2025 IEEE International Conference on Blockchain and Cryptocurrency (ICBC) | 979-8-3315-4135-4/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICBC64466.2025.11114626

AMM-based DEX on the XRP Ledger

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***Abstract*—Automated Market Maker (AMM)-based Decentralized Exchanges (DEXs) are crucial in Decentralized Finance (DeFi), but Ethereum implementations suffer from high transaction costs and price synchronization challenges. To address these limitations, we compare the XRP Ledger (XRPL)-AMM-Decentralized Exchange (DEX), a protocol-level implementation, against a Generic AMM-based DEX (G-AMM-DEX) on Ethereum, akin to Uniswap's V2 AMM implementation, through agent-based simulations using real market data and multiple volatility scenarios generated via Geometric Brownian Motion (GBM). Results demonstrate that the XRPL-AMM-DEX achieves superior price synchronization, reduced slippage, and improved returns due to XRPL's lower fees and shorter block times, with benefits amplifying during market volatility. The integrated Continuous Auction Mechanism (CAM) further mitigates impermanent loss by redistributing arbitrage value to Liquidity Providers (LPs). To the best of our knowledge, this study represents the first comparative analysis between protocol-level and smart contract AMM-based DEX implementations and the first agent-based simulation validating theoretical auction mechanisms for AMM-based DEXs.**

***Index Terms*—Automated Market Maker, XRP Ledger, Decentralized Finance, Continuous Auction Mechanism**

I. Introduction

Decentralized Finance (DeFi) has transformed financial services by using blockchain technology to offer new, transparent financial services without traditional intermediaries [1]–[7] like banks [8], lending platforms [9]–[11], centralized exchanges [12]–[14], insurance companies [15], [16], and wealth managers [17], [18]. A key part of DeFi are DEXs powered by Automated Market Makers (AMMs), first introduced by Bancor in 2017 and made popular by Uniswap [19], [20]. These DEXs use smart contracts and algorithms to enable trading without traditional market makers. The most common type of AMM used by DEXs is the Constant Function Market Maker (CFMM), with Uniswap V2's Constant Product Market Maker (CPMM) being the most widely used [20], [21].

Most AMM-based DEXs run on Ethereum and face several problems: high fees, large price changes during trades (slippage), impermanent loss for liquidity providers, and outdated prices compared to other markets [12], [22], [23]. These issues originate from AMM-based DEXs' design and their underlying infrastructure, which can lead to losses when off-chain prices move [23]–[25]. Because AMM-based DEXs often quote outdated prices compared to real-time Centralized Exchanges (CEXs), arbitrageurs can profit from these differences, which usually results in impermanent losses for LPs, as the opportunity cost of providing liquidity often outweighs the fees earned [23]–[25], particularly in Uniswap V3 [26]–[28]. While profiting from price discrepancies, arbitrageurs face slippage losses when the effective trade price differs from the initially quoted price. This occurs because AMM-based DEXs prices do not immediately update to reflect external market changes or new transactions between trade submission and finalization.

Learning from these issues, the XRPL-AMM-DEX [29] presents an alternative to existing AMM-based DEXs. It works on the XRP Ledger and aims to reduce price slippage during trades, keep prices in line with other external off-chain markets, and work more efficiently. Unlike Ethereum-based DEXs that work using smart contracts, the XRPL-AMM-DEX is integrated directly at the protocol level of the XRP Ledger. It also has a special feature called Continuous Auction Mechanism that seeks to reduce impermanent losses for LPs by giving them extra fees from traders who want to profit from price differences by participating in auctions to get a 24-hour zero-fee trading slot. This fundamental difference in infrastructure and features provides an interesting opportunity to analyze how these approaches affect AMM-based DEXs performance and characteristics.

Our study compares the XRPL-AMM-DEX with a G-AMM-DEX based on Uniswap V2, which dominates 60% of the DEXs market [30]. While Uniswap V3 introduces concentrated liquidity in price ranges $[P_a, P_b]$, it behaves similarly to V2's $[0, \infty]$ distribution for trades within the same price range. Therefore, returns and losses scale with concentration, assuming the pool's current price stays within the same price range, and especially considering that most retail LPs often provide passive liquidity around current prices due to the challenges of active management in V3 [31]. Given these similarities and theoretical considerations, our findings would likely apply to Uniswap V2 and V3 when benchmarking the G-AMM-DEX to the XRPL-AMM-DEX.

Our methodology uses agent-based simulations[1], building on literature analyzing AMM-based DEXs' performance and design trade-offs [27], [28] and drawing from literature on the relationship between LPs' impermanent losses and traders' price slippage [32]–[35], a relationship Milionis et al. [25], [36] show applies to all AMMs. Additionally, to the best of our knowledge, we conduct the first agent-based simulation of an auction mechanism for AMM-based DEXs, benchmarking the XRPL-AMM-DEX's CAM feature under various volatility

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[1]https://github.com/dlt-science/xrpl-amm

scenarios. This builds on research into LPs' impermanent losses [23], [27], [28], [37] and auction mechanism proposals and theoretical implications for AMM-based DEXs to reduce impermanent losses [38]–[40]. We simulate the underlying infrastructure of the G-AMM-DEX on Ethereum due to its DeFi popularity, layer 1 blockchain status like the XRP Ledger, and role in popularizing smart contracts [41], in which most AMM-based DEXs are built.

Our experimental results show that the XRPL-AMM-DEX, leveraging the XRP Ledger infrastructure, reduces slippage, improves price synchronization with external markets, and enhances operational efficiency. These findings highlight the importance of shorter block confirmation times for AMM-based DEXs, aligning with Fritsch and Canidio's empirical findings [23] and Milionis et al.'s theoretical modeling [42]. Also, our experiments show that as volatility increases and arbitrage opportunities grow, the CAM feature in the XRPL-AMM-DEX helps reduce LPs' impermanent losses by distributing additional fees from arbitrageurs' auctions. These results are consistent with theoretical proposals for other AMM-based DEXs auction mechanisms seeking to capture Maximal Extractable Value (MEV) value from arbitrageurs and redistribute it to LPs [38]–[40].

