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REVIEW ARTICLE

Impermanent Loss Conditions: An Analysis of Decentralized Exchange Platforms

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Abstract. Decentralized exchanges are widely-used platforms for trading cryptoassets. The most fundamental and openly-accessible type of decentralized exchange is based on automated market makers (AMMs), where traders transact against asset reserves managed by smart contracts. These assets are provided by liquidity providers in exchange for a fee. Unlike traditional markets, AMMs pool liquidity from numerous retail participants, and prices are determined by publicly-known mathematical functions. Static analysis shows that small price changes in one of the assets result in losses for passive liquidity providers due to arbitrage trading. However, most existing literature focuses on static effects and does not adequately address the dynamic impact of fees from arbitrageurs over time. Therefore, we investigate the impermanent loss problem in a dynamic setting using Monte Carlo simulations. We contribute to the literature by demonstrating that arbitrage fees may constitute the primary revenue driver for passive liquidity providers. Arbitrageurs exert opposing effects on profitability: they impose rebalancing costs but generate fee revenue. For passive liquidity providers, rebalancing costs are independent of the number of arbitrage trades, while fees are directly proportional to trading volume. Consequently, increased arbitrage activity enhances the profitability of passive liquidity providers. Moreover, we show that this effect is amplified when trading barriers are low and arbitrage competition is intense. As a result, in the absence of barriers, arbitrageurs emerge as the disproportionately predominant source of fee revenue.

1. Introduction

Decentralized exchanges (DEXs) are essential for many blockchain applications, as they enable users to access various services and allow investors to trade a wide range of cryptoassets. Compared to centralized exchanges, DEXs are easy to access, do not require customer identity verification, and can be seamlessly integrated into other decentralized financial (DeFi) services at almost no cost. The Block Research reports that the combined trading volume of all DEXs exceeded USD 1,000 billion in 2021.[1] As of 2025, these numbers are even greater; in October alone, the DEX trading volume surpassed USD 600 billion.[2]

Traditional DEXs operate without an order book. Rather than being matched with counterparties, traders exchange their assets against a liquidity pool. The prices at which traders can exchange their assets with the pool are determined by automated market makers (AMMs).

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AMMs are either simple mathematical formulas or more complex algorithms that specify the quantities and prices for the assets in the pool. These mechanisms ensure that liquidity pools never run out of any of their assets by continuously adjusting prices. For example, if a liquidity pool consists of USDC and ETH, and the amount of ETH decreases, the AMM increases the price of ETH in terms of USDC. AMMs are typically implemented as smart contracts on blockchains.

Automated market makers differ fundamentally from traditional liquidity provision in centralized markets. In traditional systems, individual market makers actively quote bid and ask prices. In contrast, AMMs differ in two ways: first, AMMs pool liquidity from individual (often passive) liquidity providers; and second, AMMs mechanically rebalance their reserves in response to trades, with prices determined by deterministic, publicly known functions rather than by strategic quoting.[3,4] Because the actions of AMMs are publicly known and observable to third parties, in particular arbitrageurs, the interaction between arbitrageurs and market makers in AMMs differs from that in traditional systems, where information about market-making actions is not publicly available. Moreover, due to their rule-based design, simple AMMs such as Uniswap V2 cannot offer differentiated fees (*i.e.*, spreads) over time or across trader types (such as between arbitrageurs or informed traders and uninformed traders), nor can they unilaterally adjust the offered prices in response to market shocks.

Due to the automated quantity and price adjustments, the total value of the assets in the liquidity pool can be lower than it would have been if the liquidity providers had simply held these assets in their wallets. This difference is called "impermanent loss" and is described by the liquidity providers' profit function.[5,6] Many practitioners have argued that impermanent loss is a major issue.[7] As a result of this belief, many DEXs updated their protocols accordingly (*e.g.*, Bancor's Impermanent Loss Protection).[6] However, the growth rates and market share of Uniswap, one of the world's largest DEXs—which did not directly address impermanent loss—suggest that impermanent loss is not necessarily the most relevant issue for liquidity providers.[1] Notably, even though newer and more complex DEX variants offering more strategic options for liquidity providers have been launched (particularly by Uniswap), the protocols of simple AMMs described above remain highly relevant in today's markets, especially for assets with lower market capitalization and trading activity.

The peer-reviewed literature on impermanent loss is limited. The earliest contribution is from Angeris *et al.* in 2021.[8] Assuming no fees, they formally analyze Uniswap V2 and show that profits of liquidity providers are negatively related to changes in market prices and that AMMs closely track the reference market price. Evans (2021) shows that these results also hold for more generalized models.[9] In addition, Angeris *et al.* (2022) compute the profit functions of liquidity providers in pools with constant function (automated) market makers.[10] Clark (2021), Fukasawa *et al.* (2022), Milionis *et al.* (2023), Deng *et al.* (2023), and Fukasawa *et al.* (2024) have demonstrated approximate hedging techniques.[11–15] Aigner and Dhaliwal (2021) describe the risk profile of a liquidity provider and compute the impermanent loss function for Uniswap V2, showing that in a static setting, even small changes in the relative price between two assets result in impermanent loss. In particular, they show that the impermanent loss is an inverted U-shaped function of the relative price changes of the underlying assets or tokens. In a similar setting, Labadie (2022) shows that impermanent loss increases faster than linearly and disappears after a price reversion.[16] Lehar and Parlour (2023) describe impermanent loss as a function of fee gains and adverse rebalancing of the AMM.[3] They show that liquidity provision is endogenously

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determined by this trade-off, a result further confirmed and extended empirically by Capponi *et al*. (2025).[4]

In contrast, traditional finance research has a well-established body of work on the profitability of liquidity providers. It is well documented that arbitrageurs and informed traders can negatively affect the profits of liquidity providers (see, *e.g.*, Chang and Wang, 2015).[17] When faced with informed trading, market makers typically respond by widening spreads, as formalized in a static setting by Glosten and Milgrom (1985) and, more recently, shown to hold in a dynamic context by Takayama (2021).[18,19] However, in the simple AMM models we analyze, market makers cannot adjust spreads in the short term because fees are fixed. Moreover, AMMs adjust prices mechanically and cannot distinguish between informed and uninformed trades. Consequently, outcomes in AMM settings may differ from those in traditional markets. Interestingly, Takayama (2021) also examines the effect of a tax set by the government, a mechanism conceptually similar to the fixed fee in AMMs.[19] Although this was not the main focus of her analysis, it is noteworthy that she concluded such a tax would slow the learning process of liquidity providers, implying that it would not necessarily benefit either them or society as a whole.

We build on the existing literature to develop a better understanding of the profit dynamics of liquidity providers in simple pooled-liquidity markets, with a particular focus on the interplay between arbitrage activities and the profits of liquidity providers. In contrast to previous AMM literature, we explicitly include accumulated arbitrage fees (*i.e.*, fees from informed traders) over time in the liquidity providers' profit function. We use an agent-based model that allows us to consider dynamic effects between participants without imposing restrictive assumptions about their interactions. For a given level of liquidity provision, we simulate the behavior of liquidity providers, traders, and arbitrageurs under various scenarios to compute the resulting profits and losses of liquidity providers based on a constant-product AMM (see, *e.g.*, Uniswap V2). This approach allows us to identify the conditions under which liquidity providers incur impermanent losses and to examine how the inclusion of fees alters the standard results from static analyses.

The remainder of the paper is structured as follows. Section 2 introduces the basic economics of AMMs. Section 3 describes the setup of our agent-based model and explains the simulation. Section 4 presents and discusses the results. Section 5 concludes.

2. The Economics of Decentralized Exchanges

As shown in Figure 1, DEXs are three-sided platforms. Liquidity providers interact with the platform by supplying assets to the liquidity pool in exchange for a fee. The liquidity pool depicted in Figure 1 consists of two assets, denoted A and B. Traders can exchange one of the two assets for the other by paying a fee. Arbitrageurs also interact with the platform whenever they perceive price differences between the exchange rate of A and B at the DEX and other markets. For example, if asset B is more valuable (relative to asset A) at another exchange, arbitrageurs will buy B from the DEX by sending asset A and a fee to the DEX in exchange for asset B. Arbitrageurs will then sell B for A at another exchange to earn a risk-free profit.

