Automated Market Making and Arbitrage Profits in Digital Assets Trading

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Abstract

Automated Market Makers (AMMs) represent a pivotal advancement within the decentralized finance (DeFi) ecosystem, enabling the exchange of digital assets without the necessity for direct counter-parties. This study delves into the effects of trading fees on the profitability of Liquidity Providers within the AMM framework, particularly exploring the potential of a Dynamic Automatic Market Maker (DAMM) to enhance price discovery and liquidity through a dynamic fee structure as opposed to the fixed flat fee structure seen in Uniswap. By comparing transaction data from the WETH-USDC pool on Uniswap V3 with ETH-USDC transactions on Binance, we aim to illuminate the interplay among price movements, trading volumes, and liquidity, as well as assess how trading fees influence arbitrage opportunities between decentralized and centralized exchanges. We consider the behaviors of traders who capitalize on price discrepancies between CEX and DEX; however, due to trading and gas fees, such arbitrageurs may abstain from trading if the total fees exceed the profit potential, thereby avoiding losses incurred from fees. Our proposed AMM dynamic fee models are designed to offer traders a fee close to a hypothetical threshold that ensures profitability from arbitrage without exploiting the protocol's dynamics, thereby mitigating losses for LPs and contributing to more effective price discovery between CEX and DEX. Ultimately, this study enhances our understanding of AMMs' operational mechanics and their significance in the broader context of digital assets trading.

Acknowledgments

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Table of Contents

Nomenclature

AMM Automated Market Maker. A system that provides liquidity to the financial market through algorithmic buy and sell orders, allowing digital assets to be traded automatically without the need for traditional market makers or order books.

CEX Centralized Exchange. A traditional financial exchange platform where users trade assets through an intermediary organization that oversees and facilitates the transactions.

CFMM Constant Function Market Maker. A type of decentralized exchange protocol that uses a mathematical function to set the price of assets and maintain a constant value for liquidity pools as trading occurs.

DAO Decentralized Autonomous Organization. A blockchain-based form of organization represented by rules encoded as a transparent computer program, controlled by organization members and not influenced by a central government.

DeFi Decentralized Finance. Blockchain-based financial systems that operate without centralized intermediaries, using smart contracts to provide services like lending, borrowing, and trading.

DEX Decentralized Exchange. A blockchain-based platform that enables users to trade cryptocurrencies directly with one another without the need for an intermediary or central authority.

LOB Limit Order Book. A trading mechanism used in centralized exchanges that lists all buy and sell orders for a specific asset, organized by price level, allowing traders to place orders with specific price limits.

LP Liquidity Provider. An individual or entity that deposits assets into a liquidity pool to facilitate trading on a decentralized exchange, earning transaction fees in return for providing liquidity.

LVR Loss versus Rebalancing. The differential outcome between an automated market making strategy and a rebalancing strategy, where the former incurs systematic losses due to price slippage compared to the latter's execution prices

List of Figures

Chapter 1

Introduction

Market making in traditional equity markets involves designated entities, known as market makers, facilitating trading by continuously offering to buy (bid) and sell (ask) securities, thereby providing liquidity to the market, and ensuring that traders can execute their trades at any given time. This narrows the bid-ask spreads, enhancing the market depth and stability. Market makers profit from the spread between the buy and sell prices while managing their inventory of stocks to mitigate risk. They use various strategies, including limit orders, to execute trades, ensuring a smooth flow of transactions and mitigating price volatility by maintaining a balanced book. Additionally, they operate in well-regulated environments, such as stock exchanges and OTC markets, and their activities are overseen by financial regulatory bodies to ensure compliance with legal standards.

While traditional financial (TradFi) markets have long been the cornerstone of global economic systems, their reliance on centralized institutions and intermediaries often results in inefficiencies, restricted access, and opaque operations. In response to these challenges, the financial landscape is witnessing a paradigm shift towards a more open, inclusive, and transparent model: Decentralized Finance (DeFi). DeFi leverages blockchain technology to eliminate the need for traditional middlemen like banks, offering a suite of financial services—from lending and borrowing to trading—directly on the blockchain (primarily the Ethereum blockchain). This democratizes access to financial services and ensures greater transparency and security, marking a significant evolution in how financial transactions can be conducted in the digital age. DeFi offers greater control over assets, lower entry barriers, and universal access, marking a significant shift towards a more inclusive and autonomous financial ecosystem.

Blockchain technology underpins DeFi's innovations, providing a decentralized network where transactions are transparently and securely recorded across chains of nodes. This decentralized architecture ensures that operations required for DeFi transactions are computed across a distributed network, facilitating an environment for financial activities without needing a trusted third party. However, the complexity and storage requirements for traditional market-making mechanisms, such as maintaining an extensive order book, present challenges within blockchain's decentralized framework. While the core objective of market making – to provide liquidity and facilitate trading – is consistent across DeFi and traditional finance, the mechanisms, environments and regulatory frameworks in which they operate exhibit significant differences.

1.1 Market Making in DeFi: Uniswap

Market making in DeFi is primarily facilitated through Automated Market Makers (AMMs), a novel mechanism inherent to decentralized exchanges (DEX) like Uniswap [3, 4], the largest DEX up to date in trading volume. AMMs deviate from traditional market-making practices by eliminating the need for order books (meaning that liquidity providers cannot specify prices at which they are willing to buy or sell) and instead utilizing mathematical formulas to determine prices based on the relative supply of assets in a liquidity pool. Participants provide liquidity by depositing pairs of assets into these pools, receiving liquidity provider (LP) tokens in return, which represent their share of the pool and entitle them to a portion of the trading fees. This model inherently requires liquidity providers to contribute two types of assets as seen in Fig. 1.1, introducing a unique set of risks and rewards. The AMM model introduces several benefits, including increased accessibility for participants to provide liquidity, reduced barriers to entry compared to traditional market making, and the democratization of financial services. However, it also presents challenges, such as the risk of impermanent loss for liquidity providers and the potential for price slippage in large trades, since price discovery is solely done by arbitrageurs.

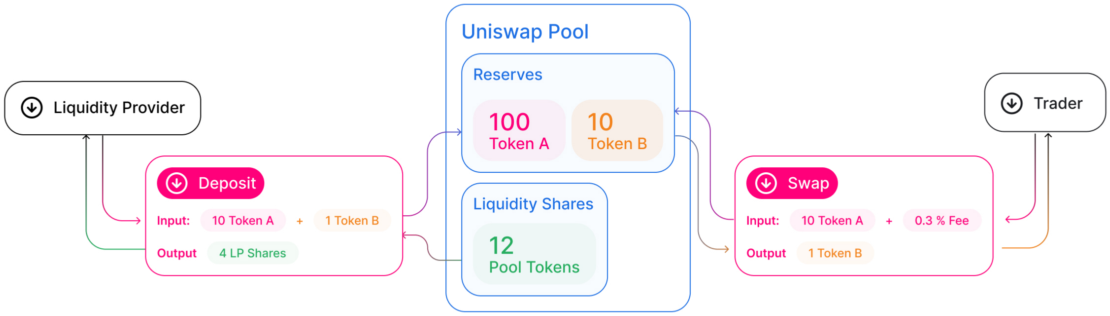


Figure 1.1: Uniswap AMM mechanism (from https://docs.uniswap.org/). Here we see how an LP provides liquidity to the pool in the form of two assets, getting LP shares for its position. On the other hand, a trader is charged a 0.3% fee every time it executes a swap. This fee charged to the trader is then distributed as a reward to LPs for providing liquidity to the pool.

Currently, Uniswap hosts a diverse array of approximately 60 asset pairs. Amongst them, a notable 80 percent of the total liquidity is concentrated in a select group of 5 pairs featuring widely-traded tokens, such as ETH/USDC. This specific pairing draws parallels with the S&P 500 in traditional finance, emblematic of high liquidity facilitating efficient trading with minimal price slippage. In contrast to its counterparts, ETH/USDC offers more stability by encompassing both a stablecoin and Ethereum, forming the foundational infrastructure for numerous DeFi applications, including lending and collateralization. Conversely, less liquid pairs share similarities with over-the-counter (OTC) fixed income securities. Both exhibit susceptibility to price volatility due to lower liquidity, resulting in wider bid-ask spreads. Institutional participants play a pivotal role in influencing both markets.

It is worth noting that market-making in DeFi, while lucrative, isn't without its risks. One of the primary risks encountered in market-making within DeFi is smart contract risk. DeFi protocols, reliant on blockchain-based smart contracts, are susceptible to exploits, potentially causing significant financial harm to liquidity providers. The immutable nature of smart contracts exacerbates the impact of any flaws, as evidenced by incidents like the DAO hack [9]. Moreover, DeFi protocols rely on oracles to fetch external market data for price feeds and asset valuations. Oracle manipulation or inaccuracies can introduce counterparty risk by distorting market information and affecting the outcome of transactions. In contrast, counterparty risk in TradFi is intricately tied to the presence of intermediaries, counterparties, and centralized clearinghouses. Delayed settlements, failed trades, and operational errors can exacerbate counterparty risk, particularly in high-frequency trading environments where transactions occur rapidly [2]. With a proper understanding of financial markets together with blockchain operability, a better DEX could be built with enhanced resilience against such vulnerabilities.

1.2 CEX vs. DEX arbitrage & LVR

Arbitrage opportunities in the crypto world arise not only between Centralized Exchanges (CEX - traditional exchanges like Binance, Coinbase, OKX, etc.) or not only between different DEXes, they also occur across both in what is called CEX-DEX arbitrage. There are two main types of arbitrage observed here: funding rate arbitrage and price arbitrage. Funding rate arbitrage is a trading strategy used with perpetual futures contracts, exploiting the differences in funding rates between various trading platforms. Funding rates are periodic payments exchanged between buyers and sellers of perpetual contracts to keep the contract prices aligned with the underlying asset's market price. If the funding rate is positive, long position holders pay short position holders, and vice versa. Arbitrageurs take advantage of discrepancies in these rates across different exchanges by opening opposing positions on two platforms, thus earning a profit from the differential without a significant risk of loss from market movements. Simpler than that, a price arbitrage takes advantage of price inefficiencies in spot markets, as CEXs and DEXs sometimes quote different prices for the same digital asset. In this paper, we will focus only on the latter: price arbitrage between CEX and DEX.

Market inefficiencies between the two arise mainly due to the discrete nature of the blockchain. In Ethereum block times are roughly 15 seconds (in Bitcoin, this could be around 10 minutes). Every trader must wait for the next block of transactions for their orders to be confirmed, and hence, the prices will only be updated once the block with the transactions is pushed into the blockchain. This behavior can be observed in 1.2. CEXes present a more granular nature, recording a higher frequency of transactions within the same time interval compared to DEXes, this makes CEXs more liquid and, for asset pairs like ETH-USDC, it is adequate to consider that the price for ETH shown in a CEX is the assets actual market price.

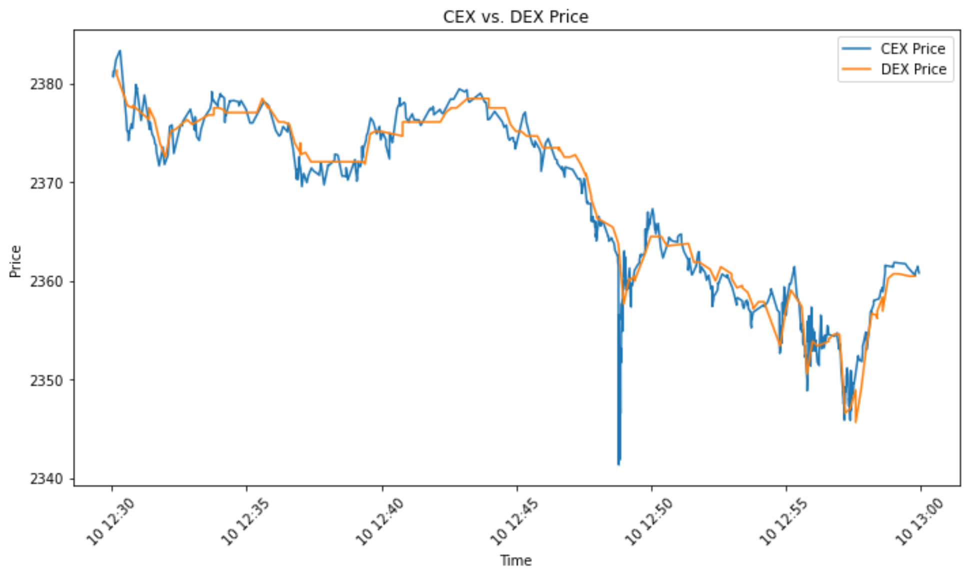


Figure 1.2: ETH-USDC Price for 1 hour interval

Given the high block time, shaving a few milliseconds off your transaction processing time has little if any impact on your profitability. This greatly levels the playing field for traders of all sizes in contrast to traditional CEX markets. There are several mechanisms and smart contract types that allow traders to exploit arbitrage opportunities. Flash loans are used for arbitrage by borrowing funds to exploit price differences of an asset across various platforms without upfront capital. The borrower executes a purchase and sale of the asset within a single transaction block, taking advantage of the price discrepancy to earn a profit. If the arbitrage is successful, the loan and fees are repaid, and the transaction is completed. If not, the transaction is reversed, ensuring no risk of loss beyond transaction fees. Mempool[1] transaction replacement involves submitting a new transaction with a

[1]Short for "memory pool," is a collection of unconfirmed transactions waiting to be included in a blockchain block. It acts as a holding area for transactions broadcasted by network participants but not yet added to the blockchain, allowing miners or validators to select which transactions to include in the next block based on criteria such as transaction fees.

higher gas price to cancel a previous one that's at risk of being preempted by another trader's transaction. This technique helps an arbitrageur avoid losses by ensuring their transaction either executes before others or not at all, effectively managing the risk of being outpaced in a competitive trading environment. The most simple type of arbitrage is simply buying and selling an asset in succession, one transaction right after the other, hoping to net an instantaneous profit. Trade batching is another common practice by arbitrageurs, where they use clever smart contracts to execute several operations simultaneously, effectively grouping multiple trades into one transaction. This allows for more efficient use of gas, reducing transaction costs and ensuring that either all components of the arbitrage play are successful or none at all, thereby minimizing risk and maximizing efficiency in fast-moving markets.

But not everything is fun and games. Recall that AMM's (which we have been using interchangeably with DEX) like Uniswap operate through two parties: the swappers (traders, exchanging one asset for another) and the Liquidity Providers (LPs). While AMMs offer unparalleled efficiency and accessibility, they also introduce inherent challenges, particularly for LPs. While LPs play a pivotal role in ensuring liquidity and facilitating trading activities, they also face a significant hurdle in the form of adverse selection costs, prominently represented by the "loss-versus-rebalancing" (LVR) phenomenon.

The LVR phenomenon encapsulates the risk incurred by LPs due to the exploitation of stale prices by arbitrageurs, leading to suboptimal outcomes for liquidity provision. This adverse selection cost not only impacts LP profitability but also undermines market efficiency by discouraging participation and hindering price discovery mechanisms [8]. Therefore, there is a pressing need to address these challenges and enhance the overall efficacy of decentralized exchanges.

