Data Extrapolation Framework for Risk Assessment of DeFi Lending Platforms

The Risk Assessment SubDAO

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Abstract

Lending platforms play a significant role in the DeFi ecosystem. To mitigate the credit risk, a lending platform must carefully determine its loan-to-value (LTV) ratios and liquidation incentives. At present, the most common methodology, developed by Gauntlet Network, and adopted by all top 3 lending platforms, is an agent based simulation. In this approach, the price trajectory of an asset is fixed, and the expected behavior of the users during the price change is simulated. As the DeFi ecosystem is relatively young, the simulation is based on relatively sparse data, which dictates hefty safety margins.

In this manuscript, a new methodology is introduced. We take real world liquidation data of popular assets from centralized exchanges, along with the price trajectory of the assets. We then extrapolate the liquidation sizes and price trajectory to the asset we wish to analyze, and simulate the outcome based on the asset available DeFi liquidity. Our approach eliminates most of the assumptions over user behavior during market crashes, and makes it more feasible to analyze the risk of a platform prior to its launch, and for multichain lending platforms, where the data for user behavior is even more sparse.

In this work, we apply the new methodology and analyze a market of Sushi LP tokens in Arbitrum network. Further we extend the model to include a liquidation backstop, and quantify its improvement over the risk parameters.

1 Background

Lending Markets. DeFi lending markets manage billions of user funds, with the top 2 platforms, namely, Compound [9] and Aave [1] holding over $20B of crypto-assets. At their core, they allow *suppliers* to deposit a set of assets, and *borrowers* to borrow them. The permissionless nature allows anyone to be a supplier and enjoy a supplier interest rate, however it also dictates that a borrower could only borrow against a collateral, and the platform becomes (partially) insolvent when a user debt exceeds his or her collateral. An insolvency event generates bad debt which comes at the expense of supplier deposits. It is the market's admin responsibility, typically a DAO, to set *risk parameters* to mitigate the likelihood of insolvency events.

Liquidations. Similar to foreclosure of real world loans, liquidators can repay the outstanding debt of a risky loan and seize the borrower collateral with a discount. This process is also permissionless, and it is practically the only barrier towards an insolvency event. After seizing the collateral, liquidators will typically try to lock their profits by selling it in the open market as quickly as possible. To date most of liquidations are done by flash bots who liquidate and sell the seized collateral in the same transaction, while facing zero price risk. This process is bounded by the *available* DeFi liquidity, and recent study [7] suggested that a backstop mechanism could scale the process. Inspired by [7], a backstop of over $100M was already deployed, and in this paper we provide, for the first time, theoretical analysis for the improvement of risk parameters with a backstop.

Risk parameters. To prevent insolvency, the market admin should set parameters that encourage successful liquidations, and reduce the insolvency risk when a liquidation process prolongs. Different platforms may offer different configurable parameters. In this work, we follow the standard that was set by Compound, and is widely adopted among other lending platforms, e.g., see [13, 11, 3, 10, 2] and for a comprehensive list see [4]. Compound standard defines three parameters, namely, *liquidation incentive*, *Collateral factor* (a.k.a loan-to-value), and *close factor.*

- *Liquidation incentive.* Liquidators are assumed to be greedy, and they will only execute a liquidation when they believe it is profitable. For this purpose a liquidation incentive is given, in the form of a discount over the seized collateral. For example, with a liquidation incentive of 5%, repaying an outstanding debt of 1000 USDC will seize a collateral worth $1050.

  Higher liquidation incentive makes the liquidation more appealing, and in particular makes it easier for the DeFi market to liquidate it. Indeed, if the discount on the collateral is bigger, then bigger collateral quantity can be sold with the same profit, as the higher sell slippage is compensated by the higher liquidation incentive.

  On the negative side, higher liquidation incentive is less appealing to users who stand to lose more as their position becomes undercollateralized.

- *Collateral factor.* If liquidations were guaranteed to be executed immediately, then the needed over-collateralization would be the size of the liquidation incentive. In practice however, liquidity crises and blockchain congestion might delay the execution of the liquidations. Lending platforms are required to maintain higher safety margins, as higher over-collateralization ratio compensates for the risk of default in the presence of execution latency. The collateral factor specifies a borrower's minimum collateral requirement w.r.t her outstanding debt.

  On the negative side, higher collateral factors increase the capital requirements for the borrowers, and facilitate lower leverage.

- *Close factor.* The close factor determines the % of debt that can be liquidated when the borrower does not meet the over-collateralization requirements. By definition, higher closing factors reduce the platform risk, as it enables liquidators to close bigger portions of the borrower position. On the other hand borrowers would find lower closing factors more appealing.