Based on the amounts of the two assets or tokens in the liquidity pool (denoted by R_A and R_B, respectively), the AMM determines the price at which traders and arbitrageurs can exchange assets with the pool. If traders or arbitrageurs send an amount of asset A (denoted by Δ_A) to the liquidity pool, they will receive an amount of asset B (denoted by Δ_B) in return, according to the

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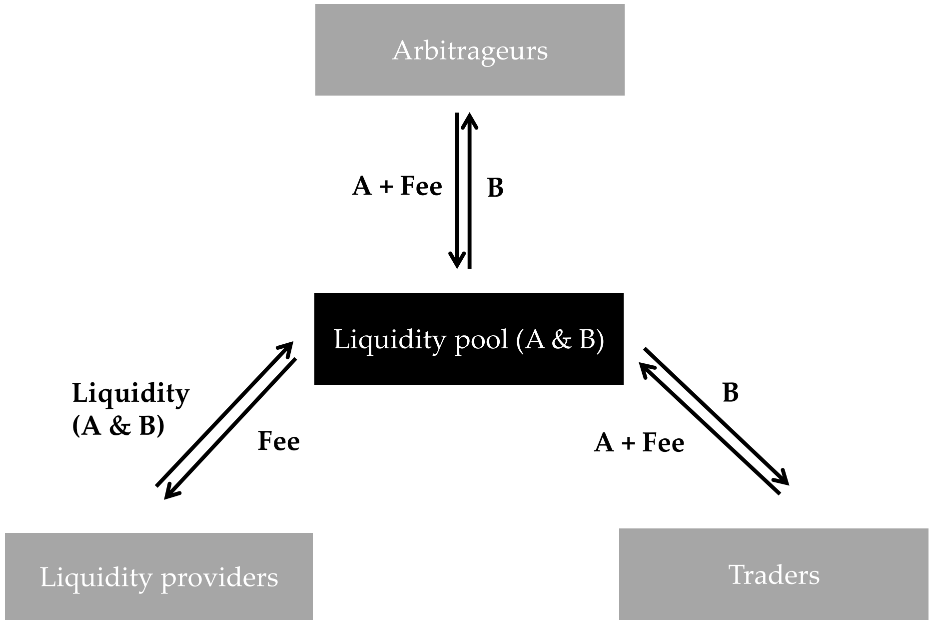

Fig. 1. Illustration of the interactions of different market participants in a DEX.

fee and the price determined by the AMM. Traders and arbitrageurs can also buy B by sending the required amount of A to the pool. The liquidity pool is initially filled with assets A and B by liquidity providers, who receive fees from the DEX for providing this liquidity.

Of particular interest is the formula that determines the exchange rates offered to traders and arbitrageurs. These algorithms adjust exchange rates based on the relative supply and demand of the assets in the pool. If there is more demand for asset B relative to A, the AMM will increase the exchange rate, so traders and arbitrageurs must send more units of A to receive one unit of B. In addition, most AMMs set prices to ensure that pools never run out of either asset.

In this paper, we focus on AMMs that use a "constant product" function, such as the one implemented in the Uniswap V2 protocol. We focus on this type because it was the first and remains the most common. Note, however, that other exchange rate formulas and algorithms exist, particularly for stable swaps (*i.e.*, asset pairs with nearly identical prices).[8,20,21] Uniswap's updated version (V3) is also based on the constant product function, but allows liquidity providers to define a price range at which the pool offers trades. While concentrated liquidity models like Uniswap V3 have gained significant traction for major trading pairs, the constant product AMM (V2) remains the dominant standard for the "long tail" of assets due to its simplicity and passive management structure. Furthermore, since concentrated liquidity is mathematically constructed as a series of constant product curves, our analysis provides a baseline for understanding fee-versus-rebalancing dynamics in more complex AMM designs.

In line with previous research, we describe the two-token/asset constant product function as

$$R_A \cdot R_B = k \tag{1}$$

where k is a constant value and R_i are the reserves, *i.e.*, denotes the amount of asset i in the liquidity pool.[8,22]

Assuming no fees, describing the new reserves at $t+1$ as the old reserves at t plus/minus the traded amounts or Δ_A and Δ_B (*e.g.*, trade asset B for asset A), it can be shown (see also Appendix

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A) that

$$(R_A - \Delta_A) \cdot (R_B + \Delta_B) = R_A \cdot R_B\,. \tag{2}$$

Consequently, the amount of asset A received (Δ_A) in exchange for a given amount of asset B sent to the liquidity pool (Δ_B) is defined by solving equation (2) for Δ_A (see also Krishnamachari *et al.*, 2021 for a general solution for more than two assets and unequal weights):[23]

$$\Delta_A = \frac{R_A \cdot \Delta_B}{R_B + \Delta_B}\,. \tag{3}$$

The resulting exchange rate offered by the liquidity pool for the demanded asset A (ε_{AMM}) describes how much of asset A a trader will receive for a certain amount of B ($\Delta_A = \varepsilon_{AMM} \cdot \Delta_B$):

$$\varepsilon_{AMM} = \frac{\Delta_A}{\Delta_B} = \frac{R_A}{R_B + \Delta_B}\,. \tag{4}$$

This exchange rate of A is a decreasing function of the amount of asset B (Δ_B) to be exchanged. Consequently, trades with larger volumes will result in lower exchange rates; *i.e.*, if traders or arbitrageurs want larger amounts of A, they must send more units of B per unit of A to the liquidity pool.

Note that the reference price of asset A offered by the AMM (p_{AMM}), which describes how much of asset B a trader has to pay (send) to receive a certain amount of A ($\Delta_A \cdot p_{AMM} = \Delta_B$), is the inverse of the exchange rate:

$$p_{AMM} = \frac{1}{\varepsilon_{AMM}} = \frac{R_B + \Delta_B}{R_A}\,. \tag{5}$$

Figure 2 illustrates the exchange rates for a trade $\Delta_B \to \Delta_A$.

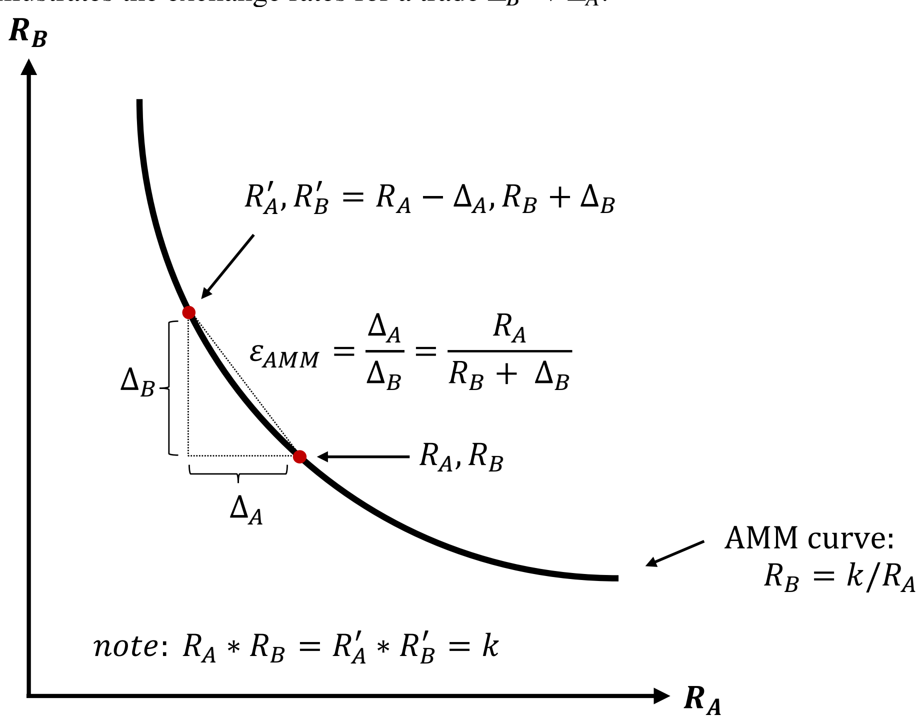

Fig. 2. Illustration of the price function of a constant product function AMM.[23]

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The curve ($R_B = k/R_A$) in Figure 2 represents all combinations of reserves R_A and R_B in the liquidity pool for which $R_A \cdot R_B = k$ holds. For every state of the reserves R_A, R_B and any amount Δ_B to be exchanged, the curve describes how much the trader receives of the other asset Δ_A.

