Future Market Making Infrastructure for Securities Trading

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ADVISORS:
DMITRY LIVDAN
EMMANUEL VALLOD

AUTHORS:
YIWEN WANG
FRANCO DELGADO
ARMAND MORIN
JOEY WEN
SAMPADA DESAI

Outline

01 Automated Market Making in De-Fi

02 LVR and Data Preprocessing

03 Dynamic Fees Models

04 Results and Conclusion

Digital Asset Markets

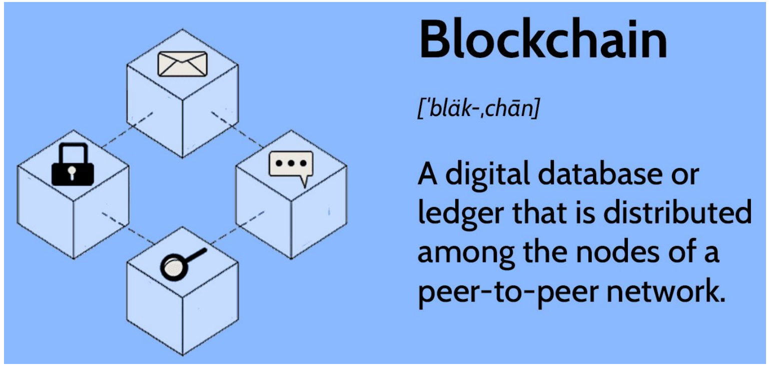
Adoption in digital assets and blockchain tech is rapidly growing

- BTC 24h volume $300bn (price at $65k)
- BTC ETF (Franklin Templeton, Fidelity, Grayscale)
- ETH 24h volume $36bn (price at $3.8k)

"The next step is going to be the tokenization of every financial asset."

Larry Fink (BlackRock CEO)

Decentralized Finance



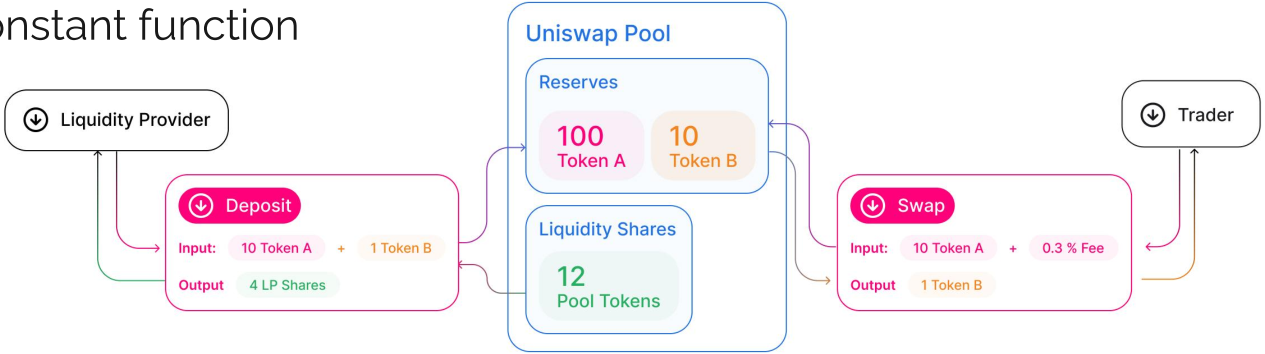
- **Reduced Costs**: self-sufficient, no need for intermediaries
- **Democratized Access**: low entry barrier
- **Enhanced Security**: recorded transactions are immutable
- **Greater Transparency**: all transactions are accessible and verifiable by all network participants

Automated Market Makers (AMMs)

UNISWAP ⟺ NYSE

- Completely Automated
- No LOB mechanism
- Transactions happen in pairs
- Price determined by constant function
- Open 24/7
- Fixed % fee per trade

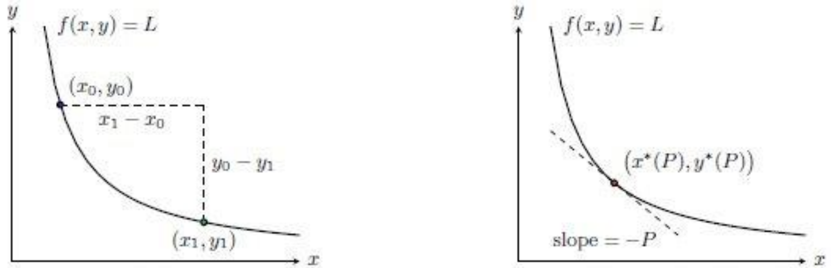
$$L = \sqrt{x \cdot y} = \sqrt{(x+\Delta x)(y+\Delta y)}$$



Uniswap

$$L = \sqrt{x \cdot y} = \sqrt{(x+\Delta x)(y+\Delta y)}$$

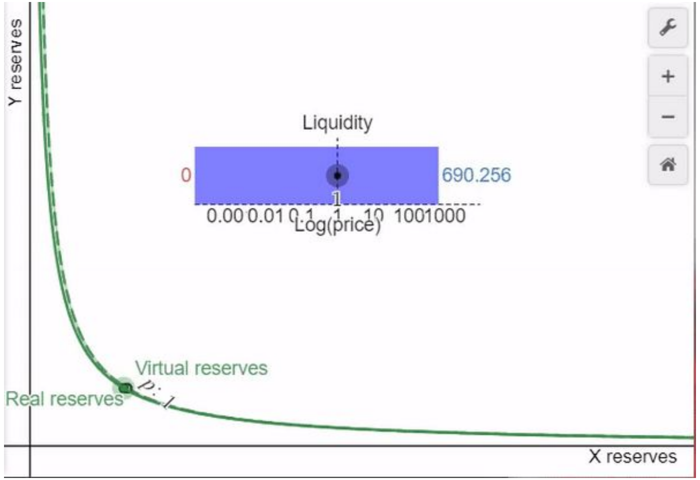
$$\Delta Price = (2\Delta y + \Delta y^2)/\sqrt{L})$$



(a) Transitions between any two points on the bonding curve $f(x,y)=L$ are permitted, if an agent contributes the difference into the pool.