As a technical restriction, the first and third parameters must be globally configured for all assets in the market, while the collateral factor is configured per asset.

2 The Risk Assessment Model

Similar to [6, 8], we aim to construct a formal model that can simulate the behavior of a lending market, and assess if the market's risk parameters are safe. A single simulation is composed of:

- A sequence of liquidations with time and sizes. I.e., when each liquidation happened, and what was each liquidation volume.
- Price trajectory of the collateral asset for every point in time.
- The available market liquidity for selling the collateral. Throughout our model we assume that liquidators will only use DeFi markets to sell the seized collateral, and hence focus on simulating only DeFi liquidity.

Our system can model lending markets with and without a dedicated B.Protocol's backstop. When such backstop exist, then the simulation also consist of:

- The available liquidity of the backstop at any point in time.

Having a model for the above, we execute a sequence of liquidations and analyze the lending market state. For simplicity we assume that an execution is successful if it does not have an insolvency event. However, the model can also embed other definitions, e.g., insolvency of at least 1% of the market size.

Our model differs from the one in ([6, 8]) as it removes the need to simulate individual user accounts. All previous works developed ad-hoc heuristics to simulate individual account behavior for given price trajectories. Those heuristics were necessary in order to simulate liquidation events. We take a different approach, by taking real world liquidation events from centralized futures exchange, and adjust their sizes to fit the expected size of the lending market. With this approach fewer core assumptions about user behavior are needed. Avoiding assumptions on user behavior is particularly important for markets who offer new assets and to markets that are deployed on new blockchains.

Given the above components, we get a full simulation of the amount of collateral that is subject to liquidation, the time the liquidation will take place, and the price during and after the liquidation. We assume that an actual (possibly partial) liquidation takes place only when the market liquidity is enough to absorb it, with slippage lower than the liquidation incentive, or alternatively if the backstop has enough liquidity. An insolvency event is when a debt liquidation did not complete before the collateral price decreased by more than its collateral factor.

In the remainder of the section we explain the first three components of the model, namely, liquidation events, price trajectories, and market liquidity. In the next section we explain the backstop concept and how we add it to the model.

2.1 Modeling liquidation events

We take liquidation events from real world data, namely, from Binance Futures exchange. We take the most popular asset that has a similar volatility as the asset we wish to simulate. In this work, we define similar as at least x0.2 and at most x5 times the volatility, and we defer the formal definition of volatility to the next subsection. We denote this sequence of liquidations as the *reference liquidations*, and the liquidation asset as the *reference asset*.

To choose the sequence of *simulated liquidation events* we ignore the volatility of the reference asset and simulated asset. Instead we fix the monthly liquidation volume, by setting a *simulation liquidation factor*, denoted by **slf**, and multiplying the liquidation volume of all reference liquidations by this factor.

When stress testing the market, we find two metrics to be relevant for deciding the **slf**:

1. Fix the maximal daily liquidation volume, and derive a **slf** to support it. This approach is useful when trying to reason about an absolute volume of daily liquidations the market could handle safely.

2. Fix the monthly liquidation volume as a percentage of the total market collateral. This is useful for conservative approaches, where, e.g., the market admin assumes that every deposited $1 will not get liquidated more than once or twice a month [1]. This approach is also useful when analyzing the effect of B.Protocol's backstop, whose size is assumed to be 20% of the total market deposits.

We note that a simulated liquidation of volume v at time t means that there is a user position with collateral v at time t that is not sufficiently over-collateralized. The exact time in which the liquidation will take place is subject to the simulated market liquidity (and backstop if applicable).

2.2 Modeling price trajectory

In the work, we use price trajectories only to simulate the platform insolvency (and not to decide if liquidation will occur). Hence, we are mostly interested in how the price behaves between the time a user position is subject to liquidation (as described in the previous subsection) and the time the full liquidation is completed (as described in the next subsection). For this purpose we try to

[1]These numbers are very aggressive for most DeFi platforms.