For example, suppose the liquidity pool consists of 50 units of A and 100 units of B. If a trader wants to receive 10 units of A in exchange for B, she must send 25 units of B to the DEX. After this trade, the liquidity pool consists of 125 units of B and 40 units of A, and the constant product function (2) holds because $100 \cdot 50 = 125 \cdot 40$. Because every trade changes the reserves within the liquidity pool, the price adjusts continuously. Since the price is defined as Δ_B/Δ_A, the spot price (p_{AMM})—which represents the price offered for an indefinite small amount—is defined by the slope of the constant product function:[23]

$$p_{AMM} = -\left(\frac{\partial R_B}{\partial R_A}\right) = \frac{k}{R_A^2}\,. \tag{6}$$

Since $k = R_A \cdot R_B$, the spot price is the ratio of the two reserves, *i.e.*,

$$p_{AMM} = R_B/R_A\,. \tag{7}$$

Assuming no fees, Angeris *et al*. (2021)[8] show that the liquidity providers' (LP) total relative gain (δ^{LP}) depends solely on the market price development

$$\delta^{LP} = \sqrt{p_m^T/p_m^1}\,. \tag{8}$$

As a result, impermanent loss (IL) can formally be described as

$$IL = \frac{W_1 \cdot \delta^{LP}}{W_1 \cdot \delta^{Ref}} - 1 = \frac{\sqrt{p_m^T/p_m^1}}{0.5 \cdot (1 + p_m^T/p_m^1)} - 1 \tag{9}$$

with δ^{Ref} denoting the relative gain of a buy-and-hold reference portfolio with two equally weighted assets and W_1 the initial wealth of the liquidity provider (note: $\delta^{Ref} = 50\% \cdot 1 + 50\% \cdot p_m^T/p_m^1$; the value of the reference asset is 1 because the portfolio is denominated in that currency).

According to (9), it follows that without any fees, a market price change will always result in an impermanent loss for the liquidity provider. Because liquidity providers earn fees for their services, their overall return has to take these fees into account. Since this overall return depends on complex interactions with arbitrageurs and traders, we develop an agent-based model to simulate these interactions.

3. The Agent-Based Model

We simulate the interactions among market prices, traders, arbitrageurs, liquidity providers, and the AMM of a liquidity pool for the highly traded WETH/USDC pair. This pool was selected because of its substantial trading volume and because one of the assets is the U.S. dollar, which allows for simpler interpretation of the results. The simulation is based on historical on-chain data collected from Uniswap V2 from May 2021 to May 2022.[24] Traders exchange WETH for USDC (or vice versa) with the liquidity pool. The AMM updates the exchange rate according to the constant product function described in Section 2. When the spot exchange rate determined by the AMM deviates from the market exchange rate, arbitrageurs trade against the liquidity pool to earn risk-free profits. During the simulation, liquidity providers do not interact with the liquidity pool.

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3.1. General Procedure—The simulation follows the steps depicted in Figure 3. One loop represents a single simulation period, defined by an actual or simulated trading event on Uniswap. This loop is repeated iteratively over the course of one year. In the baseline scenario, the number of periods corresponds to the number of trades in the Uniswap data sample. Each loop consists of calculations classified into four blocks: state calculations, arbitrageur calculations, trader calculations, and AMM calculations. Arbitrageurs check for arbitrage opportunities after each state update and after every trade, so they can act both before and after a trader's transaction. The algorithm allows for iterative execution within a single period as a precaution. However, because the optimal arbitrage-clearing quantity is derived analytically, arbitrageurs effectively restore equilibrium in a single transaction per block.

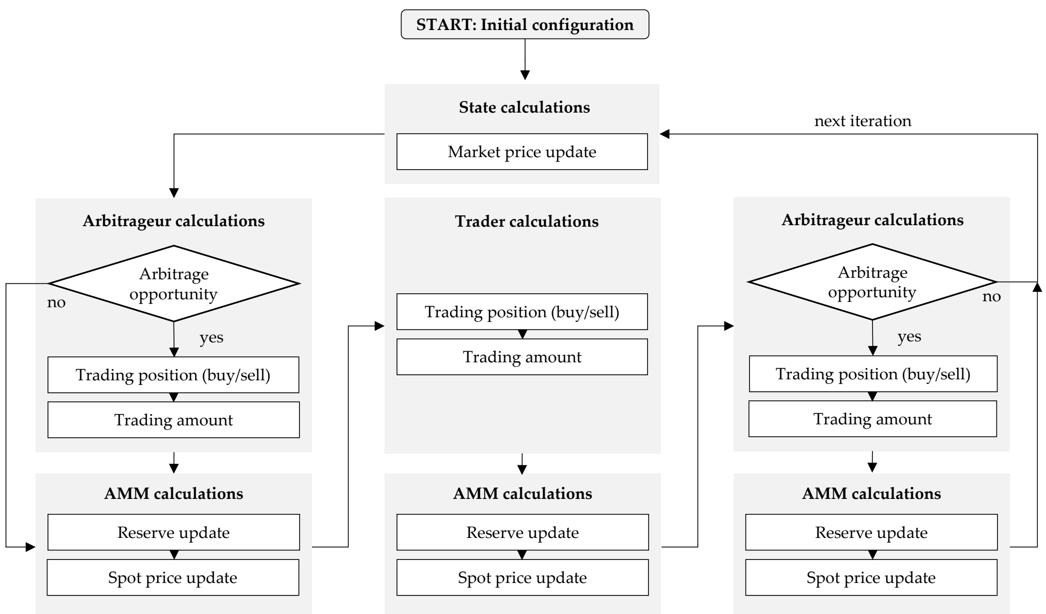

Fig. 3. Process flowchart of the ABM.

3.2. Agent Decisions and other Calculations—Initial Configuration—The simulation begins with an initial configuration that populates the "world" with representative traders and arbitrageurs as well as information on asset market prices and the number of assets in the pool. We use real values from Uniswap's WETH/USDC pool (trades, fees, pool size) and Binance (market price) in 2021. These data comprise 1.3 million trades conducted over one year (see Appendix B for more details). We explicitly exclude MEV (Maximal Extractable Value) trades, since we account for arbitrage trades endogenously.[25,26] Excluding historical MEV and arbitrage trades prevents endogeneity bias, as it avoids treating market reactions as exogenous demand shocks. In our simulation, the endogenous arbitrage agent fulfills the role of MEV bots.

State Calculations—After initialization, the simulation process begins with state calculations. First, the market prices of the relevant assets are updated.

Arbitrageurs' Actions—After the price update, arbitrageurs anticipate the AMM's behavior by calculating Uniswap's spot price (see AMM calculations) and comparing it to the market

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price. In the baseline simulation, we assume nearly perfect market conditions for arbitrageurs; that is, if spot prices deviate from market prices by more than the trading fee plus a small transaction cost, arbitrageurs trade with the AMM. Transaction costs include all components not covered by the AMM, such as fees and price impact on competing exchanges, operational costs (including gas fees), and risk compensation. While these costs (particularly gas fees) are volatile in reality, we assume constant transaction costs to isolate the structural economic drivers of LP profitability from random noise. Furthermore, by simulating a wide range of transaction cost levels (see Section 4.3), our analysis implicitly captures the economic impact of varying gas fee regimes, from low-cost environments to high-barrier periods. Conditional on this trade decision, arbitrageurs then determine the optimal amount that maximizes their profit and send it to the AMM. For example, if the spot price for asset A is significantly lower than its market price, arbitrageurs will (i) buy asset B on a competing exchange, (ii) send it to the AMM, (iii) receive asset A, and (iv) sell it on a competing exchange. In the no-fee case, arbitrageurs' profit function is

$$\pi = (p_A \cdot \Delta_A - p_B \cdot \Delta_B)\,. \tag{10}$$

It can be shown that solving this maximization problem yields the optimal amount of asset A[8]

$$\Delta_A^* = (R_A - \sqrt{(R_A \cdot R_B)/p_m})_+ \tag{11}$$

where $(x)_+ = max\{x,0\}$ for $x \in \mathbb{R}$ (see also Appendix D for the derivation and the solution, including trading fees). Accordingly, arbitrageurs trade in the opposite direction if the spot price of A is significantly above its (external) market price.

