Exploring the Panoptic Protocol: Agent-Based Simulations Across Four Trading Volume - Liquidity Scenarios

Project report

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Abbreviations

ABS	Agent-Based Simulation
APY	Annual Annual Percentage Yield
ATM	At-the-money
bCR	Buyer Collateralization Ratio
CT	Collateral Tracker
ITM	In-the-money
IV	Implied Volatility
OTM	Out-the-money
PLP	Panoptic Liquidity Provider
PU	Pool Utilization
sCR	Seller Collateralization Ratio
SM	State Manager
TVL	Total Value Locked

Chapter 1

Introduction

1.1 Panoptic Overview

The DeFi world is experiencing a surge in enthusiasm surrounding Options, thanks to innovative adaptations of traditional financial instruments within the Web3 context. Among these unconventional solutions stands out Panoptic, a pioneering perpetual options protocol operating on the Ethereum blockchain. Please consult the official documentation [1] or contracts [2] for a complete overview.

Panoptic has been ingeniously designed to operate on top of Uniswap V3, capitalizing on the cutting-edge features introduced by this concentrated liquidity protocol. One of its groundbreaking features is the establishment of a direct parallel between shorting an option and providing liquidity on Uniswap. Essentially, being a liquidity provider (LP) in Uniswap V3 is, in terms of payoff, akin to selling an option. This fundamental principle underpins Panoptic's underlying dynamics.

However, there exist two significant differentiators between Panoptic options, often referred to as "Panoptions", and their counterparts in traditional finance:

- **Absence of Expiry:** Panoptions are perpetual, devoid of any fixed expiry date, in stark contrast to conventional options that possess defined expiration periods.
- **Option Pricing**: Unlike other Web3 options protocols and traditional finance options that typically rely on the Black-Scholes model for pricing, Panoptic revolutionizes the concept of option pricing. In this novel paradigm, option cost is intrinsically linked to the price trajectory of the underlying pool. Significantly, the option premium is neither structured in the conventional Black-Scholes manner nor paid upfront. Instead, premium payment only occurs when the option buyer exercises their option, and its value is entirely contingent on the price trajectory of the pool. This innovative approach not only marks a departure from the traditional model but also ensures the protocol's autonomy by eliminating the need for oracles.

1.1.1 Panoptic Actors

The dynamics within Panoptic options involve the active participation of five primary actors, each playing a pivotal role:

- **Panoptic Liquidity Providers (PLPs):** These are central actors, requiring careful incentivization. PLPs contribute external liquidity to the Panoptic Protocol and have the ability to withdraw the same liquidity. Without their essential liquidity provision, the dynamics of options trading, both selling and buying, would be infeasible.
- **Panoptic Sellers:** These actors are responsible for selling options within the Panoptic ecosystem. An important distinction is that Panoptic Sellers do not directly sell their own liquidity. Instead, they borrow liquidity from PLPs, effectively transferring liquidity from the Panoptic pool to the corresponding Uniswap pool.
- **Panoptic Buyers:** These actors partake in the buying of options. It's crucial to note that, in Panoptic, option acquisition is contingent upon a previous sale by a Panoptic Seller. Consequently, Panoptic Buyers, in practice, restore liquidity that was initially moved to Uniswap by Panoptic Sellers back to the Panoptic pool. As is customary for option buyers, Panoptic Buyers retain the option to exercise their positions, realizing potential profits as they see fit.
- **Liquidators:** While not directly involved in the active buying and selling dynamics of options, liquidators contribute to the protocol's health and solvency. They oversee accounts with collateral balances that fall below specified thresholds, typically linked to margin requirements. Panoptic aims to utilize a liquidation bot [3] that, every block, monitors all positions opened in a pool across all accounts and triggers liquidations itself if a liquidatable account is detected.
- **Force Exercisers:** These actors are entrusted with the task of forcefully exercising options that are considerably OTM. In principle, Panoptic Sellers are typically the ones who engage in force exercising, driven by economic incentives. By initiating the force exercise of options they have previously sold, which currently reside deep in OTM territory, they trigger the premium payment mechanism from buyers.

1.1.2 Panoptic Mechanisms

1.1.2.1 Pool Utilization Regulation

The Pool Utilization (PU) is defined as the fraction of all funds deposited in the Panoptic Pool that have been moved to the Uniswap pool. Its regulation ensures the continuous health and stability of the protocol, regarding collateral and margin requirements for both option sellers and buyers.

Figure 1.1 illustrates the pivotal role of the PU value in establishing the baseline collateral requirement upon the minting of options (either through selling or buying). The relationship depicted aims to either incentivize or disincentivize liquidity interactions between the Panoptic and Uniswap pools. In instances of low PU, up to the protocol's target PU of 50%, selling options is incentivized with a low collateral requirement of 20%, enabling sellers to achieve a capital efficiency of 5x. Conversely, buying options is discouraged, necessitating the maximum collateral possible. However, the scenario undergoes a reversal in high PU situations, where buyers are favored, albeit at the expense of reducing seller's capital efficiency.

Buyers have collateral requirements to pay the option premium, while sellers need collateral to cover the option's ITM amount, adding to the base requirement previously described. The ITM amount is intricately related to price evolution, necessitating sellers to track and readjust their collateral to avoid facing liquidations.

Moreover, the protocol incorporates inherent safeguards by mandating that, when minting options, the users' balance exceeds the collateralization ratio by a minimum of 33%. This critical provision is designed to mitigate the risk of instantaneous liquidation for users who may inadvertently fall short of meeting the prescribed collateral requirements.

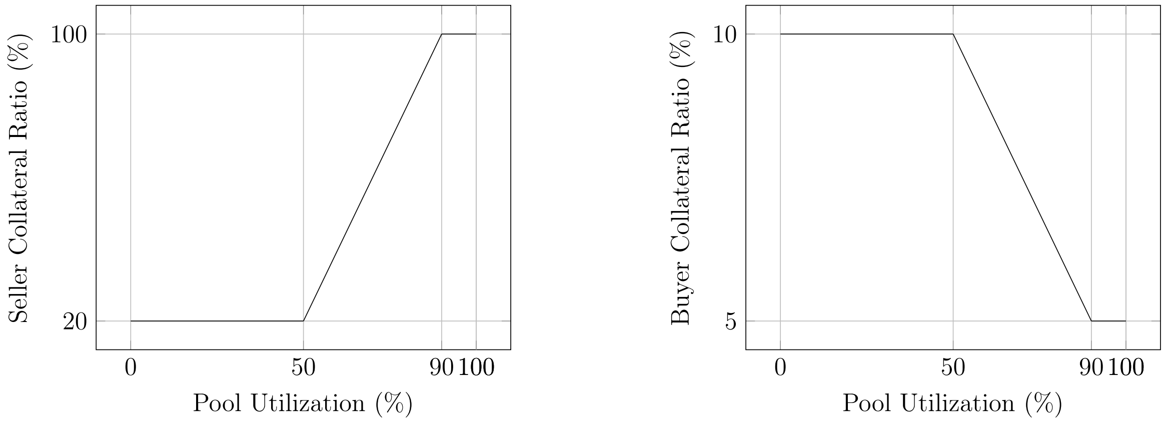


Figure 1.1: Collateralization Ratios vs Pool Utilization evolution.

1.1.2.2 Premium Pricing

One of the noteworthy innovations introduced by the Panoptic protocol revolves around its novel approach to option pricing and premium calculation. The protocol primarily relies on monitoring the fee accumulators in both tokens to calculate two crucial quantities: firstly, the fees that the buyer owes to the seller and, secondly, the total fees collected by the position.

These quantities serve as the fundamental underpinning for the premium calculation. This calculation essentially revolves around tracking when the spot price intersects the option's position. The total fees accrued are contingent not only on the duration during which the price remains within the option's position but also on market volatility. In situations characterized by high volatility, where price fluctuations are more pronounced, a greater number of swaps occur, resulting in increased fee generation (i.e. premium increases).

In addition, buyers are subject to an additional fee known as the spread and the magnitude of this fee is closely linked to the parameter denoted as ν. The spread fee is determined by the relationship between the liquidity that the buyer acquires at the option's strike price and the remaining liquidity available at that particular strike price. This ratio is further scaled by the ν parameter, which ranges arbitrarily but is constrained between 0 and 1. This definition is characterized as very opinionated and, therefore, studying its impact takes part as one of this analysis goals, as it will be further presented in Section 1.3.

1.1.2.3 Liquidation

In the event that users fail to meet the prescribed collateral requirements, the Panoptic protocol has established a safeguard mechanism that involves incentivizing liquidation of distressed accounts. Liquidators who take action to rectify such situations are rewarded, with the bonus being determined by the lesser of the solvency of the account and the account's balance before the liquidation.

Liquidations, as mentioned earlier, serve as a last resort to uphold stability within the protocol. However, in a typical context, such events are not anticipated to occur frequently. Hence, for dedicated and rational actors – specifically buyers and sellers – liquidations do not significantly impact the main metrics of the protocol, such as pool utilization.

1.1.2.4 Force Exercising

The introduction of perpetual options brought with it a notable concern: the potential risk of liquidity becoming trapped in the Uniswap pool. This risk materialized when options buyers, having purchased options from sellers, opted not to exercise their options, while also being in a not liquidatable state. Such a scenario not only impacted the option seller directly but also had repercussions on the overall dynamics of the entire protocol. This way, any external actor can force exercise an option upon payment of a fee. Refer to the Panoptic documentation for additional information on force exercising.

1.2 Agent-Based Simulation Overview

Agent-based modeling works to address a crucial gap in the blockchain industry. While theoretical foundations in new projects are often sound, understanding real-world participant behavior and its consequences on a project's overall success is generally overlooked. We built our simulation framework precisely to help fill this void, providing valuable insights comparable to the role of security audits in mitigating smart contract risks. Like security audits, economic audits are essential to detecting vulnerabilities and fine-tuning systems.

Why agent-based?

Agent-based modeling is a computational modeling technique that focuses on simulating the actions and interactions of individual agents within a complex system. In this type of modeling, each agent is represented by a set of rules, usually called policies, that govern their behavior and interactions with other agents and with the environment. The overall behavior of the system emerges from the interactions of these agents over time. The models can be used to explore how changes in individual behavior or environmental factors can affect the behavior of the system, and to predict the impact of different scenarios and project parameterizations.

In the context of blockchain technology, agent-based modeling can be used to simulate various scenarios and stress-test systems by exposing how agents behave and interact in such environments. For example, one could simulate different types of market conditions, such as a sudden drop in asset prices, or a spike in trading volume, and observe how the agents and, consequently, the system, reacts to these stressors.

In contrast to other modeling techniques, agent-based modeling allows us to capture the complexity and interdependencies of blockchain systems, which are often highly decentralized and involve numerous interacting agents. This complexity makes it challenging to predict how the system will behave in different scenarios using traditional analytical models, which often rely on simplifying assumptions and do not account for the heterogeneity of individual behaviors.

Modeling the real world

When designing our framework, a key priority was to create a tool that could simulate a diverse range of scenarios, including collective behaviors and tendencies. To achieve this, our framework supports two primary methods: modeling participant behavior through agent policies and explicitly defining specific, realistic chain scenarios within a simulation.

Agents are the driving force of a simulation, as they are designed to emulate the behavior of real participants. Armed with behavior policies and aware of the current chain state, our agents can stochastically determine which actions to submit to the chain at a given time.

Policies can be probabilistic - we may define an agent that, given a certain set of conditions, will perform a given action with a probability given by a specific statistical distribution. Furthermore, we can parameterize each of the agent's policy parameters to follow pre-observed, real-world distributions.

Our policy design gives us maximum flexibility when modeling for a specific protocol and simulation scenario, by assuring we can model rational, competitive agents that can interact with a protocol in multiple ways and with varied goals.

The DeFi ecosystem can be complex and challenging to navigate. Our framework offers a comprehensive range of scenario testing options to give teams the confidence they need to move forward. By forking the mainnet to set up simulations, Neferpitou can accurately test how a protocol would respond under real historic events - providing unparalleled insight into the inner workings of DeFi protocols.

1.3 Analysis Goals

The objective of this engagement was to formulate pertinent testing scenarios for the Panoptic protocol and to construct realistic and coherent interactions among all Panoptic actors. This endeavor aimed to facilitate an efficient evaluation of the protocol's mechanisms. To achieve this, we leveraged historical data pertaining to Panoptic's various agent types and employed Game Theory, particularly in delineating the actors' incentives. It is worth noting that, in alignment with the Panoptic team's recommendations, we aimed to infuse realism into agent behaviors while maintaining minimal complexity.

Once the agent-based setup was established, we pursued simulations of increasing complexity (four simulation stages). These simulations enabled an exploratory analysis of the protocol, addressing pivotal questions related to the efficiency and functionality of the main protocol mechanisms and its parameters. Several key inquiries included:

- **Q1)** Is the target pool utilization of 50% consistently achieved and sustained over time?

- **Q2)** To what extent does the collateral requirement and PU relation incentivize or disincentivize the behaviors of option sellers and buyers?
- **Q3)** Are Panoptic Liquidity Providers suitably incentivized to participate in the Protocol, considering the associated risks?
- **Q4)** How do Uniswap V3's pools' trading volume, liquidity, and implied volatility (IV) impact the answers to the aforementioned questions?

These represent the central questions addressed in this report. It is pertinent to note that a comprehensive presentation of the metrics used to evaluate these topics and others will be provided later in the report.

1.4 Report Outline

This report comprises six distinct chapters, with the present section serving as the Introduction.

Chapter 2 delves into the modeling of the four specified scenarios. This chapter expounds upon the utilization of Uniswap V3 pools and outlines the methods employed to ensure the scenarios are executed within the Neferpitou framework.

Chapter 3 offers insight into the rationale governing the modeling of agents employed in our simulations. It discusses the pertinent input variables, the conditions dictating their actions, and the manner in which they execute those actions. The chapter also provides an overview of the range values for each input, contributing to the formation of distinct agent profiles.

Chapter 4 delves deeper into the methodology applied throughout the simulations process. It elucidates the systematic steps taken to construct the simulations effectively and accurately. Additionally, this chapter catalogs the various metrics under assessment during the simulations and outlines supplementary investigations conducted on the protocol.

Chapter 5 offers a comprehensive presentation of the outcomes obtained at each stage and within each scenario. A detailed discussion of these results is also provided.

Finally, in Chapter 6, we encapsulate the key conclusions derived from the simulations analysis and offer recommendations for future developments and enhancements.

Chapter 2

Scenarios Modelling

As previously mentioned, Panoptic is intricately integrated with Uniswap V3, where the options being minted correspond to positions opened within Uniswap pools. Given this fundamental connection, it became imperative to establish scenarios capable of emulating various contexts within Uniswap V3 pools, particularly concerning trading volume and liquidity provision. The subsequent sections delineate the chosen contexts and expound upon the methods used to meticulously enforce them.

2.1 Utilized Uniswap V3 Pools in Testing Scenarios

In alignment with the previously outlined analytical objectives, it was deemed essential to execute agent-based simulations across four discrete scenarios, each characterized by distinct levels of trading volume (low and high) and liquidity (low and high). To achieve this, we selected four specific Uniswap V3 pools that align with the defined scenarios. The following table summarizes this information.

Table 2.1: Uniswap V3 pools that replicate the four trading volume - liquidity scenarios.

Scenario	**Liquidity**	**Trading Volume**	**Token0**	**Token1**	**Fee** [%]
1	Low	Low	DAI	ETH	0.3
2	Low	High	PEPE	ETH	0.3
3	High	Low	WBTC	ETH	0.3
4	High	High	USDC	ETH	0.05

Our selection of pools for utilization in these scenarios is grounded in the data sourced from Uniswap Info, as outlined below:

- **Scenario 1**: The selection of the DAI-ETH-3000 pool is substantiated by the pool's low Total Value Locked (TVL), which stood at approximately $12m as of November 7, 2023, and its modest average 24-hour trading volume over the past year, roughly ranging from $1m to $2m [4].
- **Scenario 2**: The PEPE-ETH-3000 pool was deemed a suitable choice, considering its low TVL, which was approximately $3.4m as of November 7, 2023, and

its relatively robust average 24-hour trading volume over the past eight months, approximately ranging from $5m to $25m [5].

- **Scenario 3**: For this scenario, our selection was the WBTC-ETH-3000 pool, primarily owing to its high TVL, which amounted to roughly $181m on November 7, 2023, and its relatively low average 24-hour trading volume over the past year, approximately fluctuating between $5m to $20m [6].
- **Scenario 4**: We consider the USDC-ETH-500 pool a good fit for this scenario, taking into account its high TVL recorded at approximately $226m on November 7, 2023, and its relatively robust average 24-hour trading volume over the past year, typically ranging from $200m to $400m [7].

Giving the historical relation between these pools' token0 and token1 and their trading volume-liquidity conditions, we anticipate that Scenario 3 will exhibit relatively low implied volatility (IV), while Scenarios 1 and 4 will manifest moderate IV levels (albeit under significantly distinct market conditions), and Scenario 2 is expected to display relatively high IV. Nevertheless, a confirmation of the suitability of these pools for faithfully replicating the intended scenarios will be provided in Section 5.1.

Evidently, to faithfully recreate the target scenarios, we employ price trajectories and their associated liquidity distribution trajectories sourced from these pools. These were extracted from blockchain data spanning the previous year. This approach ensures that our simulations encompass realistic, coherent and representative trajectories. The subsequent section provides a detailed elucidation of the methodologies employed to enforce the occurrence of these trajectories within the simulation framework.

2.2 Uniswap V3 State Manager

The Uniswap V3 State Manager (SM) is crucial for simulating the behaviour of liquidity pools with concentrated liquidity in agent-based simulations. It ensures that the pool's spot price and liquidity distribution follow predefined paths, in accordance with the desired scenarios mentioned in the previous section. This way, we are able to enforce that the Panoptic Protocol is tested in different contexts within Uniswap.

The SM's configuration targets both price and liquidity trajectories. It specifies actions for specific steps (i.e., blocks) in the simulation, remaining inactive otherwise. The target trajectories are coherent but independent, meaning the SM's actions to achieve the target prices may occur in different time steps than those to achieve the target liquidity distribution. Furthermore, depending on the simulated scenario, the frequency of these actions will also be diverse. For example, in a high trading volume scenario, a larger number of targets and subsequent actions from the SM are expected than in low trading volume scenarios.

2.2.1 Configuring and Enforcing Price Trajectories

The SM employs a designated price trajectory as input, setting a target spot price for each block, as illustrated in Table 2.2. Additionally, a threshold parameter is incorporated for adjustments. In simulation steps with a target price, the SM checks if the price deviation between the target and the current spot price exceeds the threshold. If this condition is met, it executes a swap; otherwise, it remains inactive. For the current simulations, we have set this threshold to zero to ensure maximum accuracy.

Table 2.2: Spot Price Trajectory Example

Block Number	**Asset Price**
1	0.0005583227417774
22	0.0005585895615015
30	0.00055934753197
...	...

Concerning the swap transaction, the SM modifies the quantity of token X (token0) or Y (token1) it needs to **supply** to the pool to align its price with the target. The choice of token depends on whether the target is higher or lower than the current price, as outlined below:

- If the target spot price (p_{target}) is **lower** than the current price ($p_{current}$), the SM calculates the amount of token X needed to decrease the spot price from the current level to the target, using the following equation:

$$\Delta X = L \times \left(\frac{1}{\sqrt{p_{target}}} - \frac{1}{\sqrt{p_{current}}}\right) \tag{2.2.1}$$

- Likewise, if the target spot price is **higher**, the SM calculates the amount of token Y needed to increase the pool's current price to the target, using the following equation:

$$\Delta Y = L \times \left(\sqrt{p_{target}} - \sqrt{p_{current}}\right) \tag{2.2.2}$$

The L parameter in the equations refers to liquidity, as per the Uniswap V3 definition. Note that these are simplified equations since, in fact, due to the concentrated-liquidity nature of the protocol, these calculations must be performed tick by tick [8].

2.2.2 Configuring and Enforcing Liquidity Trajectories

The configuration for the liquidity trajectory in the SM closely resembles that of the price trajectory. An input file is provided to indicate when to update liquidity and at which ticks. Table 2.3 presents an example of this input file.

Table 2.3: Liquidity Distribution Trajectory Example

	Tick Distances from the Spot Tick					
Block	-15	...	0	+1	...	+15
1	10050	...	250000	300000	...	20230
20	10050	...	250000	300000	...	20230
27	20050	...	260000	320000	...	30500

The SM evaluates the liquidity of thirty-one ticks, including the spot tick (identified as $'0'$) at that specific block and a range of fifteen tick spacings to the left and right of that spot tick. We choose to update the liquidity within this interval because we consider it unreasonable for a change in price to dislocate the spot price more than 15 tick spacings from the current spot. This approach helps reduce the number of required transactions.

Two additional parameters specified in the configuration are the liquidity threshold and the maximum number of positions. The liquidity threshold is determined by the difference between the liquidity values in each adjacent tick within the specified interval. The maximum number of positions represents the cap on the total positions that can be created, combining adjacent liquidity ticks based on the threshold. These two parameters define a trade-off between accuracy in following the liquidity distribution around the spot and the number of transactions to be placed in the corresponding liquidity update block (indicated in the input file). Figure 2.1 illustrates this impact for twenty ticks at left and right of the spot.

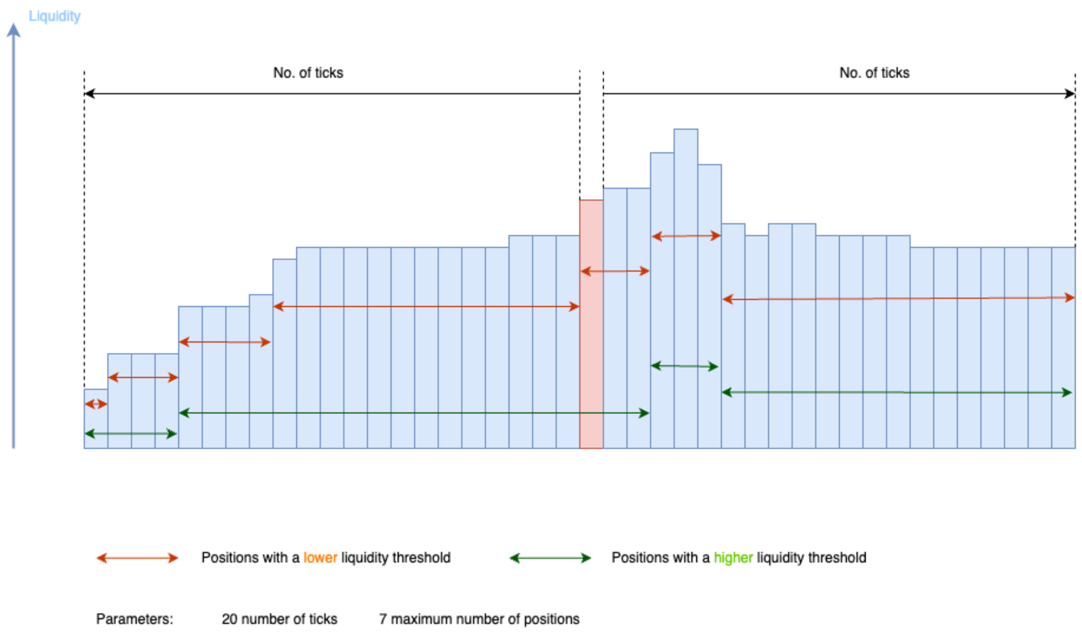


Figure 2.1: The impact of the liquidity threshold and the maximum number of positions on accurately following the target.

These thresholds, however, are not fixed. We have set the interval for the liquidity threshold from 1 to 10% and for the maximum number of positions from 6 to 15, and we use an iterative algorithm to assess the best combination in each liquidity update block to represent the target liquidity distribution. This algorithm runs every time there is a liquidity update. After the calculations are performed and the new positions defined, the SM closes his old positions, opens the new ones, and deposits the necessary funds accordingly to the target of that block.

Chapter 3

Agents Modelling

In the Neferpitou framework, an Agent is the primary entity representing a user in the blockchain environment. Agents have programmable behavior and are configurable by nature, which ensures that the simulated environment is not just a hollow replica but a dynamic, intricate, and accurate reflection of real-world blockchain interactions.

Agents are prompted to act at each iteration of a simulation. Then, each agent will follow their own specific behavior and logic to decide whether to act, and if so, what specific transactions they should submit. In the context of this study, we have developed three main types of agent, in order to have simulations that reflect the existing Panoptic protocol roles, as described in Section 1.1.1.

It is crucial to underscore that the roles of liquidators and force exercisers are not included in our modeling. As mentioned earlier, in stage 4 simulations, agents operate efficiently and rationally, ensuring the protocol's normal functionality. Their vigilant monitoring of collateral in each option mitigates the risk of reaching a liquidation status. Consequently, the incorporation of a liquidation role is not as pivotal in the simulations outlined in this report.

Concerning force exercisers, the previously emphasized idea holds: the OTM exercise mechanism integrated into the buyer's agent logic already encompasses scenarios where the option is deeply OTM, essentially achieving the same outcome as a force exercise.

In the upcoming sections, we will delineate the modeling of the agents, encompassing both their states of actions and the various profiles. It is pertinent to note that certain decisions are contingent upon the simulation stages delineated in our analysis. A comprehensive elaboration and rationale for these dependencies will be expounded upon in Chapter 4.

3.1 Panoptic Liquidity Provider Agent

As a liquidity provider, the PLP agent is responsible for adding and removing liquidity to/from the Panoptic pool. They may provide either just one or both tokens of the pair being traded in the corresponding Uniswap pool.

3.1.1 Agent Description

The PLP logic determines when exactly does the agent increase or decrease their position in the protocol. Moreover, it determines in which scenarios the PLP agent wants to remain outside of the protocol for a period of time.

Table 3.1 outlines the relevant and configurable parameters of the PLP agent. Then, at each iteration, the PLP agent will always consult the respective Panoptic Collateral Tracker (CT_X or CT_Y, depending on the agent's *token_to_provide parameter*) to inspect its state. Namely, the agent reads the CT's total_assets, total_shares, as well as its own balance in the CT vault. Additionally, the agent will need to know the APY of the CT they provide (or intend to) liquidity in.

Figure 3.1 shows the state diagram of the PLP agent. The *already_PLP* variable is set to **true** if the agent is already a PLP (its balance in the CT vault is positive), and to **false** otherwise.

Table 3.1: Configurable parameters of the PLP agent

Parameter	Description/Usage
position_tracker	Tracks the amount of shares and assets the agent has in the pool.
token_to_provide	Which token(s) the agent will provide.
amount_x/y	The amount of each token the agent will provide.
action_frequency	How frequently the agent will act, in terms of blocks.
min_apy_to_provide	APY threshold from which the agent provides liquidity.
min_apy_to_remove	APY threshold bellow which the agent removes liquidity.
apy_num_days	APY moving average period.
remove_share	The ratio of their shares the PLP will remove under certain conditions.

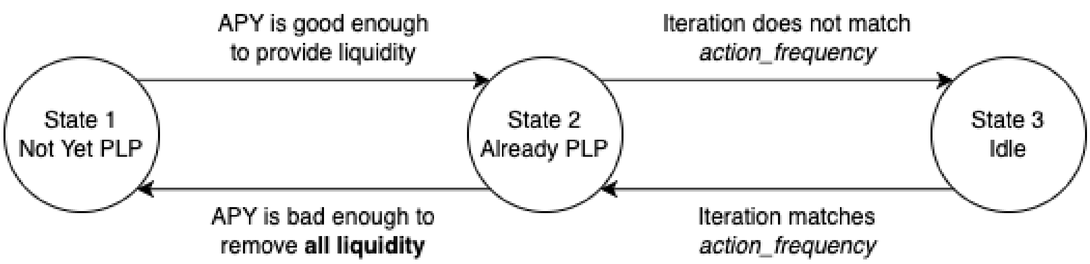


Figure 3.1: PLP Agent State Diagram.

Next, we present a more formal definition of the APY.

Annual Percentage Yield (APY) Calculation

This metric is calculated by the simulator's Snapshooter module in order to avoid redundant calculations on the agents' side. The metric is calculated as the average APY in the last N days. The Snapshooter can be configured with different values of N, depending on the needs of each simulation.

$$share\_price_{i-1} = \frac{total\_assets_{i-1}}{total\_shares_{i-1}} \tag{3.1.1}$$

$$share\_price_{i} = \frac{total\_assets_{i}}{total\_shares_{i}} \tag{3.1.2}$$

$$returns_{i} = \frac{share\_price_{i} - share\_price_{i-1}}{share\_price_{i-1}} \tag{3.1.3}$$

$$apy_{i} = (1 + returns_{i})^{365} - 1 \tag{3.1.4}$$

$$average\_N\_apy = \frac{\sum_{0}^{N} apy_{i}}{N} \tag{3.1.5}$$

PLP agents will use this metric to make their decisions, reading the value matching their configured *apy_num_days* parameter. As we will mention in Chapter 4, we have used different values across different simulation stages. Namely, we have configured PLP agents with apy_num_days = 2 and apy_num_days = 7, meaning the agents check the 2-days or 7-days moving average APY.

3.1.1.1 State 1 - Agent is not yet a PLP

In this state, the PLP agent has no position in the Panoptic protocol. Hence, it will assess whether it should enter the protocol as a liquidity provider or not. To do so, it first consults the current N-day average APY (see Section 3.1.1), and then compares it with its *min_apy_to_provide* parameter. The agent will deposit amount_x/y in the respective CT if Equation 3.1.6 is satisfied.

$$\text{average\_N\_apy} \geq \text{min\_apy\_to\_provide} \tag{3.1.6}$$

3.1.1.2 State 2 - Agent already is a PLP

In this state, the PLP agent already has provided liquidity to the protocol, and hence it will check the health of their position.

It starts by checking if a sufficiently large loss has occurred due to protocol insolvency, caused by a liquidation. To do so, it randomy adjusts its *max_loss* according to a Normal distribution $X \sim \mathcal{N}(\mu = 1, \sigma = 0.1)$. Sampling a value X from this distribution, the agent will check if the loss is greater than X of its previous position's worth. If so, the PLP agent decides to leave the protocol, effectively moving to State 4.

In the remaining cases, the agent will assess whether it should reduce or increase its position in the protocol. To do so, it first consults the current N-day average APY (see 3.1.1), and then compares it with its *min_apy_to_remove* parameter. If Equation 3.1.7 is satisfied, the agent reduces their position by $remove\_share \times amount\_x/y$ (effectively closing their position if this amount surpasses what they currently have deposited in the CT vault).

$$\text{average\_N\_apy} \leq \text{min\_apy\_to\_remove} \tag{3.1.7}$$

If, on the contrary, Equation 3.1.7 is not satisfied, then the agent will perform the same comparison as it does in State 1. This is, if Equation 3.1.6 is satisfied, the agent will increase its deposit in their respective CT by amount_x/y.

To introduce stochastic behavior in the PLP agent, in this state we randomly modify the *min_apy_to_remove* and *min_apy_to_provide* variables according to a Normal distribution $X \sim \mathcal{N}(\mu = 1, \sigma = 0.2)$. In particular, we sample a value from X and use the sample as a multiplicative factor on both variables. The result of this calculation are the updates values which both these threshold variables should take when applying Equations 3.1.6 and 3.1.7.

3.1.1.3 State 3 - Idle

Just like normal users, our PLP agent does not check their position at every single new block. For this reason, we created this State 3 which can be seen as more of a sub-state of State 2. In fact, when the agent has a position in the Panoptic protocol, it only checks their position every action_frequency blocks. When this frequency has not been reached, the agent stays in State 3 and does nothing.

3.1.2 Agent Profiles

In the context of PLPs, we have designed two primary profiles that can further adapt to various sub-profiles based on specific input values. These profiles are essential for catering to different PLP behaviors:

- **Passive PLPs:** This profile characterizes PLPs that exhibit relatively low reactivity to the protocol's state or any external market conditions. They tend to adopt a more passive and cautious approach in the options market, making decisions that are often less influenced by complex factors. Passive PLPs are commonly observed among new market participants who may have limited experience and a more straightforward decision-making process.
- **Active PLPs:** In contrast, Active PLPs are highly responsive to the protocol's state or external market conditions. They display a greater diversity in their decision-making, involving more intricate risk assessments when it comes to providing and removing liquidity. They exhibit higher tolerance for patience and a more comprehensive evaluation of market dynamics. These actors consider a broader range of factors before making their decisions.

To ensure a well-balanced representation of diverse PLP profiles, we have carefully defined the allowable range of input values, striking a balance between realism and complexity. In Table 3.2, we present the considered range values for the input parameters of both Passive and Active PLPs.

Table 3.2: Range of values for Passive and Active PLPs input parameters.

	Profile			
PLP Input Parameter	Passive		Active	
token_to_provide	X or Y			
amount_x/y	Pool Dependent (check here))			
action_frequency (blocks)	For steps 1 and 2: 50400 to 64800	Remaining steps: 50400 to 100800	Three sub-profiles for steps 1 and 2: - 7000 to 10000 - 10000 to 21600 - 21600 to 50400	Three sub-profiles for remaining steps: - 14000 to 21600 - 21600 to 36000 - 36000 to 50400
min_apy_to_provide	0.01 to 0.03		Two sub-profiles - 0.050 to 0.075 - 0.075 to 0.125	
min_apy_to_remove	0 to 0.01		Two sub-profiles - 0.02 to 0.03 - 0.04 to 0.05	
apy_num_days (days)	For steps 1 and 2: 2	Remaining steps: 7	For steps 1 and 2: 2	Remaining steps: 7
remove_share	0.10 to 1.0		0.10 to 0.20	
max_loss	0.10 to 0.90		0.15 to 0.35	

token_to_provide

PLPs have been categorized into two primary groups based on the tokens they contribute: one group focuses on providing token X, while the other concentrates on supplying token Y. Throughout each simulation, this division is maintained, with half of the PLP population contributing token X and the remaining half contributing token Y.

amount_x/y

The determination of the quantities of the corresponding tokens (X or Y) contributed by individual PLPs stems from a comprehensive investigation into liquidity provision practices on Uniswap. In seeking reference values that would appropriately guide the allocation of token amounts to PLPs, we postulated a resemblance between the liquidity provision dynamics, particularly in terms of the provided amount value, of PLPs and Uniswap LPs.

Consequently, our study not only categorized the outcomes based on the type of token but also distinguished between profiles based on activeness. In this context, Uniswap LPs were categorized into two groups: those who, on average, provided liquidity with a frequency of less than one week (considered active) and those who, on average, engaged in liquidity provision with a frequency exceeding one week (deemed passive).

As an illustration, in Figure 3.2, we present a pie chart illustrating the outcomes of our investigation for the DAI-ETH-3000 pool in the context of the Passive PLP profile, specifically focusing on the deposits made in DAI. The legend provides information on the deposit amount intervals, expressed in the corresponding token unit, which we have categorized in Uniswap and subsequently applied to the PLPs deposit amounts. For example, in our simulation framework, we have 6.15% of our Passive PLPs in the to deposit between 2006.12 and 3009.18 DAI. For brevity, the remaining pie charts can be found in Appendix A.

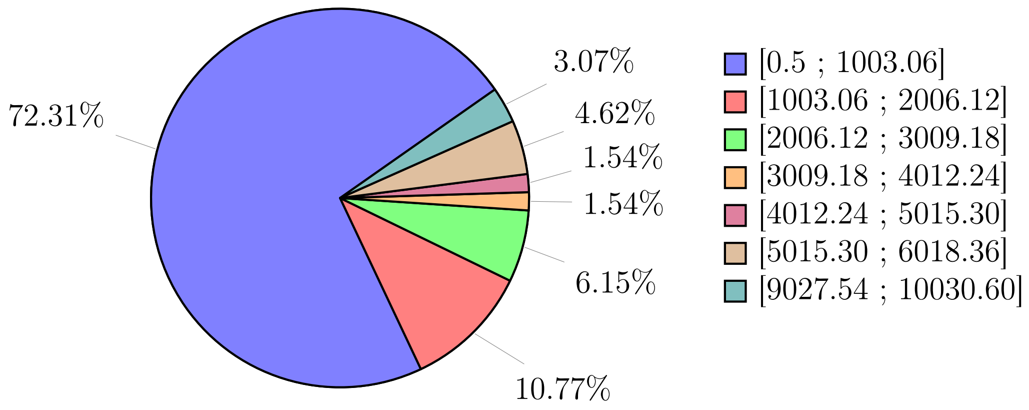


Figure 3.2: Token X amount distribution for Passive PLPs in the DAI-ETH-3000 pool.

action_frequency

In what concerns frequency of action, Active PLPs, true to their name, engage in more frequent actions compared to Passive PLPs. To ensure a diverse representation within the group of Active PLPs, we further segment them into distinct sub-profiles, resulting in a more varied population. These sub-profiles include those who take action on a nearly daily basis, those with a frequency spanning from one day to half a week, and those with a frequency ranging from half a week to a full week. In contrast, Passive PLPs exhibit a less frequent engagement pattern, with a minimum action frequency of one week, which can extend up to two weeks.

min_apy_to_provide and *min_apy_to_remove*

The selection of values for both the *min_apy_to_provide* and *min_apy_to_remove* parameters was carefully guided by the expected yield from staking ETH. To this end, a multiple of such crypto risk free rate is used as an anchor for the parameter choices herein. At the time of modelling, the base value was 5%.

Considering the distinction between Passive PLPs, characterized by their relative naivety and limited complexity in their decision-making processes, and Active PLPs, who are more thorough and responsive, we set varying thresholds for these two groups. Passive PLPs, being less demanding, were assigned lower minimum APY values for both providing and removing liquidity. Specifically, the range for Passive PLPs is set between 1% and 3% APY for providing liquidity and 0% to 1% APY for removing liquidity.

In the case of Active PLPs, we further divided them into two sub-profiles. The first sub-profile demands an APY range of 5% to 7.5% for providing liquidity and 2 to 3% to remove, while the second sub-profile, characterized by higher demands and complexity, requires an APY range of 7.5% to 12.5% for providing liquidity and 4% to 5% to remove.

A noteworthy constraint we implemented relates to the relative values of the minimum APY to remove compared to the minimum APY to provide. This constraint dictates that the minimum APY to remove must be lower than the minimum APY to provide. This decision is grounded in the common understanding that negative factors tend to have a more pronounced impact on decision-making, especially in financial matters. Hence, we incorporated this bias towards caution in the parameter ranges, resulting in lower values for APY when removing liquidity as opposed to providing it.

Note that if the APY measured is within both threshold ranges (to remove and to add liquidity), then the PLP does not add nor remove liquidity.

apy_num_days

In steps 1 and 2, PLPs assess the 2-day moving average of APY, while in the subsequent steps, they shift their focus to the 7-day moving average. This decision is influenced by the distinct timeframes associated with these groups of steps: 8 days for steps 1 and 2 and 56 days (roughly, 2 months) for the remaining steps. For the latter, the 7-day moving average is anchored in the Lido staking statistics, where this metric serves as a reference [9].

remove_share

Passive PLPs encompass a broader and more diverse group, including both risk-averse and risk-seeking new users. This diversity is reflected in their range of actions, which essentially spans the entire spectrum, allowing them to withdraw anywhere from 10% to 100% of their shares when specific conditions arise. In contrast, Active PLPs adopt a more focused and cerebral approach, leading to a narrower range of responses. As more thoughtful participants, they do not immediately remove the majority of their liquidity when the *minimum_apy_to_remove* condition is met.

3.2 Option Seller Agent

The Seller agent actively engages in the Panoptic protocol by selling options - this means moving liquidity from the Panoptic pool to the Uniswap pool. The agent's responsibilities encompass not only the opening and closing of positions but also diligent collateral management to avoid liquidations.

3.2.1 Agent Description

For simplicity, at each time instance, the seller agent holds up to one short option of a given *token_type*, with a certain *strike* tick and *width*. In each simulation iteration, the seller agent assesses its position status to update its internal state. Specifically, if the agent has an open position, it checks for buyer activity, such as the purchase of parts of its position's liquidity or the exercise of options by these buyers.

Moreover, Figure 3.3 illustrates that, regardless of its current state, the agent acts at defined frequencies, determined by *freq_roll_collat_check* and *base_mint_frequency*. The latter undergoes random adjustments, ensuring variability in the agent's option minting frequency. Table 3.3 showcases the configurable parameters of this agent that we will be referencing in the following sections.

Table 3.3: Configurable parameters of the Seller agent

Parameter	Description/Usage
strategy	Whether the seller mints a Put or Call option
base_mint_frequency	How frequently the seller enters State 1
freq_roll_collat_check	How frequently the seller enters States 2 and 3.
amount_deposit	The amount of collateral the seller deposits
factor_k	Distance of the option strike tick from the spot tick
max_collat_ratio	Maximum accepted collateralization ratio when minting an option
factor_collat_ratio	A collateral safety margin
max_blocks_hanging	Maximum number of blocks the seller awaits before rolling an option

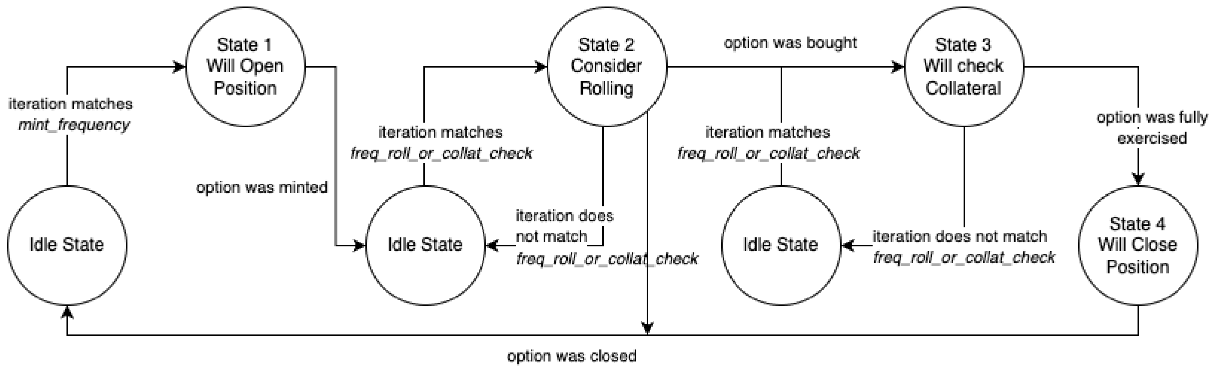


Figure 3.3: Seller Agent State Diagram.

3.2.1.1 State 1 - Will Open Position

In this state, the agent has the goal to open a new position. Two elements of the option are already defined: the *isLong* parameter is set to 0, since this is an option seller, and *tokenType* is defined by the agent's *strategy* parameter. Additionally, the agent must determine three defining aspects of an option position: its *strike* tick (from now on, referred as *strike_tick*), *width*, and *amount*. Since the user mints one single option with one single leg at a time, we will now reference the option *amount* as its *position_size*.

Previewing the effect of Minting an Option

We have assumed that the seller agent always uses *amount_ deposit* as its collateral amount. We fix this variable so that the agent can calculate two values: the maximum *positionSize* it can mint, and what will be the resulting *seller_ collateral_ ratio* of the respective CT if they do. These complex calculations estimate what will the be pool utilization of the respective CT if an option is minted, given the collateral that the user already has deposited and the collateral that the user may have to deposit additionally to achieve *amount_ deposit*.

This phase of the policy returns a pair $(position\_size, future\_sell\_collat\_ratio)$. The seller agent will then evaluate equation 3.2.1 and only acts if it evaluates to false. If indeed the *future_ sell_ collat_ ratio* is still acceptable for the agent, then it will deposit liquidity in the respective CT - this amount taking into account *factor_ collat_ ratio* and the required amount to make up *amount_ deposit* deposited assets in this CT.

$$future\_sell\_collat\_ratio > max\_collat\_ratio \tag{3.2.1}$$

Deciding Option's Strike and Width

Having deposited the collateral it needs, the agent will calculate the *strike* and *width* of the position to be opened. The *strike_tick* is calculated according to equation 3.2.2, where *tick_ spacing* and *current_ spot_ tick* refer to the underlying Uniswap pair.

$$strike\_tick = \begin{cases} current\_spot\_tick + factor\_k \times tick\_spacing, & \text{if strategy is } Short\,Call \\ current\_spot\_tick - factor\_k \times tick\_spacing, & \text{if strategy is } Short\,Put \end{cases} \tag{3.2.2}$$

Having decided on the option's *strike*, the agent calculates the width according to equation 3.2.3, where $random()$ uniformly samples elements of a set of values, and $range(lower\_bound,\ upper\_bound,\ step)$ generates a set of integer numbers.

$$width = \begin{cases} random\big(range(2,\ 2 \times factor\_k,\ 2)\big), & \text{if } strike\_tick \text{ is even} \\ random\big(range(1,\ 2 \times factor\_k + 1,\ 2)\big), & \text{if } strike\_tick \text{ is odd} \end{cases} \tag{3.2.3}$$

The seller agent then uses all of this information to build the *tokenId* artifact required to mint an option. In the next iteration, upon receiving a transaction receipt confirming that the option was minted, they will proceed to the next phase of their state diagram (see Figure 3.3).

3.2.1.2 State 2 - Will Consider Rolling or Burning Position

In this state, the seller has an open option that has not been bought yet. The first thing the agent checks is if the current seller collateral ratio of their respective CT is above *max_collat_ratio*. If so, it is 33% likely to burn it, and 66% likely to roll it to a different *strike* otherwise. If this threshold has not been surpassed, then the agent decides to roll its option.

Deciding Roll Direction

In the most likely case that the user decides to roll their position, it will first check if it should increase, decrease, or take no action on the position's *strike*. This step varies whether the agent has a *Short Call* or *Short Put* strategy, but it regardless analyses if the option is currently in range or not, and if the option is OTM or ITM.

For a *Short Call* option, the user will decrease their option's *strike_ tick* if their option is out of range and if there have passed at least *max_ blocks_ hanging* since the option was first minted or last rolled. Then, the agent is 50% likely to increase the *strike_ tick* if the option is OTM in-range, and will always increase the *strike_ tick* if the option is ITM.

For a *Short Put* option, the difference is that under the same conditions and probabilities, the outcome is the opposite: the user will increase its option's *strike_tick* when the option is out of range and there have passed at least *max_blocks_hanging* since the option was first minted or last rolled. Similarly, it has a 50% chance to decrease the *strike_tick* of an OTM in range option, and always decreases the *strike_tick* of an ITM option.

Executing the Roll

Depending on the previous analysis, the agent increases or decreases the option's *strike_tick* respectively to:

$$current\_spot\_tick + factor\_k \times tick\_spacing$$

or

$$current\_spot\_tick - factor\_k \times tick\_spacing$$

If this calculated *strike_tick* ends up being the same as the current option's *strike_tick*, then the user does nothing.

To make sure that it can perform this roll, the agent also checks if it is still comfortably collateralized, taking into account the option's notional value and the safety margin imposed by the protocol. In the next iteration, it will return to the Idle state, until their option is bought or until another *freq_roll_collat_check* blocks go by.

3.2.1.3 State 3 - Will Check the Collateralization of Position

The seller agent reaches this state when some buyer has bought an option in the same range as the agent has minted an option. In other words, this state is reached when some of the seller's liquidity has been moved back to the Panoptic pool due to buyers' actions. The Seller agent will then check the collateral health of its position.

The agent calculates what is the currently required collateral amount for its option. Then, if this *required_collateral* value is higher than its current balance in the protocol, the user will deposit this difference. In the next iteration, it will return to the Idle state, until its option is exercised, or until another *freq_roll_collat_check* blocks go by.

3.2.1.4 State 4 - Will Close Position

In this state the seller agent burns their position, effectively closing it. Then, after *mint_frequency* blocks, it will re-enter State 1 and begin the whole flow again.

3.2.2 Agent Profiles

In the pursuit of incrementally introducing complexity and realism into simulations, we have devised two primary profiles for seller agents, resulting in distinct agent behaviors when configuring input parameter values. This approach allows us to capture two specific behavioral archetypes:

- **Naive Sellers:** As implied by the name, this profile encapsulates an agent with minimal constraints on their actions concerning the protocol's state or external market conditions. While their actions are rational, they lack informed thresholds, representing an inexperienced trader following a straightforward and naive decision-making process.

- **Dedicated Sellers:** In contrast, this profile characterizes a more experienced trader who utilizes the current protocol's state to assess and determine their course of action. With a clear profile regarding activity, patience, risk (of various types), and capital efficiency, this profile is designed to represent a more realistic and typical Panoptic client, particularly in the context of selling options.

It is worth noting that, in line with the valuable recommendations from the Panoptic team for simplifying complexity, we have implemented decision parameters exclusively focusing on direct protocol variables. However, we recognize the importance of factoring in the price tendency as a critical influence on agent decisions. Therefore, modelling agents with this features should be something to consider in future simulations and analysis.

At this stage, we present the initial version of the seller agents. To ensure a well-balanced representation of diverse profiles, we have meticulously defined the allowable range of input values, detailed in Table 3.4 for both Naive and Dedicated Sellers. It is important to mention that the two profiles will not coexist in the simulations. The Naive Seller profile is only used in the first simulation stages (1, 2 and 3) of reduced complexity, while the Dedicated Seller profile is used for the more realistic and representative simulations (from Stage 4 on-wards).

Table 3.4: Range of values for Naive and Dedicated Sellers input parameters.

	Profile	
Input Parameter	Naive	Dedicated
strategy	"Short Call" or "Short Put"	
amount_deposit	1 to 5 times the average amount deposited by PLPs	
base_mint_frequency (blocks)	6000 to 8400, in steps 1-2 7200 to 28800, in step 3	Two sub-profiles: - 7200 to 18000 - 18000 to 28800
freq_roll_or_collat_check (blocks)	6000 to 8400	150 to 3600
factor_k	Three sub-profiles: - 1 or 2 or 3 - 4 or 5 or 6 or 7 - 8 or 9 or 10	
max_collat_ratio	Above 1	Three sub-profiles: - 0.30 to 0.45 - 0.45 to 0.70 - 0.70 to 1.0
factor_collat_ratio	0.4	Three sub-profiles: - 0.35 - 0.40 - 0.45
max_blocks_hanging	6000 to 8400	7200 to 50400

strategy

Aligned with the objectives of this analysis and aiming to minimize complexity in both implementation and result evaluation, we have decided to keep option trading strategies the simple as possible within our simulation framework. This entails restricting sellers to the most basic possibilities, whereby they can only engage in either short call options or short put options (of a single leg). Our focus lies not in maximizing individual trading profits but rather in comprehensively studying protocol dynamics. We contend that these simpler strategies are as effective in achieving our research objectives as more intricate and evolved alternatives.

In each simulation, one-half of the sellers are exclusively permitted to short call options, while the other half is restricted to shorting put options, maintaining the potential for a balanced offer. Any observed imbalance would be attributed to conditions guiding agent actions. Also note that, for simplicity, each seller can sell only one option at a time.

amount_deposit

This parameter holds a certain degree of subjectivity when determining input values. Opting for small values would hinder the study of the impact of PU variation and subsequent collateralization ratio changes. Conversely, selecting high values would diminish the influence of PLP actors, artificially inflating APYs and accelerating PU saturation, as elaborated further on. Considering that sellers also function as liquidity providers to the Panoptic Pool, it felt natural to link the deposit amount to the amounts deposited by PLPs, hence the utilization of the average amount deposited by PLPs.