II. Related Work

A. AMM-based DEX

AMM-based DEXs have revolutionized DeFi, providing innovative ways to exchange assets and provide liquidity [12], [43]. The CPMM model, popularized by Uniswap V2 [21], forms the basis of many AMM-based DEXs [12], [21]. This model uses a simple bonding curve to set asset prices [12]. As the field has grown, various AMM-based DEXs designs have emerged, each addressing specific market needs. These include Uniswap V3's concentrated liquidity, Balancer's multi-asset pools, Curve.fi's focus on similar-valued assets, and DODO's use of external price feeds [12]. Despite these innovations, most AMMs remain adaptations of the CPMM model, highlighting its importance in DeFi [12], [21].

A key challenge in AMM-based DEX design is balancing LPs and traders' interests. Milionis et al. [25], [42] show that LPs' impermanent losses stem from price slippage, as AMMs only update prices during trades, unlike Limited Order Books (LOBs) market makers who actively adjust quotes in response to buy and sell orders activity [44]. This limitation often results in suboptimal pricing, with trading fees frequently insufficient to offset LPs for arbitrage losses [23], [37], especially in Uniswap V3 [45], where active liquidity management may disadvantage retail investors [31].

Proposed solutions include reducing block time to minimize arbitrage opportunities and associated LPs losses [23], implementing dynamic fee structures that adjust based on market volatility [28], and introducing governance mechanisms for fee adjustment, such as Uniswap V3's DAO voting system[2] and

[2]https://gov.uniswap.org/t/uniswap-v3-fees-factory-owner-amendment/23187

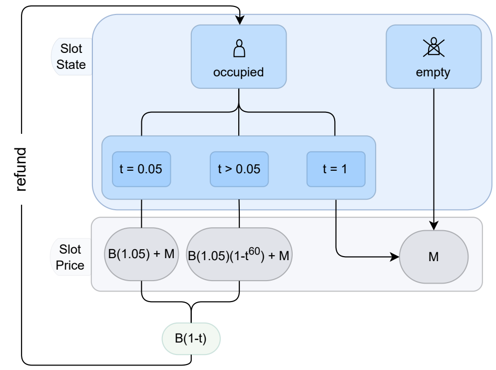

Fig. 1: XRPL-AMM-DEX's CAM slot price-schedule algorithm

the XRPL-AMM-DEX's votable trading fee governance [29]. Other innovations involve developing auction mechanisms for fee-setting rights [38], similar to traditional market-making practices in LOBs for setting bid-ask spreads according to volatility [46]–[49], batch auctions [39], and auctions to get the right for a trade to be placed first in a block of transactions [40]. Among these auction mechanisms, the XRPL-AMM-DEX proposes a CAM [29] for auctioning daily zero-fee trading slots (Fig. 1).

B. Performance evaluation

AMM-based DEXs performance evaluation employs various techniques, with GBM commonly generating price data for analyzing impermanent loss, price slippage, and price synchronization with an external market [25], [27], [28]. Agent-based simulations examine LPs-trader dynamics [27], [28] with some research incorporating stochastic volatility [25] or historical price data [23]. Our methodology builds on this foundation by employing GBM for stochastic price data generation and Binance data for realistic market conditions. However, unlike [25], we model fee-paying arbitrageurs. Additionally, we test the XRPL-AMM-DEX's CAM under specific volatility scenarios.

Most existing AMM-based DEXs research predominantly focuses on Ethereum-based DEXs [12] because of Ethereum's pivotal role in the popularization of smart contracts [41], in which most DEXs are built. These DEXs based on smart contracts execute on top of a blockchain via, most of the time, the Ethereum Virtual Machine (EVM). This architecture often lags in transaction execution speed compared to native transactions [12], leading to increased slippage. Therefore, to the best of our knowledge, no other AMM-based DEXs exist at the protocol level of a blockchain, making this inaugural study particularly valuable for understanding the performance implications of protocol-level integration versus traditional smart contract implementations.

III. AMM-based DEX on the XRP Ledger (XRPL)

We used the CPMM at the core of our G-AMM-DEX for benchmark with the XRPL-AMM-DEX's Geometric Mean

Market Maker (G3M) constant product formula. The G3M is similar to CPMM for ensuring constant liquidity and enables algorithmic pricing based on the ratio of two tokens in the pool [32]:

$$C = Q_A^{W_A} \times Q_B^{W_B} \tag{1}$$

The reserves (Q_A and Q_B) in the pool before and after each trade must have the same normalized weight (W) with C remaining constant. The price at the current state of the pool (or time t_0) is the Spot-Price (SP), which is the slope of the conservation function or, to be more exact, the weighted ratio of the tokens A and B balances in the current state of the pool. The SP also needs to incorporate the trading fee (up to 1%) of the liquidity pool ($TFee$), which is charged on the portion of the trade that changes the ratio of tokens in a pool. Then, the SP is defined as:

$$SP_A^B = \frac{\frac{Q_B}{W_B}}{\frac{Q_A}{W_A}} \times \frac{1}{1 - TFee} \tag{2}$$

Therefore, when a trade removes some amount of asset A from the pool, they must put some amount of asset B to preserve C represented in the following swapping functions:

a) Swap Out: Minimum amount Δ_B of token B to put into the pool to receive Δ_A amount of token A:

$$\Delta_B = Q_B \left[(\frac{Q_A}{Q_A - \Delta_A})^{\frac{W_A}{W_B}} - 1 \right] \frac{1}{1 - TFee} \tag{3}$$

b) Swap In: Maximum amount of Δ_A to receive for paying Δ_B amount of token B:

$$\Delta_A = Q_A \left[1 - (\frac{Q_B}{Q_B + \Delta_B \cdot (1 - TFee)})^{\frac{W_B}{W_A}} \right] \tag{4}$$