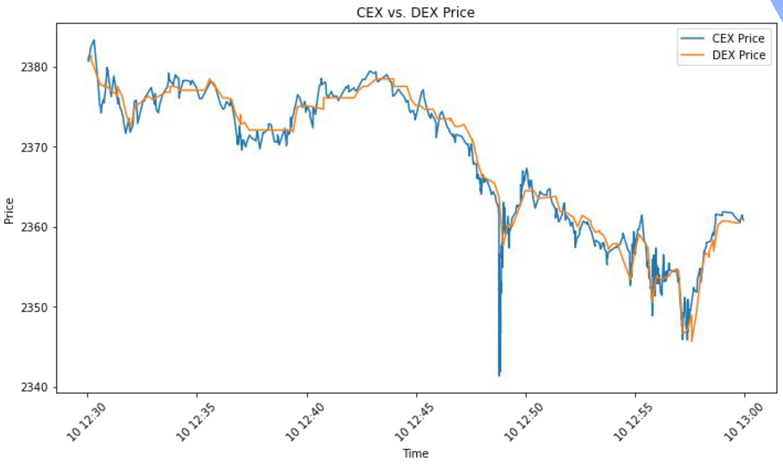
(b) Arbitrageurs ensures that, when the price is P, pool reserves shift to the point on the bonding curve where the slope is equal to $-P$.

Figure 1: Illustration of a CFMM.



CeFi - DeFi arbitrage

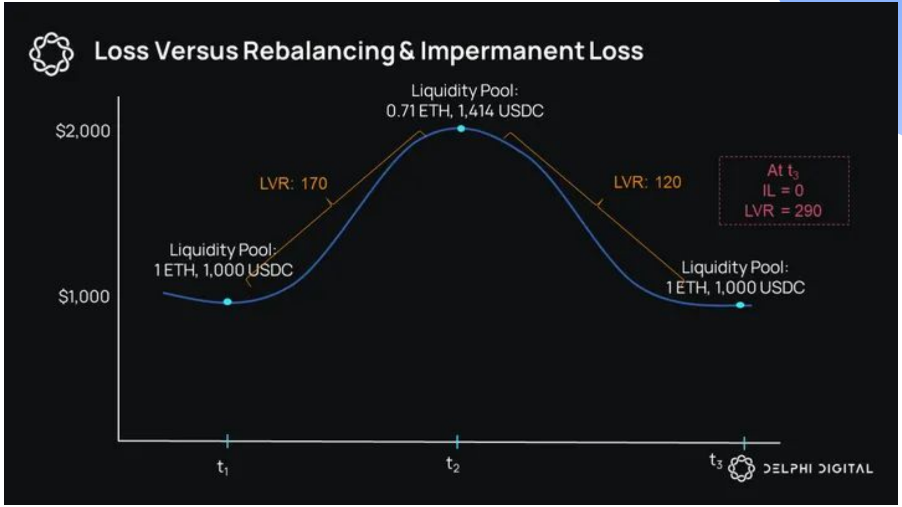
#	Pool	TVL ↓	Volume 24H	Volume 7D
1	WBTC/ETH 0.3%	$379.37m	$19.73m	$373.21m
2	USDC/ETH 0.05%	$180.11m	$254.13m	$2.61b
3	USDC/ETH 0.3%	$131.45m	$4.45m	$276.27m
4	WBTC/ETH 0.05%	$104.74m	$62.41m	$845.62m
5	FRAX/USDC 0.05%	$87.39m	$714.66k	$8.14m



- CEX price is referred to as the "fair price"
- DEX has stale price due to passive price update (15s update time)
- 60% of the total MEV revenues are toxic order flows

Loss-Versus-Rebalancing (LVR)

- LVR refers to LPs' adverse selection cost due to the information asymmetry between the maker (LP) and taker (informed trader)
- LP is a "losing game" due to the adverse price impact
- They need to be compensated by transaction fees
- Larger price difference -> higher LVR -> more losses to LP's -> less participation



$$\text{LP P\&L}_t = \underbrace{\mathsf{FEE}_t}_{\text{accumulated fees}} + \underbrace{V_t - V_0}_{\substack{\text{change in pool}\\ \text{reserve value}}} = \underbrace{\int_0^t x^*(P_s)\,dP_s}_{\text{market risk}} + \underbrace{\mathsf{FEE}_t - \mathsf{LVR}_t}_{\text{fees minus LVR}}$$

LPs effectively sold ~0.29 ETH at ~$1414 < $2000

Objectives: Design a Dynamic Fee AMM

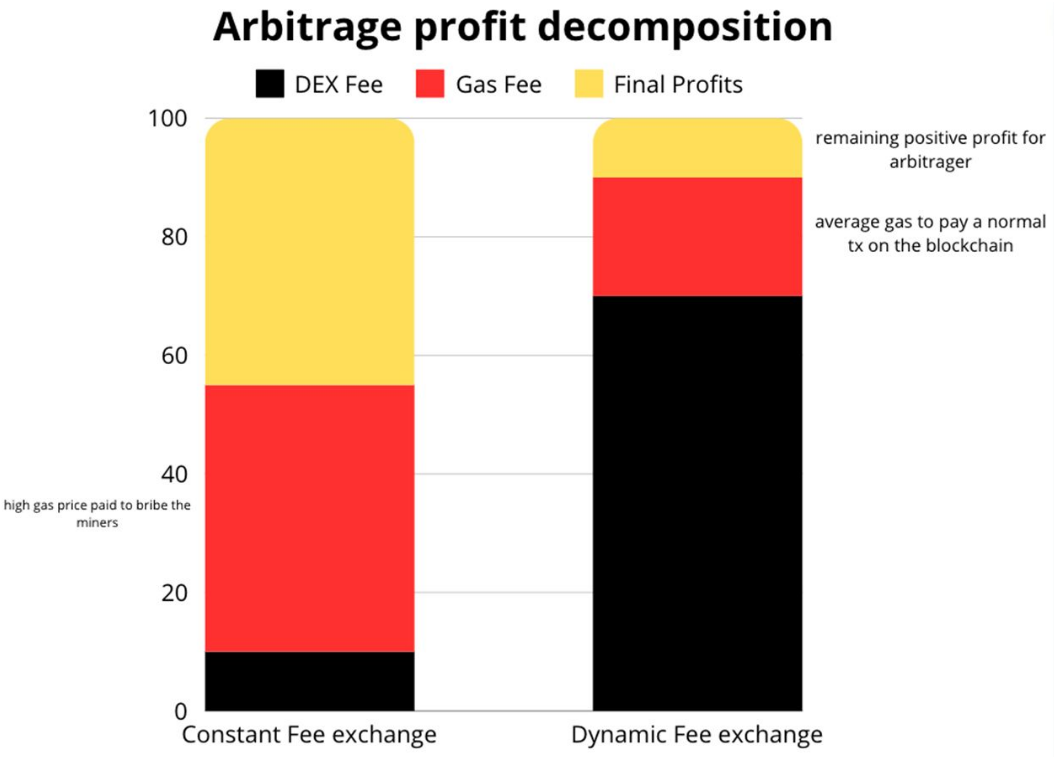
Ensure Price Discovery while Improving Market Liquidity

Mitigate the adverse selection, **LVR** and ensure arbitrageurs still have **profit margin.**

Democratize Finance Wealth Redistribution

Reduce noise trader fee, increase arbitrageurs fee.