AMM Calculations—Whenever agents (arbitrageurs or traders) trade, they send one of the two assets to the liquidity pool. These trades trigger AMM calculations according to the constant product function ($R_A \cdot R_B = k$). Based on the asset type and amount provided, the AMM calculates how much they will receive in return and how much will be captured as fees. In addition, due to the accumulated fees, the AMM updates the constant k for the next trade.

Traders' Actions—Next, the trader submits an order to the AMM and exchanges an amount of A tokens ($-\Delta_A$) for B tokens (Δ_B) or vice versa. In the baseline simulation, historical trading patterns are derived directly from Uniswap's WETH/USDC transaction data. Thus, actions are determined by the actual amounts provided by individual traders to the AMM. The resulting trading prices are determined endogenously by the AMM's pricing formula. After each trade and before the next iteration begins, another round of arbitrageur calculations takes place.

Liquidity Providers' Actions—Liquidity providers supply assets at the beginning of the simulation and remain passive thereafter. While in reality they may change the amount supplied in response to pool profitability, we assume no portfolio adjustments in order to isolate their profitability under specific conditions. We explicitly do not assume the loss-versus-rebalancing (LVR) benchmark common in the financial market literature that assumes liquidity providers continuously replicate the trades executed in the liquidity pool on external markets. In line with most AMM literature, we exclude this benchmark, as it is inconsistent with the passive liquidity provision mechanism central to simple AMMs.

3.3. Experiments—To analyze the factors that influence the profits of liquidity providers, we conduct four sets of experiments. Following the approach used in other AMM studies,[3,8] we measure liquidity providers' profits by comparing the value of the liquidity pool at the end of the experiment with the value of the same assets under a simple buy-and-hold strategy.

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We begin by validating that our model behaves as intended, testing hypotheses related to how trading activity and pool size affect liquidity providers' profits. Building on this foundation, we examine how changes in the ETH price, implemented through varying price growth rates, affect profitability outcomes. Finally, we investigate how transaction costs, and consequently the degree of arbitrageur competition, influence liquidity providers' profits.

Trading Activity—An increase in trading volume increases accumulated trading fees over time, which should increase liquidity providers' profits. To test this, we adjust trading volume by creating a subset consisting of only every *n*th trade and then analyze the impact on profits.

Liquidity—Liquidity providers' income consists of fees from traders and arbitrageurs. The larger the liquidity pool, the lower the ratio of fees to liquidity, which reduces liquidity providers' profits. We adjust liquidity by increasing the initial pool size, *i.e.*, by increasing the initial WETH/USDC reserves.

Growth—The literature predicts that without fees, either a positive or negative trend in market prices results in an impermanent loss for the liquidity provider.[5] To test this, we adjust the trend of the ETH price, simulating a price feed using geometric Brownian motion to match various expected growth rates g.[27] We also adjust traded quantities so that trading volumes remain unchanged:

$$p_t = p_{t-1} \cdot e^{(g-0.5\cdot\sigma^2)\cdot\Delta t+\sigma\cdot\sqrt{\Delta t}\cdot z_t}. \tag{12}$$

Arbitrageur Transaction Costs—High arbitrageur activity is generally believed to negatively impact liquidity providers' profits. For example, Milionis *et al.* (2023) show that any arbitrage profit results in losses for liquidity providers.[28] In our experimental setup, arbitrageurs execute trades whenever the spot price deviates from the market price by more than the combined sum of protocol fees and transaction costs (τ). Consequently, we adjust τ to evaluate the impact of arbitrage intensity on overall profitability:

$$p_m > p_{AMM} \cdot 1/(1 - fees - \tau)\,. \tag{13}$$

Note that theoretically, transaction costs serve also as a proxy for the level of competition, as both factors dictate the execution threshold for arbitrage trades. Inferred from industrial organization literature, a monopolistic arbitrageur has a strategic incentive to "wait" for larger price discrepancies to increase marginal revenue (*MR*). In contrast, an environment with intense competition creates a preemption game (see, *e.g.*, Fudenberg and Tirole, 1985; Dixit and Pindyck, 1994),[29,30] where the "fear of preemption" forces arbitrageurs to act immediately once the marginal cost (*MC*) is covered and the net present value of the trade is near zero. Consequently, lower transaction costs simulate a highly competitive environment that drives more frequent trading events (see also, *e.g.*, Oehmke, 2009; Zigrand, 2006; Gromb and Vayanos, 2010).[31–33]

4. Results and Discussions

This section presents the results from the experiments in three steps. First, we replicate standard results regarding trading activity and pool size from previous studies. Second, we discuss the effects of different market price changes. Finally, we analyze how competition among arbitrageurs affects liquidity providers' profits.

4.1. Standard Results—Based on the baseline scenario (see Appendix B), we first test whether we can replicate standard results from the literature; namely, that an increase in trading

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activity or a decrease in provided liquidity increases the profitability of liquidity providers. To determine this, we run simulations with adjusted trading volumes and initial liquidity pool sizes. Unsurprisingly, and in line with theory, the simulations show that higher trading activity results in more accumulated fees, which increases liquidity providers' profits. In addition, an increase in liquidity decreases profitability because fees are distributed over a larger amount of invested capital (see Appendix E).

4.2. Market Price Changes—To understand the effect of fees, we analyze how market price changes affect liquidity providers' profits. First, we test whether we can replicate results from the literature analyzing impermanent loss under the no-fee assumption. We then conduct the same analysis but introduce protocol fees and compare the results.

No-Fee Experiment—Based on the baseline scenario, we test whether we can replicate previous analyses that assume zero fees.[5] We do this by setting all fees and transaction costs to zero. We then run experiments with different market trends for the simulated ETH price path. Specifically, we vary the yearly price trend from -90% (*i.e.*, a price decrease from 2,765 USD to 277 USD) to +90% (*i.e.*, a price increase from 2,765 USD to 5,254 USD). For all runs, we simulate liquidity providers' profits. We find the impermanent loss pattern described by several papers (see also Figure 4).[8] However, as explained earlier, incorporating fees is essential for a complete analysis.

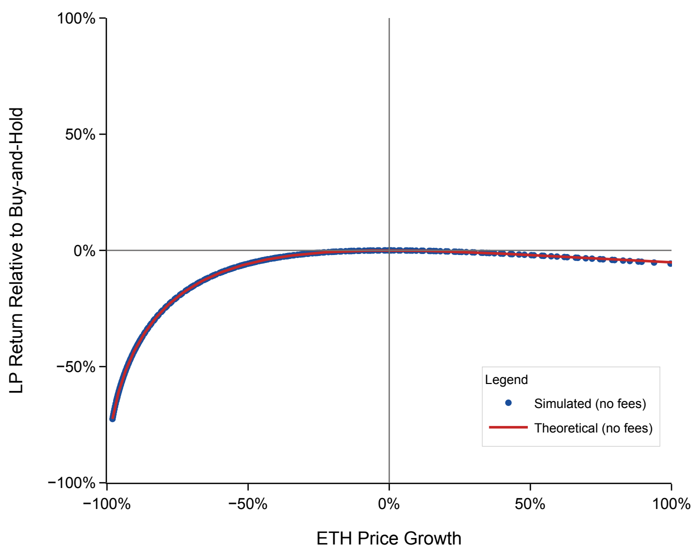

Fig. 4. Growth Experiment without Fees: Simulation of liquidity providers' profits under different market trends. Profits are measured as the return on investment relative to a Buy-and-Hold strategy. Example: If ETH prices increase by +50% over one year, liquidity provision returns (excl. fees) are 2% lower than those of a Buy-and-Hold strategy.

Fee Experiment—We now analyze whether the results change when we assume positive trading fees. We run the same experiments as above but with fees included.