The selection of the 1 to 5 range was determined through a series of testing simulations, during which we closely observed the outcomes, focusing on the evolution of PU and APY. This interval demonstrated a sensible progression for PU and realistic APY levels. Additionally, it aligns with the magnitude order of PLP deposits, making it a reasonable choice based on our assessment.

base_mint_frequency

In the initial two stages of the simulations (steps 1 and 2), we incorporate Naive Sellers engaging in daily option minting. Given the absence of buyers in these stages, their minting actions are dispersed across the simulation period, spanning 8 days, as explained in Chapter 4. Transitioning to Stage 3, the base frequency widens its range to encompass intervals between 1 to 4 days. This is due to the fact that the simulation duration is larger (roughly, 2 months). In this context, no scattering is necessary due to the presence of option buyers.

For Dedicated Sellers (ie., subsequent simulation stages), the base frequency is further delineated into two sub-profiles: 1 to 2.5 days and from 2.5 to 4 days. As elucidated in the preceding section, this parameter operates solely as a base for option minting frequency. A scaling factor between 0.5 to 1.5 is applied to recalibrate the frequency for subsequent actions. Consequently, the effective minimum minting frequency can be as short as half a day, while the maximum can extend up to 6 days.

freq_roll_or_collat_check

Naive Sellers conduct daily assessments of their options, including the rolling of positions and checking collateral requirements. In contrast, Dedicated Sellers contemplate rolling their positions more frequently, within intervals ranging from every 150 blocks, which is around 30 minutes, to 3600 blocks, which is around 12 hours. While this does not necessarily imply immediate position rolling, it signifies a heightened vigilance to avoid unfavorable scenarios, such as being ITM. This heightened frequency also applies to collateral checks in order to avoid liquidations.

It is crucial to highlight that the attribute of being a dedicated seller, evident in stage 4 simulations, entails a more rational decision-making process and a lower frequency of actions (i.e., more deliberate compared to naive behavior). This characteristic enables the execution of simulations where the impact of liquidations is either absent or, at the very least, minimized.

factor_k

In Panoptic, the distance between the strike and spot ticks plays a crucial role in determining the speed at which an option may become ITM, but also accumulate premium. To capture varying dynamics, we have established three sub-profiles for this distance parameter. In the first sub-profile ($factor\_k$ ranging from 1 to 3), the option has the potential to become ITM and accumulate premium at a relatively faster pace, whereas in the last sub-profile ($factor\_k$ from 8 to 10), this process unfolds more gradually.

However, this trade-off is also contingent on the option width. To introduce diversity in the possible combinations of these two parameters and achieve distinct option risk profiles, we consider the input $factor\_k$ to define the option width as presented in the previous section in Equation 3.2.3. This computational logic is embedded directly in the code and is not a configurable parameter. This design choice aims to prevent the unintentional minting of options that are already ITM, thereby streamlining implementation and analysis processes.

max_collat_ratio

The collateralization ratio is directly tied to capital efficiency. In our framework, Naive Sellers, devoid of considerations for efficiency, accept any required collateralization ratio during option minting. Conversely, among Dedicated Sellers, we delineate three sub-profiles, each featuring distinct maximum acceptable collateralization ratios. The most capital-efficient Dedicated Sellers adhere to collateralization ratios ranging from the minimum of 20% up to a value within the 30% to 45% range. In the intermediate level, the maximum collateralization ratio spans from 45% to 70%. Lastly, the least capital-efficient Dedicated Sellers are willing to collateralize their options from the minimum up to the 70% to 100% range.

It is noteworthy that these thresholds exclusively apply at the moment of option minting, as elucidated earlier, and not during the process of rolling the option.

factor_collat_ratio

Concerning liquidation risk, we have devised three distinct sub-profiles for the Dedicated Seller. The most risk-prone sub-profile involves depositing 1.35 times the minimum required collateral, whereas the least risky sub-profile opts for 1.45 times the minimum required collateral. For the Naive Seller, we establish the intermediate risk level (also available for the Dedicated), setting the collateral deposit at 1.4 times the minimum required collateral upon option minting.

max_ blocks_ hanging

For Naive Sellers, the parameter *max_blocks_hanging* is configured within the range of 6000 to 8400 blocks, mirroring the same range as the frequency for checking rolling option conditions. This range selection primarily aims to encourage sellers to roll the option almost daily when it is OTM (if it is ITM and no one bought, this is guaranteed).

For Dedicated Sellers, the *max_blocks_hanging* parameter is characterized by a wider range, accommodating various levels of seller patience when waiting for OTM option to be bought. This parameter spans from 1 day to 7 days. Sellers with *max_blocks_hanging* ranging from 1 to 2 days are considered less patient, those with 3 to 5 days exhibit medium patience, and those exceeding 5 days are regarded as very patient. If the option remains unclaimed after this specified period, sellers proceed to roll it.

3.3 Option Buyer Agent

The Option Buyer Agent is an active participant in the Panoptic protocol, transitioning liquidity from Uniswap to Panoptic pools. This agent is tasked with identifying, purchasing, and managing options offered by Seller Agents. It also monitors necessary collateral requirements and decides when to exercise options.

3.3.1 Agent Description

Similar to the Seller Agent, the Buyer Agent handles only one option at a time for simplicity. It constantly evaluates available options to possibly make a purchase. Post-purchase, the agent keeps track of the due premium, evaluates the option's profitability, and monitors the elapsed time since purchase to decide on exercising the option or not. The process flow is depicted in Figure 3.4.

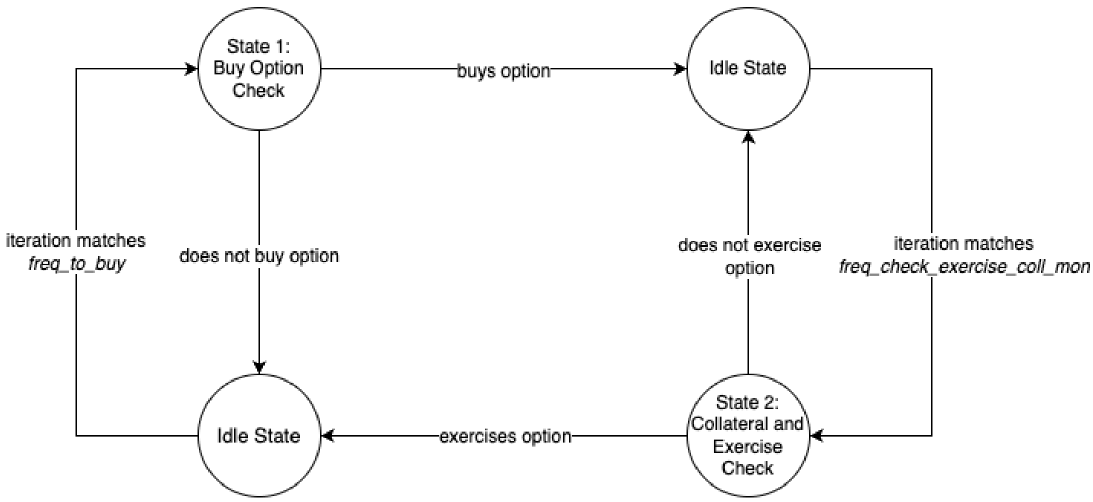


Figure 3.4: Buyer Agent State Diagram.

The agent operates on defined frequencies, set by *base_freq_ buy* and *freq_ checkpoint_ exercise_ coll_ mon*, for buying options and monitoring them, respectively. The frequency *base_freq_ buy* is subject to random variations to introduce unpredictability in buying behavior. Table 3.5 lists the agent's adjustable parameters.

Table 3.5: Configurable Parameters of the Buyer Agent

Parameter	Description/Usage
$strategy$	Whether the buyer buys a Put or Call option
$base\_freq\_buy$	Frequency of the buyer entering State 1
$freq\_checkpoint\_exercise\_coll\_mon$	Frequency of the buyer entering State 2
$amount\_deposit$	Collateral amount deposited by the buyer
$fraction\_to\_buy$	Proportion of the selected option to be purchased
$factor\_collat\_ratio$	Margin added to collateral for safety purposes
$blocks\_passed\_end\_otm$	Time frame to determine an option's non-profitability status ('out-the-money')
$factor\_premium\_accrued\_end\_otm$	Multiplier for calculating premiums on non-profitable options
$factor\_k\_low$	Lower boundary for option selection criteria regarding the strike price
$factor\_k\_up$	Upper boundary aiding in option selection regarding the strike price
$initial\_minimum\_yield\_end\_itm$	Initial yield threshold for profitable options ('in-the-money')
$patience\_metric\_end\_itm$	Time the agent waits for an option to turn profitable before reassessing its strategy
$redefinition\_value\_end\_itm\_threshold$	Adjusts profitability benchmarks based on market changes
$max\_decrease\_end\_itm$	Maximum allowable decline in an option's value while remaining profitable

3.3.1.1 State 1 - Might Buy Option

In this state, the Buyer Agent scans the market for options that align with its settings.

Deciding which Option to buy

Before browsing the available options, the buyer calculates the tick interval, ie. the k_target_low and k_target_up, and maximum width in which it is interested. The parameters k_target_low and k_target_up are calculated according to Equations 3.3.1 and 3.3.2 if the buyer seeks call options and Equations 3.3.3 and 3.3.4 if it seeks put options. In these equations, $tick\_spacing$ and $current\_spot\_tick$ refer to the underlying Uniswap pool.

- If the strategy is **'Long Call'**:

$$k\_target\_low = current\_spot\_tick + factor\_k\_low \times tick\_spacing \tag{3.3.1}$$

$$k\_target\_up = current\_spot\_tick + factor\_k\_up \times tick\_spacing \tag{3.3.2}$$

- if the strategy is **'Long Put'**

$$k\_target\_low = current\_spot\_tick - factor\_k\_low \times tick\_spacing \tag{3.3.3}$$

$$k\_target\_up = current\_spot\_tick - factor\_k\_up \times tick\_spacing \tag{3.3.4}$$

Concerning the maximum width's calculation, this depends, once more, on the agent's strategy, as seen by Equation 3.3.5. The *random()* function uniformly samples elements of a set of values, and *range(lower_ bound, upper_ bound)* generates a set of integer numbers.

$$width = \begin{cases} random\big(range(1,\ 2 \times factor\_k\_up + 1)\big), & \text{if strategy is } Long\,Call \\ random\big(range(1,\ 2 \times factor\_k\_low + 1)\big), & \text{if strategy is } Long\,Put \end{cases} \tag{3.3.5}$$

Buying an Option

Upon identifying a suitable option within the defined parameters, the agent calculates the amount to invest and the collateral to deposit, using the following equations, respectively:

$$amount\_to\_buy = position\_size \times fraction\_to\_buy \tag{3.3.6}$$

$$deposit\_amount = 0.1 \times (1 + factor\_collat\_ratio) \times amount\_to\_buy \tag{3.3.7}$$

The agent deposits the calculated collateral and attempts to purchase an option with the desired characteristics.

3.3.1.2 State 2 - Collateral Monitoring and Exercise Check

Holding an option, the agent periodically assesses its collateral and decides whether to exercise the option.

Collateral Monitoring

The Buyer uses the *calculateAccumulatedFeesBatch* function in the Panoptic pool to find out the total premium due. If the premium is more than zero, they then deposit this amount into the relevant Collateral Tracker, adding a safety margin for extra security.

Exercise Check

Regarding the exercise check, the Buyer can observe one of three cases:

- **OTM out-of-range**: The spot tick is not within the buyer's position range and it is above/below the strike tick for a call/put option;
- **OTM in-range**: The same as above, but with the spot tick inside the buyer's position range;
- **ITM**: The spot tick is below/above the strike tick for a call/put option.

When an option is OTM out-of-range, the Buyer checks if the option was ever in range. If it was never in range and the buying block was more than *blocks_ passed_ end_ otm* ago, the agent exercises the option. For both OTM out-of-range and OTM in-range cases, the option is exercised if at least one of the following conditions is met:

- the number of blocks in range is larger than half of *blocks_ passed_ end_ otm*;
- the buying block was more than *blocks_ passed_ end_ otm* ago;
- *premium_ accrued* is larger than *premium_ accrued_ end_ otm*.

When the option is ITM, the agent calculates the options's yield, which is the quotient between the its net profit (given by Equation 3.3.8) and its investment as shown in equation 3.3.10.

$$net\_profit = \begin{cases} amount\_bought \times spot\_price \times \left(1 - \dfrac{strike\_price}{spot\_price}\right) \times (1 + fee) - premium\_owed, & \text{if strategy is } Short\,Call \\ amount\_bought \times \left(1 - \dfrac{spot\_price}{strike\_price}\right) \times (1 + fee) - premium\_owed, & \text{if strategy is } Short\,Put \end{cases} \tag{3.3.8}$$

$$investment = amount\_deposited + 0.001 \times amount\_bought \tag{3.3.9}$$

$$option\_yield = \frac{net\_profit}{investment} \tag{3.3.10}$$

Note that $0.001 \times amount\_bought$ corresponds to a commission paid and that all the calculation are in Token1 units, ie. in ETH. Moreover, note that *amount_bought* and *amount_deposited* are post-buying variables, but, evidently, calculated by Equations 3.3.6 and 3.3.7, respectively.

If the calculated *option yield* exceeds the *minimum_ yield_ end_ itm*, the agent opts to exercise the option. In cases where this is not met, the agent reassesses its investment strategy. This reassessment occurs if it has been more than *patience_ metric_ end_ itm* iterations since the agent was last in State 2. During this reevaluation, the *minimum_ yield_ end_ itm* is recalculated, as detailed in Equation 3.3.11. It is important to note that the starting point for this parameter is the *initial_ minimum_ yield_ end_ itm*. Finally, if the difference between the current *minimum_ yield_ end_ itm* and the initial value exceeds the threshold set by *max_ decrease_ end_ itm*, the agent proceeds to exercise the option.

$$\begin{aligned} \text{minimum\_yield\_end\_itm} = {} & (1 - \text{redifinition\_value\_end\_itm\_threshold}) \\ & \times \text{minimum\_yield\_end\_itm} \end{aligned} \tag{3.3.11}$$

Replicate Force Exercise

It is crucial to emphasize that the subsequent segment of the agent's logic is designed to emulate the impacts of Force Exercising actions without directly implementing a force exercise action. As elaborated in Section 1.1, the option seller holds the most significant incentives for executing a Force Exercise on their own option. However, incorporating this functionality into the simulation framework posed challenges and would necessitate core changes. Moreover, instead of introducing an external party (explicit Force Exercisers agents), which would escalate complexity and primarily extend simulation time without substantial benefits for the protocol analysis objectives, we opted for an alternative approach.

In our simulation framework, we aim to replicate the most critical effect of a force exercise — specifically, the exercise of an option with a strike too distant from the spot. It is noteworthy that we do not explicitly focus on tracking the exact profit or loss of individual seller or buyer agents. Consequently, we contend that the effects of force exercises can be adequately replicated when a buyer exercises their option far OTM. This mechanic is incorporated in the more global and generic OTM exercise dynamic, where after a certain period has been reached, the buyer exercises the option. If the option is far OTM, then this can be viewed as a force exercise.

3.3.2 Agent Profiles

The incorporation of a realistic dimension into the simulation, with a mindful approach to preventing an unwarranted increase in complexity within the seller's agent profiles, is also extended to the buyer's agent profiles. Consequently, two primary buyer profiles come into focus:

- **Naive Buyers:** Aptly named, this profile envelops agents with minimal constraints on their actions, allowing for a more unrestricted response to the protocol's state or external market conditions. Despite their rational decision-making, these buyers operate without well-defined thresholds, reflecting the characteristics of traders who are still in the early stages of gaining experience and tend to follow a straightforward and less nuanced decision-making process.
- **Dedicated Buyers:** In sharp contrast, this profile characterizes traders with more experience, skillfully leveraging the current protocol's state to evaluate and shape their actions. Marked by a clear profile detailing activity levels, patience, considerations for various types of risks, and yield requirements, this profile is meticulously designed to mirror a more authentic and common Panoptic client, especially within the realm of buying options.

Reiterating our commitment to simplifying complexity, as previously emphasized in the seller's section, we have implemented decision parameters exclusively focused on direct protocol variables. Once more, acknowledging the importance of the price tendency as a key factor influencing agent decisions, we recommend that in future studies this feature is included.

Moving forward, we introduce the initial version of buyer agents. To ensure a comprehensive representation of diverse profiles, we have meticulously defined the allowable range of input values, as outlined in Table 3.6, for both Naive and Dedicated Buyers. It is noteworthy that these two profiles will not coexist within the simulations. The Naive Buyer profile is exclusively employed during the Stage 3 simulations. In contrast, the Dedicated Buyer profile is deployed for subsequent simulations (from Stage 4 onward), providing a more realistic and representative depiction of the buyer behavior.

Note that we did not define a max_collat_ratio for the buyer, as we did for the seller. This is because we consider the difference between 5% and 10% not that relevant for the buyer's decision. The most relevant factor is compatibility with existing short options. This way, we are able to reduce the number of agents.

[Continues in the next page]

Table 3.6: Range of values for Naive and Dedicated Buyers input parameters.

	Profile	
Input Parameter	Naive	Dedicated
strategy	"Long Call" or "Long Put"	
freq_checkpoint_buy (blocks)	7200 to 28800	Two sub-profiles: - 7200 to 18000 - 18000 to 28800
freq_checkpoint_exercise_coll_mon (blocks)	6000 to 8400	150 to 3600
fraction_to_buy	0.5 to 0.88(8)	
factor_k_up	Three sub-profiles: - 3 if "Long Call" , 1 if "Long Put" - 7 if "Long Call" , 4 if "Long Put" - 10 if "Long Call" , 8 if "Long Put"	
factor_k_low	Three sub-profiles: - 1 if "Long Call" , 3 if "Long Put" - 4 if "Long Call" , 7 if "Long Put" - 8 if "Long Call" , 10 if "Long Put"	
factor_collat_ratio	0.4	Three sub-profiles: - 0.35 - 0.40 - 0.45
blocks_passed_end_otm (blocks)	50400 to 100800	
factor_premium_accrued_end_otm	0.50	0.33(3) to 0.66(6)
initial_minimum_yield_end_itm	0.05 to 0.10	Three sub-profiles: - 0.05 to 0.10 - 0.10 to 0.15 - 0.15 to 0.25
patience_metric_end_itm (blocks)	Higher than simulation timeframe	3200 to 7200
redefinition_value_end_itm_threshold	0	0.03 to 0.075
max_decrease_end_itm	0	0.3 to 0.5

strategy

In accordance with the seller's profile section, buyers adopt one of two straightforward strategies: either long call or long put. Despite the simplicity of these strategies, the aim is to investigate protocol-related parameters without compromising simulation results. We believe that utilizing these fundamental approaches, coupled with a substantial number of agents in the simulation, allows us to replicate the broader protocol dynamics associated with more complex strategies.

In each simulation iteration, half of the buyers are exclusively engaged in long call options, while the remaining half is confined to long put options. Any discerned imbalances are attributed to the specific conditions guiding agent actions.

base_freq_buy

Similar to the approach taken for Naive Sellers in Stage 3, the base frequency for

Naive Buyers spans intervals from 1 to 4 days.

For Dedicated Buyers, the base frequency is further categorized into two sub-profiles: 1 to 2.5 days and from 2.5 to 4 days. As explained in the preceding section, this parameter exclusively serves as the base for the frequency of option buying. Employing the same scaling factor as used for sellers, the effective minimum buying frequency can be as brief as half a day, while the maximum may extend up to 6 days.

freq_ checkpoint_ exercise_ coll_ mon

Naive Buyers perform a daily assessment of their options, specifically focusing on exercising conditions and collateral requirements. In contrast, Dedicated Buyers conduct assessments at varying frequencies, occurring at intervals ranging from every 150 to 3600 blocks. This frequency range of 30 minutes to 12 hours aligns with their intrinsic inclination to monitor the protocol, aiming to evade liquidation due to insufficient collateral while also capitalizing on exercising opportunities to maximize profit.

It is essential to emphasize that possessing the trait of being a dedicated buyer, as observed in stage 4 simulations, involves a more reasoned decision-making process and a reduced frequency of actions (i.e., more attentive compared to naive behavior). This particular feature facilitates the conduct of simulations wherein the influence of liquidations is either nonexistent or, at the very least, mitigated.

fraction_ to_ buy

The inherent constraints embedded in the Panoptic protocol dictate that a buyer can purchase, at most, 0.88(8) of the liquidity initially sold with a pre-determined strike and width specifications. Consequently, buyer agents are permitted to acquire liquidity up to this intrinsic threshold.

Additionally, recognizing that verifying buying conditions does not automatically imply a buyer will proceed with purchasing liquidity, we deem it appropriate to ensure that, as long as other buying conditions are met, the buyer will acquire, at a minimum, half of the liquidity available in a given liquidity chunk. This adjustment aligns with the general dynamics of the protocol.

factor_ k_ up and *factor_ k_ low*

Within the Panoptic framework, buyers are restricted in moving liquidity back to the Panoptic Pool exclusively from chunks of liquidity previously sold by sellers on Uniswap. Consequently, buyers cannot adhere to a rigid set of liquidity position parameters, as this poses the risk of these conditions never being fully achievable, or at least highly probable, leading to a potential hindrance in the liquidity purchase process.

Inevitably, the introduction of $factor\_k\_up$ and $factor\_k\_low$ parameters for buyers became imperative. These parameters enable buyers to explore option liquidity within a specified range of distances (in tick spacing units) from strike prices to the spot price, rather than being restricted to a single strike price. To capture the diversity of buyer behavior, three sub-profiles were created: those seeking liquidity in positions with strikes spaced between 1 and 3 tick spacings from the spot tick, those exploring positions with strikes spaced between 4 and 7 tick spacings, and those investigating positions with strikes between 8 and 10 tick spacings from the spot tick.

Buyers refrain from searching for options beyond the 10 tick-spacing distance mark due to what we consider an irrational approach. Force exercising costs diminish significantly for distances greater than 10 tick spacings from the strike. Acknowledging this, and considering the protocol's indications that options beyond this distance are highly unlikely to become ITM, buyers avoid acquiring options within this high tick spacing distance range.

Furthermore, the impact of these parameters extends to the selection process for the width of an option to be purchased, as demonstrated earlier in Equation 3.3.5. However, it is important to acknowledge a limitation inherent in this modeling approach, driven by the necessity for complexity reduction: buyers do not take into account the implications of their chosen width, particularly concerning the higher or lower premium they may accrue. This aspect presents an opportunity for enhancement in subsequent simulation studies.

factor_collat_ratio

The collateralization ratio, as elucidated earlier, plays a crucial role in determining capital efficiency within the Panoptic protocol, while considering liquidation risks. Consequently, we adopted identical profiles for this parameter, aligning with the reasoning applied to both Naive and Dedicated Sellers.

blocks_passed_end_otm

The *blocks_passed_end_otm* parameter serves as an indicator of the buyer's tolerance for an OTM option when evaluating exercising conditions. A timeframe ranging from a week to two weeks has been designated for this parameter.

While it may have been plausible to introduce sub-profiles for this parameter, mirroring the approach taken with other parameters, a strategic decision was made to avoid undue complexity. Implementing sub-profiles across all parameters could lead to an intricate simulation requiring a substantial number of agents, consequently elongating the simulation duration. To streamline the simulation process and mitigate potential complications, it is our position that the *blocks_passed_end_otm* parameter, while undeniably significant in representing the buyer's patience with OTM options, does not necessitate sub-profiles for an enhancement of simulation dynamics.

It should be noted that this threshold applies when the option is OTM, but the spot tick is outside the position's range. In the case it is OTM but in-range, the buyer is accumulating debt (as premium) without a corresponding return, hence his patience should be, necessarily, smaller. More specifically, we have reduced directly in half ($0.5 \cdot blocks\_passed\_end\_otm$). This is directly implemented in the code.

Moreover, this threshold integrates the force exercising mechanism into the simulations. Options that are OTM often persist in that state for a significant duration. Upon reaching the threshold, the buyer exercises these deep OTM options, mimicking a force exercising action.

factor_premium_accrued_end_otm

Buyers are tasked with monitoring the accrued premium in their options, a pivotal aspect influencing their decisions when confronted with OTM options. In conjunction with the previously mentioned *blocks_passed_end_otm* parameter, these considerations serve as fundamental determinants guiding a buyer's choice to exercise OTM options. In alignment with our commitment to maintaining a manageable level of complexity in buyer profiles, we have opted for a singular threshold value for both Naive and Dedicated Buyers. For Naive Buyers, this threshold is set at 0.5, representing 50% of the collateral deposited (*deposit_amount*). Conversely, Dedicated Buyers operate within a broader range, with values spanning from 0.33 (33.33% of the deposit amount) to 0.66 (66.66% of the deposit amount). This diversified range for Dedicated Buyers accommodates various risk appetites, ranging from more conservative to more venturesome profiles.

initial_minimum_yield_end_itm

A pivotal factor in the decision-making process regarding the exercise of a specific option is the anticipated profit. This metric essentially gauges the yield that a buyer would attain by exercising the option under prevailing protocol conditions.

Consequently, each buyer is equipped with a parameter intricately linked to this metric: the *initial_minimum_yield_end_itm* parameter. Naive Buyers operate within a singular profile, encompassing a range from 5% to 10% yield (0.05 to 0.1). In contrast, Dedicated Buyers are categorized into three sub-profiles, offering a nuanced representation of diverse user preferences. The sub-profiles cater to a spectrum of risk appetites: conservative users stipulate an initial minimum yield threshold ranging from 5% to 10% (0.05 to 0.1), risk-seeking users set this threshold between 15% and 25% (0.15 to 0.25), and moderate users seek a yield within the 10% to 15% range (0.10 to 0.15).

It is crucial to note that the minimum value (0.05 or 5%) and the maximum value (0.25 or 25%) were determined based on anchored reference values, specifically the typical yield from ETH staking and options trader's perception of a high yield value. This approach ensures that the more conservative option buyers anticipate a yield equivalent to that of staking ETH, aligning risk and compensation. Furthermore, the conception of a high yield value for options traders was approximated through collaborative discussions with the Panoptic team.

patience_metric_end_itm

To prevent buyers from becoming trapped in an endless loop, persistently awaiting an option to move sufficiently ITM to meet their *initial_minimum_yield_end_itm* parameter, the *patience_metric_end_itm* parameter has been introduced. This parameter serves to adjust the buyer's yield requirement, diminishing it and thereby increasing the likelihood of exercising the option in the subsequent evaluation of exercising conditions.

In this context, Naive Buyers maintain a static yield requirement throughout the entire simulation, reflecting their uncomplicated decision-making process. In contrast, Dedicated Buyers exhibit a patience range between half a day and one day. This range is deemed appropriate for buyers to effectively modify their yield requirement, given a frequency of checking exercise conditions every 50 blocks (worst-case scenario in terms of frequency). Consequently, within this range, buyers will scrutinize the option's adherence to the preceding yield requirement at least 64 times before initiating an update, considering a *patience_metric_end_itm* value of 3200 blocks.

redefinition_value_end_itm_threshold

When an option fails to meet the initial yield requirement for an extended period (exceeding *patience_metric_end_itm*), the buyer initiates the process of redefining its yield requirement, as discussed earlier.

The extent of this redefinition is directly influenced by the *redefinition_value_end_itm_threshold* parameter. For Naive Buyers, who do not engage in the redefinition of their yield requirement, this parameter can be set to 0. Dedicated Buyers, on the other hand, operate within a range of 3% to 7.5% (0.03 to 0.075) for redefinition in each iteration. This range was chosen as it is considered reasonable; in the worst-case scenario (with a 7.5% adjustment at each iteration), it would necessitate nine consecutive iterations for the yield requirement to decrease by approximately 50% of its initial value, assuming the prior nine requirements were insufficient for the buyer to exercise.

max_decrease_end_itm

In a situation where the redefinition of the yield requirement proves insufficient for the buyer to exercise, even after numerous iterations, the yield requirement would theoretically decrease continuously to an unrealistically small value. This is compounded by the equally unrealistic amount of patience the buyer would need to endure for such a decline to occur.

To mitigate this scenario, the *max_decrease_end_itm* parameter is introduced into the buyer's profile. If the decrease in the yield requirement surpasses the specified threshold in the *max_decrease_end_itm* parameter, calculated as a percentage relative to the initial yield requirement, the buyer is compelled to exercise the option.

Once again, considering that redefinition does not occur for Naive Buyers, this parameter is set to 0 for this buyer profile. In the case of Dedicated Buyers, the range of values for this parameter spans from 30% to 50% (0.3 to 0.5) of the maximum decrease from the initial yield requirement. This range accommodates diverse buyer profiles, ranging from more conservative (30%) to risk-seeking (50%) with respect to this specific parameter.

Chapter 4

Simulation Methodology Outline

Within this chapter, we delve into the methodology employed to derive meaningful simulation results. Our approach involved a gradual increase in the simulation's complexity, wherein we systematically introduced different types of protocol actors. At each juncture, we validated their behavior, ensuring they executed accurate non-reverting transactions under specific conditions. Concurrently, in every step, we verified and compiled metrics, culminating in the final stage, allowing for a comprehensive analysis of the protocol. In total, we conducted four distinct steps, which we will elucidate in the subsequent sections.

4.1 Stages 1 and 2: Exploring PLPs and Option Sellers Dynamics

The initial two stages served as a controlled testing scenario for PLPs and Sellers, aiming to assess agent proportionality and interactions. These stages differentiate solely in the total number of agents and the profiles assigned to PLPs. In Stage 1, only Passive PLPs were employed, whereas Stage 2 incorporated both Passive and Active PLPs. In both stages, Naive Sellers were used.

Given the absence of option buyers, sellers, upon minting an option, proceeded solely to roll it, leading to protocol activity stagnation. Due to this, simulations were conducted for an 8-day protocol activity timeframe in these initial stages. To mitigate the protocol's post-minting stagnation, Naive Seller activity was evenly distributed throughout the timeframe. In Stage 1, two Naive Sellers acted daily, totaling 16 sellers, which was enough to encompass each existing sub-profile. Furthermore, following the argument that sellers also serve as PLPs and that both these actors should impact the protocol, a fixed proportionality of one to one between sellers and PLPs was maintained (to be used in every subsequent stage). Therefore, in the first stage, 16 Passive PLPs were used, which were also enough to cover all sub-profiles.

In Stage 2, the same rationale was upheld, requiring more PLPs to cover each Active PLP sub-profile (24 in total). Recognizing the perceived relevance of the Active PLP role, a proportionality of 25/75 between Passive and Active PLPs was established. Consequently, Stage 2 comprised 8 Passive PLPs in a total of 32 PLPs. To maintain the

PLP-Seller ratio, 32 sellers were incorporated, resulting in a total of 64 agents within the simulation. The table below summarizes these simulation parameters.

Table 4.1: Simulation Parameters in Stages 1 and 2.

	Stage	
Simulation Parameters	1	2
Simulation Timeframe	8 days (57600 blocks)	
Number of Passive PLPs	16	8
Number of Active PLPs	0	24
Number of Naive Sellers	16	32
Total Number of Agents	32	64

These stages served the purpose of verifying our ability to accurately track liquidity and price trajectories, ensuring the simulated scenarios aligned with our expectations. Considering these stages as early control stages, testing one trajectory was deemed sufficient, leaving tests with more price and liquidity trajectories to the last stage, where the protocol is complete.

Furthermore, we conducted an assessment of metrics crucial for addressing the key questions in our analysis, outlined in Section 1.3. These metrics, pertaining to PLPs and Sellers, were evaluated in these initial stages and continued to be assessed in subsequent stages. The following outlines the metrics under evaluation:

1. **Daily Trading Volume**: The total value of funds exchanged in the Uniswap pool, measured in ETH, on a daily basis.

2. **Daily Average Implied Volatility**: The daily average implied volatility within Uniswap's pool, expressed on an annualized basis. This is given by the following equation [10]:

$$\text{IV}[\%] = 2 \cdot \phi \cdot \sqrt{\frac{Daily\,Trading\,Volume}{Spot\,Liquidity}} \cdot 365 \cdot 100 \tag{4.1.1}$$

   where ϕ is the pool's swapping fee.

3. **PLPs Daily APY:** The daily two-day moving average (from Stage 3 onward, seven days) APY to assess returns for PLPs.

4. **Daily Pool Utilization**: The minimum, maximum and average pool utilization, per day.

5. **Daily Seller Collateralization Ratio**: The minimum, maximum and average base collateralization ratio for option minting (when sold), per day.

6. Additional Secondary Metrics:

   (a) **PLPs Deposits and Withdrawals**: The number of deposits and withdrawals along with the respective mean amounts.

(b) **Sellers Mints**: The number of options minted (of each type) and the mean size of the corresponding positions.

(c) **Sellers Rolls**: The number of options rolled OTM, ATM (in position range) and ITM.

Finally, it is important to note that these stages were also used to assess the deposit amounts from Sellers at which, under specific conditions, the Pool Utilization saturates. This process was undertaken to verify the correct implementation of the PLPs and Sellers actions, since this is a scenario with a predetermined outcome, as it will be seen next.

Pool Utilization Saturation

To provide clarity, we have defined PU saturation as the maximum achievable pool utilization under conditions where PLPs deposit funds solely at the beginning (without additional deposits, as this would decrease PU, or without withdrawing funds, as this would raise PU further) and Sellers exclusively mint options (without rolling, as such action would decrease PU due to collateral depositing). Note that, in the protocol's reality, this will never happen due to the existence of the commission fees and due to cross-collateralization, which allows accounts to utilize funds without depositing collateral. However, it is a scenario that allows the team to verify the agents correct interaction with Panoptic's contracts.

To determine this saturation value, for a given collateral tracker, we computed the pool utilization after a seller's mints an option with a certain $PositionSize$ using the following formula:

$$PU_{after} = \frac{inAMM + PositionSize}{TotalAssets + Margin \cdot sCR \cdot PositionSize} \tag{4.1.2}$$

where $inAMM$ represents the assets deposited in the Uniswap pool before the seller's action, $TotalAssets$ is the total amount of assets (from the corresponding token) provided to the protocol and $Margin = 1 + factor\_collat\_ratio$, with SCR being the seller's collateralization ratio, thus making $Margin \cdot SCR \cdot PositionSize$ the collateral deposited in the Panoptic Pool.

Considering that the seller's collateralization ratio is given by $SCR = -0.8 + 2 \cdot PU_{after}$ (as observed on the left of Figure 1.1 for PU_{after} between 50% and 90%), we can rearrange Equation 4.1.2 and obtain a second-degree equation, as follows:

$$a \cdot PU_{after}^2 + b \cdot PU_{after} + c = 0 \, , \text{ with } \begin{cases} a = 2 \cdot Margin \cdot PositionSize \\ b = TotalAssets - 0.8 \cdot Margin \cdot PositionSize \\ c = -(inAMM + PositionSize) \end{cases} \tag{4.1.3}$$

By applying the quadratic formula, we derive an equation for PU_{after}, and the solution can be visualized in this Desmos graphic [11].

To determine the saturation value, we let $PositionSize$ tend to infinity, implying that the seller deposits a substantial amount of collateral to mint large positions in Uniswap. This approach leads to the saturation value, expressed as follows:

$$PU_{saturation} = 0.2 + \sqrt{0.04 + \frac{1}{2 \cdot Margin}} \tag{4.1.4}$$

For a detailed deduction, check Appendix B).

It is important to note that the minimum value for $Margin$ is 1.33(3) as mandated by the protocol. Consequently, the maximum possible value for pool saturation is 84.42%, falling within the previously assumed range.

Finally, since in stages 1 and 2, all the sellers are naive, having $factor\_collat\_ratio = 0.4$, the expected saturated pool utilization is:

$$PU_{saturation}\Big|_{factor\_collat\_ratio=0.4} = 83.019\% \tag{4.1.5}$$

Verifying this value with simulation results indicates a correct implementation of the PLPs and, specially, Sellers actions.

4.2 Stages 3 and 4: Adding Option Buyers Dynamics

In Stages 3 and 4 of the simulation, option buyers are introduced, resulting in a more realistic depiction of the Panoptic protocol's functionality. This inclusion enables the observation of complete selling-buying cycles, contributing to a dynamic Pool Utilization. While the roles of Force Exercisers and Liquidators are still absent, these stages provide meaningful results reflecting the performance of Panoptic mechanisms. Stage 3 involves both Naive Sellers and Buyers, simulating a protocol with inexperienced or uninformed traders. In contrast, Stage 4 exclusively employs Dedicated Sellers and Buyers, aiming for a closer representation of the protocol's reality.

Regarding the number of agents, the goal remains to include at least one representation of each sub-profile in both stages. For Stage 3, where Naive Profiles are used for sellers and buyers, the maximum number of sub-profiles is dictated by Active PLPs, resulting in 24 Active PLPs and 8 Passive PLPs (75/25 proportionality). Maintaining the one-to-one proportion between PLPs and Sellers explained in Section 4.1, there are 32 Naive Sellers. Additionally, a one-to-one proportion between Sellers and Buyers is maintained to allow PU to float unbiasedly and create a balanced interaction between these agents.

In Stage 4, on the other hand, the number of agents is determined by Dedicated Sellers and Buyers sub-profiles. To ensure the inclusion of at least one representation of each sub-profile, a minimum of 36 Dedicated Sellers and 36 Dedicated Buyers is necessary, maintaining the desired one-to-one proportionality. It's noteworthy that for the $factor\_collat\_ratio$, featuring three sub-profiles, we adopt a non-prescriptive approach, applying a uniform random distribution of the three values across all agents. Although this method does not guarantee an equal representation of the three sub-profiles, it enables a reduction of one-third in the total number of agents, enhancing simulation time efficiency without sacrificing realism. Additionally, adhering to the established proportionality, there are 36 PLPs, with 25% classified as Passive and the remaining 75% as Active.

Considering the simulation time frame, we struck a balance between computation duration and obtaining representative results. To achieve this, we took the duration of the Panoptic testing Epochs as a reference (Epoch 1 lasting one week [12], and Epoch 2 lasting two weeks [13]). We opted to scale this timeframe and conducted simulations over eight weeks (56 days) to ensure the generation of long-term results.

Table 4.2 provides a detailed summary of the outlined simulation parameters for Stages 3 and 4.

Table 4.2: Simulation Parameters in Stages 3 and 4.

	Stage	
Simulation Parameters	3	4
Simulation Timeframe	56 days (403200 blocks)	
Number of Passive PLPs	8	9
Number of Active PLPs	24	27
Number of Naive Sellers	32	0
Number of Dedicated Sellers	0	36
Number of Naive Buyers	32	0
Number of Dedicated Buyers	0	36
Total Number of Agents	96	108

The simulations regarding stage 4 are expected to produce the most insightful results regarding the behavior of Panoptic mechanisms, as detailed in Chapter 3. Consequently, we will carry out simulations in this stage with diverse price and liquidity trajectories to gain insights into how different trajectories impact key metrics of Panoptic.

In these stages, additional metrics were incorporated alongside those outlined in Section 4.1, taking into account the introduction of buyer dynamics. They are synthesised below:

1. **Daily Buyer Collateralization Ratio**: The minimum, maximum and average base collateralization ratio for option minting (when bought), per day.

2. **Weekly Ratio of Bought Call Options versus Bought Put Options**: The ratio between the number of call options and put options bought, calculated on a weekly basis. We also present the global number of options bought and its median amount.

3. **Global and Weekly Ratio of Exercised versus Bought Options**: The ratio between the number of options exercised by buyers and the total number bought, computed on a weekly basis.

4. **Weekly Number of Exercised Call Options versus Exercised Put Options, both ITM and OTM**: The number of call options exercised ITM and OTM, as well as the number of put options exercised ITM and OTM, calculated on a weekly basis.

5. **Global Exercising Yield and Loss**: The minimum, maximum and average yield earned by the buyers when exercising options ITM. It is calculated using Equation 3.3.10 (see Section 3.3.1). Moreover, the minimum, maximum and average loss taken by the buyers when exercising OTM. This is computed as the ratio between the premium and commission paid and the initial collateral deposited follows:

$$\begin{aligned}\text{buyer\_loss} &= -\frac{premium\_owed + 0.001 \cdot amount\_bought}{amount\_deposited} \\ &= -\frac{premium\_owed + 0.001 \cdot amount\_bought}{(1 + factor\_collat\_ratio) \cdot buy\_collat\_ratio \cdot amount\_bought}\end{aligned} \tag{4.2.1}$$

6. **Weekly Ratio of Option Premium versus Position Size**: The minimum, maximum, and average premium's relative magnitude to option's position size, per week.

Chapter 5

Simulation Results and Discussion

In this chapter, we showcase the outcomes of the simulation stages outlined in the preceding chapter. Our aim is to present concise and comprehensible representations of the results, conducting a thorough analysis for each scenario across the designated metrics. To maintain brevity without sacrificing insights, certain visual aids are referenced in the appendix. These results facilitate a detailed comprehension of the distinct influences of each protocol role on the primary mechanisms of the Panoptic protocol. Ultimately, the assessment of these results will determine whether they indicate a robust and effective functioning of the protocol.

5.1 Stage 1 Results

As detailed in Section 4.1, we conduct simulations lasting 8 days with a total of 32 agents at this stage. This serves as a control phase for evaluating the dynamics of PLPs and Sellers, and also to validate the theoretically obtained Pool Utilization saturation value, as outlined here.

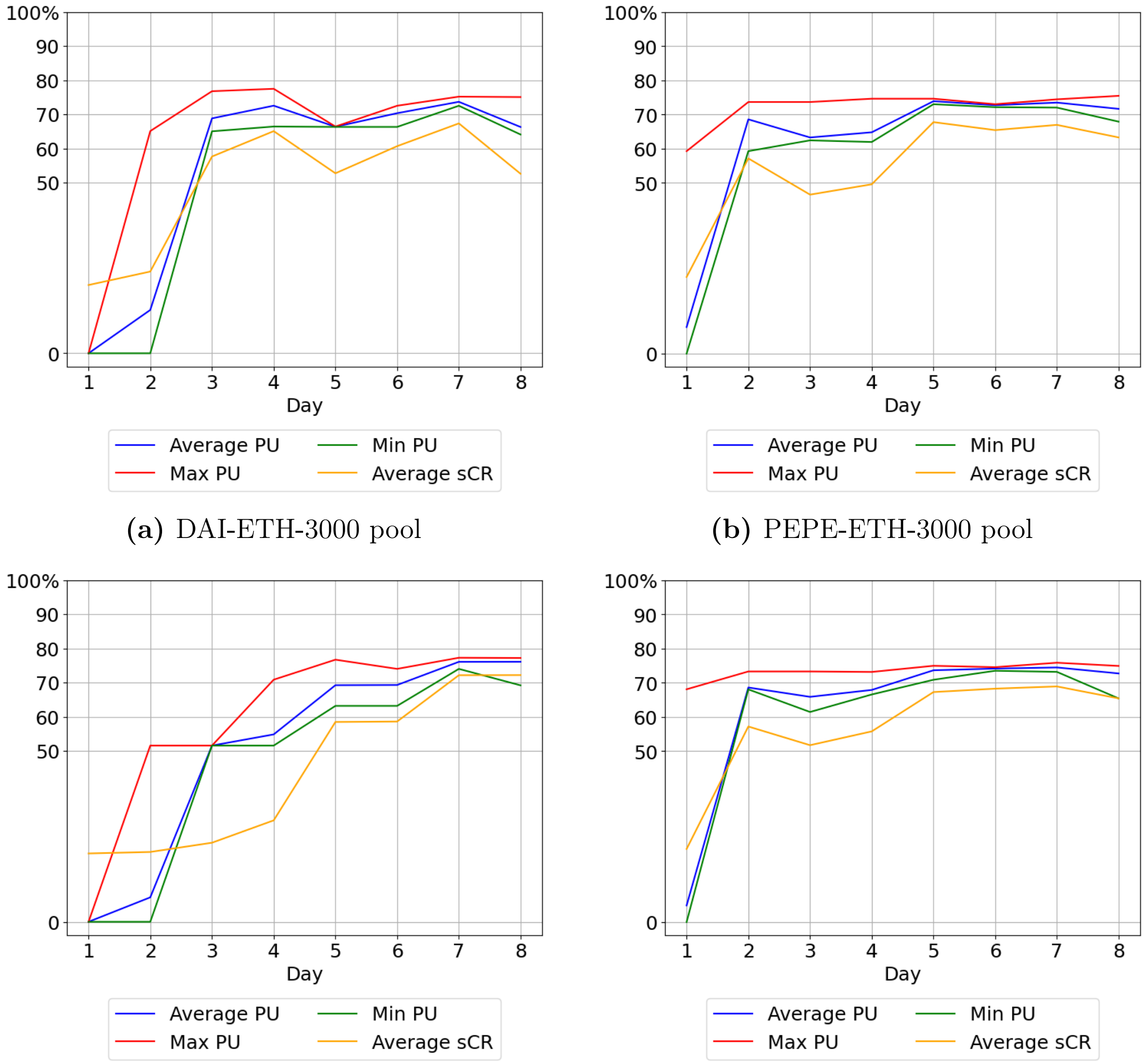
Concerning the former, as the results closely resemble those of Stage 2, and for the sake of brevity, we direct readers to the Appendix C, Section C.1, for the outcomes of this stage. A more comprehensive analysis of liquidity/trading volume scenarios and agent dynamics metrics will be presented in the subsequent Section 5.2.

Regarding PU saturation, we designed specific simulation test cases, varying the *amount_deposit* parameter across three levels. The first reflects the range employed in definitive simulations (1 to 5), the second sets the parameter to 100, and the third simulates the infinite limit by setting the parameter to 5000. Moreover, for the second and third sets, we imposed that Sellers would not roll their positions. Regarding withdrawals, the occurrence of these events was already avoided due to the input values presented in Section 3.1.2.

Analysis of the figures presented below (Figures 5.1, 5.2 and 5.3) and those present in Appendix C.2 reveals that, across all pools, the maximum PU increases proportionally with the *amount_deposit* value, aligning with expectations. Furthermore, as the *amount_deposit* increases, the convergence accelerates rapidly. This is clearly visible in all pools but with more emphasis in the WBTC and DAI pools. In these pools, the range of 1 to 5 exhibits a slower and fluctuating convergence, with a delayed ascent and descent pattern following the peak PU, with every scenario reaching a different final value.

This behavior is absent in the second and third test cases, where PU quickly stabilizes at its maximum value within 1 or 2 days and remains constant throughout the simulation. This discrepancy is due to the fact that for the first set, sellers were allowed to roll their positions, and since the collateral amount is of the same magnitude as that of the PLPs, it makes the PU fluctuate. However, in the second and third sets, as mentioned, these rolls did not happen, making the convergence much more straightforward.

Finally, the key takeaway is the consistent attainment of the expected theoretical PU value of 83.019% across all pools as *amount_deposit* tends to infinity (see Figure 5.3). This not only validates our demonstration but instills confidence in the effective performance of our agents.



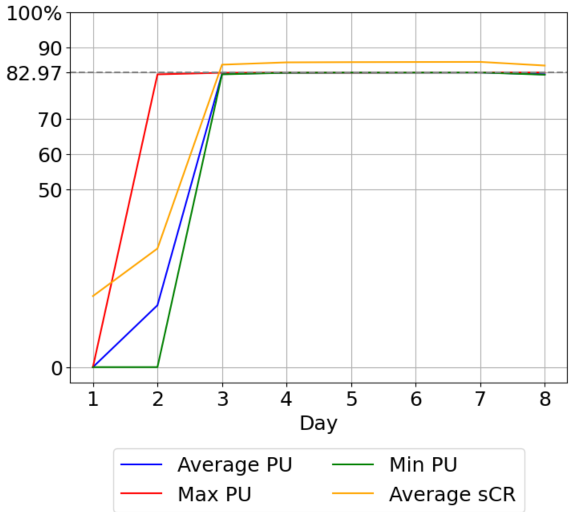
(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

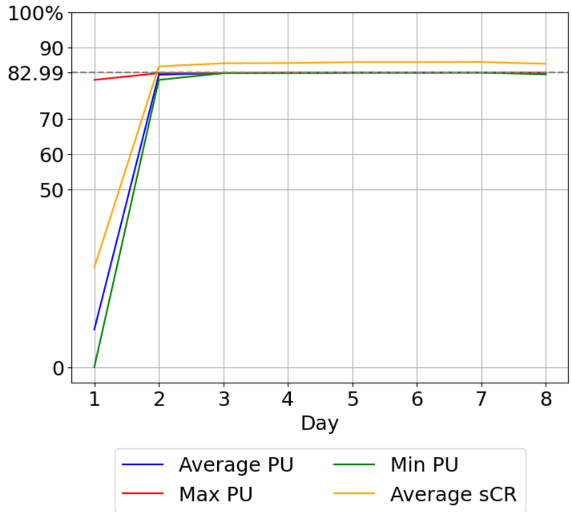
(c) WBTC-ETH-3000 pool

(d) USDC-ETH-500 pool

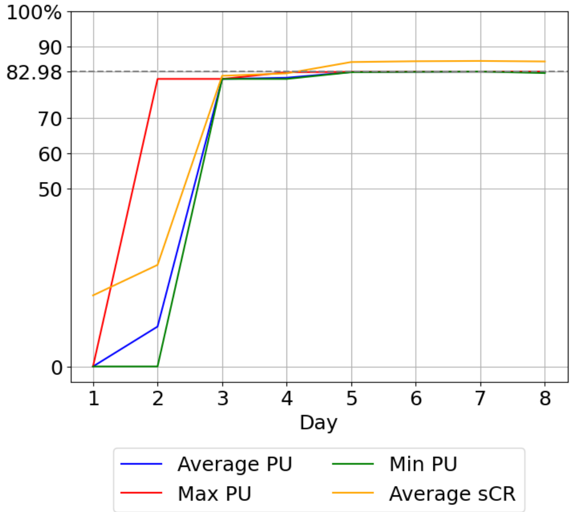
Figure 5.1: Token0 PU saturation and Seller's Collateralization Ratio for the four trading volume - liquidity scenarios, with the seller's *deposit_amount* input values between 1 and 5.



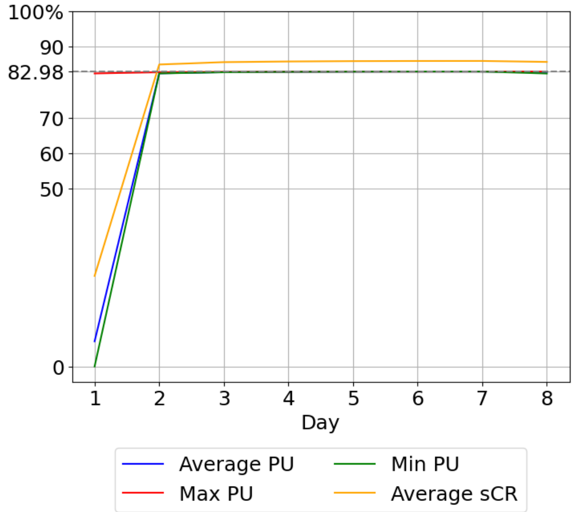
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.2: Token0 PU saturation and Seller's Collateralization Ratio for the four trading volume - liquidity scenarios, with the seller's *deposit_amount* input values as 100.