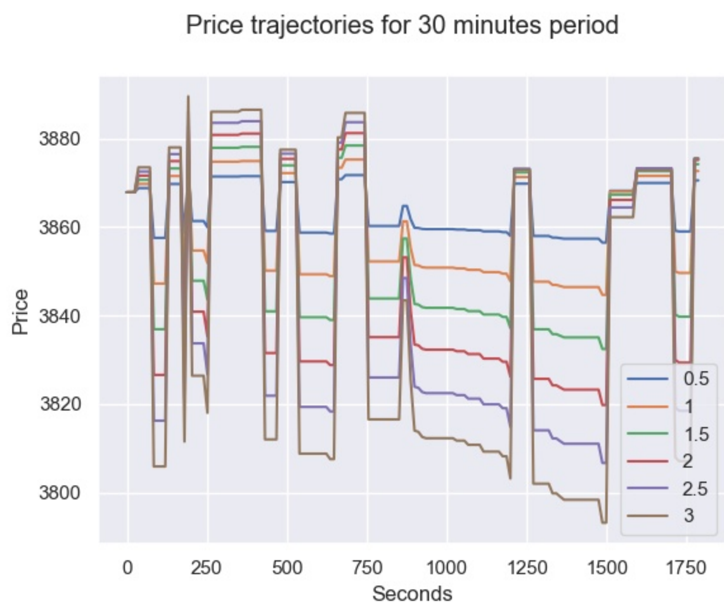

Figure 1: Simulated price trajectories for different STD ratio that range between 0.5 and 3.

have a price simulation that is approximating short time frames. For a time duration of T minutes, we define the T *price average volatility* as the average T minutes price standard deviation, and denote it for an asset a by $\mathbf{vol(a)_T}$. Further, we define the *STD ratio* as the ratio $\frac{\mathbf{vol(sa)_T}}{\mathbf{vol(ra)_T}}$, where sa (respectively ra) is the simulated (resp. reference) asset. For example if the average volatility of SPELL is x2.8 higher than the one of ETH, then the corresponding STD ratio is 2.8.

Having the STD ratio in hand, we amplify, in every minute, the price change by that ratio. In our example, if between time t and $t+1$, the ETH price changed (either up or down) by 0.1%, then the simulated SPELL price will change by 0.28%. Our numerical results show that if the STD ratio is under 5, then the simulated asset average volatility corresponds to its real world average volatility.

The intention of this process is not to simulate the long term price trajectory of the asset. But rather to sync the expected price changes along with the expected liquidations. In other words, we want that after every simulated liquidation the simulated price will behave similarly to the one of the reference asset after a reference liquidation. In Figure 1 we illustrate the short term simulated price for five different STD ratios. It shows that the price decreases are amplified when the ratio increases. The price increases are also amplified, however, as depicted in Figure 2, higher STD ratio skew the trajectory downwards. This stems from the fact that if one asset price movement is $(-5\%, +5\%)$, and a second asset price movement is $(-10\%, +10\%)$, then the second asset total

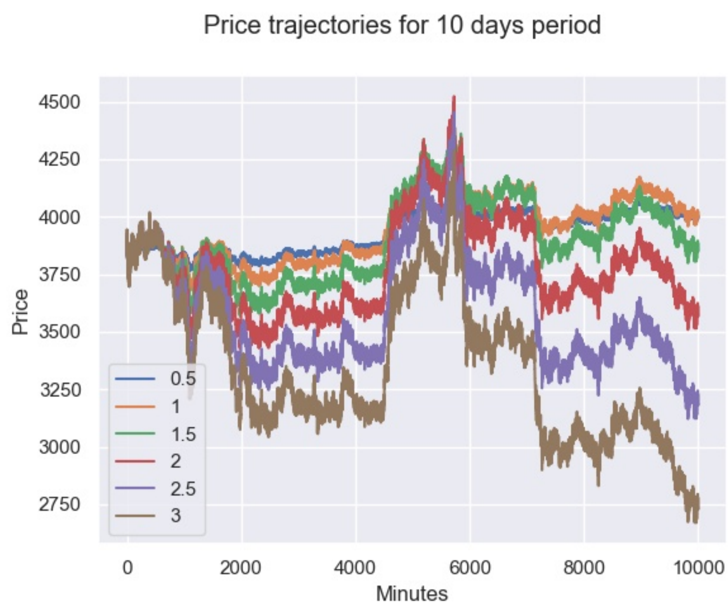

Figure 2: Simulated price trajectories for different STD ratio that range between 0.5 and 3.

price decrease is bigger. Overall the bias towards price decreases makes our simulation more conservative, and as depicted in Table 2.2 achieves our main goal, which is to create a simulated asset with the same average volatility.