Target Variable Calibration



Assumptions

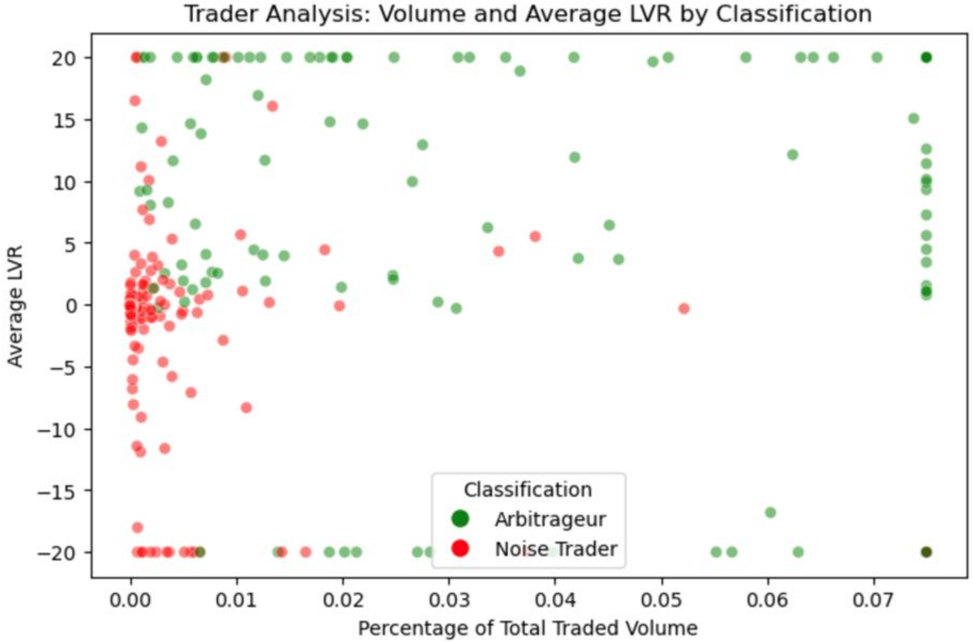
- CEX depth is **infinite**
- No CEX fees
- Static single DEX pool
- Arbitrage is performed exclusively across 2 venues (Binance - Uniswap)
- **Single LP Behavior**
- ETH Gas Fee auction simplification. Take gas fee as endogenous parameter
- Difficulties of the simulation (joint process of price difference and order arrival)

Data Preparation

DEX Data	**WETH-USDC pool on Uniswap V3**
CEX Data	**ETH-USDC transactions on Binance**
Time Period	**January 1, 2024 - January 31, 2024**

Arbitrageurs and Noise Traders

- **Arbitrageurs** are traders who capitalize on price differences across decentralized and centralized exchanges to secure profits.
- **Noise Traders** are participants who engage in transactions within the AMM pools for idiosyncratic reasons.



Single-factor Fee Model

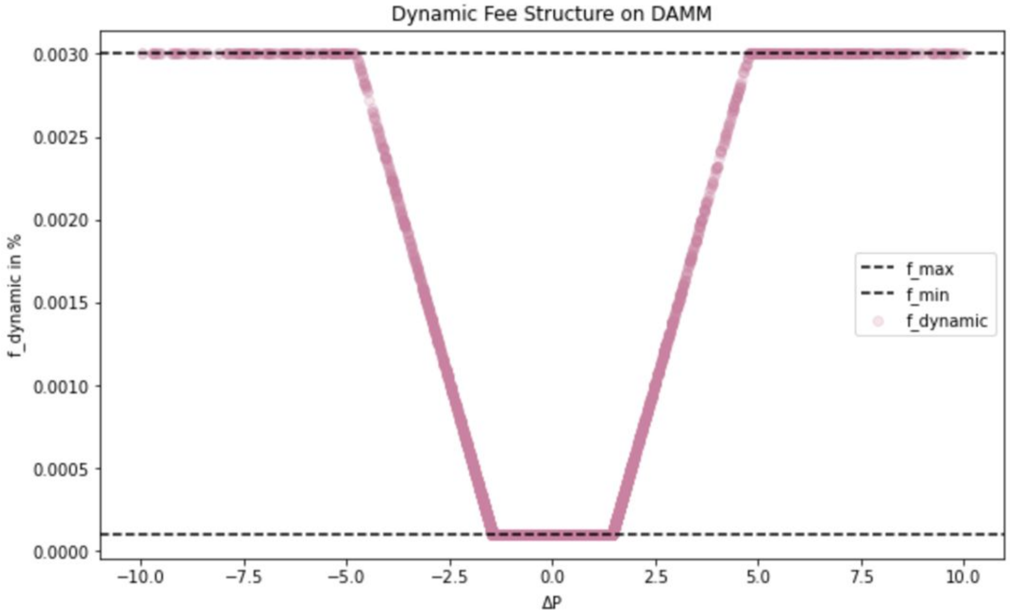
In this study, we designed a dynamic fee model that depends exclusively on the Δp observed between CEX and DEX prices. More specifically, on the z-score of the observed Δp. In general, the model follows the following equations

$$f_{buy} = min(max(f_{min}, \omega \cdot Z(\Delta p) - s), f_{max})$$
$$f_{sell} = min(max(f_{min}, -\omega \cdot Z(\Delta p) - s), f_{max})$$

Where:

- $\Delta p = p_{cex} - p_{dex}$
- $Z(\Delta pi) = \Delta pi - \mu\sigma$
- μ, the average Δp on the calibration period
- σ, the standard deviation on the calibration period
- f_{min} and f_{max}, the lower and upper bound of buying and selling fees
- ω, parameter for weight attached to Δp in the calculation of fees
- s, parameter from deviation from the hypothetical max fee

Dynamic Fee Structure on DAMM



Adjust Fee Based on Order Direction. This plot shows a combination of both f_{buy} and f_{sell}, *which are symmetrical on x = 0.*