In light of these considerations, our study is motivated by a dual objective: to engineer a dynamic transaction fees model that ensures fairness in trading activities between traders and AMMs while simultaneously improving market efficiency. By developing a nuanced understanding of the underlying economics of AMMs, particularly from the perspective of LPs, we seek to devise innovative solutions that mitigate the adverse effects of LVR and promote a more equitable and efficient marketplace.

Furthermore, our endeavor aligns with broader objectives within the decentralized finance (DeFi) ecosystem, which strives to democratize access to financial services and foster inclusive participation in global markets. By addressing the challenges posed by AMM liquidity provision, we aim to contribute towards the realization of these objectives, facilitating greater financial inclusion and empowerment for a diverse array of market participants. Through our research efforts, we aspire to pave the way for a more resilient and equitable decentralized financial infrastructure that empowers individuals and communities worldwide.

1.3 Literature Review

In recent years, the prominence of AMMs, specifically constant function market makers (CFMMs) has risen, establishing them as the primary mechanism for decentralized exchange on blockchains. This shift is particularly notable when compared to the traditional electronic limit order books (LOBs) prevalent in centralized exchanges. Milionis et al. (2022) [8] delved into the unique advantages and disadvantages offered by CFMMs, emphasizing their computational efficiency and suitability for the blockchain environment. CFMMs, especially Uniswap, are computationally efficient, requiring minimal storage and enabling quick matching computations. Unlike LOBs, which scale with the number of orders, CFMMs' closed-form algebraic computations operate efficiently in the resource-constrained blockchain environment. Additionally, CFMMs, relying on passive liquidity providers (LPs), offer advantages in handling a "long-tail" of illiquid assets, circumventing the need for active market makers [8]. Milionis's other paper [7] introduced a novel approach inspired by the Black-Scholes model to understand the returns of providing liquidity in CFMMs. This model focuses on constructing a quantitative and qualitative framework akin to option pricing, analyzing factors affecting LP profitability. The paper introduces the concept of "loss-versus-rebalancing" (LVR) as the performance gap between CFMM LPs and a rebalancing strategy, revealing the underperformance source as price slippage due to passive liquidity provision to arbitrageurs. In the presence of trading fees, LVR, dependent on asset volatility and CFMM bonding function's marginal liquidity, provided a theoretical understanding of modelling LP's returns.

Furthermore, David et al.(2023) [1] examined the prevalent fixed fee structure in AMMs like Uniswap within the context of DeFi. By extending Kyle's market model [5] to the decentralized setting, it advocates for dynamically adjusting AMM fees based on asset price volatility to optimize liquidity provider earnings and mitigate adverse selection risks. The study highlights the feasibility and benefits of dynamic fee structures, pointing towards a crucial refinement in AMM design to enhance efficiency and adaptability in response to evolving market conditions.

There are broadly two design philosophies to tackle the LVR problem: LVR minimization/reduction and LVR redistribution. LVR minimization/reduction can either be achieved via a low-latency oracle to inform CFMM LP of the current market price or via a LVR rebate parameter that allows arbitrageurs to execute a portion of the CEX-DEX arbitrage trade. This is the model that we will focus on, the oracle will look at the past p&l of the trader as well as the price on different CEX platforms to provide a custom fee to the trader at a given time. The additional profits will then remain in the pool for the liquidity providers and give them more profits at the end. The primary concern with the LVR reduction approach is the reduced order flow directed to the LVR minimization/reduction pool because the exchange will become less attractive for arbitrageurs. This results in LPs incurring greater losses as they catch less volume compared to traditional CFMM pools. Instead of merely minimizing LVR, the future seems to be in redistributing LVR back to the LPs. LVR redistribution includes the dynamic fee model and the auction model: the dynamic fee model imposes price discrimination on informed and uninformed order flows based on pattern recognition. The auction model allows CEX-DEX arbitrageurs to pay LPs for the right to be the first trade per block at the application level. In the realm of LVR redistribution, both the dynamic fee and auction approaches present distinct trade-offs: the dynamic fee model may cause uninformed flows to suffer from higher swap fees during high market volatility, while the auction model presents greater execution challenges, including building a competitive bidding market in a timely manner to allow uninformed traders to trade with the pool.

There are some AMM protocol proposals using dynamic fees for LVR reduction and market efficiency. One of them is the Diamond protocol (McMenamin et al. (2023)) [6]. Diamond addresses the LVR issue by introducing a mechanism where block producers auction off the right to exploit arbitrage opportunities within the pool. The proceeds from these auctions are shared between the liquidity pool and the block producer, creating a system where both parties have a vested interest in minimizing unnecessary LVR and maximizing protocol revenue.

Dyson Finance (`https://dyson.finance/`) is another DeFi DEX with an innovative solution to fixed fees. It adjusts transaction fees based on the reserve ratio of the two assets in a trading pair, responding to the intensity of trading and market demand for each asset. Initially, transaction fees for both buying and selling operations start at 0%. The fees then dynamically adjust based on changes in the liquidity pool's reserve. For example, if the reserve of token A in a trading pair decreases by a certain percentage, an equivalent additional fee is applied to subsequent transactions involving the sale of token A. This mechanism ensures that fees are responsive to market activity, increasing during periods of high demand for a particular asset, thereby discouraging potential arbitrage that might destabilize the pool's value. Moreover, fees for buying and selling different assets within the same trading pair are adjusted independently. Dyson Finance assumes that reverse trades—selling an asset back to the pool shortly after its purchase—are more likely to be arbitrage operations. To counteract this, Dyson imposes higher fees on such reverse trades, effectively increasing the cost for arbitrageurs and thereby protecting the liquidity providers and the token-holding community by redistributing profits through premiums and token sharing. Finally, transaction fees decrease over time, with fees halving after every specified "t seconds" until they return to zero. This time-based adjustment ensures that fees do not remain indefinitely high after a spike in trading activity

Chapter 2

Data Treatment

This study conducts a comprehensive analysis of cryptocurrency transactions by comparing data from both decentralized and centralized exchange platforms, specifically focusing on the Ethereum blockchain's WETH-USDC pool on Uniswap V3 and the ETH-USDC transactions on Binance. The objective is to compare price dynamics, trading volumes, and liquidity provision on these platforms during the period from January 1, 2024, to January 31, 2024.

We used only one month of data given the granularity used, as we are looking at individual transaction level data.

2.1 DEX Data Acquisition: Uniswap V3

Data collection from Uniswap V3 was facilitated through direct queries to the blockchain, utilizing the GraphQL API provided by The Graph at `https://api.thegraph.com/subgraphs/name/uniswap/uniswap-v3`. The selected pool, identified by its address "0x88e6a0c2ddd26feeb64f039a2c41296fcb3f5640", was targeted for its 0.05% fee tier, indicative of significant liquidity and trading activity.

2.1.1 Variables Extracted:

- amount0, amount1: Quantities of the respective tokens swapped in a transaction. The sign of the variable determines whether that token is aggregated or subtracted from the pool. If $amount0 > 0 (< 0)$, then an amount0 of token0 is added to the pool while an amount1 of token1 is subtracted from the pool.

- amountUSD: The USD value of the swap.
- origin, sender, recipient: Addresses associated with the transaction.
- timestamp: Timestamp of the transaction.
- gasUsed: The amount of gas used for the transaction.
- gasPrice_wei, gasPrice_eth: The price of gas in wei and its equivalent in ETH.
- blockNumber: The block number in which the transaction was included.
- symbol0, symbol1: Symbols of the tokens involved in the swap.
- price: The price of the token derived from the swap data, i.e.
- tcost_usd: The transaction cost in USD.

The data was processed using the Python Pandas library, structuring it into a DataFrame for analysis. This process enabled a detailed examination of the liquidity dynamics and transaction behaviors within the specified DEX environment.

2.2 CEX Data Acquisition: Binance

Transaction data for the ETH-USDC pair was collected from Binance, one of the foremost centralized exchanges. This dataset allows for a direct comparison with the DEX data, particularly in terms of price movements and trading volume.

2.2.1 Variables Extracted:

- trade ID: Unique identifier for each trade.
- price: The execution price of the trade.

- qty, base_qty: Quantities of the traded assets.
- time: Timestamp of when the trade occurred.
- is_buyer_maker: Boolean flag indicating whether the buyer is the maker.

This Binance dataset, comprising over 4.73 million transactions, was also structured using Pandas, facilitating a comparative analysis with the Uniswap V3 data to explore differences in trading patterns, price discovery, and liquidity effects between CEXs and DEXs.

2.3 Processing

In a few cases in the descentralized data we found 0's for the amount transacted. These were discarded.

The price evolution for the period of evaluation can be seen in Fig. 2.3.

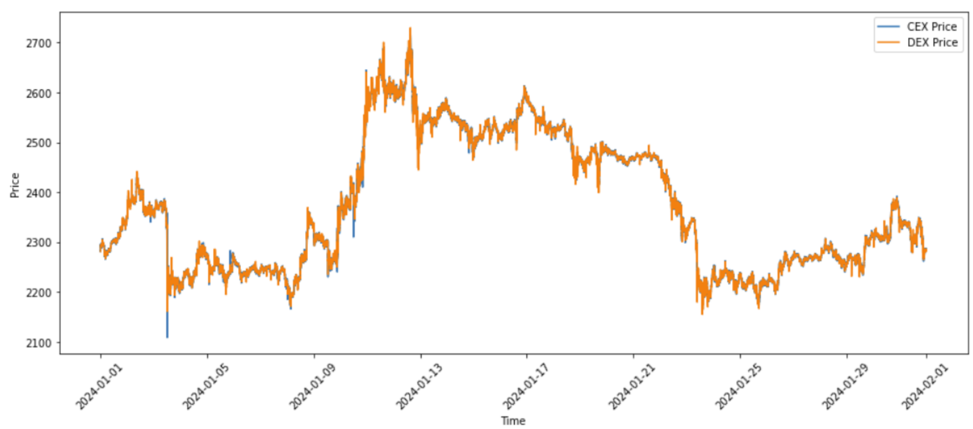


Figure 2.1: ETH-USDC Price from January 1st to 31st 2024

Given the inherent disparity in the granularity of data between transactions on a centralized exchange and swaps within a decentralized exchange pool (as seen in Fig. 1.2), specifically Uniswap, this study implements a data alignment technique to facilitate the comparison of price differences across these platforms. The challenge arises from the more granular nature of the CEX data, which records a higher frequency of transactions within the same time interval compared to the DEX data. A direct comparison of transaction prices at identical timestamps is not feasible due to the asynchronous nature of the data points, as can be seen in Fig. 2.3. To fix this, we matched the DEX transactions only to the closest (in the forward direction) datapoint in the CEX data. This means that we only consider the CEX datapoints closest to the corresponding DEX datapoint and discard the others. Our final dataset in this approach, contains the same number of transactions as the DEX data.

An illustrations of this can be seen in Fig. 2.3, following from Fig. 2.3.

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

Figure 2.2: CEX and DEX Data Examples

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

Figure 2.3: CEX data is matched to DEX.

2.4 Arbitrageurs and Noise Traders

We distinguish two kinds of agents in the model besides liquidity providers:

Arbitrageurs are traders who capitalize on price differences across decentralized and centralized exchanges to secure profits. They continuously monitor AMM pools and external market prices, executing trades that exploit any discrepancies for immediate gain. This activity not only aligns AMM prices with broader market values, enhancing market efficiency and liquidity, but also helps to minimize price slippage, benefiting the trading ecosystem at large.

Noise Traders are participants who engage in transactions within the AMM pools for reasons unrelated to market fundamentals, such as speculation or personal preferences.

These traders may opt for AMMs over CEXes due to factors like avoiding know-your-customer (KYC) protocols or evading the credit risks of custodial platforms. While their activities initially affect AMM pool prices, arbitrageurs quickly counter these impacts by aligning prices with those on CEXes. From the perspective of liquidity providers, noise traders primarily generate fee revenue, despite the temporary price fluctuations they cause.

In our research, the identification and classification of trader behavior patterns as arbitrageurs or noise traders is crucial. To systematically classify traders into these categories, we adopt a methodology predicated on analyzing trade data from both DEXs and CEXs. The process begins with the aggregation of a unique list of sender addresses from DEX transactions. Each sender represents a distinct trading entity whose activities are scrutinized to ascertain their trading strategy. For each sender, we meticulously examine all corresponding DEX trades against contemporaneous CEX price data. An arbitrageur is hypothesized to exploit price discrepancies across these platforms, executing trades that not only capitalize on these differences but also contribute to aligning DEX prices with those on CEXs. The magnitude of the price difference and the subsequent price movement towards convergence serve as primary indicators of arbitrage activity.

To quantify the significance of a trader's impact, we assess the total trade volume against a benchmark. This threshold delineates the upper echelon of trade sizes, distinguishing between routine trading activities and those indicative of strategic arbitrage. Traders whose activities satisfy the criteria of exploiting substantial price discrepancies and whose total trading volume surpasses the large trade threshold are classified as arbitrageurs. Conversely, traders not meeting these conditions are labeled as noise traders, a classification that encompasses a broad spectrum of trading behaviors driven by speculation, sentiment, or less systematic strategies.

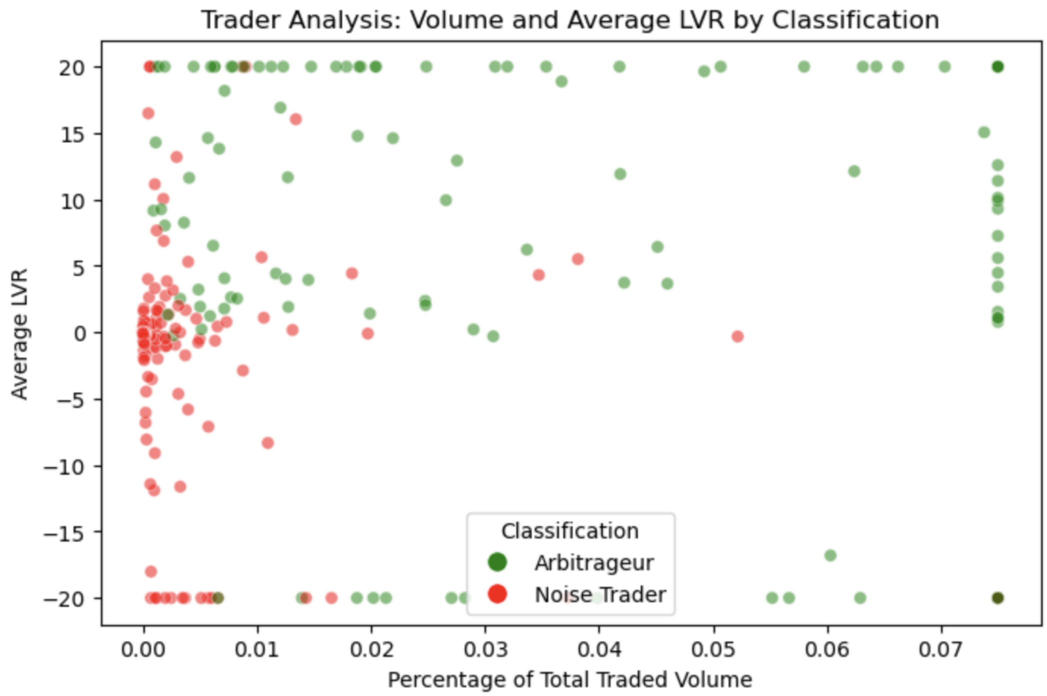


Figure 2.4: Comparative Analysis of Trader Volume Share and Profitability by Classification

Figure 2.4 compares traders' market activity with their average LVR, while also distinguishing between Arbitrageurs (green) and Noise Traders (red). In regions where the LVR is 0 or negative, there is a pronounced clustering of red points, signifying the presence of a substantial number of Noise Traders. This observation aligns with the expectation that Noise Traders are often less profitable, as they tend to engage in trades that do not consistently yield profit. Conversely, in areas where the LVR is positive, we see a prevalence of green points, indicative of a higher concentration of Arbitrageurs. This is consistent with the anticipated behavior of Arbitrageurs, who leverage market inefficiencies to make a profit, thus typically achieving a positive LVR. The presence of these green points in the positive LVR region corroborates the notion that Arbitrageurs are indeed making a profit. Moreover, towards the higher end of the trade volume spectrum, the plot is dotted with green points, suggesting that Arbitrageurs are not only making profitable trades but are also significantly active in the market. The cluster of green points at higher trade volumes substantiates the idea that Arbitrageurs are engaged in frequent trading, a strategy often associated with their role in exploiting arbitrage opportunities across the market.