Figure 5 depicts liquidity providers' returns (y-axis) for different market price trends (x-axis). The results show that liquidity providers profit relative to a buy-and-hold strategy as long as market prices do not drop by more than 75% or increase by more than 300% within a year. Thus, changes in the market price only have a significant effect on liquidity providers' profits for

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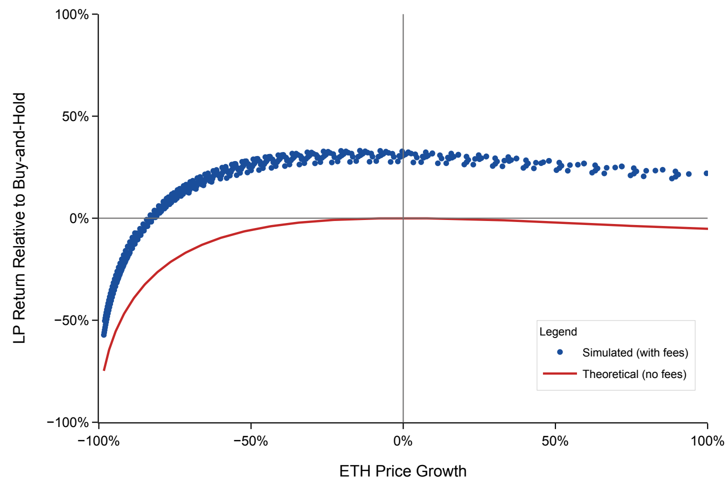

Fig. 5. Growth Experiment with Fees: Simulation of liquidity providers' profits under different market trends. Profits are measured as the return on investment relative to a Buy-and-Hold strategy. Example: If ETH prices increase by +50% over one year, liquidity provision returns (including fees) are 25% higher than those of a Buy-and-Hold strategy.

exceptionally strong price movements.

The reason for this result is the impact of arbitrageurs and traders on the profits of liquidity providers: on the one hand, arbitrage trades change the composition of assets in the pool, leading to a decrease in the profits of liquidity providers ("rebalancing losses"). On the other hand, traders and arbitrageurs pay a fee for each trade, which increases profits ("fee gains"). The overall outcome depends on the relative size of these two effects: if rebalancing losses exceed fee gains, the net result is negative (*i.e.*, liquidity providers earn less from fees than they lose from rebalancing). The fee effect depends strongly on the ratio of trading volume to liquidity (see also the standard results above). With the ratio in our baseline model of about 100/2 (11.9 billion USDC / 250 million USDC), the rebalancing effect outweighs the fee effect only in the case of exceptionally strong price movements.

4.3. Arbitrageurs' Transaction Cost Changes—Finally, we analyze the impact of arbitrageurs' transaction costs on liquidity provider returns. It is commonly assumed that high arbitrageur activity adversely affects the profitability of liquidity providers. However, arbitrageurs also pay fees, resulting in a more complex effect. We analyze the effect of arbitrageurs by varying their barriers to trading with the liquidity pool (*i.e.*, their transaction costs). Specifically, we assume transaction costs ranging from 0 to 5% and simulate the profits of liquidity providers. The results are shown in Figure 6.

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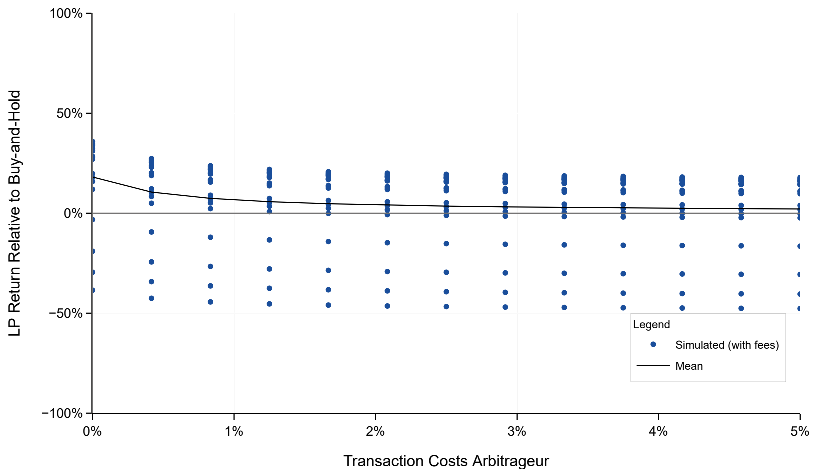

Fig. 6. Arbitrage Transaction Cost Experiment: Simulation of liquidity providers' profits given varying transaction cost levels for arbitrageurs. Profit is measured as the return on investment relative to a Buy-and-Hold strategy. Example: If the transaction cost for arbitrageurs is 1%, liquidity provision returns (including fees) are on average 10% higher than the Buy-and-Hold benchmark.

As illustrated in Figure 6, our simulations reveal a noteworthy finding: as transaction costs for arbitrageurs rise, liquidity providers' profits decrease. This suggests that increased activity by arbitrageurs actually boosts LP profitability, contradicting the popular belief that arbitrage activity is inherently a drag on profits. The dynamic nature of this setting accounts for this result. Although arbitrageurs reduce liquidity providers' profits through rebalancing losses, they also contribute positively by generating fee income. It can be shown that rebalancing losses are independent of the number of arbitrage trades and remain consistent over time, as shown in equation (8). Conversely, fee gains increase with arbitrage activity. As shown in Figure 7, when transaction costs are very low, arbitrageurs become the primary source of fee income for liquidity providers, surpassing fees from uninformed traders.

Figure 7 shows the distribution of fee income to liquidity providers, distinguishing between fee income from uninformed traders and arbitrageurs. The figure shows that the relative importance of fees from arbitrageurs increases as transaction costs decrease, underscoring that arbitrageurs are not merely neutralizers of price discrepancies but also active contributors to the profitability of liquidity providers. Assuming zero transaction costs, arbitrageurs account for more than 80% of total revenue in our simulation. As transaction costs rise, this share as well as overall revenue declines until uninformed traders become the main source of income. Thus, consistent with our previous finding that arbitrage activity may enhance overall returns, Figure 7 shows that arbitrageurs become the dominant source of income for liquidity providers when trade barriers are sufficiently low. To test the robustness of these results, we conducted sensitivity analyses by varying trading volumes, price growth, and trade sizes. The findings remain robust across different scenarios (see Appendix F).

Taken together, these results reveal a basic trade-off: while arbitrage trades generate one-time rebalancing losses, they also contribute substantial fee revenue over time. Our analysis shows that the fee effect dominates when transaction costs are sufficiently low. This finding differs from static analyses, where fee gains from arbitrageurs are often overlooked or modeled as a single

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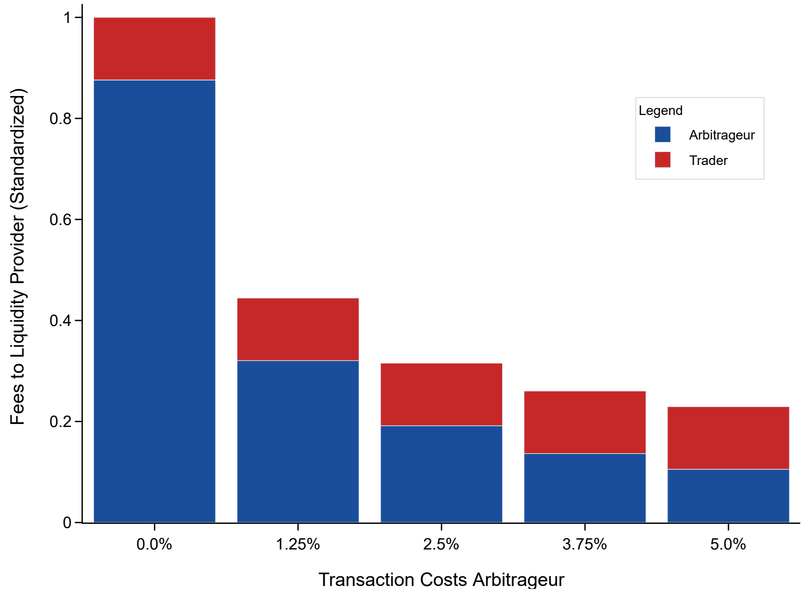

Fig. 7. Liquidity Provider Revenue Split under Varying Transaction Costs: Simulation of revenue streams given varying transaction cost levels for arbitrageurs. Revenue is measured as accumulated fees from arbitrageurs and uninformed traders. Values are standardized by total revenues observed in the zero-transaction-fee experiment. Bars represent mean values averaged over multiple simulation runs; see also the Arbitrage Transaction Cost Experiment.

trade. Our simulation shows that these fees are relevant. Therefore, fee gains from arbitrageurs should be considered in addition to rebalancing losses and trader fee gains when analyzing liquidity providers' profits and understanding market equilibria.