Model Calibration

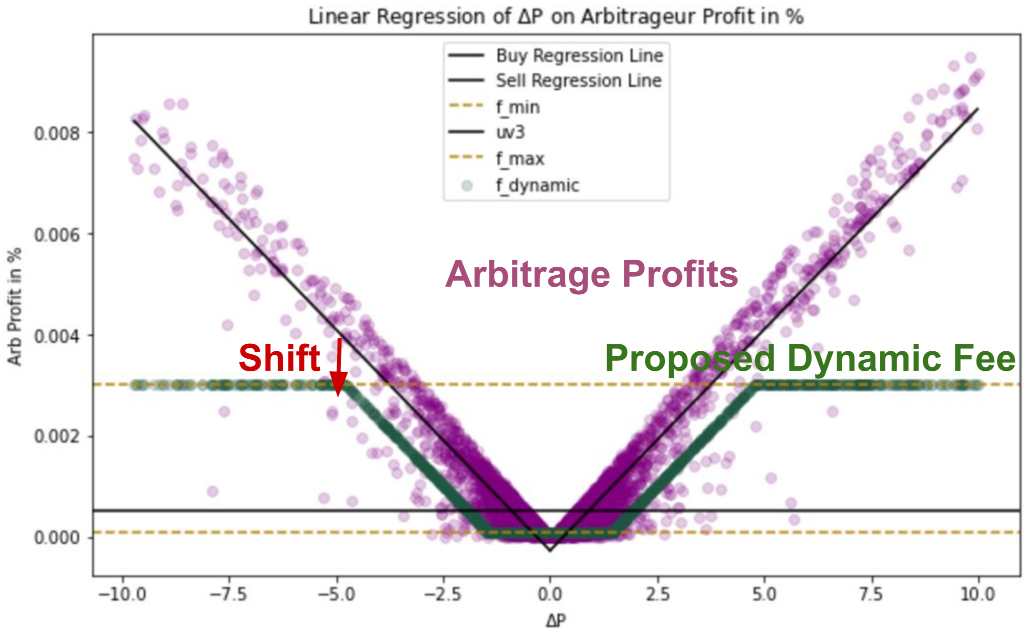
Our objective is to establish a dynamic fee structure, which adjusts linearly based on the price disparity.

1. **Data Winsorization**. The training dataset -> positive PnL, concentrates on transactions where $Z(\Delta p) \in [-10, 10]$.
2. **Regression**. OLS to regress winsorized PnL on $Z(\Delta p)$ to find the linear dynamic fee's gradient ω.

$$PnL = \frac{x_i \cdot \Delta p - t\_cost}{x_i}$$

3. **Parameter Optimization**. The shift parameter s% is calibrated by maximizing the dynamic fee, with the constraint that trading volume must stay above a certain threshold.
4. **Fee Structure**. Use the ω and shift s% to calibrate the straddle shape fee structure.
5. **Data Fitting**. Use the above fee structure to fit all the transactions from January 2024.

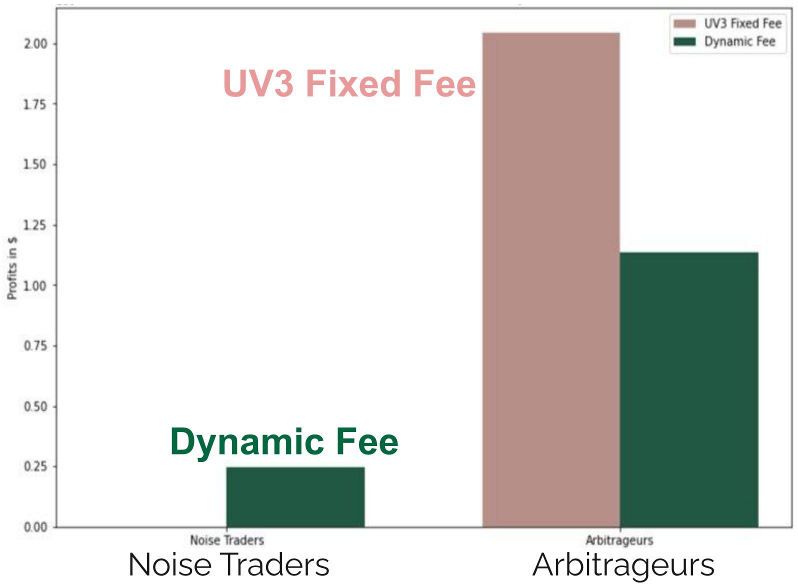
Calibration Result

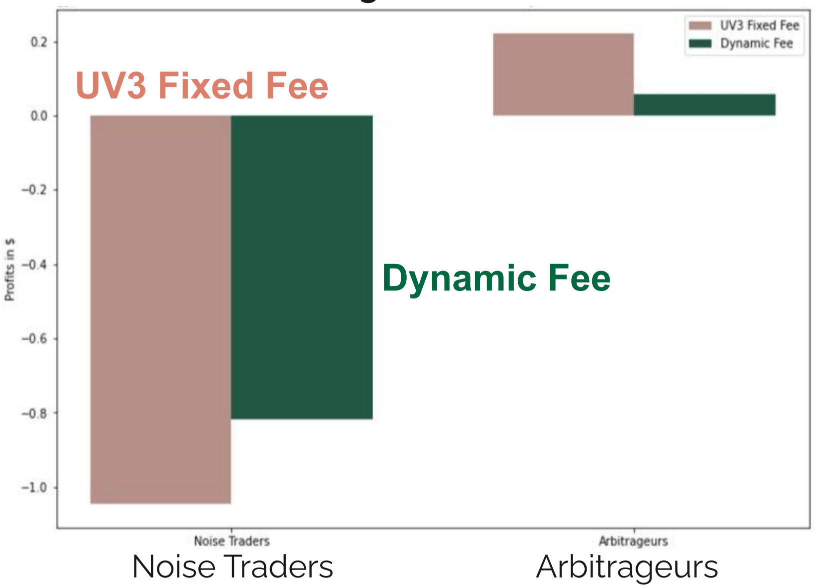


- **Arb Profits on Delta P.** Where we find f_{sell} to the left of Z(Δp) = 0 and f_{buy} to the right of Z(Δp) = 0.
- The **continuous black lines** are the regression lines, used to estimate ω, showing the maximum fee an arbitrageur would be willing to pay to enter a trade.