Particularly, the less liquidity there is in the pool, the more a single trade/swap may affect the price:

$$\text{Price Impact} = \frac{\text{Price}_{\text{post-swap}}}{\text{Price}_{\text{pre-swap}}} - 1 \tag{5}$$

During the swapping of tokens A and B, considering that the transaction is submitted at time t_0 but executed at time t_1, the actual executed price differs from the Spot-Price. Therefore, the actual executed price or Effective Price (EP) of the trade is:

$$EP_A^B = \frac{\Delta_B}{\Delta_A} \tag{6}$$

This relationship between the Spot-Price and Effective Price is the slippage, which may occur because of market movements between the delay ($t_0 - t_1$) when the trade transaction is submitted (t_0) versus finalized (t_1):

$$\text{Slippage} = \frac{\text{Effective Price}}{\text{Spot-Price}} - 1 \tag{7}$$

Slippage is one of the main MEV issues faced by AMM-based DEXs [50], [51]. On the other hand, similar to traders experiencing slippage, LPs face impermanent loss from opportunity costs due to price volatility of their supplied assets in DEXs, with volatility significantly intensifying in DEXs during market shocks [52].

TABLE I: Simulation parameters for different scenarios: XRPL-AMM-DEX vs. G-AMM-DEX (Test-1 and Test-2) and XRPL-AMM-DEX's CAM.

Parameter	Test-1	Test-2	XRPL-AMM-DEX's CAM
XRPL network fees (USD Coin (USDC))	**1**	0.00001	0.00001
Ethereum network fees (USDC)	**1**	4	4
XRPL block interarrival time (seconds)	4	**8**	4
Ethereum block interarrival time (seconds)	12	**8**	12
Safe profit margin (%)	1.5	1.5	1.5
Maximum slippage (%)	4	4	4

A. Continuous Auction Mechanism

The XRPL-AMM-DEX's CAM (Fig. 1) enables LPToken holders to bid for daily zero-fee trading slots, attracting arbitrageurs while maintaining standard access for other users. Winners retain slots until outbid or until the 24-hour period expires (Fig. 1).

IV. Testing Methodology

A. Data and environment modelling

For our analysis, we choose the ETH/USDC pair, a top-ten Uniswap pool based on Total Value Locked (TVL) [53], [54], using USDC as numéraire. To evaluate the XRPL-AMM-DEX (with and without its CAM) against a G-AMM-DEX, we combine two types of price data: 1) simulated data via GBM and 2) real market data from Binance. Our goal is to test how each AMM-based DEX design responds to different market conditions for fee structures, block times, and market volatilities, focusing on price synchronization, LPs returns, and arbitrage metrics (slippage, profits).

1) Simulated GBM data: We use GBM to generate 5,000 price points over five days, starting with 1,000 USDC per ETH, consistent with Black and Scholes [55] 's groundbreaking options pricing model and Merton [56] 's application of it to corporate debt valuation modeling [55], [56] while in AMM-based DEXs research, GBM is used for analyzing impermanent loss, slippage, and price synchronization with an external market [25], [27], [28], [57]. GBM is described by the formula: $S_t = S_0 \cdot e^{(\mu - \frac{\sigma^2}{2})t + \sigma W_t}$, where S_t is the price at time t, S_0 is the initial price, μ is the drift or expected return, σ is the volatility of returns, t is the time elapsed, and W_t is a Wiener process, introducing random normal noise into the model. Following empirical evidence [58]–[60], we set the initial daily GBM mean to 0.8% and volatility to 7.7%. Also, by adjusting drift (μ) and volatility (σ), we can test the XRPL-AMM with CAM under low, moderate, or high volatility.

2) Real market price data: To confirm whether GBM-like patterns hold in actual market conditions for the AMM-based DEXs, we also replicate our tests (Table I) using five days of historical Binance ETH/USDC prices[3] (1-5 January 2024).

3) Environment and tests: We ran two tests on a shared reference market, excluding the CAM feature of the XRPL-AMM-DEX. In **test-1**, both networks have a 1 USDC fee, doubling the XRPL minimum fee of 0.00001 USDC used in **test-2** to anticipate fee fluctuations. In **test-2**, block times are equalized at eight seconds [61], [62], while safe profit

[3] https://data.binance.vision/data/spot/daily/klines/ETHUSDC/1s/

margin and maximum slippage values reflect realistic ranges (0.5%–5% [63]). Next, we analyze the CAM feature of the XRPL-AMM-DEX through two strategies (§IV-B0b): XRPL-AMM-DEX-CAM-A (optimal for LPs) and XRPL-AMM-DEX-CAM-B (optimal for arbitrageurs). We set $\mu = 1\%$ for these simulations and choose three volatility levels (5%, 12.5%, and 20%), simplifying each auction slot to a single user. Table I summarizes the parameters.

B. Agent-based simulation

We adopt agent-based modeling[4] to examine how both AMM-based DEXs designs affect trading, liquidity, and price discovery under various conditions. This approach, common in Finance and Economics when modeling heterogeneous market participants who interact in stochastic and sometimes non-linear ways [64], [65], captures behaviors like herd [66], contrarian [67], and arbitrage strategies (particularly relevant for testing the XRPL-AMM-DEX 's CAM). These interactions are often complex to capture in closed-form equilibrium models and can be obscured in live blockchain systems because of network congestion and delays, dynamic transaction fees, etc.

