Deviations from Tradition: Stylized Facts in the era of DeFi

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SCUOLA NORMALE SUPERIORE

Summary

1. Introduction
2. Maximal Extractable Value (MEV)
3. MEV Effects
4. Orderflow
5. Conclusion

Introduction

A Quick Introduction

- Ethereum (2015) blockchain kickstarted **Decentralized Finance** (DeFi) thanks to **smart-contracts**
- **Decentralized Exchanges** (DEXs) replace Centralized Exchanges (CEXs) in DeFi using **Automated Market Makers**.
- **Uniswap v3**, on Ethereum, is one of the most popular DEXs.
- Focus on 2023-2024, 15 pairs.

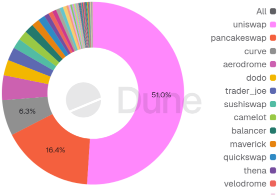


Figure 1: Distribution of activities between 01/01/2023 and 31/12/2024 in the major DEXs on Ethereum.

- **Normal Pairs:**
  - USDC–WETH, WETH–USDT, WBTC–USDC, WBTC–USDT
- **Volatile Pairs:**
  - WBTC–WETH, LINK–WETH, MNT–WETH, UNI–WETH
- **Stable Pairs:**
  - USDC–USDT, DAI–USDC, DAI–USDT, USDe–USDT
- **Synthetic Pairs:**
  - WETH–weETH, wstETH–WETH, WBTC–LBTC

Motivation

We aim to understand how the **new market framework** introduced by blockchain-based platforms like Uniswap **changes the statistical properties of returns and liquidity**. Thus, we perform an analysis of these quantities at very high frequencies.

CEX (Limit Order Book)	**DEX (AMM)**
Reference price: mid-price	Reference price: marginal price $S = \frac{R_Y}{R_X}$
Continuous-time matching/validation	Discrete-time validation (block-based batching)
Price moves via market/limit orders and cancellations	Price moves only via swaps
Submission order $\approx$ execution order	**Submission order $\neq$ execution order (re-ordering within blocks)**

Possible applications

- Reference study for researchers and practitioners.
- Starting point for a **generative models for AMM**.

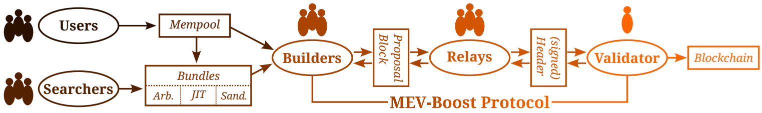
Maximal Extractable Value

Maximal Extractable Value (MEV)

MEV refers to the profit extractable by rearranging transactions, adding new ones, or censoring others

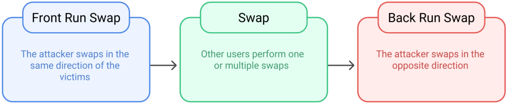
- Before being executed, a transaction is received by an Ethereum node and stored in a **mempool**

- A **priority fee** is usually attached to the transaction, enhancing its chances of early inclusion in a block (on-chain auction for block space)
- Almost 90% of the blocks are validated via **MEV-Boost** (*Proposer-Builder-Separation* implementation by Flashbots)
- MEV-Boost moved the auction for block space off-chain and gave the role of creating blocks to the **searchers**, **block builders**, and **validators** $\longrightarrow$ MEV extraction is shaped by off-chain bidding among these parties

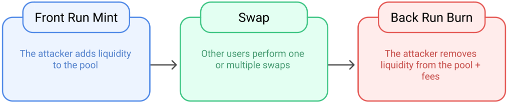


MEV Strategies

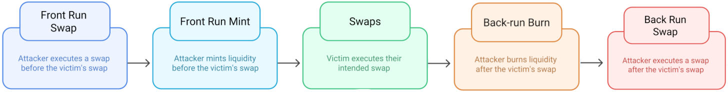
- **Arbitrage** – Exploiting price mismatches between different pools, different DEXs or DEX and CEX.
- **Sandwich Attacks** – Placing trades around a large swap to profit from price impact.