Model Empirical Analysis

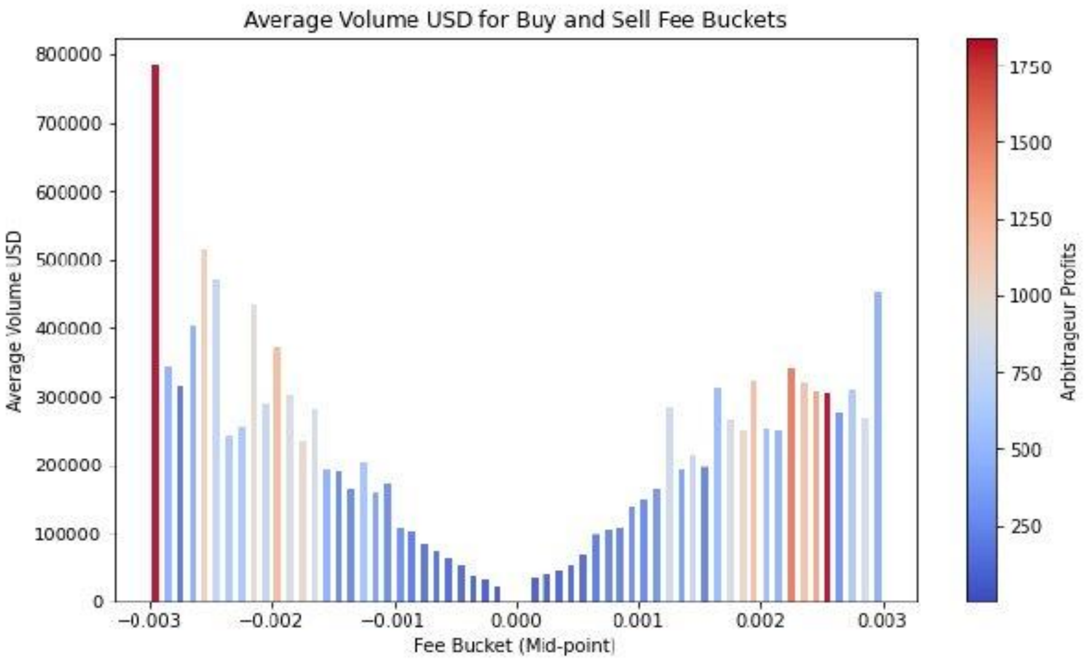
Profit Redistribution before and after Dynamic Fee





- Overall, 98% of the trades are charged less than the Uniswap V3 proxy 5bps.
- 3.645% of the transactions are classified as arbitrageur trades.

Model Empirical Analysis



Higher fee buckets corresponds to **higher profits**, which ensures that the dynamic fee model punishes arbitrageurs with higher profits while lowering the cost for others.

Multi-factor Fee Model

$$f_{buy/sell} = \sum_{i=1}^{n} min(max(f_{min}, \omega_i f_i(g_i)), f_{max}) \quad f_i(g_i) \propto m_i g_i$$

Where:

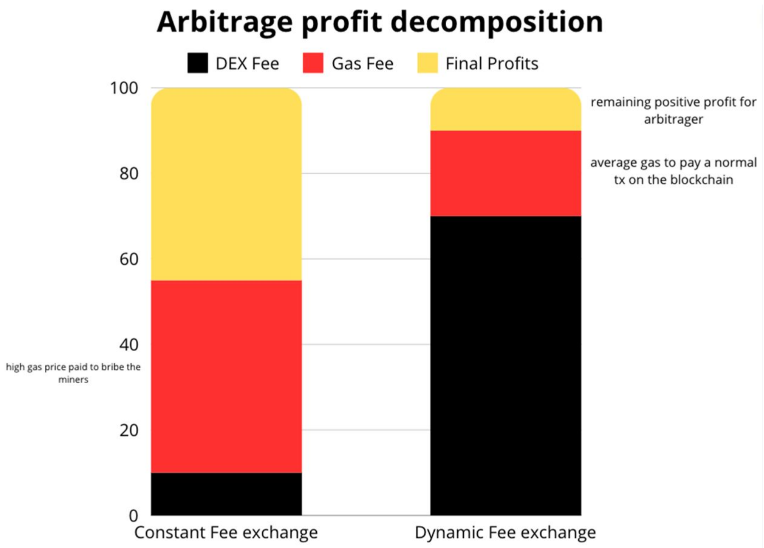
- f_{min} and f_{max}, the lower and upper bound of buying and selling fees for each independent feature
- f_i, the fee of a single factor model
- ω_i, the weight associated with the factor

	Amount USD	Arbitrage PnL %	Volatility
swap 0	100 $	2 %	10 %
raw fee	0.01 %	0.1 %	0.01 %
weight	50 %	30 %	20 %
Total combined fee	0.012 %		

Factors Considered

- Price Difference: $P_{diff} = P_{cex} - P_{dex}$
- Arbitrager Profit in theory:

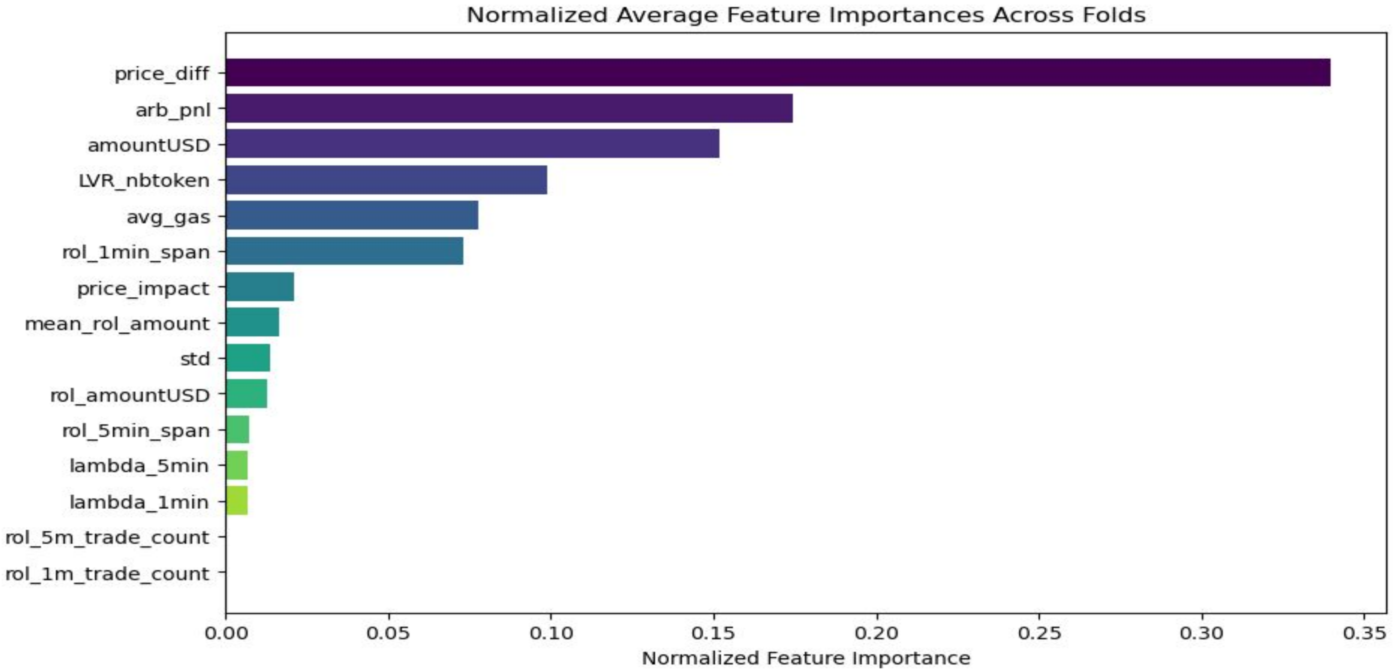
  arb_profit = P_{diff} * AmountUSD
- Amount traded in USD
- Average Gas used in the last 30 blocks to get an idea of how much should a “normal” tx spend to get executed
- Price impact on the Pool Dex
- Volatility
- Volume
- Lambda: param of the poisson process to get the trading frequency on the pool



