Dynamic Fees for Automated Market Making

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Outline

- Automated Market Making in De-Fi
- LVR & Data Preprocessing
- Dynamic Fees Model
  - Single-Factor Model
  - Multi-Factor Model
- Results & Conclusion

Market Making in Traditional Finance

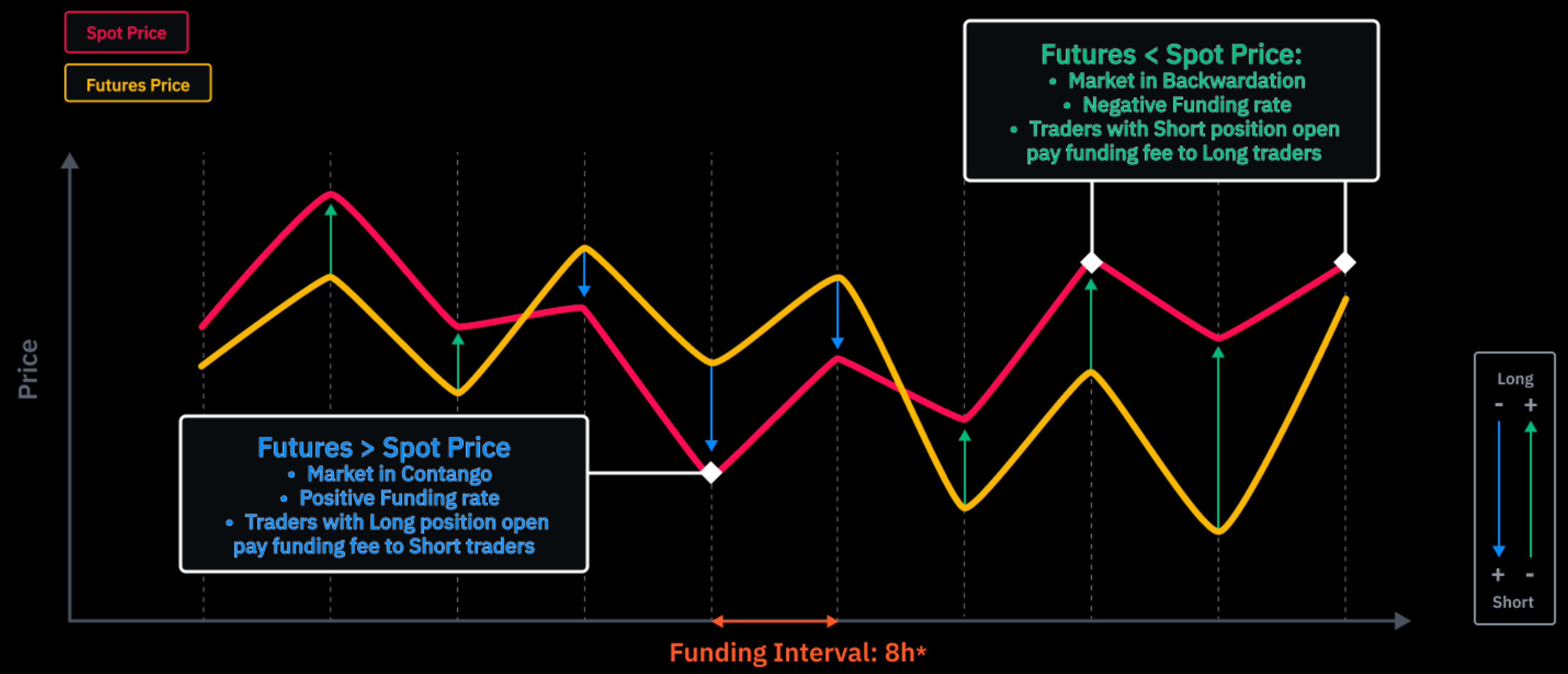
Market Making - Providing liquidity by continuously offering to buy and sell securities.

Importance - Narrowing bid-ask spreads, enhancing market depth and stability.

Strategies - Limit orders, managing inventory, maintaining balanced books.

Regulation - Market makers operate in regulated environments overseen by financial regulatory bodies.

Funding Rate - Perpetual Future Contract vs Spot Trading



- **Funding Rate** is the periodic 8h rate (could be positive or negative) determined by the difference between futures prices and spot prices.
- **Premium Index** (P) = [Max (0, Impact Bid Price – Index Price) – Max (0, Index Price – Impact Ask Price)]/Index Price

Transition to Decentralized Finance (DeFi)

- **Challenges of traditional financial markets:**
  - Inefficiencies
  - Restricted access
  - Opaque operations
- **DeFi's solution:**
  - Leverages blockchain technology to eliminate intermediaries, offering financial services directly on the blockchain.
- **Benefits of DeFi:**
  - Democratized access
  - Greater transparency
  - Smart contract

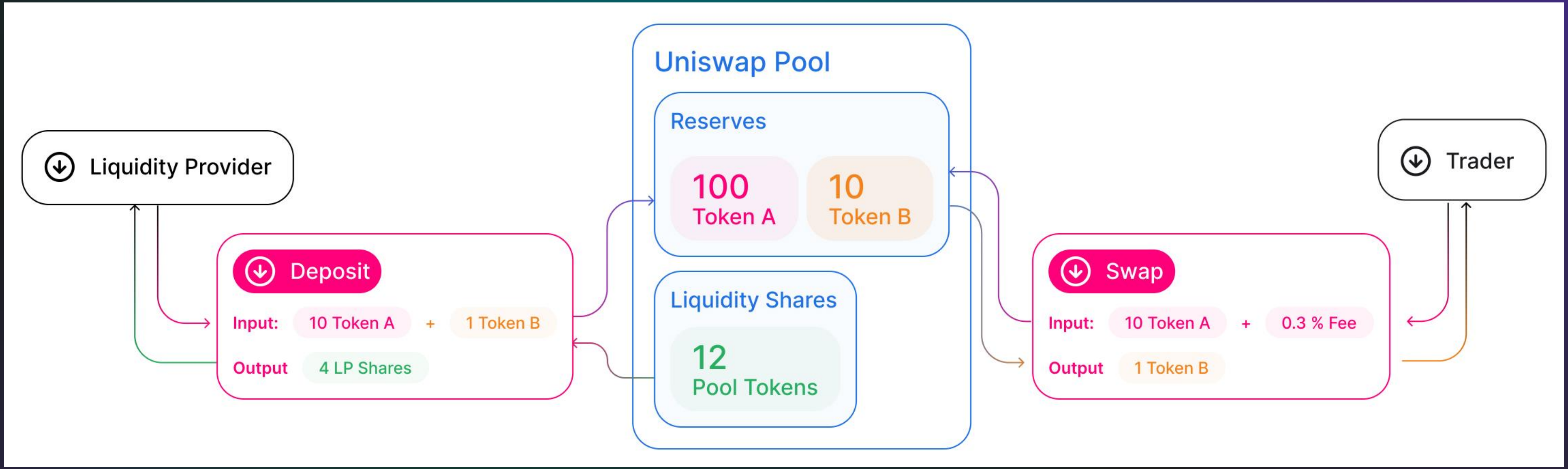
Automated Market Maker - Uniswap

- **No order books – Deterministic formulas for prices instead.**
- **Inserts Liquidity Pools:**

#	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

- **80% of the total liquidity is concentrated in a select group of 5 pairs featuring widely-traded tokens**