- **Just-in-Time (JIT) Liquidity** – Temporarily providing liquidity before a large trade to earn fees, then withdrawing it immediately.



- **Mixed JIT+Sandwich** - A JIT liquidity provision encapsulated in a sandwich attack.



MEV Strategies - JIT Liquidity

- Almost 40-50% of all the mints were involved in JIT events

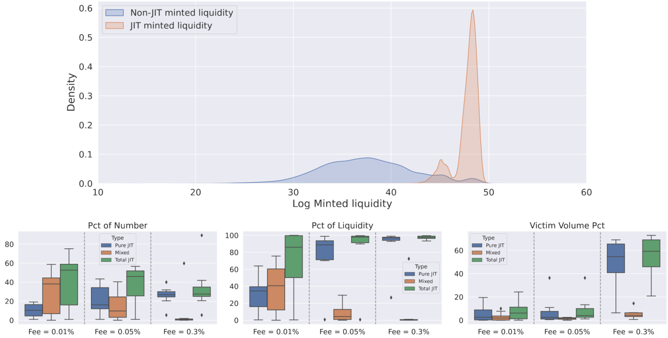


Figure 2: USDC-WETH KDE for JIT vs non-JIT liquidity (upper) and JIT-related percentages wrt fee tiers across all pairs (lower).

MEV Strategies - Sandwich attacks

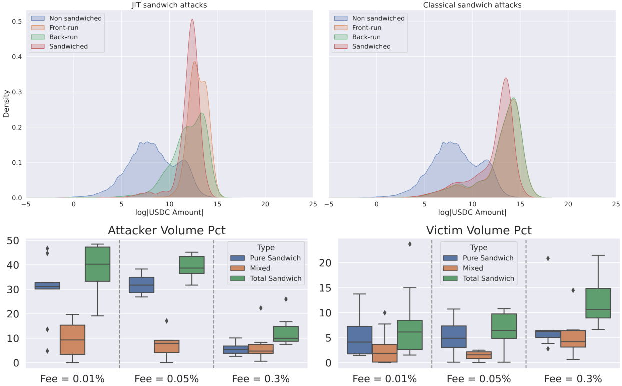


Figure 3: USDC-WETH KDEs of log |USDC amount| in discovered sandwich attacks ($\sim$ 30 000) (upper) and sandwich-related percentages wrt fee tiers across all pairs (lower).

MEV Effects

Returns Autocorrelation

Very peculiar behaviour for the returns **AutoCorrelation Function** (ACF) computed at swap-time.

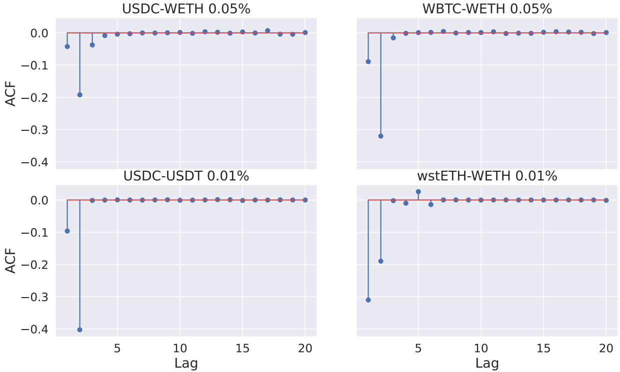


Figure 4: Returns ACF at swap-time. The red bands correspond to the 95% significance level obtained via bootstrap

- **Strong negative autocorrelation** in **swap-time** at **lag 1,2,3** for half of the pools.
- **This dynamics disappears in physical-time**