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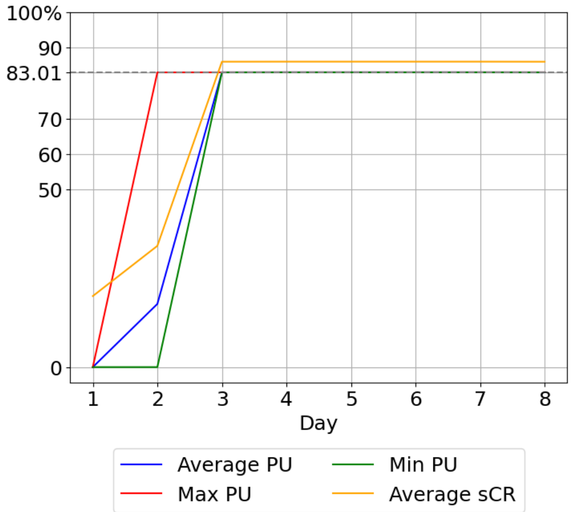
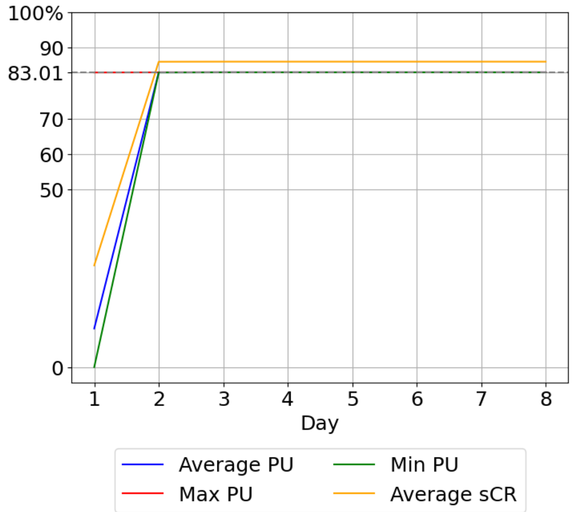
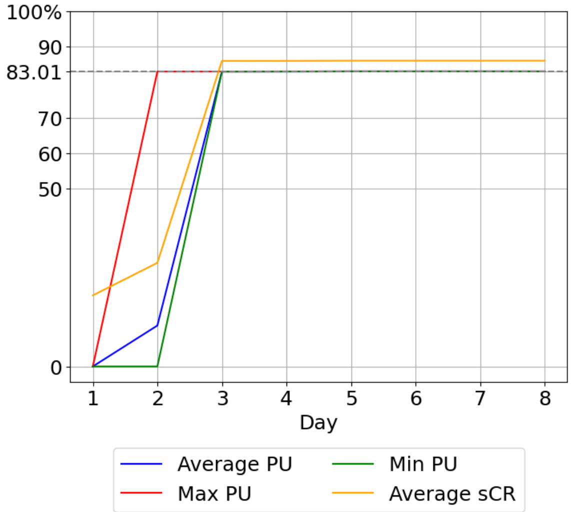


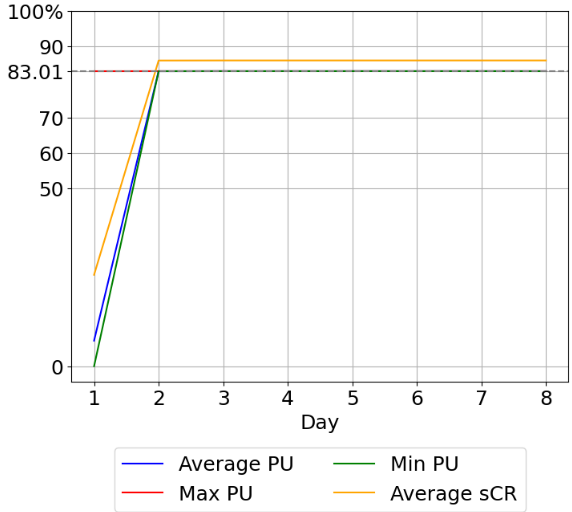
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

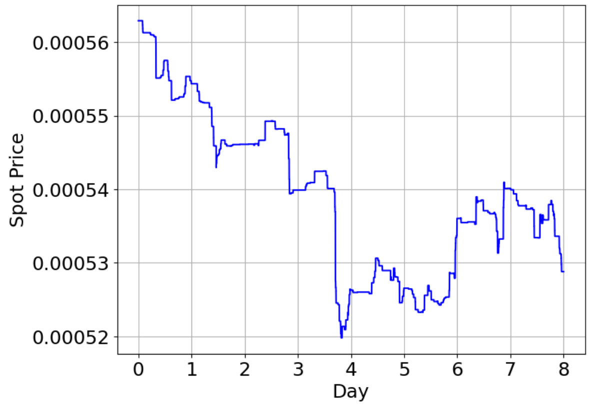
Figure 5.3: Token0 PU saturation and Seller's Collateralization Ratio for the four trading volume - liquidity scenarios, with the seller's *deposit_amount* input values as 5000.

5.2 Stage 2 Results

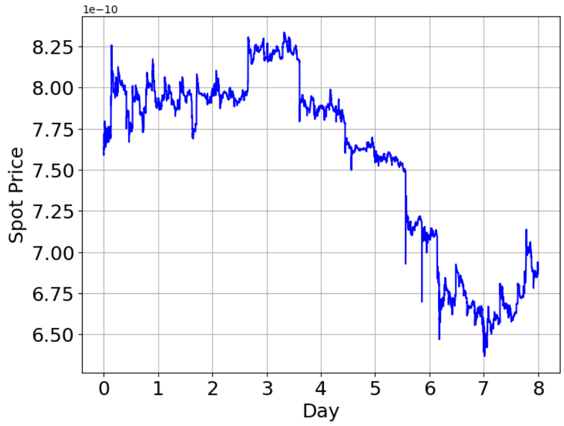
In this section, we start by confirming that the pools used replicate four distinct scenarios based on trading volume and liquidity. Subsequently, we present all the results obtained for the metrics listed in Section 4.1.

5.2.1 Confirming Scenarios

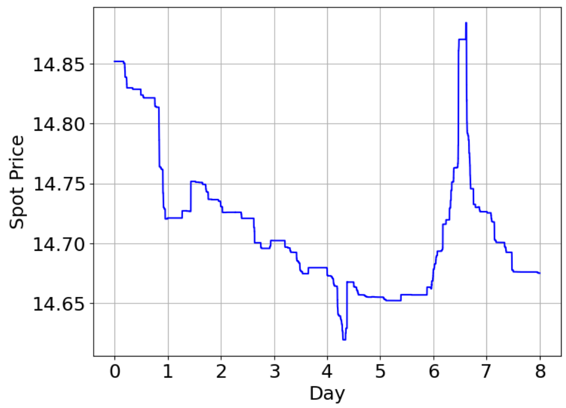
Firstly, in Figure 5.4, we illustrate the spot price trajectories of the pools enforced by the State Manager over the 8-day simulation timeframe. It is noteworthy that this trajectory was used both in this and the previous stage and it corresponds to the initial 8 days of the extended trajectory used in the subsequent stages, spanning a total of 56 days.



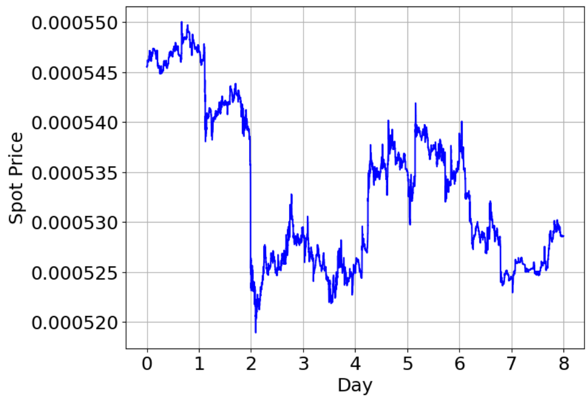
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



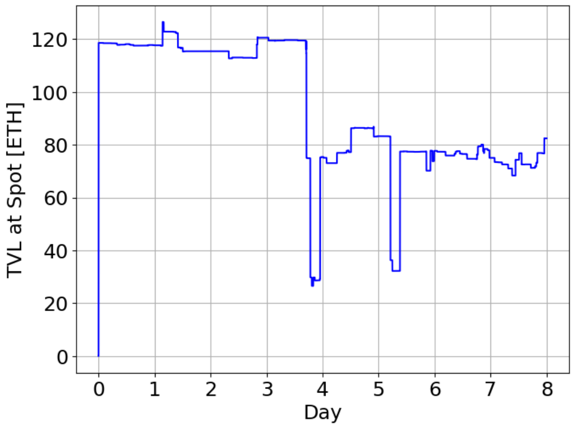
(d) USDC-ETH-500 pool

Figure 5.4: Spot price evolution, expressed as Token1/Token0 ratio, in each scenario pool for Stage 2 simulations.

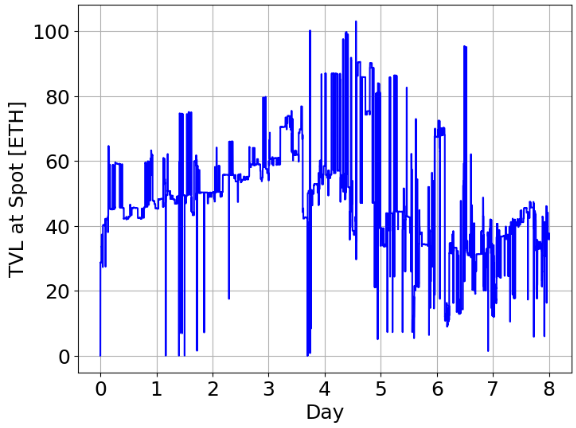
Next, we present the liquidity trajectories for the pool's spot tick imposed by the State Manager in the Uniswap Pool, based on the input target and the Option Sellers' actions, in the 8-day simulation. We express Uniswap's L parameter converted to TVL in ETH units for easy assessment of relative liquidity values between pools.

Observing Figure 5.5, we can conclude that the DAI and PEPE pools have low TVL (in the order of dozens of ETH) compared to the other two pools, whose TVL is in the order of hundreds/thousands. This confirms the intended scenarios regarding liquidity, as indicated in 2.1.

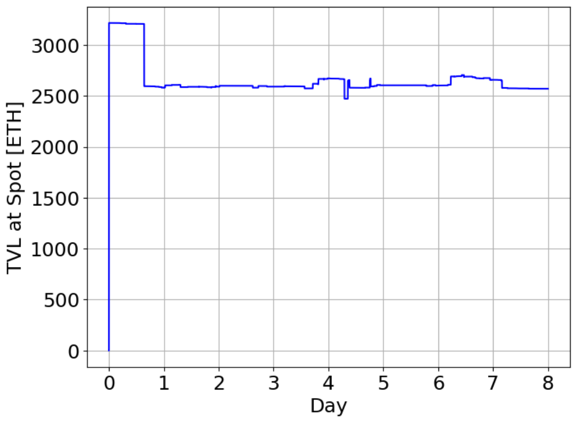
In further observations, it is apparent that, despite the WBTC pool having a higher TVL than the USDC pool, it also maintains a more stable spot, indicating lower activity, and/or a more uniform distribution of liquidity around the spot. On the contrary, the PEPE pool displays constant variations in TVL at and around the spot tick, implying continuous spot fluctuations, signaling high activity, and/or diverse tick liquidity around the spot.



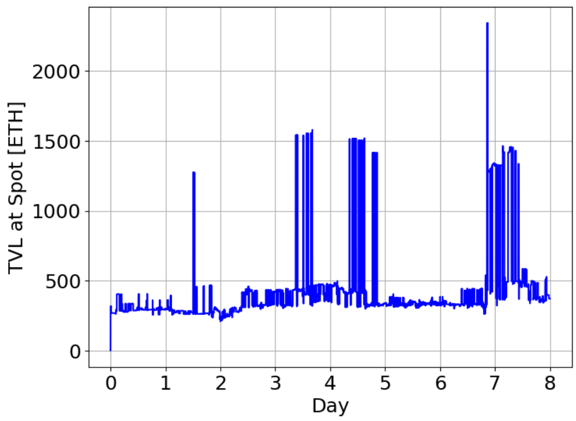
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



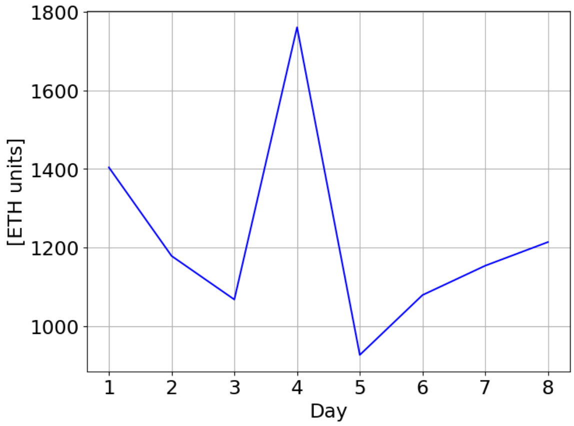
(d) USDC-ETH-500 pool

Figure 5.5: Total Value Locked at the spot tick, expressed in ETH units, in each scenario pool for Stage 2 simulations.

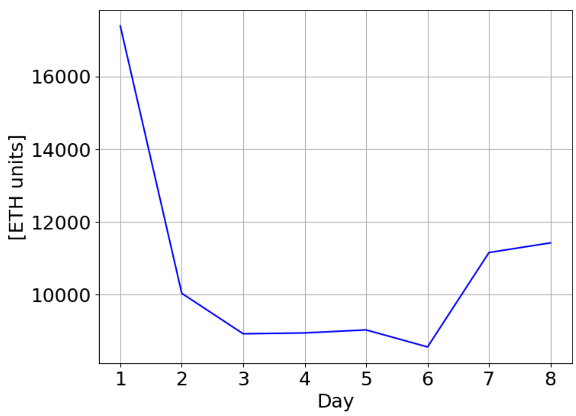
Concerning the scenario's trading volume aspect, Figure 5.6 showcases the daily trading volume for each simulation day. Once more, we may confirm the accuracy of pools chosen to replicate the four trading-volume-liquidity scenarios.

In the DAI pool, the daily trading volume is on the order of thousands of ETH, aligning with the scenario of low trading volume. On the other hand, the USDC pool exhibits a daily trading volume on the order of hundreds of thousands, confirming its scenario as having high trading volume.

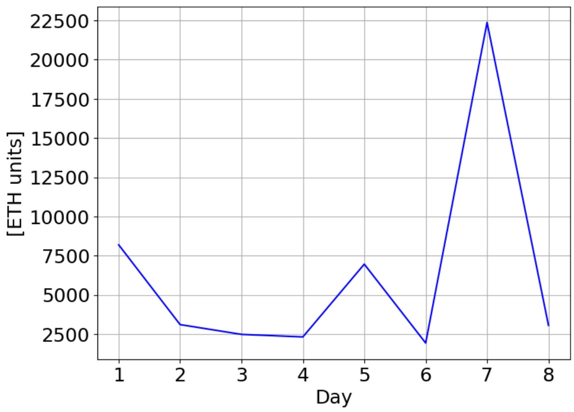
While the PEPE and WBTC pools have trading volumes of the same magnitude, the TVL values previously shown allow us to assert that the PEPE pool has high trading volume (roughly 100 times larger than the TVL), and the WBTC pool has low trading volume (around 2-3 times the TVL). This observation effectively confirms the proposed scenarios.



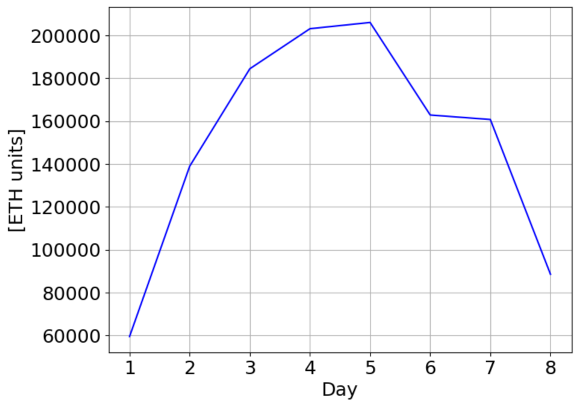
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



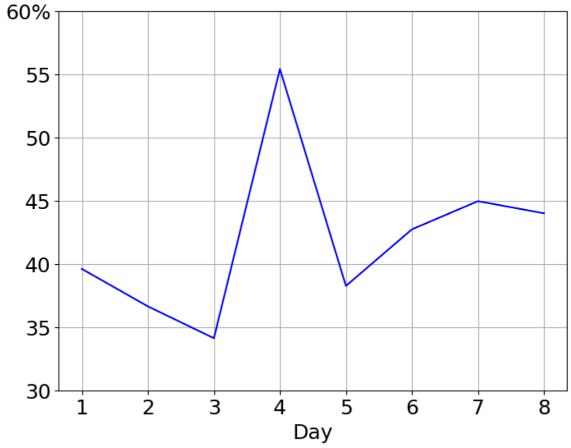
(d) USDC-ETH-500 pool

Figure 5.6: Daily Trading Volume, expressed in ETH units, in each scenario pool for Stage 2 simulations.

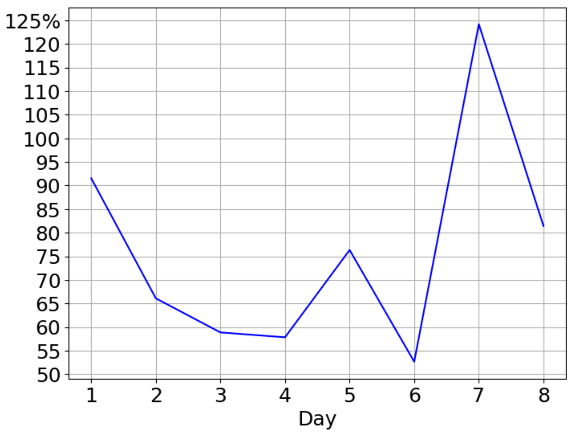
Finally, in Figure 5.7, we present the daily annualized implied volatility, calculated using Equation 4.1.1. IV is highly relevant in the realm of options trading, and in the context of our analysis, we will assess whether there is any influence of the IV on the metrics evaluated.

Regarding the average values of IV for each pool, it is evident that the PEPE pool has the highest IV values, while the WBTC pool has the lowest. This observation aligns with expectations, considering the low and high correlation, respectively, existing between Token0 and Token1 in these pools. Furthermore, the remaining two pools exhibit intermediate and similar IV values, as anticipated due to the similarities between their token correlations (DAI and USDC being both $1-value stablecoins).

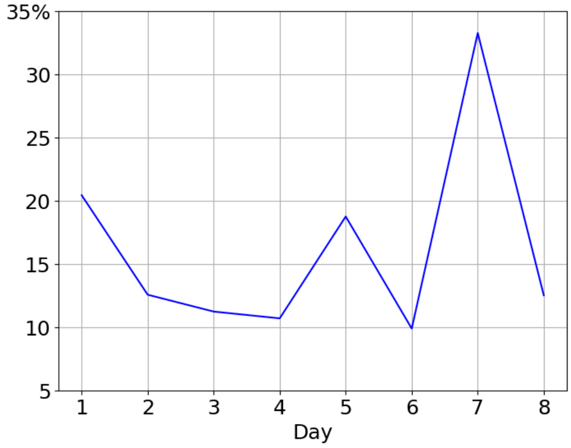
It is important to note that while all these results serve as an initial confirmation of the proposed scenarios, we will re-confirm the scenarios for each 8-week price/liquidity trajectory used in the next and last stages.



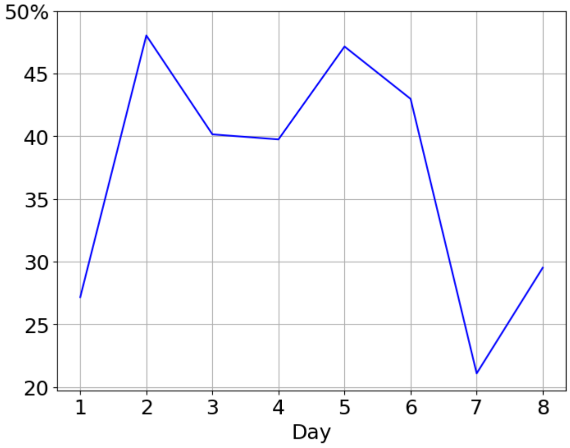
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.7: Daily Annualized Implied Volatility in each scenario pool for Stage 2 simulations.

5.2.2 Pool Utilization and Seller Collateralization Ratio

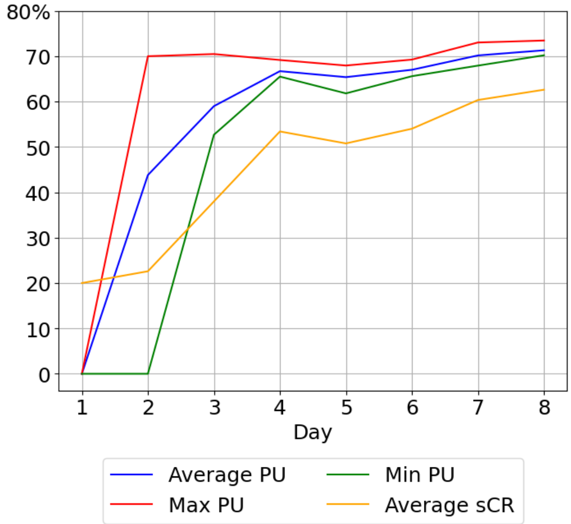
An analysis of the pool utilization and seller collateralization ratio values, depicted in multiple plots (see Figures 5.8 and 5.9), sheds light on the dynamics of pools with only sellers in the simulation, devoid of buyer counterparts. The findings affirm the anticipated trend: the average pool utilization and, consequently, the seller collateralization ratio exhibit a predominantly monotonous increase across various pools for both tokens. While some minor decreases are observed in certain instances, these fluctuations do not disrupt the overall upward trajectory, persisting until the simulation's conclusion.

The isolated instances of marginal PU reduction, exemplified by the PEPE pool for Token0 (in this case, PEPE), can be rationalized by specific temporal occurrences. For instance, during the transition from day 2 to day 3 in the simulation, PLP deposits surpassed the mint amounts of sellers, leading to a more substantial increase in Panoptic Pool funds compared to Uniswap. It is crucial to note that, given the absence of buyers, these localized decreases have minimal impact on the global upward trend of PU.

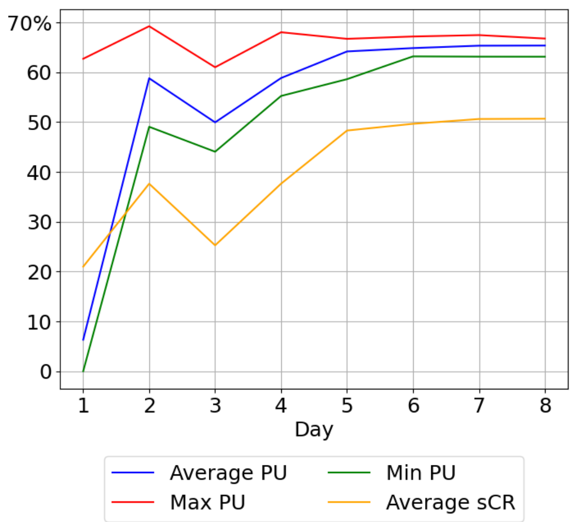
Moreover, these Stage 2 simulations substantiate the earlier assertions in this report.

While an increasing trend in PU is discernible, it ultimately plateaus at lower values than those identified in the PU saturation test cases. The latter, proven to be the highest attainable values under the specified conditions, set a benchmark that the PU in these simulations does not surpass.

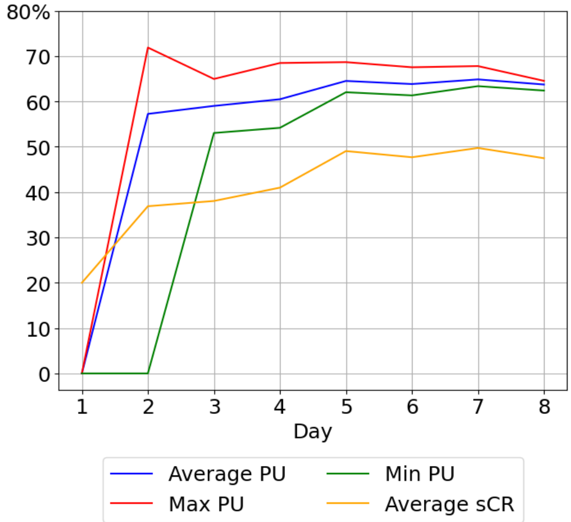
Finally, it is noteworthy that no direct relation between the PU trend and implied volatility seems to be present. This is expected, as neither PLPs nor Naive Sellers consider IV or even the price in their actions.



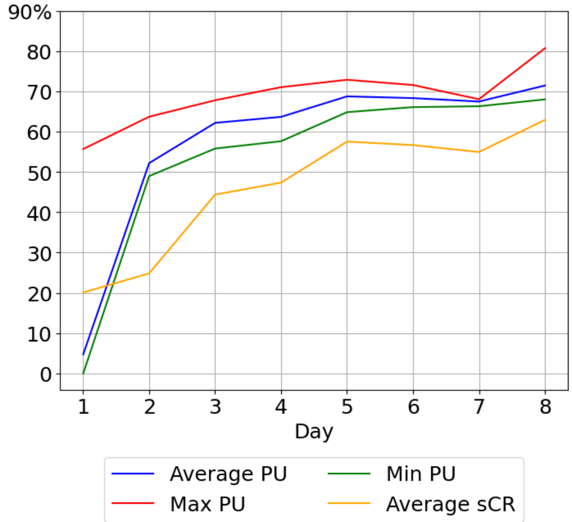
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.8: Pool Utilization and Seller Collateralization Ratio (Token0) for the four pools tested in Stage 2.

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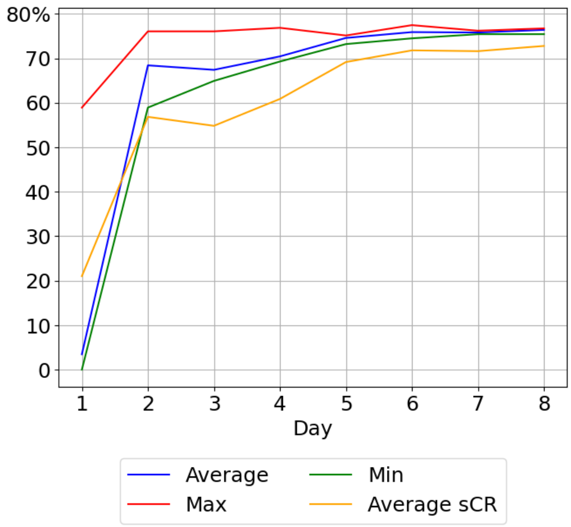
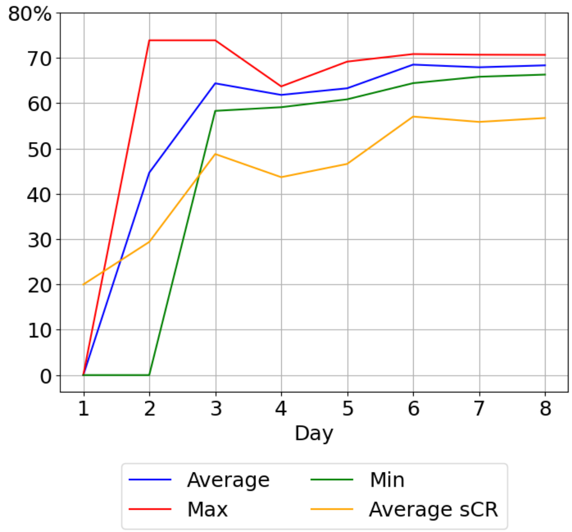
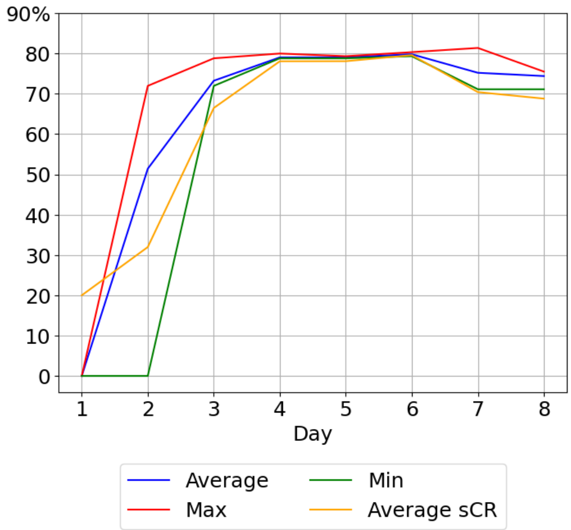


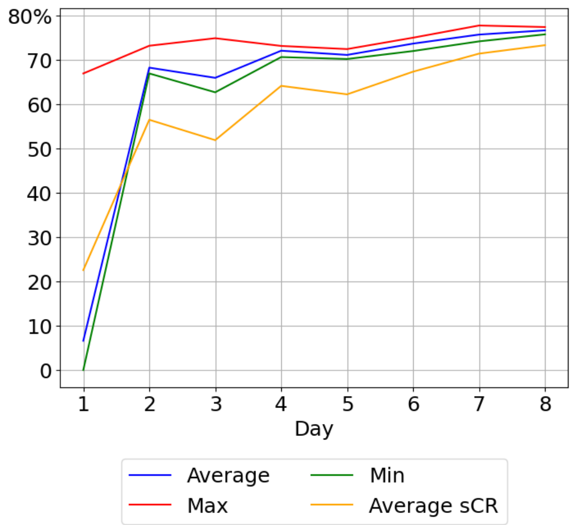
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.9: Pool utilization and Seller Collateralization Ratio (Token1) for the four pools tested in Stage 2.

5.2.3 PLP APYs and Additional Metrics

The findings pertaining to PLP withdrawals, as presented in Tables 5.1 through 5.3, align with the observed PU trends. Across all tested pools, withdrawals are either nonexistent or minimal, exerting negligible influence on the PU's evolution throughout the simulation. This is underscored by the fact that the PU never surpasses its theoretical maximum value, assuming no withdrawals. If withdrawals had played a significant role, there might have been occasional instances of PU exceeding saturation values on certain days. Such an occurrence, however, is not evident, and it would not discredit the earlier results.

Examining the outcomes related to deposits and withdrawals reveals a distinct contrast between the two identified profiles: active profiles, living up to their name, exhibit heightened engagement in both depositing and withdrawing funds. Notably, the prevalence of active profiles surpasses that of passive ones, providing the former with a heightened awareness of the protocol and, consequently, more opportunities for active participation.

Table 5.1: Number count and median amount of PLPs (active and passive) deposits and withdrawals as well as sellers' mints and rolls, for DAI-ETH-3000 pool.

	PLPs								**Sellers**			
	Active				**Passive**				**Mints**		**Rolls**	
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**					
	DAI	ETH	DAI	ETH	DAI	ETH	DAI	ETH	DAI	ETH	DAI	ETH
Count	51	12	1	0	5	4	0		16	16	29	36
Median amount	644.816	0.477	450.594	-	718.615	0.661	-		7137.332	3.733	-	

Table 5.2: Number count and median amount of PLPs (active and passive) deposits and withdrawals as well as sellers' mints and rolls, for PEPE-ETH-3000 pool.

	PLPs								**Sellers**			
	Active				**Passive**				**Mints**		**Rolls**	
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**					
	PEPE	ETH	PEPE	ETH	PEPE	ETH	PEPE	ETH	PEPE	ETH	PEPE	ETH
Count	49	53	0	1	6	6	0		16	16	49	34
Median amount	9.428e8	1.299	-	0.591	3.579e9	1.182	-		9.473e9	7.769	-	

Table 5.3: Number count and median amount of PLPs (active and passive) deposits and withdrawals as well as sellers' mints and rolls, for WBTC-ETH-3000 pool.

	PLPs								**Sellers**			
	Active				**Passive**				**Mints**		**Rolls**	
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**					
	WBTC	ETH	WBTC	ETH	WBTC	ETH	WBTC	ETH	WBTC	ETH	WBTC	ETH
Count	54	12	0		6	4	0		16	16	13	8
Median amount	0.177	2.924	-		0.148	5.103	-		2.003	17.923	-	

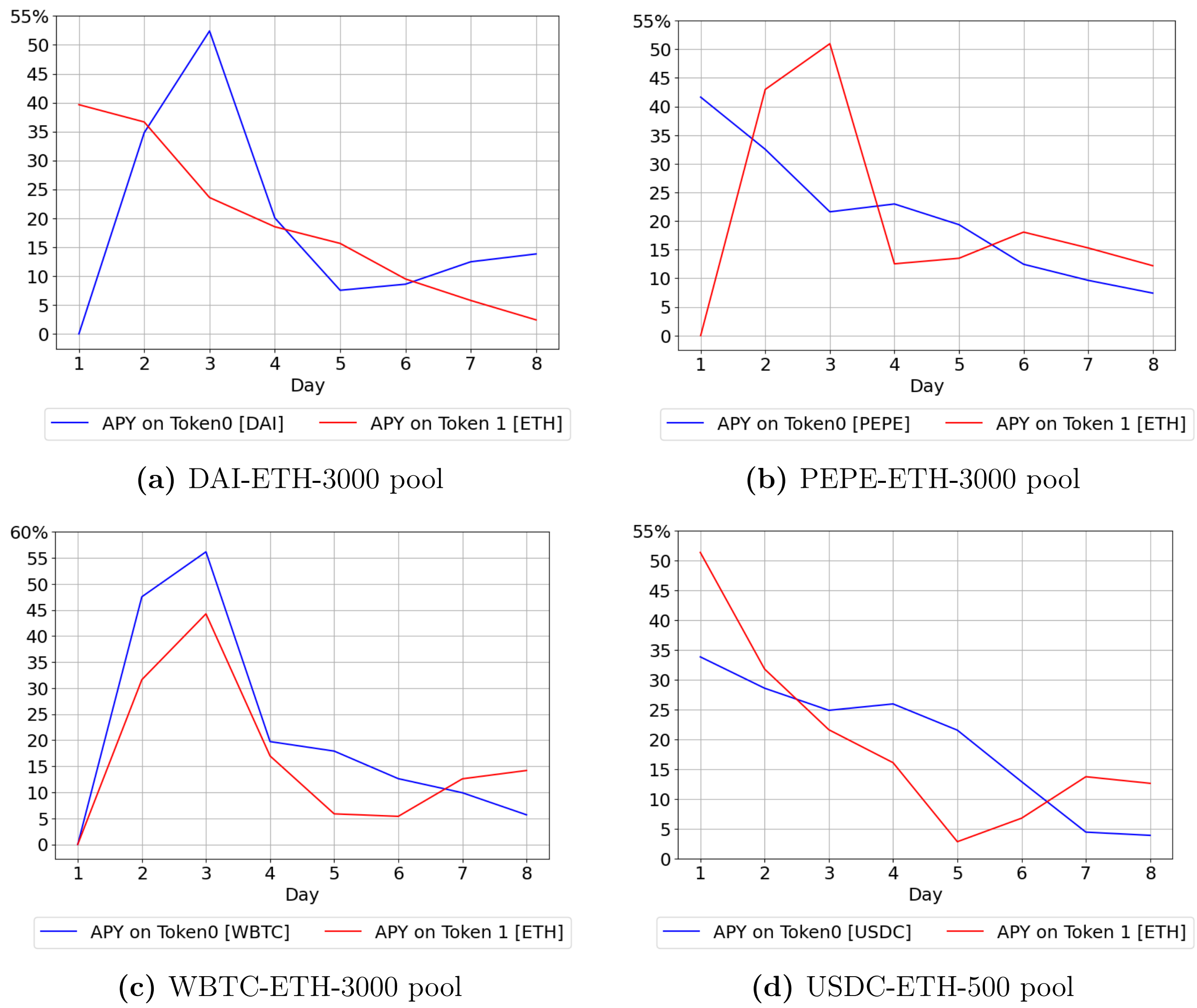
Table 5.4: Number count and median amount of PLPs (active and passive) deposits and withdrawals as well as sellers' mints and rolls, for USDC-ETH-500 pool.

	PLPs								**Sellers**			
	Active				**Passive**				**Mints**		**Rolls**	
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**					
	USDC	ETH	USDC	ETH	USDC	ETH	USDC	ETH	USDC	ETH	USDC	ETH
Count	44	12	3	0	7	4	0		16	16	48	35
Median amount	7081.888	1.491	42831.978	-	6545.421	1.229	-		53879.921	10.816	-	

Moreover, the data unmistakably indicates that deposit activities outweigh withdrawal activities across all pools. This assertion finds support in the tabulated results and is visually confirmed by the plots in Figure 5.10. Here, the 2-day moving average consistently exceeds 5% for the majority of the simulation in all pools. Considering that a significant segment of PLPs exhibit an APY threshold for withdrawal below 5%, the observed discrepancy between deposit and withdrawal activities becomes comprehensible.

Another noteworthy observation is that, with the exception of the PEPE-ETH pool, the remaining pools tend to attract a substantial majority of deposits in Token0 rather than Token1. This finding is reinforced by the plots in Figure 5.10. In the PEPE pool, the 2-day moving average APY curve for Token0 (PEPE) consistently attains higher values than the corresponding curve for Token1 throughout the majority of the simulation. Consequently, this pool is more prone to accumulating more deposits in Token0 compared to other pools, where the Token1 curve consistently remains higher.

Finally, it should be noted that the high APY values at the beginning result from the Panoptic Pool receiving the first deposits in each token. Within the simulation, the APY tends to decrease in all pools. Additionally, there is no clear relation between the APY and the IV (see Figure 5.7), as pools with both high and low IV have similar APY values. This was anticipated, as PLPs do not take into account IV or even the price in their actions.



(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

(c) WBTC-ETH-3000 pool

(d) USDC-ETH-500 pool

Figure 5.10: PLPs 2-day moving average annualized percentage yield for the four pools tested in Stage 2.

Concerning the seller's metrics (mints and rolls data in Tables 5.1 to 5.4) as anticipated, an equal number of mints occur in Token0 and Token1. In terms of rolls, the number of rolls is comparable in both tokens, with a slight inclination towards more rolls in Token0 for all pools except the DAI pool. Furthermore, the global number of rolls is significantly different in the WBTC pool, comparing with the remaining ones. This can be due not only to different roll action frequency, which can lead to different number of opportunities, but, most importantly, due to the fact that this is the pool with the lowest IV. Therefore, when seller's compute the new strike price to roll, higher is the probability of that new strike price being exactly equal to its current one, due, precisely, to the fewer price fluctuations observed in this pool. This, in fact, leads to a situation where the seller does not perform the roll, hence the fewer number of rolls in this pool.

5.3 Stage 3 and 4 Results

In Stages 3 and 4, we introduced Option Buyers to delve into the core of the protocol and analyze complete option trading cycles. As outlined in Chapter 4, Stage 3 features only naive agents (sellers and buyers) representing inexperienced option traders. In Stage 4, agents are dedicated, implying more stringent requirements for their actions. Throughout both stages, we maintained the use of the same 8-week price and liquidity trajectories for a given pool, aiming to demonstrate their adherence to the outlined scenarios. For the sake of brevity and under the assumption that regular users of Panoptic will be Dedicated Option Sellers and Buyers, we will solely present the Stage 4 results. However, we will still include comparisons with the results of Naive agent simulations whenever relevant distinctions arise. All Stage 3 results are fully accessible in Appendix D, which also provides a more concise description.

Next, we will reconfirm the scenarios evaluated within each simulation and analyze every metric outlined in both Sections 4.1 and 4.2.

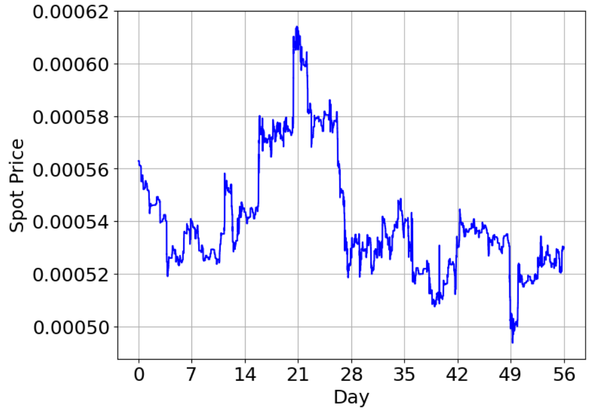
5.3.1 Reconfirming Scenarios

In the following figures, we can observe that, once again, the State Manager achieves its goal of reproducing the correct simulation environment for every intended liquidity-trading volume scenario. For the 56-day timeframe, the price trajectories used are presented in Figure 5.11. They are realistic and reliable as intended.

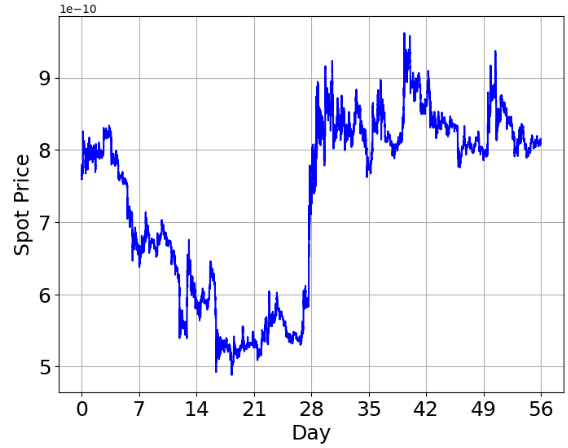
Concerning the liquidity aspect of the scenarios, we observe once more, in Figure 5.12, that DAI and PEPE pools have low liquidity, especially when compared, in terms of relative liquidity, to the other two pools analyzed: WBTC and USDC. Furthermore, as in Stage3 (see Figure D.1), the effect of larger stakeholders is observed in the DAI and USDC pools.

With respect to trading volume, it is evident from Figure 5.13 that PEPE and USDC pools once again encompass the relatively high trading volumes in contrast with the DAI and WBTC pools, as intended. In addition, one important pattern can be observed, in contrast with the results obtained in Stage 3. Here, all pools show an increasing tendency over the simulation timeframe. As a consequence, the IV tendency is also increasing, as observed in Figure 5.14.

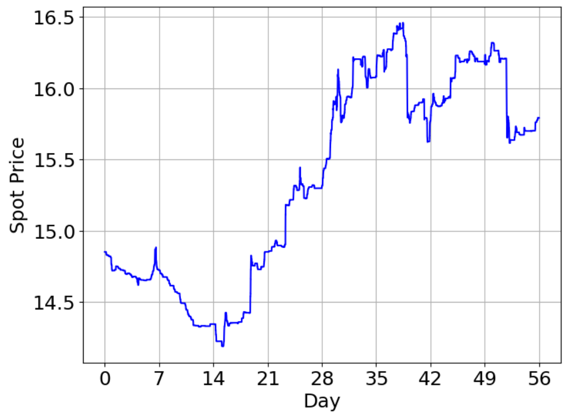
Nevertheless, the same relative positions in terms of scenarios are maintained: clearly, the PEPE pool is still the most volatile and representative of low liquidity and high trading volume; WBTC pool still remains the less volatile pool; USDC pool remains with the highest liquidity and still considerable IV, representing the most active and liquid pool; DAI pool, although with considerable IV, lacks activity.



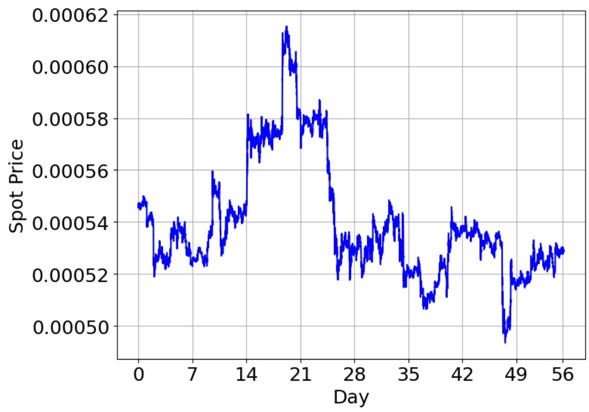
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool

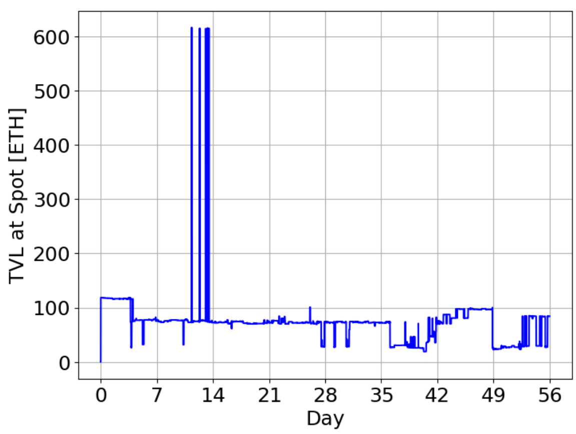


(c) WBTC-ETH-3000 pool

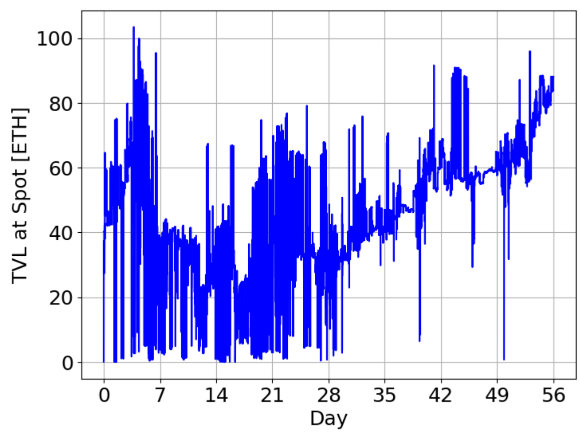


(d) USDC-ETH-500 pool

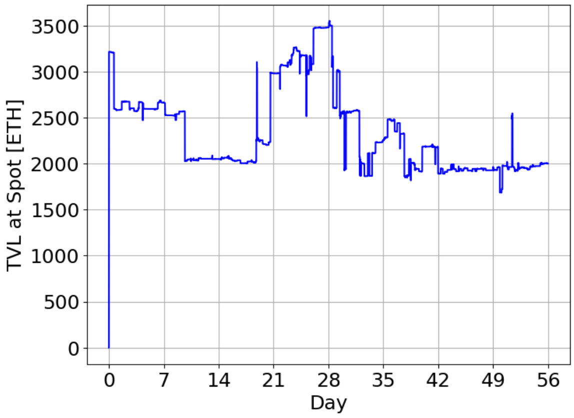
Figure 5.11: Spot price evolution, expressed as Token1/Token0 ratio, in each scenario pool for Stage 4 simulations.



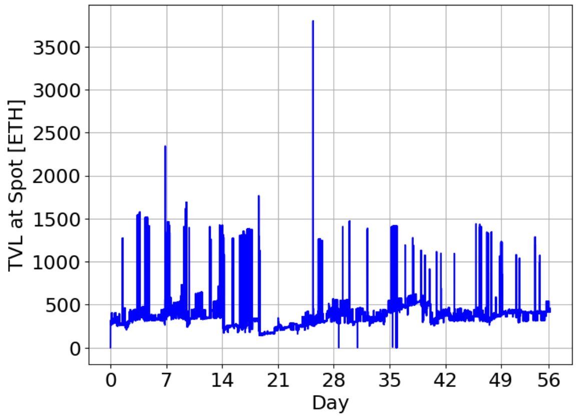
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool

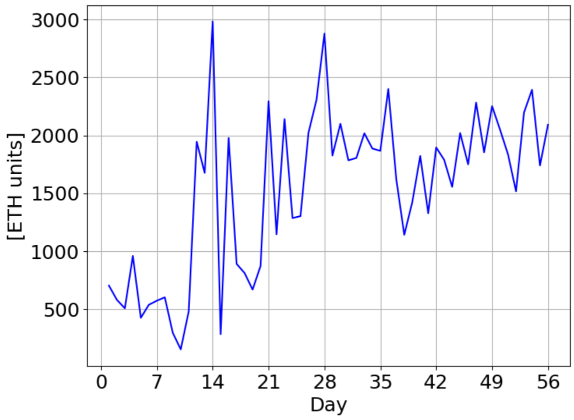


(c) WBTC-ETH-3000 pool

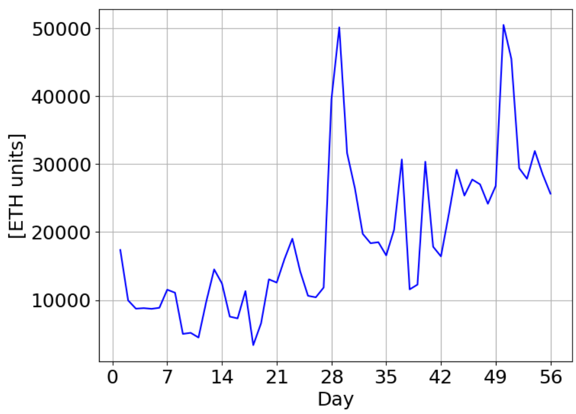


(d) USDC-ETH-500 pool

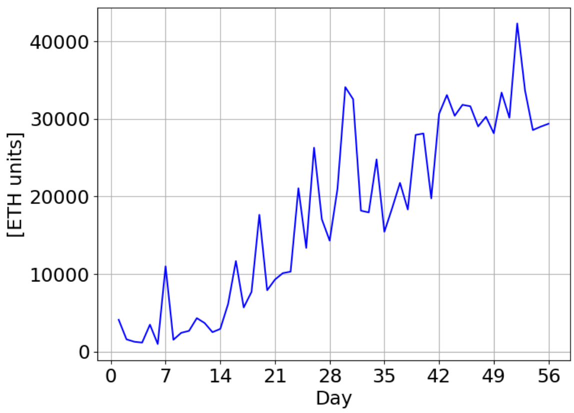
Figure 5.12: Total Value Locked at the spot tick, expressed in ETH units, in each scenario pool for Stage 4 simulations.



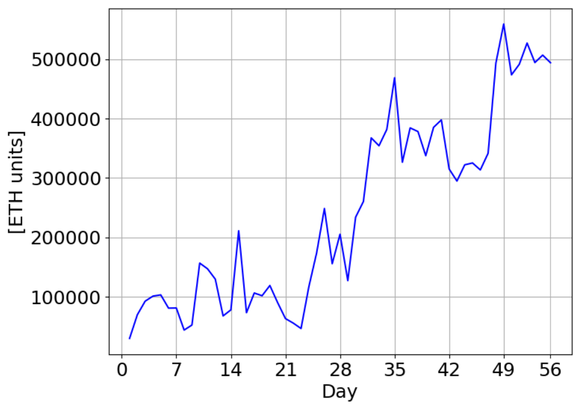
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.13: Daily Trading Volume, expressed in ETH units, in each scenario pool for Stage 4 simulations.

