominant crypto instrument (~\$62T notional in 2025, >3× spot). On-chain, the market is *one* venue:



Daily perp volume by protocol, all chains. Hyperliquid is **41%** of all decentralized perp volume — larger than the next ten venues combined.

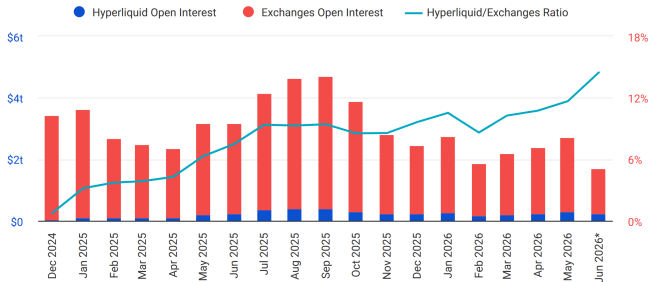
Source: DefiLlama.

Why care? (2) The on-chain share is rising

And it is winning share from *centralized* exchanges — the part of the market we usually *cannot* see at the wallet level:



Hyperliquid vs Exchanges Monthly Open Interest



SOURCES: THE BLOCK, DEFILLAMA
UPDATED: JUN 23, 2026

The Hyperliquid/exchange OI ratio has roughly tripled, to ~14%.
Source: The Block, DefiLlama.

This paper

Setting: the complete on-chain record of Hyperliquid — every order, fill, and liquidation, under a stable wallet ID. ~\$1.95T notional, 386,211 wallets, Mar–Nov 2025.

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Three steps:

- ↪ **Classify** wallets from on-chain behavior \Rightarrow market makers / retail / algos.
- ↪ **Account** for each group's dollar P&L (complete-market, sums to zero).
- ↪ **Explain** the losses via four channels: fees, execution cost, post-trade reversion, liquidations.

The headline: retail finances the venue

After fees, **retail loses ~\$731M**; market makers and algos are net positive.

Retail P&L, M_{120} accounting	\$M
Voluntary trading — taker	-141
Voluntary trading — maker	+63
Forced liquidations (net of ADL)	-152
Fees	-502
Total, after fees	-731

- ↪ A clean, transparent decomposition.
- ↪ My comments are about *what is doing the work*.

My comments:

Comments/observations:

#1: Participants classification is the load-bearing wall.

#2: The retail “slippage premium” — mechanical or behavioral?

#3: Why does retail lose? Immediacy vs. information.

+ minor comments at the end.

Comment #1: Participants classification.

Comment #1a: Every dollar passes through the labels

The paper is conditioned on three labels (MM, retails, algos) from *behavioral thresholds* — no on-chain ground truth.

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... and it labels only *part* of the bucket:

- ↪ **Affirmative:** retail_a/b/c — carry a real frontend share.
- ↪ **Weak:** retail_d (low-activity, *no* frontend) + the unclassified default residual.

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↪ It would be useful to see **headline P&L for the affirmative core (retail_a/b/c) beside full retail.** *If the core still finances the venue, the result is robust to the thin bucket.*

Comment #1b: Can “Algo” really be 2.3% of volume?

In a venue running $\sim 200\text{k}$ orders/sec at sub-second latency, **2.3% algorithmic volume** (Table 1) seems implausibly small.

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Implication: The 2.3% measures *where the line was drawn*, not how much algo trading occurs.

- ↪ “MM earns, retail loses” may partly be *automated* earns, *manual* losses.
- ↪ So the labels are not retail / market-maker / algo, but really **algorithmic liquidity providers** / **frontend-&-residual takers** / non-MM automated takers.

Comment #2: The retail “slippage premium” —
mechanical or behavioral?

Comment #2: Split the execution cost

Retail pays **2.10 bps** slippage vs. **0.19** for MMs — $\sim 11\times$.
Alarming? Split the cost (Eq. 4):

bps of taker notional	MM	Algo	Ret
Half-spread (<i>asset / book</i>)	0.37	0.38	0.33
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The “premium” lives entirely in the part the trader controls.

Comment #2: Low depth elasticity — skill, or objective?

Why does retail pay more slippage?

- ↪ Because retail does not shrink its orders when the book thins: market makers scale order size to displayed depth **2.5×** more than retail (Table 7).

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Ask: do longer-holding wallets show low elasticity *regardless* of group? That separates objective from skill.

Comment #3: Why does retail lose?
Immediacy vs. information.

Comment #3a: What is new here?

“Retail loses to sophisticated players” is the *prior*, not the finding:

- ↪ Documented in equities and assumed in crypto.
- ↪ Crypto perp retail are leveraged, self-selected, possibly sophisticated (e.g., cash and carry) — losing across *all* counterparties is the striking part.

And the flow mechanics are *familiar*: MM/algo contrarian, supplying liquidity to trend-chasers — standard inventory/liquidity provision.

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Two things are genuinely new — and under-sold:

- ↪ The **channel decomposition** on a zero-sum ledger.
- ↪ **Why** retail loses: immediacy, not information — via loss-realizing closes (next slide).

Comment #3b: Immediacy, not information

Two ways to lose money trading. Which is retail?

- ↪ **Information**: you are *wrong about prices* — buy before they fall. A prediction failure.
- ↪ **Immediacy**: you pay to trade *now* — spread + slippage + fees. The price of speed, even when right.

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- ↪ but only for retail does it revert hard enough:
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Takeaway: Retail pays the spread to close *now*, paying for speed when it can least afford to. Is it because they are unskilled or they have to?

Minor comments

- ↪ **SVAR placement.** Results sit in the appendix; the main-text home is missing (broken ?? refs, e.g. pp. 22, 39).
- ↪ **“Disagreement lives in openings”** is true on *sign* (Table 11) — but the economic action is in retail's LRC. Worth stating both.
- ↪ **Distribution of retail losses.** \$731M over 377k wallets is ~\$1.9k each, but surely skewed — whales vs. the mass changes the welfare read.

Summary

A terrific, novel dataset and a clean decomposition.

I learned a lot — looking forward to the next version!