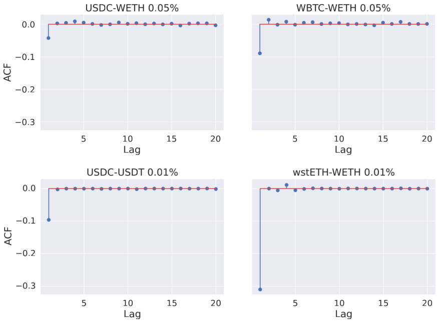
Returns Autocorrelation - Understanding peaks

Peaks at lag 1

- **Bid-ask bounce** generates the negative peak at lag one in TradFi
- In AMMs, there is no bid-ask spread
- Possible source: **reverse trade arbitrages** (Capponi and Jia - 2025).
- Let swaps $\to \mathcal{S}_t$, log returns $\to R_t$ and fee rate $\to \eta$
  - We tested the null hypothesis H_0 : $\mathbb{P}(\text{sign}(\mathcal{S}_t) = -\text{sign}(\mathcal{S}_{t+1}) \| R_t| > \eta) \leq \mathbb{P}(\text{sign}(\mathcal{S}_t) = -\text{sign}(\mathcal{S}_{t+1}) \| R_t| \leq \eta)$
  - Bootstrap hypothesis test $\to H_0$ rejected
  - ACF conditioned on $|R_t| > \eta$ recovers negative peaks
  - ACF conditioned on $|R_t| \leq \eta$ is slightly positive

Peaks at lags 2 and 3

- Source: **sandwich attacks**
- ACF of R_t, conditioned on the absence of sandwich attacks between t and $t + l$ ($l > 0$, swap-time)



Transition Probabilities

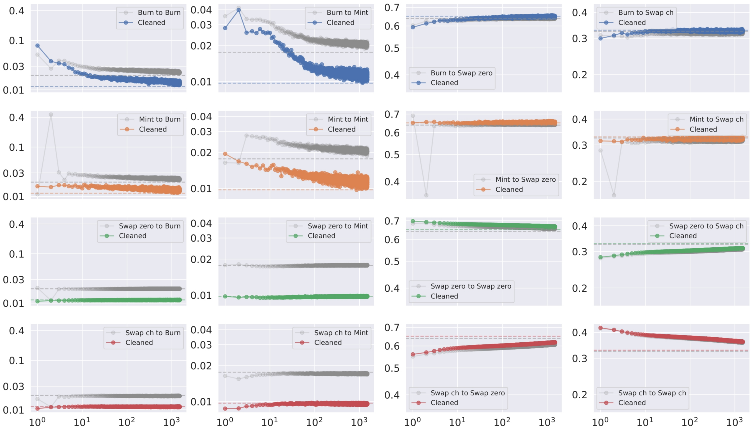


Figure 5: USDC-WETH 0.05% fee - Transition probabilities $\mathbb{P}(e_{t+l} = E | e_t = E')$, with $E, E' \in \{Burn, Mint, Swap\ zero, Swap\ ch\}$. *Swap zero* and *Swap ch* are for swap events without or with tick change. Gray dots display the full data with the presence of JIT events

Orderflow

Trade Direction Autocorrelation

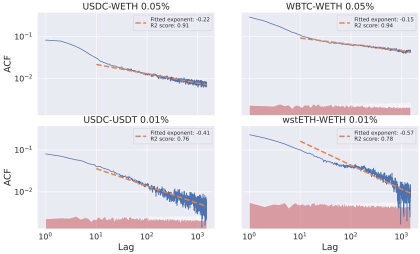


Figure 6: Trade signs ACF, swap-time. The sign series is built by assigning 1 to swaps from X to Y and -1 to the opposite. The ACF is fitted by a power law.