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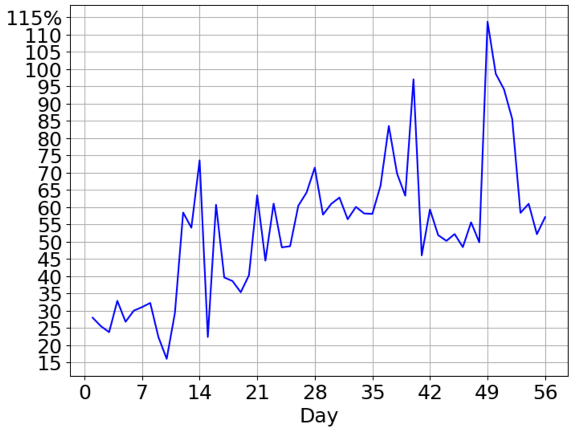
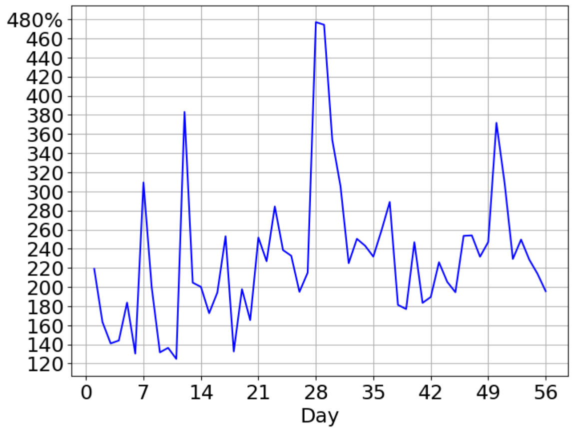
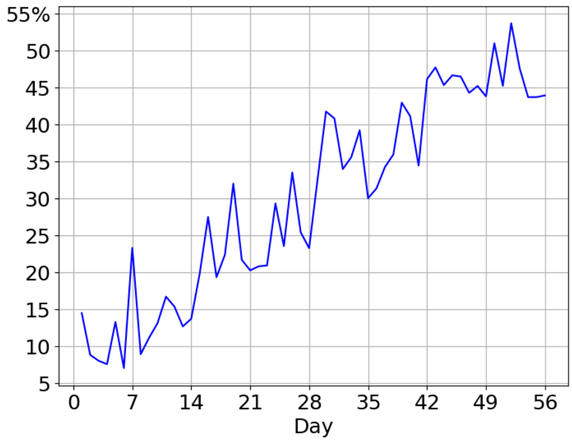


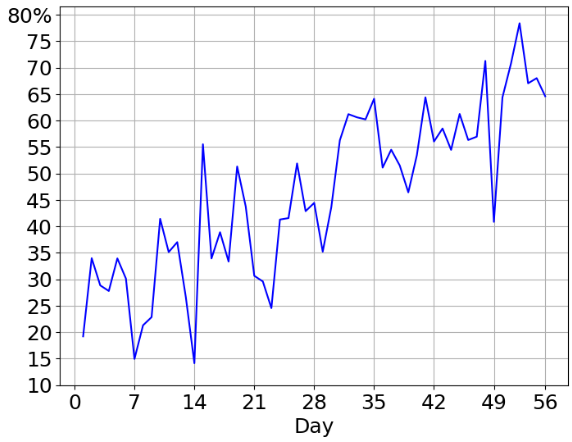
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.14: Daily Annualized Implied Volatility in each scenario pool for Stage 4 simulations.

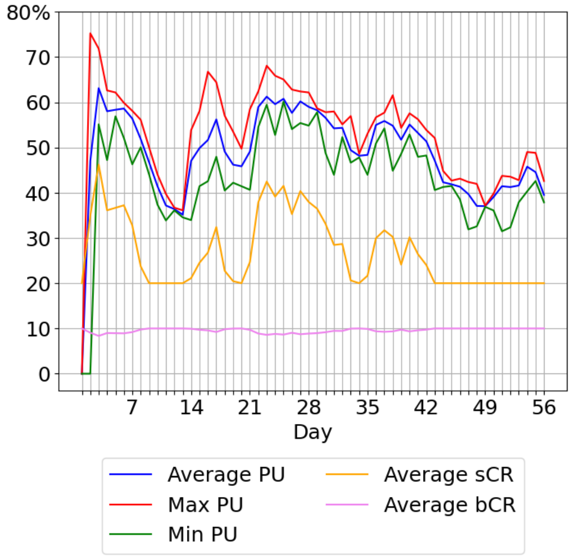
5.3.2 Pool Utilization and Seller / Buyer Collateralization Ratios

The initial observation of Figures 5.15 and 5.16 reveals that, across all scenarios, the maximum PUs are attained within the first half-week. During this period, all sellers are in the process of minting their initial options, thereby transferring liquidity to Uniswap, while buyers have not yet initiated their engagement. Subsequently, starting from the latter half of the first week, buyer activity commences, leading to a noticeable decrease in PU. As the regular dynamics take effect, the equilibrium PU value becomes more evident.

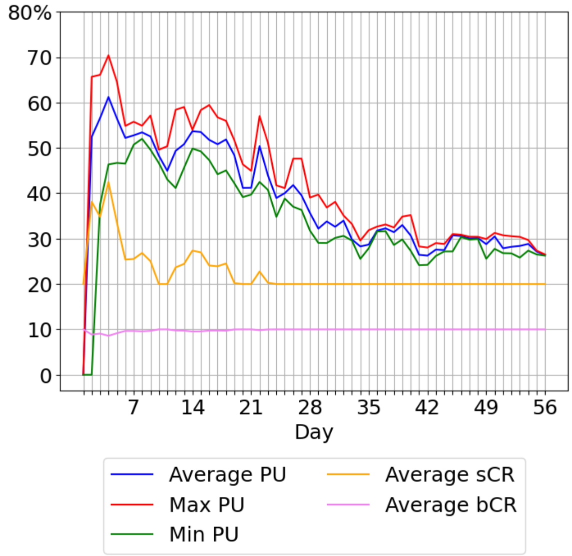
Analyzing the dynamics across different tested pools reveals insights into the stability mechanisms devised by the Panoptic protocol to prevent extremely high or low PU values. Clear patterns emerge when the PU surpasses the range of 60% to 70%: the accelerated increase in seller collateralization ratios creates less favorable conditions for sellers to participate, leading to decreased capital efficiency. Consequently, this discourages seller participation and results in a subsequent decrease in PU.

Conversely, when PU falls below 50%, the maximum incentive for sellers comes into play, i.e., the minimum seller collateralization ratio. While it is observed that the PU drops below 50% and remains in that circumstance for a significant period in the DAI and

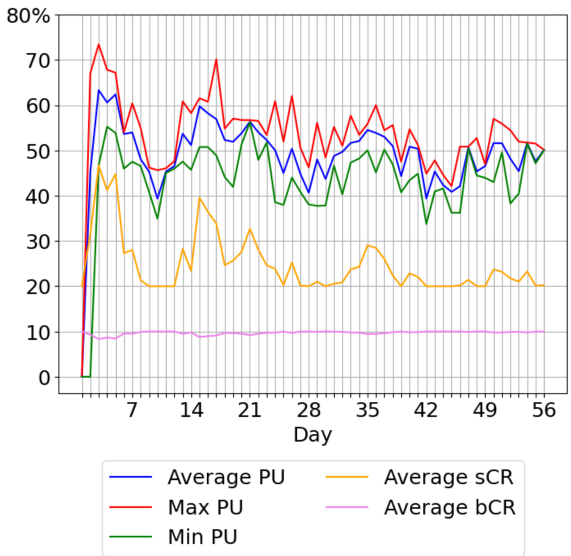
PEPE pools, one of two outcomes occurs: the PU returns to a value close to 50%, as seen in the DAI pool, or it stabilizes at a lower value, as observed in the PEPE pool. In either case, the dynamics of collateral ratios play a stabilizing role, preventing divergence and maintaining PU stability. Therefore, we may infer from this analysis that the liquidity-trading volume scenarios do not impact significantly PU behaviour, which was something already observed in Stage 3 (see here).



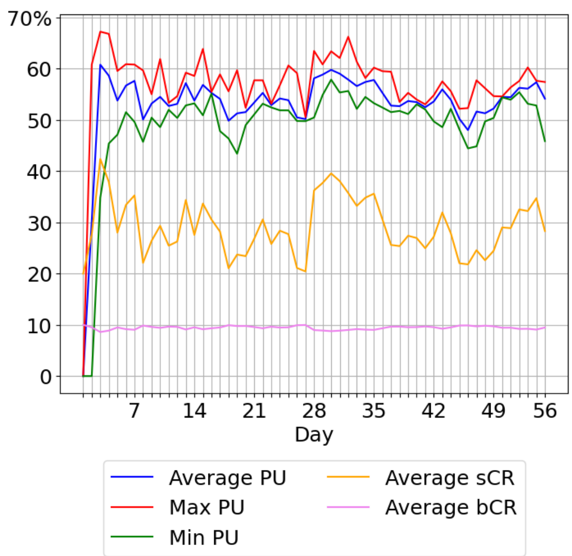
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.15: Pool Utilization and Seller Collateralization Ratio (Token0) for the four pools tested in Stage 4.

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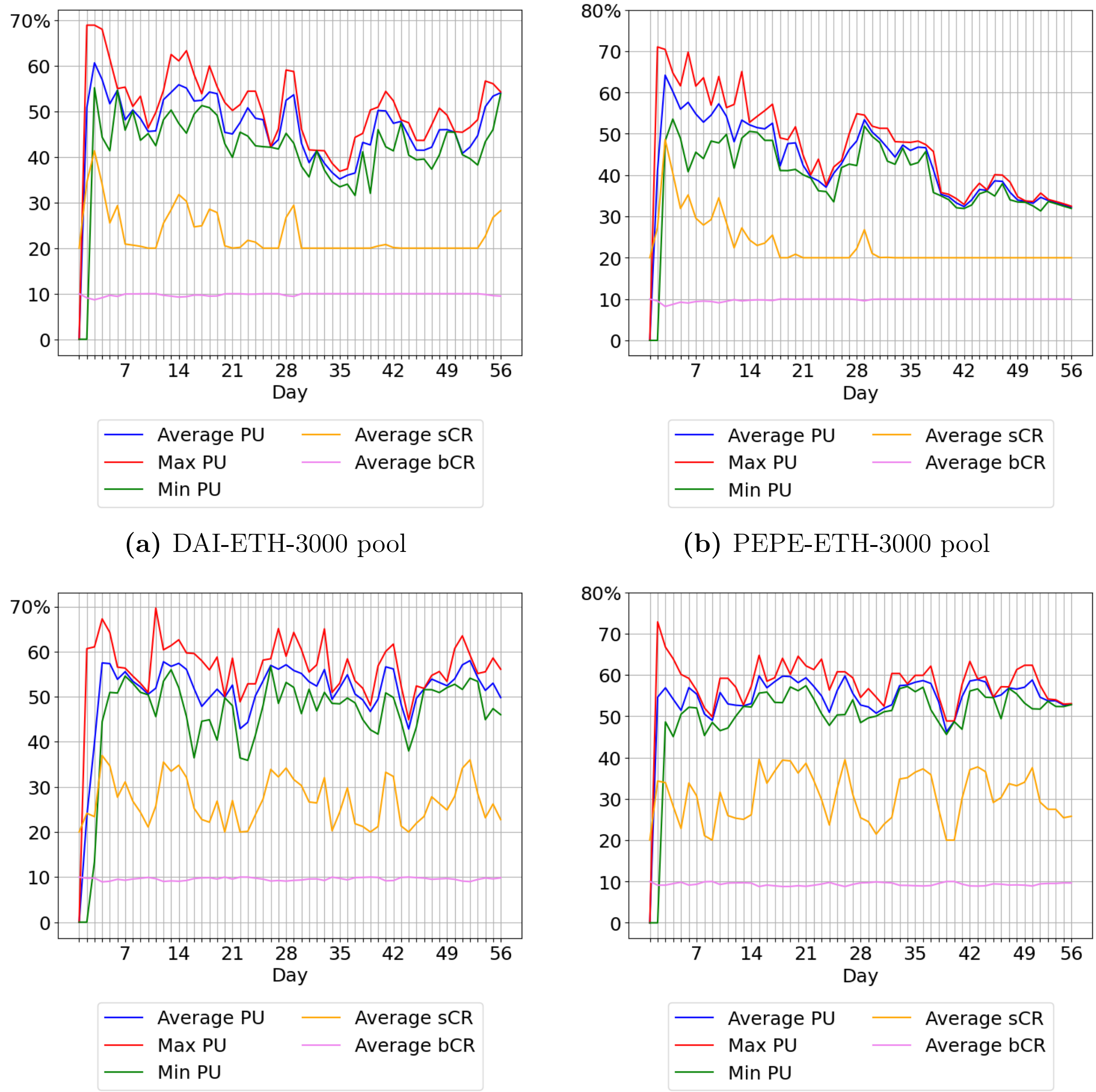


(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

(c) WBTC-ETH-3000 pool

(d) USDC-ETH-500 pool

Figure 5.16: Pool utilization and Seller Collateralization Ratio (Token1) for the four pools tested in Stage 4.

Finally, when comparing PU evolution between Token0 (Figure 5.15) and Token1 (Figure 5.16), one can conclude that, for the same pool, they exhibit remarkable similarity. They either stabilize from the beginning with minor oscillations (as seen in the USDC pool) or undergo more considerable fluctuations (as observed in the DAI and WBTC pools) around an anchor target value. Alternatively, the evolution is primarily characterized by an initial dominant decrease, ultimately stabilizing at a low value (around 30%) for both Token0 and Token1 in the PEPE pool.

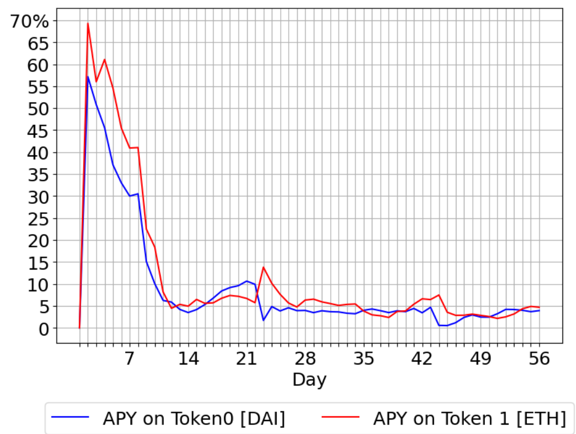
It is relevant to remind the reader that these agents do not take into consideration the past price evolution when deciding whether to mint an option. The inclusion of such an aspect would perhaps bring a more evident discrepancy between the PUs for each token.

5.3.3 PLP APYs

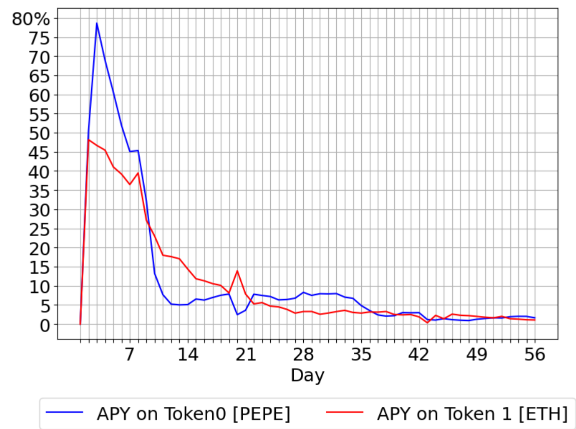
Regarding PLP APYs, numerous similarities between scenarios can be underscored once again. Not only is the overall evolution consistent across pools in this Stage 4, but when compared to the results from Stage 3, as provided in the appendix here, the patterns also exhibit substantial resemblance. Consequently, it is reasonable to assume that, once a stable context is effectively established, PLP APYs tend to oscillate around a target value of approximately 5% (lower for the high volatility scenario - PEPE pool).

While certain spikes are observed in specific APY curves, such as WBTC, primarily due to localized surges in depositing funds in Panoptic (direct funding by PLPs or collateral depositing by sellers and buyers), they do not significantly deviate from the overarching asymptotic decreasing trend.

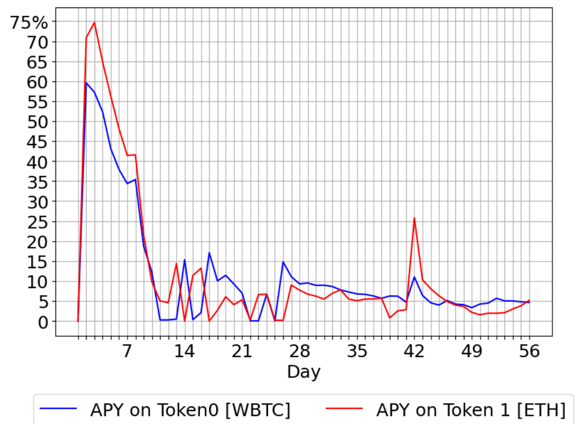
Lido's staking APR [9] is considered to be the crypto risk free rate. Panoptic liquidity providers stand to earn only slightly higher rewards in every liquidity-trading volume scenario. However, it is worth considering that being a pure PLP (when not engaging in option trading) may involve more risk due to the possibility of liquidations in case the protocol becomes insolvent. This may indicate a need for additional incentives for PLPs.



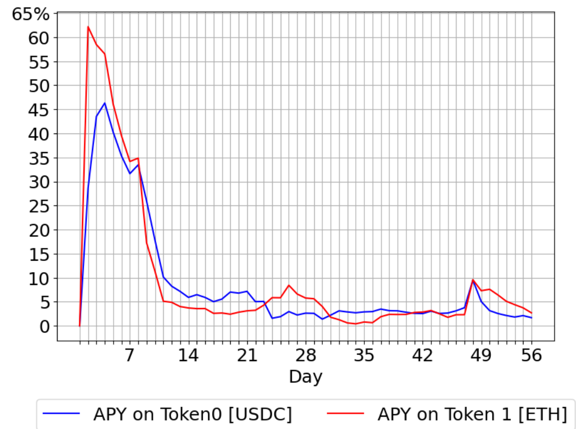
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.17: PLPs 2-day moving average annualized percentage yield for the four pools tested in Stage 4.

In fact, at certain points in the simulation, the APY plunges to extremely low levels, approaching 0%, thereby motivating PLPs with a low APY threshold to withdraw their funds. This statement is supported by the results presented in Tables 5.5 to 5.8.

Across most pools, a balance appears to be struck between the number of withdrawals in both tokens. The most significant disparity is observed in the WBTC pool, primarily due to more frequent instances of extremely low APY, even hitting 0%, on Token1.

Regarding deposits, we observe that for all pools, except the WBTC pool, there are more deposits for Token1 than for Token0, even though the APYs appear similar most of the time. This may indicate that, at the time of PLP action, the APY for Token1 was often above the *min_apy_to_provide* threshold compared to Token0. Alternatively, it could be attributed to the randomness in the generation of this threshold, with values closer to the lower boundary for agents depositing Token1 (token y). In the end, the most pertinent metric is the APY itself, where we do not observe any evident distinction. This aligns with expectations since these tokens exhibit similar PU behaviors, and the agents do not consider the price trajectory for their actions.

Finally, when comparing these results to the equivalent ones from Stage 3 (see here), we observe that there was a larger number of withdrawals in Stage 4 simulations, suggesting that, in general, the presence of dedicated option sellers and buyers resulted in slightly lower APYs in general, or at least, more oscillations towards lower values (as in the WBTC case). This is something to take into consideration since it seems that the presence of more informed option traders has a negative impact, although low, on the PLPs APYs on both tokens. Once again, some more incentives for PLPs may be thought upon.

Table 5.5: Number count and median amount of deposits and withdrawals of PLPs, for DAI-ETH-3000 pool in Stage 4 simulations.

	PLPs							
	Active				**Passive**			
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
	DAI	ETH	DAI	ETH	DAI	ETH	DAI	ETH
Count	58	96	15	21	21	31	0	
Median amount	773.101	0.558	3794.327	2.243	1264.303	0.583	-	

Table 5.6: Stage 4 number count and median amount of deposits and withdrawals of PLPs, for PEPE-ETH-3000 pool in Stage 4 simulations.

	PLPs							
	Active				**Passive**			
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
	PEPE	ETH	PEPE	ETH	PEPE	ETH	PEPE	ETH
Count	85	103	20	26	19	25	0	
Median amount	1.165e9	0.925	4.853e9	3.308	9.859e7	1.659	-	

Table 5.7: Number count and median amount of deposits and withdrawals of PLPs, for WBTC-ETH-3000 pool in Stage 4 simulations.

	PLPs							
	Active				**Passive**			
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
	WBTC	ETH	WBTC	ETH	WBTC	ETH	WBTC	ETH
Count	112	102	22	39	22	30	2	5
Median amount	0.169	3.488	0.278	11.204	0.543	3.179	0.546	3.058

Table 5.8: Stage 4 number count and median amount of deposits and withdrawals of PLPs, for USDC-ETH-500 pool in Stage 4 simulations.

	PLPs							
	Active				**Passive**			
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
	USDC	ETH	USDC	ETH	USDC	ETH	USDC	ETH
Count	68	85	25	26	23	27	0	1
Median amount	3720.407	1.532	7151.921	5.825	3187.019	2.926	-	4.049

5.3.4 Sellers Additional Metrics

In the tables below, we present the results regarding the sellers' mint and roll operations. It should be mentioned that we introduce a slight distinction in our definitions of ITM and OTM. In this context, ATM refers to the spot price being within the position range. For put options, OTM is when the spot price is above the position's upper tick, while for call options, OTM is when the spot price is below the position's lower tick. The reverse holds for ITM. Additionally, please note that in the tables, we provide the median size of the positions minted.

Table 5.9: Number count and median amount of sellers' mints and rolls, for DAI-ETH-3000 pool in Stage 4 simulations.

	Sellers									
	Mints		**Rolls**							
			Global		**ITM**		**ATM (in-range)**		**OTM**	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	76	78	30	23	12	23	18	0	0	0
Median amount	9303.757	9.267	-							

Table 5.10: Number count and median amount of sellers' mints and rolls, for PEPE-ETH-3000 pool in Stage 4 simulations.

	Sellers									
	Mints		**Rolls**							
			Global		**ITM**		**ATM (in-range)**		**OTM**	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	81	72	114	49	81	49	33	0	0	0
Median amount	2.368e10	12.309	-							

Table 5.11: Number count and median amount of sellers' mints and rolls, for WBTC-ETH-500 pool in Stage 4 simulations.

	Sellers									
	Mints		**Rolls**							
			Global		**ITM**		**ATM (in-range)**		**OTM**	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	77	75	41	1	3	1	38	0	0	0
Median amount	2.230	53.768	-							

Table 5.12: Number count and median amount of sellers' mints and rolls, for USDC-ETH-500 pool in Stage 4 simulations.

	Sellers									
	Mints		**Rolls**							
			Global		**ITM**		**ATM (in-range)**		**OTM**	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	74	70	105	93	85	92	20	1	0	0
Median amount	49655.71	33.501	-							

Concerning the minting of options, an expected balance is observed between the number of calls and puts sold. There is no consideration of the trajectory from the agents; hence, they mint options regardless.

Conversely, a noticeable discrepancy arises in the case of rolls, with more rolls observed in Token0 than in Token1. Moreover, we observe that these rolls occur either ITM or ATM. This differs significantly from Stage 3 results (check here), where the majority of the rolls occurred OTM. This is essentially due to the *max_blocks_hanging* threshold, which in Stage 4 is greater, giving more time for the option to be bought, whereas in Stage 3 (and in the previous stages) it forced the sellers to roll their positions daily.

The most particular case in this metric is the WBTC pool, where we observe that 93% of the options rolled were calls ATM. Considering that most of the price trajectory is ascending, we may infer that these rolls were caused due to the spot price being above the option's strike price. With a more detailed look, we may infer similar reasoning for the remaining pools. For example, the DAI and USDC pools have both a great ascent and descent in price, which may justify the similar value for the calls and puts rolled ITM.

In conclusion, we may state that our agents rolled their positions rationally and contributed to the normal Panoptic dynamics. The type of scenario had no significant influence.

5.3.5 Option Buying and Exercising Metrics

Next, we present the simulation results regarding the buying and exercising actions and their impact.

5.3.5.1 Number and Ratio of Options Bought and Exercised

In Table 5.13, we display the overall number of bought and exercised options for both call and put types. Additionally, the global ratio between these two actions throughout the simulation is provided.

Table 5.13: Number of Options Bought and Exercised for each pool tested in Stage 4 simulations.

	No. Options Bought		No. Options Exercised		Exercised / Bought Options Ratio
Pool	**Calls**	**Puts**	**Calls**	**Puts**	
DAI	60	75	51	65	0.86
PEPE	66	52	59	48	0.91
WBTC	70	57	59	49	0.85
USDC	48	39	42	33	0.86

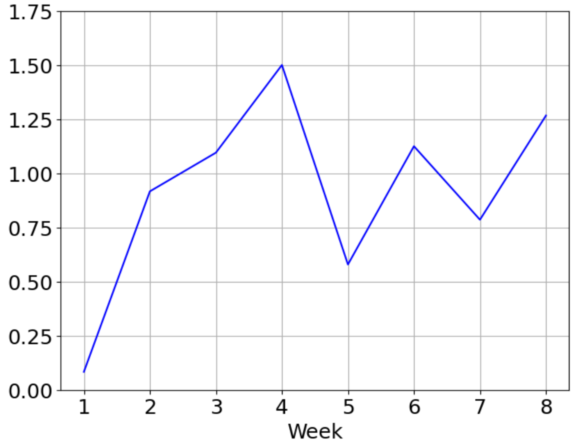
The main observation from this table is that all scenarios demonstrate comparable ratios between the number of exercised and purchased options, despite variations in the quantities of each option type. These ratios are slightly higher than those observed in Stage 3 (see here), which aligns with the increased sophistication of Stage 4 agents. Furthermore, this consistency implies that, irrespective of the price and liquidity trajectories, the general behaviors of the agents remained consistently similar. This alignment was expected, as the agents' actions are not contingent on specific price trends.

For reference, we also provide in Table 5.14 the median amount of the options bought.

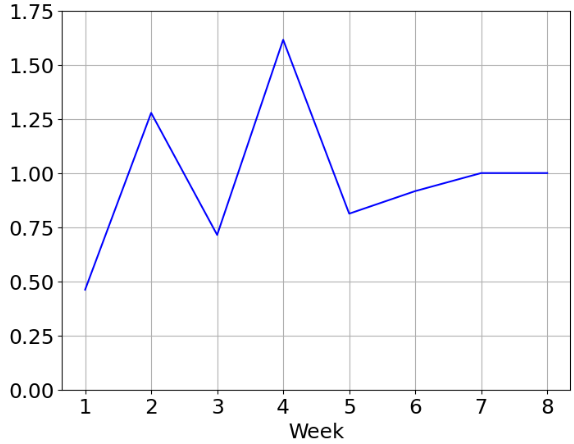
Table 5.14: The median amount of the call and put options bought in each scenario pool for Stage 4 simulations.

	Pool			
Option Type	DAI	PEPE	WBTC	USDC
Calls	6178.974	1.695e10	1.461	29853.927
Puts	6.148	9.276	37.696	24.461

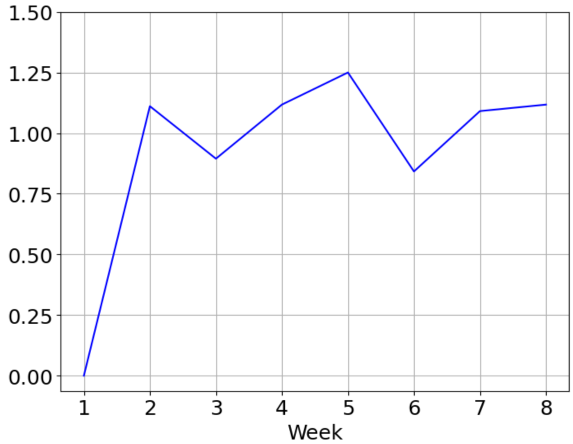
Concerning the weekly ratio between the number of options exercised and the number of options bought, the results depicted in the plots below indicate that, across all pools, the evolution is generally characterized by a balance, with a tendency to hover around the value of 1. Although we observe occasional spikes in opposite directions in consecutive weeks in every pool due to specific moments in the price trajectory, no significant differences between liquidity-trading scenarios are evident. Thus, we may conclude that, with the current modeling, this metric is not sensitive to the varying scenarios and its respective trading volume and IV characteristics.



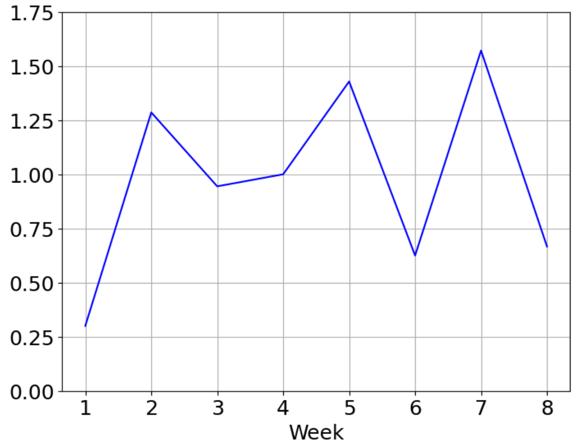
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



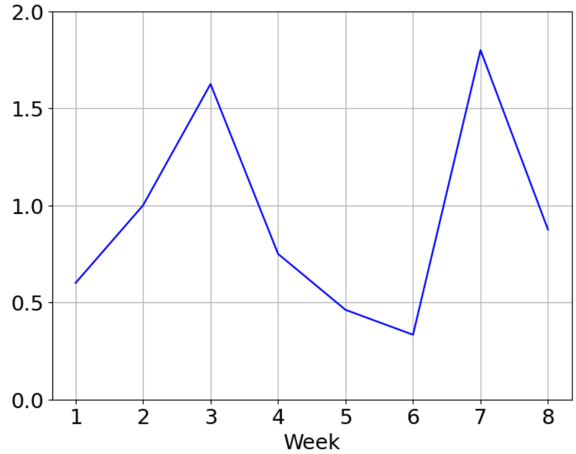
(d) USDC-ETH-500 pool

Figure 5.18: Ratio between the number of exercised and bought options on a weekly basis in each scenario pool for Stage 4 simulations.

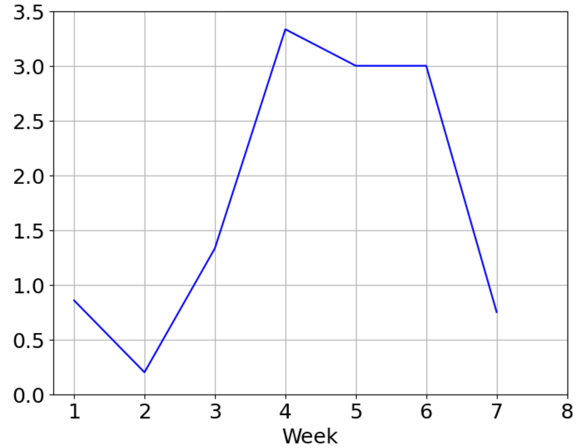
5.3.5.2 Ratio between the number of Call and Put Options Bought

Before analyzing the results for the weekly ratio between long calls and long puts shown in Figure 5.19, it is important to remember that, with the current modeling, option buyers (or sellers) do not consider the past price tendency in their decisions for purchasing options. However, when exercising them, the price tendency plays a primary role, as we will be able to evaluate in the next section. Upon exercising, options buyers are free to go buy another option (in our approach, they are limited to holding one option at a time). Hence, there is an indirect and *a posteriori* influence of the price tendency on the number of options bought.

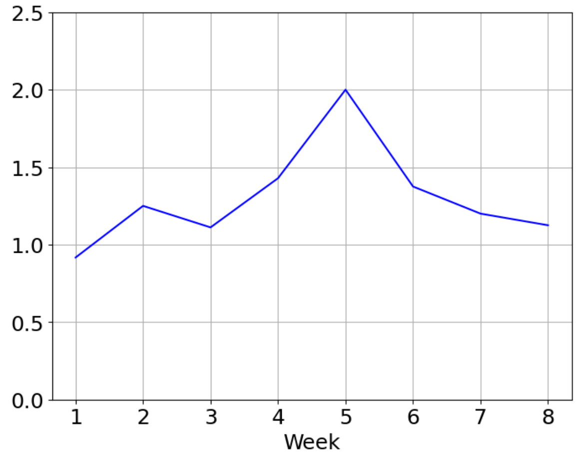
With this in mind, we observe that, in general, there is no discernible pattern in the results, although there are observable differences relative to Stage 3 results (check here). In Stage 3, there was a more evident alternance of the ratio around 1, whereas at this stage, the ratio has more consistency above or below one before turning below or above one, respectively. Nonetheless, this inevitably happens in all pools, except for WBTC, which we will address briefly. These differences from Stage 3 may be attributed essentially to the increase in exercising (and buying) frequency (reduction in the number of blocks) and the conditions to do so, as aforementioned.



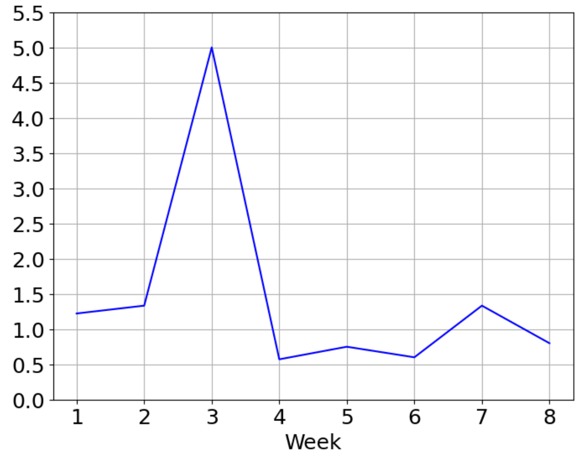
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.19: Ratio between the number of call options and put options bought on a weekly basis in each scenario pool for Stage 4 simulations.

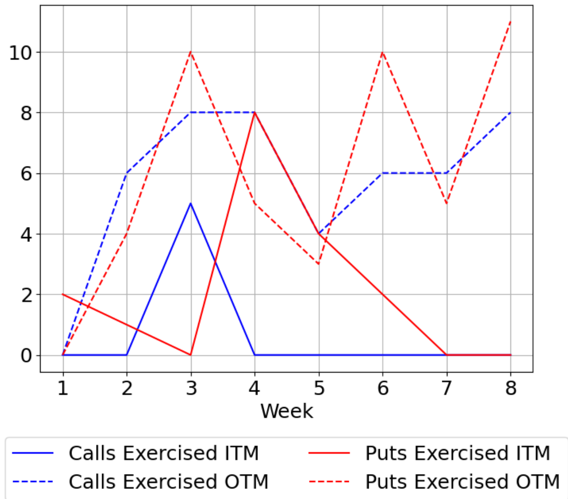
In particular, we observe that at this stage, DAI and USDC pools have more similar behaviors than before, which is more expected due to their similar trajectory. However, their peaks on the third week, coincident with a surge in the price, have quite different magnitudes. This discrepancy can be partially attributed to the randomness not only in the base frequency of buyer actions in the simulation but also to the stochastic component that updates the new frequency of actions for each agent at every block. Also, it is dependent on the number and type of options that were exercised previously.

Another difference from Stage 3 is in the PEPE pool. At this stage, most of the timeframe, the ratio is above 1. As it will be possible to state in the next metric, most of the options exercised in those weeks were, in fact, calls, opening the opportunity, as explained before, for call buyers to act more.

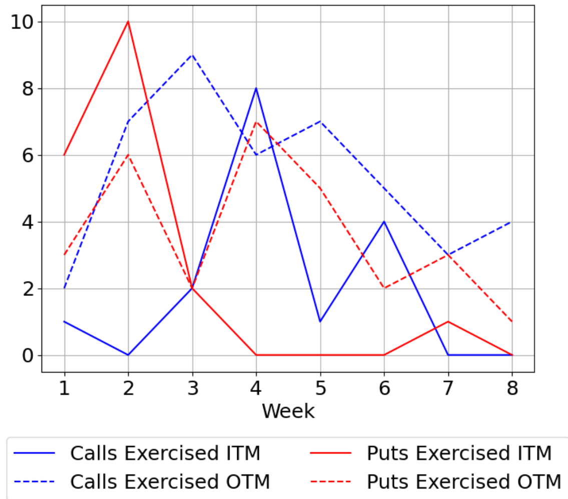
Finally, when observing the results for the WBTC pool, we verify that, except for the first week, the number of long calls surpassed long puts, although not so pronounced as in the PEPE pool. In fact, we may attribute once more to the more prominent exercising of calls instead of puts (as it can be observed in the next section and as it was already observed in Table 5.13), caused by the consistent uprising price trajectory. A complementary analysis is provided next.

5.3.5.3 Number of Call and Put Options Exercised ITM and OTM

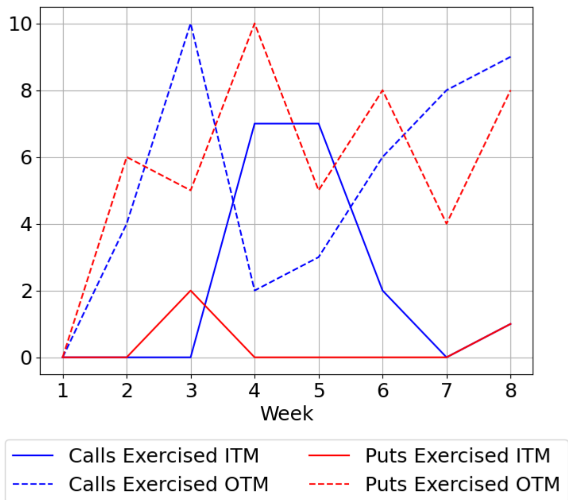
We present in Figure 5.20 the results related to the number of exercised calls and puts in an ITM or OTM position, as per our original definition. In these results, we can identify direct relationships with the price trajectories since these are the main influences on these metrics.



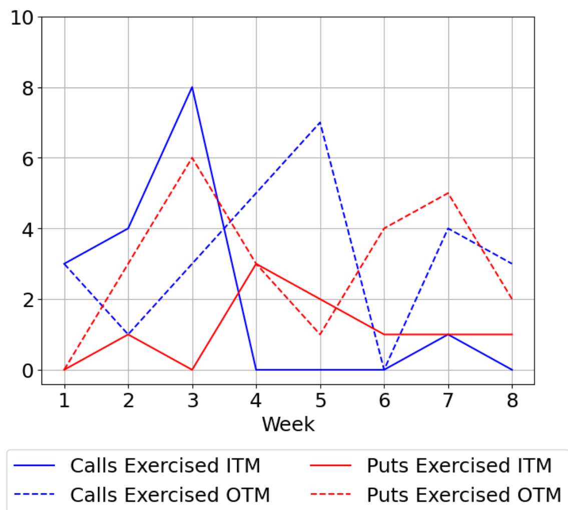
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.20: Number of call options and put options exercised both ITM and OTM on a weekly basis in each scenario pool for Stage 4 simulations.

In particular, in the DAI pool, we observe that for the whole timeframe, there is a clear prevalence of exercised OTM calls over ITM calls. This can be largely attributed to the evolution of the spot price, which is predominantly decreasing, specially after the beginning of week 4. Interestingly, the only instances of exercised ITM calls occur just before the initial decrease in week 4, with five exercises of ITM calls in week 3. Conversely, in the USDC pool where the price trajectory is integrally similar, the results are not so similar. This shows that not only does the trajectory influence, but the agent's timing and preferences for exercising in terms of yield and patience also play a primary role.

The influence of the price trajectory is also very noted in the WBTC pool, where the number of exercised OTM puts consistently exceeds, by a significant margin, the number of ITM puts exercised. This can be partially attributed to the price evolution in this pool. Specifically, the WBTC pool exhibits a prominent upward trend from the third to the sixth week, which notably impacts the performance of long puts. Identical conclusions are withdrawn from the decreasing price tendency in the first two weeks, which led to the number of calls exercised OTM surpassing the ITM exercises.

At last, it is relevant to say that regarding scenario distinction with respect to the trading volumes and IVs, these results are not sensible. Once more, this was expected due to the nonexistent consideration of such parameters for the agents' exercising action.

5.3.5.4 Exercising Yield and Loss

On Tables 5.15 and 5.16, we present the results concerning the exercising yield and loss metrics.

Table 5.15: Mean, minimum and maximum values for the yield derived from exercising ITM options for the four pools tested in Stage 4 simulations.

	Exercising Yield (%)		
Pool	**Mean**	**Minimum**	**Maximum**
DAI	10.766	-70.467	38.495
PEPE	25.749	-179.456	117.710
WBTC	13.273	-10.876	34.931
USDC	19.807	-39.652	62.245

Table 5.16: Mean, minimum and maximum values for the loss derived from exercising OTM options in each scenario pool for Stage 4 simulations.

	Exercising Loss (%)		
Pool	**Mean**	**Minimum**	**Maximum**
DAI	-11.980	-0.714	-69.933
PEPE	-62.392	-0.714	-271.736
WBTC	-4.625	-0.714	-44.517
USDC	-19.658	-0.714	-67.529

In these metrics, the PEPE pool stands out distinctly from the remaining pools. Not only does this pool exhibit the highest average exercising yield among the different pools, but it also records the highest mean exercising loss (in absolute terms). This observation reinforces the notion of a high-volatility pool, translating into a scenario characterized by high risk and high reward.

Conversely, the WBTC pool occupies the other end of the spectrum. Although it does not boast the lowest exercising yield among the pools, it clearly exhibits the narrowest range between the minimum and maximum exercising yields. Additionally, it is the pool with the most modest exercising loss values, lowest in absolute terms. These findings align with the anticipated behavior of a low-volatility pool.

It is important to clarify and remind the reader that the reason for which there are negative exercising yields with the option ITM is that the option's position accumulated premium to a point where the ITM amount was not enough to compensate. At the end of the buyer's patience to exercise, after multiple readjustments of their initial yield objective, the option's profit did not meet that requirement and, after reaching the maximum threshold related to the decrease of yield relative to its initial value, they exercised with an actual loss. Additionally, one should draw the reader's attention to the fact that the minimum loss possible, which is registered on Table 5.16, comes from an OTM exercise from a buyer in a condition where no premium was accumulated.

It is also relevant to compare these results to the ones of Stage 3 (see here). The most evident observation we can make is that, namely, the maximum yields at Stage 4 are, in general, lower than for Stage 3, but so are the losses (in absolute values). This is essentially due to the fact that at Stage 3, agents would consider exercising options on a daily basis, and here that frequency was somewhat between thirty minutes and twelve hours, allowing less time for yield or loss growth.

Moreover, the dedicated buyers present in this stage incorporate two thresholds that can account for the variations in results compared to those obtained in Stage 3: the patience to alter their target yield for exercising and the maximum acceptable decrease in relation to their initial yield target. The introduction of these two thresholds, absent in Stage 3, enhances the rationaty of the decision-making process for exercising from the buyer's perspective.

Furthermore, it is evident that the mean values for yield in Stage 4 are lower in all pools than those observed in Stage 3. This is partly due to the fact that the minimum values in Stage 3 are consistently positive, in contrast to the negative minimum yield values observed in Stage 4. This behavior was previously explained in an earlier paragraph. Such a rigid and somewhat unrealistic pattern is not typical in a buyer's profile. In Stage 4, the introduction of the aforementioned thresholds leads to a more realistic approach. When a buyer chooses to exercise with a loss, it leads to negative values in the minimum yield column. Since this systematic behavior is characteristic of Stage 4 buyers, the mean yield values are also impacted and decrease accordingly.

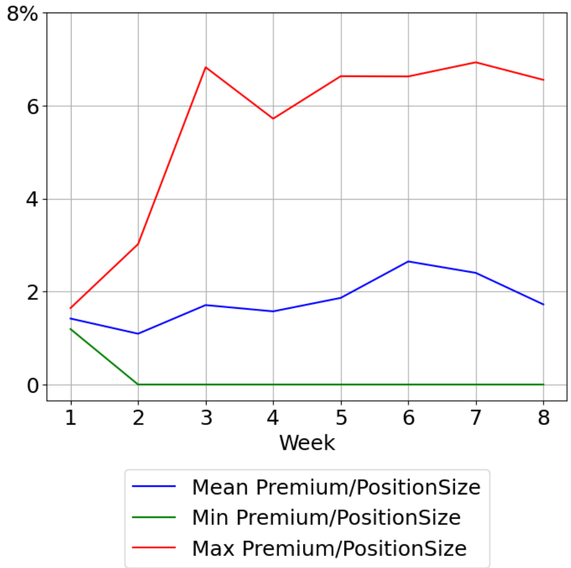
5.3.5.5 Premium's Relative Magnitude to Option's Position Size

The results concerning the premium's relative magnitude to the corresponding option's position size are presented in Figure 5.21. Here, it is once more visible the nature of each pool.

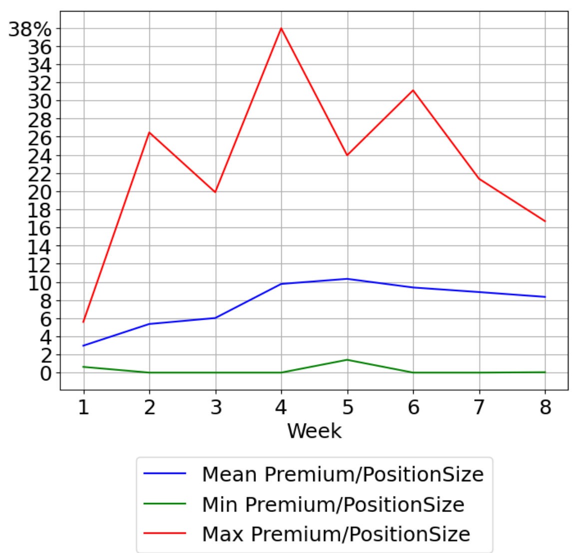
In this metric, the WBTC pool stands out, showing that, among the scenarios tested, the accumulated premium is significantly lower, solidifying its identity as the pool with the lowest IV. This lower IV implies fewer spot price changes, resulting in a less probable accumulation of premiums. Curiously, in comparison with the results from Stage 3 (check here), this is the only scenario where, for these trajectories, the accumulated premium was on average higher than in Stage 3. In all others, the contrary was verified.

In contrast, the PEPE pool, characterized by the highest spot price changes and thus a high IV, exhibits the highest accumulated premium in options. Furthermore, excluding the PEPE pool, the remaining pools fail to surpass the 10% mark of premium accumulated. This falls well below the threshold for buyers to exercise their options in an OTM position, precisely due to the relatively low premiums accrued.

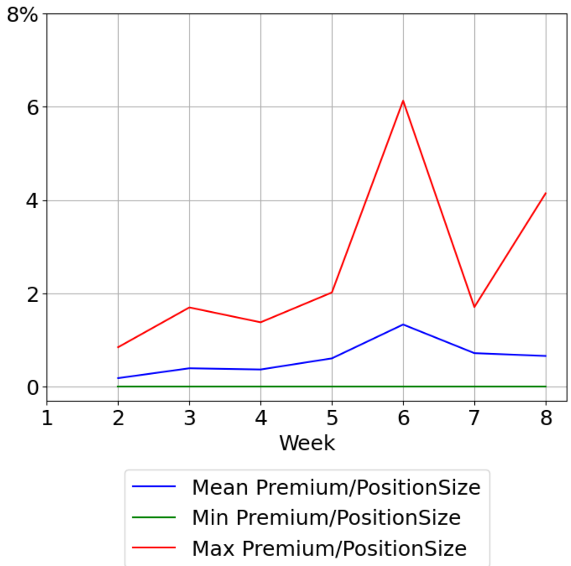
Finally, it is important to address the relation between these percentage values and the initial buyer collateralization ratios imposed by the Panoptic Protocol to afford the payment of the option premiums. These ratios fall between 5% and 10%. As per this analysis, they seem to be very fit for all scenarios except for the low liquidity-high trading volume scenario (the PEPE pool). In this case, it is highly likely that if the option buyers do not readjust their collateral regularly, they will be margin-called, posing a risk for the Protocol if liquidations do not work as expected. In the limit, the protocol may become insolvent.



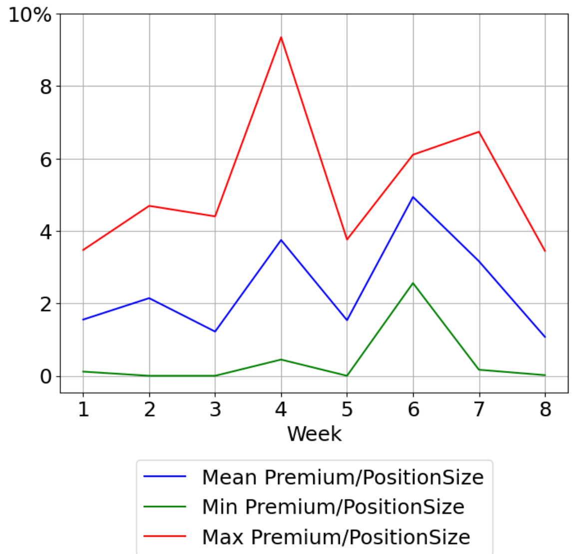
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure 5.21: The magnitude of the premium accrued in relation to the position size of the option in each scenario pool for Stage 4 simulations.

5.4 Results for Diverse Price and Liquidity Distribution Trajectories

The comprehensive study of the protocol also encompasses testing various trajectories for each pool. This involves observing the extent to which variations in both price and liquidity, and consequently, trading volume and IV, influence Panoptic's metrics. In addition to the already presented price and liquidity distribution trajectories, which we will refer to as trajectories A, we are now introducing Stage 4 simulation results for two additional trajectories, referred to as B and C.

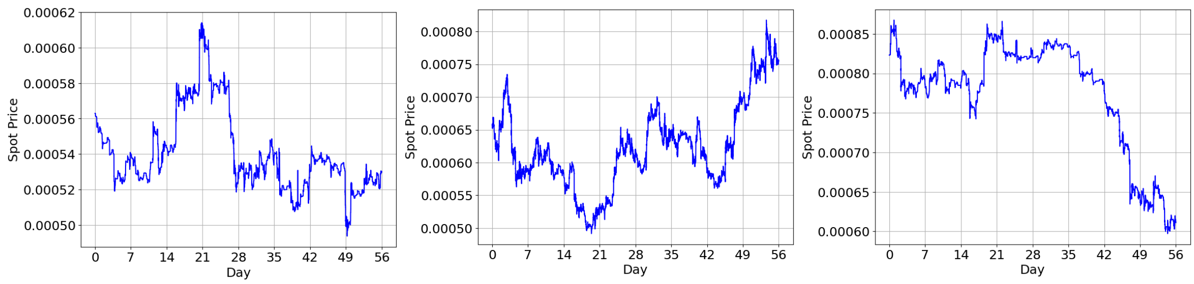
For the sake of brevity, this section presents only the results of larger relevancy for the protocol mechanisms analysis or that prove to be significantly different due to variations in the price and liquidity input files. The remaining metrics and results are available for consulting in Appendix E. Furthermore, at this section, we present the results by pool since now it is of greater relevance to discuss the impact of changing the input trajectories on the different trading volume-liquidity scenarios.

5.4.1 DAI-ETH-3000 Pool: Low Liquidity and Low Trading Volume Scenario

5.4.1.1 Spot Price Trajectories and IV Evolution

In this subsection, the aim is to introduce the trajectories employed for the price trajectory. For the sake of brevity, we show the respective TVL trajectories and trading volume evolution on Appendix E.1. Moreover, we assess here the impact of the aforementioned quantities on the overall evolution of implied volatility throughout the simulation timeframe.

Figure 5.22 depicts the price trajectory used. A notable distinction between deploying price trajectory A and price trajectory B is immediately apparent: the former exhibits an overall neutral tendency with an increase and subsequent fall between the third and fourth weeks, while the latter features a decreasing tendency until the end of the third week, followed by a dominating increasing tendency. At last, trajectory C encompasses higher spot prices and, in contrast, it presents a strong decreasing tendency from the fourth week onwards. Hence, it can be inferred that these three trajectories encompass a reasonably diverse set of economic situations, providing a robust testing ground for evaluating the protocol's performance.