Uniswap Mechanism

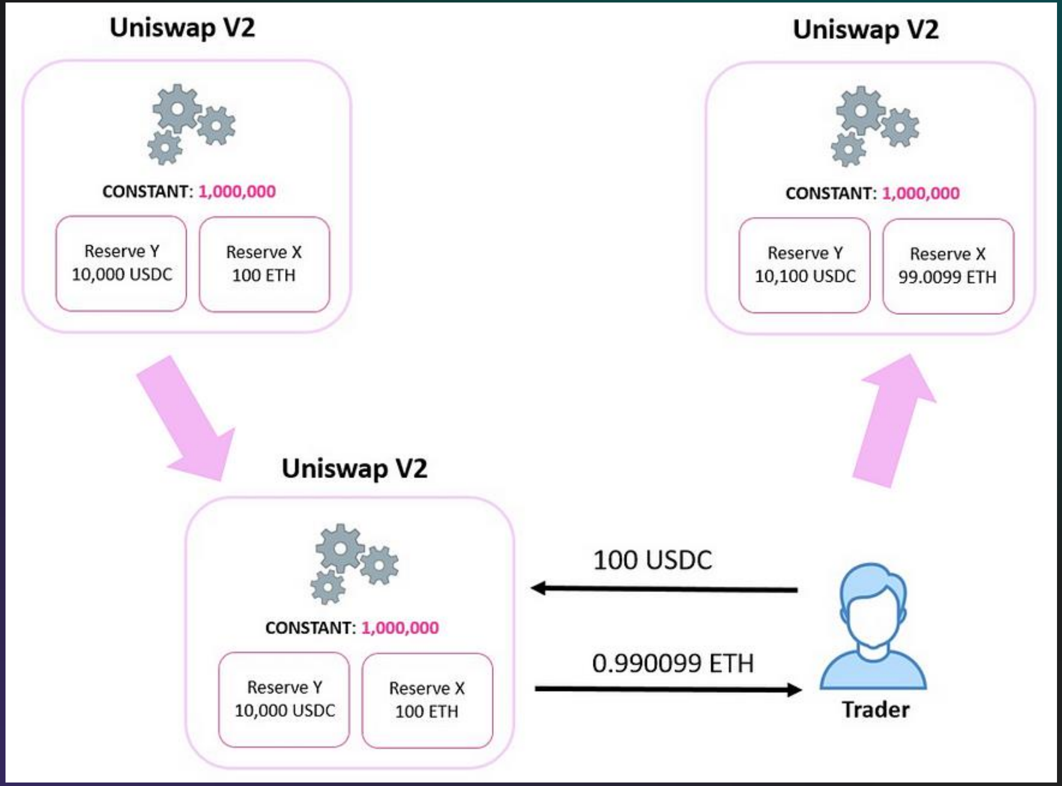


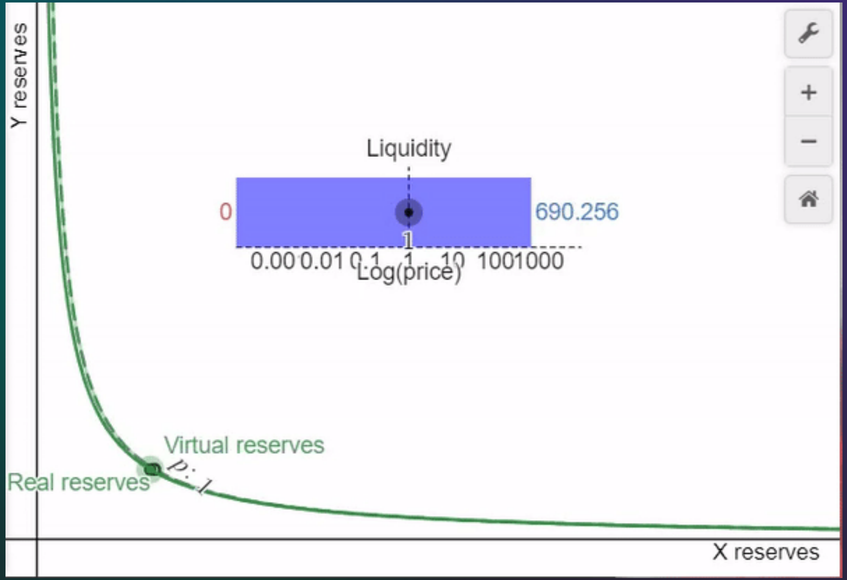
- Liquidity providers (LPs) deposits two assets to the pool, in exchange of LP shares.
- Traders are charged a fixed fee every time it executes a swap.
- This fee charged to the trader is then distributed among LPs.

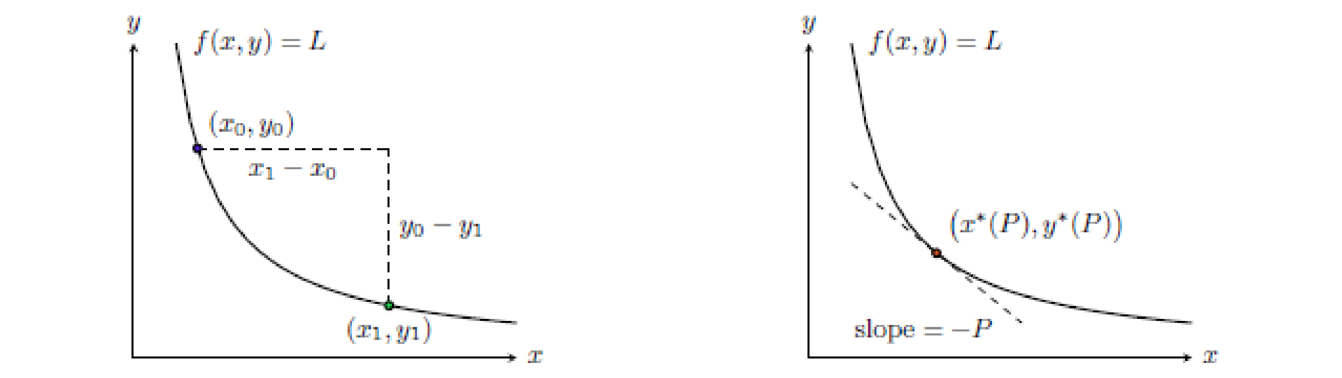
Uniswap Mechanism contd.

- **Constant Function Market Maker:**

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







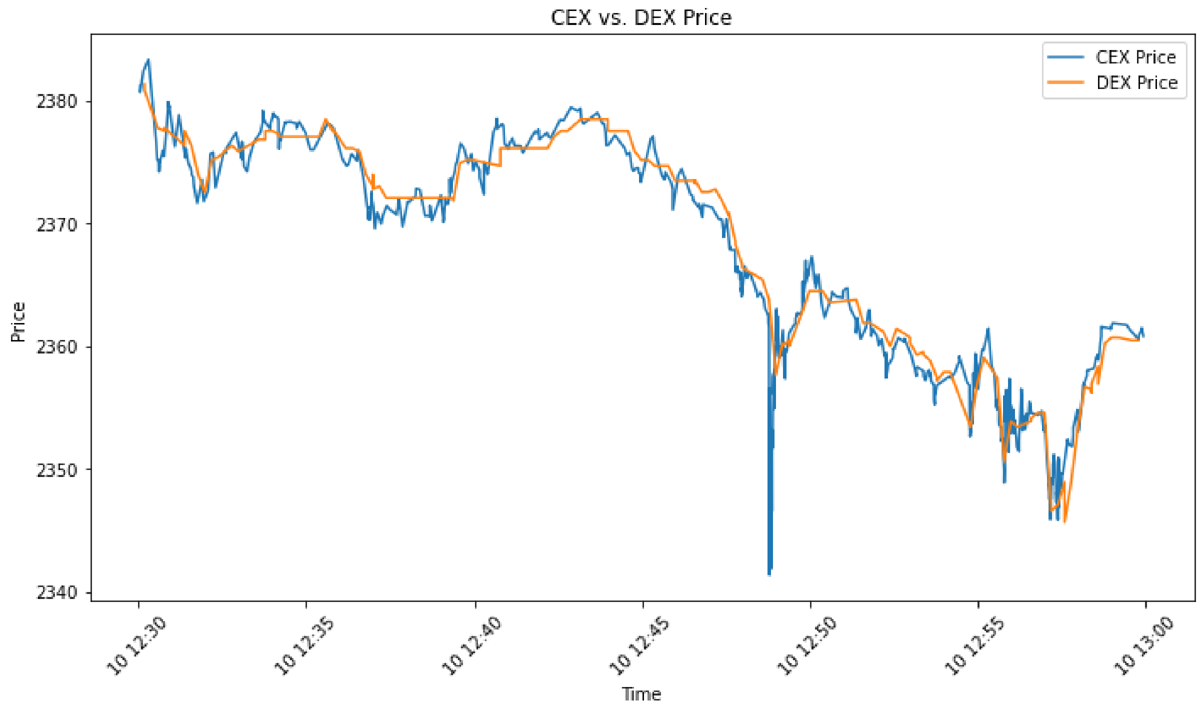
(a) Transitions between any two points on the bonding curve $f(x, y) = L$ are permitted, if an agent contributes the difference into the pool.