Chapter 3

Dynamic Fee Model

To promote both price discovery and liquidity within the pool, we want to introduce a dynamic fee structure in comparison to the fixed flat fee structure in Uniswap.

As mentioned in the sections above, traders benefit from price differences between CEX and DEX, Binance and Uniswap in the scope of this paper. But given that they have to pay for trading and gas fees, if the the total fees are too high, they might not end up entering a trade, as it may result in losses incurred from fees (referring only to arbitrageurs).

In fact, an arbitrageur will only execute a trade in the DEX if,

$$\begin{aligned} (x_i - x_i f - g)\,\frac{p_{cex}}{p_{dex}} &> x_i, \text{ if } p_{cex} > p_{dex} \\ (x_i - x_i f)\,\frac{p_{cex}}{p_{dex}} - g &> x_i, \text{ if } p_{cex} < p_{dex} \end{aligned} \tag{3.0.1}$$

where,

- p_{dex}, the current AMM price (pool price)
- p_{cex}, the current price in CEX (market price)
- x_i, the initial amount to be traded by the arbitrageur
- f, trading fees % charged by the protocol
- g, \$ gas fees paid for the transaction to be executed

- s, the percentage arbitrageur profits DAMM allows within a certain price difference range

This being said, we consider it important to create an oracle-informed[1] dynamic fee model that constantly measures the price difference between the market price (CEX) and the AMM pool's price (DEX) to offer adequate fees and minimize LVR losses.

A way to reduce LVR is to reduce the % profit of an arbitrageur. Following from Eq. 3.0.1, an arbitrageurs % profit is calculated as:

$$\%profit = \frac{x_i * \Delta p - TransactionCosts}{x_i} \tag{3.0.2}$$

where the arbitrageur gains from the price difference minus the gas fees paid to the blockchain and the swap fee charged by the pool. We can interpret % profit as the maximum hypothetical extra fee a trader would be charged for it to make no profit nor loss; in other words, it is the maximum fee an arbitrageur is willing to pay to enter a trade. As the goal of market-making is to provide volume and liquidity to the market, it is necessary to encourage people to provide liquidity. This is only possible if they can get rewarded for their action, ultimately making liquidity-providing profitable. If the profits of arbitrageurs are too large, then it does not make liquidity providing profitable, reducing the liquidity of the exchange and thus the trading volume on it, as orders will have a more significant impact on the price.

The idea of our AMM dynamic fee models is to offer traders a fee close to this hypothetical fee (never surpassing it), where they can still make arbitrage profits but without exploiting the dynamics of the protocol, allowing LP's to get fewer losses, while also contributing to price discovery between CEX and DEX.

From this intuition, we have developed two models with different calibration approaches. We will be comparing the performance of both. The first model is characterized by its intuitive nature, leveraging a minimal set of parameters to establish a direct and comprehensible link to market dynamics, including Δp. This simplicity facilitates a straightforward understanding of how market factors influence the fee calculation and

[1] System that provides external data to a blockchain, e.g. market prices

the logic behind it. Conversely, the second model adopts a more intricate approach, delving into a deeper and more detailed analysis. Although this complexity allows for a potentially more accurate reflection of market conditions, it also renders the model less transparent and more challenging to interpret. In both approaches, we have distinguished arbitrageurs from noise traders, as mentioned in Section 2.4.

3.1 Assumptions

In our study, we formulate a model for the trading of a risky asset (ETH) and a numéraire (USDC), considering the option to trade these assets on both a CFMM and a CEX.

CEX depth. In our model, we make the assumption that the CEX has infinite depth, allowing the risky asset to be traded on the CEX without causing any price impact. In real-world scenarios, especially for highly liquid trading pairs, this assumption is likely to be reasonably accurate. This is supported by the observation that a significant majority of trading volume in liquid pairs occurs on centralized exchanges compared to decentralized exchanges, suggesting a higher market depth on CEXes. However, for less liquid tokens that are not actively traded on centralized exchanges, this assumption may be less applicable.

Static DEX pool. To simplify our analysis, we assume that, besides engaging in trades with incoming liquidity-demanding agents, the pool remains static. Specifically, we assume that liquidity providers do not introduce (”mint”) or withdraw (”burn”) reserves during the period under consideration, making them passive participants.

Ideal arbitrageur. There is a population of arbitrageurs, able to frictionlessly trade at the external market price, continuously monitoring the CFMM pool. When an arbitrageur interacts with the pool, we assume they maximize their immediate profit by exploiting any deviation from the external market price. Arbitrageurs trade myopically because of competition. If they choose to forgo immediate profit but instead wait for a larger mispricing, they risk losing the profitable trading opportunity to the next arbitrageur.

CEX fees. Given that our focus is on AMM’s and their structure, we assume that traders benefiting from CEX-DEX arbitrage pay all trading fees involved in the arbitrage, to the DEX, i.e. CEX trading fees are zero.

LP behaviour. Several other papers analyze microfounded models of strategic liquidity provision on AMMs. We do not take a stance on the behavior of liquidity providers here; instead, we simply take as given the level set which the CFMM LP is on at any given point in time. The cost of not modelling strategic LP behavior is that our framework cannot make sharp predictions about how the level of CFMM liquidity provision responds to changes in market design. However, the benefit is that our quantification of CFMM LP losses is robust to different underlying models of strategic LP behavior.

3.2 Single Factor Model

In this study we took inspiration from options to propose a straddle-like fee structure AMM (We will call it DAMM, Dynamic AMM). Given that LVR has a linear relationship with arbitrageurs' PnL, 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 equation:

$$\begin{aligned} f_{\text{buy}} &= \min(\max(f_{min}, \omega * Z(\Delta p) - s), f_{max}) \\ f_{\text{sell}} &= \min(\max(f_{min}, -\omega * Z(\Delta p) - s), f_{max}) \end{aligned} \tag{3.2.3}$$

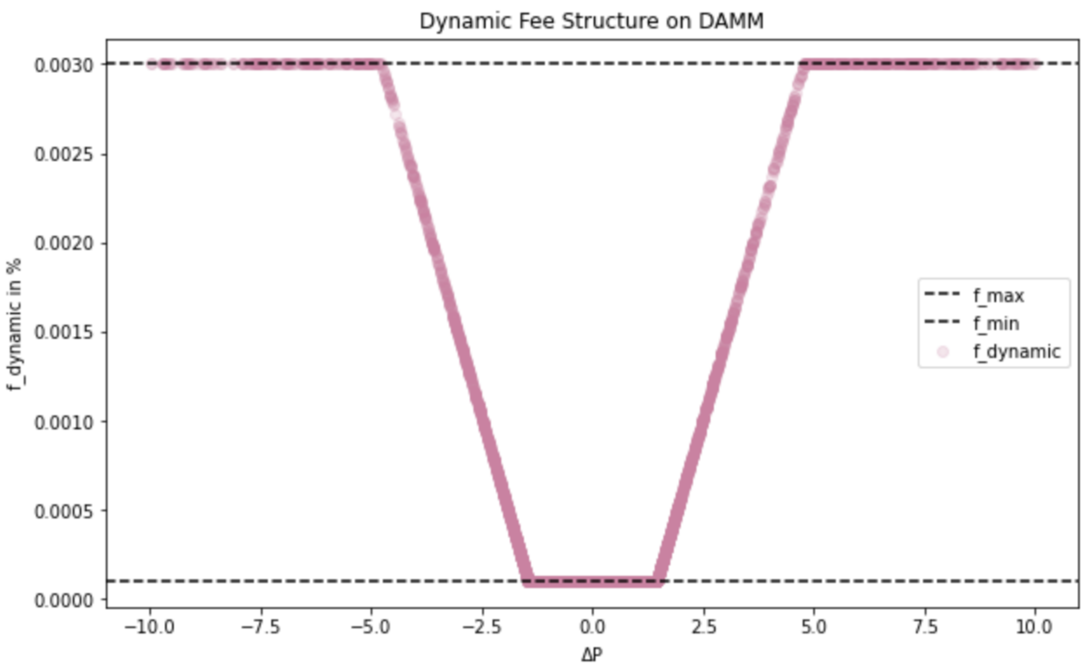
where,

- $\Delta p = p_{cex} - p_{dex}$
- $Z(\Delta p_i) = \frac{\Delta p_i - \mu}{\sigma}$
- μ, is the average Δp on the calibration period
- σ, is the standard deviation on the calibration period
- f_{min} and f_{max}, the lower and upper bound of buying and selling fees charged to the traders

- ω, the parameter which determines the weight attached to the price difference $p_{cex} - p_{dex}$ in the calculation of fees

- s, parameter which determines the deviation from the hypothetical max fee

In the case when the price difference $\Delta p = p_{cex} - p_{dex}$ is positive, in order to make profit, arbitrageurs will buy from a DEX and sell to the CEX. f_{buy} would increase with price difference until reaching f_{max} and f_{sell} would be decreased to a minimum to promote noise traders activities, which on average don't contribute to LVR losses to LP's. On the other hand, if $\Delta p < 0$, f_{sell} should increase as Δp becomes more negative, until reaching f_{max}, and f_{buy} would be at a minimum. An illustration of these dynamics can be found in Fig. 3.2.



`Figure 3.1: Adjust Fee Based On Order Direction. This plots shows a combination of both` f_{buy} `and` f_{sell}`, which are symmetrical on` $x = 0$

We decided to standardize the Δp for easiness of interpretation.

3.2.1 Model calibration

As seen from Eq. 3.0.1, a trader's profit in a CEX-DEX price arbitrage equals to the price difference minus the total transaction cost (gas fees + pool fee). From all January

2024 DEX transactions, only 3.15% of them have non-negative LVR profits. Since this fee structure is designed to redistribute arbitrageurs' PnL (LVR minus transaction cost) to noise traders and LPs, we only use non-negative profits to calibrate the fee model parameters.

The objective is to establish a dynamic fee structure, which adjusts linearly based on the price disparity, incorporating both lower and upper limits to restrict the minimum and maximum fees beyond certain price difference thresholds. We adopt the fee boundaries of $f_{\min} = 1$ bps and $f_{\max} = 30$ bps, derived from the fixed fee tiers of the Uniswap V3 pool.

$s\%$ is shifted down from the regression line to enable arbitrageurs to achieve consistent profits within a price difference z-score range of approximately $[-2, 2]$. This approach deters price discovery for minor price differences, while promoting significant transactions based on concentrated information for larger price disparities. This strategy serves a dual purpose: firstly, it shields concentrated liquidity providers (LPs) from impermanent loss due to excess asset volatility, enhancing trading efficiency. Secondly, it guarantees that arbitrageurs are motivated to execute large-scale trades, crucial for maintaining the decentralized exchange (DEX) price closely aligned with the centralized exchange (Cex) price.

1. **Data Winsorization** The training dataset is refined by selecting only those transactions that result in a positive Profit and Loss (PnL), and it concentrates on transactions where $Z(\Delta P) \in [-10, 10]$, falls within the range of -10 to 10. In the one month data we are using, CEX price is systematic lower than DEX price. In order to calibrate a symmetric fee model, ΔP is transformed into a z socre to avoid bias on selling fees. This subset of the data highlights the activities of profitable arbitrageurs within the pool.

2. **Regression** we use OLS to regress winsorized PnL on $Z(\Delta P)$ to find the linear dynamic fee's gradient ω.

3. **Parameter Optimization** The shift parameter $s\%$ is calibrated by maximizing the DAMM fee, with the constraint that trading volume must stay above a certain

threshold. The more DAMM charges, the more profits LPs will have, which increases the liquidity of the pool. On the other hand, it takes into consideration that people will leave if the fee is too high, as trades might become unprofitable given the trader's risk appetite, in turn reducing the vitality of the pool. If they used to make positive profits on the arbitrage opportunity, we assume they will not perform a trade and DAMM will get 0 fee if their profits are cut in half with the new fee. If they used to make negative profits, we assume they will not enter into a trade if their profits are twice as negative.

4. **Fee Structure** Use the ω and shift $s\%$ to calibrate the straddle shape fee structure. Adjust the straddle shape fee structure by calibrating it with the parameter ω and incorporating a shift of $s\%$.

5. **Data Fitting** Use the above fee structure to fit all the transactions from January 2024 will give us a new dynamic fee in both percentage and notional value.

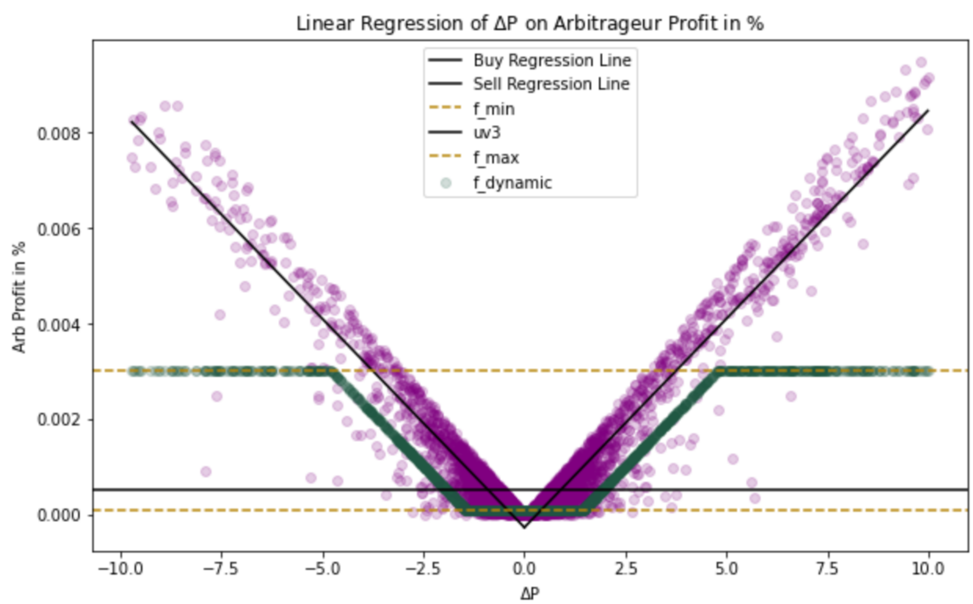


Figure 3.2: Arb Profits on Delta P. Where we find f_{sell} to the left of $Z(\Delta p) = 0$ and f_{buy} to the right of $Z(\Delta p) = 0$. The violet points represent the true arbitrage profits given a $Z(\Delta p)$ as obtained from the calibration data. The continuous black lines are the regression lines, used to estimate ω, showing the maximum fee an arbitrageur would be willing to pay to enter a trade. In green, the proposed dynamic fee.