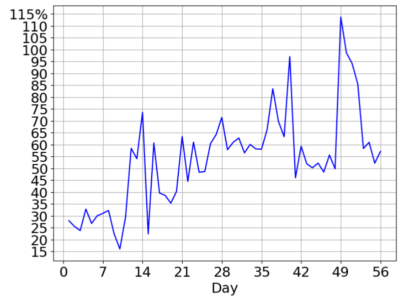


(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

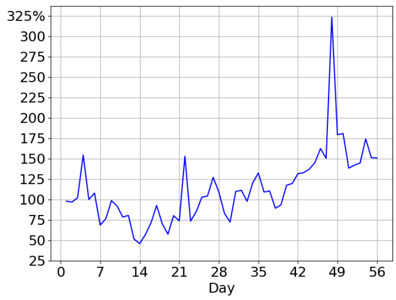
Figure 5.22: Comparison of the different spot price trajectories in the DAI pool Stage 4 simulations.

Regarding the evolution of IV, distinct patterns are also noticeable in Figure 5.23. Trajectory A is marked by an IV value predominantly around 60%, while trajectory B's IV hovers around the 100% mark for the most part, reaching its peak at 325% by the end of the seventh week. Trajectory C presents an intriguing pattern in IV evolution, closely resembling that of trajectory B: characterized by oscillation around a certain value, and when week 7 commences, both trajectories share the same upward trend. The significant distinction lies in the absolute values observed. Trajectory C is evidently less volatile, with a baseline value around 50% in the initial seven weeks, reaching a peak of 150%.

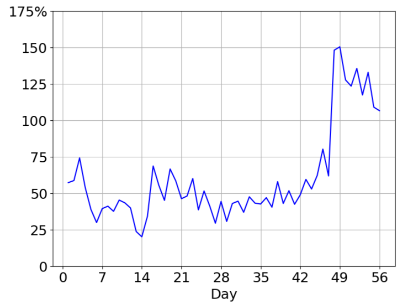
Once more, it can be inferred that employing these varied trajectories (price and liquidity) facilitates the testing of the protocol in diverse economic environments.



(a) Trajectory A.



(b) Trajectory B.



(c) Trajectory C.

Figure 5.23: Evolution of IV in the DAI pool Stage 4 simulations for the different trajectories.

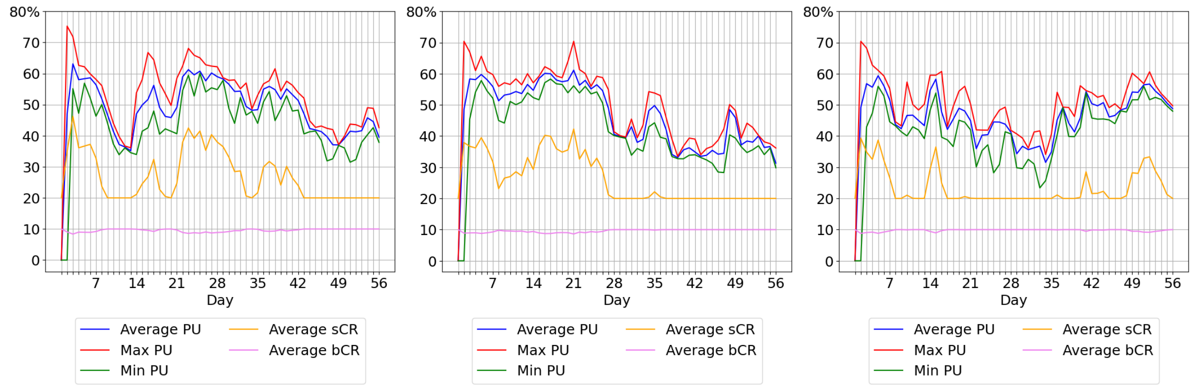
5.4.1.2 Pool Utilization and Seller/Buyer Collaterization Ratios

The results pertaining to the pool utilization for Token0 (see Figure 5.24) indicate that in trajectory B the PU remains close to the 60% mark on average, while in trajectory A, a sudden drop is observed at the beginning of the first week, followed by a recovery to previous levels by the end of the second week. Subsequently, trajectory B exhibits a decreasing tendency towards the second half of the simulation's timeframe, settling at values around the 30-40% mark. In contrast, trajectory A, despite ultimately reaching values similar to those observed in trajectory B, maintains a more constant evolution in PU, hovering around the 50-60% range until the end of the sixth week.

The addition of a third trajectory, C, brings forth a new observation, particularly concerning the PU evolution in the latter part of the simulation. While the initial two trajectories exhibit an overall declining trend, trajectory C, starting from week 6, demonstrates a distinct upward trajectory towards the target PU of 50%.

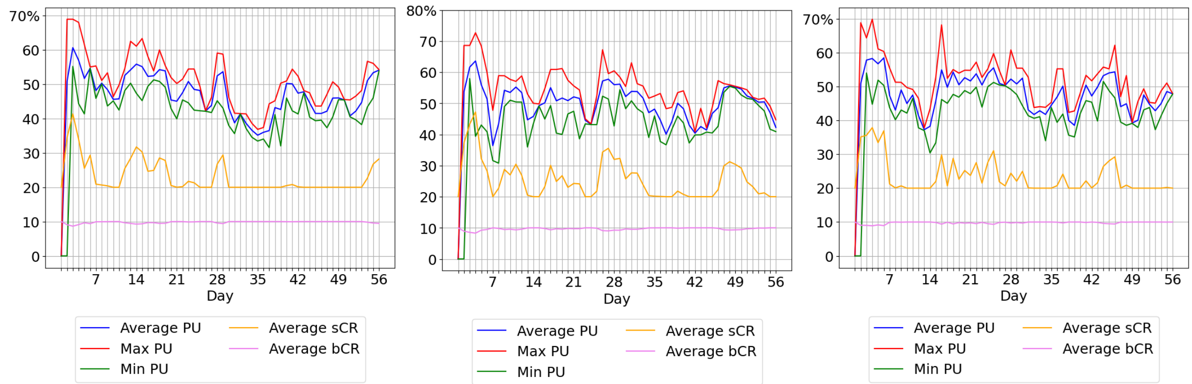
Regarding the results for Token1 (see Figure 5.25), similar conclusions can be taken. The results for trajectories A and B are very similar with only one noticeable difference between them: trajectory A's PU ends the simulation with an increasing tendency while trajectory B's PU ends with a decreasing tendency. Concerning Trajectory C, while there was a noticeable difference from these trajectories for Token0, its PU in Token1 does not provide any additional meaningful insights.

Overall, there is no systematic extreme difference in the evolution of PU between the three trajectories. This can be partially explained by the fact that agents do not consider the evolution of the spot price when buying or selling their options. The spot price evolution only influences the faster or slower exercise of options. This is also evident since we see no evident relation with the IV magnitude or evolution. As previously observed, they are quite different but that does not impact these results.



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure 5.24: Evolution of Token0 PU in the DAI pool Stage 4 simulations for the different trajectories.



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure 5.25: Evolution of Token1 PU in the DAI pool Stage 4 simulations for the different trajectories.

5.4.1.3 PLP APYs

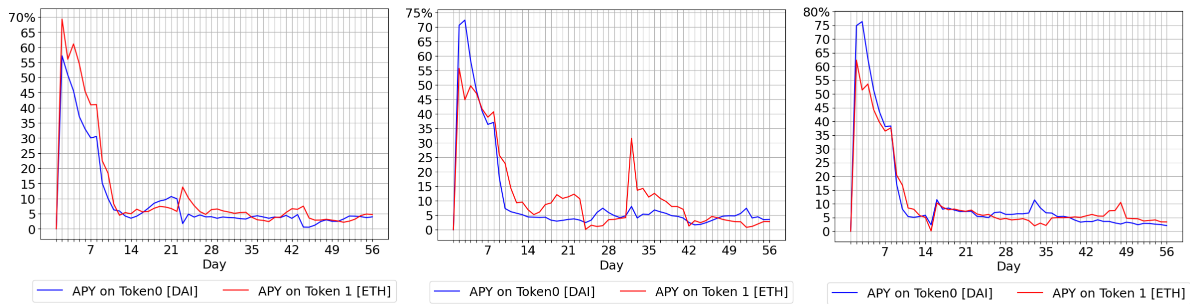
The analysis of PLP APY plots in Figure 5.26 shows many similarities between Trajectory A and C, with peaks of APY in the same order of magnitude. Contrarily, the comparison between trajectory A and B offers intriguing insights.

Firstly, despite both trajectories exhibiting a similar asymptotic behavior, the PLP APY for trajectory A tends to remain below the 5% mark. Sporadic surges in APY do not reach as high peaks as in trajectory B, with the highest peak occurring in Token1 and not surpassing 15%.

In the plot for trajectory B, it is observed that not only does the APY tend to be slightly higher than 5% for a significant portion of the simulation timeframe (especially

Token1), but it is also notable that the highest peak (excluding the non-stabilized initial peak) for this trajectory is more than double (approximately reaching slightly above 30%) compared to the one observed in trajectory A. This can be attributed to increased activity from both sellers and buyers, particularly in terms of deposit amounts, which include collateral readjustments.

The consistent tendency for the IV to be higher in trajectory B may explain the results for APY. With a higher IV, the spot price tends to oscillate more quickly, contributing not only to a higher premium accrued, with the corresponding consequence of a higher frequency of collateral readjustments by buyers, but also to the fact that an option can oscillate more frequently between an ITM and OTM status. This, in turn, necessitates more collateral deposits by sellers to cover potentially higher ITM amounts.



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure 5.26: Evolution of PLPs APY in the DAI pool Stage 4 simulations for the different trajectories.

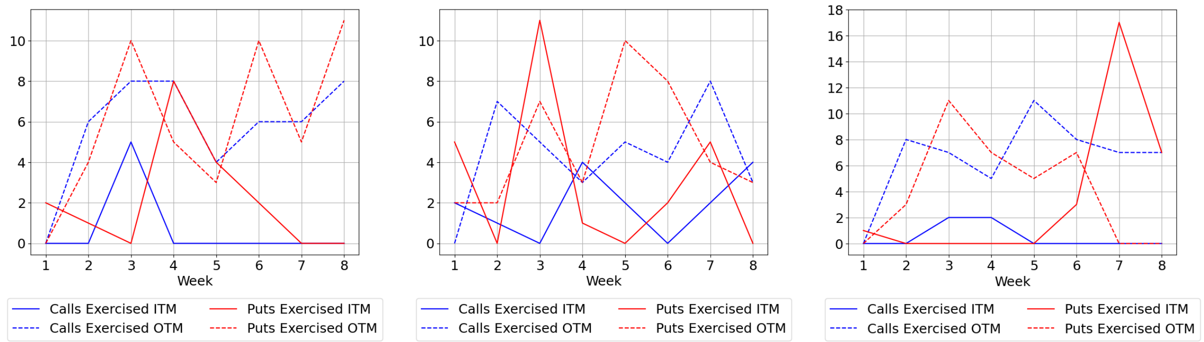
5.4.1.4 Option Buying and Exercising Metrics

Next, we present some of the metrics regarding the buyers activity. The remaining are available in Appendix E.1.

Number of Call and Put Options Exercised ITM and OTM

In Figure 5.27, we reveal the results concerning the exercise of ITM and OTM calls and puts. The primary distinction between trajectories A and B is that the highest peak in trajectory B is observed in OTM puts exercised, resulting from a significant price decrease in week 3. This behavior is also mirrored in trajectory A, where a considerable price decrease in week 4 leads to a peak in the number of puts exercised ITM, surpassing the OTM ones for this trajectory. This once again underscores the influence of the spot price on the exercising behavior of the agents, although there are no significant differences between the dynamics of different trajectories.

A significant observation from the results of Trajectory C is the highest peak in the number of exercised puts among the trajectories tested. Specifically, in week 7 of the simulation, the ITM exercised puts reaches 17. This can be attributed to the more aggressive decrease observed in that week for spot price, aligning with the overall decreasing trend that dominates in this trajectory. Furthermore, it is not surprising to observe an even greater dominance of OTM calls exercised over ITM calls exercised than in other trajectories. This is also a result of the prevalent decreasing trend, as mentioned earlier, which evidently favors long puts over long calls.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.27: Number of exercised calls and puts, ITM and OTM, in the DAI pool Stage 4 simulations for the different trajectories.

Exercising Yield and Loss

Regarding the yield and loss resulting from exercising ITM and OTM options, a noticeable discrepancy emerges when employing different trajectories, particularly with respect to the price trajectory, as evidenced in Tables 5.15 and 5.16. This sensitivity arises due to the exercising moment being highly dependent on the spot price evolution.

Table 5.17: Mean, minimum and maximum values for the yield derived from exercising ITM options in the DAI pool Stage 4 simulations for the different trajectories.

	Exercising Yield (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	10.766	-70.467	38.495
B	16.041	-134.171	90.287
C	29.437	-35.010	87.340

Table 5.18: Mean, minimum and maximum values for the loss derived from exercising OTM options in the DAI pool Stage 4 simulations for the different trajectories.

	Exercising Loss (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	-11.980	-0.714	-69.933
B	-31.364	-0.714	-148.290
C	-8.980	-0.714	-57.922

In trajectory B, the spot price exhibits a broader range of values during the simulation timeframe compared to trajectory A (ranging from 0.0005 to 0.0008 in the former and from 0.0005 to 0.00062 in the latter). This implies more price oscillation, providing more opportunities for exercise. Additionally, the previously discussed IV results in this report also support the notion that trajectory B is more volatile than trajectory A. Consequently, it is unsurprising that the yield results for trajectory B surpass those of trajectory A. However, it is noteworthy that the loss in trajectory B is also higher, aligning with the typical pattern observed in a highly volatile pool, characterized by a high-risk/high-reward dynamic.

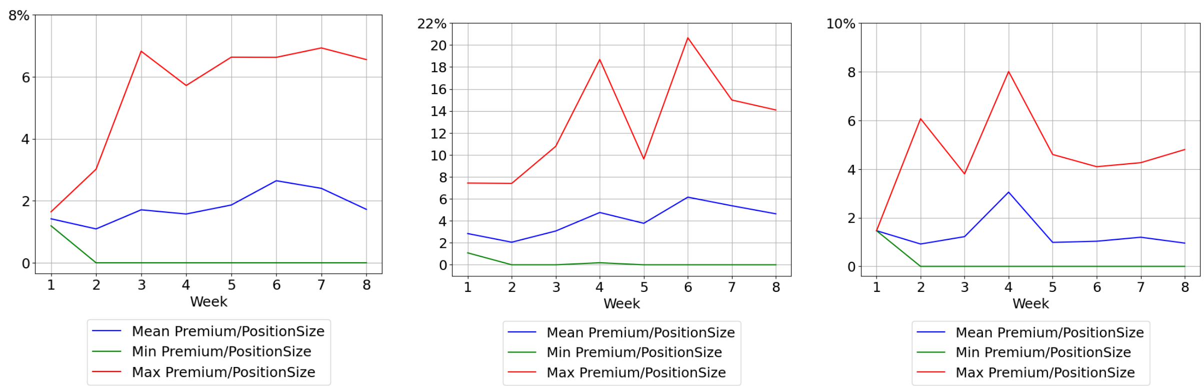
Surprisingly, Trajectory C results deviate from the expected pattern typically observed. Despite having IV values of a similar magnitude to those of Trajectory A, the yield of exercising in this trajectory appears to be asymmetrically positive. The mean is noticeably higher than the other two trajectories (though less volatile than B), the minimum yield, in absolute terms, is significantly lower, indicating fewer actual losses from exercising ITM options (i.e., less premium accrued), and the maximum yield is essentially the same as Trajectory B's. This trend is not only evident in exercising ITM options but also holds true for the loss incurred from exercising OTM options: mean and maximum values, in absolute terms, are lower than those in Trajectories A and B. Given the current agent lineup, especially in terms of buyers, Trajectory C appears to be the scenario where the payoff reward is much more favorable for these agents.

Premium's Relative Magnitude to Option's Position Size

Concerning the comparison of the premium's relative magnitude to the option's position size, visible in Figure 5.28, a significant insight emerges when examining the results from two of the three trajectories employed - A and B. Results from Trajectory C do not provide any additional direct useful insights regarding this metric.

As previously highlighted, the maximum values for accrued premiums consistently remained below the 8% mark relative to the option's position size, indicating stability with respect to liquidation risk. This stability is attributed to the practice, mentioned earlier, where buyers consistently deposited 10% of the option's position size as collateral. For the trajectory A price and liquidity inputs, this collateral amount proved sufficient to cover the accrued premium, eliminating the need for buyers to make drastic collateral adjustments.

In contrast, trajectory B's results present a distinct observation. Although the mean relative magnitude of the accrued premium still falls below the 10% threshold, the maximum values exceeded this mark in the majority of the weeks. This suggests that buyers likely needed to readjust their collateral. As previously explained, the foundational concept of the buyer agent in this stage assumed a sufficient dedication to collateral adjustments, preventing the buyers from entering a liquidatable status and thereby avoiding liquidation. This is validated by the absence of significant disruptions in pool utilization, indicating the robust health of the protocol.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.28: Ratio between premium accrued and the option's position size in the DAI pool Stage 4 simulations for the different trajectories.

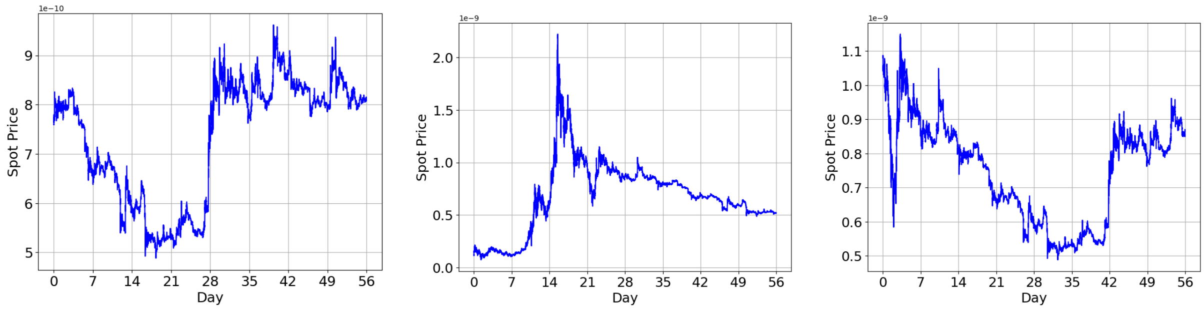
5.4.2 PEPE-ETH-3000 Pool: Low Liquidity and High Trading Volume Scenario

5.4.2.1 Spot Price Trajectories and IV Evolution

The plot illustrating spot price trajectories unveils significantly distinct evolutions for this variable. Trajectory B stands out with a much more aggressive evolution, experiencing an extreme price surge in the third week. Conversely, trajectory A exhibits a considerable increase at the end of the fourth week but is incomparable to the one observed in trajectory B.

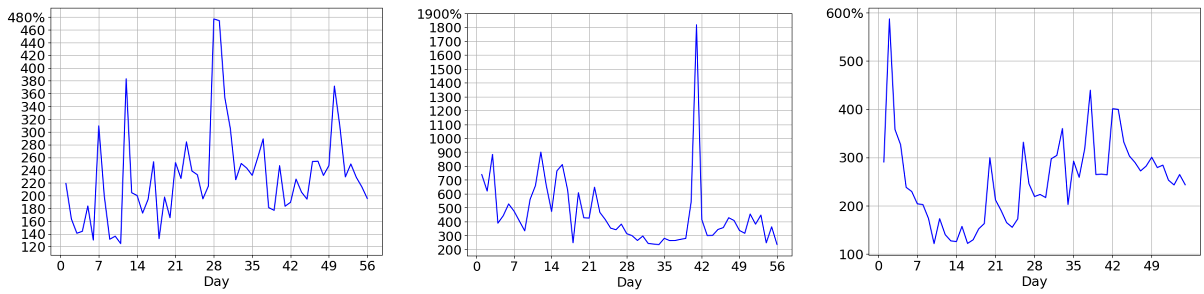
Building on the more aggressive pattern described in the previous paragraph for trajectory B, the evolution of the IV precisely mirrors this trend. It remains consistently above the 200%-300% mark, reaching a peak of 1900% at the end of the sixth week.

The spot price evolution in trajectory C exhibits an initial sudden drop and immediate recovery within the first week. It then follows a pattern similar to trajectory A, with a delay: a decreasing trend persists up to the seventh week (instead of the fourth week in trajectory A), followed by a steep increase leading to a more constant evolution afterwards. In fact, that sudden drop and recovery leads, precisely, to the highest peek of IV in this pool.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.29: Comparison of the different spot price trajectories in the PEPE pool Stage 4 simulations.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

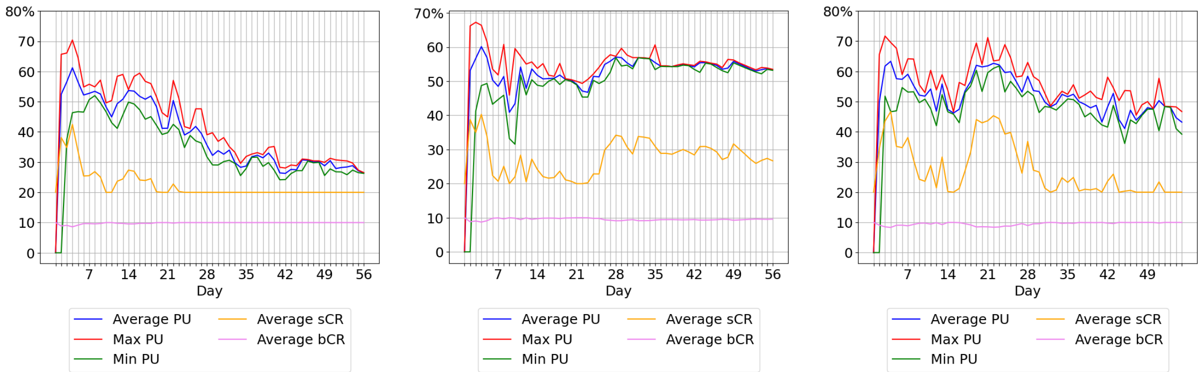
Figure 5.30: Evolution of IV in the PEPE pool Stage 4 simulations for the different trajectories.

At last, note that the plots referring to the TVL at spot tick trajectories and to the evolution of the trading volume are given in Appendix E.2. Once more they attest the low liquidity high trading volume scenario.

5.4.2.2 Pool Utilization and Seller/Buyer Collaterization Ratios

The comparison between the pool utilization results for Token0 (see Figure 5.31) obtained for trajectory A and B provides intriguing insights. As observed earlier, trajectory A's PU evolution is dominated by a decreasing tendency, reaching a value below 30% by the end of the simulation. Conversely, trajectory B's PU exhibits a very stable evolution, consistently residing in the 50%-60% range. In fact, as we will see next in Figure 5.34, the activity related to the exercising of calls significantly decreases after the second week, even reaching nullity as in weeks 4 and 6. This occurrence contributes to a more monotonous behavior in terms of Panoptic's dynamics, as evidenced by the PU evolution.

The Token0 PU results for trajectory C show some similarities with the evolution observed in trajectory A: a global decreasing tendency is evident, although not as pronounced as in trajectory A.



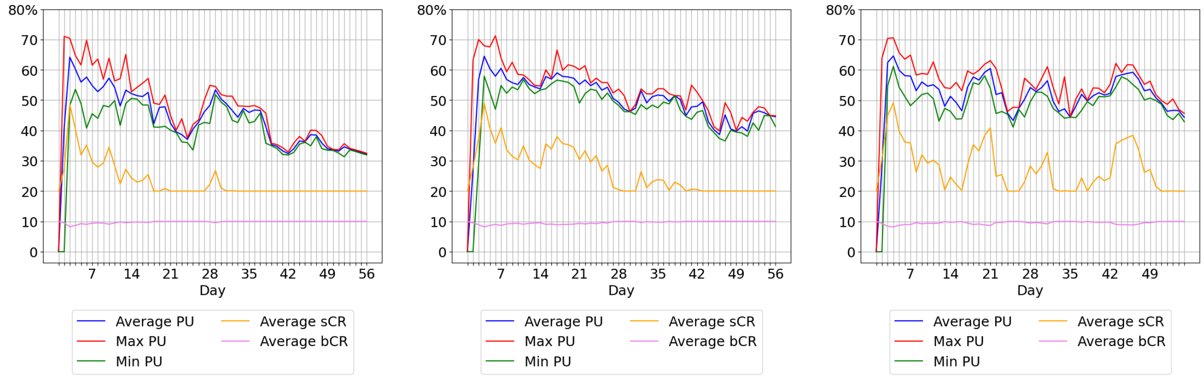
(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.31: Evolution of Token0 PU in the PEPE pool Stage 4 simulations for the different trajectories.

Concerning Token1's pool utilization results, showcased in Figure 5.32, no meaningful distinction is observed between trajectories A and B. Each trajectory exhibits an overall dominant decreasing tendency in the PU for this token throughout the simulation timeframe, with trajectory A's PU slightly lower than that of trajectories B (around 30% in the former and 45% in the latter). An interesting conclusion drawn from this analysis is that, in both a high volatility scenario (trajectory A) and a super high volatility scenario (trajectory B), the dynamics of buying and deposits had a more significant impact on the PU evolution than the dynamics of selling and exercising.

A significant observation from the results of trajectory C is the fluctuation in both the seller's collateralization ratio (sCR) and the PU for Token1. This trajectory exhibits the most unstable sCR, characterized by frequent and substantial increases and decreases. This behavior aligns with the corresponding PU evolution, which consistently returns to values around 60%, prompting the protocol's defense mechanism (i.e., increasing sCR) to maintain a balance between funds in the Panoptic Pool and Uniswap. Consequently and in contrast, in trajectory C, it becomes evident that the dynamics of selling and exercising – actions that shift funds from Panoptic to Uniswap – had a more pronounced impact than buying and deposit dynamics, which tend to favor the opposite flow. However, this reaffirms that the mechanisms in place to prevent an excessive imbalance of funds towards

Uniswap (i.e., an imbalance favoring selling and exercising) are operating correctly and as anticipated.

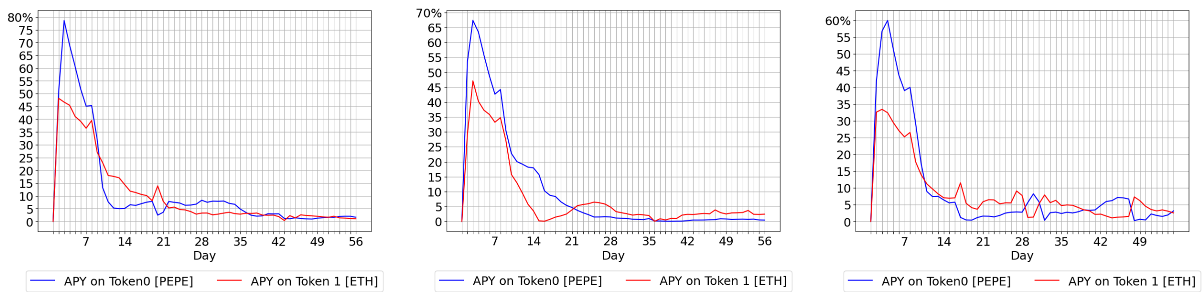


(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.32: Evolution of Token1 PU in the PEPE pool Stage 4 simulations for the different trajectories.

5.4.2.3 PLP APYs

In Figure 5.33, the results for PLP APYs show no significant distinction among the three trajectories. While in trajectory B, particularly after the beginning of the third week, APY for Token 1 consistently stays above APY for Token 0 due to lower activity in agent dynamics for Token 0, the overall evolution pattern of APY for both trajectories remains consistent. trajectory C has more spikes in this evolution, but the overall trend aligns with the other two, asymptotic around a target value (slightly lower than 5%).



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.33: Evolution of PLPs APY in the PEPE pool Stage 4 simulations for the different trajectories.

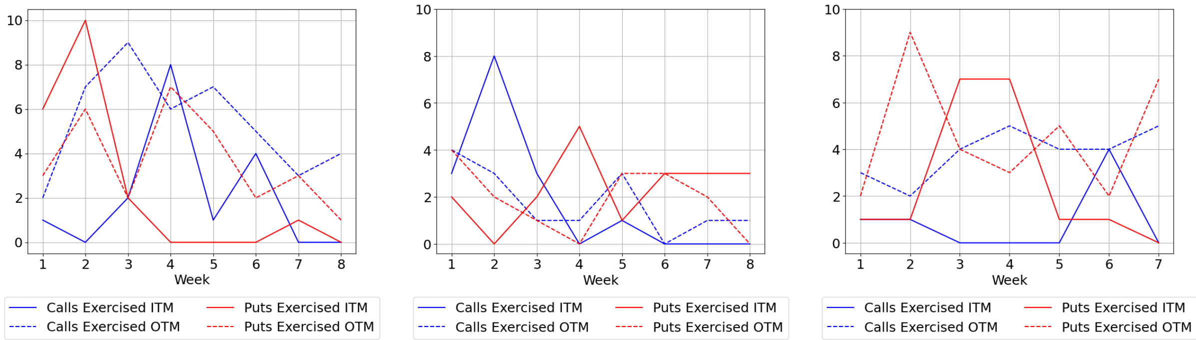
5.4.2.4 Option Buying and Exercising Metrics

Next, we present some of the metrics regarding the buyers activity. The remaining are available in Appendix E.2.

Number of Call and Put Options Exercised ITM and OTM

The results depicted in Figure 5.34 show that options exercised OTM, whether puts or calls, are significantly less frequent in trajectory B compared to trajectory A. This is evident in the fact that the peak for OTM exercises in trajectory B is only 4 (both calls and puts, occurring in week 1), while in trajectory A, the peak reaches 9 (specifically for calls exercised OTM). Additionally, in trajectory A, there is a consistent trend of achieving numbers higher than 4 throughout the weeks.

Concerning trajectory C, a noteworthy difference emerges in weeks 3 and 4 between ITM puts exercised and ITM calls exercised. The clear dominance of the exercise of ITM puts over ITM calls can be attributed to the persistent decreasing trend in this trajectory since week 1, a pattern and tendency that do not recur in the simulation.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.34: Number of exercised calls and puts, ITM and OTM, in the PEPE pool Stage 4 simulations for the different trajectories.

Exercising Yield and Loss

The results for yield and loss are presented in Tables 5.19 and 5.20. Firstly, we observe the effects of the higher volatility of trajectory B, when compared to trajectory A, which results in a high-risk, high-reward scenario.

Table 5.19: Mean, minimum and maximum values for the yield derived from exercising ITM options in the PEPE pool Stage 4 simulations for the different trajectories.

	Exercising Yield (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	25.749	-179.456	117.710
B	62.519	-154.325	179.146
C	21.602	-134.831	72.451

Table 5.20: Mean, minimum and maximum values for the loss derived from exercising OTM options in the PEPE pool Stage 4 simulations for the different trajectories.

	Exercising Loss (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	-62.392	-0.714	-271.736
B	-83.048	-0.714	-295.917
C	-70.305	-0.714	-243.311

Both the mean and maximum values, in absolute terms, are higher in trajectory B than in the other trajectories. An interesting observation is that the minimum value is lower (in absolute terms) in trajectory B, suggesting a somewhat non-symmetrical risk-reward situation where buyers could expect a better yield with trajectory B and not as high of a loss, particularly in an ITM option. However, the results show that if the option is OTM, the mean loss is indeed higher in trajectory B.

This behavior might imply that in trajectory B, even though the spot price tends to oscillate more often and in a more aggressive way, when an option becomes ITM, the spot price probably does not return to the ATM range, thus not accruing as much premium as in trajectory A. This justifies the relatively less unfavorable minimum yield value in trajectory B compared to trajectory A, but not in trajectory C, where the minimum yield is the lowest.

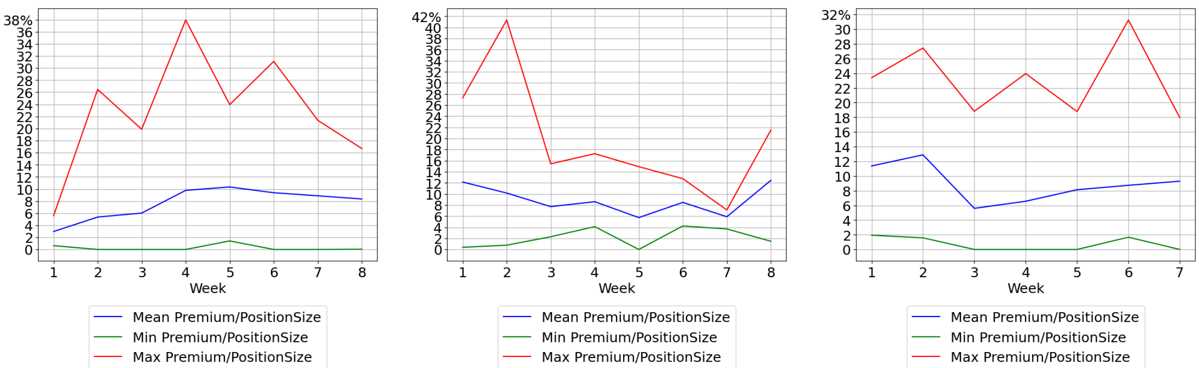
In fact, the results of trajectory C unveiled an anticipated pattern concerning the values of exercising yield and loss, taking into account the comparison of IV values between the three trajectories.

Premium's Relative Magnitude to Option's Position Size

Results for premium accrued indicate that the mean relative magnitude of premium accrued to the option's position size is approximately equal in all trajectories. Trajectory A has a slightly higher mean, hovering around 10% in the last weeks of simulations, while trajectory B and C tends to be around 8% in the same period. However, it is trajectory C that attains the highest peak of mean premium accrued among all trajectories - around 13%. Furthermore, an intriguing observation lies in the evolution of the mean premium accrued in this trajectory. After week 3, there is a discernible monotonous increasing trend in this metric, coinciding with the also increasing tendency observed in this simulation concerning the IV metric. This is expected, as the rise in IV leads to a higher likelihood of spot price changes, consequently increasing premium, as previously stated.

With the respect to the maximum premium, curiously, it is in trajectory B where the highest peak is observed with almost 42% premium accrued relative to position size. Even so, results from both trajectories A and C clearly show consistently higher maximum relative premiums in the following weeks, with the trend for trajectory C being more stable (consistently above 18%). This can also explain the fact that, recurring once again to the results presented in Figure 5.34, the number of exercising options OTM is in general higher in trajectories A and C. Premium in these trajectories tends to accrue much more, leading to some buyers exercising OTM more often than those in trajectory B.

Finally, it is important to note that the maximum premium accrued is generally characterized by markedly high values, well above the 10% mark, likely resulting in multiple collateral readjustments.



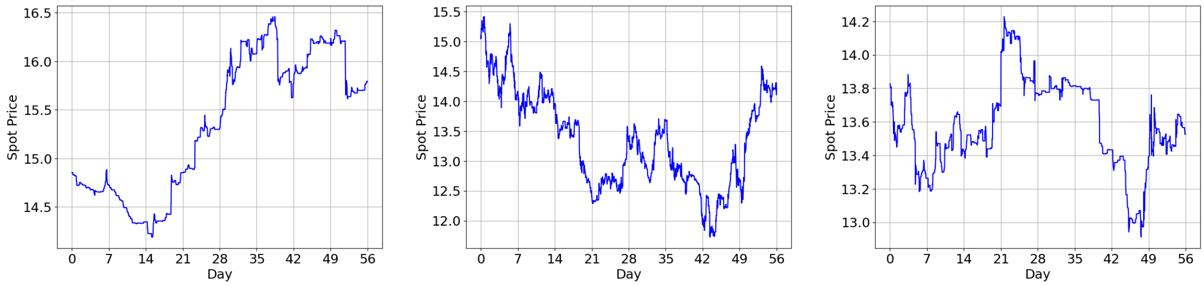
(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.35: Ratio between premium accrued and the option's position size in the PEPE pool Stage 4 simulations for the different trajectories.

5.4.3 WBTC-ETH-3000 Pool: High Liquidity and Low Trading Volume Scenario

5.4.3.1 Spot Price Trajectories and IV Evolution

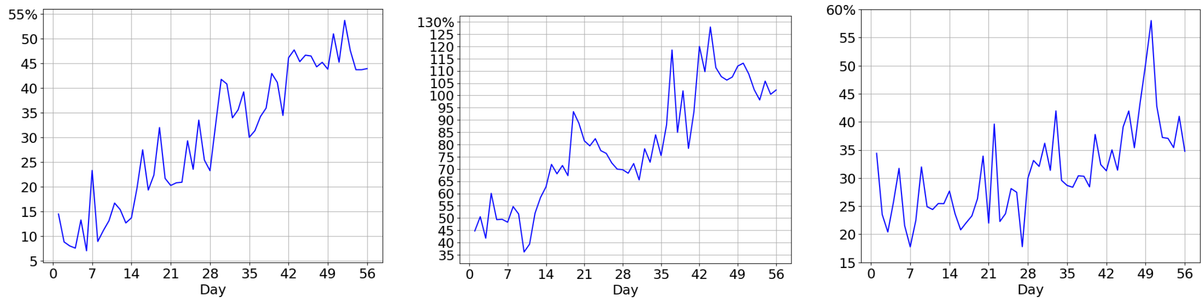
The choice of trajectories for the WBTC-ETH-3000 pool followed a similar rationale to that of the other pools: creating a set of trajectories to thoroughly test the protocol in diverse economic environments. This diversity is evident in the selected spot price trajectories (Figure 5.36): trajectory A features a prominent increasing spot price tendency; trajectory B is characterized by a prevailing decreasing trend until week 7, followed by a robust increasing trend; trajectory C exhibits the most aggressive changes, lacking a clear dominant trend over a sufficiently long time period.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.36: Comparison of the different spot price trajectories in the WBTC pool Stage 4 simulations.

With respect to the IV evolution, despite all trajectories having a common increasing trend, Trajectory B distinctly stands out, reaching values that are twice as high as the highest recorded in trajectories A and C. This is very relevant as it allows to test the protocol's mechanisms in a high liquidity, low trading volume scenario (see the respective plots in Appendix E.3), but in a high volatility ambient.

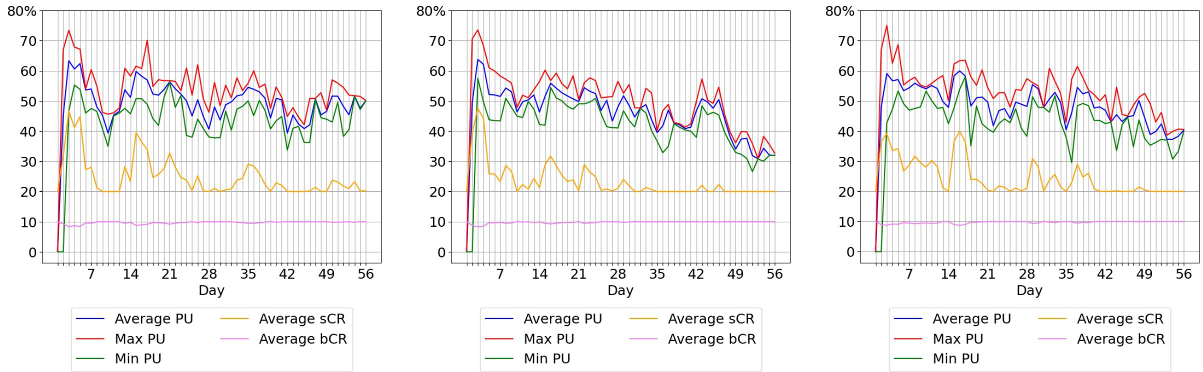


(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.37: Evolution of IV in the WBTC pool Stage 4 simulations for the different trajectories.

5.4.3.2 Pool Utilization and Seller/Buyer Collaterization Ratios

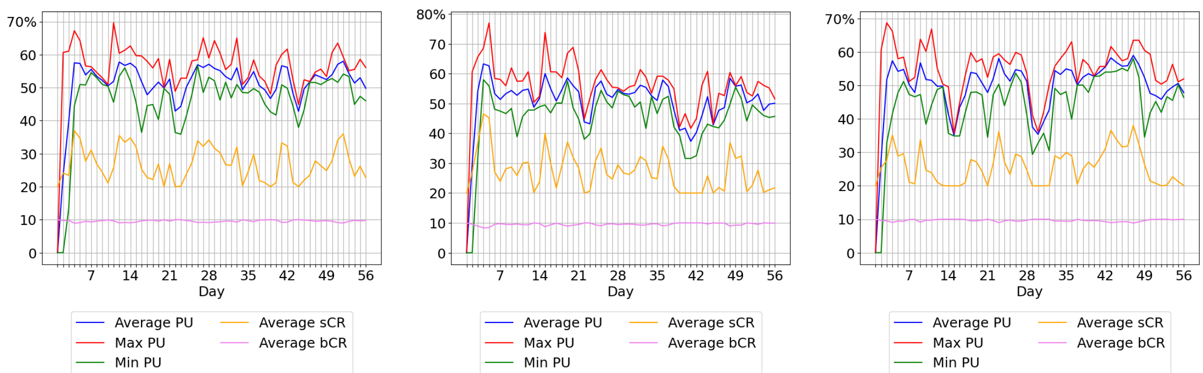
The results for PU evolution in Token0 and Token1 are shown in Figures 5.38 ans 5.39. Concerning Token0's PU, we observe that, while trajectories B and C tend to exhibit a slightly more pronounced decreasing tendency, with trajectory B reaching as low as 30%, trajectory A is mainly characterized by a constant evolution with oscillations around an anchor value of 50% (the protocol's target PU). In the case of trajectory B, the protocol appears to resist the tendency of PU to reach dangerously low values, showing a trend toward stabilization in this metric during the last week.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.38: Evolution of Token0 PU in the WBTC pool Stage 4 simulations for the different trajectories.

The PU evolution for Token1 in the different trajectories demonstrates, once again, the robustness of the protocol mechanisms to prevent an unhealthy state. Specifically, in trajectory C, week 5 is characterized by a substantial decrease followed by a significant increase (around a 20% swing). Nevertheless, the protocol shows resilience when facing such dramatic and extreme variations, with the corresponding changes in sCR and bCR allowing the protocol, in terms of PU values for Token1, to stabilize at the end of that same week.

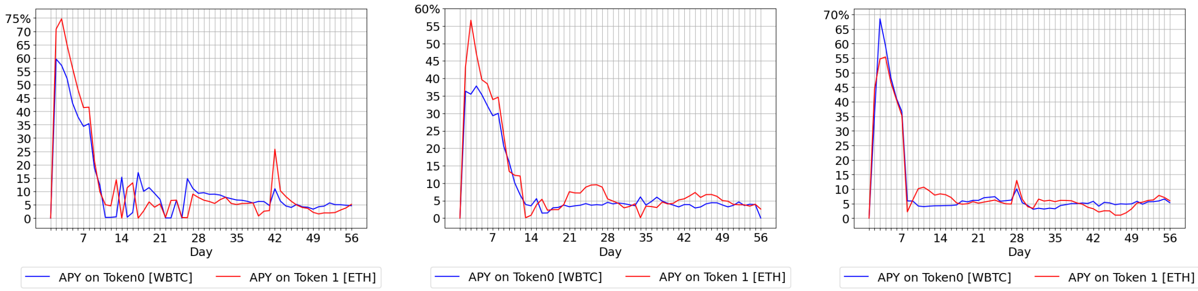


(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.39: Evolution of Token1 PU in the WBTC pool Stage 4 simulations for the different trajectories.

5.4.3.3 PLP APYs

The APY results for PLPs in all trajectories exhibit a similar asymptotic trend, consistent with observations in other pools. There is a convergence towards a mark around 5%; however, both trajectories A and B have several moments when the APY on both tokens falls below this mark and approaches 0%. Naturally, this led to an increased number of withdrawals in these trajectories, even for Passive PLPs, which can be checked in Appendix E.3.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

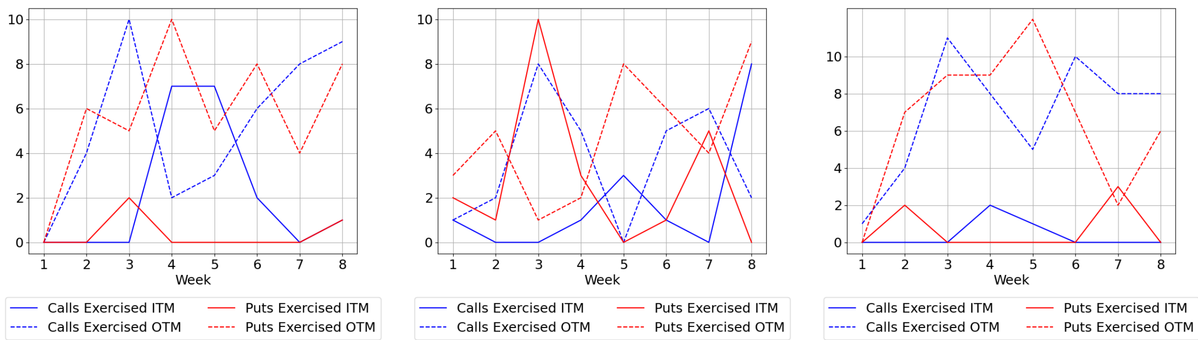
Figure 5.40: Evolution of PLPs APY in the WBTC pool Stage 4 simulations for the different trajectories.

5.4.3.4 Option Buying and Exercising Metrics

Next, we present some of the metrics regarding the buyers activity. The remaining are available in Appendix E.3.

Number of Call and Put Options Exercised ITM and OTM

In Figure 5.41, a significant disparity apparent in the comparison of the three trajectories is the marked difference between the exercised OTM calls and puts compared to ITM calls and puts in trajectory C. This distinction is likely attributed to the timing and patience levels of the agents, given the relatively small premium accrued in this pool (shown next in Figure 5.42). This alone shouldn't be the main cause of such a number of OTM exercises, as seen in contrast in Trajectory A, which also has a relatively low premium accrued.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.41: Number of exercised calls and puts, ITM and OTM, in Stage 4 WBTC pool simulations for the different trajectories.

Exercising Yield and Loss

The results for yield and loss are presented in Tables 5.21 and 5.22.

Firstly, regarding the yield obtained from exercising ITM options reveal, we verify that, despite trajectory B having the highest IV values registered throughout the simulation, it appears to entail higher risk rather than higher reward. This is evident from its mean value, which is the lowest among the three trajectories, as well as the minimum yield, which is also the lowest in absolute terms.

Furthermore, in terms of losses, trajectory B is not the most rewarding for buyers, as it records the highest mean and maximum loss in absolute terms. However, all three trajectories are characterized, especially in terms of their mean (whether yield or loss), by modest values compared to other pools. Hence, we may reaffirm that the high liquidity, low trading volume scenario is the worst for trading, in this case, longing these single call and put options.

Table 5.21: Mean, minimum and maximum values for the yield derived from exercising ITM options in the WBTC pool Stage 4 simulations for the different trajectories.

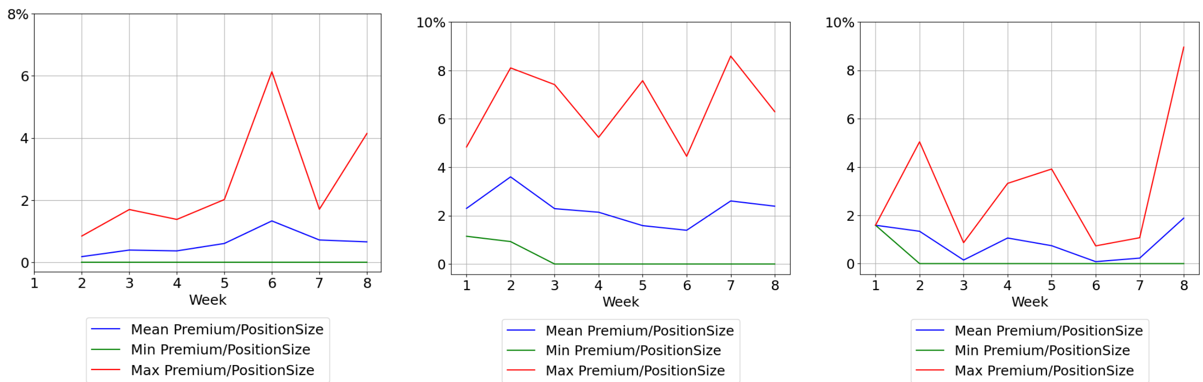
	Exercising Yield (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	13.273	-10.876	34.931
B	2.883	-62.0715	46.275
C	3.159	-28.671	25.228

Table 5.22: Mean, minimum and maximum values for the loss derived from exercising OTM options in the WBTC pool Stage 4 simulations for the different trajectories.

	Exercising Loss (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	-4.625	-0.714	-44.517
B	-13.138	-0.714	-54.830
C	-5.748	-0.714	-64.706

Premium's Relative Magnitude to Option's Position Size

Finally, Figure 5.42 shows that, even in the higher volatility trajectory, B, in these scenarios, the premium's relative size does not increase significantly. This contrasts with what has already been observed in the previous two scenarios and will be seen in the next. It demonstrates, once again, the low profitability of this scenario for trading, in this case, shorting options. For the same reason, it is unlikely for this scenario to pose a risk to the protocol in terms of liquidation consequences.



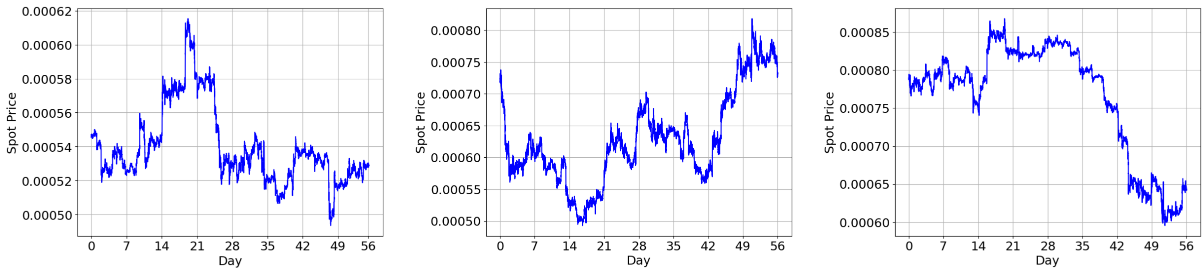
(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.42: Ratio between premium accrued and the option's position size in the WBTC pool Stage 4 simulations for the different trajectories.

5.4.4 USDC-WETH-500: High Liquidity and High Trading Volume Scenario

5.4.4.1 Spot Price Trajectories and IV Evolution

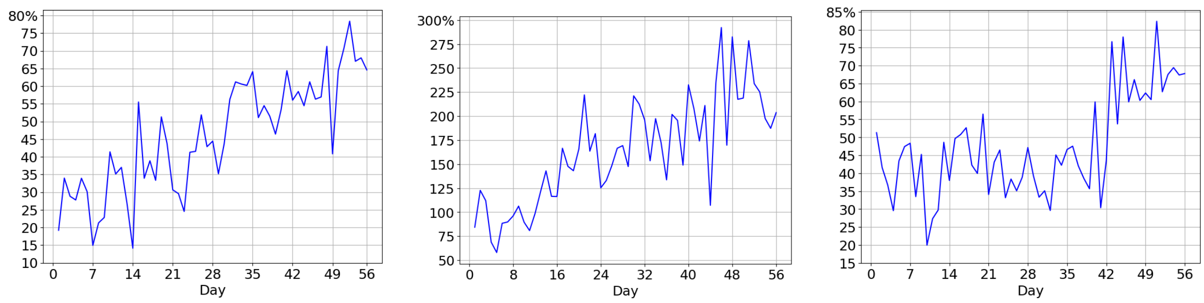
The three selected trajectories for the USDC-WETH-500 pool provide a robust set of distinct spot price scenarios to assess the protocol's performance in this specific pool. Trajectory A, as previously highlighted, undergoes a substantial rise and fall approximately midway through the simulation's timeframe. Trajectory B appears to be the most volatile, characterized by constant and significant spot price changes throughout the entire simulation. Finally, trajectory C exhibits the most consistent decreasing trend, with this pattern becoming completely dominant after the fourth week.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.43: Comparison of the different spot price trajectories in the USDC pool Stage 4 simulations.