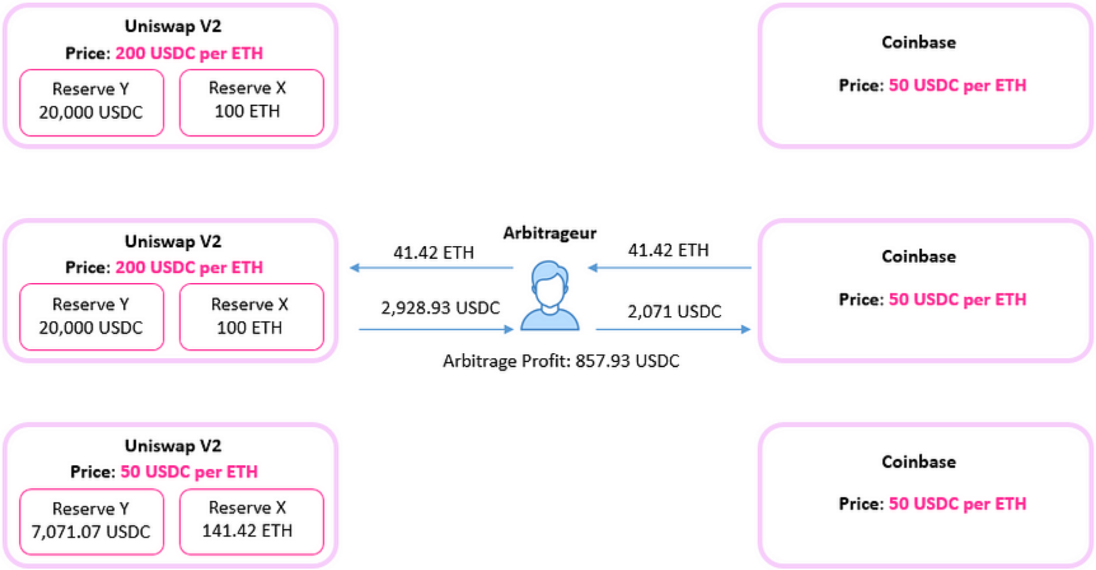
(b) Arbitrageurs ensures that, when the price is P, pool reserves shift to the point on the bonding curve where the slope is equal to $-P$.

Figure 1: Illustration of a CFMM.

CEX-DEX Arbitrage

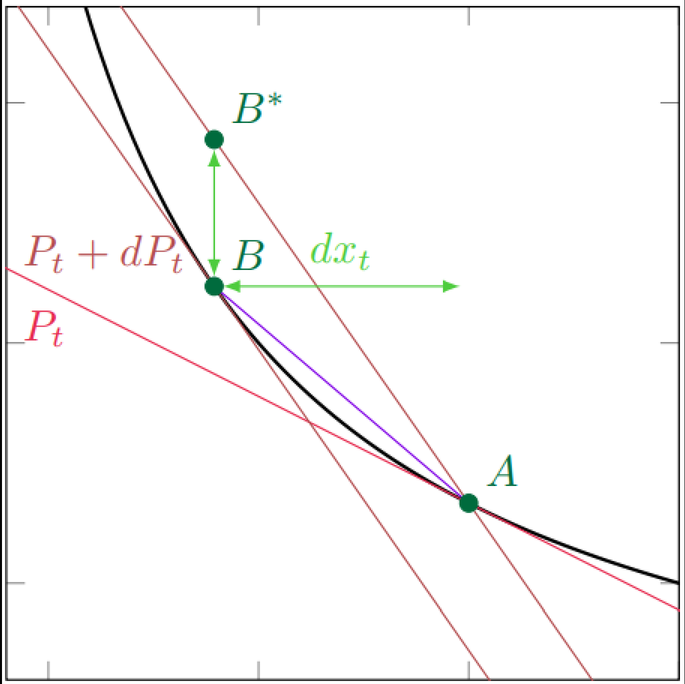
- **Price discrepancies, opportunities for arbitrageurs:**
  - **CEX is more liquid (add 24h traded volume here)**
  - **DEX has stale prices**
  - **Flash Loans (borrowing funds wo collateral), Mempool Tx replacement, Batching.**





Loss-Versus-Rebalancing (LVR)

- The LVR phenomenon encapsulates the risk incurred by LPs due to the exploitation of stale prices in DEXs by arbitrageurs, leading to suboptimal outcomes for liquidity provision.



LVR and CFMM LP Price Slippage

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

- If prices increase to $Pt + dPt$, the slope of the brown line, the CFMM trades to point B.
- The rebalancing strategy trades instead at the price $Pt + dPt$, to point B^*.
- LVR is the vertical gap between B and B^*.

Study Objectives

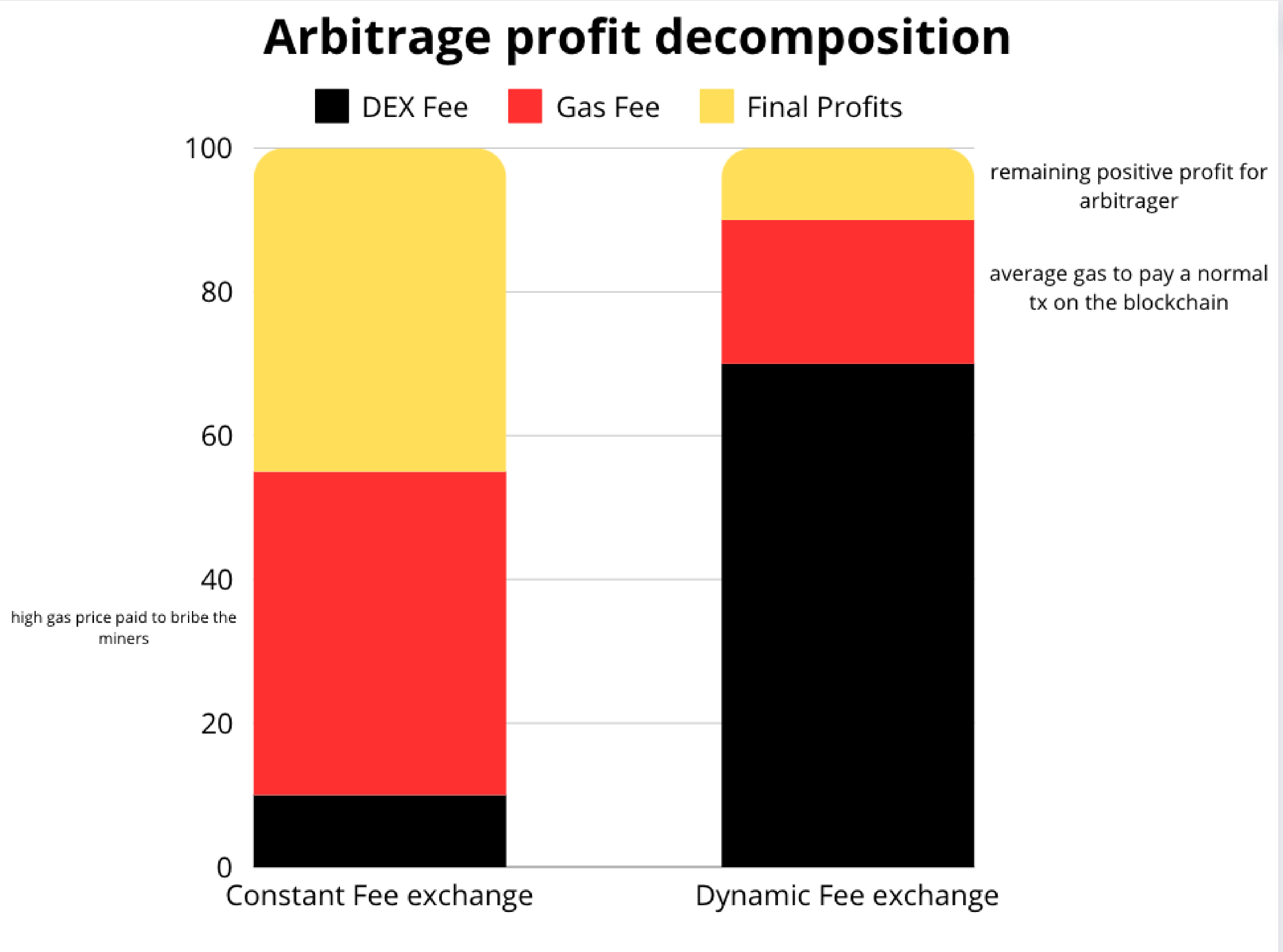
Ensure Price Discovery While Improving Market Efficiency

- By developing a dynamic fee AMM, from the perspective of LPs, we seek to mitigate the adverse effects of LVR and promote a more liquid marketplace; from the perspective of traders, we charge lower fees for lower LVR PnLs.

Democratize Finance Wealth Redistribution

- Through our research efforts, we aspire to pave the way for a more resilient and equitable decentralized financial infrastructure that empowers Noise Traders and redistribute Arbitrageurs' profits.