5. Conclusion

In this paper, we investigated the problem of impermanent losses in decentralized exchanges with automated market makers. We modeled the dynamic interactions among liquidity providers, traders, and arbitrageurs, and explicitly incorporated the accumulated fees from both traders and arbitrageurs into the profit function of liquidity providers. Using an agent-based model, we simulated one of the most common AMM smart contract designs (the constant product AMM) and examined the behavior of participants under various scenarios.

Our analysis demonstrates that impermanent losses are less severe than previously believed. While static analyses indicate that small price changes can result in losses for liquidity providers, our experiments, which incorporate the dynamic effects of fee accumulation over time, suggest that price changes do not necessarily lead to losses. We find that impermanent losses only occur when price changes are permanent, unexpected, and sufficiently large. A liquidity provider's return is positively influenced by trading fees and negatively impacted by (permanent) price changes and by the volume of liquidity provided. In a competitive environment, the level of liquidity provision is determined by expected price changes and trading volumes. Consequently, impermanent losses occur only when there are unexpected changes in these variables and when accumulated fees do not offset the losses.

A core contribution of our study is the explicit quantification of the role of arbitrageurs. In AMMs, arbitrage is structurally essential. Without arbitrage, an AMM fails to perform price

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discovery, becoming mispriced and non-functional. Arbitrage is therefore a prerequisite for AMMs to provide value to traders. While the benefits for traders are well understood, the impact on liquidity providers has historically been viewed as a trade-off, with arbitrage often portrayed as an extractor of value from liquidity providers. Our results challenge the prevailing intuition. We demonstrate that in passive liquidity pools, decreasing trading barriers for arbitrageurs is Pareto optimal: both traders and liquidity providers benefit simultaneously as arbitrage activity intensifies. Rebalancing losses are static and largely independent of arbitrage intensity (as long as some arbitrage exists), whereas fees paid by arbitrageurs are dynamic and scale positively with arbitrage activity. As a consequence, once arbitrage activity is present, higher levels of arbitrage increase the profits of passive liquidity providers. The perceived trade-off between arbitrage and profits of liquidity providers is therefore an artifact of static modeling. When temporal dynamics and fee accumulation are properly accounted for, arbitrage improves welfare for passive liquidity providers.

Our findings have implications beyond the specific V2 model simulated here. Since Uniswap V3 and similar concentrated liquidity protocols are mathematically based on the constant product formula ($x \cdot y = k$) applied within specific price ticks, the core mechanism we identified likely applies to these protocols as well. However, concentrated liquidity introduces a leverage effect: both fee accumulation and rebalancing losses are amplified. While we hypothesize that for a passive liquidity provider, the positive correlation between arbitrage activity and LP profitability holds for V3, the specific dynamics would need to be determined by a dedicated simulation. We therefore consider our results the foundational “base case” upon which concentrated liquidity dynamics are built.

Additionally, our results suggest that outcomes differ between passive and active liquidity providers. While some literature on traditional financial markets suggests that higher trading activity increases losses for very active liquidity providers, our results show the opposite in the AMM setting for passive agents. We believe this effect could also generalize to traditional markets: more arbitrage trades may benefit passive liquidity providers but could harm highly active ones. This insight provides a foundation for future research on the interaction between trading activity and liquidity provision in both AMM and traditional market contexts.

We conclude that an arbitrage-friendly environment with low transaction costs can improve overall market welfare and benefit liquidity providers on passive liquidity pools in the long run. Since arbitrage cannot be eliminated, passive liquidity providers should foster an arbitrage-friendly environment. Developers should prioritize creating these conditions rather than attempting to restrict arbitrage activity.

Author Contributions

All authors contributed significantly to the conceptualization and development of the ideas presented in this manuscript. MH conceived the original idea, developed the code to perform the simulations, and conducted the analysis. Both MH and HD interpreted the results, wrote the manuscript, and jointly discussed and incorporated the revision suggestions.

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Conflict of Interest

The authors declare that they have no known conflicts of interest as per the journal's Conflict of Interest Policy.

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Appendix A: Introduction to Automated Market Makers

The generalized form of constant product AMM formulas is defined by

$$\prod_{i=1}^{n} R_i^{w_i} = k\,, \tag{14}$$

where k is a constant value, R_i are the reserves, *i.e.*, the actual amount of asset i in the liquidity pool, and w_i is the weight that determines the ratio of the reserves in the pool. For the purpose of simplicity, we focus on the simplest form with two assets and equal weights, which is also used by Uniswap V2. Note that our main results also hold for more complex functions. In line with previous research,[8,22] we describe the two-token/asset constant product function by

$$R_A \cdot R_B = k\,. \tag{15}$$

So that (15) holds, each interaction of traders or arbitrageurs with the liquidity pool must, therefore, adjust the reserves R_A and R_B such that k remains constant:

$$R_A^t \cdot R_B^t = k\,, \tag{16}$$

$$R_A^{t+1} \cdot R_B^{t+1} = k\,. \tag{17}$$

Thus, a trade must satisfy

$$R_A^{t+1} \cdot R_B^{t+1} = R_A^t \cdot R_B^t\,. \tag{18}$$

Assuming no fees, describing the new reserves in $t+1$ as the old reserves in t plus or minus the traded amounts Δ_A and Δ_B (trade asset B for asset A), we can express (18) as

$$(R_A - \Delta_A) \cdot (R_B + \Delta_B) = R_A \cdot R_B\,. \tag{19}$$

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Appendix B: Data

Variable	Mean	Std. Dev.	Min	Median	Max
Trading volume (daily, USDC)	51.4m	64.7m	7.0m	34.0m	729.7m
Number of trades (daily)	3,811	1,854	1,602	3,169	11,809
Liquidity (daily, USDC)	241.4m	47.7m	176.4m	223.6m	447.6m
ETH price (daily, USD)	3,191	713	1,786	3,143	4,810

Table 1. Summary Statistics of Historical Trading, Liquidity, and Price Data: This table presents summary statistics for trading volume, transaction counts, and liquidity, based on on-chain Uniswap v2 USDC/WETH data and ETH market prices from Dune.[24,25] The statistics include MEV transactions (approx. 7 billion USDC) and micro-trades (<0.01 USDC), but exclude 765 invalid entries with zero USDC flow; pool reserves consist of USDC and WETH; liquidity is denominated in USDC (calculated as USDC reserves times two due to the equal-weighting constraint).

Variable	Historical value	Initial value
Pool size	241.4m USDC (average)	250m USDC
Trading volume per year (Q)	11.9bn USDC	11.9bn USDC
Growth of the market price (g)	0%	0%
Market price return volatility (σ)	1.2	1
Number of trades (N)	1.31m	1.31m
Time period (T)	1 year	1 year
Protocol fee (fee)	0.3%	0.3%

Table 2. Historical Data from Reference Datasets and Initial Values: Historical trading and price data are based on the data described in Table 1, excluding MEV and micro-transactions.

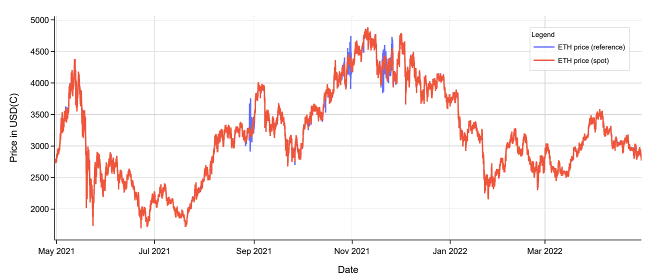

Fig. 8. Visualization of Historical ETH Prices (Market Price vs. Uniswap V2 Spot Price).