We simulate block interarrival times to approximate each DEX' underlying infrastructure, removing the frictions of smart contracts and other blockchain-specific limitations but focusing on core design differences, including the XRPL-AMM-DEX's CAM (Fig. 1). We set a 0.3% trading fee, matching four of the top five Uniswap pools.[5] Our two agents are:

a) Exchange users: Perform swap transactions, exchanging one asset for another. To reflect high market volatility and herd mentality [66], users have an 80% chance to trade ETH and a 20% chance to abstain. Users are influenced by previous actions, with a 60% probability of mimicking and 40% of acting contrary, representing the mix of herd and contrarian behaviors in these markets [67]. Order sizes range from 0.01 to 2 ETH.

b) Arbitrageurs: Following rational arbitrage theory [68] with risk-adjusted profit targeting, these agents act as "price balancers", exploiting price differences between the AMM and external markets. They buy ETH or USDC from the pool when prices diverge, aiming to sell for profit elsewhere. Their strategy involves: 1) Identify price difference: $|Price_{AMM} - Price_{ExternalMarket}| > 0$. 2) If a discrepancy exists, determine asset quantity for price alignment using equations (3) and (4). 3) Compute potential profits by re-selling in the external market: $Profits_{potential} = \Delta^-_{assetOut} - \Delta^+_{assetIn} - networkFees$. 4) Market microstructure research [69], [70] demonstrates that arbitrageurs need minimum profit margins to cover transaction costs and inventory risks, particularly in DEXs, where these costs are amplified by MEV competition [51], [71]. Therefore, arbitrageurs execute when risk-adjusted returns exceed a risk-premium threshold, named as "Safe Profit Margin": $\frac{Profits_{potential}}{\Delta^+_{assetIn}} > SafeProfitMargin$

[4]https://github.com/dlt-science/xrpl-amm
[5]https://app.uniswap.org/explore/pools

Then, the arbitrage condition can be expressed in Iverson bracket notation[6]:

$$[\![|Price_{AMM} - Price_{ExternalMarket}| > 0]\!] \cdot [\![\frac{\Delta^-_{assetOut} - \text{networkFees}}{\Delta^+_{assetIn}} - 1 > \text{SafeProfitMargin}]\!] = 1$$

In addition to the above, arbitrageurs on the XRPL-AMM-DEX-CAM (XRPL-AMM-DEX with CAM) can bid for the discounted trading fee based on two distinct strategies:

1) Case A: XRPL-AMM-DEX-CAM-A: This scenario favors liquidity providers over arbitrageurs, but their interaction is more complex than a zero-sum game. Arbitrageurs often bid for and hold slots for entire blocks. The simulation starts on day three, providing arbitrageurs with historical data to estimate profits under a 0% trading fee scenario. This approach aligns historical and simulated data at S_0 (1000 USDC/ETH), mimicking real market conditions where traders may use the available information (including past) to guide their strategies. So, the weighted average bid limit, P, is determined using exponential smoothing to prioritize recent data. Arbitrageurs cap their bids at P and adjust them based on daily profit trends until the minimum bid price, M, exceeds P. They calculate the LPToken value relative to USDC as follows:

$$LPToken_{RelativePrice} = \frac{SP_A^B \cdot Q_A + Q_B}{Q_{LPTokens}}$$

where $A = ETH$ and $B = USDC$. The expected outcomes from this strategy are (a) decreased arbitrageurs profits and (b) increased LPs returns.

2) Case B: XRPL-AMM-DEX-CAM-B: This scenario favors arbitrageurs over liquidity providers, with minimal competition. An arbitrageur secures the slot at the minimum bid M when empty (Fig. 1) and controls it for 24 hours, repeating until the simulation ends. The anticipated outcomes from this structure are (a) maximal profits for arbitrageurs and (b) minimal returns for liquidity providers.

3) Number of arbitrageurs: In Case A (§IV-B1), arbitrageurs bid continuously until $M > P$, yielding the same outcome regardless of arbitrageur count. In Case B (§IV-B2), daily bidding produces equivalent results, whether from multiple arbitrageurs or one renewing daily. Still, we conducted simulations with varying numbers, consistently obtaining similar results. We settled on using five arbitrageurs in our final simulations.

C. Set up

All scenarios begin with initial pool reserves of 50,000 ETH and 49,850,000 USDC, setting the initial ETH price for GBM pricing at 1,000 USDC to match the external market price (S_0) and 2,281.57 USDC using real market price data. Table I summarizes key parameters: network fees, block times, safe profit margin, and so on, used to compare the XRPL-AMM-DEX (with and without CAM) and the G-AMM-DEX. We repeat the simulations on both GBM (multiple volatility levels) and Binance data.

[6]The Iverson bracket notation denotes that $[\![P]\!] = 1$ if the proposition P is true and 0 otherwise.

V. Results

Given that the results for arbitrageur profits, LPs returns, and impermanent loss are nearly identical, we consolidated XRPL-AMM-DEX-CAM-A and B as XRPL-CAM for clarity in figures and reports. Similarly, we abbreviate XRPL-AMM-DEX to XRPL-AMM using both terms interchangeably, but both referring to the AMM-based DEX in the XRP Ledger. Results are averages from multiple simulations due to random transaction processing, the results of which vary slightly between tests. While specific values may vary, the key insights lie in the relative performance differences between the AMM-based DEXs across various market scenarios with simulated and historical price data.

TABLE II: Average arbitrageurs' profits, transaction costs & transaction frequency for XRPL-CAM vs. G-AMM-DEX with different volatilities.

Volatility		Profits (USDC)	Fees (USDC)	Transaction Count	
				Realized (%)	Unrealized
$\sigma = 5\%$	XRPL-CAM-A	97,251	0.0002	16 (31.4%)	35
	XRPL-CAM-B	180,303			
	G-AMM-DEX	174,686	53	13 (4%)	311
$\sigma = 12.5\%$	XRPL-CAM-A	235,937	0.001	72 (18.3%)	322
	XRPL-CAM-B	823,910			
	G-AMM-DEX	760,056	230	58 (4.8%)	1,150
$\sigma = 20\%$	XRPL-CAM-A	468,500	0.002	159 (15.4%)	875
	XRPL-CAM-B	2,159,411			
	G-AMM-DEX	1,985,052	512	128 (4.2%)	2,938

TABLE III: Average LPs' returns under different volatilities for XRPL-CAM vs. G-AMM-DEX.