Target Variable Calibration



Assumptions

- CEX depth is <u>infinite</u>
- No CEX fees
- Static single DEX pool
- Ideal theoretical arbitrage profits (no other pools or triangular arb)
- <u>Single LP behavior</u>
- ETH Gas Fee auction simplification. Take gas fee as endogenous parameter
- No MEV / block Tx ordering consideration
- 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:

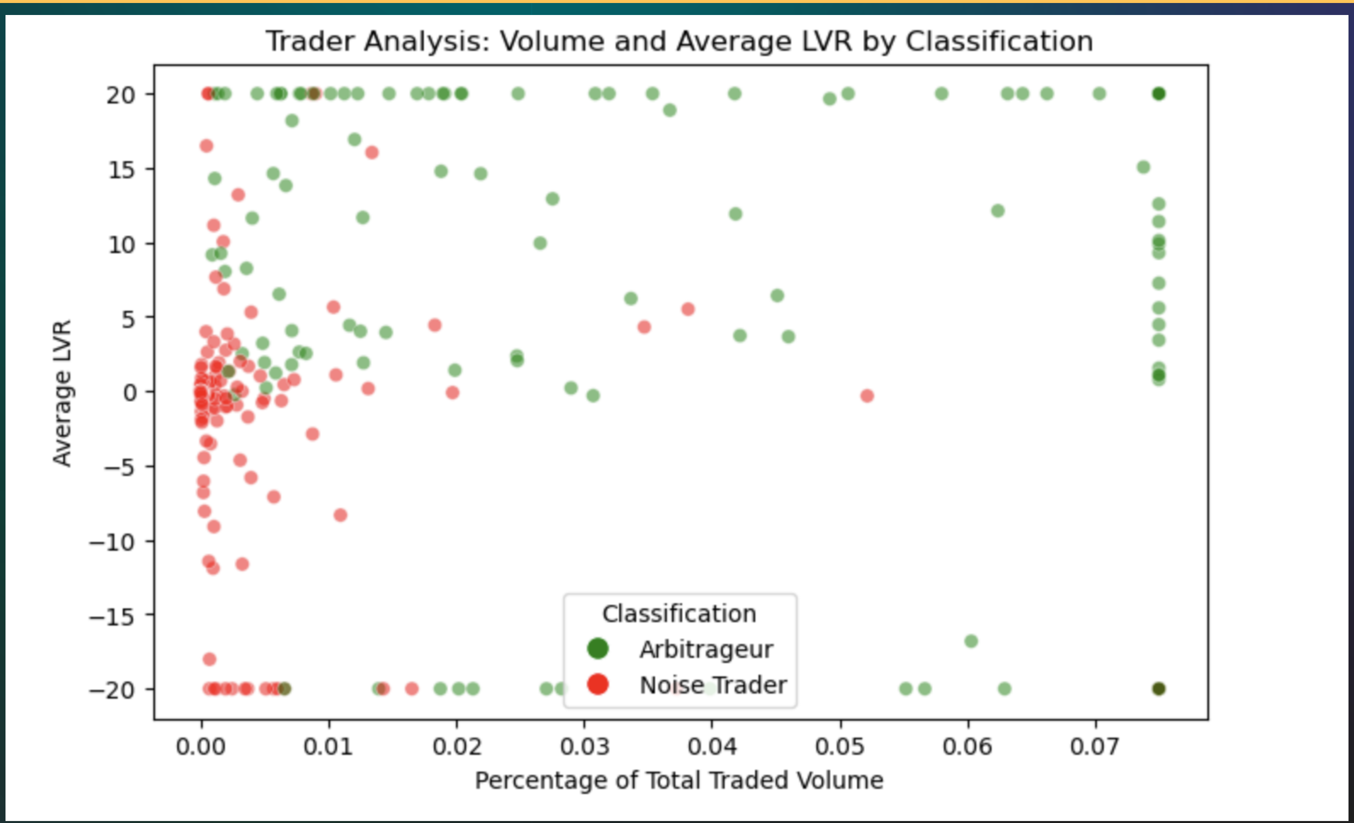
January 1, 2024 to January 31, 2024

CEX	
Price	Timestamp
100	00:00:05.123
101	00:00:06.523
103	00:00:07.192
100	00:00:15.870
97	00:00:32.030

DEX		
Price	Amount	Timestamp
98	10	23:59:00
100	90	00:00:08
99	30	00:00:37

Price_CEX	Timestamp_CEX	Price_DEX	Amount_DEX
103	00:00:07.192	100	90
97	00:00:32.030	99	30

Arbitrageurs and Noise Traders



- **Arbitrageurs:** traders who capitalize on price differences across decentralized and centralized exchanges to secure profits.
- **Noise Traders:** 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:

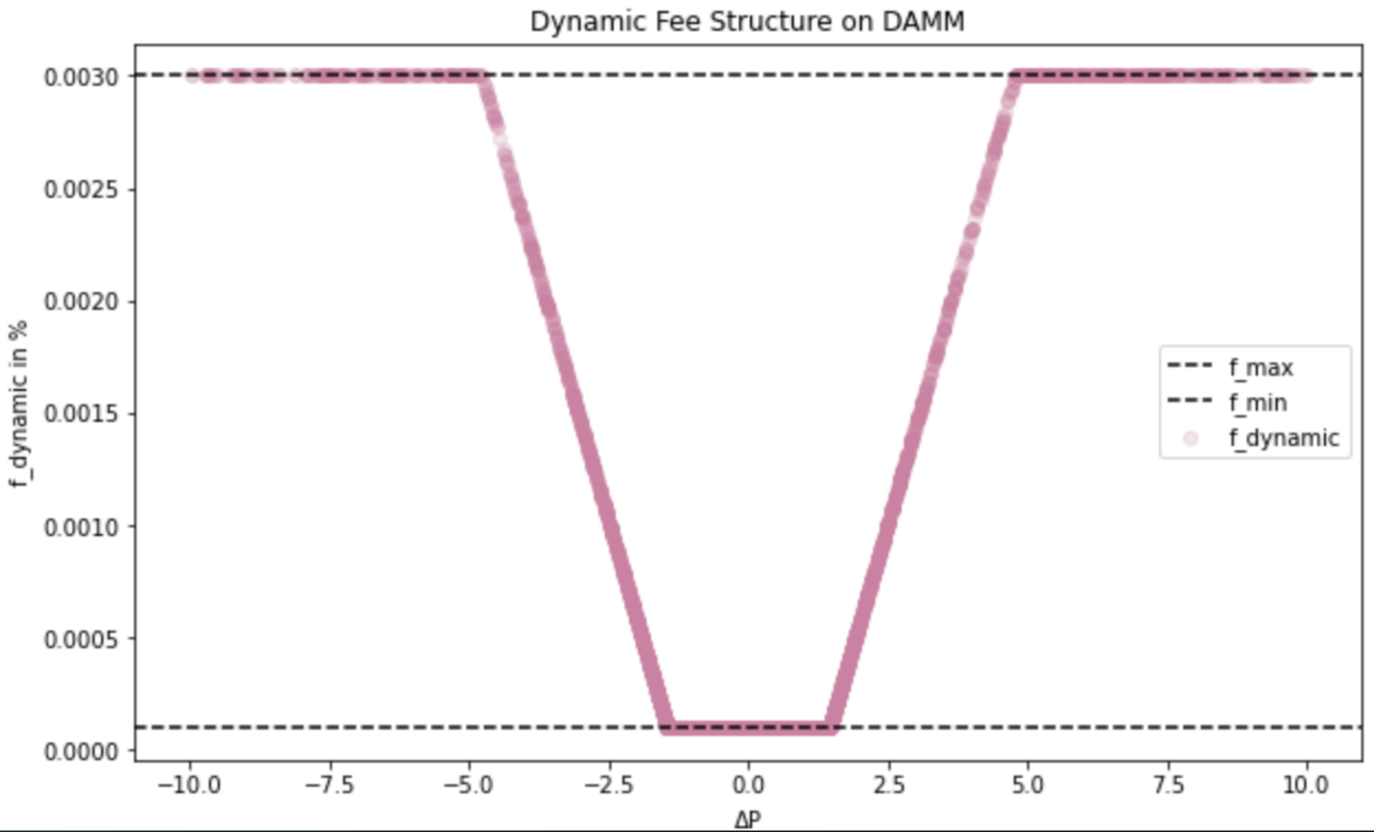
$$f_{buy} = min(max(f_{min}, \omega \cdot Z(\Delta p) - s), f_{max})$$

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

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 for deviation from the hypothetical max fee**