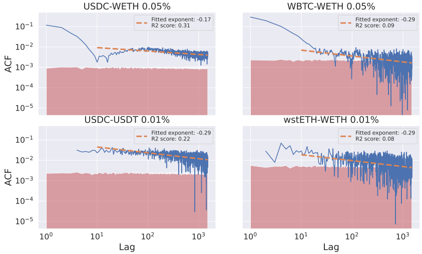


Figure 7: Trade signs ACF, tick-time. The series is built by averaging the signs of all the trades between two tick changes.

Trade Direction Autocorrelation - General Overview

- The long memory property vanishes when using physical-time. This could be due to information aggregation.

Why is there long memory in the sign ACF?

CEXs usually display long memory time series. The main hypotheses are based on:

- **Meta-orders** (Lillo and Farmer - 2004). ACF persistence is introduced by splitting large orders into smaller one and trading them.

- **Herd effect** (LeBaron and Yamamoto - 2007). Strong persistence can be due to a follower-leader mechanism.

- **Can we give a weight to these two possible explanations?**

Decomposing the ACF (Tóth et al. - 2015)

- We decomposed the autocorrelation function into two components: one accounts for swaps made by the same wallet and the other one for swaps made by different wallets.
- We have

$$C(\tau) = \frac{1}{N} \sum_t \sum_{i,j} \epsilon_t^i \epsilon_{t+\tau}^j - \left(\frac{1}{N} \sum_t \sum_i \epsilon_t^i \right)^2$$

This expression can be rearranged as

$$C(\tau) = C_{split}(\tau) + C_{herd}(\tau)$$

where

$$C_{split}(\tau) = \frac{1}{N} \sum_i \left[\sum_t \epsilon_t^i \epsilon_{t+\tau}^i - \frac{1}{N} \left(\sum_t \epsilon_t^i \right)^2 \right]$$

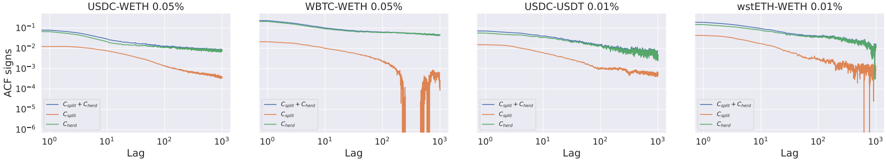
$$C_{herd}(\tau) = \frac{1}{N} \sum_{i \neq j} \left[\sum_t \epsilon_t^i \epsilon_{t+\tau}^j - \frac{1}{N} \left(\sum_t \epsilon_t^i \right) \left(\sum_t \epsilon_t^j \right) \right]$$

Decomposing the ACF (Tóth et al. - 2015)

- The **herding component dominates the autocorrelation** values when tracking swaps by who initialized the swap ('origin' in our data), a notable departure from what we find in traditional markets.
- Possible reasons: gas costs, absence of native way to split orders (TWAP or VWAP) and/or hide the intention (iceberg orders), OTC trades for large swaps.
- The result survives even when filtering out MEV strategies and it is robust also to *routing*

Routing

When users want to submit an order on Uniswap, they can either interact directly with specific pools or rely on Uniswap's routing system (or third-party protocols like 1Inch or CoW Swap) that leverages specialized router smart contracts to identify the most efficient way to execute the trade, in order to achieve the best possible execution price



Conclusion

Conclusion

- We have found **significant differences** in stylized facts between DeFi and TradFi
- These deviations are associated to MEV strategies + mempool
- The **ACF of returns shows negative peaks** at lag 1 (reverse arbitrages), 2 and 3 (sandwich attacks)
- We found **long-memory in the order flow** mostly due to herd effects
- JIT events (almost half of the mints) induce peaks at lag 2 in the transition probabilities
- Not discussed here
  - Very weak correlation between volatility and provision range
  - Volatility spikes during liquidity crisis: big swaps can drain active liquidity to near zero, causing sharp, typically unprofitable price jumps.
  - Significant intraday patterns in several pools

Thanks for your attention!

Figure 8: Deviations From Tradition: Stylized Facts in the era of DeFi