The evolution of IV in these three trajectories further supports the conclusions drawn in the previous paragraph. Specifically, trajectory B emerges as the one with the highest IV values and the most pronounced fluctuations in this metric, as was the case in the previous scenarios, making it very valuable to assess the protocol's behavior interacting with this environment.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

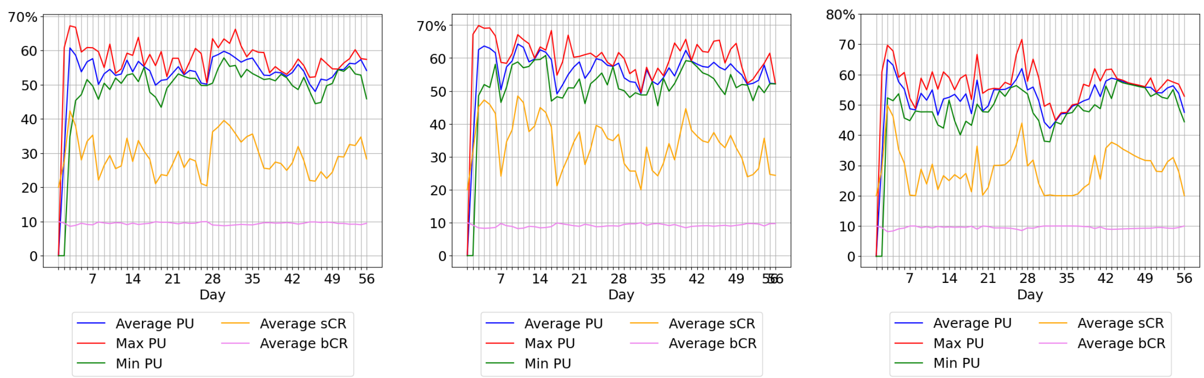
Figure 5.44: Evolution of IV in the USDC pool Stage 4 simulations for the different trajectories.

5.4.4.2 Pool Utilization and Seller/Buyer Collaterization Ratios

The PU results for Token0, depicted in Figure 5.45, yield insightful conclusions. Specifically, trajectory B exhibits a constant correction mechanism triggered by the increase in the seller collateralization ratio to prevent the PU from escalating further. The sCR only reaches its baseline of 20% once (approximately halfway through the simulation). For the remaining duration, it consistently surpasses this baseline, indicating that dynamics related to selling and exercising have a more significant impact than those of buying and deposits. Despite this, the protocol performs well to maintain its overall health, as the evolution of the sCR prevents the PU from diverging, confining it to a reasonably healthy range between 50% and 60%.

Trajectory A, on the other hand, shares some similarities in terms of the sCR rarely reaching its baseline, although the increases observed in this parameter typically do not reach as high as in trajectory B. Overall, the PU evolution for this trajectory tends to be more constant, with rises and drops being more moderate than in trajectory B. Furthermore, it is important to remind that the IV values were quite different between the two trajectories, which shows once more its irrelevancy in the PU results with the current modeling.

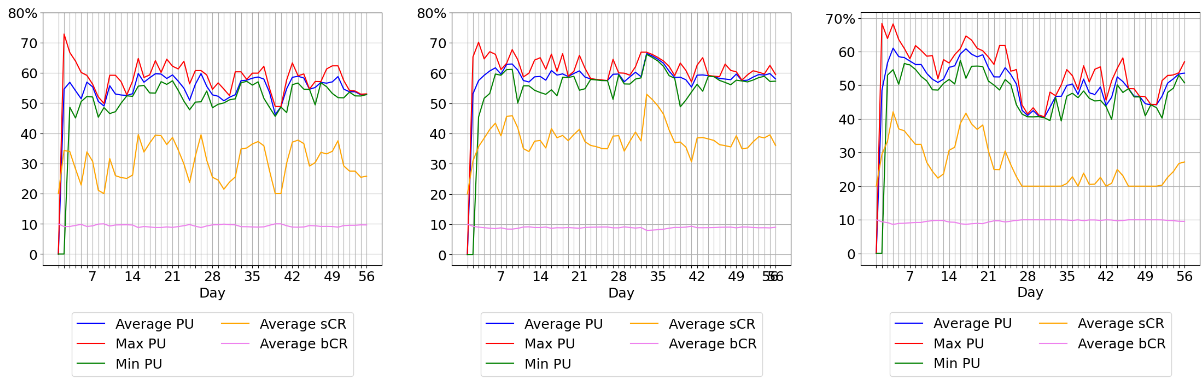
At last, trajectory C shows the largest range in the PU for Token0. In fact, it reaches values both above 70% and below 40%, something that was not verified in the other two trajectories. It is, therefore, in this trajectory that the PU most consistently hovers around the protocol's target pool utilization.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.45: Evolution of Token0 PU in the USDC pool Stage 4 simulations for the different trajectories.

Similar conclusions can be drawn from the analysis of the PU evolution for Token1 - see Figure 5.46. However, a notable and crucial difference is evident in trajectory B regarding the evolution of the sCR. While it remains the trajectory with the highest sCR, as observed in Token0, the sCR for Token1 tends to hover around the 40% mark - more than double its baseline of 20%. The buyer collateralization ratio is also slightly lower than its baseline of 10% and remains lower for the majority of the simulation. This indicates a more adverse environment for the protocol, as its defense mechanisms (sCR and bCR) seldom reach their baseline values. Nevertheless, as in the case of PU for Token0, the protocol demonstrates excellent performance in preventing abnormal and dangerous values for PU throughout the entire simulation.



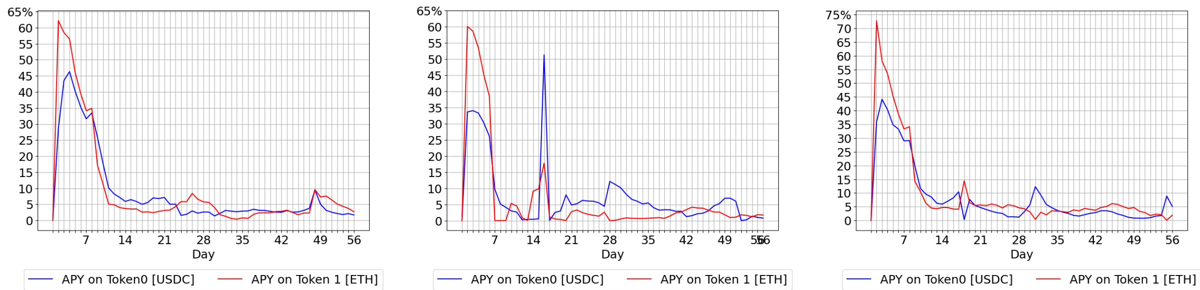
(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.46: Evolution of Token1 PU in the USDC pool Stage 4 simulations for the different trajectories.

5.4.4.3 PLP APYs

Concerning PLP APYs, the results show in Figure 5.47 for the three trajectories do not yield novel conclusions. The most significant difference lies in the surge of APY at the beginning of the third week in trajectory B, observed in both Token0 and Token1 (more pronounced in the former). This surge is likely attributed to more intense activity related to deposits.

Once again, as observed in the previous scenarios, there are instances in all trajectories when the APY falls below 5%, even reaching 0%. This leads to a well-founded conclusion that the current APY for PLPs acts as a discouraging factor for their participation in the protocol, solely as liquidity providers. Additional incentives should be considered to prevent a lack of liquidity in the protocol.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.47: Evolution of PLPs APY in the USDC pool Stage 4 simulations for the different trajectories.

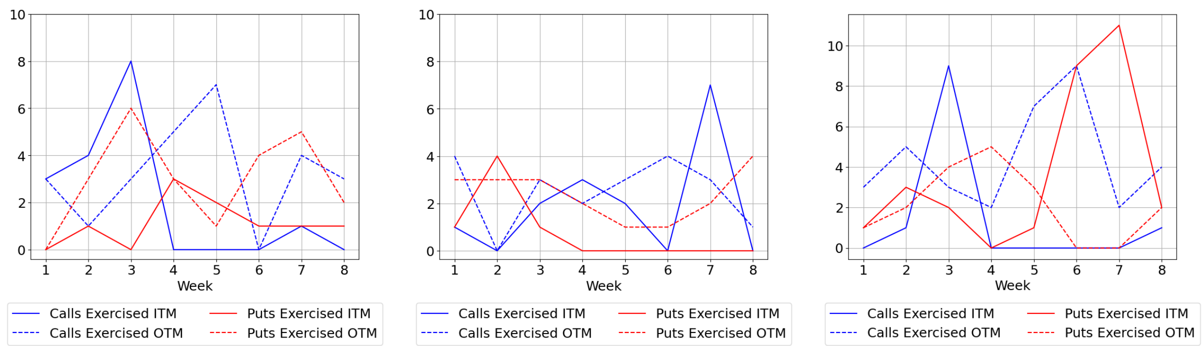
5.4.4.4 Option Buying and Exercising Metrics

Next, we present some of the metrics regarding the buyers activity. The remaining are available in Appendix E.4.

Number of Call and Put Options Exercised ITM and OTM

The results presented in Figure 5.48 for Trajectory B indicate that the overall number of exercised options, whether OTM or ITM, calls or puts, tends to be lower than in the other two trajectories, surpassing the 4-options exercised mark only once (in week 7). The high volatility of the corresponding price trajectory was not reflected in this metric, as we would expect some more exercising actions. Another unexpected mismatch from the correlation with the price trajectory is the absence of exercises for ITM put options from week 4 onwards. The trajectory is only strongly upwards after week 7, so it would not be expected an early lack of this type of exercises. Nonetheless, and in contrast, the exercises of calls ITM and puts OTM, after this week, align more with expectations. Therefore, it is likely that in the case of the lack of ITM exercises for puts, the timing of option buying and exercising by the dedicated agents was not compatible.

When analysing trajectory C results, we also verify the correlation with the price trajectory. There are two notable peaks in exercising ITM options: in week 3 for calls, aligning with the highest increase in price, and in week 7 for puts, aligning with the highest decrease in price (see Figure 5.43). This distinct behavior with two substantial peaks of ITM exercising options (both calls and puts) is unique to this trajectory.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.48: Number of exercised calls and puts, ITM and OTM, in Stage 4 USDC pool simulations for the different trajectories.

Exercising Yield and Loss

In Tables 5.23 and 5.24, we observe an outstanding result among the values obtained in the exercising yield and loss metric in the three trajectories. In trajectory B, the minimum yield observed is 12.678%. This indicates that every single buyer, upon exercising ITM options, effectively experienced a positive yield, since the premium accrued was not enough to surpass the ITM amount. This is in stark contrast to the outcomes in the remaining trajectories in this pool and all other trajectories in three different pools, where the minimum yield was consistently negative.

In contrast, it is in this trajectory that the losses for buyers exercising OTM are larger, aligning with previous observations regarding trajectories with the highest IV, as it is the case. Furthermore, despite trajectory B recording, in fact, the highest values of IV throughout the simulation, it does not guarantee the highest mean exercising yield or the maximum yield, as observed in other pools. Notably, trajectory B exhibits the smallest range between the minimum and maximum yields obtained. Overall, trajectory B may not be as favorable for buyers, as the risk-reward balance seems to be asymmetrically dominated by risk rather than reward.

Table 5.23: Mean, minimum and maximum values for the yield derived from exercising ITM options in the USDC pool Stage 4 simulations for the different trajectories.

	Exercising Yield (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	19.807	-39.652	62.245
B	27.628	12.678	56.096
C	30.096	-32.856	82.247

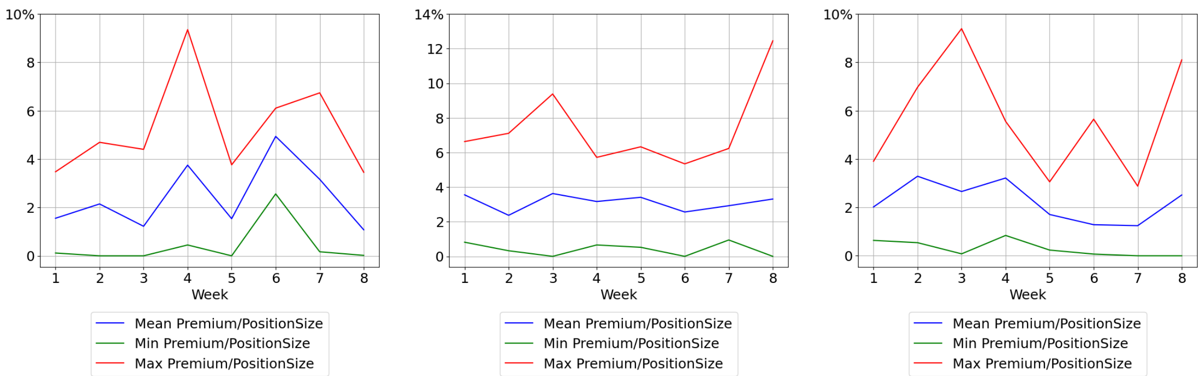
Table 5.24: Mean, minimum and maximum values for the loss derived from exercising OTM options in the USDC pool Stage 4 simulations for the different trajectories.

	Exercising Loss (%)		
Trajectory	**Mean**	**Minimum**	**Maximum**
A	-19.658	-0.714	-67.529
B	-27.052	-0.714	-89.663
C	-20.947	-0.714	-67.817

Premium's Relative Magnitude to Option's Position Size

Finally, the results depicted in Figure 5.49 promote an interesting conclusion. In fact, we observe that the premium's relative magnitude to the option's position size does not pose significant differences between trajectories, especially in trajectory B, despite its elevated IV values throughout the simulation. In fact, this high IV had minimal impact. This is something that has already been observed in the WBTC pool, but not in the DAI and PEPE pools. Therefore, we may infer that the higher IV only impacts the premium accrued relative to the option's size in the low liquidity scenarios. This makes sense since the liquidity in question represents a larger slice of the Uniswap's liquidity in the DAI and PEPE pools than in the WBTC and USDC pools.

In addition, we may also observe that the mean value, in all trajectories, remains well below the 10% collateral deposits made by buyers, and the maximum value only surpasses this threshold in the last week of trajectory B. We may conclude that overall, the protocol maintains its health, steering clear of potential liquidation consequences.



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure 5.49: Ratio between premium accrued and the option's position size in the USDC pool Stage 4 simulations for the different trajectories.

Chapter 6

Conclusions and Recommendations

The objective of this report was to comprehensively test the Panoptic protocol across four economic scenarios, specifically focusing on Uniswap's pool liquidity (low and high) and trading volume (low and high). The study incorporated various agent profiles, including PLPs, sellers, and buyers, and involved different price and liquidity distribution trajectories. The study progressed through different stages, each increasing in complexity, to discern trends and understand how the protocol's mechanisms interacted.

In Stages 1 and 2, we assessed the protocol's behaviour in a shorter timeframe (8 days) with only PLPs and Option Sellers. The results highlighted that the absence of buyers rendered the protocol's dynamics incomplete. However, valuable insights were gained regarding the potential maximum value the PU could reach in such circumstances, approximately saturating at 83%. Overall, Stages 1 and 2 provided an initial understanding of the protocol's behavior in its starting phase, when liquidity is first introduced, and the first options are minted and rolled.

The inclusion of buyers in Stages 3 and 4, with naive agents in the former and dedicated agents in the latter, enabled a comprehensive visualization of option buying and selling dynamics and their impact on key protocol metrics, allowing us to answer to the objective questions proposed in Section 1.3.

Q1) Is the target pool utilization of 50% consistently achieved and sustained overtime?

The findings demonstrated the efficacy of the implemented mechanisms, particularly the sCR and bCR, in maintaining the protocol's health across diverse scenarios. Specifically, we observed that, in general, the target pool utilization of 50% was recurrently the average. Additionally, we did not consistently observe PU values above 70% or below 30%, which could indicate dysfunctionality of the protocol. Even when these boundaries were approached, the protocol's response led the PU towards the target, providing an answer to our second objective question.

Q2) To what extent does the collateral requirement and PU relation incentivize or disincentivize the behaviors of option sellers and buyers?

We thoroughly explored the answer to this question and we verified that the collateral requirements, closely tied to the PU value, effectively controlled selling and exercising dynamics, regulating the flow of deposits towards Uniswap.

In terms of the pressure on the deposit flow towards Panoptic, mainly driven by buying and deposits, it was observed that while the protocol still managed the PU well, avoiding very low values, there might be room for improvements in controlling this aspect. For instance, adjusting the lower bound of the sCR, currently set at 20%, could potentially allow more sellers to participate, alleviating pressure on the buying/deposit side and facilitating a recovery of the PU to healthier levels. This adjustment could be implemented using a moving average of the PU value over a specified period (e.g., 5 days). If the PU consistently remains low for an extended duration, the mechanism of lowering collateral requirements for sellers would activate, encouraging their participation further.

Q3) Are Panoptic Liquidity Providers suitably incentivized to participate in the Protocol, considering the associated risks?

When analyzing the results regarding PLP APYs, it became evident that additional incentives for PLPs should be considered. Considering that Lido's staking yield is considered the crypto-native risk-free scenario, the yield generated by PLPs in the simulations performed is not considerably higher that the staking yield. However, PLPs face additional risks compared to stakers in Lido. Therefore, slightly increasing the fee for participating in the protocol (which essentially goes to PLPs) and perhaps introducing additional fees in other actions (e.g., exercising ITM) could improve the APY values. This, in turn, may incentivize more individuals to become PLPs.

This conclusion aligns with the observations made in Stage 3, suggesting that the introduction of more informed option traders (dedicated buyers and sellers) resulted in slightly lower APYs for PLPs. While the impact is low, it suggests that the presence of more sophisticated participants in the options market has some influence on PLP rewards. This insight should be taken into consideration when designing incentive structures for PLPs in the Panoptic protocol.

Q4) How do Uniswap V3's pools' trading volume, liquidity, and implied volatility impact the answers to the aforementioned questions?

As mentioned, the pivotal focus of this study was to understand how the protocol's dynamics were affected by market conditions. Thus, it was essential to define the right pools for testing and to choose varied price and liquidity distribution trajectories to expose different pressures on the agents' actions.

Firstly, as already pointed out, in all liquidity and trading volume scenarios, the protocol's health was kept intact, even when volatility was significantly larger in scenarios where typically low IVs were expected. Concerning the impact on the agents' actions, in all metrics, it was possible to identify correlations between some market trends and the rolling, selling, buying, or exercising of options. However, it was also evident that this impact was quite low, and no significant differences were found in some of those metrics between different trajectories. As pointed out throughout the report, in the profile of simplifying the approach, some realism in this matter was lost, namely the fact that seller and buyer agents should consider price tendencies and IV expectations to act.

Nonetheless, several conclusions distinguishing the scenarios could be drawn. The low liquidity, high trading volume scenario (represented by the PEPE pool) was confirmed to be the high-risk, high-reward scenario for option trading, providing both high yields/losses and losses/yields for buyers/sellers. In contrast, the high liquidity, low trading volume scenario (represented by the WBTC pool) posed to be the safer choice for more conservative traders. However, as seen in Section 5.4, this was not always the case, especially for buyers. When IV increased in this scenario, the losses became larger than the rewards, not being attractive for buyers. Even for sellers, the premiums accrued, on average, were significantly lower when compared to other scenarios. Hence, we may infer that this scenario poses to be less attractive for Panoptic actors. The conclusions regarding the intermediate IV scenarios pointed the high liquidity, high trading volume scenario (represented by the USDC pool) as more attractive than the low liquidity, low trading volume. In fact, the USDC pool's higher activity led to relatively higher rewards for the options traders, with similar loss rates.

Additionally, it should be mentioned that the results regarding the magnitude of the accrued premium relative to the option's position size also suggest potential improvements contingent on the pool's IV characteristics. Specifically, in pools and trajectories characterized by high IV values, marked by steep and frequent spot price changes, there is a tendency for the mean premium accrued to approach the 10% mark (the upper bound of bCR). More significantly, the maximum values of premium accrued in such scenarios can rise to notably high levels, reaching up to four times the value of the upper bound of bCR. While the simulations conducted demonstrated that the premium accrued reaching these values did not lead to drastic consequences due to the agents' dedication, it raises concerns about the robustness of the system in less ideal conditions.

In a real-world scenario, individuals, even if largely dedicated, may occasionally forget to monitor their collateral, potentially leading to liquidations with unknown consequences for the protocol's health. As a result, a potential enhancement is to increase the upper bound of the bCR, perhaps even equalizing it to the lower bound of the sCR, i.e., 20%. The suitability of this adjustment would be contingent on the specific pool characteristics. For low IV pools, the existing 10% upper bound might sufficient, but in more volatile pools, it could be reasonable to consider modifying this threshold.

Final Remarks

In conclusion, based on this study, we may state that the protocol's mechanisms work as expected, and the suitability of Panoptic for incentivizing options trading in DeFi exists. We have made some recommendations in the areas we considered improvement could be achieved. Nonetheless, none of them are considered deterrents for the normal functioning of Panoptic.

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[6] *Uniswap Info - WBTC / ETH 0.3%*. Accessed: 2023-11-7. URL: https://info.uniswap.org/#/pools/0xcbcdf9626bc03e24f779434178a73a0b4bad62ed.

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[13] *Here's a complete breakdown of Epoch 2 in a snapshot*. Accessed: 2023-11-16. URL: https://twitter.com/Panoptic_xyz/status/1721573282120679508.

Appendix A

PLPs Deposit Amounts Distribution

In this appendix, we present a collection of pie charts representing the PLP distributions utilized in each testing scenario, categorized by each pool, both tokens within that pool, and the activeness profiles of both Passive and Active PLPs, as detailed in Section 3.1.2.

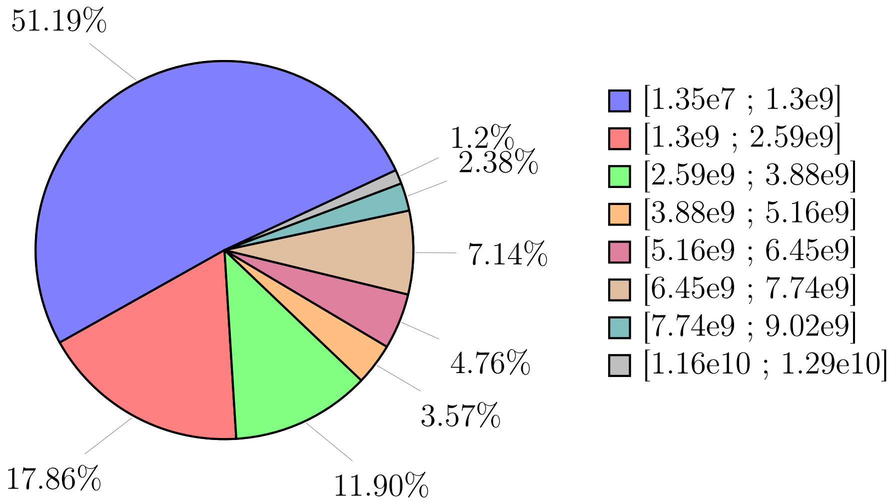


Figure A.1: Token X amount distribution for Passive PLPs in the PEPE-ETH-3000 pool.

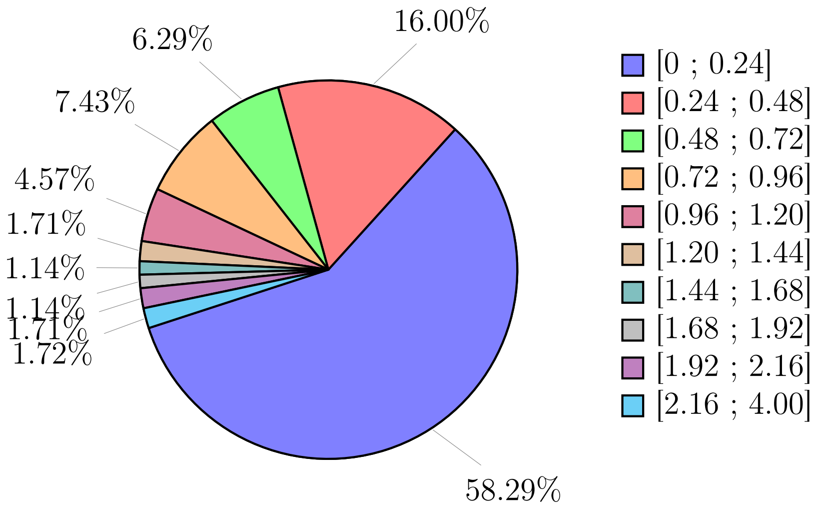


Figure A.2: Token X amount distribution for Passive PLPs in the WBTC-ETH-3000 pool.

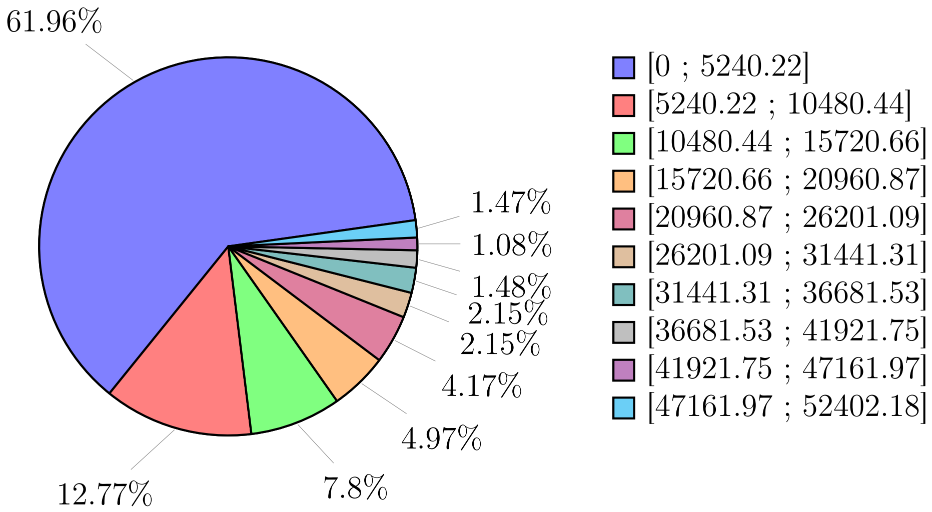


Figure A.3: Token X amount distribution for Passive PLPs in the USDC-ETH-500 pool.

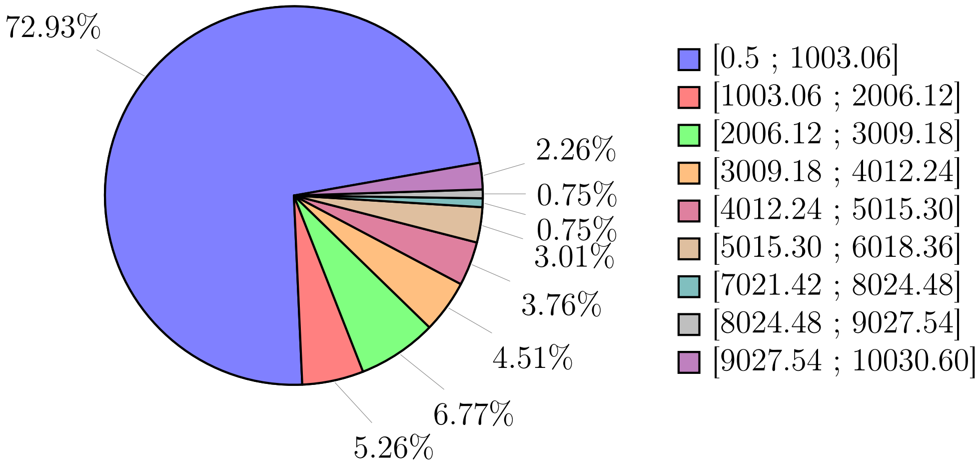


Figure A.4: Token X amount distribution for Active PLPs in the DAI-ETH-3000 pool.

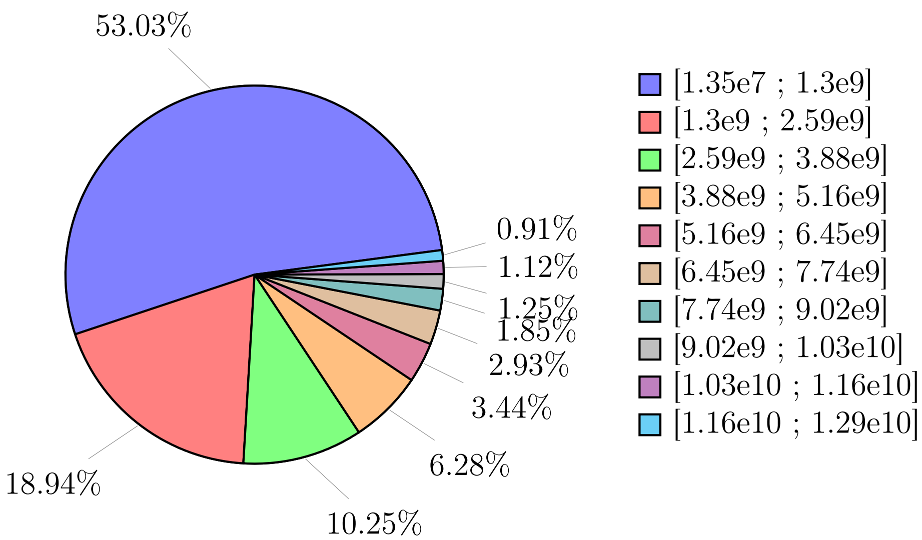


Figure A.5: Token X amount distribution for Active PLPs in the PEPE-ETH-3000 pool.

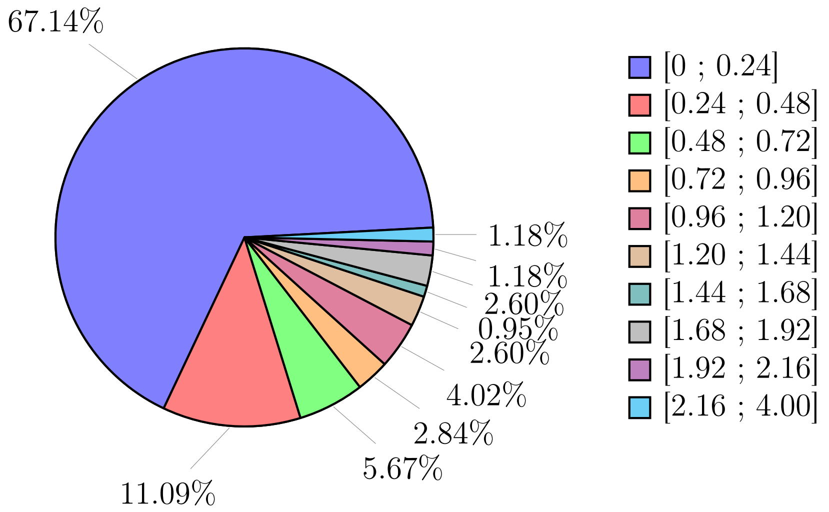


Figure A.6: Token X amount distribution for Active PLPs in the WBTC-ETH-3000 pool.

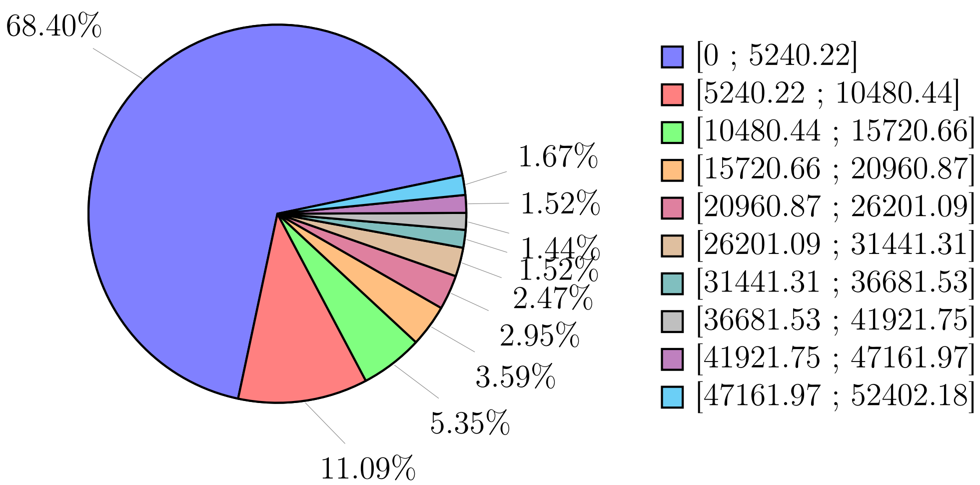


Figure A.7: Token X amount distribution for Active PLPs in the USDC-WETH-500 pool.

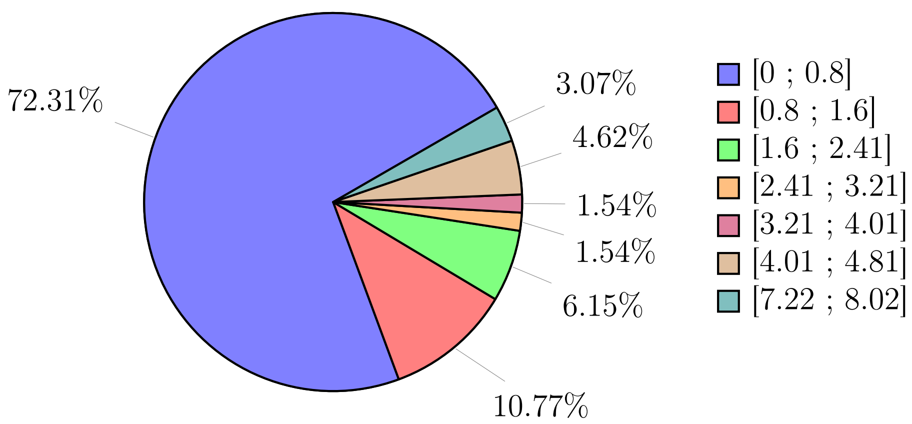


Figure A.8: Token Y amount distribution for Passive PLPs in the DAI-ETH-3000 pool.

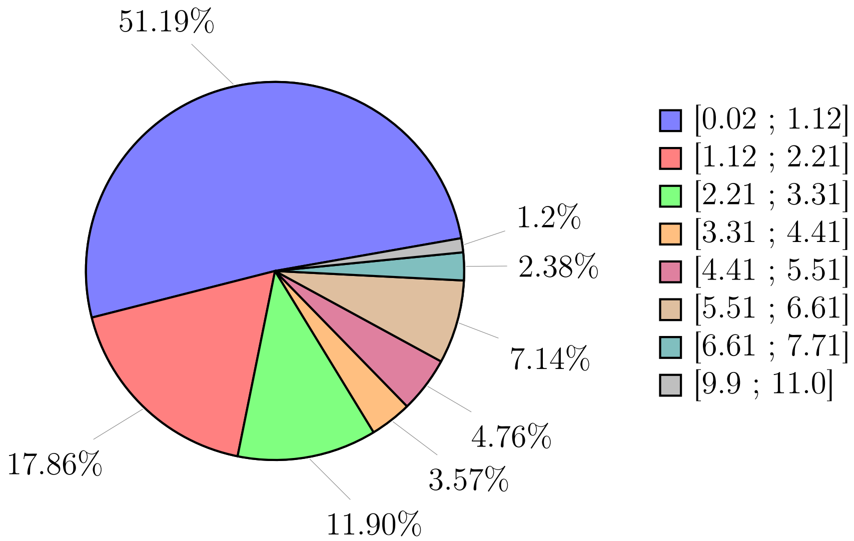


Figure A.9: Token Y amount distribution for Passive PLPs in the PEPE-ETH-3000 pool.

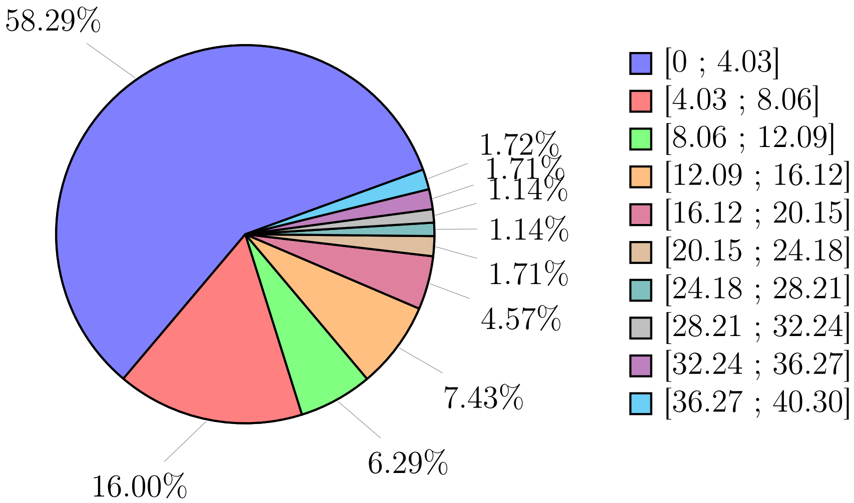


Figure A.10: Token Y amount distribution for Passive PLPs in the WBTC-ETH-3000 pool.

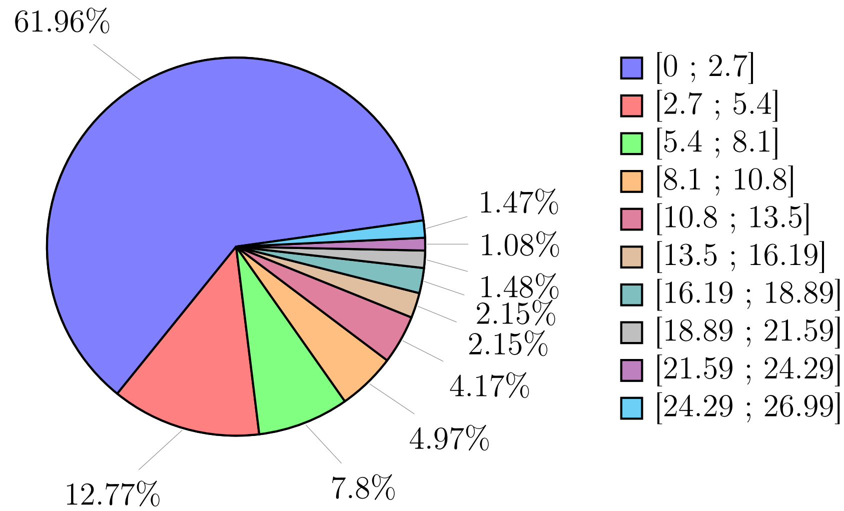


Figure A.11: Token Y amount distribution for Passive PLPs in the USDC-ETH-500 pool.

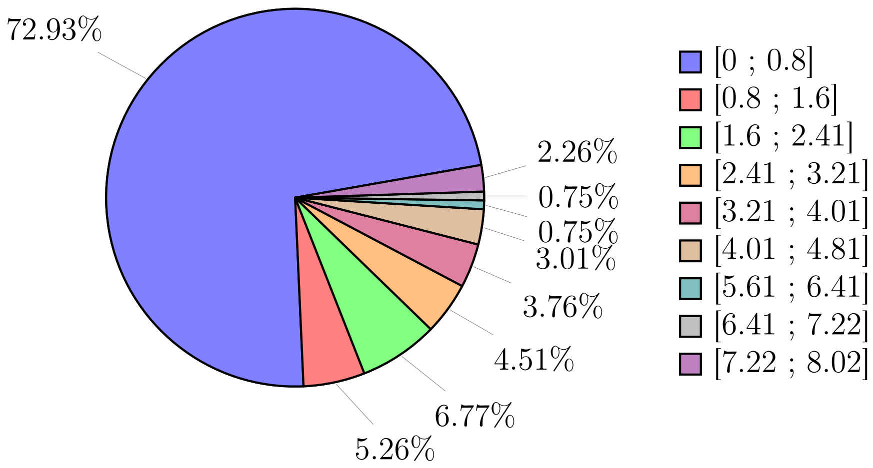


Figure A.12: Token Y amount distribution for Active PLPs in the DAI-ETH-3000 pool.

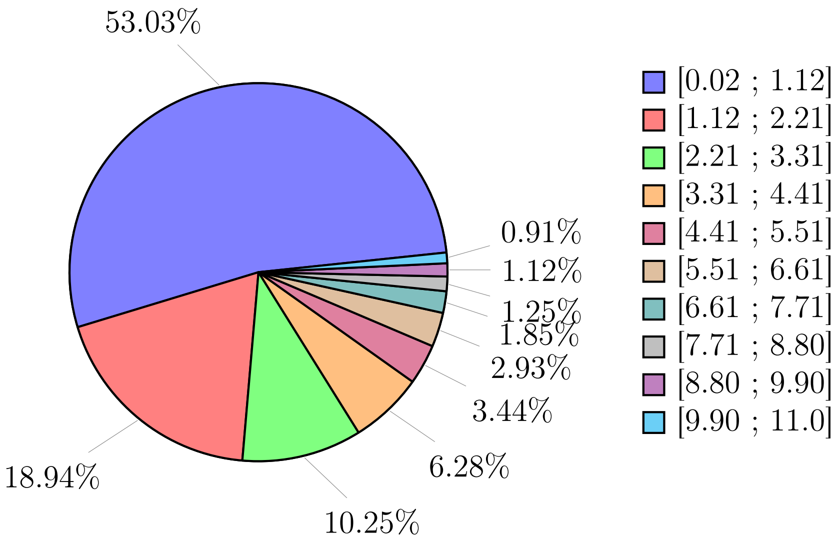


Figure A.13: Token Y amount distribution for Active PLPs in the PEPE-ETH-3000 pool.

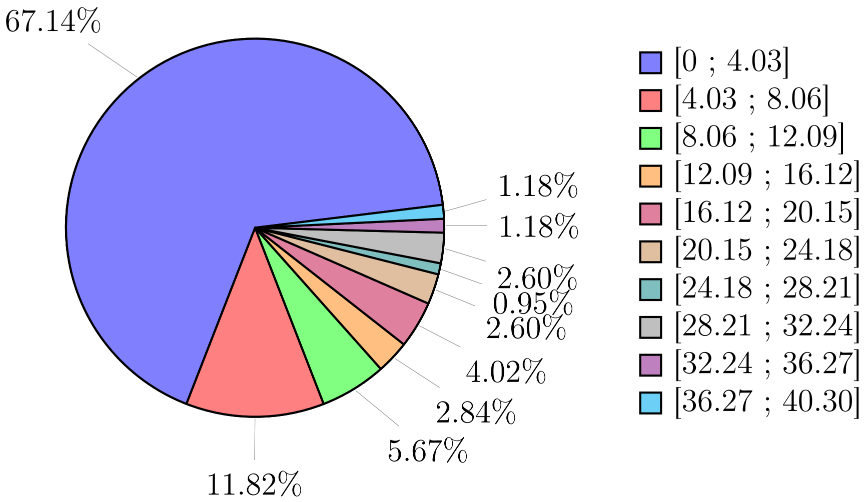


Figure A.14: Token Y amount distribution for Active PLPs in the WBTC-ETH-3000 pool.

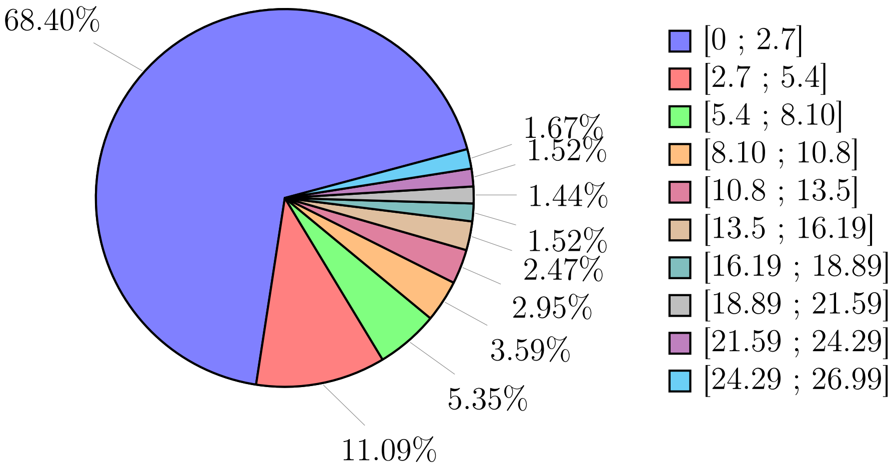


Figure A.15: Token Y amount distribution for Active PLPs in the USDC-ETH-500 pool.

Appendix B

PU Saturation Calculations

In this appendix, we intend to provide a more detailed deduction of the $PU_{saturation}$ formula presented in 4.1.

By applying the quadratic formula to Equation 4.1.2 we obtain the following equation:

$$PU_{after} = \frac{0.8 \cdot M_{argin} \cdot P_{ositionSize} - T_{otalAssets}}{2 \cdot 2 \cdot M_{argin} \cdot P_{ositionSize}} +$$

$$+ \frac{\sqrt{(-0.8 \cdot M_{\text{argin}} \cdot P_{\text{ositionSize}} + T_{\text{otalAssets}})^2 - 4 \cdot 2 \cdot M_{\text{argin}} \cdot P_{\text{ositionSize}} \cdot (-I_{\text{nitialAMM}} - P_{\text{ositionSize}})}}{2 \cdot 2 \cdot M_{\text{argin}} \cdot P_{\text{ositionSize}}}$$

Performing some simplifications:

$$PU_{after} = 0.2 - \frac{TotalAssets}{4 \cdot Margin \cdot PositionSize} +$$

$$+ \sqrt{\left(0.2 + \frac{TotalAssets}{4 \cdot Margin \cdot PositionSize}\right)^2 + \frac{inAMM}{2 \cdot Margin \cdot PositionSize} + \frac{1}{2 \cdot Margin}}$$

Finally, we may apply the limit to infinity in $PositionSize$ and get the saturation value for pool utilization:

$$PU_{saturation} = \lim_{PositionSize \to +\infty} PU_{after} =$$

$$= 0.2 - \frac{TotalAssets}{\infty} + \sqrt{\left(0.2 + \frac{TotalAssets}{\infty}\right)^2 + \frac{inAMM}{\infty} + \frac{1}{2 \cdot Margin}} =$$

$$= 0.2 + \sqrt{0.04 + \frac{1}{2 \cdot Margin}}$$

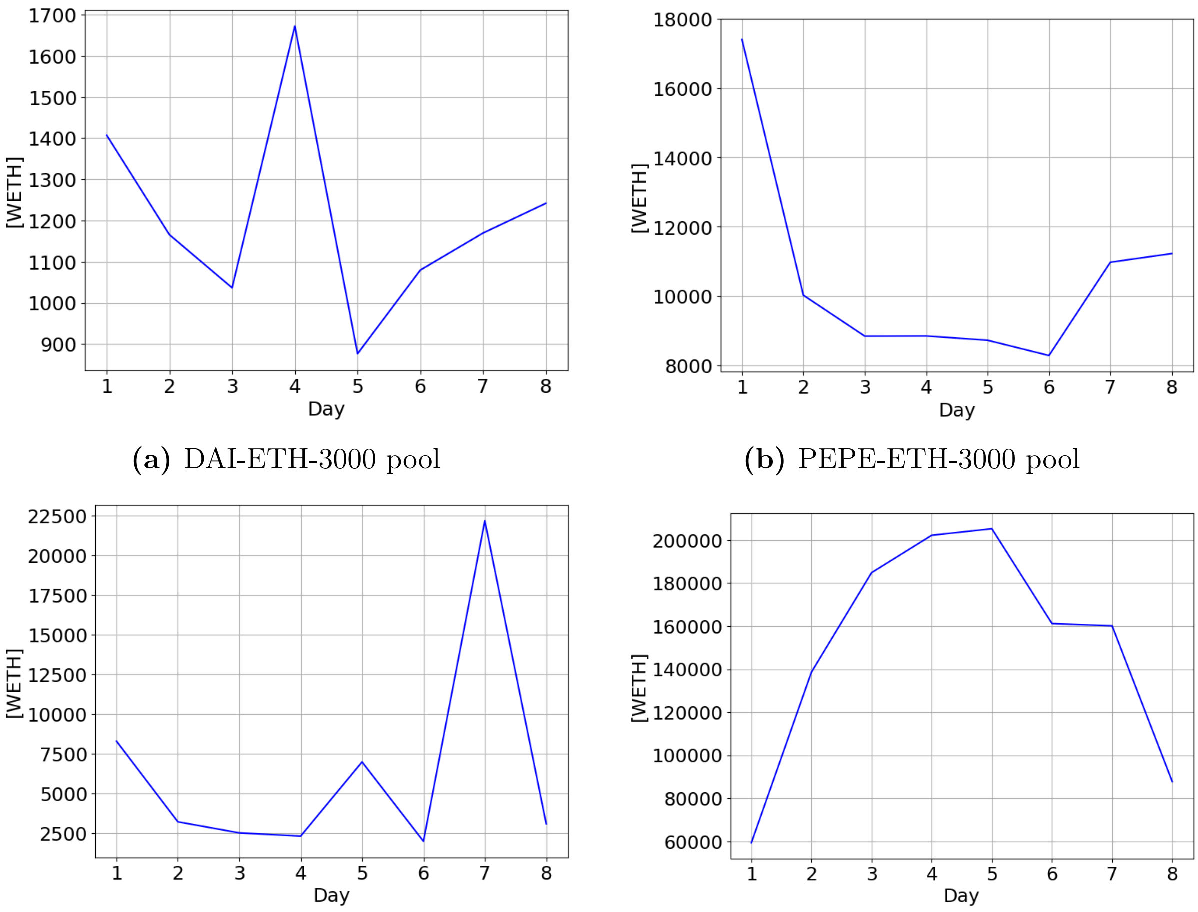
Appendix C

Stage 1 Results Compilation

In this appendix, we present visual representations of the results obtained in Stage 1 for all scenarios (refer to Section C.1), focusing on the metrics listed in Section 4.1. Additionally, we include the results from simulations conducted to test the PU saturation value (refer to Section C.2).