Dynamic Fee Structure on DAMM



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

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

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

Model Calibration

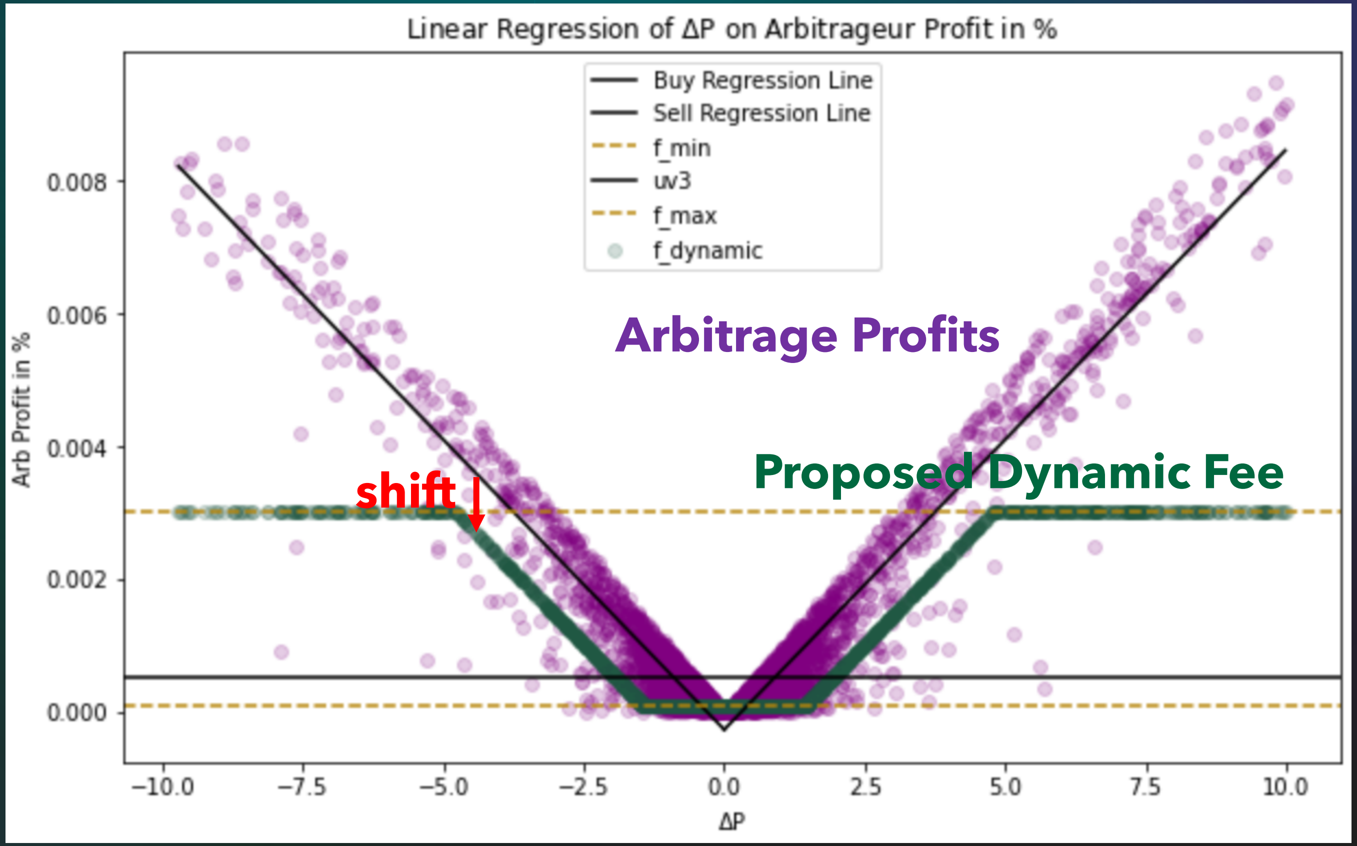
Our objective is to establish a dynamic fee structure, which adjusts linearly based on the price disparity.

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

$$\%PnL = \frac{x_i * \Delta p \; - TransactionCosts}{x_i}$$

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.**

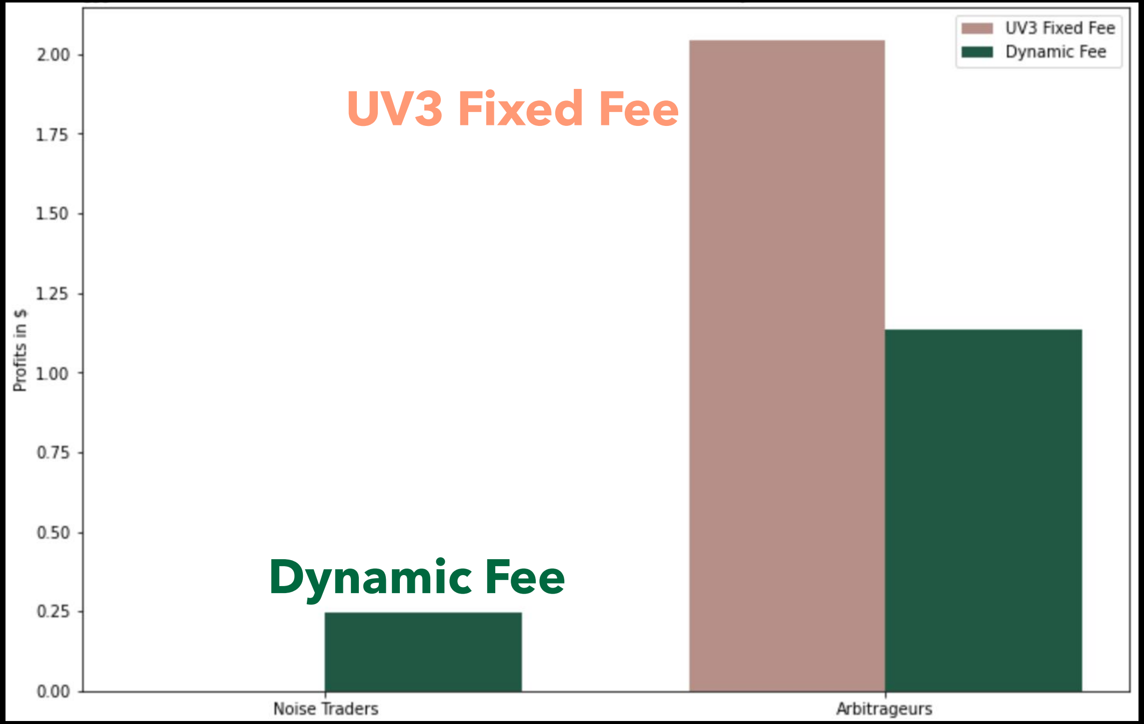
Calibration Result

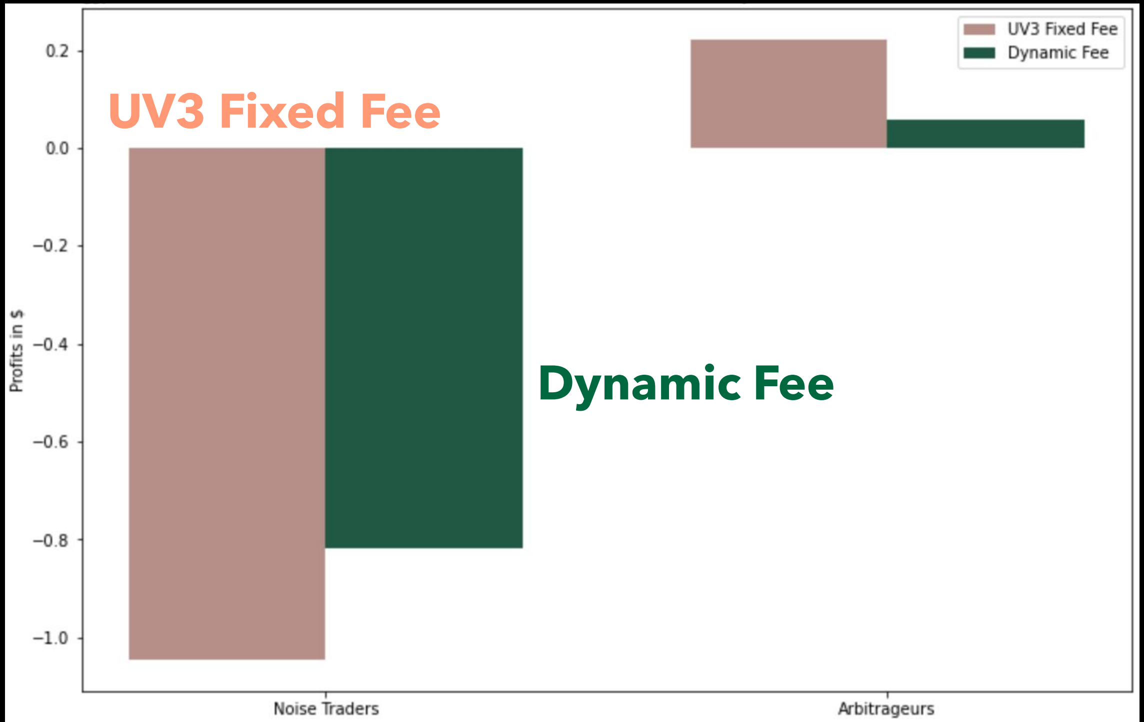


- **Arb Profits on Delta P.** Where we find f_{sell} to the left of Z(Δp) = 0 and f_{buy} to the right of Z(Δp) = 0.
- The **continuous black lines** are the regression lines, used to estimate ω, showing the maximum fee an arbitrageur would be willing to pay to enter a trade.