STD ratio	30 minutes average volatility
0.5	0.499
1	1.000
1.5	1.500
2	2.0003
2.5	2.50007
3	3.001
4	4.004

2.3 Modeling market liquidity

In our current analysis we focus on multichain liquidity, where most of the DeFi liquidity resides in constant product automated market makers (e.g., Sushiswap [12], Quickswap [5]). Constant product AMMs have relatively sticky liquidity, and as opposed to orderbook exchanges tend to remain stagnant even during extreme market conditions. The $x \cdot y = k$ invariant provides a well defined slippage function for every volume size. To simulate the effect of the liquidations on the market, we fix a time parameter T and assume that the market price converges to the price trajectory every T minutes. During the T minutes interval, we accumulate the total liquidation volume that was executed in the interval, and compose the corresponding slippage over the current simulated price trajectory. For example, if the current price trajectory (i.e., market price) is \$7, \$1M of liquidations were executed in the last T minutes, and the slippage for \$1M quantity is 10%, then we assume that \$1M quantity can be sold in the DeFi market for price \$6.3.

The value of T depends on how long it is expected for liquidity to flow from its main venue, e.g., from a centralized exchange to Ethereum, or from Ethereum to an L2 or other L1. We note that in particular we assume the liquidations do not affect the overall price trajectory. This assumption is easy to justify in multichain markets, where most of the asset liquidity is outside the blockchain of the lending market.

3 Backstop

With B.Protocol's backstop [7], users provide liquidity that is used for liquidations (e.g., repay USDC debt in return to ETH collateral), and after liquidation happens, an automatic re-balance process begins. The re-balance process converts the seized collateral back to the original asset (e.g., the ETH collateral is converted back to USDC). The rebalance is done by offering the collateral for sale according to the market price, which is determined according to a price oracle. An optional discount on market price is given according to the backstop's imbalance size (the size of collateral to sell w.r.t. base asset in the pool), and the exact formula is depicted in B.Protocol's whitepaper [7]

In the backstop latest architecture, as user deposits are expected to sit idle for the majority of the time (when liquidations do not occur), the system will deposit it, on behalf of the users, to the lending market where it is used for supply, and will withdraw it only to facilitate liquidations.

Formally the system is composed of four main components, namely:

1. The **IDLE** component stores pooled liquidity (user deposits), and uses the deposited funds as supply for the lending markets when they are not used for liquidations.

2. The **BITE** component connects the **IDLE** component to lending platforms that rely on the Bacstop AMM (B.AMM) for liquidations. Upon request it withdraws funds from the **IDLE** component, executes a liquidation, and transfers the (discounted) seized collateral to the **REBALANCE** component. E.g., it withdraws USDC from the pooled liquidity, and transfers the ETH that was received during the liquidation.

3. The **REBALANCE** component is in charge of selling the liquidated collateral, in return to the underlying token of the liquidated asset. The return of the sale is transferred to the **RETURN** component.

4. The **RETURN** component deposits the funds back in the **IDLE** component. Meaning it deposits the USDC back to the supply market, and

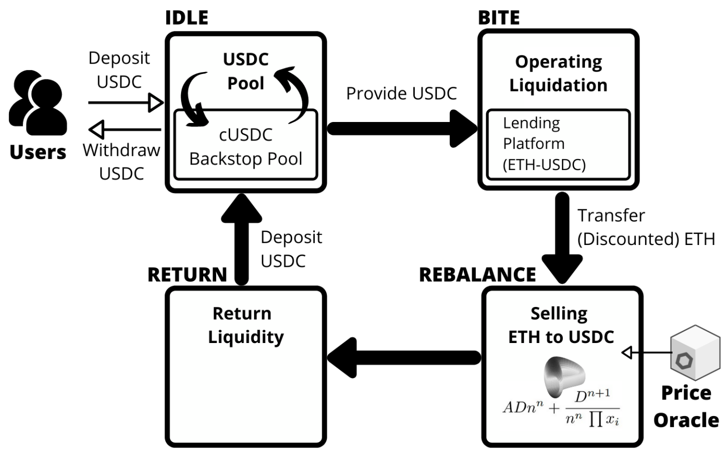

Figure 3: B.AMM high level design.

transfers the cUSDC to the possession of the backstop.

The interaction between the four components is depicted in Figure 3 and described in details in the BAMM whitepaper [7].

3.1 Theoretical model

In order to simulate the system, we need to construct a model that describes how the **REBALANCE** model will perform. Namely, how quickly it will rebalance the inventory. In this work, we do not investigate the backstop's PnL, and we refer the readers to [7] for a more comprehensive analysis. Recall that in the previous section we defined a model for market liquidity. Given this model, we simulate the role of the backstop with the two following assumptions:

- We assume the size of the backstop is 20% of the total market supply.
- We assume that the market utilization does not exceed 80%.

The first assumption is based on the incentive guidelines we provide to platforms who use B.Protocol's backstop, i.e., to provide an extra incentive for backstop depositors, so it would capture at least 20% of the deposited supply. The most organic incentive is allocating some of the market admin fees to backstop liquidity providers, and more aggressive incentives can be made in the form of liquidity mining rewards.