Volatility	Scenario	Returns (USDC)		
		CAM Bids	Trading Fees	Total
$\sigma = 5\%$	XRPL-CAM-A	96,528 (10%)	875,883 (90%)	972,411
	XRPL-CAM-B	12,233	877,947	890,180
	G-AMM-DEX	–	900,401	900,401
$\sigma = 12.5\%$	XRPL-CAM-A	526,500 (38%)	870,565 (62%)	1,397,065
	XRPL-CAM-B	10,269	871,100	881,369
	G-AMM-DEX	–	948,282	948,282
$\sigma = 20\%$	XRPL-CAM-A	1,980,951 (64%)	1,113,244 (36%)	3,094,195
	XRPL-CAM-B	14,566	1,104,358	1,118,924
	G-AMM-DEX	–	1,264,858	1,264,858

1) Trading Volume: Trading volumes[7] increase with market volatility for both XRPL-CAM and G-AMM-DEX, with XRPL-CAM consistently outperforming G-AMM-DEX by an average of 4% across all volatility regimes. At $\sigma = 5\%$, XRPL-CAM registered 157,979,186 USDC versus G-AMM-DEX's 155,723,926 USDC; at $\sigma = 12.5\%$, volumes increased to 191,209,656 versus 182,497,061 USDC; and at $\sigma = 20\%$, trading activity escalated substantially to 289,189,151 versus 273,181,521 USDC, respectively.

In test-1 and test-2, trading volumes show remarkable similarity across both AMM-based DEXs using simulated and historical price data. With equalized network fees and different block interarrival times (test-1), XRPL-AMM-DEX volume was 170,746,887 USDC versus G-AMM-DEX's 170,721,881 USDC, a 0.015% difference. With varied fees and equalized block interarrival times (test-2), the difference increased to 0.23%: XRPL-AMM-DEX at 170,277,799 USDC and G-AMM-DEX at 169,890,854 USDC.

2) Price Synchronization: XRPL-CAM consistently outperforms G-AMM-DEX in price alignment across all volatility levels. Comparing 80th percentile price gaps at $\sigma = 5\%$, XRPL-CAM achieves 1.7% versus G-AMM-DEX's 1.9% (11.8% difference); at $\sigma = 12.5\%$, the gap widens to 1.9% versus 2.3% (21% difference); and at $\sigma = 20\%$, this divergence further amplifies to 2.1% versus 2.7% (28.6% difference).

Using a moving average, XRPL-CAM shows superior stability, never exceeding 2.4% divergence across all scenarios, versus G-AMM-DEX's 4.5%. Fig. 7 illustrates this trend. In test-1, with equal network fees but different block interarrival times, XRPL-AMM-DEX outperformed G-AMM-DEX in 90% of cases. In test-2, this advantage dropped to 60% with equal block interarrival times but different fees (Fig. 2).

3) Price Impact: Price impact increases with market volatility for all AMM-based DEXs, with the gap between XRPL-CAM and G-AMM-DEX widening at higher volatilities (Fig. 5 illustrates these trends). At $\sigma = 5\%$, both mechanisms show similar average impacts, though G-AMM-DEX exhibits more outliers. At $\sigma = 12.5\%$, XRPL-CAM maintains a lower, more consistent mean price impact. This divergence amplifies at $\sigma = 20\%$, where G-AMM-DEX's mean price impact exceeds XRPL-CAM by 10.3%, indicating superior price stability in the latter mechanism under elevated market volatility.

In test-1, XRPL-AMM-DEX showed less price impact than G-AMM-DEX with equal network fees and varying block time: 80% of values remained below 3.3% for XRPL-AMM-DEX, versus 3.55% for G-AMM-DEX – a 7.6% difference. Test-2, with equal block times and different fees, shows similar price impact distributions for both AMM-based DEXs. Fig. 4 confirms this, with overlapping Cumulative Distribution Function (CDF) curves in test-2.

4) Slippage: XRPL-CAM consistently shows lower slippage than G-AMM-DEX. Comparing 80th percentile slippage values at $\sigma = 5\%$, XRPL-CAM records 1.36%versus G-AMM-DEX's 1.67% (22.3% difference); at $\sigma = 12.5\%$, values of 1.58% versus 1.82% (15.2% difference) are observed; and at $\sigma = 20\%$, the disparity reaches 1.73% versus 2.07% (19.7% difference).

For test-1 and test-2, CDFs (Fig. 3) show that with equal interarrival block times, slippage is nearly identical on both AMMs. However, with realistic block times for the XRP Ledger and Ethereum, XRPL-AMM-DEX exhibits less slippage. In test-1, 80% of slippages on G-AMM-DEX approach just below 1.8%, while on XRPL-AMM-DEX, they are around 1.65% – an 8.8% reduction.

5) Impermanent/divergent Loss: Table III shows LPs' returns increase with market volatility, primarily from CAM bids and trading fees. Despite lower trading fee returns, XRPL-CAM-A outperforms XRPL-CAM-B and G-AMM-DEX in high volatility. XRPL-CAM-A achieves 67% higher returns than G-AMM-DEX, while XRPL-CAM-B exhibits marginally inferior performance with returns 7.25% below those of G-AMM-DEX. This differential performance underscores the protocol-specific sensitivity to volatility regimes and liquidity dynamics.

[7] All analyses throughout the paper include normal users' trading volume and fees. Their difference is negligible as identical transactions are simultaneously placed on both AMM-based DEXs.

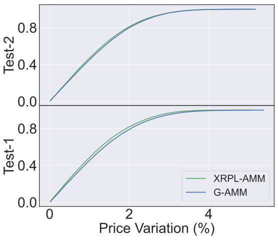

Fig. 2: Test-1 and Test-2 Cumulative Distribution Functions (CDFs) of the price sync. with the reference market for XRPL-AMM-DEX vs. G-AMM-DEX.

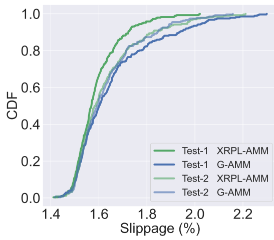

Fig. 3: Test-1 and Test-2 CDFs of the slippage.