Model Calibration

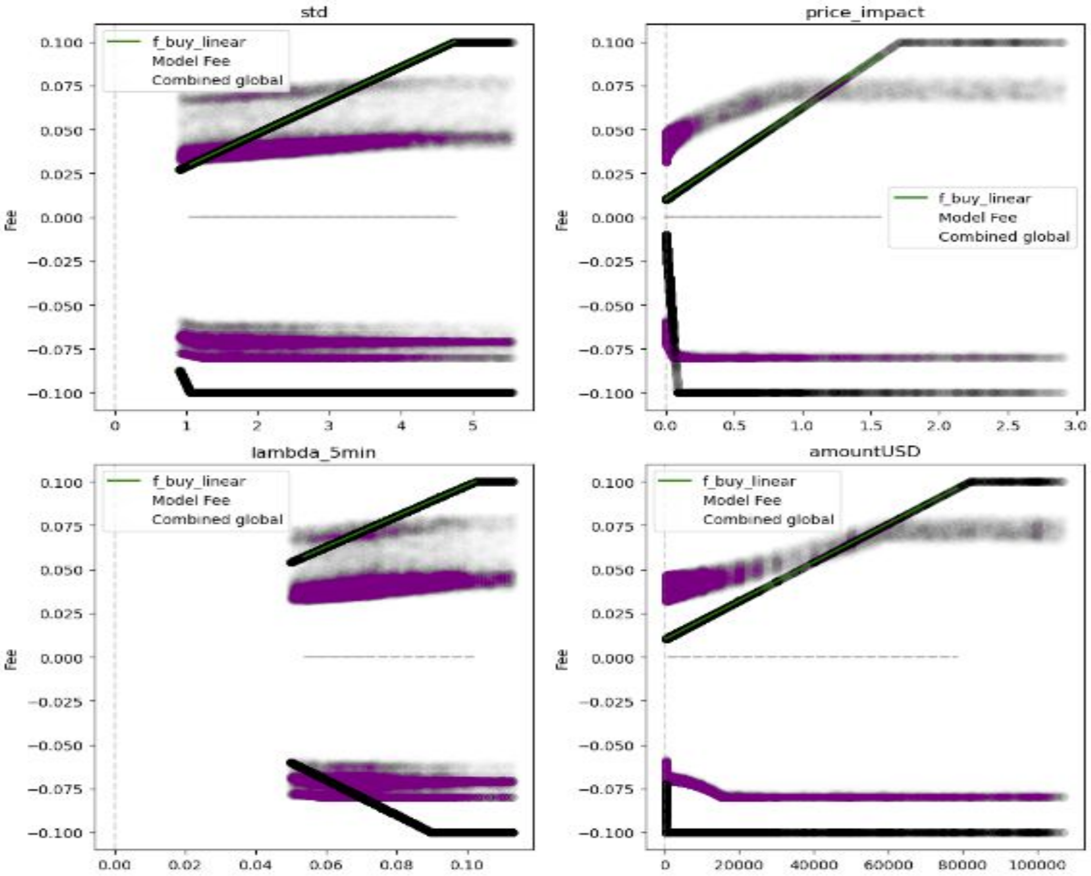
1. Data Segmentation. The dataset is initially segmented into two subsets based on the direction of the transaction - purchases (buy) and sales (sell).
2. Feature-Based Quantile Scaling. For each relevant feature in the dataset (e.g., price difference, transaction volume, etc.), quantile based scaling boundaries are established.
3. Setting f_{min} and f_{max}. We give fixed values for these across all features, with f_{min} = 0.01 and f_{max} = 0.1.
4. Estimating the fee per Feature. Find the slope of the linear model. Apply the buying and selling fee to each factor and then combine them using the weights
5. Compute the performance metrics of the model. Loop again to find the optimal values for the model (trade of for the price update/discover and the LP profitability)