C.1 Metrics Evaluation Results

Daily Trading Volume



(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

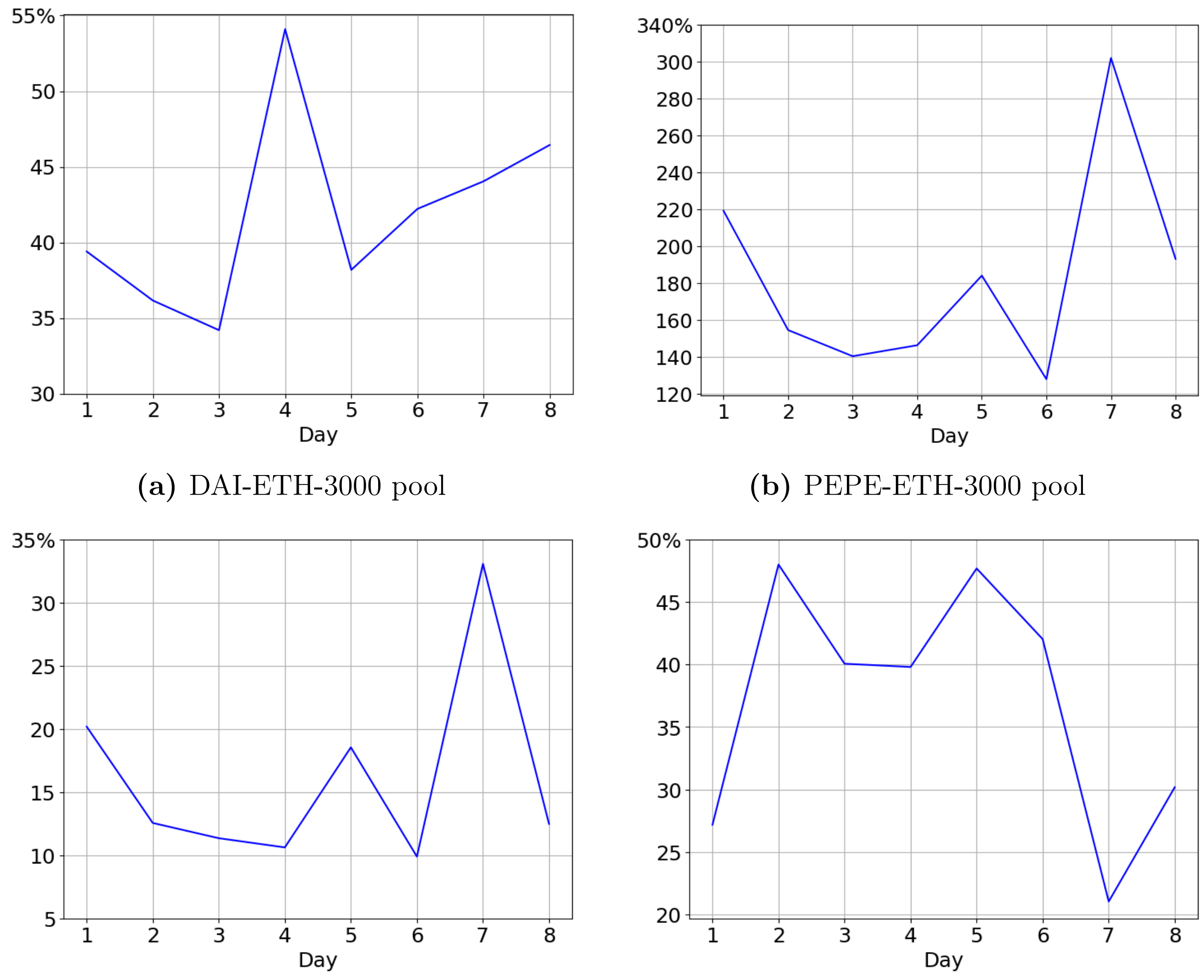
(c) WBTC-ETH-3000 pool

(d) USDC-ETH-500 pool

Figure C.1: Daily Trading Volume, expressed in ETH units, in each scenario pool for Stage 1 simulations.

In Figure C.1, we present the 24-hour trading volume resulting from Stage 1 simulations. As anticipated by the outlined scenarios, the DAI and USDC pools clearly exhibit low and high trading volumes, respectively. Regarding the PEPE and WBTC pools, these have trading volumes of the same order. However, as explained in Stage 2 (refer to Section 5.2.1), in relation to their liquidity values, they also confirm the expected scenarios.

Daily Implied Volatility



(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

(c) WBTC-ETH-3000 pool

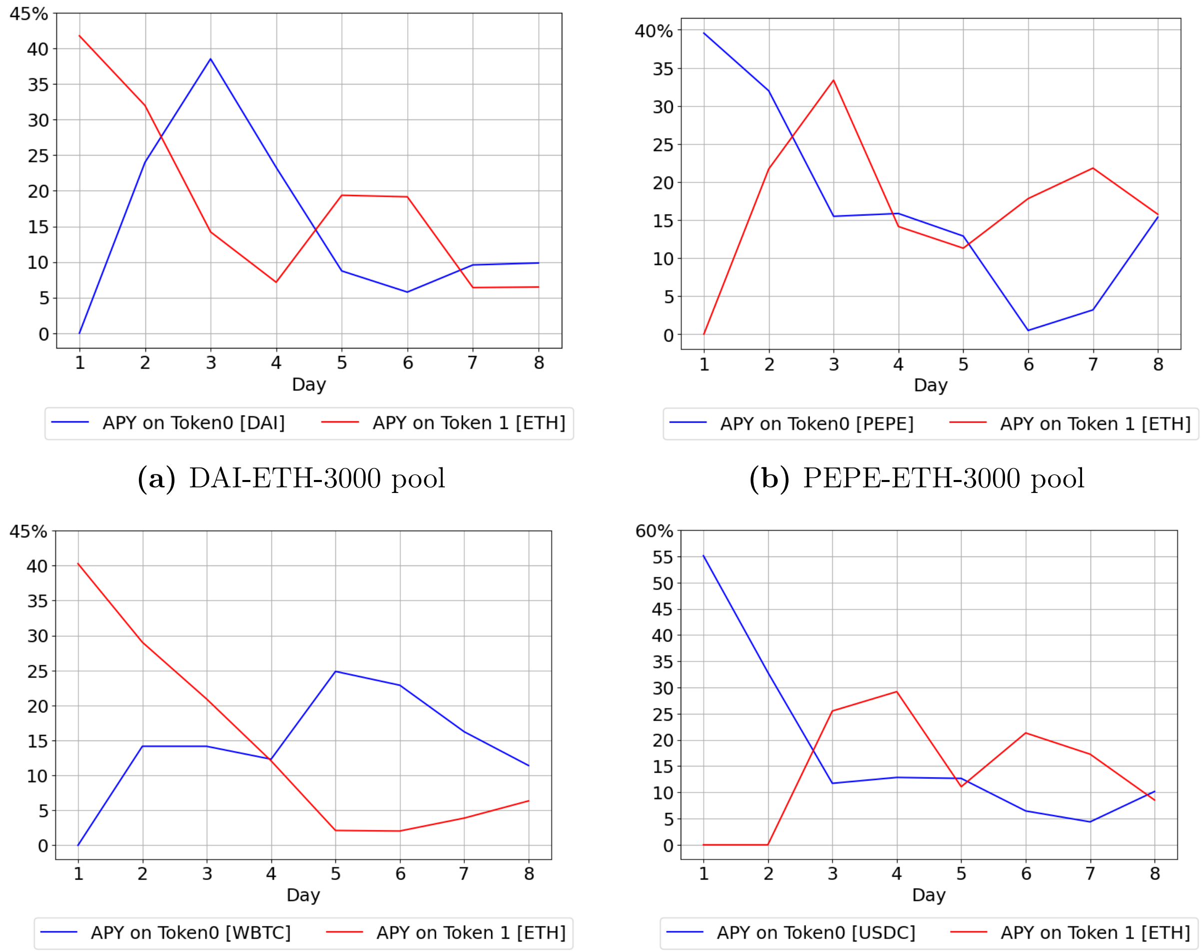
(d) USDC-ETH-500 pool

Figure C.2: Daily Annualized Implied Volatility in each scenario pool for Stage 1 simulations.

In Figure C.2, we showcase the daily implied volatility of the pools used in simulations. Once again, as expected, the PEPE and WBTC pools exhibit, on average, higher and lower implied volatilities, respectively. The two remaining pools have intermediate and very similar values, owing to the similarities between their token correlations (DAI and USDC are both $1-value stablecoins).

PLPs APY

In Figure C.3, we present the results for the PLP's APY metrics for each tested pool. The high values at the beginning result from the Panoptic Pool receiving the first deposits in each token. Within the simulation, the APY tends to decrease in all pools. At this stage, Passive PLPs have low requirements for their APY values in terms of depositing or withdrawing funds, so these values did not significantly impact the agents' actions.



(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

(c) WBTC-ETH-3000 pool

(d) USDC-ETH-500 pool

Figure C.3: Daily PLPs APY (2 days moving average) in each scenario pool for Stage 1 simulations.

PLPs and Sellers Additional Metrics

In the following tables, we present the number of deposits and withdrawals performed by PLPs, as well as the number of mint and roll operations performed by option sellers. This information provides the reader with an understanding of the volume of operations and their order of magnitude in terms of funds moved. Note that in the "Mints", we present the median size of the position minted.

Table C.1: Number count and median amount of PLPs deposits and withdrawals as well as sellers' mints and rolls, for DAI-ETH-3000 pool, for Stage 1 simulations.

	PLPs				**Sellers**			
	Deposits		**Withdrawals**		**Mints**		**Rolls**	
	DAI	ETH	DAI	ETH	DAI	ETH	DAI	ETH
Count	14	8	0		8	8	17	9
Median amount	754.096	0.522	-		4478.244	2.255	-	

Table C.2: Number count and median amount of PLPs deposits and withdrawals as well as sellers' mints and rolls, for PEPE-ETH-3000 pool, for Stage 1 simulations.

	PLPs				**Sellers**			
	Deposits		**Withdrawals**		**Mints**		**Rolls**	
	PEPE	ETH	PEPE	ETH	PEPE	ETH	PEPE	ETH
Count	13	11	0		8	8	24	19
Median amount	3.651e9	0.847	-		1.057e10	3.173	-	

Table C.3: Number count and median amount of PLPs deposits and withdrawals as well as sellers' mints and rolls, for WBTC-ETH-3000 pool, for Stage 1 simulations.

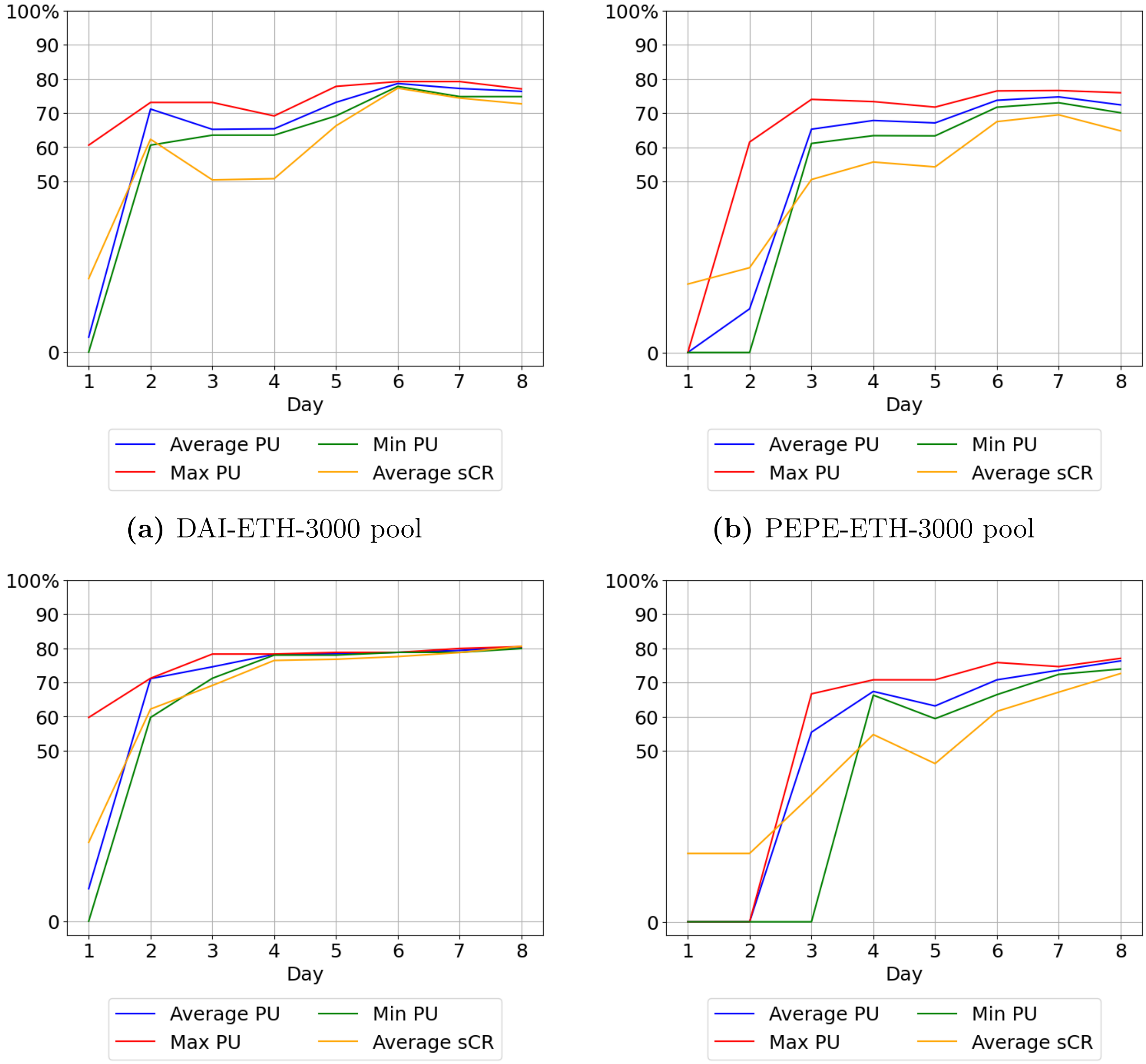
	PLPs				**Sellers**			
	Deposits		**Withdrawals**		**Mints**		**Rolls**	
	WBTC	ETH	WBTC	ETH	WBTC	ETH	WBTC	ETH
Count	13	8	0		8	8	3	3
Median amount	0.209	3.069	-		1.300	16.263	-	

Table C.4: Number count and median amount of PLPs deposits and withdrawals as well as sellers' mints and rolls, for USDC-ETH-500 pool, for Stage 1 simulations.

	PLPs				**Sellers**			
	Deposits		**Withdrawals**		**Mints**		**Rolls**	
	USDC	ETH	USDC	ETH	USDC	ETH	USDC	ETH
Count	12	8	0		8	8	28	13
Median amount	6347.913	1.890	-		44039.617	7.906	-	

C.2 Testing PU Saturation for Token1 - Results

In Figures C.4, C.5, and C.6, we present graphics illustrating the evolution of pool utilization in each scenario for various seller-deposited amounts during the PU Saturation testing simulations.



(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

(c) WBTC-ETH-3000 pool

(d) USDC-ETH-500 pool

Figure C.4: Token1 PU saturation and Seller's Collateralization Ratio for the four trading volume - liquidity scenarios, with the seller's *deposit_amount* input values between 1 and 5.

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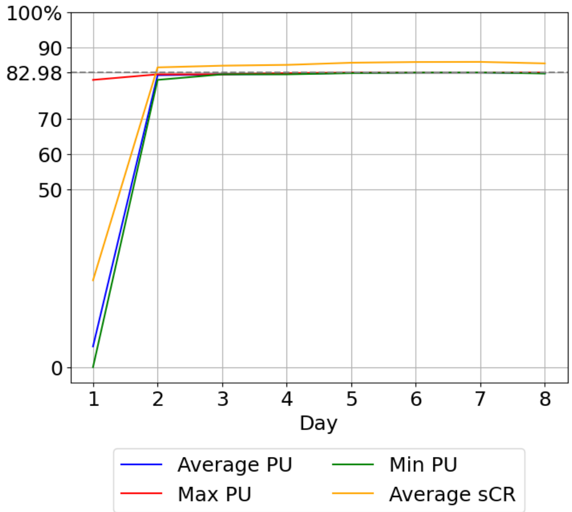
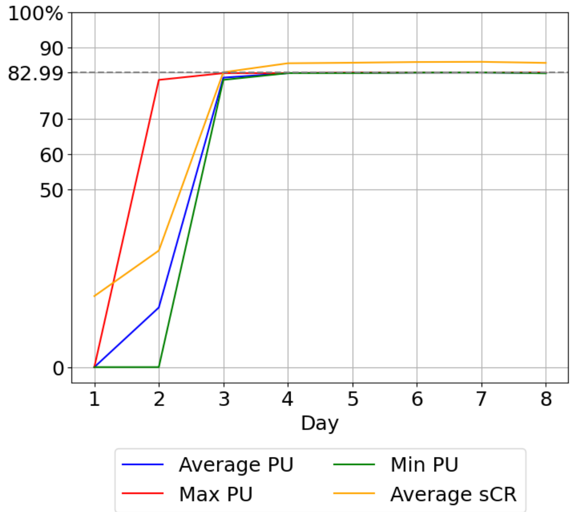
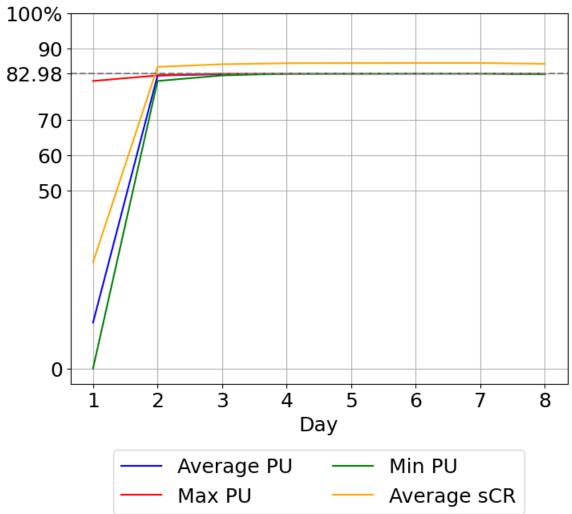


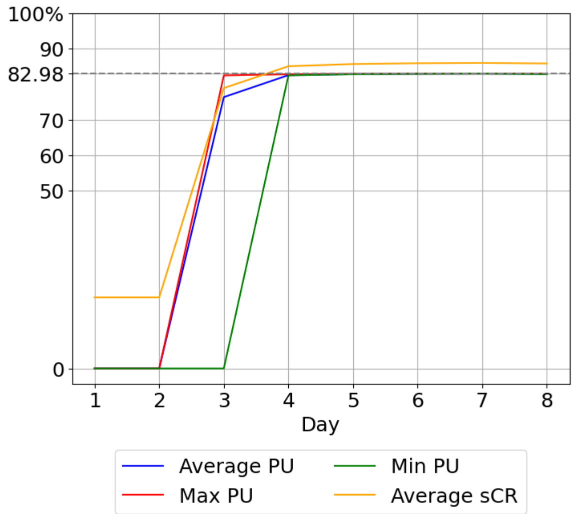
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure C.5: Token1 PU saturation and Seller's Collateralization Ratio for the four trading volume - liquidity scenarios, with the seller's *deposit_amount* input values as 100.

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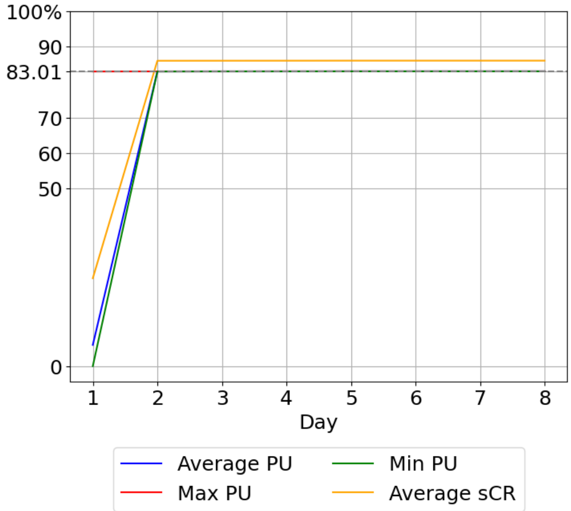
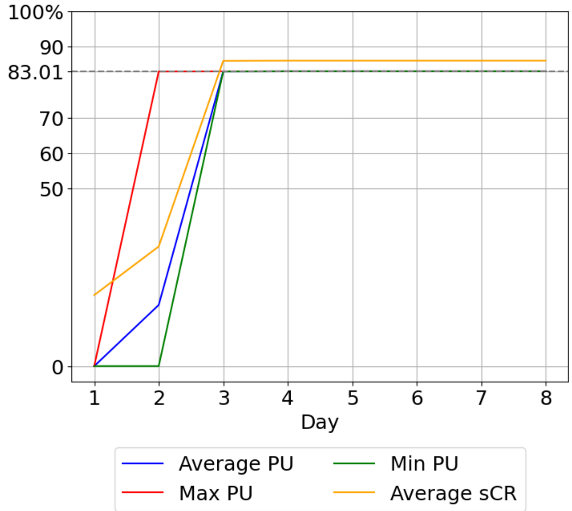
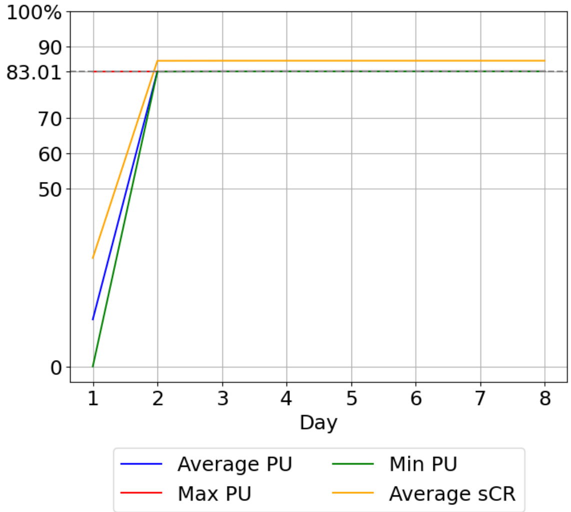


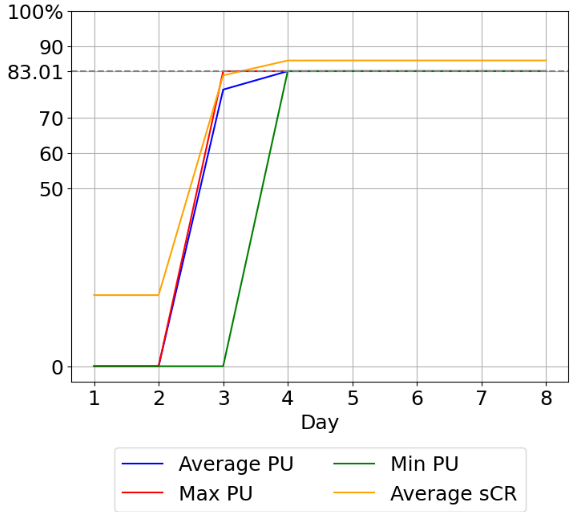
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

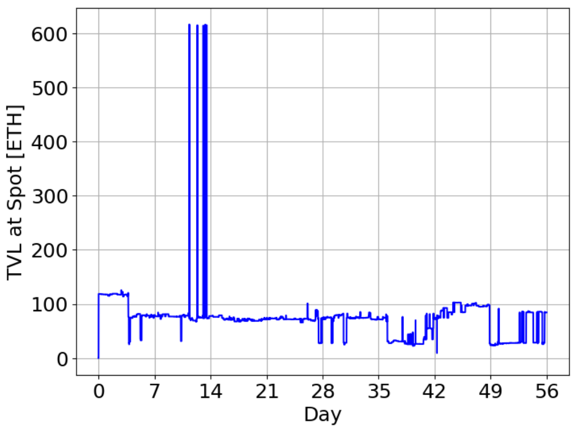
Figure C.6: Token1 PU saturation and Seller's Collateralization Ratio for the four trading volume - liquidity scenarios, with the seller's *deposit_amount* input values as 5000.

Appendix D

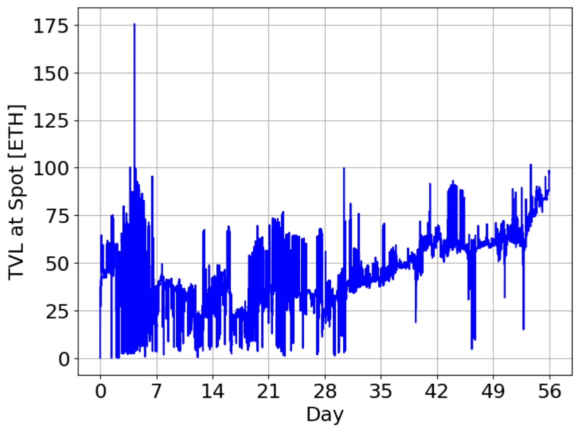
Stage 3 Results Compilation

In this appendix, we provide visual representations of the results obtained in Stage 3, emphasizing all scenarios and focusing on the metrics listed in Sections 4.1 and 4.2. Additionally, we do a concise analysis of the most relevant aspects.

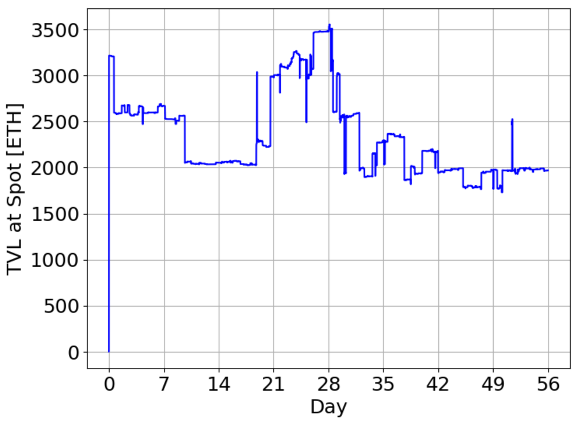
TVL at Spot Tick



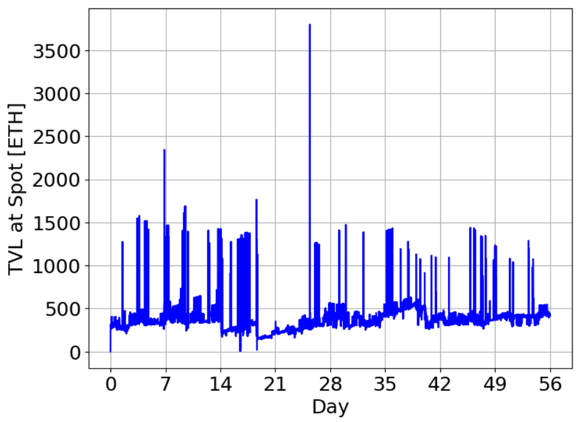
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool

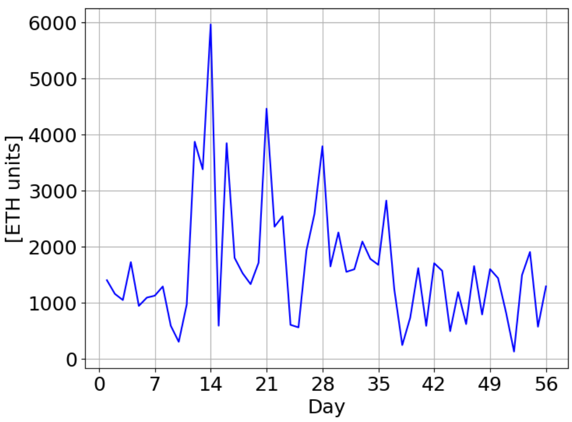


(d) USDC-ETH-500 pool

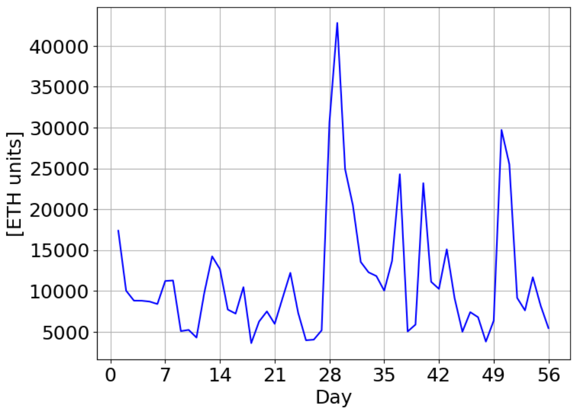
Figure D.1: Total Value Locked at the spot tick, expressed in ETH units, in each scenario pool for Stage 3 simulations.

Similar to Stage 4, as explained in subsection 5.3.1, the scenarios for the price trajectories used in each pool are also achieved for the 56-day time frame. From Figure D.1, we observe that DAI and PEPE pools have low liquidity, whereas in the WBTC and USDC pools, the liquidity is relatively high. It is noteworthy to mention that in these simulations, we are able to observe the effects of significant stakeholders (whales) interacting with the pools by depositing/withdrawing large funds. This discrepancy in liquidity is evident, especially in the DAI pool around the 10th to 14th day and in the USDC pool around the 25th day. This way, we were able to ensure some more realism and diversity.

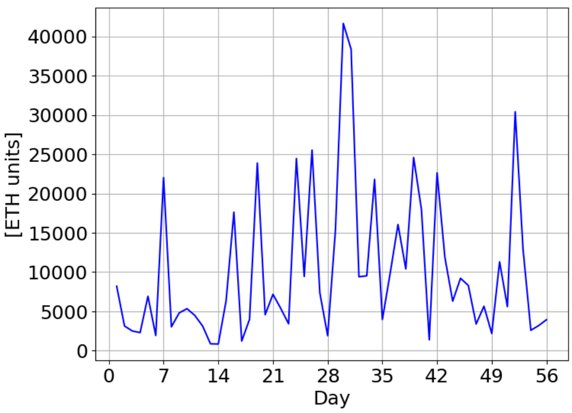
Daily Trading Volume



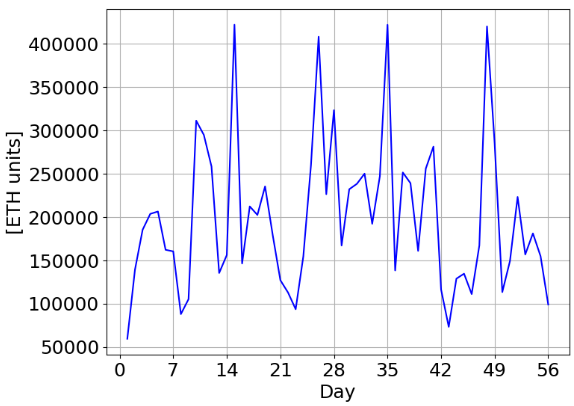
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool

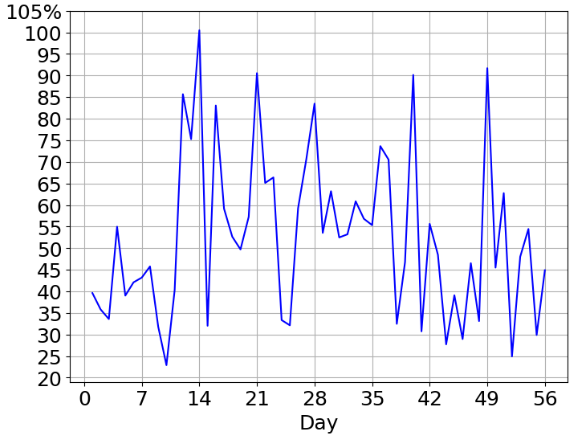


(d) USDC-ETH-500 pool

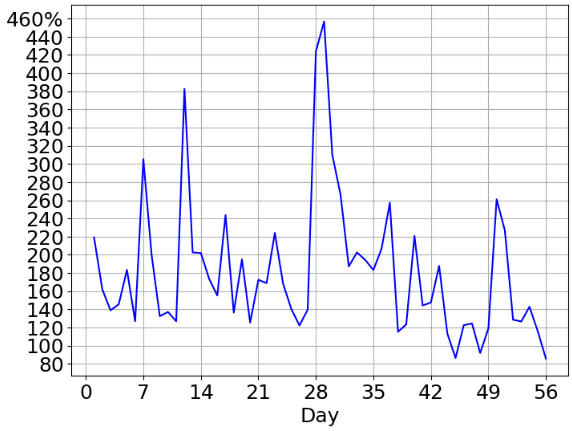
Figure D.2: Daily Trading Volume, expressed in ETH units, in each scenario pool for Stage 3 simulations.

Concerning trading volume, the intended scenarios are also achieved. Relative to the TVL, DAI and WBTC pools exhibit low trading volumes (roughly, 20 times and 6 times the TVL, respectively), whereas the PEPE and USDC pools evidently have high trading volumes on average (roughly, 300 times and 250 times the TVL, respectively).

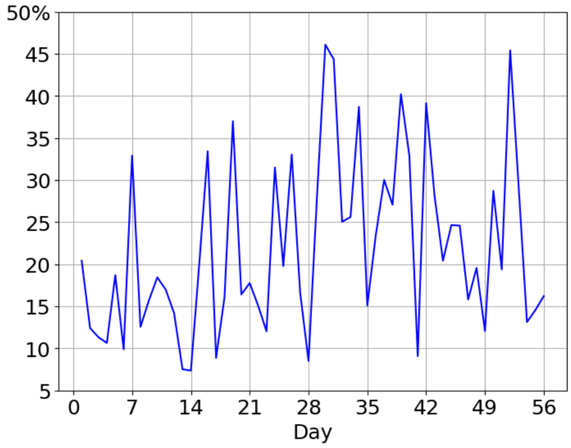
Daily Implied Volatility



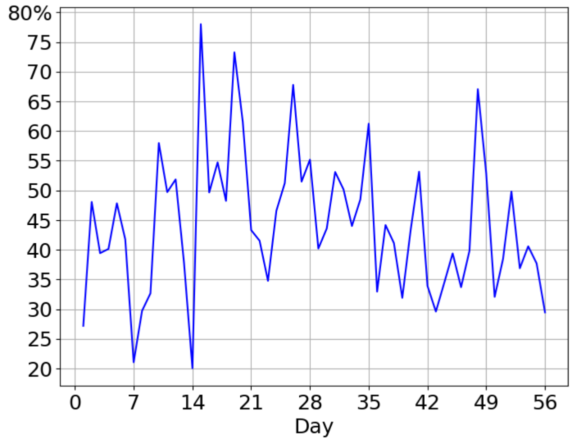
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure D.3: Daily Annualized Implied Volatility in each scenario pool for Stage 3 simulations.

As observed in the previous stages, the expected magnitudes of implied volatility are confirmed. The PEPE pool, with low liquidity and high trading volume, exhibits the largest IV consistently. We can observe the highest IV around the 28th day, coinciding with the time when the largest daily trading volumes occurred, as can be checked in Figure D.2(b). Contrarily, we verify relatively low IV in the WBTC pool. The remaining two exhibit relatively intermediate values on average.

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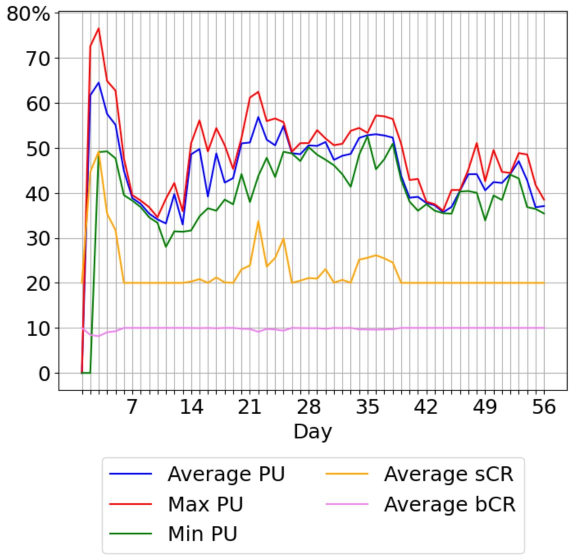
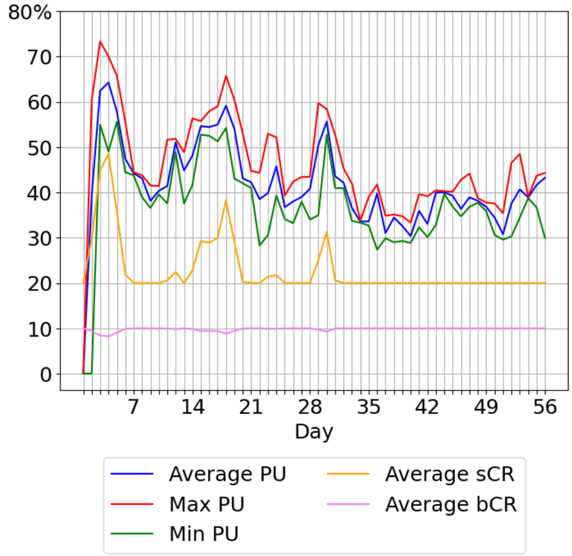
Pool Utilization and Seller and Buyer Collateralization Ratios for Token0/1

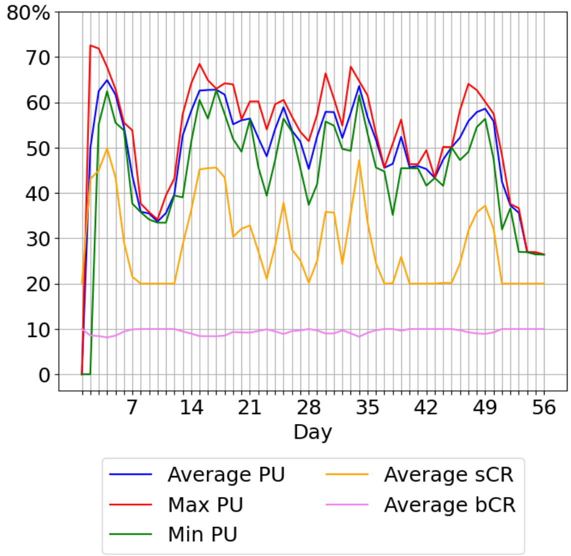
For Token0:



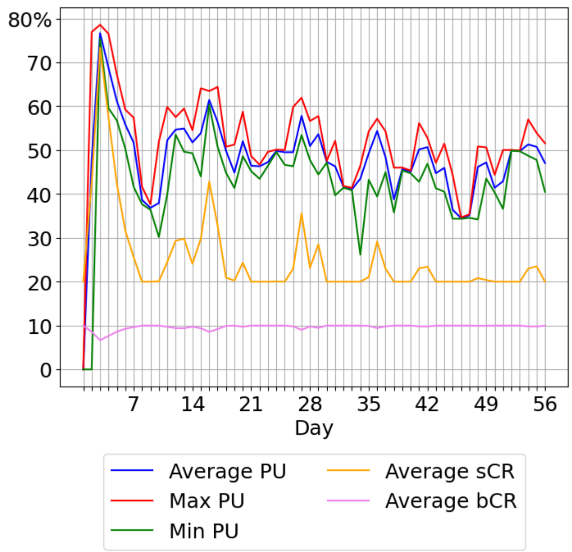
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

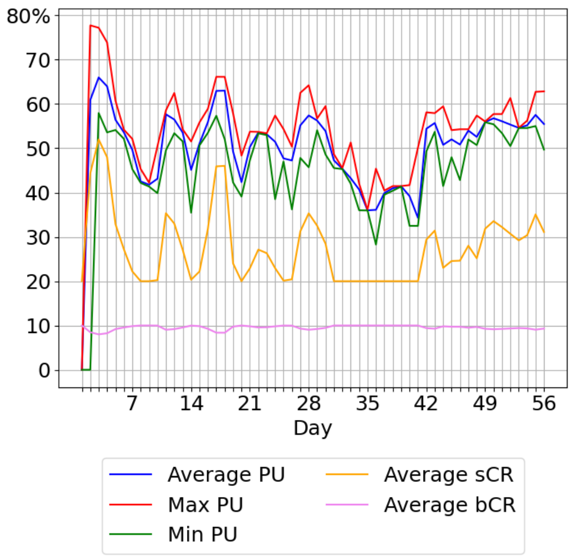
Figure D.4: Pool utilization, Seller Collateralization Ratio and Buyer Collateralization Ratio (Token0) for the four pools tested in Stage 3 simulations.

Upon observing this figure, it becomes apparent that in all scenarios, the average PU, after the initial expected abrupt increase (due to exclusive selling action) and decrease (due to exclusive buying action), tends to cyclically hover around an average value throughout the simulation. In all the pools, except for the WBTC pool, this average seems to be approximately 50%, aligning with the target pool utilization. This holds true for almost all the simulation time span, except from the 6th week onwards, in the DAI and PEPE pools, where we observe a decrease (more pronounced in the latter). The

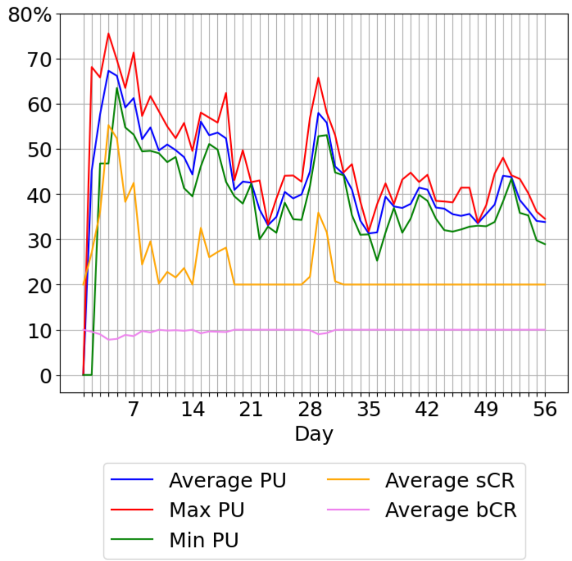
USDC pool exhibits a more consistent tendency. Finally, referring to the WBTC pool, this average value seems to be within the 50-60% range, verifying a decrease from the 6th week as well, which is particularly abrupt in the last week.

Nevertheless, even though the PU does not consistently circle the 50% target, we can still affirm the existence of equilibrium in the sellers/buyers dynamics and, more crucially, affirm the protocol's health in terms of Token0 fund balancing mechanisms for all scenarios, though with special evidency in the high liquidity, high trading volume scenario of the USDC pool.

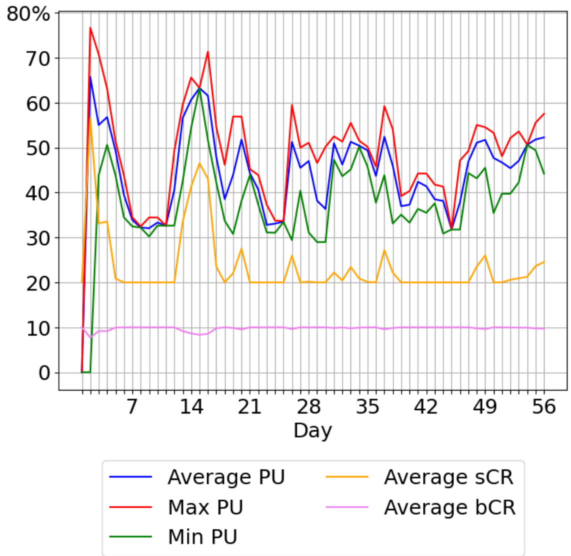
For Token1:



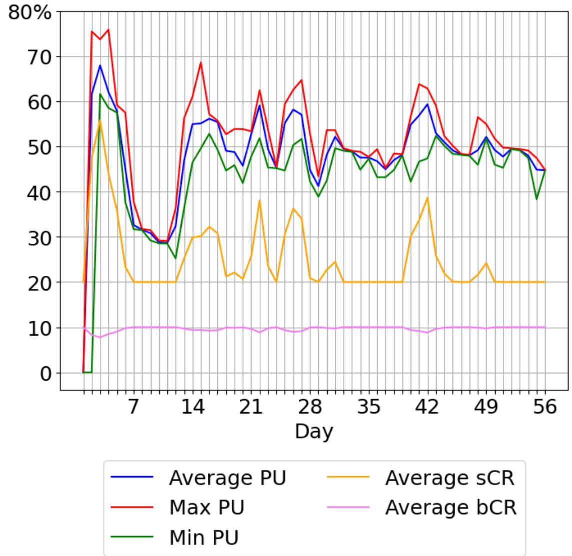
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



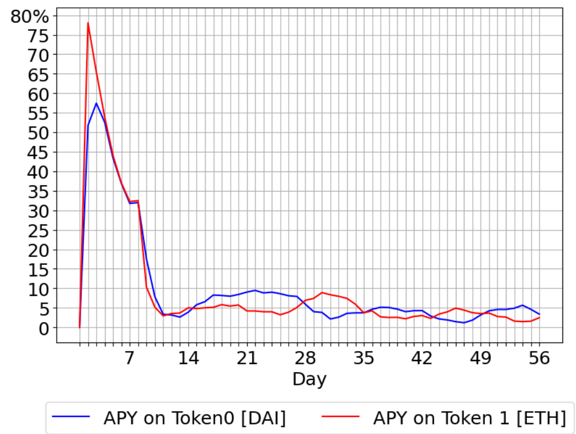
(d) USDC-ETH-500 pool

Figure D.5: Pool utilization, Seller Collateralization Ratio and Buyer Collateralization Ratio (Token1) for the four pools tested in Stage 3 simulations.

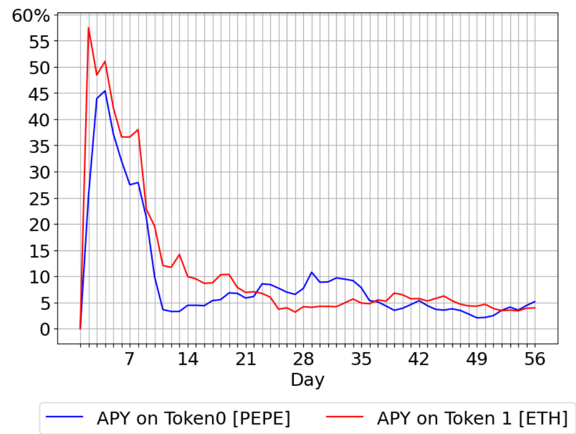
Comparing Token1's PU with Token0's PU, the analysis remains very similar. One notable difference is observed in the USDC pool, where the expected decrease starting from the latter half of the first week is more pronounced compared to Token0. Nevertheless, the recovery is also robust, and we observe an even more steady hovering around the PU target value throughout the simulation. Additionally, in the low liquidity low trading volume scenario (DAI pool), there is a more sustained hovering of PU around the 50% target than observed for Token0, persisting throughout the simulation and even ending with an increasing tendency. Similar observation can be taken from the WBTC pool results.

Let it be noted that the maximum PU values in each token, occurring in the first half week, as expected (almost no buying actions, only selling), never surpass the saturation value.

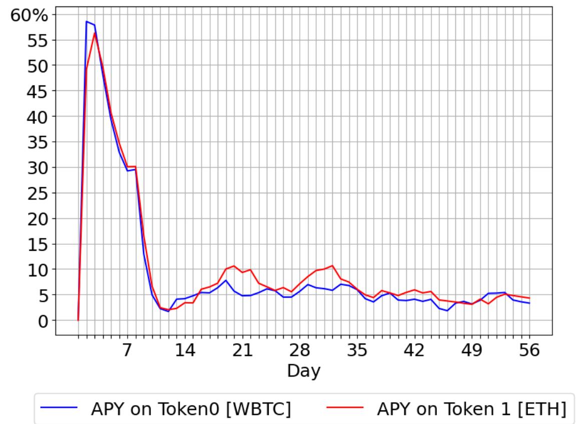
PLP's APYs



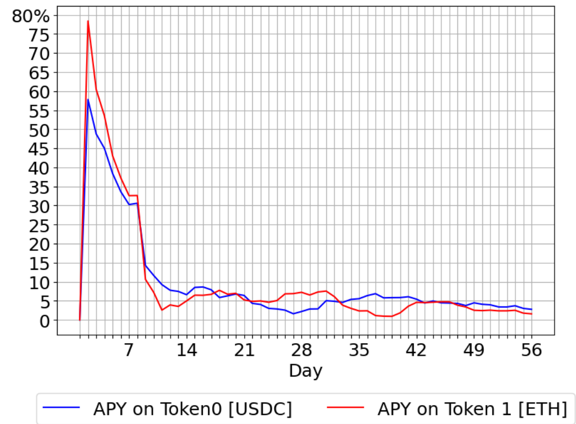
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure D.6: Daily PLPs APY (7 days moving average) in each scenario pool for Stage 3 simulations.

Concerning PLPs returns, it is evident that after the initial spike, marked by a surge in minting activity and fewer PLP deposits, the APYs across all scenarios tend to decrease and stabilize at an average value around 5%. Both tokens take turns having the highest APY, but the overall average remains remarkably consistent. Notably, the fluctuations in all scenarios are not overly prominent.

PLP's and Seller's Additional Metrics

In the following tables, we present the number of deposits and withdrawals performed by PLPs, as well as the number of mint and roll operations performed by option sellers. This information provides the reader with an understanding of the volume of operations and their order of magnitude in terms of funds moved.

Deposits and Withdrawals

Table D.1: Number count and median amount of deposits and withdrawals of PLPs, for DAI-ETH-3000 pool in Stage 3 simulations.

	PLPs							
	Active				**Passive**			
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
	DAI	ETH	DAI	ETH	DAI	ETH	DAI	ETH
Count	55	57	13	15	28	24	0	
Median amount	791.026	0.568	3165.298	2.625	547.616	0.549	-	

Table D.2: Number count and median amount of deposits and withdrawals of PLPs, for PEPE-ETH-3000 pool in Stage 3 simulations.

	PLPs							
	Active				**Passive**			
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
	PEPE	ETH	PEPE	ETH	PEPE	ETH	PEPE	ETH
Count	74	76	14	10	27	26	0	
Median amount	1.206e9	1.184	9.242e9	5.136	1.715e9	0.516	-	

Table D.3: Number count and median amount of deposits and withdrawals of PLPs, for WBTC-ETH pool in Stage 3 simulations.

	PLPs							
	Active				**Passive**			
	Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
	WBTC	ETH	WBTC	ETH	WBTC	ETH	WBTC	ETH
Count	62	79	17	11	20	23	0	
Median amount	0.190	3.081	0.387	8.629	0.197	4.725	-	

Table D.4: Number count and median amount of deposits and withdrawals of PLPs, for USDC-ETH-500 pool in Stage 3 simulations.

	PLPs							
	Active				Passive			
	Deposits		Withdrawals		Deposits		Withdrawals	
	USDC	ETH	USDC	ETH	USDC	ETH	USDC	ETH
Count	91	50	16	14	26	20	0	1
Median amount	3738.897	2.400	16705.057	7.364	6541.622	2.323	-	4.313

ITM, ATM and OTM Rolls

Here, we introduce a slight distinction in our definitions of ITM and OTM. In this context, ATM refers to the spot price being within the position range. For put options, OTM is when the spot price is above the position's upper tick, while for call options, OTM is when the spot price is below the position's lower tick. The reverse holds for ITM. Additionally, please note that in the tables, we provide the median size of the minted positions

Table D.5: Number count and median amount of sellers' mints and rolls, for DAI-ETH-3000 pool in Stage 3 simulations.

	Sellers									
	Mints		Rolls							
			Global		ITM		ATM (in-range)		OTM	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	64	53	116	85	2	20	21	19	93	46
Median amount	8133.055	9.572					-			

Table D.6: Number count and median amount of sellers' mints and rolls, for PEPE-Puts-3000 pool in Stage 3 simulations.

	Sellers									
	Mints		Rolls							
			Global		ITM		ATM (in-range)		OTM	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	69	73	280	229	51	86	53	43	176	99
Median amount	1.887e10	10.687					-			

Table D.7: Number count and median amount of sellers' mints and rolls, for WBTC-Puts-3000 pool in Stage 3 simulations.

	Sellers									
	Mints		**Rolls**							
			Global		**ITM**		**ATM (in-range)**		**OTM**	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	58	70	106	37	0	3	50	1	56	33
Median amount	1.978	28.707	-							

Table D.8: Number count and median amount of sellers' mints and rolls, for USDC-Puts-500 pool in Stage 3 simulations.

	Sellers									
	Mints		**Rolls**							
			Global		**ITM**		**ATM (in-range)**		**OTM**	
	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts	Calls	Puts
Count	66	62	304	257	116	92	41	14	147	151
Median amount	52762.053	35.019	-							

Number of Options Bought and Exercised

In Table D.9, we present the aggregate number of purchased and exercised options for both call and put types. Additionally, we include the overall ratio between these two actions throughout the simulation.