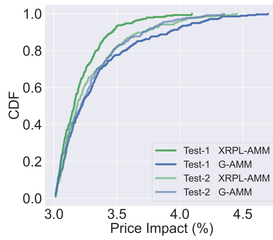

Fig. 4: Test-1 and Test-2 CDFs of the price impact.

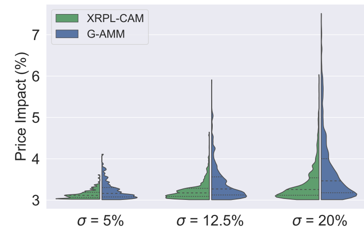

Fig. 5: Price impact caused by arbitrageurs under three varying volatilities. The dotted lines represent the first, second (median), and third quartiles.

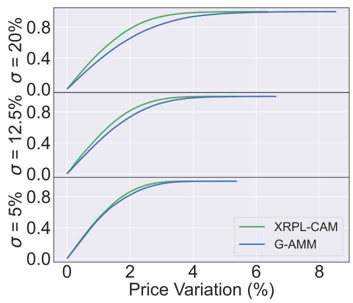

Fig. 6: CDFs of the price difference with the external market for three volatilities.

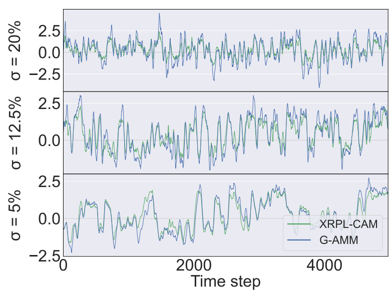

Fig. 7: 30-period moving averages of price discrepancies (%) with external markets across three volatilities.

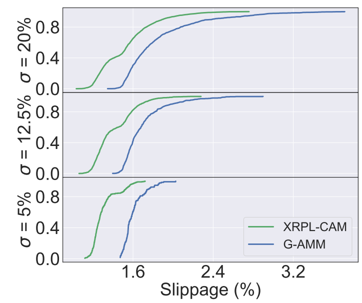

Fig. 8: CDFs of the slippage for three volatilities.

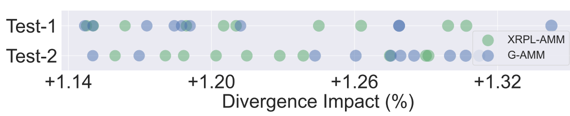

Fig. 9: LPs' divergence gains for Test-1 and Test-2 accross XRPL-AMM-DEX and G-AMM-DEX.

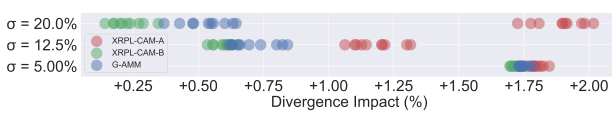

Fig. 10: Divergence loss/gain for XRPL-CAM vs. G-AMM-DEX with different volatilities.

CAM contributions to total returns in XRPL-CAM-A to reach 64% at $\sigma = 20\%$, indicating aggressive arbitrageur bidding in volatile markets, taking advantage of price fluctuations. At all volatility levels, LPs in XRPL-CAM-A consistently show more divergence gain than XRPL-CAM-B while G-AMM-DEX experienced divergence loss:

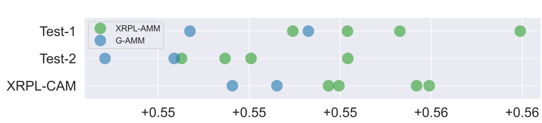

Fig. 11: LPs' divergence gains for XRPL-AMM-DEX (with and without CAM) vs. G-AMM-DEX (CDF) using historical price data from Binance

- $\sigma = 5\%$: XRPL-CAM-A $+1.8\%$, G-AMM-DEX $+1.75\%$, XRPL-CAM-B $+1.72\%$
- $\sigma = 12.5\%$: XRPL-CAM-A $+1.18\%$, G-AMM-DEX $+0.7\%$, XRPL-CAM-B $+0.6\%$
- $\sigma = 20\%$: XRPL-CAM-A $+1.9\%$, G-AMM-DEX -0.5%, XRPL-CAM-B $+0.2\%$

Fig. 10 illustrates growing disparities between XRPL-CAM-A and others as volatility increases. XRPL-CAM-B closely mirrors G-AMM-DEX, indicating comparable worst-case scenarios for LPs.

For test-1 and test-2, LPs on XRPL-AMM-DEX outperformed G-AMM-DEX in 7 out of 10 simulations, with a marginal 0.35% advantage. In test-1, XRPL-AMM-DEX's LPs earned average returns of 954,394 USDC with a $+1.22\%$ divergence gain, while G-AMM-DEX yielded 951,561 USDC returns and a $+1.21\%$ divergence gain. Test-2 showed XRPL-AMM-DEX's LPs achieving 951,984 USDC returns with a $+1.23\%$ divergence gain, compared to G-AMM-DEX's 948,364 USDC returns and $+1.26\%$ divergence gain. Despite similar overall results, test-2 revealed a 2.4% higher divergence gain for LPs on G-AMM-DEX. Fig. 9 depicts divergence gain distributions for both tests. Test-1 shows minimal difference, while test-2 reveals a skew to the right for G-AMM-DEX values compared to XRPL-AMM-DEX, indicating marginally higher divergence gains.

6) Arbitrageurs' Profits, Transaction Cost & Transaction Frequency: In XRPL-CAM-B (best-case scenario for arbitrageurs), profits exceed G-AMM-DEX 70% of the time at $\sigma = 5\%$, and 90% at $\sigma = 12.5\%$ and $\sigma = 20\%$. By

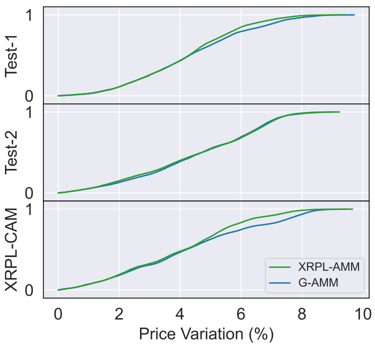

Fig. 12: Price Sync. with Reference Market for XRPL-AMM-DEX (with and without CAM) vs. G-AMM-DEX (CDF) using historical price data from Binance.