The dynamic fees established by the model as a function of Δp can be seen as the green lines in Fig. 3.2.2. As seen in Eq. 3.2.3, the shift parameter s is equivalent to the y-axis translation of the black regression lines into the green dynamic fee lines. It is imperative to mention that in this plot, the dynamic f_{buy} is found as the green line to the right of $Z(\Delta p) = 0$, and it is f_{min} to the left of it. On the other hand, f_{sell} is shown to the left of $Z(\Delta p) = 0$ and it is equal to f_{max} to the right of it.

3.2.2 Empirical Analysis

Given the previous distinction, we made sure to strongly filter out arbitrageurs, finally realizing that 3.645% of the transactions are classified as arbitrageur trades. We did this because most losses to LVR for LP's happen due to large arbitrage profits. That is why our regression is on the hypothetical arbitrage profits and $Z(\Delta p)$ only use this reduced dataset.

The regression line yields a value of $\omega = 0.0009$ for the slope parameter. The slope is approximately 1 (scale adjusted) but slightly less pronounced. This adjustment is due to scenarios where significant price difference prompt arbitrageurs to bid higher transaction fees to prioritize their trades at the forefront of the blockchain. This strategy maximizes the chances for successful execution of the arbitrage opportunity on the decentralized exchange (DEX) while minimizing the adverse impact on price.
After the optimization, we got a shift $s = 0.002$, and finally, Eq. 3.2.3 becomes:

$$\begin{aligned} f_{\text{buy}} &= \min(\max(0.01\%, 0.0009 * Z(\Delta p) - 0.002), 0.3\%) \\ f_{\text{sell}} &= \min(\max(0.01\%, -0.0009 * Z(\Delta p) - 0.002), 0.3\%) \end{aligned} \tag{3.2.4}$$

We will discuss the result in 3 parts:

1. **From Noise Trader's Perspective**

   For noise traders that had positive PnL, the imposition of a fixed 5% fee rendered their profits negligible. However, the introduction of a dynamic fee structure, allowing them to pay the minimum fee (f_{min}), enabled them to enhance their earnings.

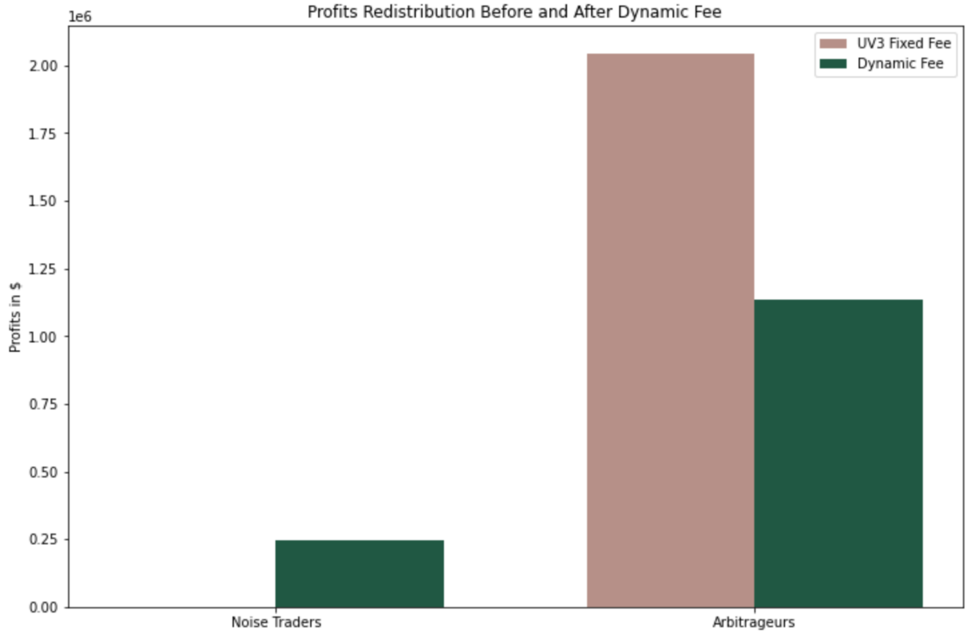


Figure 3.3: Positive Profit Redistribution by Trader Type

For negative PnL noise traders, their PnLs were improved significantly. This adjustment not only incentivized them to conduct more trades but also likely contributed to an increase in the overall liquidity of ticks.

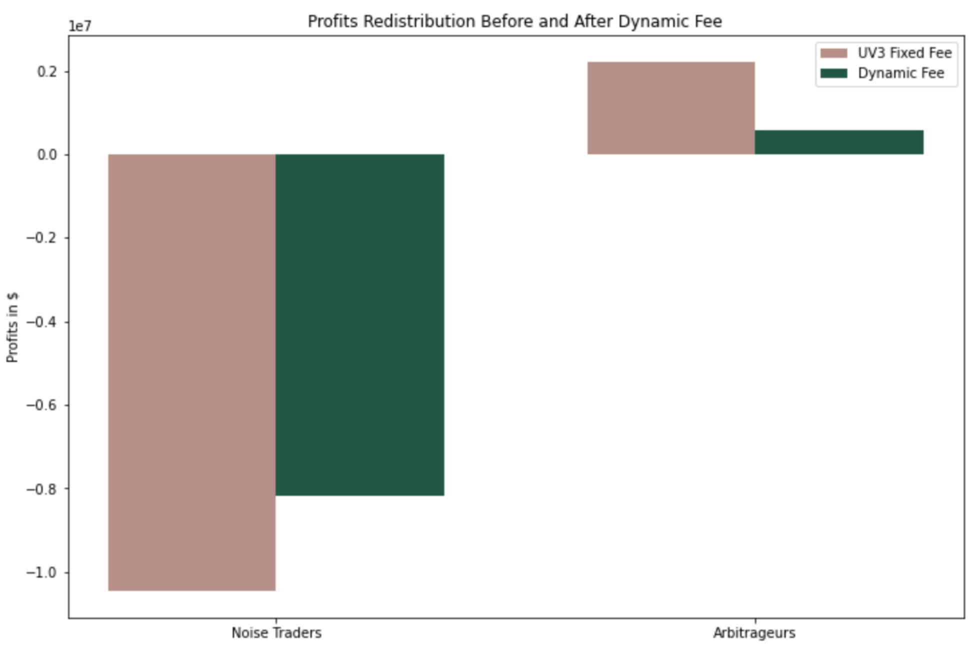


Figure 3.4: All Profit Redistribution by Trader Type

2. **From Arbitrageur's Perspective**

For Arbitrageurs engaging in trades with smaller price differences, their profits diminish substantially, compensating for the Liquidity Providers' (LPs) impermanent loss during price fluctuations. Their fees, scaling linearly with the price difference, effectively match those of Centralized Exchanges (CEX), erasing any margin for profit. This setup is likely to discourage them from engaging in CEX-DEX arbitrage on minor price discrepancies. However, with a maximum fee (f_{max}) capped, the DAMM model still motivates arbitrageurs to pursue trades with larger price gaps. The significant trading volumes driven by these larger discrepancies play a crucial role in the price discovery process within DEX pools.

3. **From Liquidity Provider's Perspective**

   The total fee levied by DAMM exceeds that of Uniswap by 0.07%. This not only results in LPs earning higher fees, but they may also enjoy the advantage of increased tick liquidity, given that noise traders are subject to significantly lower fees, increasing the overall liquidity of the pool.

Overall, 98.3181% of the trades are charged less the Uniswap V3 proxy 5 bps. From Fig. 3.5, we can see that the higher fee buckets corresponds to higher profits, which ensures that the dynamic fee model punishes arbitraguers with higher profits while lowering the cost for others.

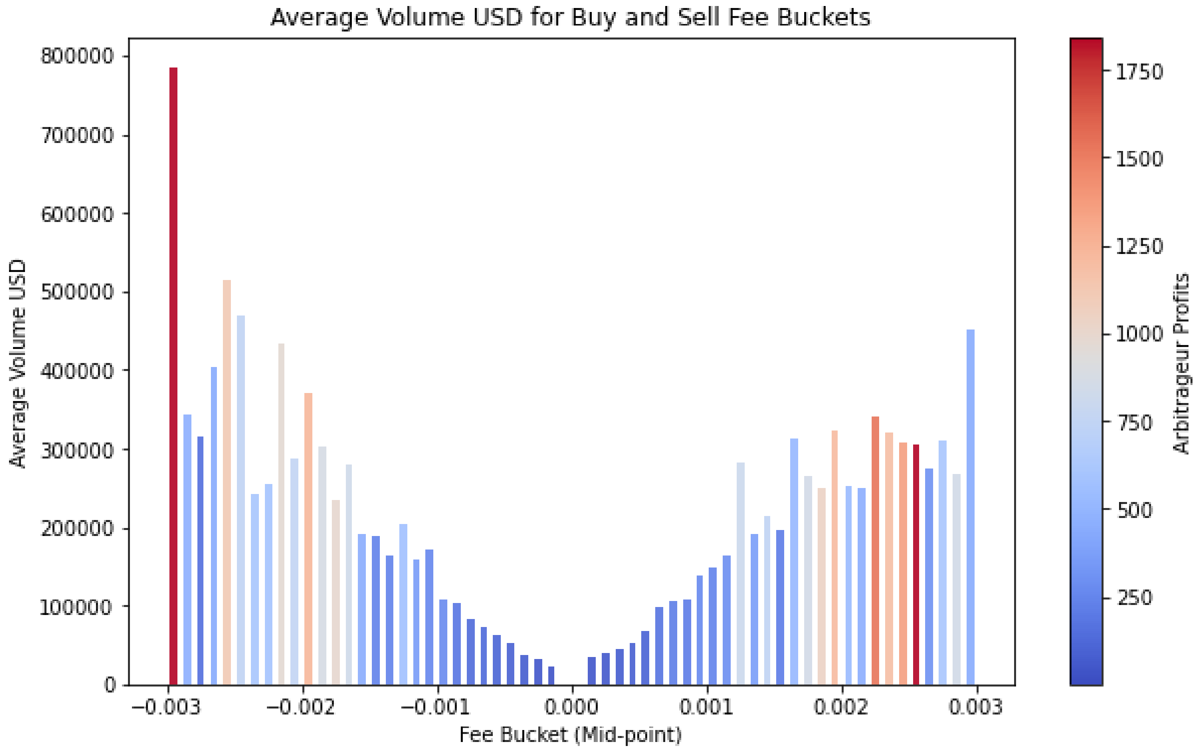


Figure 3.5: Avg Trading Volume Bucket by Dynamic Fee. The high selling fee has higher PnL than buying fee is due to the systemetic higher DEX price. Arbitrageurs buy on CEX and sell on DEX, making significant profits.

3.3 Multi-factor fee model

This model is similar to the previous one but its calibration approach is more complex. The fees are determined by the following equation:

$$
\begin{aligned}
f_{buy/sell} &= \sum_{i=1}^{n} \min(\max(f_{min}, \omega_i f_i(g_i)), f_{max}) \\
f_i(g_i) &\propto m_i g_i
\end{aligned}
\tag{3.3.5}
$$

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 m_i 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

This model can be summarized as a linear combination of fees obtained from each factor weighted with the individual factor importance to the final global fee f.

For example, Table 3.1 is sample swap data that we used to calibrate our fee model, with each column corresponding to a feature in the factor model.

Tx_id	Amount1 (buy swaps)	Arb pnl (%)	Volatility	Amount1 fee	Arb pnl fee	Volatility fee	Amount1 weighted fee	Arb pnl weighted fee	Volatility weighted fee
0	-100	0.02	0.10	0.01	0.10	0.010	0.005	0.030	0.002
1	-50	0.01	0.20	0.01	0.01	0.055	0.005	0.003	0.011
2	-30	0.01	0.15	0.0357	0.01	0.010	0.0178	0.003	0.002

`Table 3.1: Sample data with feature importance: {'arb_pnl': 0.3, 'std': 0.2, 'amount1': 0.5}`

These parameters were chosen after running a Random Forrest Regression over multiple features from the transaction data available, in order to find the feature importance in determining the traders % profit.

3.3.1 Model Calibration

The global fee for a swap transaction is determined through a multi-step process that integrates transaction-specific data, feature-based adjustments, and weighted contributions from various transaction characteristics. This methodology aims to compute a fee that reflects both the market dynamics captured by the dataset and the intrinsic value or risk associated with each transaction.

1. **Data Segmentation.** The dataset is initially segmented into two subsets based on the direction of the transaction—purchases (buy) and sales (sell). This distinction allows for differentiated fee calculations that account for the inherent differences in buying versus selling transactions.

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. These boundaries, determined by specified lower and upper quantiles from the feature data, serve to winsorize the feature values and mitigate the impact of outliers on the model calibration.

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. These thresholds help in identifying the range within which the majority of transactions occur, allowing for a more focused and representative fee adjustment. For instance, we set $g_{i,max} = q(0.95)$ and $g_{i,min} = p(0.05)$.

4. **Setting f_{min} and f_{max}.** We give fixed values for these accross all features, with $f_{min} = 0.01$ and $f_{max} = 0.1$

5. **Estimating the Fee per Feature f_i** After using quantiles to find q_{min} and q_{max} in the previous step, now for each feature we find the slope of the line to fit the fees to, m_i by simply taking $f_{max} - f_{min}/g_{max} - g_{min}$, where $g_{max/min}$ were obtained through the quantile process described before.

6. **Calculating Factor Weights ω_i.** Weights for each feature fee are derived through feature importance after applying random forest regression. This ML model is applied to the original dataset over the hypothetical fee (as described in the Single-Factor model). The feature importance then tells us what variables have more impact on the fees, and are normalized to 1. We use these as weights ω_i. These weights adjust the fee on the feature's value, ensuring that the fee scales appropriately with the feature's impact on the swap factors.

7. **Adjusted Fee.** Adjusted fees are applied to each transaction within the buy and sell subsets. This step involves calculating a fee for each transaction based on its feature values, using the previously determined weights and scaling factors.