Model Empirical Analysis

Profit Redistribution Before and After Dynamic Fee

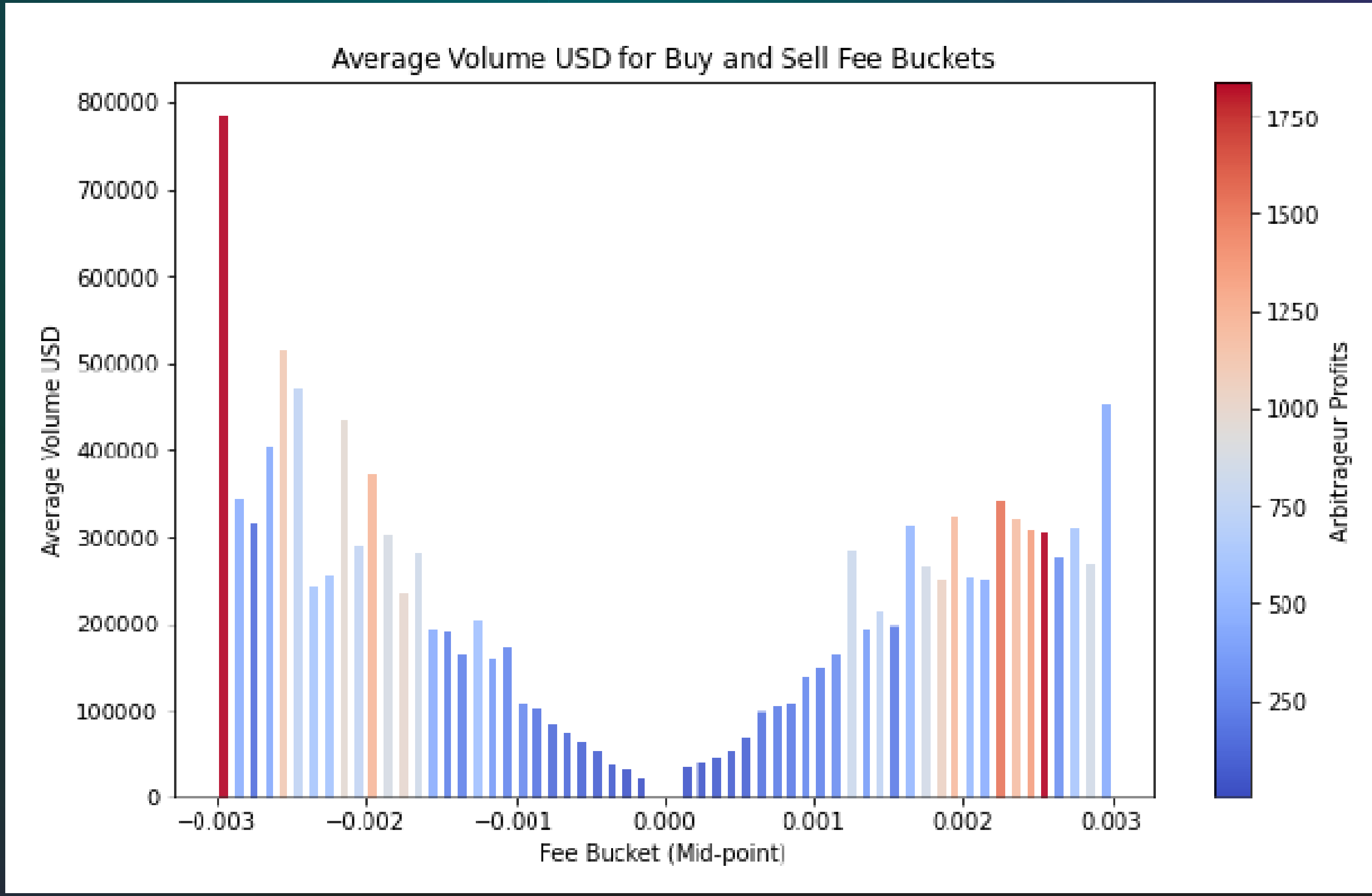




Noise Traders Arbitrageurs Noise Traders Arbitrageurs

- Overall, 98% of the trades are charged less than the Uniswap V3 proxy 5 bps.
- 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

- **The fees are determined by the following equation:**

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

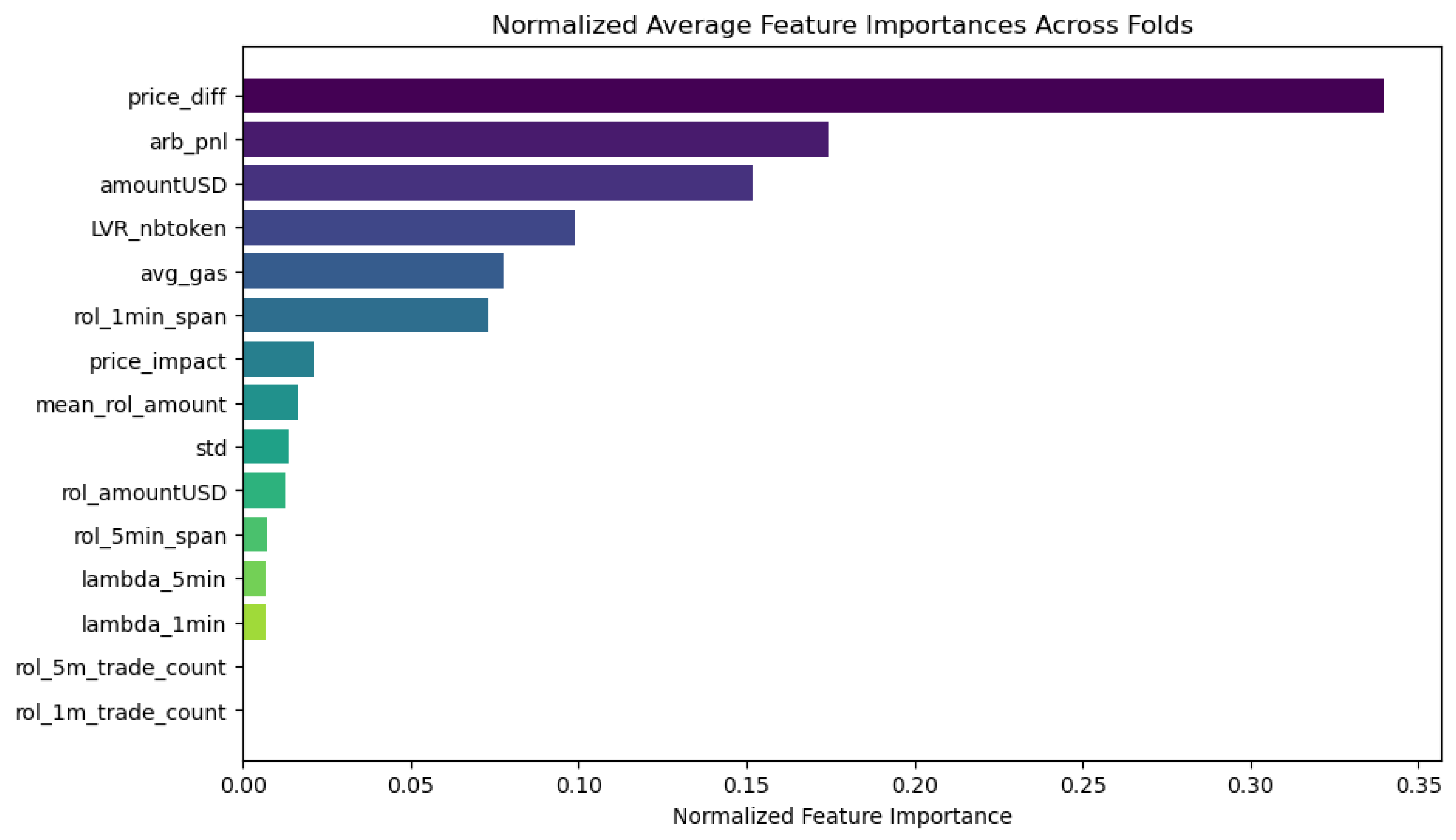
where,

- f_{min} **and** f_{max}**, the lower and upper bound of buying and selling fees for each independent feature**
- g_i**, factors like the price difference (Δp), arbitrageurs PnL from the arbitrage (PnL), rolling price volatility from the last 100 datapoints (**σ_{100}**), price impact (PI), among others**
- f_i**, linear function with slope mi mapping a specific factor i to a fee** f_i
- ω_i**, the parameter which determines the weight attached to the factor-individual fees** f_i