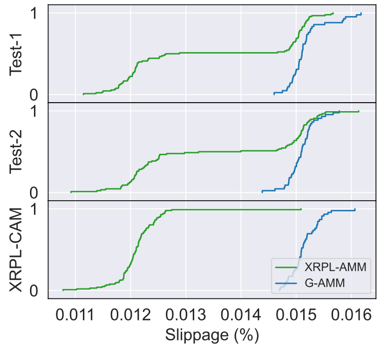

Fig. 13: Slippage for XRPL-AMM-DEX (with and without CAM) vs G-AMM-DEX (CDF) using historical price data from Binance.

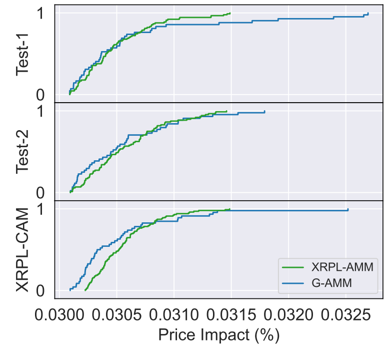

Fig. 14: Price Impact for XRPL-AMM-DEX (with and without CAM) vs. G-AMM-DEX (CDF) using historical price data from Binance.

TABLE IV: Test-1 and Test-2 average arbitrageurs' profits, transaction costs & transaction frequency for XRPL-AMM-DEX vs. G-AMM-DEX.

Test		Profits (USDC)	Fees (USDC)	Transaction Count	
				Realized (%)	Unrealized
Test-1	XRPL-AMM-DEX	384,410	29	29 (10%)	260
	G-AMM-DEX	382,696	28	28 (4%)	634
Test-2	XRPL-AMM-DEX	376,272	0.0003	27 (5%)	476
	G-AMM-DEX	360,581	107.6	27 (6%)	454

TABLE V: Average arbitrageurs' profits, transaction costs & transaction frequency for XRPL-CAM vs. G-AMM-DEX with different volatilities.

Volatility		Profits (USDC)	Fees (USDC)	Transaction Count	
				Realized (%)	Unrealized
$\sigma = 5\%$	XRPL-CAM-A	97,251	0.0002	16 (31.4%)	35
	XRPL-CAM-B	180,303			
	G-AMM-DEX	174,686	53	13 (4%)	311
$\sigma = 12.5\%$	XRPL-CAM-A	235,937	0.001	72 (18.3%)	322
	XRPL-CAM-B	823,910			
	G-AMM-DEX	760,056	230	58 (4.8%)	1,150
$\sigma = 20\%$	XRPL-CAM-A	468,500	0.002	159 (15.4%)	875
	XRPL-CAM-B	2,159,411			
	G-AMM-DEX	1,985,052	512	128 (4.2%)	2,938

contrast, XRPL-AMM-DEX-CAM-A (worst-case scenario for arbitrageurs) never outperforms G-AMM-DEX since most of the profits they could have made went to liquidity providers. Table V reveals:

- *Profits*: XRPL-CAM-B averages 7% higher than G-AMM-DEX, while XRPL-CAM-A is 208% lower. This gap narrows with increased volatility, with increased arbitrage opportunities leading to higher profits.
- *Transaction Costs*: XRPL-CAM fees are significantly lower. At $\sigma = 12.5\%$, G-AMM-DEX fees (230 USDC) are 23 million percent higher than XRPL-CAM (0.001 USDC). This disparity grows with volatility, with XRPL-CAM experiencing a slight rise in fees and G-AMM-DEX seeing a more noticeable surge.
- *Transaction Count*: Both AMMs see increased transactions (realized and unrealized) with higher volatility. G-AMM-DEX typically records more unrealized transactions at all volatility levels, suggesting frequent slippage condition violations. XRPL-CAM's realized transaction percentage decreases with volatility, while G-AMM-DEX consistently shows a lower realization rate of transactions.

For test-1 and test-2, XRPL-AMM-DEX arbitrageurs showed 60% higher profitability across both scenarios. With equalized network fees, the profit difference was minimal (0.45%) but widened to 4.4% with varied fees (Table IV). In test-2, G-AMM-DEX arbitrageurs paid 35,866,567% more in transaction fees for the same number of transactions placed on the XRPL-AMM-DEX. Despite G-AMM-DEX recording 2.3 times more placed transactions, only 4% were realized versus 10% on XRPL-AMM-DEX.

7) Findings using Real Market Price Data: We also replicate Test-1, Test-2, and CAM tests to capture realistic market conditions using historical Binance price data. This allows us to validate our findings under empirical price dynamics. Across divergence gains, price impact, price variation, and slippage, XRPL-AMM outperforms G-AMM-DEX consistently, and XRPL-AMM-CAM further narrows price deviations:

a) Divergence gains: (Fig. 11): Divergence gains show minimal differences between the AMMs, with XRPL-AMM maintaining a slight edge across all scenarios ($+0.555$ vs $+0.552$ in Test-1; $+0.552$ vs $+0.550$ in Test-2). Adding CAM maintains this marginal advantage ($+0.555$ vs $+0.552$).

b) Price impact: (Fig. 14): The XRPL-AMM and G-AMM-DEX demonstrate nearly identical price impact in both tests (3.05% vs 3.06%), and this efficiency persists with CAM implementation (3.056% vs 3.052%).

c) Price synchronization: (Fig. 12): The XRPL-AMM achieves better price alignment in both tests (4.22% and 4.54% deviation) compared to G-AMM-DEX (4.38% and 4.59%), with the XRPL-AMM-DEX's CAM feature further reducing deviation to 4.02%.

d) Slippage: (Fig. 13): XRPL-AMM consistently outperforms G-AMM-DEX across all tests (1.35% vs 1.52% in Test-1; 1.36% vs. 1.51% in Test-2), with its CAM feature further reducing slippage to 1.21% while G-AMM-DEX remains at 1.51%, representing a 20% improvement.