8. **Data Reintegration and Weighted Fee Summation.** The adjusted buy and

sell subsets are recombined into a single dataset. A global fee for each transaction is then computed by summing the weighted fees across all considered features. This summation integrates the influence of multiple transaction characteristics into a single fee metric.

9. **Normalization and Final Adjustments.** The combined fee is normalized (e.g., divided by 100 if necessary) to ensure it falls within a reasonable and interpretable range.

3.3.2 Empirical Analysis

The factors we used in the analysis are the following:

- Δp, CEX-DEX price difference $p_{cex} - p_{dex}$
- **Arb_PnL**, theoretical arbitrage an arbitrager can make with the basic CEX-DEX arbitrage (i.e. $\Delta p * x_i$, where x_i is the trade value
- **Avg_gas**, average gas paid by transactions in the last 30 blocks
- **lambda_1min, lambda_5min**, coefficients of the Poisson process using a 1 and 5-minute rolling period to count the arrival transaction number. It helps us to know when the market is busy and people are rushing to make their arbitrage
- **std**, the rolling standard deviation of the last 100 transactions in the pool
- **LVR_nbtoken**, the number of tokens that the LVR profits represent
- **rol_AmountUSD**, is a proxy for the volume on the rolling period
- **rol_1min_span**, rolling average of trades per minute
- **rol_1m_trade_count**, number of trades in 1 minute
- **Price_impact**, the amount by which a trade moves the price of the pool. Price impact is inversely proportional to the liquidity in the pool. We want to charge a higher fee when the liquidity is low in the pool (i.e. trades have a large price impact)

then this incentivizes LP to put in more money because they receive a higher fee after each swap and then the liquidity comes back. $PI = \frac{2x_i + x_i^2}{p_{dex} * liquidity_{pool}}$

We run 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 in order to get the feature importance.

The feature importance, normalized, can be seen in Fig. 3.3.2, where the CEX-DEX price difference and the arbitrageurs profit is highest, as was expected (since the target variable in the regression is directly proportional to the price difference itself). Average gas has an interesting relevance as well given that it directly affects the potential profit in arbitrage and can be a determining factor when entering a trade. In Fig. 3.3.2 we can easily see the proportion to which each feature contributes to the total fee.

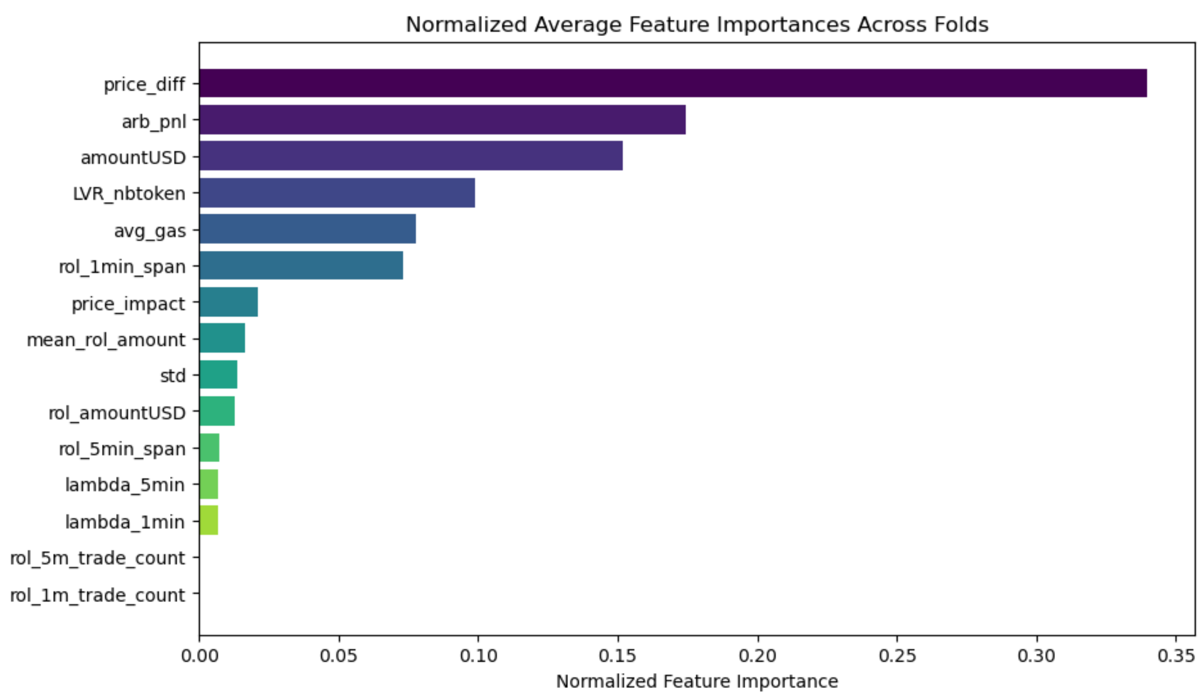


Figure 3.6: Feature importance when determining the fee per trade.

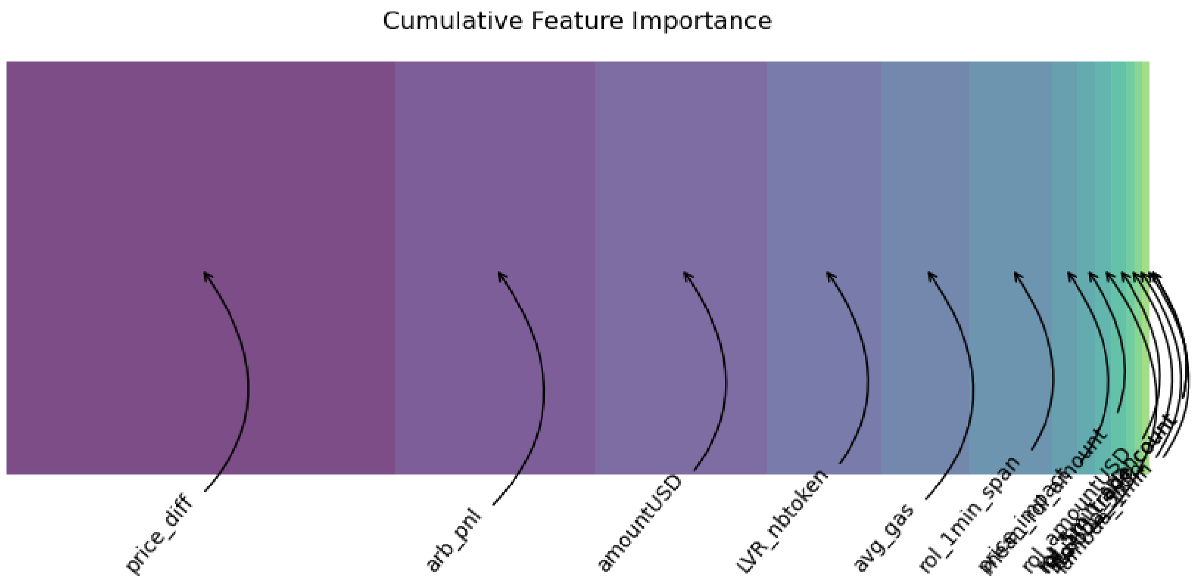


Figure 3.7: Cumulative view of the feature importance.

We decided to test two types of multi-factor models: a 5-factor TradFi model taking the most relevant factors seen from the feature selectio an non-exclusive to DeFi, and a 7-factor model, which includes 2 factors exclusive from interactions in DeFi (CEX-DEX price difference Δp and the $avg_g as$).

As described above, to find the weights attributed to each factor, we ran again a random forest regressor utilizing only these factors, for each model obtaining the following weights:

Feature importance	
5-factor weights	7-factor weights
std: 0.17,	std': 0.07,
price_impact:0.15,	price_impact': 0.07,
lambda_1min: 0.12,	lambda_1min: 0.05,
lambda_5min: 0.14,	Lambda_5min: 0.05,
amountUSD: 0.4	amountUSD': 0.27
	price_diff': 0.25,
	arb_pnl': 0.25,

The resulting fees for each factor can be seen in Fig. 3.3.2 and 3.3.2.

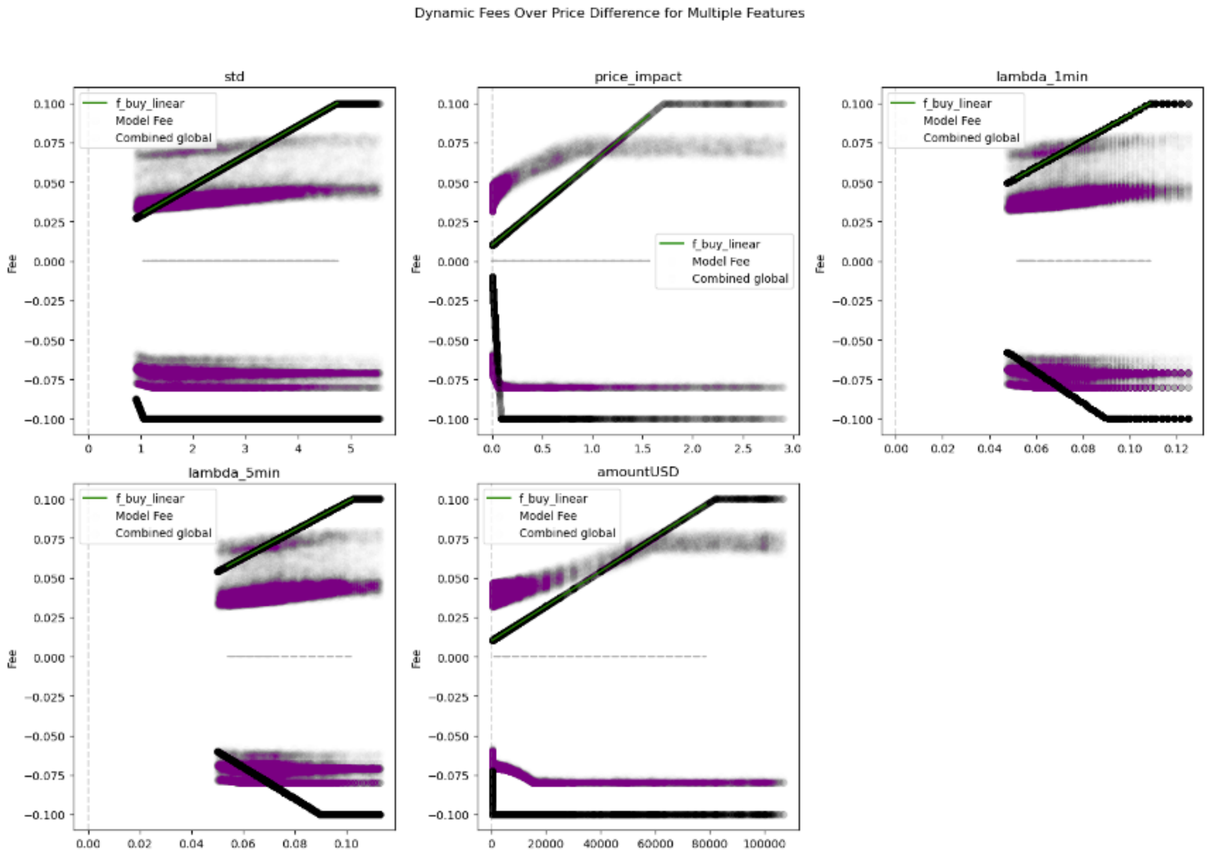


Figure 3.8: 5 factor model dynamic fee structure

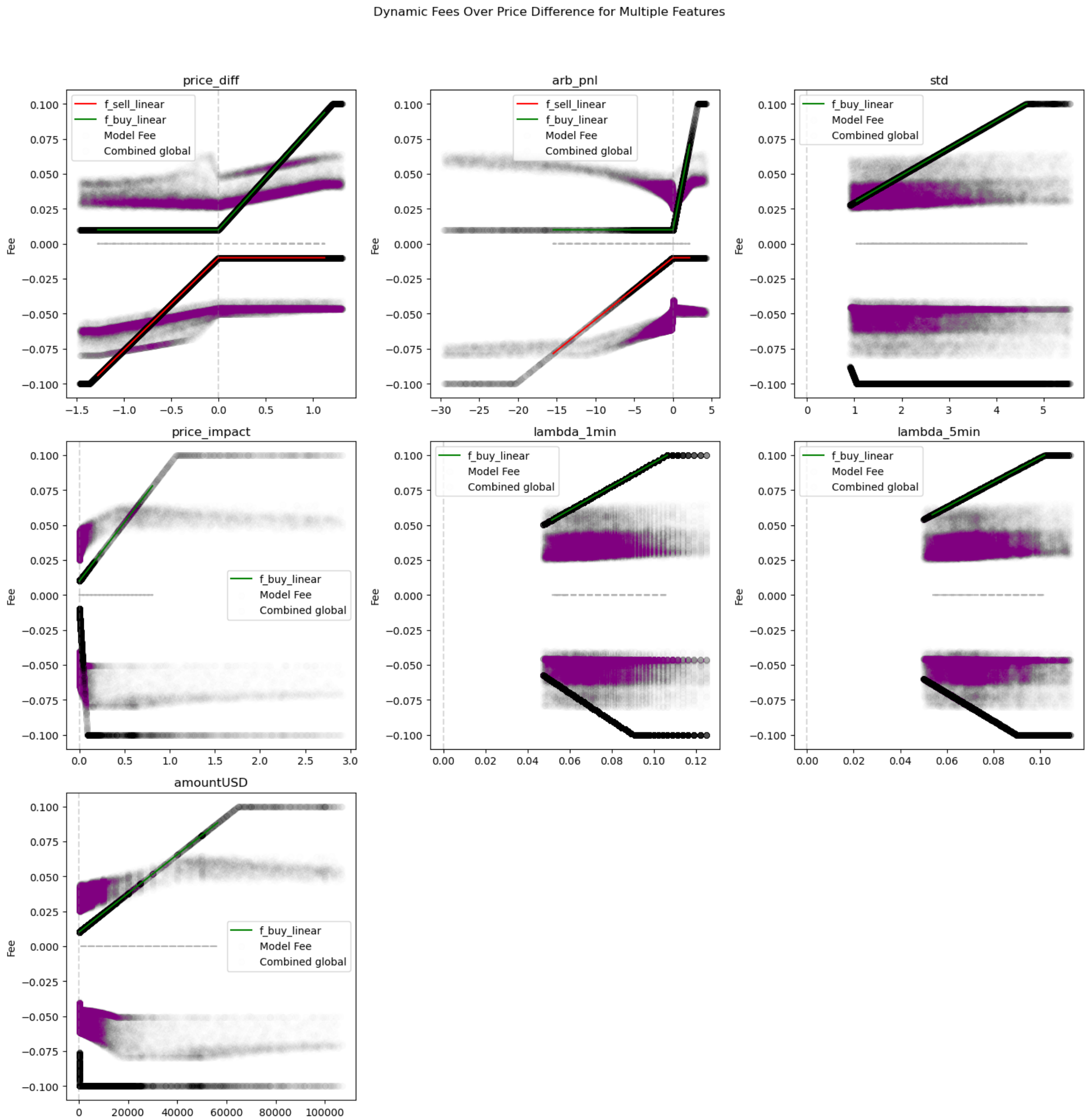


Figure 3.9: 7 factor model dynamic fee structure

In each of these plots, we can see the black with the green dotted line on top represents the fees for each factor. The purple areas represent what the global fee would be on that specific feature held constant.