Model Calibration

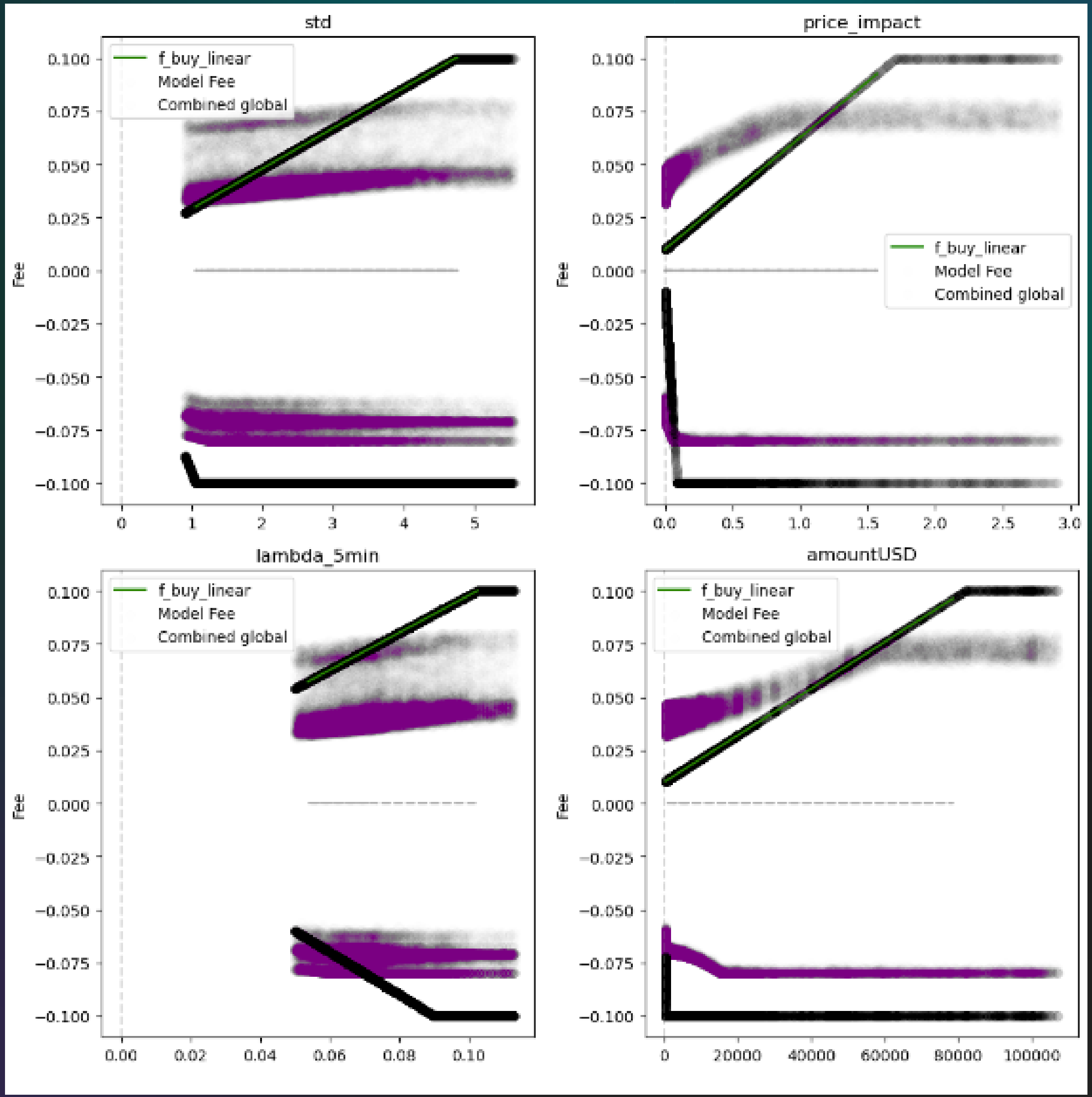
1. **Data Segmentation**. The dataset is initially segmented into two subsets based on the direction of the transaction—purchases (buy) and sales (sell).
2. **Feature-Based Quantile Scaling**. For each relevant feature in the dataset (e.g., price difference, transaction volume, etc.), quantile-based scaling boundaries are established.
3. **Selecting $g_{i,max/min}$**. Within each transaction subset (buy and sell) and for a given feature, max and min thresholds are calculated for the given feature using quantiles.
4. **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.
5. **Estimating the Fee per Feature fi**. we find the slope of the line to fit the fees to, mi by simply taking $\frac{f_{max} - f_{min}}{g_{max} - g_{min}}$.

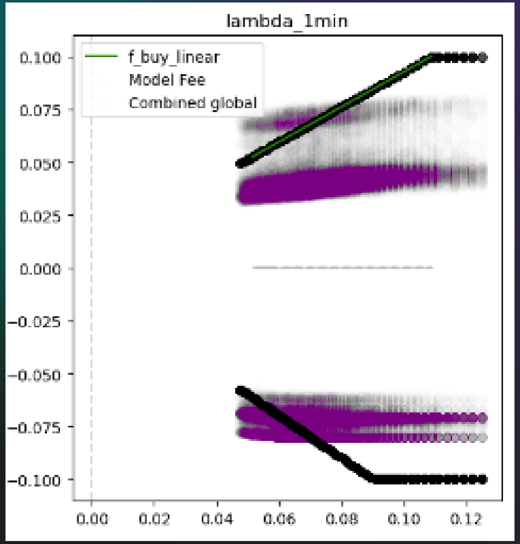
Random Forest Features Importance



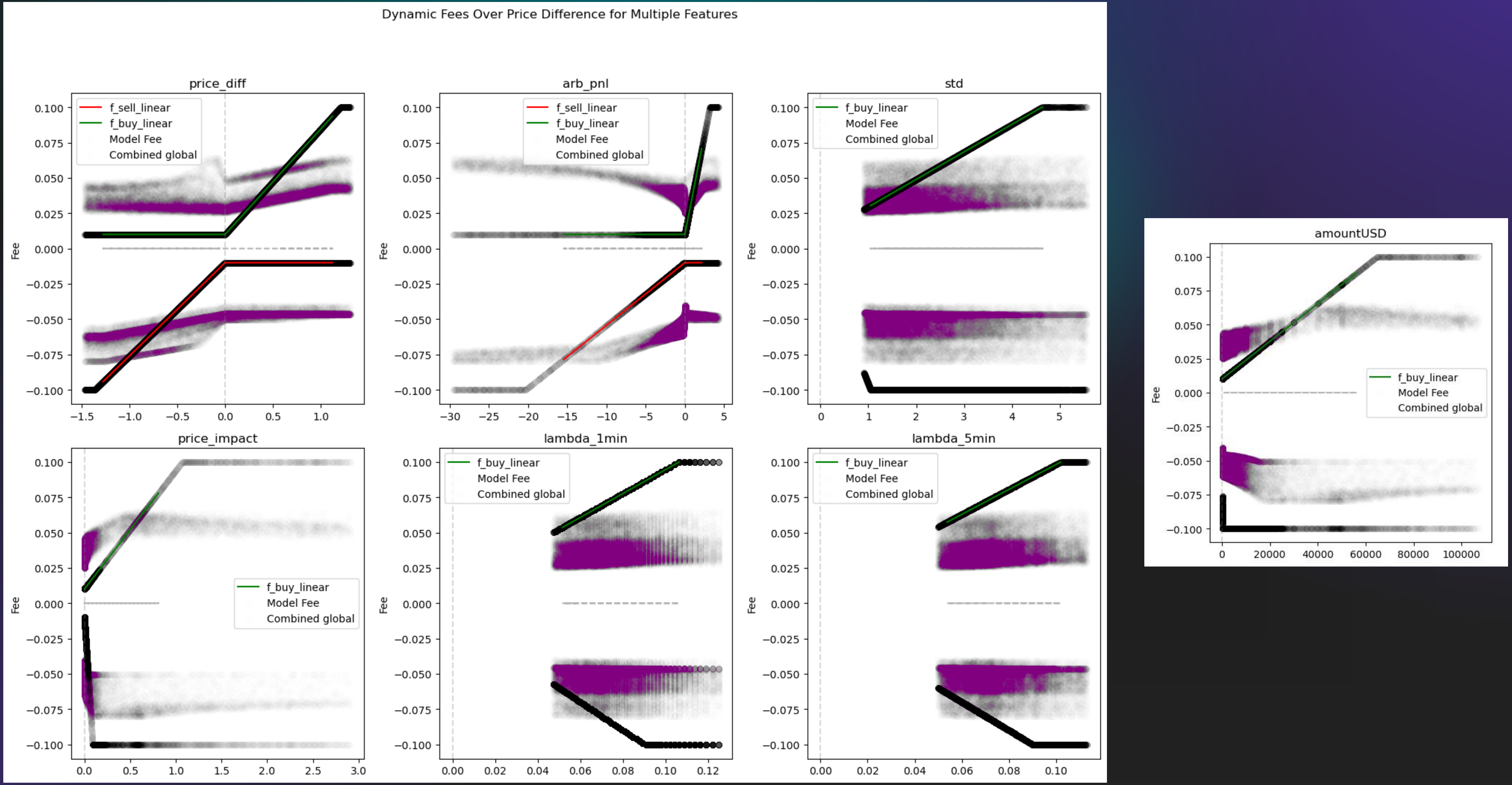
We ran a Random Forest Regression model over the features, having the hypothetical fee (i.e. the maximum % profit an arbitrageur could make on a trade) as target variable to get the feature importance.