Overall, these real-data tests confirm the earlier simulation trends. Using historical Binance data, XRPL-AMM outperforms G-AMM-DEX in price alignment (4.22% vs 4.38%), slippage (1.35% vs 1.52%), and divergence gains ($+0.555$ vs $+0.552$), with similar price impact (3.05% vs 3.06%). The CAM further improves performance, reducing price synchronization to 4.02% and slippage by 20%.

VI. Discussion

Our comparison of XRPL-AMM-DEX (without CAM) and G-AMM-DEX reveals that XRP Ledger 's faster block times [72] lead to better price synchronization, higher transaction realization, reduced slippage, and lower price impact. These findings align with recent empirical and theoretical studies [23], [42], highlighting the importance of shorter block confirmation times for AMM-based DEXs.

Why does blockchain infrastructure matter so much for AMM-based DEXs, and why should it be a consideration for their design? Unlike market makers' active role responding to trading activity in LOBs [44], AMMs update prices only when trades occur against the liquidity pools of their DEX. Intuitively, a blockchain infrastructure that processes transactions faster allows AMM-based DEXs to react faster to market changes with an external market, keeping prices in sync and reducing slippage. This ripple effect even touches impermanent loss, given its relationship with price slippage [25]. Our results validate this intuition.

Even with faster infrastructure, AMM-based DEXs face another issue: MEV attacks. For instance, Ethereum-based DEXs are particularly vulnerable because Ethereum's transparent mempool and miner-controlled ordering [73], [74] create a playground for attackers. Miners can cherry-pick transactions order, sparking a high-stakes race among arbitrageurs and attackers competing for prime positions in the next block [50], [51], [75]. By contrast, the XRPL-AMM-DEX leverages the XRP Ledger's pseudo-random transaction ordering[8], significantly reducing the risk of front-running attacks [76]–[78]. While this does not make it immune – sandwich attacks, for example, remain a threat [78] – it is a substantial defensive boost that could reduce price slippage.

Beyond speed and security, the underlying infrastructure affects AMM-based DEXs in other crucial ways. Most AMM-based DEXs run on smart contracts competing for computational resources. These smart contracts can be resource-hungry, potentially consuming more gas fees than native transactions, depending on their complexity and data payloads. This resource competition could directly impact transaction costs and execution speed. Moreover, the blockchain's fee structure is pivotal in market dynamics. XRPL-AMM-DEX's lower network fees boost arbitrageur profits and trading volume (§V). This increased activity helps keep prices aligned with external markets. In contrast, G-AMM-DEX's higher fees lead to broader price impact spreads, indicating more significant trade-induced market disturbances. These fee differences highlight how infrastructure choices can significantly shape an AMM-based DEX's market efficiency and liquidity.

The XRPL-AMM-DEX's CAM further enhances these advantages. For LPs, XRPL-CAM yields higher returns and lower divergence loss in their best-case scenarios, while arbitrageurs see more profits in their best-case scenario. In typical conditions, LPs benefit from higher earnings and reduced divergence loss, especially in volatile markets. This aligns with theoretical proposals for auction mechanisms in AMM-based DEXs [38]–[40]. Interestingly, as volatility increases, the proportion of transactions executed by auction slot holders decreases from 86% at $\sigma = 5\%$ to 51% at $\sigma = 20\%$. This trend likely results from increased competition and slippage constraints. A fascinating insight is that when we level the playing field by equalizing transaction fees and block times, the XRPL-AMM-DEX performs remarkably similar to G-AMM-DEX. This highlights how crucial the underlying infrastructure is in shaping AMM-based DEXs dynamics.

[8]https://github.com/XRPLF/XRPL-Standards/discussions/34

VII. Limitations and future work

Our agent-based simulations use simplifying assumptions such as fixed Ethereum fees, one GBM-generated price path, constant pool sizes, single users per auction slot, and no dynamic voting or pathfinding [29]. Despite these simplifications, our results align with recent research on slippage, impermanent loss, and auction mechanisms [38]–[40], [42], highlighting how faster block times, lower fees, and built-in auctions improve market efficiency in AMM-based DEXs. Additionally, we used block interarrival times as a proxy for infrastructure efficiency to level the playing field in benchmarking the G-AMM-DEX, akin to Uniswap V2 that runs in smart contracts, versus the XRPL-AMM-DEX implemented at the protocol-level. Future studies could integrate more intricate factors, such as dynamic fees, diverse pool sizes, and multiple concurrent auction participants. It is important to note that the XRPL-AMM-DEX is relatively new, launching in early 2024 [79] with \$80.37 million TVL [80], compared to Ethereum's \$50.06 billion [81] at the time of this writing. As it grows, it may face unforeseen challenges [82], and real-world adoption could impact its price synchronization and liquidity differently.

VIII. Conclusion

Our findings, using simulated and real market price data, show that the XRPL-AMM-DEX leverages two key elements to reduce impermanent loss and price slippage: the XRP Ledger's shorter block times for rapid price synchronization, and its CAM feature to incentivize beneficial arbitrage during volatility. These elements benefit both arbitrageurs and LPs, enhancing overall market efficiency. This inaugural study ventures into the unexplored domain of AMM-based DEXs in the XRP Ledger and provides, to the best of our knowledge, the first agent-based simulation of an auction mechanism for AMM-based DEXs, experimentally validating implications from theoretical proposals [38]–[40]. However, as the XRPL-AMM-DEX is still in its early stages, at the time of this writing, its long-term success will depend on adoption rates, real-world market conditions, and its adaptability to the evolving DeFi landscape.

Acknowledgements

This work was supported by the UK Centre for Blockchain Technologies (UK CBT) and by Ripple under the University Blockchain Research Initiative (UBRI) [83].

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