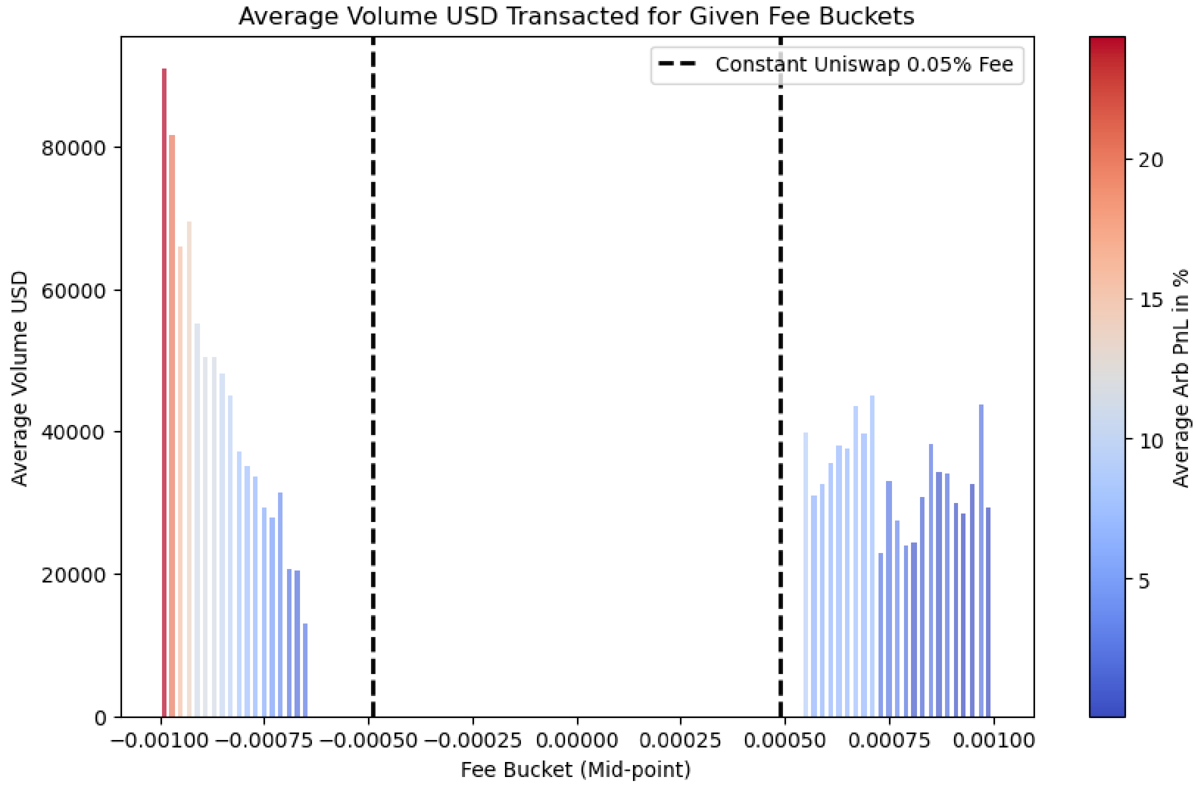


Figure 3.10: 7 factor model final fee average volume traded per fee bucket. Similarly to Fig. 3.5, because CEX was systematically lower than DEX, the selling fee corresponds to higher volume and higher profits.

We can see that trades with higher profits are charged with higher fees, which aligns with the single factor model. We effectively punished arbitrageurs with higher profits and kept the fee low for the rest of the users.

	Constant fee model	5 Factors Model (TradeFi Factors)	7 Factors Model (DeFi Factors)	2 Factors Model (Arb P&L, Volatility)	2 Factors Model (price diff, amountUSD)	10 Factors Model
Percent of additional profits of the dynamic fee over the constant fee model	0.00%	0.00%	0.00%	0.01%	0.01%	0.05%
Price impact percent improvement (decreased impact) of the dynamic fee model	0.00%	0.00%	0.00%	0.01%	0.01%	0.05%
Average dynamic selling fee (%)	-0.05	-0.07	-0.05	-0.07	-0.08	-0.07
Average dynamic buying fee (%)	0.05	0.05	0.04	0.05	0.05	0.05
Impermanent loss in %	-1	-1	-1	-1	-1	-1
Average t cost in $		93.06	47.31	90.89	100.51	38.77
Average on 1 min selling_fee	-0.05	-0.05	-0.03	-0.04	-0.05	0.04
Average on 1 min buying_fee	0.05	0.02	0.02	0.02	0.02	0.02
Weighted average buying_fee ($)	0.05	0.06	0.05	0.05	0.07	0.06
Weighted average selling_fee	-0.05	-0.08	-0.06	-0.08	-0.09	-0.08
Accuracy of the fees (in the range of the constant fee trader will be willing to pay)	100%	7.53%	9.86%	7.81%	7.40%	4.20%
Feature importance	NA	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	arb_pnl 0.54, std 0.47	Price diff 0.4, amount USD 0.6	LVR nb token 0.12, Price diff 0.25, Arb pnl 0.15, std 0.07, Price impact 0.06, Lambda 1min 0.04, Lambda 5min 0.05, amountUSD': 0.27

Figure 3.11: Fee Model Benchmark Table

In Fig. 3.3.2 we can see the results from the models. We decided to test for 2 two-factor models with different parameters to see their performance with fewer features and a model with 10 factors, which provided better LVR reduction while maintaining arbitrageur interaction in the trades. Nevertheless, this would be a difficult model to implement in an AMM as it requires heavy data processing and oracle service for many of the features.

Chapter 4

Conclusion and Future Work

In our study, we have undertaken a thorough examination of Automated Market Makers (AMMs), with a focus on addressing the challenges faced by Liquidity Providers (LPs) due to adverse selection costs and the Loss Versus Rebalancing (LVR) phenomenon. Recognizing the crucial role LPs play in ensuring the functionality of DEXs like Uniswap, we pursued solutions to enhance LP profitability and market efficiency. Central to our investigation was the development of a dynamic transaction fees model designed to balance fairness between traders and AMMs and to improve market efficiency.

We proposed a dynamic fee model, which adjusts fees based on the ongoing price difference between the market price on centralized exchanges (CEX) and the AMM pool price on decentralized exchanges (DEX). This model aims to minimize LVR losses by setting fees that approach the hypothetical maximum an arbitrageur is willing to pay without incurring a loss—thus preserving arbitrage profits without exploiting the protocol's mechanics and ensuring that providing liquidity remains an attractive and profitable endeavor.

Our analysis revealed that a dynamic fee structure, in contrast to the fixed flat fee of Uniswap, promotes both price discovery and liquidity within the pool. We tested two distinct models; the first leverages a minimal set of parameters for intuitive fee calibration, while the second employs a more complex, granular approach to closely mirror market conditions. Both models distinguish between arbitrageurs and noise traders, acknowledging their different impacts on the market.

The results indicated that with the right fee calibration, it is possible to reduce the percentage profit of an arbitrageur, increase the percentage of noise traders, aligning their incentives with those of LPs and thus enhancing the overall liquidity and trading volume of the exchange.

The dynamic fee model's efficacy was evident through rigorous testing. In Model 1, by selectively filtering out arbitrageur trades, we found that 3.645% of the transactions fall under this category. This precision is key since LP losses to LVR are predominantly due to outsized arbitrage profits. Our regression analysis, focused on hypothetical arbitrage profits and the price impact variable $Z(\Delta p)$, revealed a slope parameter (ω) of 0.0009. This suggests that Arbitrageurs are inclined to pay slightly higher fees during periods of significant price differences, which serves to prioritize their trades and optimize the trade execution on DEXs, ultimately mitigating adverse price impacts.

From the perspective of Noise Traders with positive Profit and Loss (PnL), the shift from a static 5% fee to a dynamic fee model (where fees never exceed the hypothetical maximum profit) has been transformative, allowing them to retain and even augment their earnings. For those with negative PnL, the dynamic fee adjustment not only improved their PnL but also likely spurred an increase in trade activity, enriching the pool's overall liquidity. On the other hand, Arbitrageurs operating on smaller price differentials now find their profits significantly curtailed, leveling the playing field for LPs who previously suffered from impermanent loss during market fluctuations. Even with fees that scale linearly with price differences, the DAMM model ensures that Arbitrageurs can still engage in profitable trades when significant price discrepancies arise, driving crucial volumes that aid in DEX price discovery.

Ultimately, our findings have substantial implications for the DeFi ecosystem. The dynamic fee model posits a win-win scenario where LPs benefit from slightly higher total fees than Uniswap, and noise traders enjoy reduced costs, thereby fostering a more liquid and efficient marketplace. Notably, 98.3181% of trades incurred fees lower than Uniswap V3's proxy, validating the model's design to impose higher fees on more profitable arbitrageurs while alleviating costs for others. This nuanced approach to fee structuring holds the promise of reinforcing liquidity provision as a lucrative venture, enticing more participants to contribute to the liquidity pool, and thus perpetuating a virtuous cycle of volume and efficiency within the world of decentralized trading.

Through a deep dive into the economics underlying AMMs and the exploration of innovative solutions to mitigate LVR impacts, our study contributes to the broader objectives of the decentralized finance (DeFi) ecosystem, promoting financial inclusion and fostering a more equitable and efficient marketplace.

4.1 Limitations & Constraints

In our study, the dynamic fee models present promising solutions yet are not without their limitations. First, the reliance on CEX prices relayed to DEXs via Oracle exposes the system to vulnerabilities such as Oracle Attacks. These attacks, perpetrated by malicious actors, can manipulate transmitted data, leading to adverse effects like price manipulation, degradation of pool vitality, loss of trust, and impermanent loss exposures for LPs.

Moreover, implementing the proposed model in a real-world scenario introduces certain operational complexities, particularly due to the necessity of frequent recalibrations of its parameters, namely the slope (ω) and the shift ($s\%$). These parameters are derived from empirical data, reflecting the dynamic and ever-evolving nature of DEX. As such, the model's accuracy and effectiveness are contingent upon its alignment with current market conditions, necessitating periodic adjustments. This requirement adds a layer of complexity to the DAMM framework.

However, it's important to recognize that while frequent recalibration might give us more accurate results, an approximate value for ω and $s\%$ can often suffice. This practical threshold provides temporal stability based on historical analysis.

In summary, while the initial model development and periodic recalibration introduce complexity to the DAMM framework, strategic approaches to parameter estimation and adjustment can mitigate these challenges. By leveraging approximate values and incorporating adaptive mechanisms, it's feasible to maintain the DAMM's efficacy without the need for constant retraining.

4.2 Possible Extensions

As mentioned, we made hard assumptions on the pool dynamics, arbitrageur selection and behaviour, and gas fees. An extension of this work would be to accurately replicate the liquidity dynamics of a Uniswap asset pair pool, in this case, the WETH-USDC 0.05% pool, where pool equations are put into place in our simulator and we get new pool prices and liquidity each time a trade occurs.

Another extension would include the LP dynamics, where the amount of liquidity provided is incentivized by the potential fees they may earn, considering the trading volume and fees. A more complete yet complex version of this would be to consider a UniswapV3 pool, where the liquidity in an asset pair pool has a distribution along the price of one asset against the other. This distribution constantly changes as, in reality, LPs prefer their liquidity to be located in a range as close as possible to the pool's price, making constant changes in the liquidity allocation of the pool.

Our developed backtesting framework for market-making strategies showcased the viability and efficacy of dynamic transaction fee models in maximizing LPs' earnings. Subsequent work could broaden the framework's scope to encompass a wider array of market conditions and trading scenarios, thereby furnishing more comprehensive insights into strategy performance.

While this study contributes significant insights into the profitability and efficacy of dynamic transaction fee strategies within DEXs, the ever-evolving nature of technology and market dynamics mandates ongoing research and adaptation. Future investigations could probe emerging trends, such as advancements in DeFi protocols and the evolution of transaction fee structures, to inform more nuanced and effective market-making strategies.