5-factor Model Result





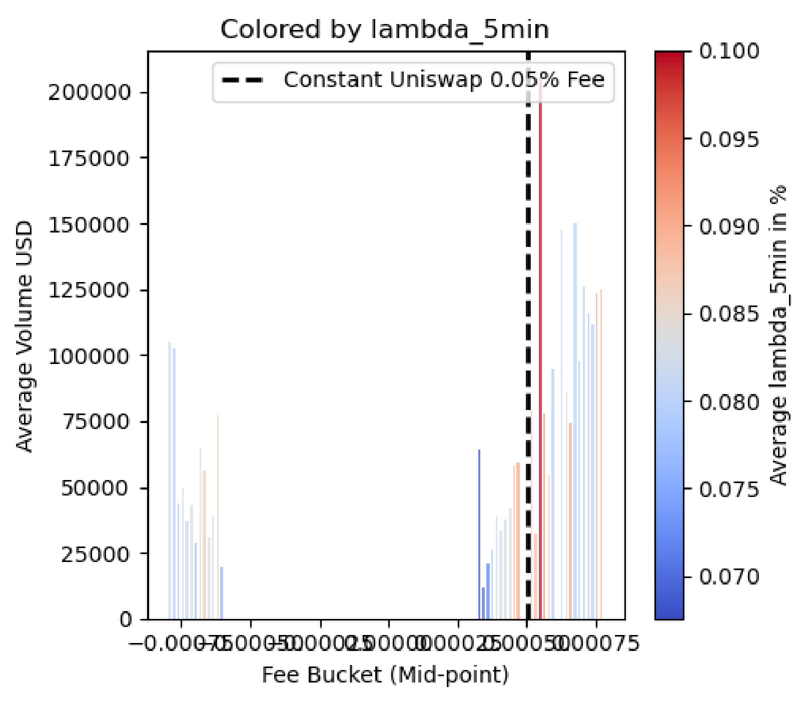
7-factor Model Result

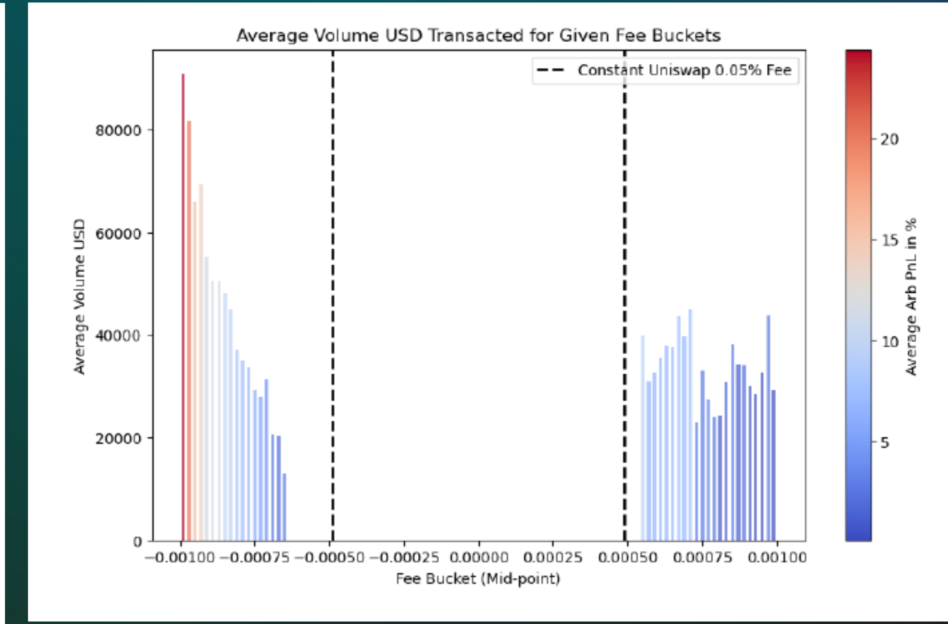


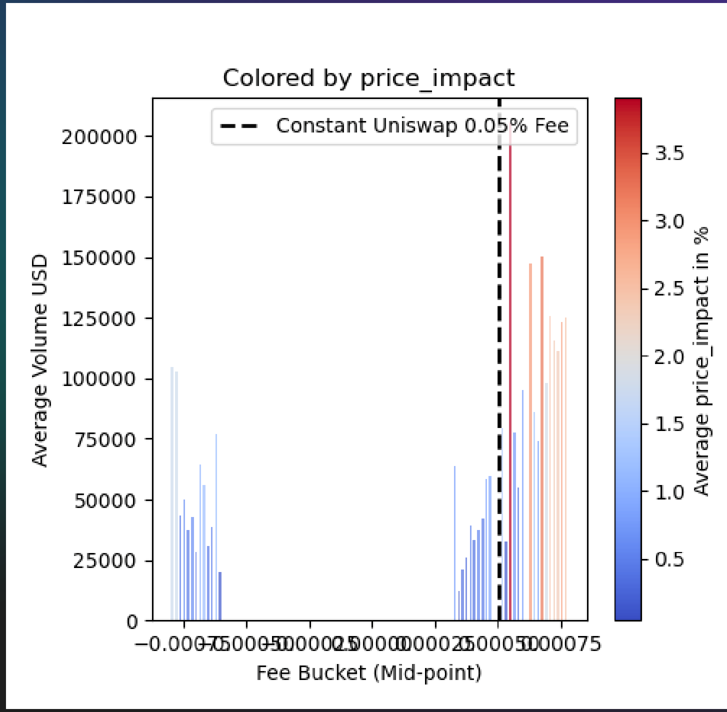
Models Benchmarks

	Constant Fee Model	5 Factors Model (TradeFi Factors)	7 Factors Model (DeFi Factors)	10 Factors Model
Percent of additional profits of the dynamic fee over the constant fee model	0.0 %	0.0 %	0.0 %	0.05 %
Price impact percent improvement (decreased impact) of the dynamic fee model	0.0 %	0.0 %	0.0 %	0.05 %
Average dynamic selling fee (%)	-0.05	-0.07	-0.05	-0.07
Average dynamic buying fee (%)	0.05	0.05	0.04	0.05
Impermanent loss in %	-1	-1	-1	-1
Average t-cost in $	150.12	93.06	47.31	38.77
Weighted average buying_fee (%)	0.05	0.06	0.05	0.06
Weighted average selling_fee (%)	-0.05	-0.08	-0.06	-0.08
Accuracy of the fees (in the range of the constant fee trader will be willing to pay)	100%	7.53%	9.86%	4.2%
Feature Importance		std: 0.17, price_impact: 0.15, lambda_1min: 0.12, lambda_5min: 0.14, amountUSD: 0.4	price_diff': 0.25, arb_pnl': 0.25, std': 0.07, price_impact': 0.07, lambda 1min: 0.05, Lambda 5min: 0.05, amountUSD': 0.27	

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 fee low for the rest of the users.**

Limitations & Constraints

- <u>Reliance on CEX Prices:</u>
  - **Vulnerabilities:** Exposed to Oracle Attacks, allowing malicious actors to manipulate transmitted data.
  - **Adverse Effects:** Potential for price manipulation, degradation of pool vitality, loss of trust, and impermanent loss exposures for LPs.
- <u>Operational Complexities:</u>
  - Smart contract implementation on uniswap v4
  - **Parameter Recalibrations:** Necessity of frequent adjustments of parameters such as slope (ω) and shift (s%).
  - **Derived from Empirical Data:** Reflecting the dynamic nature of DEX, requiring alignment with current market conditions and periodic adjustments.

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Thank you!

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