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Appendix C: Derivation of the Spot Market Price and Exchange Rate (Fees)

Calculations including fees with $\gamma = 1 - fee$:

$$(R_A - \Delta_A) \cdot (R_B + \gamma \cdot \Delta_B) = R_A \cdot R_B \tag{20}$$

Amount A

$$\Delta_A = \frac{R_A \cdot \gamma \cdot \Delta_B}{R_B + \gamma \cdot \Delta_B} \tag{21}$$

The resulting exchange rate offered by the liquidity pool for the demanded asset A (ε_{AMM}), which describes how much of asset A a trader receives for a certain amount of B ($\Delta_A \cdot \varepsilon_{AMM} = \Delta_B$), is

$$\varepsilon_{AMM} = \frac{\Delta_A}{\Delta_B} = \frac{\gamma \cdot R_A}{R_B + \gamma \cdot \Delta_B}\,. \tag{22}$$

This exchange rate of A is a decreasing function of the amount of asset type B (Δ_B) to be exchanged. Consequently, trades with larger volumes result in a lower exchange rate; that is, if traders or arbitrageurs want larger amounts of A, they must send more units of B per unit of A to the liquidity pool. Note that the reference price of asset A offered by the AMM (p_{AMM}), which describes how much of asset B a trader has to pay (send) to receive a certain amount of A ($\Delta_A \cdot p_{AMM} = \Delta_B$), is the inverse of the exchange rate:

$$p_{AMM} = \frac{1}{\varepsilon_{AMM}} = \frac{R_B + \gamma \cdot \Delta_B}{\gamma \cdot R_A}\,. \tag{23}$$

For infinite small trades, this results in

Spot exchange rate:

$$\varepsilon_{AMM} = \frac{\Delta_A}{\Delta_B} = \gamma \cdot \frac{R_A}{R_B} \tag{24}$$

Spot price:

$$m_{AMM} = \frac{1}{\varepsilon_A} = \frac{1}{\gamma} \cdot \frac{R_B}{R_A} \tag{25}$$

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Appendix D: Derivation of the Arbitrageur's Maximization Problem

If the market price for asset A (p_A) is significantly larger than its spot price m_{AMM}, arbitrageurs will (i) buy asset B (Δ_B) on a competing exchange, (ii) send it to the AMM, (iii) receive asset A (Δ_A), and (iv) sell it on the competing exchange. In this case, arbitrageurs profit function is

$$\pi = p_A \cdot \Delta_A - p_B \cdot \Delta_B \,. \tag{26}$$

Denominated in the reference market prices, this results in the following maximization problem:

$$\begin{aligned} \max_{\Delta_A} \quad & \pi = p_m \cdot \Delta_A - \Delta_B \\ \text{subject to} \quad & (R_A - \Delta_A) \cdot (R_B + \gamma \cdot \Delta_B) = R_A \cdot R_B, \\ & \Delta_A, \Delta_B > 0 \,. \end{aligned} \tag{27}$$

In a **first step**, we put the constraint (AMM's constant product function) into the maximization problem: to find the optimal Δ_A^*, we solve AMM's constant product formula (20) for Δ_B and put the solution into the investors' profit function (27). The resulting profit function depends solely on quantity Δ_A and not anymore on Δ_B:

$$\Delta_B = \frac{1}{\gamma} \cdot \left(\frac{R_A \cdot R_B}{R_A - \Delta_A} - R_B \right) , \tag{28}$$

$$\pi = p_m \cdot \Delta_A - \frac{1}{\gamma} \cdot \left(\frac{R_A \cdot R_B}{R_A - \Delta_A} - R_B \right) . \tag{29}$$

Note that, in this form, the objective function resembles the problem of a profit-maximizing firm operating in a competitive goods market and selling good Δ_A:

$$\pi(\Delta_A) = \text{Revenues}(\Delta_A) - \text{Costs}(\Delta_A) \tag{30}$$

with

$$Revenues = p_m \cdot \Delta_A \tag{31}$$

and

$$\text{Costs} = \frac{1}{\gamma} \cdot \left(\frac{R_A \cdot R_B}{R_A - \Delta_A} - R_B \right) . \tag{32}$$

To optimize profits, investors seek the quantity Δ_A^* for which marginal revenue (MR) equals marginal cost (MC). Thus, in the **second step**, we calculate marginal costs and marginal revenues:

$$MR = MC \,, \tag{33}$$

$$p_m = \frac{1}{\gamma} \cdot \frac{R_A \cdot R_B}{(R_A - \Delta_A)^2} \,. \tag{34}$$

In a **third step**, we solve for the optimal quantity Δ_A^*:

$$\Delta_A = R_A \pm \sqrt{\frac{R_A \cdot R_B}{\gamma \cdot p_m}} \,. \tag{35}$$

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Solution for positive Δ_A, Δ_B, R_A, R_B, and p_m

$$\Delta_A^* = \left(R_A - \sqrt{\frac{R_A \cdot R_B}{\gamma \cdot p_m}} \right) \tag{36}$$

and

$$\Delta_B^* \cdot \gamma = \sqrt{R_A \cdot R_B \cdot \gamma \cdot p_m} - R_B \,. \tag{37}$$

Furthermore, it can be shown that

$$\Delta_A^* = R_A \cdot \left(1 - \sqrt{\frac{p_{AMM}}{\gamma \cdot p_m}} \right) \tag{38}$$

and

$$\Delta_B^* = \frac{1}{\gamma} \cdot R_B \cdot \left(\sqrt{\frac{\gamma \cdot p_m}{p_{\text{AMM}}}} - 1 \right) \,. \tag{39}$$

Note, if the AMM asks for a fee ($fee > 0$), arbitrageurs trade less and with smaller amounts. Including fees, arbitrageurs face higher marginal costs since they receive less for any amount sent to the protocol; see $1/\gamma$ in (28).

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Appendix E: Standard Results

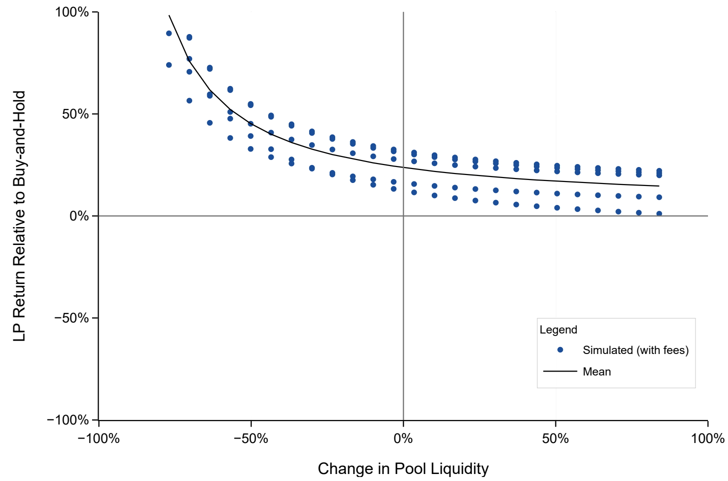

Fig. 9. Liquidity Experiment: Simulation of liquidity providers' profits under reduced and increased liquidity scenarios. Profits are measured as the return on investment relative to a Buy-and-Hold strategy. Example: A 50% reduction in liquidity (relative to the original dataset) results in liquidity provider average returns (incl. fees) that are 50% higher than the Buy-and-Hold benchmark.