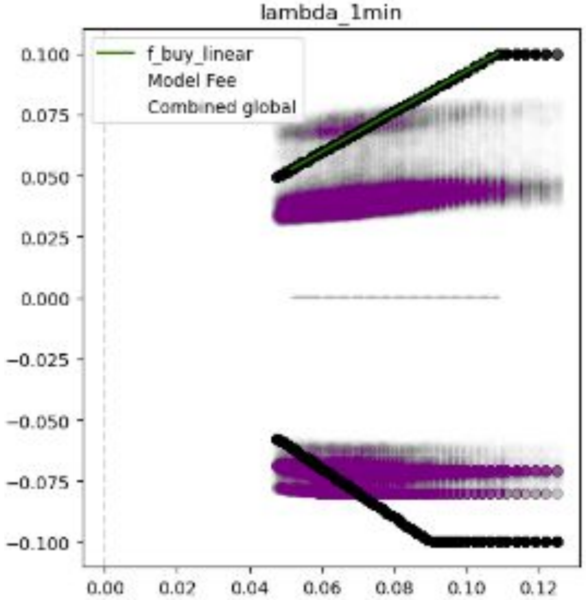
Random Forest for Feature Importance



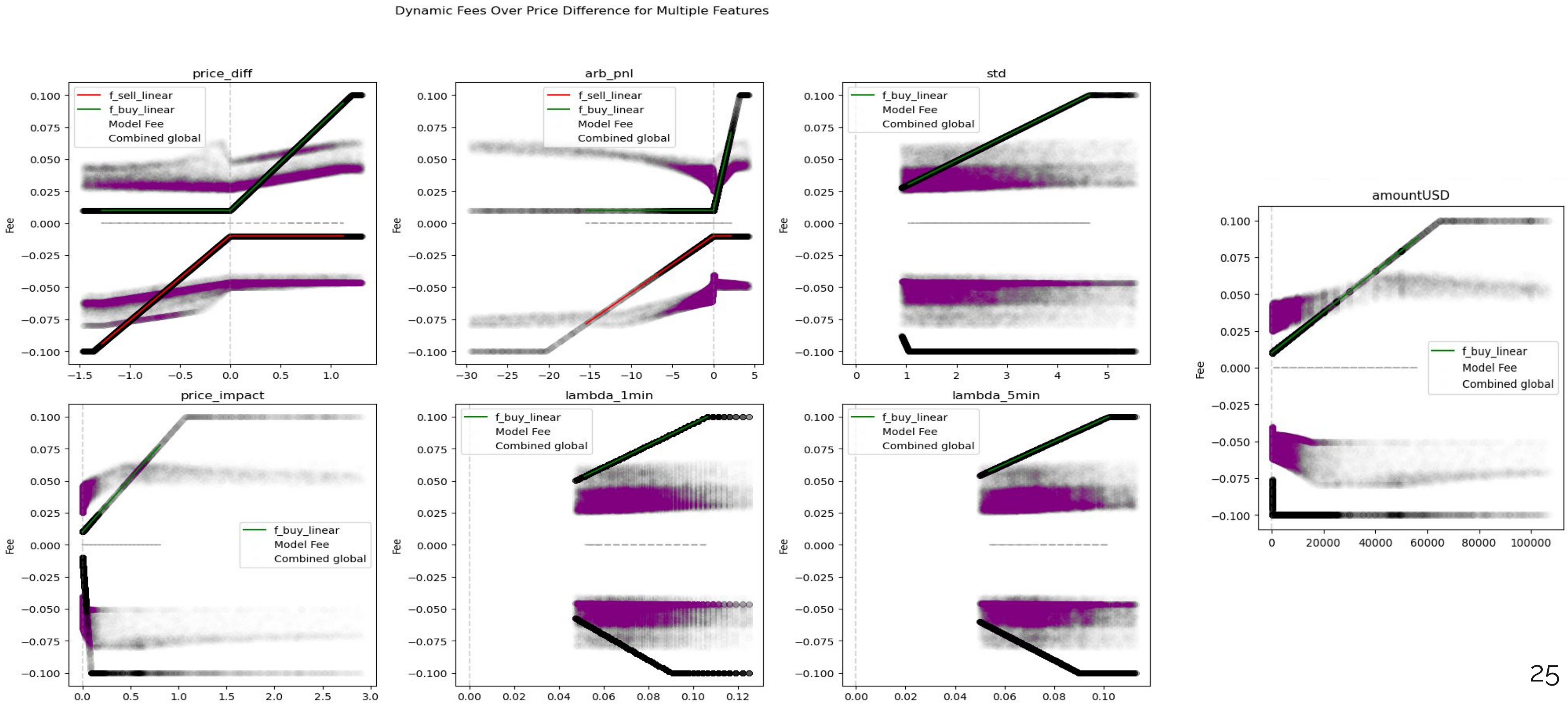
We ran a **Random Forest Regression** model over the features, having the **hypothetical fee** (i.e. the maximum % profit an arbitrageur could make on a trade) as target variable to get the feature importance.