Table D.9: Number of Options Bought and Exercised for each pool tested in Stage 3 simulations.

	No. Options Bought		**No. Options Exercised**		**Exercised / Bought Options Ratio**
Pool	**Calls**	**Puts**	**Calls**	**Puts**	
DAI	58	48	49	40	0.84
PEPE	56	64	50	55	0.88
WBTC	63	58	50	51	0.83
USDC	56	50	46	42	0.83

The primary takeaway from this table is that all scenarios exhibit similar ratios between the number of exercised and bought options, despite variations in the quantities of each option type. This suggests that, regardless of the price and liquidity trajectories, the overall behaviors of the agents were consistently similar. This alignment was anticipated as the agents' actions are not contingent on specific price trends.

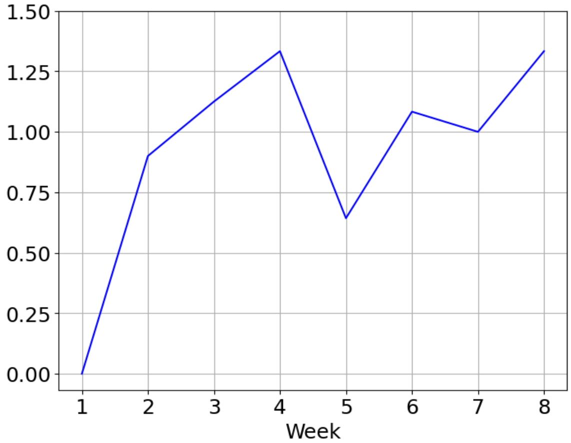
Additionally, we present in Table D.10, the median amount of the options bought.

Table D.10: The median amount of the call and put options bought in each scenario pool for Stage 3 simulations.

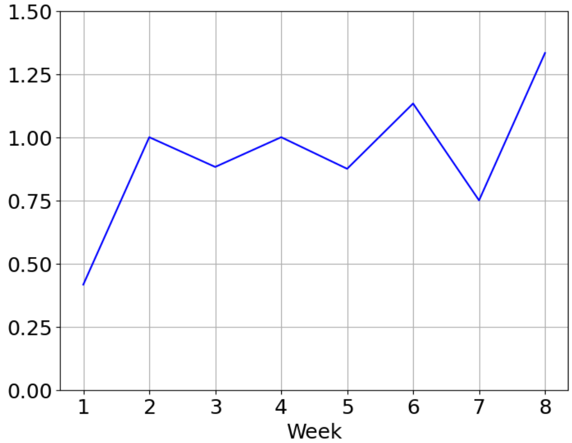
	Pool			
Option Type	DAI	PEPE	WBTC	USDC
Calls	5190.386	1.315e10	1.214	37897.304
Puts	7.353	7.168	21.817	24.678

Ratio between the number of Options Exercised and Bought

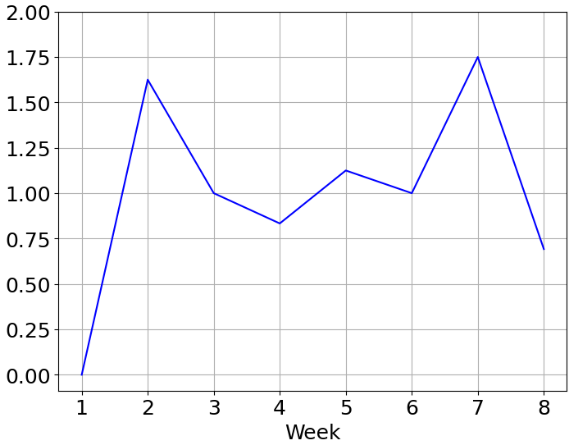
In Table D.9, we have presented the simulation's global ratio between the number of options exercised and bought. Here, we show the weekly evolution of this ratio.



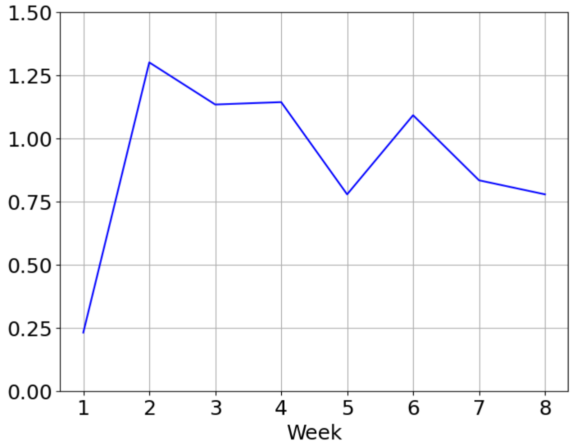
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



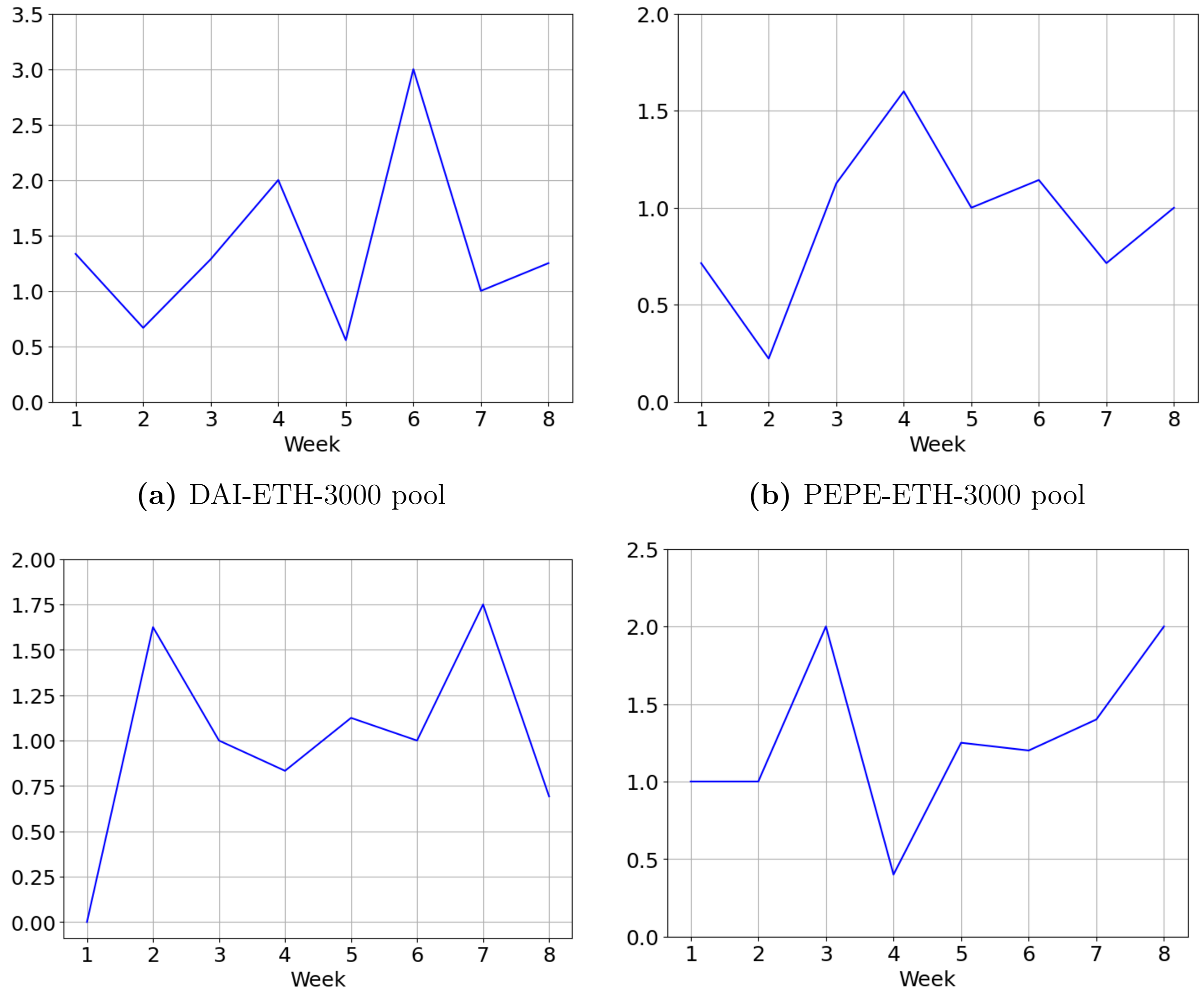
(d) USDC-ETH-500 pool

Figure D.7: Ratio between the number of exercised and bought options on a weekly basis in each scenario pool for Stage 3 simulations.

Once more, we can not observe any clear pattern in the results. In each scenario, there are weeks with more options bought than exercised, and vice versa. Naturally, all scenarios share an initial week with higher buying activity. The overall ratio tends to be below one, primarily influenced by the low value in the first week.

Furthermore, we can affirm that there is no apparent correlation with the price trajectory and the pool's implied volatility. This outcome was anticipated, as these actions are not dependent on the price or implied volatility trends.

Ratio between the number of Call and Put Options Bought



(a) DAI-ETH-3000 pool

(b) PEPE-ETH-3000 pool

(c) WBTC-ETH-3000 pool

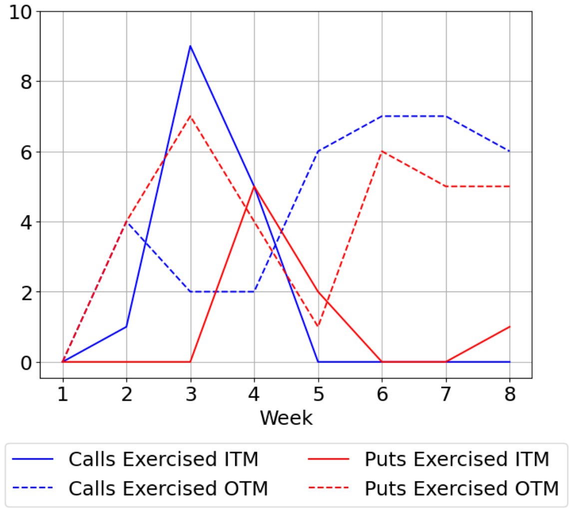
(d) USDC-ETH-500 pool

Figure D.8: Ratio between the number of call options and put options bought on a weekly basis in each scenario pool for Stage 3 simulations.

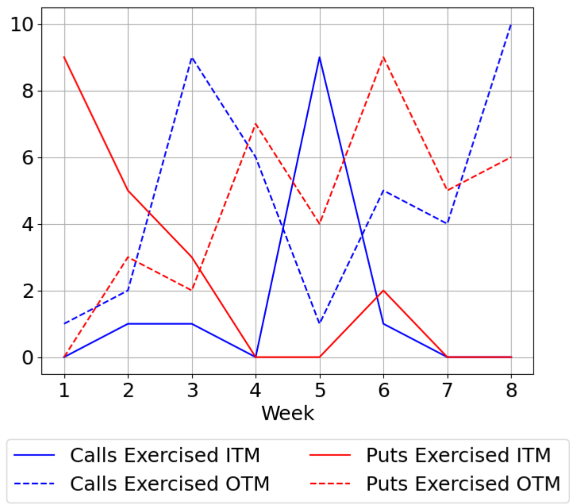
We observe that there is no discernible pattern in the results. Across various scenarios, there are weeks where the number of call options bought surpasses that of put options, and vice versa. These outcomes are solely dependent on the compatibility between buyer and seller options, which, in turn, relies on the input configurations. It might be assumed that these ratios directly hinge on the number of options sold, but this is not necessarily the case. For instance, in the USDC pool, the ratio is consistently below 1 for most weeks, indicating more puts being bought. However, as indicated in Table D.8, there are more calls minted than puts. Additionally, as anticipated, no clear relations with the price trajectories can be established.

Number of Call and Put Options Exercised ITM and OTM

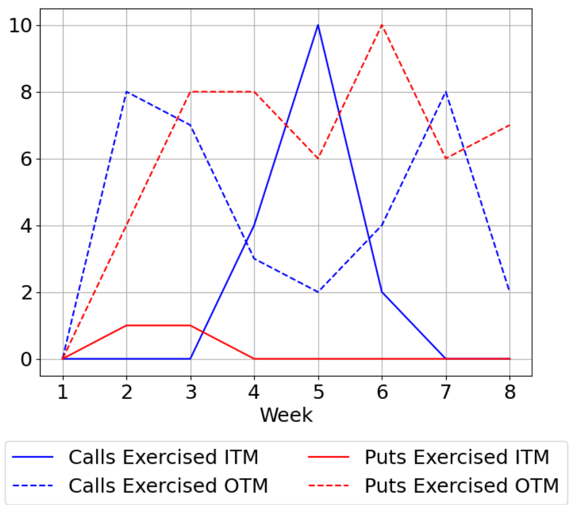
In an overview, we observe in Figure D.9 that in the majority of weeks across all scenarios, OTM exercises surpassed ITM exercises, except for the USDC pool, where the



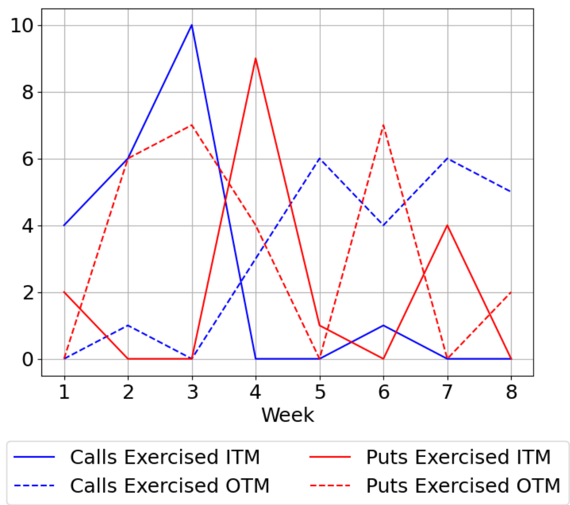
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

Figure D.9: Number of call options and put options exercised both ITM and OTM on a weekly basis in each scenario pool for Stage 3 simulations.

number of weeks in each case are equal. Given that the buyers are naive at this stage, this may indicate poor timing in their buying actions in alignment with the price tendencies, leading to the exercise of most options OTM over time.

Furthermore, DAI and USDC pools exhibit quite similar patterns, coinciding in weeks where ITM exercises surpassed OTM exercises (peaking at week 3 for calls and week 4 for puts). This alignment is primarily due to the identical price trajectories of these two pools (refer to Figure 5.11 in Section 5.3). This relationship with price is particularly evident during peaks, where week 3 corresponds to an upward price movement, and week 4 corresponds to a downward price movement.

This correlation with price trajectories is also noticeable in other scenarios. For instance, in the PEPE pool, the first three weeks align with a downward price movement, justifying more exercised put options ITM than OTM and more exercised call options OTM than ITM. Similarly, in the WBTC pool, where the price tends to rise from the second week onward, it is natural that there were consistently more put options being exercised OTM than ITM.

Finally, it is important to mention that, as expected, there is no relation between the number of call or put options being exercised with the price tendency.

Exercising Yield and Loss

In the following tables, we present the yield obtained by buyers when exercising their options ITM according to Equation 3.3.10 (Table D.11) or their loss when exercising OTM according to Equation 4.2.1 (Table D.12).

Table D.11: Mean, minimum and maximum values for the yield derived from exercising ITM options for the four pools tested in Stage 3 simulations.

	Exercising Yield (%)		
Pool	**Mean**	**Minimum**	**Maximum**
DAI	24.794	8.365	53.825
PEPE	69.075	8.082	229.455
WBTC	18.744	5.040	36.699
USDC	21.488	7.167	58.422

Table D.12: Mean, minimum and maximum values for the loss derived from exercising OTM options in each scenario pool for Stage 3 simulations.

	Exercising Loss (%)		
Pool	**Mean**	**Minimum**	**Maximum**
DAI	-23.515	-0.714	-91.349
PEPE	-95.479	-0.714	-418.941
WBTC	-3.681	-0.714	-18.421
USDC	-26.452	-0.714	-79.748

It is evident that in the PEPE pool, the gains are the highest, but so are the losses (even greater in our simulations). We may attribute this to the large implied volatility exhibited by this low-liquidity, high trading volume scenario. In contrast, the scenario with the lowest implied volatility (WBTC pool) results in the lowest gains for buyers, but once again, the lowest losses as well.

Premium's Relative Magnitude to Option's Position Size

Concerning the premium earned by sellers (and lost by buyers) upon option exercising, we observe that the average is lower than 10% of the buyer's position size in every scenario, at the exception of the PEPE pool, where it can reach almost 20% aligning with the conclusions withdrawn earlier.

Note that the plots for DAI and WBTC pools only start in the second week since there are no exercised options in the first week.

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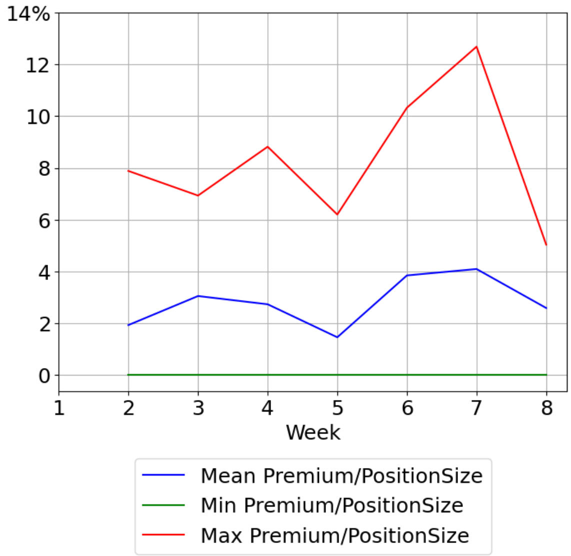
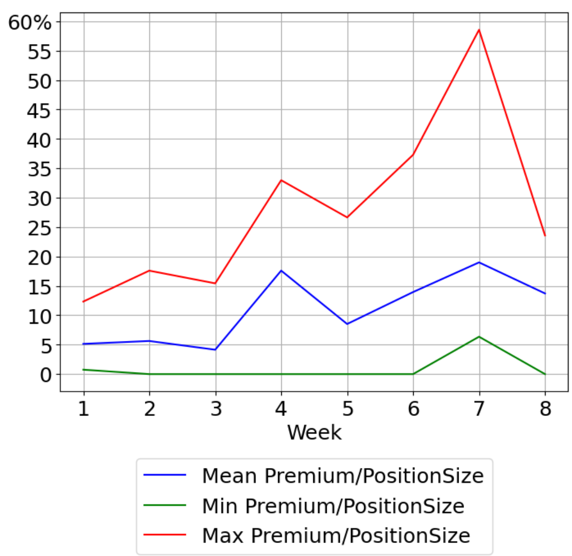
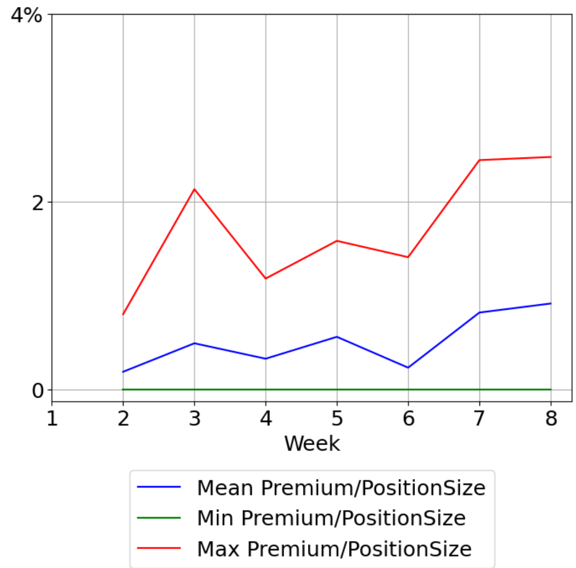


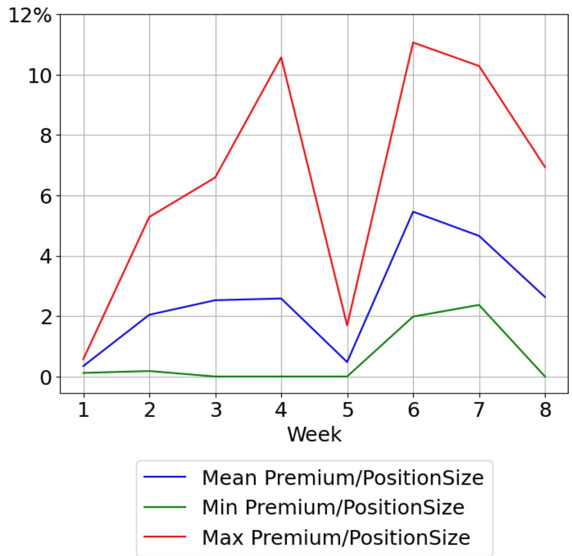
(a) DAI-ETH-3000 pool



(b) PEPE-ETH-3000 pool



(c) WBTC-ETH-3000 pool



(d) USDC-ETH-500 pool

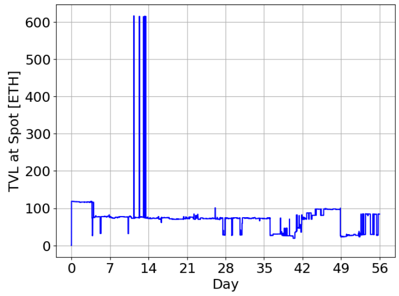
Figure D.10: The magnitude of the premium accrued in relation to the position size of the option in each scenario pool for Stage 3 simulations.

Appendix E

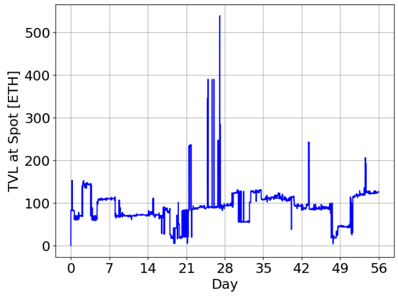
Extra Stage 4 Results using different Price and Liquidity Distribution Trajectories

E.1 DAI-ETH-3000 Pool

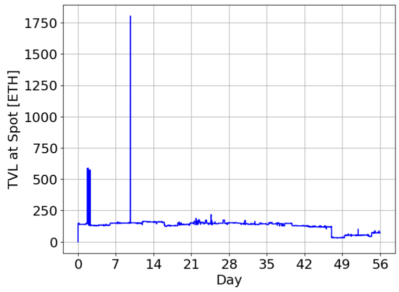
TVL at Spot Tick



(a) Trajectory A.



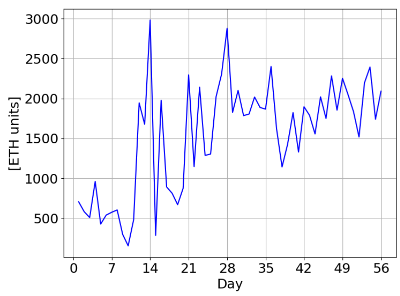
(b) Trajectory B.



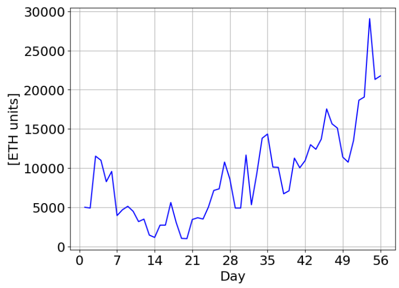
(c) Trajectory C.

Figure E.1: Different trajectories for TVL at the spot tick, expressed in ETH units, used in Stage 4 simulations for DAI-ETH-3000 pool.

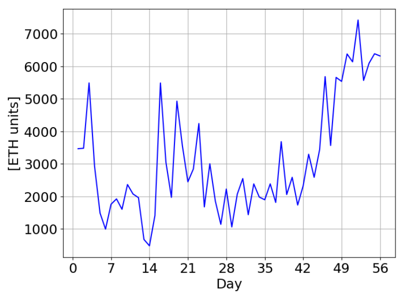
Daily Trading Volume



(a) Trajectory A.



(b) Trajectory B.



(c) Trajectory C.

Figure E.2: Evolution of daily trading volume in the DAI pool Stage 4 simulations for the different trajectories.

PLPs Additional Metrics

Table E.1: Number count and median amount of deposits and withdrawals of PLPs, in the DAI pool Stage 4 simulations for the different trajectories.

		PLPs							
		Active				Passive			
		Deposits		Withdrawals		Deposits		Withdrawals	
Trajectory	**Quantity**	**DAI**	**ETH**	**DAI**	**ETH**	**DAI**	**ETH**	**DAI**	**ETH**
A	Count	58	96	15	21	21	31	0	
	Median amount	773.101	0.558	3794.327	2.243	1264.303	0.583	-	
B	Count	77	123	28	25	21	33	0	
	Median amount	773.101	0.558	2565.852	0.558	1264.303	0.583	-	
C	Count	73	104	14	22	21	32	0	
	Median amount	755.980	0.558	2688.638	2.242	1264.303	0.583	-	

Sellers Additional Metrics

Table E.2: Number count and median amount of sellers' mints and rolls, in the DAI pool Stage 4 simulations for the different trajectories.

		Sellers									
		Mints		Rolls							
				Global		ITM		ATM (in-range)		OTM	
Trajectory	**Quantity**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**
A	Count	76	78	30	23	12	23	18	0	0	0
	Median amount	9303.757	9.267	-							
B	Count	75	94	116	48	54	47	62	1	0	0
	Median amount	9676.906	8.413	-							
C	Count	75	81	33	42	5	40	28	2	0	0
	Median amount	11373.273	9.160	-							

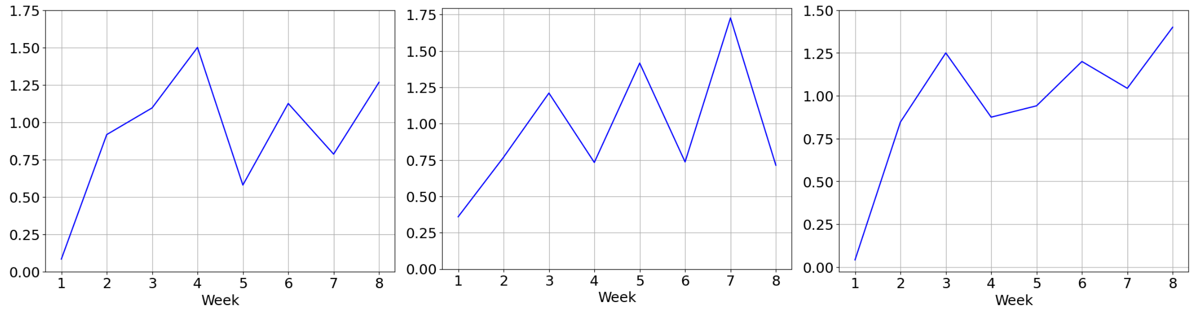
Number and Ratio of Options Bought and Exercised

Table E.3: Number of Options Bought and Exercised for each pool tested in the DAI pool Stage 4 simulations for the different trajectories.

	No. Options Bought		No. Options Exercised		Exercised / Bought Options Ratio
Trajectory	**Calls**	**Puts**	**Calls**	**Puts**	
A	60	75	51	65	0.86
B	61	67	50	63	0.88
C	63	71	57	61	0.88

Table E.4: The median amount of the call and put options bought in the DAI pool Stage 4 simulations for the different trajectories.

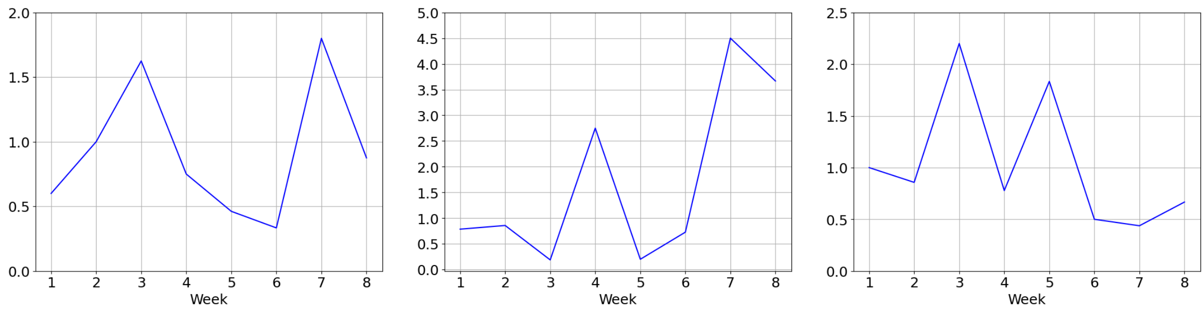
	Trajectory		
Option Type	A	B	C
Calls [DAI]	6178.974	7008.151	8794.993
Puts [ETH]	6.148	4.962	6.676



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure E.3: Ratio between exercised and bought options in the DAI pool Stage 4 simulations for the different trajectories.

Ratio between the number of Call and Put Options Bought

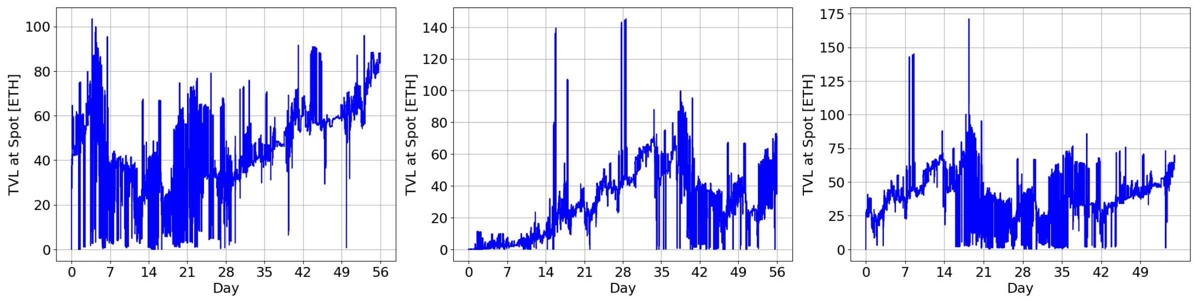


(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure E.4: Ratio between bought calls and puts in the DAI pool Stage 4 simulations for the different trajectories.

E.2 PEPE-ETH-3000 Pool

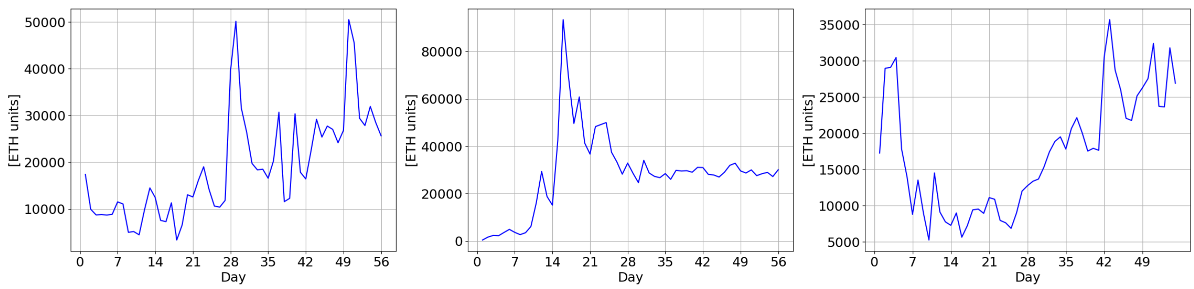
TVL at Spot Tick



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure E.5: Different trajectories for TVL at the spot tick, expressed in ETH units, used in Stage 4 simulations for PEPE-ETH-3000 pool.

Daily Trading Volume



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure E.6: Evolution of daily trading volume in the PEPE pool Stage 4 simulations for the different trajectories.

PLPs Additional Metrics

Table E.5: Number count and median amount of deposits and withdrawals of PLPs, in the PEPE pool Stage 4 simulations for the different trajectories.

		PLPs							
		Active				**Passive**			
		Deposits		**Withdrawals**		**Deposits**		**Withdrawals**	
Trajectory	**Quantity**	**PEPE**	**ETH**	**PEPE**	**ETH**	**PEPE**	**ETH**	**PEPE**	**ETH**
A	Count	85	103	20	26	19	25	0	
	Median amount	1.165e9	0.925	4.853e9	3.308	9.859e8	1.659	-	
B	Count	78	58	13	19	10	24	0	
	Median amount	1.431e9	0.771	8.260e9	2.164	1.570e9	0.981	-	
C	Count	81	100	32	35	17	27	1	0
	Median amount	1.052e9	0.754	2.748e9	1.841	2.031e9	0.981	1.406e9	-

Sellers Additional Metrics

Table E.6: Number count and median amount of sellers' mints and rolls, in the PEPE pool Stage 4 simulations for the different trajectories.

		Sellers									
		Mints		**Rolls**							
				Global		**ITM**		**ATM (in-range)**		**OTM**	
Trajectory	**Quantity**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**
A	Count	81	72	114	49	81	49	33	0	0	0
	Median amount	2.368e10	12.309					-			
B	Count	51	61	154	52	151	51	3	1	0	0
	Median amount	1.591e10	9.908					-			
C	Count	67	77	65	75	40	74	25	1	0	0
	Median amount	1.556e10	11.415					-			

Number and Ratio of Options Bought and Exercised

Table E.7: Number of Options Bought and Exercised for each pool tested in the PEPE pool Stage 4 simulations for the different trajectories.

	No. Options Bought		**No. Options Exercised**		**Exercised / Bought Options Ratio**
Trajectory	**Calls**	**Puts**	**Calls**	**Puts**	
A	66	52	59	48	0.91
B	29	38	29	34	0.94
C	44	57	37	52	0.88

Table E.8: The median amount of the call and put options bought in the PEPE pool Stage 4 simulations for the different trajectories.

	Trajectory		
Option Type	A	B	C
Calls [PEPE]	1.695e10	1.204e10	1.274e10
Puts [ETH]	9.276	7.307	7.812

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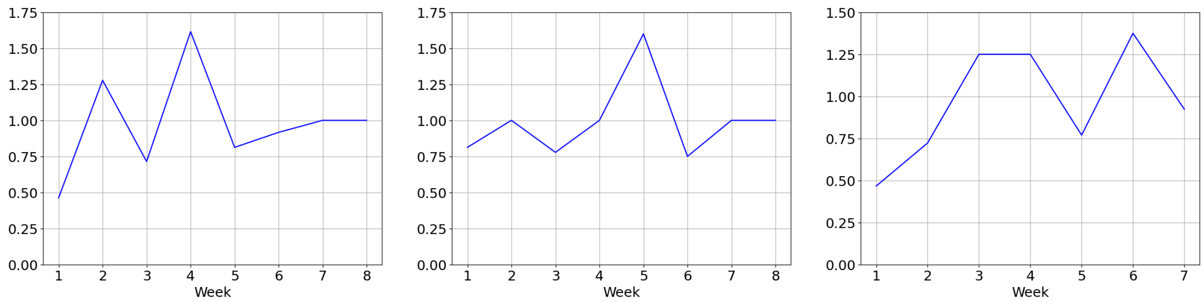
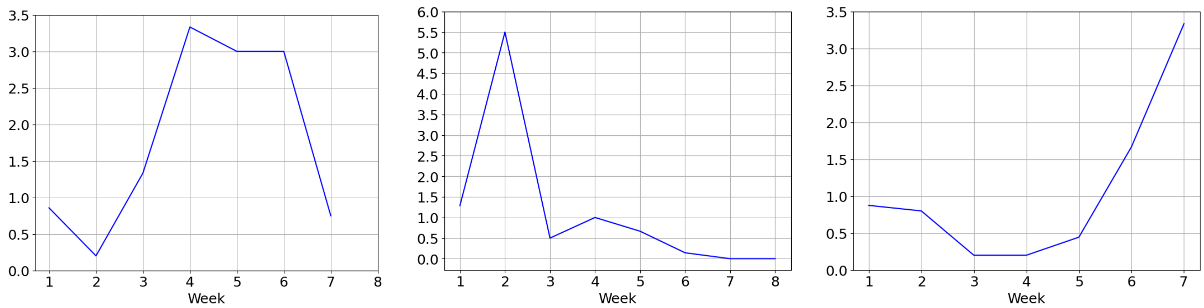


(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure E.7: Ratio between exercised and bought options in the PEPE pool Stage 4 simulations for the different trajectories.

Ratio between the number of Call and Put Options Bought

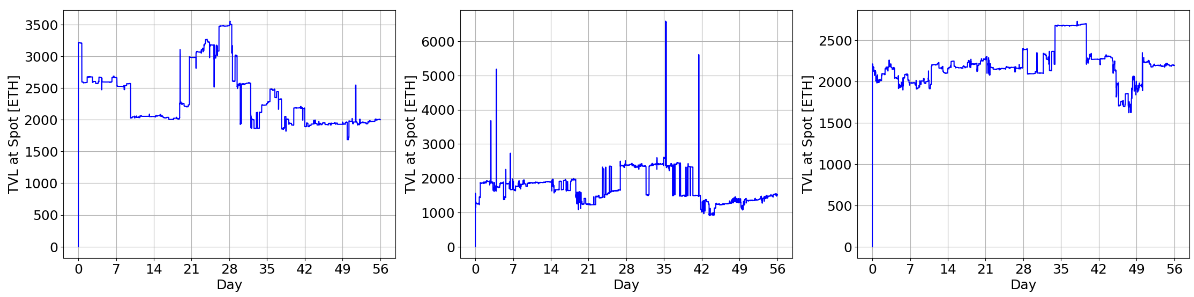


(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure E.8: Ratio between bought calls and puts in the PEPE pool Stage 4 simulations for the different trajectories.

E.3 WBTC-ETH-3000 Pool

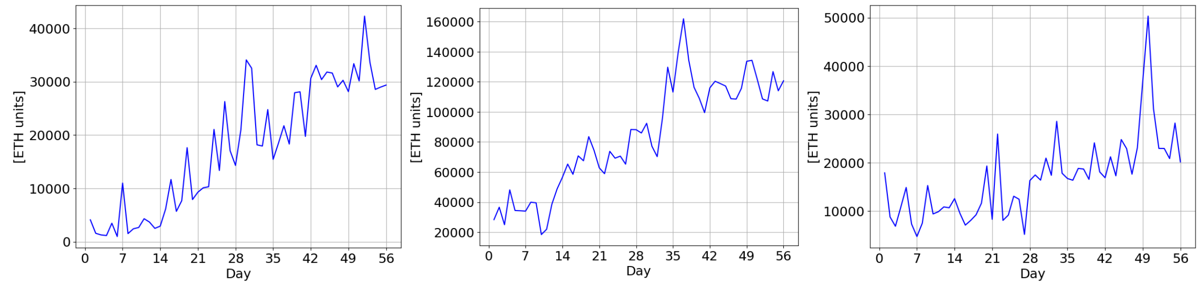
TVL at Spot Tick



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure E.9: Different trajectories for TVL at the spot tick, expressed in ETH units, used in Stage 4 simulations for WBTC-ETH-3000 pool.

Daily Trading Volume



(a) Trajectory A. (b) Trajectory B. (c) Trajectory C.

Figure E.10: Evolution of daily trading volume in the WBTC pool Stage 4 simulations for the different trajectories.

PLPs Additional Metrics

Table E.9: Number count and median amount of deposits and withdrawals of PLPs, in the WBTC pool Stage 4 simulations for the different trajectories.

		PLPs							
		Active				Passive			
		Deposits		Withdrawals		Deposits		Withdrawals	
Trajectory	**Quantity**	**WBTC**	**ETH**	**WBTC**	**ETH**	**WBTC**	**ETH**	**WBTC**	**ETH**
A	Count	112	102	22	39	22	30	2	5
	Median amount	0.169	3.488	0.278	11.204	0.543	3.179	0.546	3.058
B	Count	66	85	19	23	24	30	1	3
	Median amount	0.155	3.815	0.236	11.198	0.671	3.179	2.086	9.582
C	Count	54	80	13	25	24	30	0	
	Median amount	0.169	3.815	0.229	11.005	0.543	3.179	-	

Sellers Additional Metrics

Table E.10: Number count and median amount of sellers' mints and rolls, in the WBTC pool Stage 4 simulations for the different trajectories.

		Sellers									
		Mints		Rolls							
				Global		ITM		ATM (in-range)		OTM	
Trajectory	**Quantity**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**
A	Count	77	75	41	1	3	1	38	0	0	0
	Median amount	2.230	53.768	-							
B	Count	66	84	47	14	8	14	39	0	0	0
	Median amount	2.235	49.814	-							
C	Count	77	76	28	3	0	3	28	0	0	0
	Median amount	2.375	53.682	-							

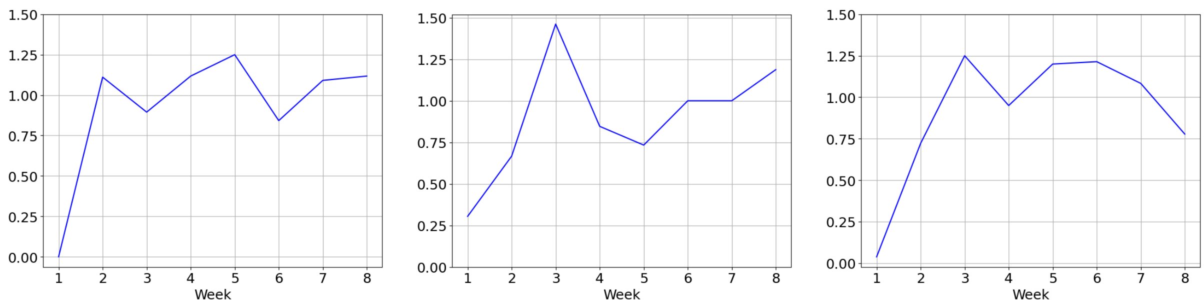
Number and Ratio of Options Bought and Exercised

Table E.11: Number of Options Bought and Exercised for each pool tested in the WBTC pool Stage 4 simulations for the different trajectories.

	No. Options Bought		**No. Options Exercised**		**Exercised / Bought Options Ratio**
Trajectory	**Calls**	**Puts**	**Calls**	**Puts**	
A	70	57	59	49	0.85
B	50	70	43	60	0.86
C	71	68	57	52	0.83

Table E.12: The median amount of the call and put options bought in the WBTC pool Stage 4 simulations for the different trajectories.

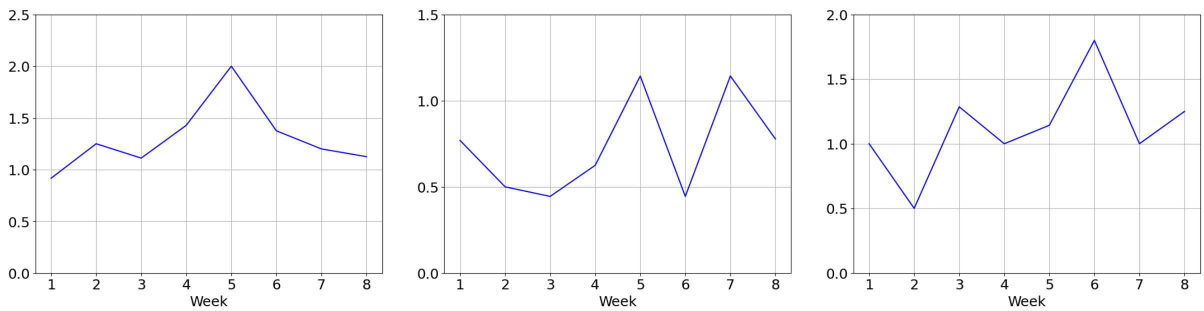
	Trajectory		
Option Type	A	B	C
Calls [WBTC]	1.461	1.545	1.658
Puts [ETH]	37.696	33.871	33.608



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure E.11: Ratio between exercised and bought options in the WBTC pool Stage 4 simulations for the different trajectories.

Ratio between the number of Call and Put Options Bought

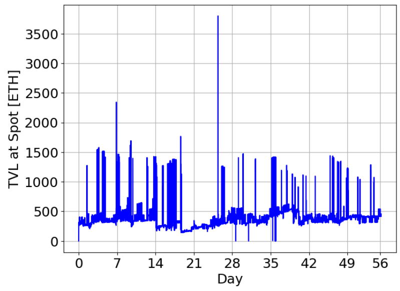


(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

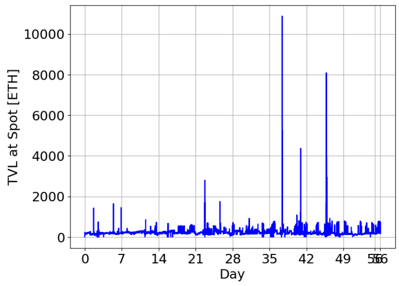
Figure E.12: Ratio between bought calls and puts in the WBTC pool Stage 4 simulations for the different trajectories.

E.4 USDC-ETH-500 Pool

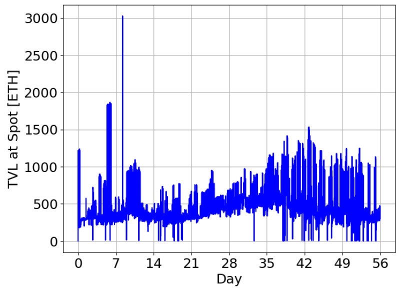
TVL at Spot Tick



(a) Trajectory A.



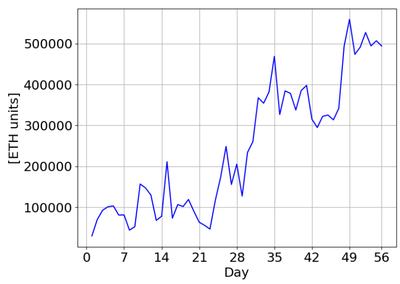
(b) Trajectory B.



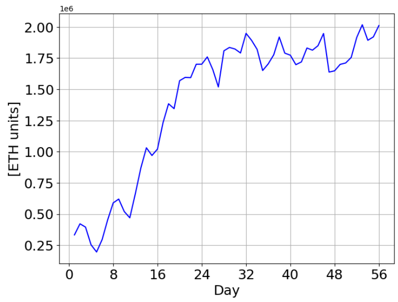
(c) Trajectory C.

Figure E.13: Different trajectories for TVL at the spot tick, expressed in ETH units, used in Stage 4 simulations for USDC-ETH-500 pool.

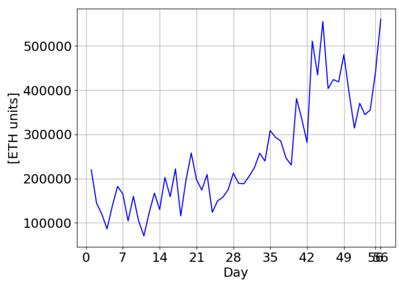
Daily Trading Volume



(a) Trajectory A.



(b) Trajectory B.



(c) Trajectory C.

Figure E.14: Evolution of daily trading volume in the USDC pool Stage 4 simulations for the different trajectories.

PLPs Additional Metrics

Table E.13: Number count and median amount of deposits and withdrawals of PLPs, in the USDC pool Stage 4 simulations for the different trajectories.

		PLPs							
		Active				Passive			
		Deposits		Withdrawals		Deposits		Withdrawals	
Trajectory	**Quantity**	**USDC**	**ETH**	**USDC**	**ETH**	**USDC**	**ETH**	**USDC**	**ETH**
A	Count	68	85	25	26	23	27	0	1
	Median amount	3720.407	1.532	7151.921	5.825	3187.019	2.926	-	4.049
B	Count	80	55	39	27	20	18	3	5
	Median amount	3720.407	1.532	7436.233	3.986	3187.019	2.926	3680.568	5.915
C	Count	87	68	28	21	22	30	0	
	Median amount	3720.407	1.532	9181.821	6.101	3187.019	2.926	-	

Sellers Additional Metrics

Table E.14: Number count and median amount of sellers' mints and rolls, in the USDC pool Stage 4 simulations for the different trajectories.

		Sellers									
		Mints		Rolls							
				Global		ITM		ATM (in-range)		OTM	
Trajectory	**Quantity**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**	**Calls**	**Puts**
A	Count	74	70	105	93	85	92	20	1	0	0
	Median amount	49655.713	33.501					-			
B	Count	67	67	185	119	167	119	18	0	0	0
	Median amount	47254.312	26.337					-			
C	Count	72	77	103	131	74	131	29	0	0	0
	Median amount	51910.664	34.155					-			

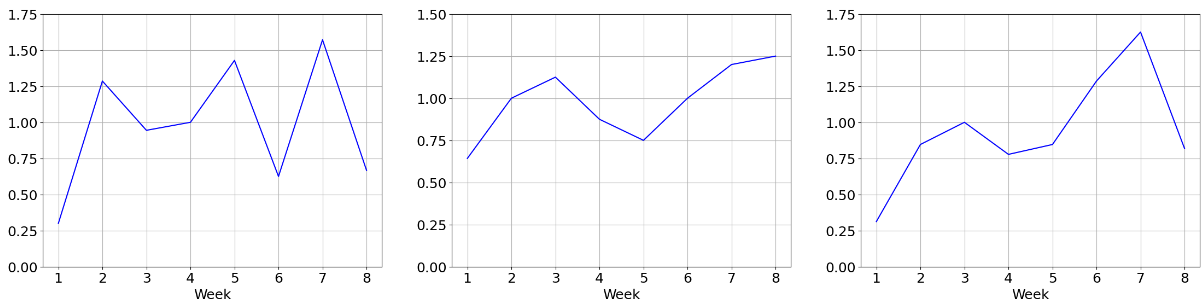
Number and Ratio of Options Bought and Exercised

Table E.15: Number of Options Bought and Exercised for each pool tested in the USDC pool Stage 4 simulations for the different trajectories.

	No. Options Bought		**No. Options Exercised**		**Exercised / Bought Options Ratio**
Trajectory	**Calls**	**Puts**	**Calls**	**Puts**	
A	48	39	42	33	0.86
B	38	26	35	25	0.94
C	49	53	47	46	0.90

Table E.16: The median amount of the call and put options bought in the USDC pool Stage 4 simulations for the different trajectories.

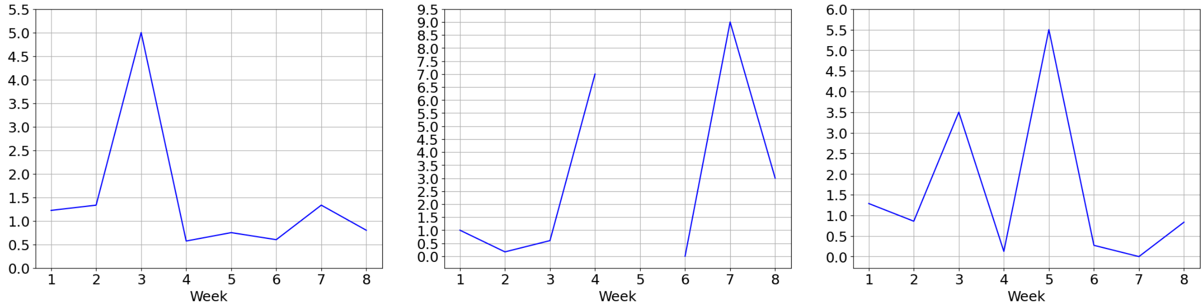
	Trajectory		
Option Type	A	B	C
Calls [USDC]	29853.927	28112.392	34755.832
Puts [ETH]	24.461	15.145	26.460



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure E.15: Ratio between exercised and bought options in the USDC pool Stage 4 simulations for the different trajectories.

Ratio between the number of Call and Put Options Bought



(a) Trajectory A. **(b)** Trajectory B. **(c)** Trajectory C.

Figure E.16: Ratio between bought calls and puts in the USDC pool Stage 4 simulations for the different trajectories. Note that the absence of a value in week 5, in trajectory B, means there were no put options bought.