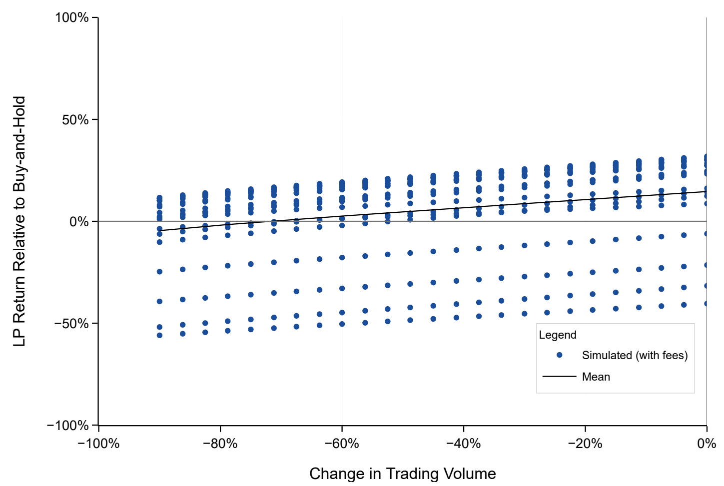

Fig. 10. Trading Volume Experiment: Simulation of liquidity providers' profits with varying trading activity in the pool. Profits are measured as the return on investment relative to a Buy-and-Hold strategy. Example: If trading activity decreases by 60% (relative to the original dataset), liquidity provision average returns (incl. fees) drop to the level of the Buy-and-Hold strategy.

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Appendix F: Sensitivity Analysis

$Vol. = 100\%$ $Vol. = 75\%$ $Vol. = 50\%$ $Vol. = 25\%$ $Vol. = 10\%$

$\sigma = 0.1$

$\sigma = 0.5$

$\sigma = 1$

$\sigma = 1.5$

$\sigma = 2$

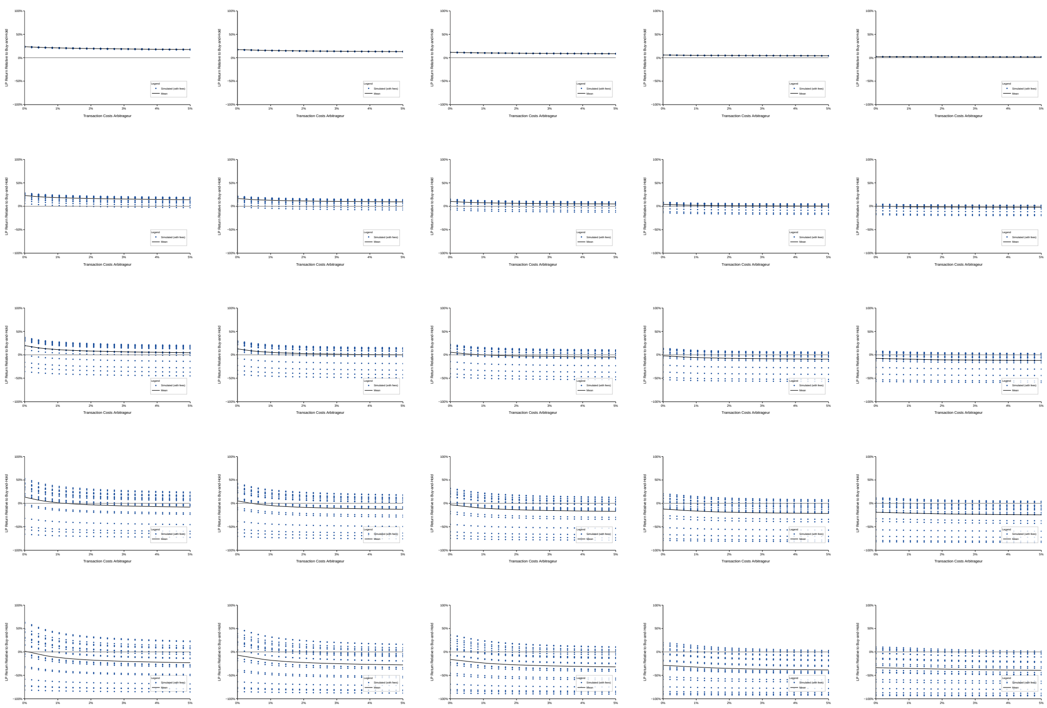

Table 3. Sensitivity of the Arbitrage Transaction Cost Experiment: Simulation of liquidity providers' profits with varying transaction costs for arbitrageur trading. The simulation is replicated for lower transaction volumes of uninformed trades (100% to 10%) and for lower and higher volatility of the ETH market price (baseline: $\sigma = 1$).

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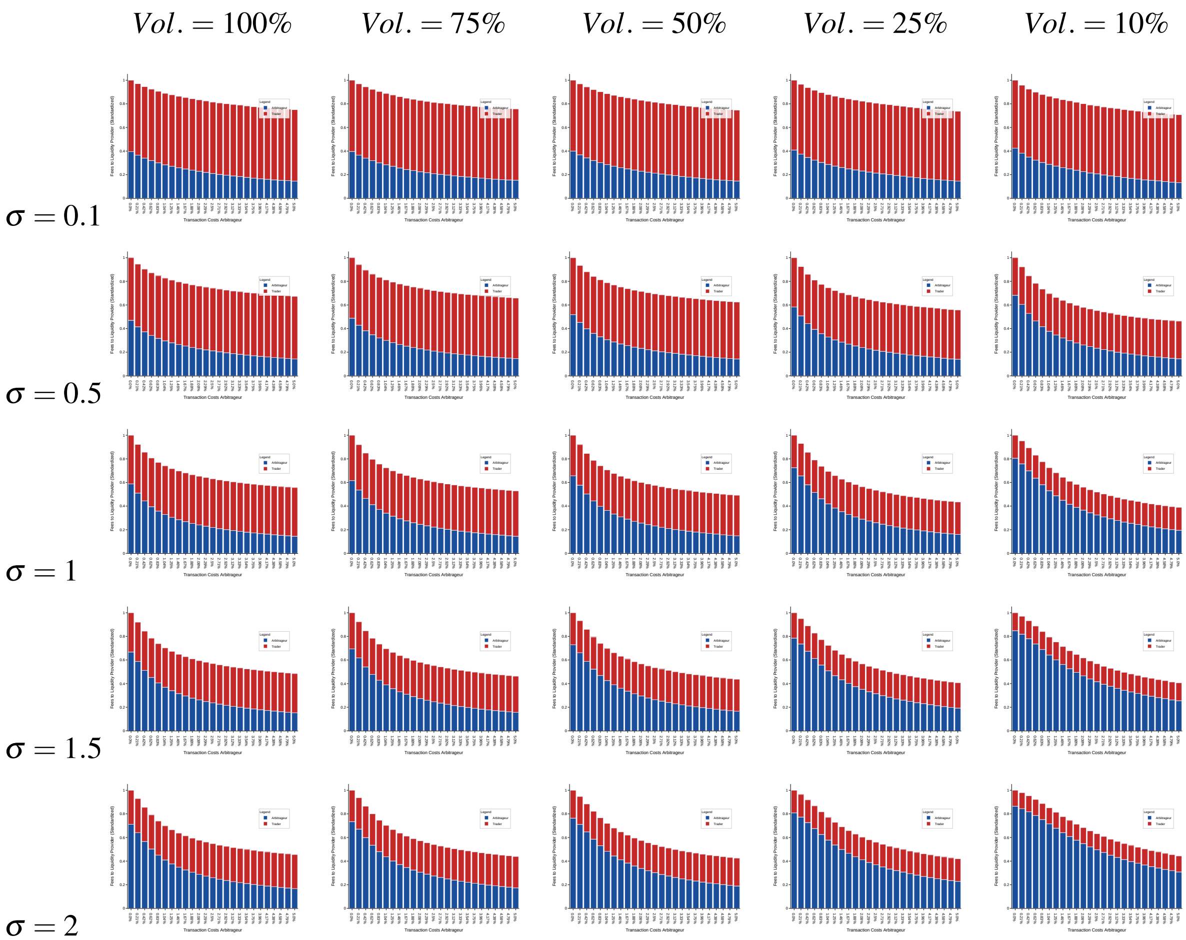

Table 4. Sensitivity of the Liquidity Provider Revenue Split Analysis: Simulation of revenue streams given varying transaction cost levels for arbitrageurs. Revenue is measured as accumulated fees from arbitrageurs and uninformed traders. Values are standardized by total revenues observed in the zero-transaction-fee experiment. Bars represent mean values averaged over multiple simulation runs. The analysis is replicated for different transaction volume levels of uninformed trades (100% to 10%) and for lower and higher volatility of the ETH market price (baseline: $\sigma = 1$).

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