5-factor Model Result





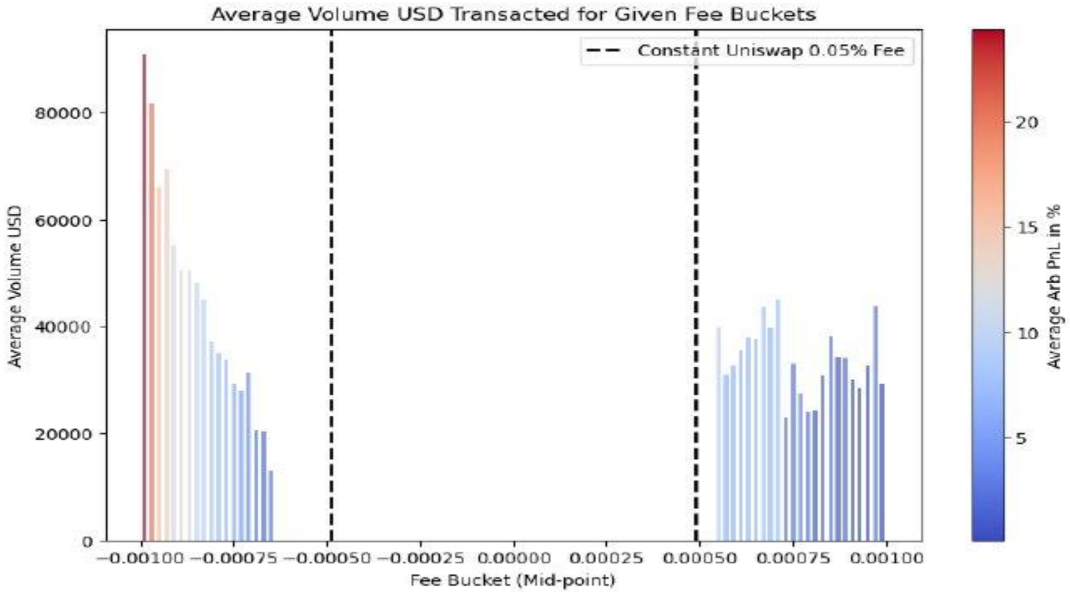
7-factor Model Result



Model Benchmarks

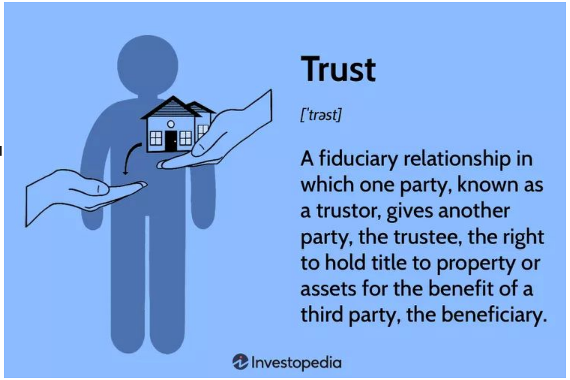
Model	Constant Fee	5 Factors (TradeFi Factors)	7 Factors (DeFi Factors)	10 Factors
Additional Profits for the Pool	0 %	2.4 %	8.2 %	12.1 %
Price Impact Improvement (decrease)	0 %	2.3 %	7.6 %	10.8 %
Avg. Selling Fee	-0.05 %	-0.07 %	-0.05 %	-0.07 %
Avg. Buying Fee	0.05 %	0.05 %	0.04 %	0.05 %
Avg. t-cost	150 $	93 $	47 $	38 $
Impermanent Loss	-1 %	-1 %	-1 %	-1 %
Accuracy of Fees	100 %	7.53 %	9.86 %	4.2 %
Feature Importance		Amount USD: 40 % Volatility: 17 % Price Impact: 15 % Lambda 5min: 14 % Lambda 1min: 12 %	Amount USD: 27 % Price difference: 25 % Arbitrage PnL: 25 % Volatility: 7 % Price Impact: 7 % Lambda 1min: 5 % Lambda 5min: 5 %	

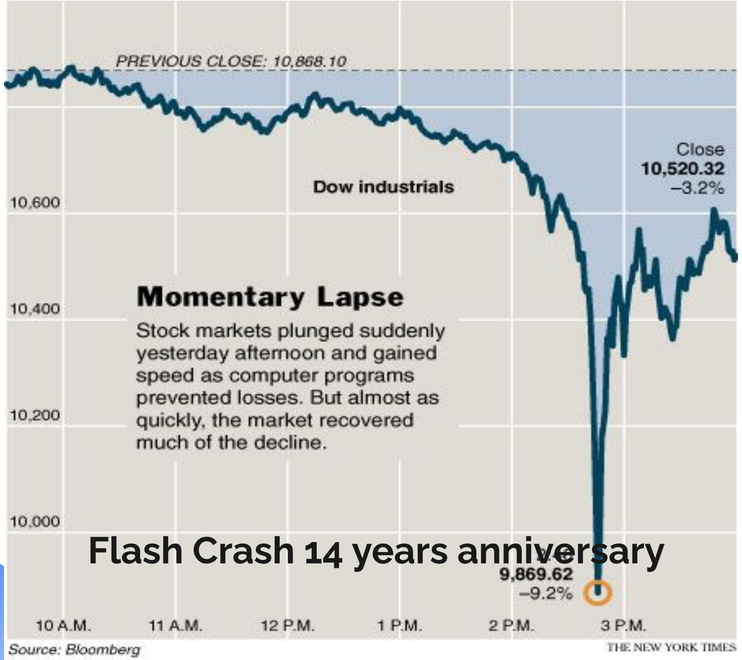
Model Empirical Analysis



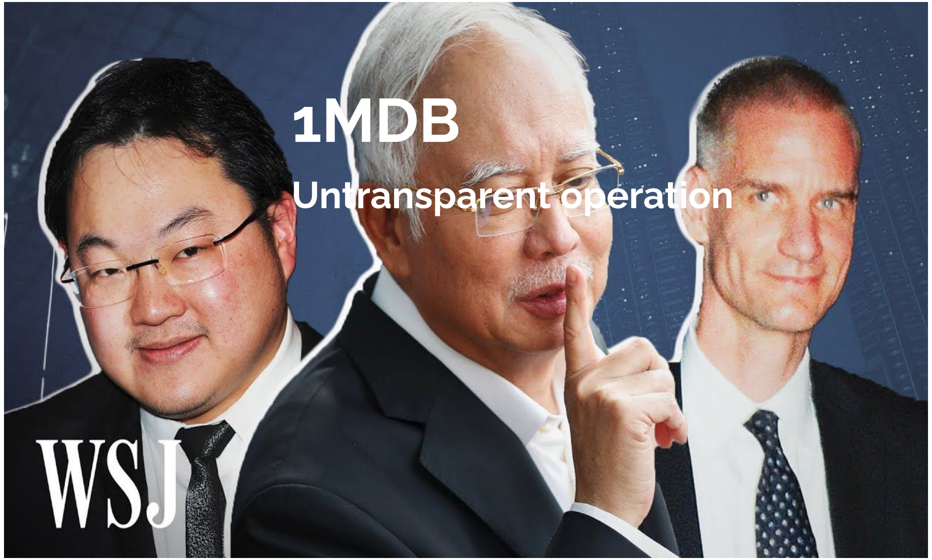
- **Trades with higher profits** are charged with **higher fees**, which aligns with the single factor model
- We punished arbitrageurs with higher profits, keeping the fees low for the rest of the users.

Conclusion: It's all about ...





Flash Crash 14 years anniversary



1MDB

Untransparent operation

Conclusion

Enhanced Liquidity and Price Discovery	Fair and Adaptive Fee Structure	Increased Participation and Volume	Financial Democratization
Dynamic Fee to reduce LVR costs, while still incentivize arbitrageurs.	Higher Fee for Higher Profits	96% of the trades pay LESS fee than on Uniswap	Redistribution of wealth from arbitrageurs to noise traders and LPs encourages a broader participation in the DeFi ecosystem.

Implement DAMM

- Smart contract based dynamic fee
  - Expensive to compute on chain – Off chain API, providing params w and s.
  - Simple Fee Function based on Price Difference and Trading Volume

- Oracle Assisted AMM
  - Multiple data feeders
  - Encrypt Oracles

Integrate DAMM with NYSE

- Regulation: Convert rights to an asset into a digital token on a blockchain
    - Tokenize Real World Asset
- Settlement Risk
    - Centralized Counterparty (CCP)

- Fraud Prevention

Thank you!

- Yiwen Wang: yiwenwang@berkeley.edu, linkedin.com/in/charlize-ywang/
- Armand Morin: armand_morin@berkeley.edu, linkedin.com/in/armand-morin/
- Franco Delgado: franco_delgado@berkeley.edu, linkedin.com/in/franco-delgado-d/
- Sampada Desai: sampada_desai@berkeley.edu, linkedin.com/in/sampada-desai/
- Joey Wen: hao.wen@berkeley.edu, linkedin.com/in/hao-jwen/