Chapter 5

Appendix

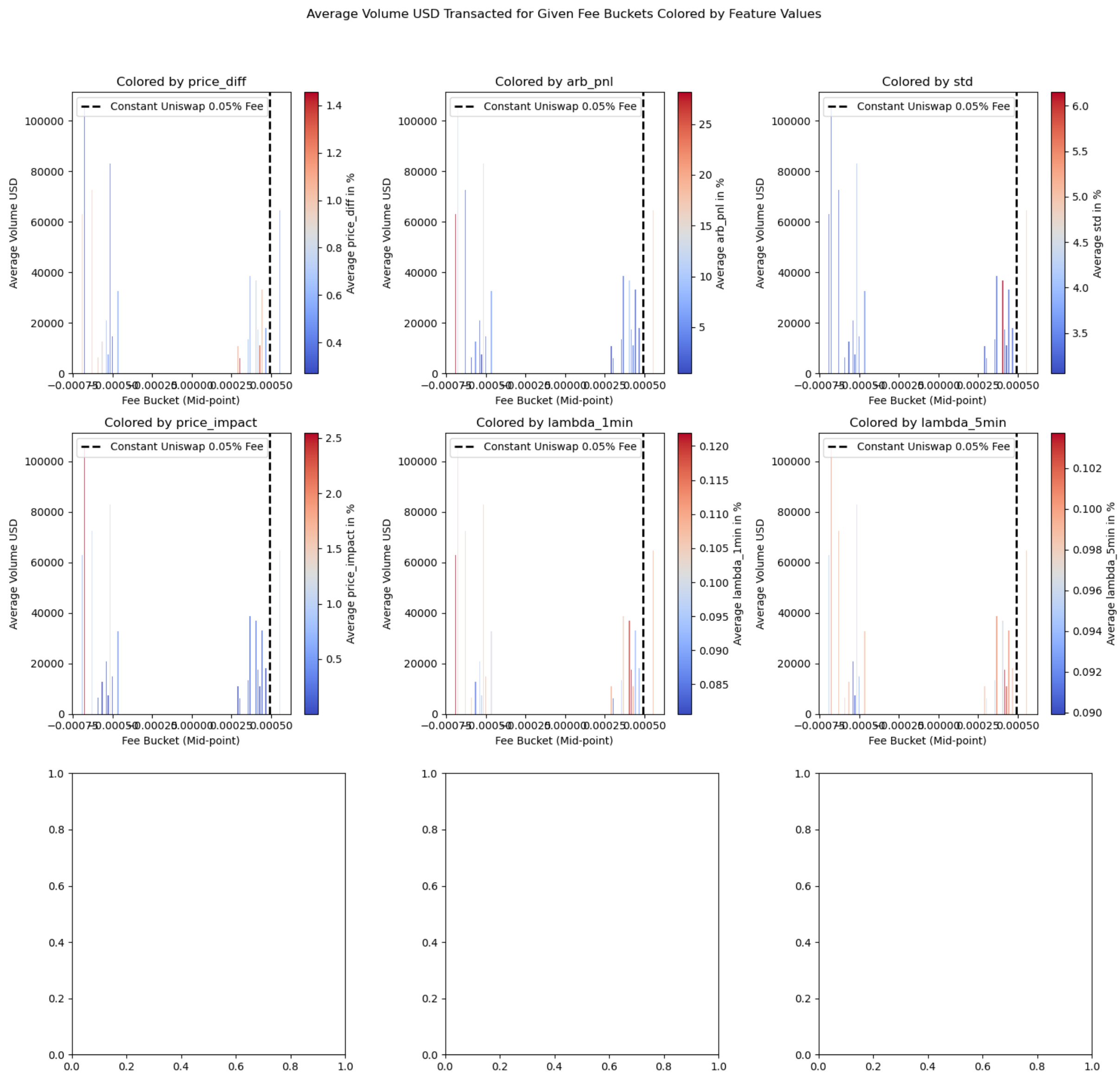


Figure 5.1: Fee Model Benchmark Table

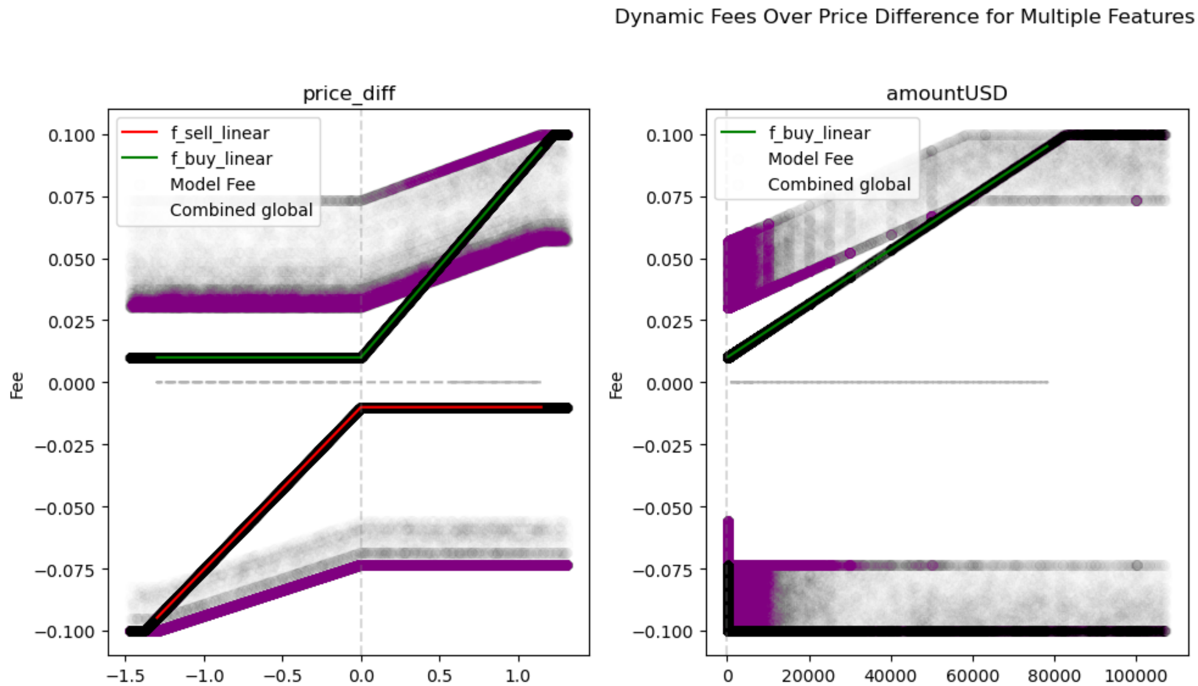


Figure 5.2: Fee Model Benchmark Table

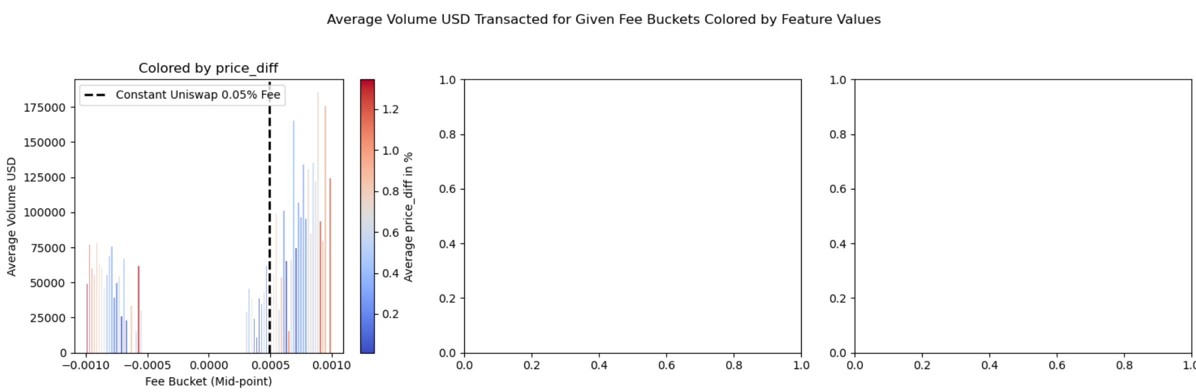


Figure 5.3: Fee Model Benchmark Table

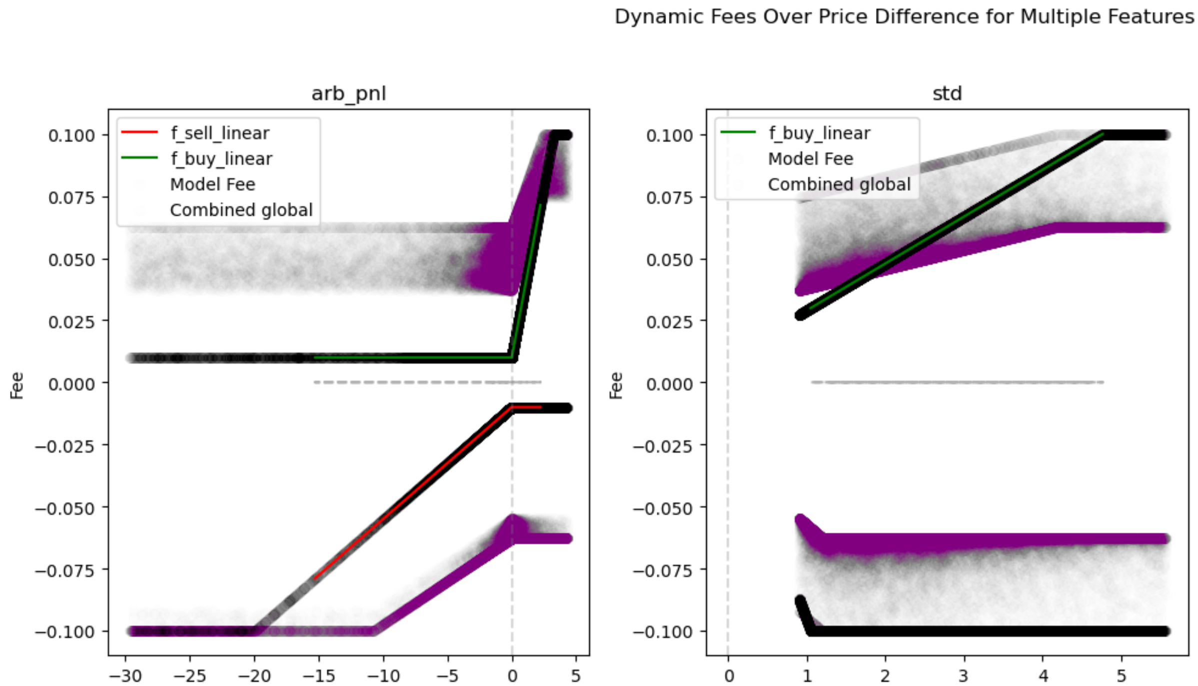


Figure 5.4: Fee Model Benchmark Table

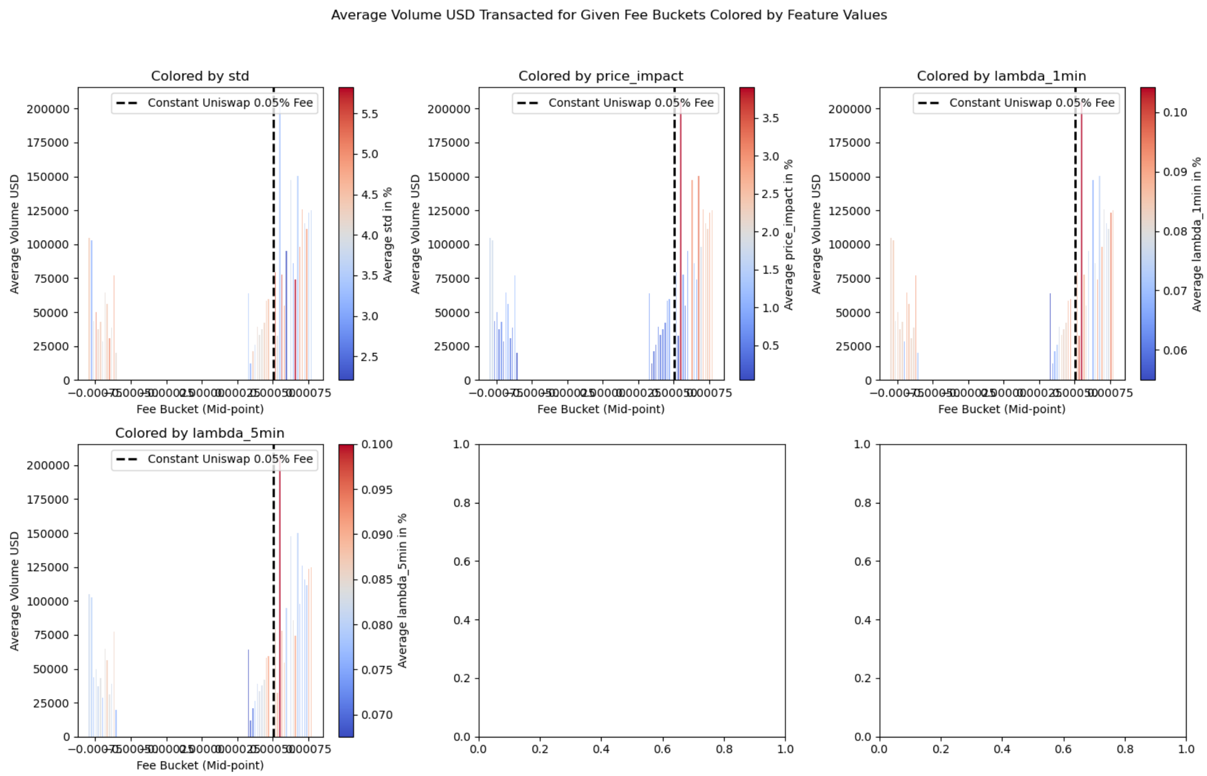
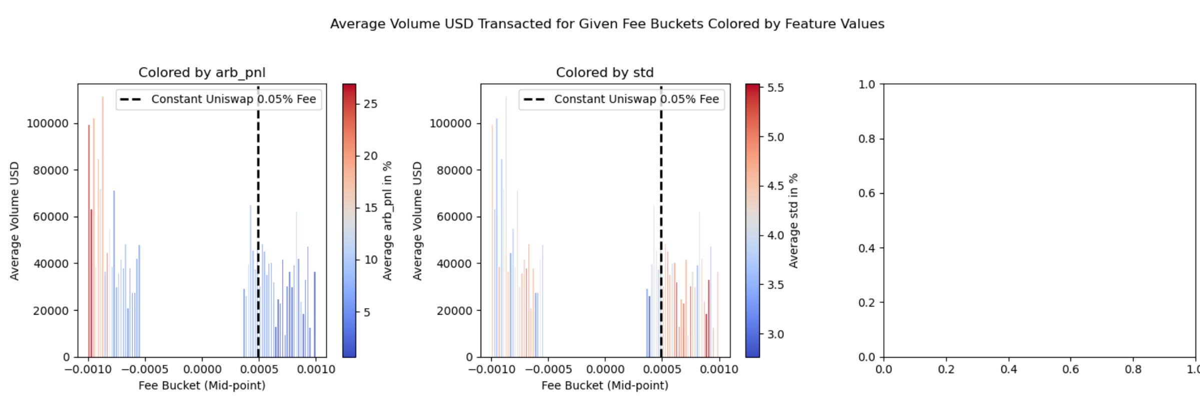


Figure 5.5: Fee Model Benchmark Table



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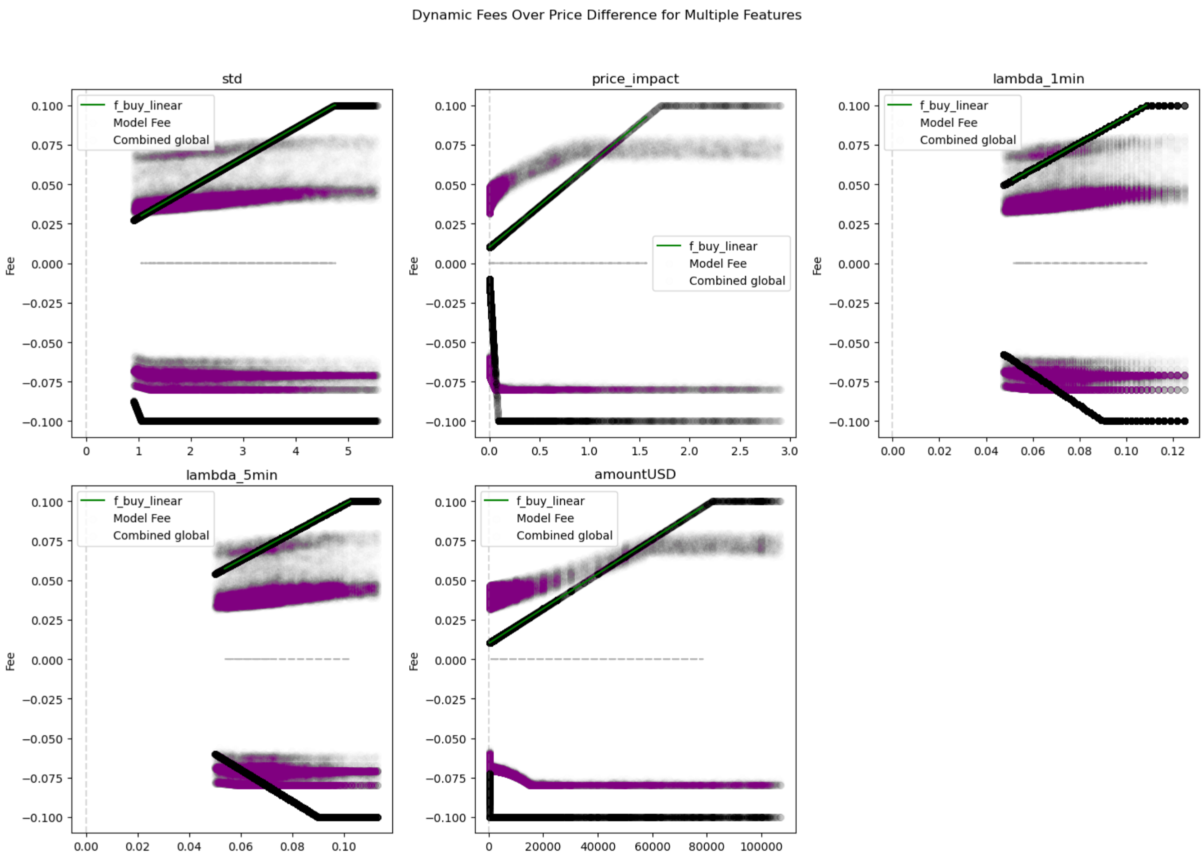
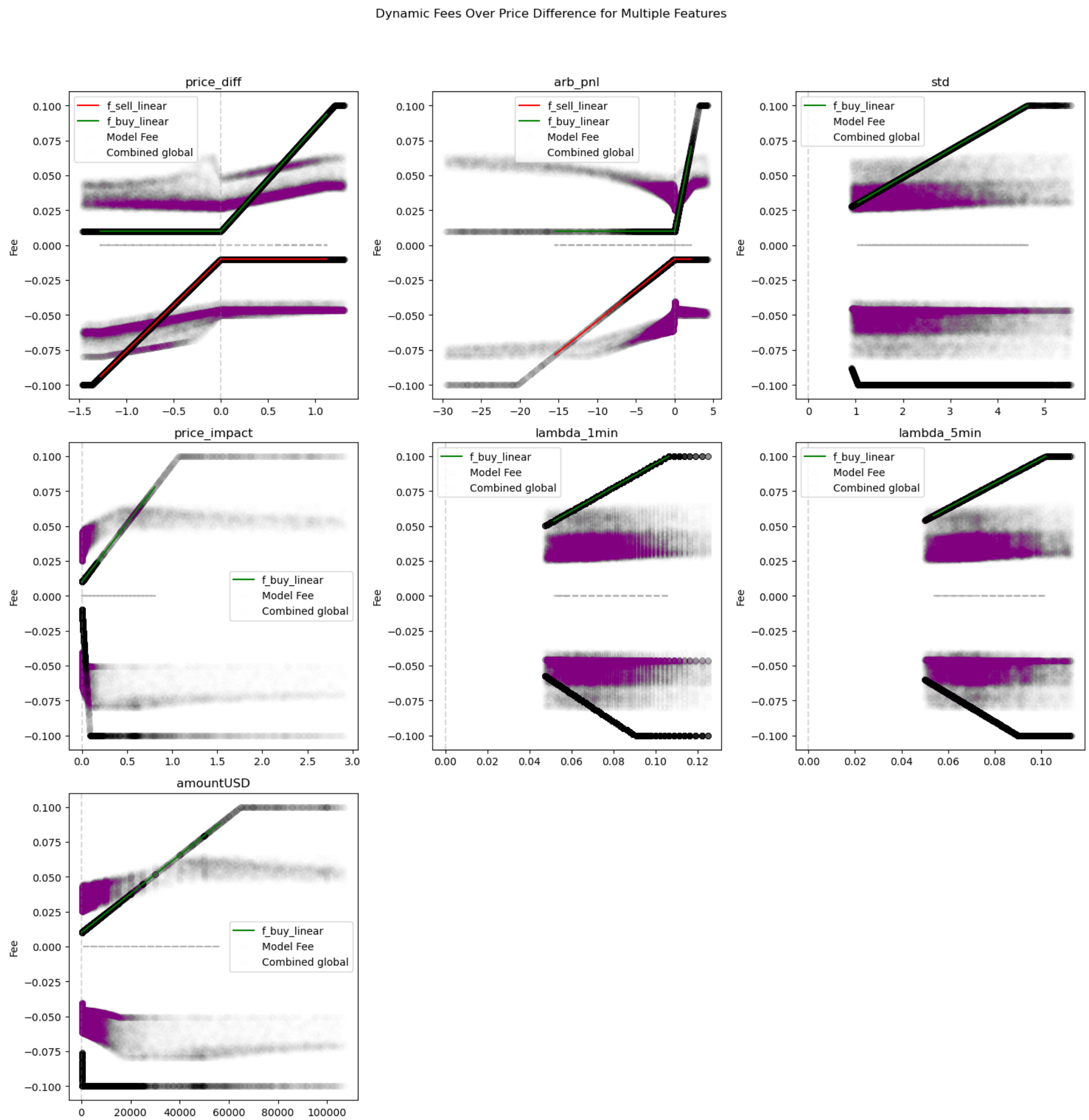


Figure 5.7: Fee Model Benchmark Table



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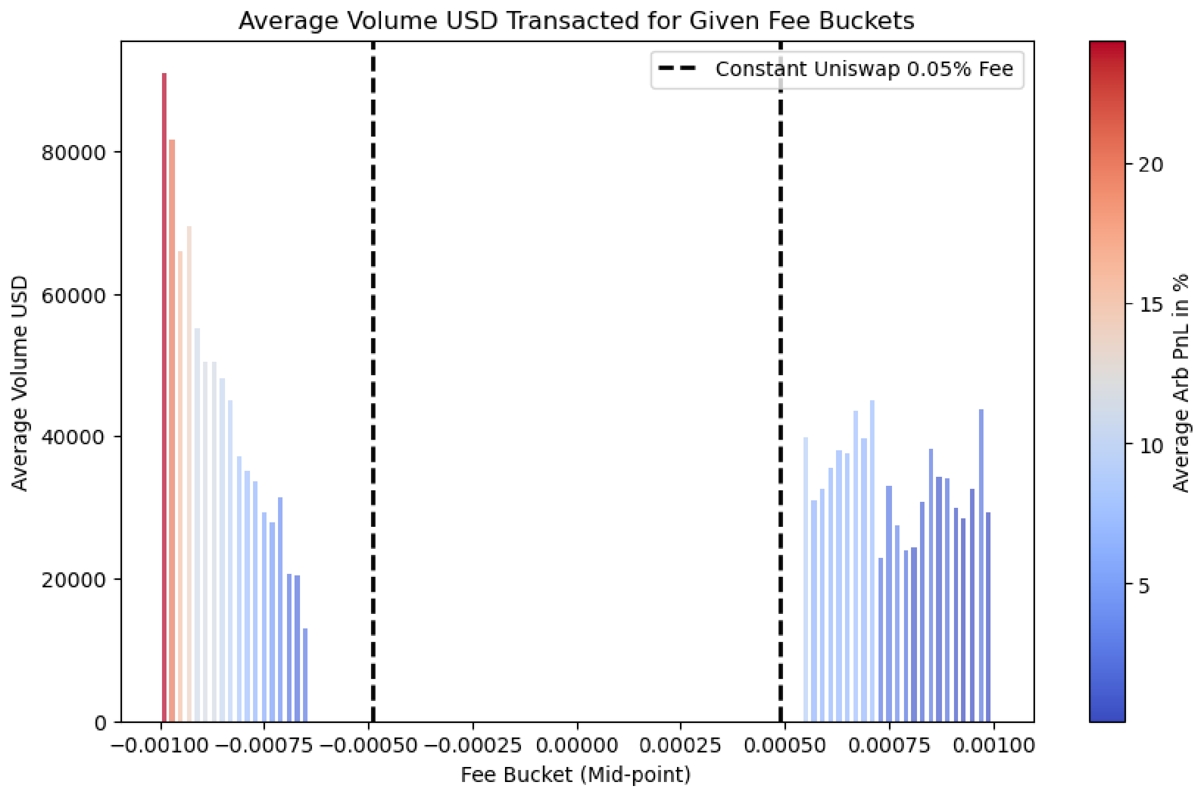

Figure 5.9: Fee Model Benchmark Table

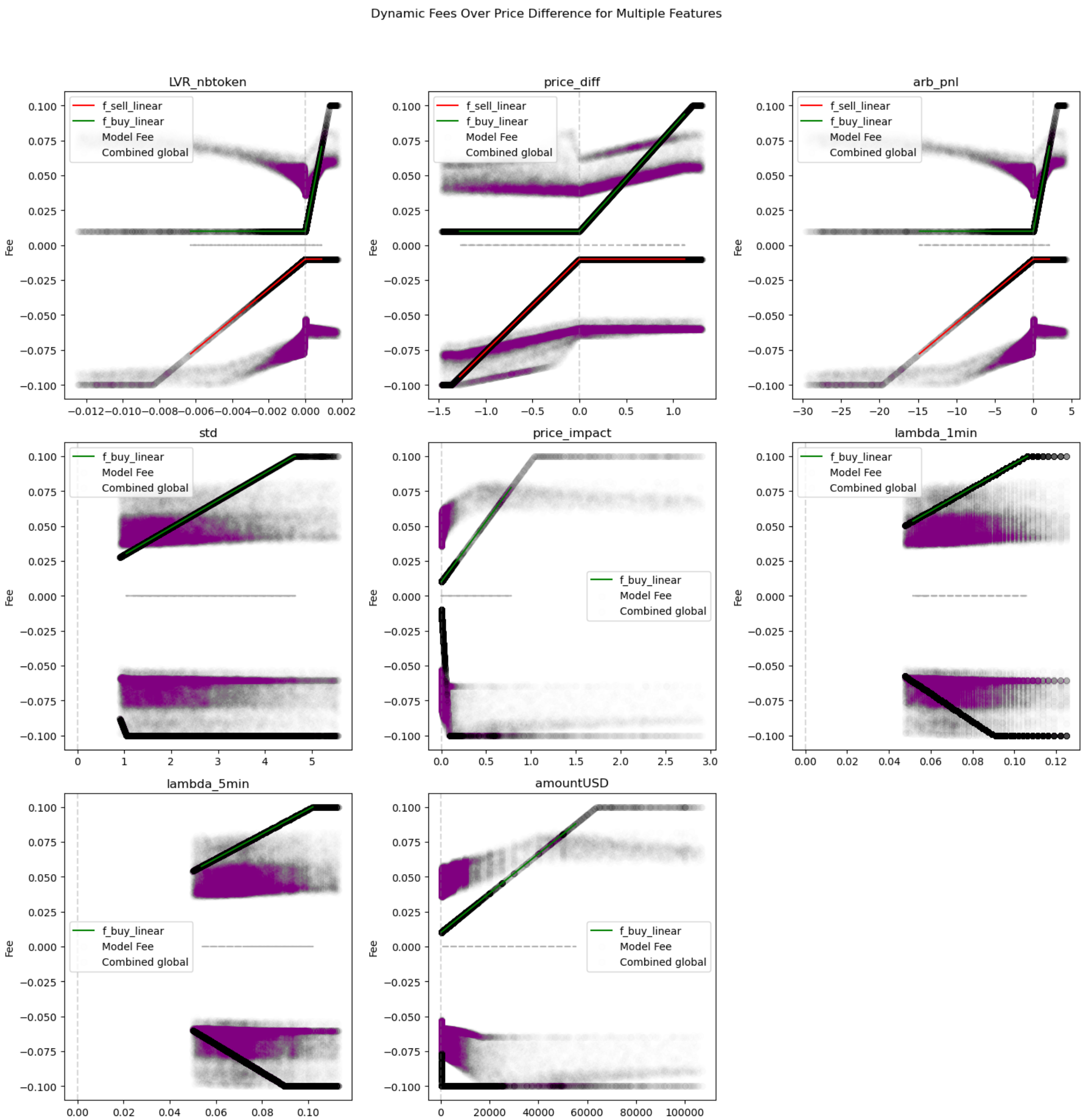

Figure 5.10: Fee Model Benchmark Table

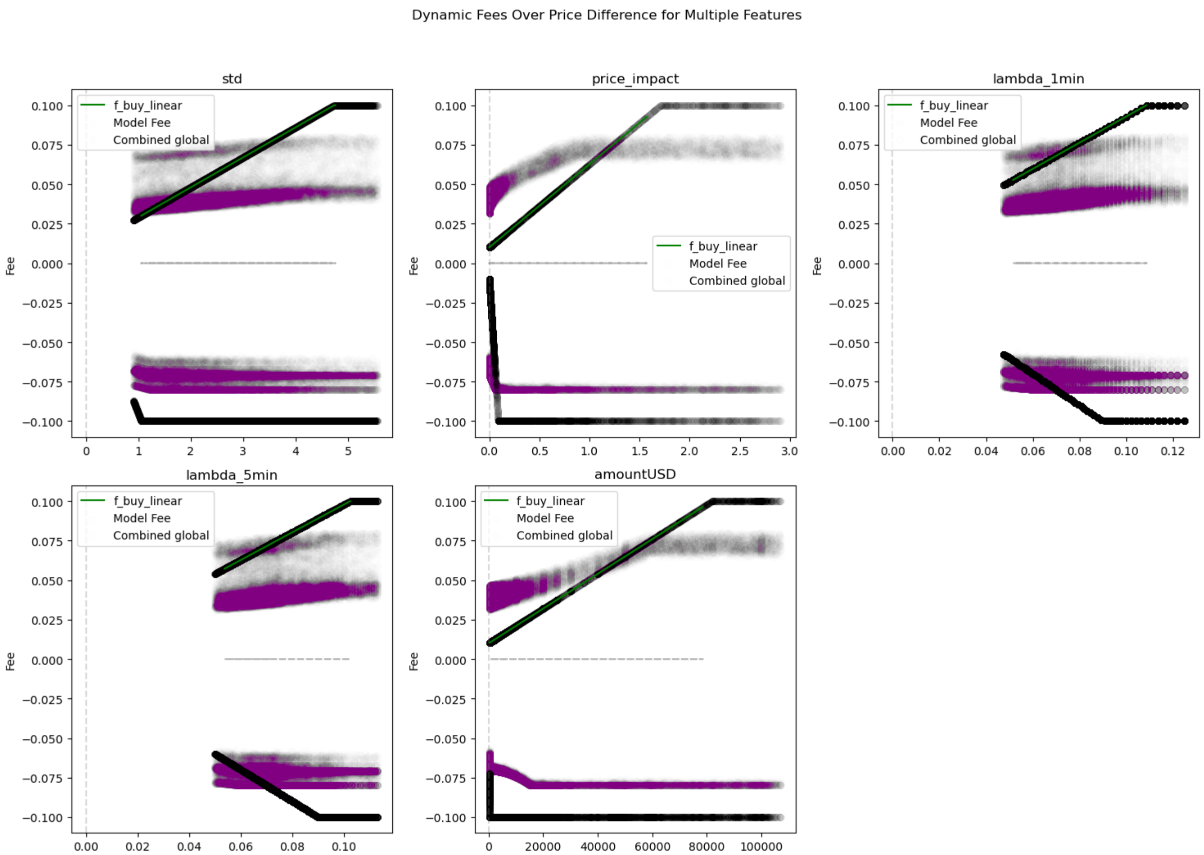

Figure 5.11: Fee Model Benchmark Table

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