The second assumption is based on the common interest curves in DeFi. All consist of sharp interest increase when reaching 80% utilization.

Setting the monthly liquidation volume as a multiple of the market supply (e.g., the monthly liquidation volume is x2 the total market supply), and having a backstop as a fixed fraction of the total supply allows us to simulate the liquidation execution. For this purpose we concurrently simulate both the size of the backstop and the executed liquidations.

- Whenever a liquidation is needed, it is instantly executed by the backstop, provided it has sufficient liquidity.
- The backstop sells the seized collateral whenever the market liquidity can absorb it with a slippage that matches the backstop selling discount.

4 Analyzing Sushi LP Token Lending Market on Arbitrum L2

In this section, we run a simulation for a market that has four supply assets, and a single borrow asset. The supplied assets are ETH and three Sushi LP tokens, and we elaborate on each of them in a dedicated subsection. The debt asset is ETH. For every supply asset (that is not ETH), we run independent simulations, which outputs the maximum price decrease (in %) of a position collateral before it was fully liquidated, and we denote this value by *max drop*. The condition for solvency is

Collateral factor >= 1 - max drop - liquidation incentive

If the condition is violated, then an insolvency event occurs.

Throughout all simulations we fix the liquidation incentive to 10%, and the closing factor to 50%. We use ETH as the reference asset and take long ETH/USD liquidations on Binance Futures. We take every monthly activity as an independent simulation, and fix the market ETH supply to be a certain % of that month's liquidation volume, and we simulate a monthly liquidation volume that is a certain factor of the supplied ETH collateral. We simulate each run with a backstop that holds 0-50% of the supplied ETH collateral. Where 0% simulates a run without a backstop. Finally, we set the time interval T for the market liquidity and price trajectory modeling to be 30 minutes.

In Subsection 4.1 we present the data of the reference asset, and then in Subsection 4.2 we present the simulation results.

4.1 Reference Asset

We take ETH to be the reference asset, and use the ETH/USD long liquidations from Binance Futures exchange. We take liquidations that occurred between March 2021 to March 2022 (see Figure 4). During that time period, almost 3M ETH were liquidated, where on average 200K ETH were liquidated per month, with a standard deviation of 300K ETH. This shows the liquidation volume distribution is far from uniform.

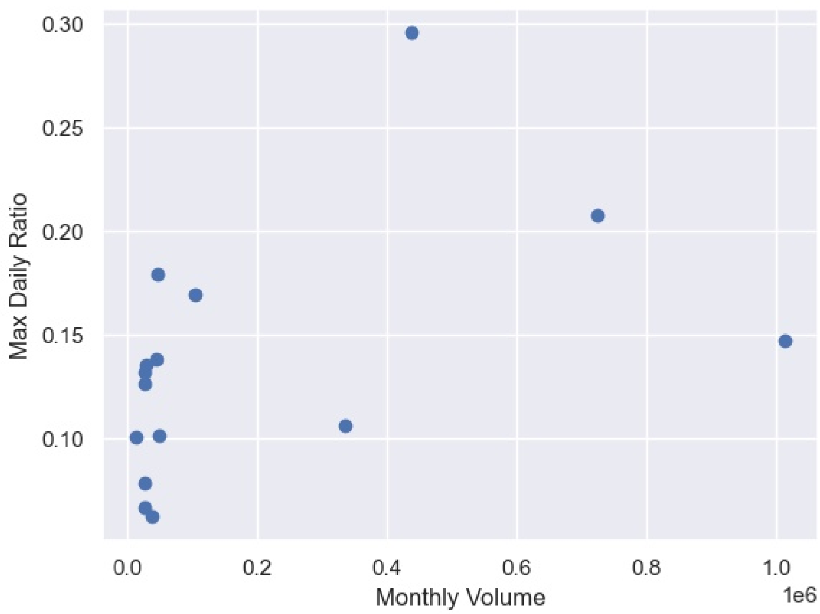

Figure 4: Monthly liquidation volume, in 1M ETH scale, and the ratio between the maximum daily liquidation volume to the total monthly liquidation volume.

Analyzing the intra-month activity, we observe that on average the day with the biggest amount of liquidations was accounted for 13.6% of the monthly liquidation volume, and one day in April 2021 had 29.5% of that month liquidation volume.

The calculated $\mathbf{vol(ETH)_{30}}$ is 0.2%.

4.2 Simulated assets

Suhsi LP token (SLP). Sushi liquidity pools are a place to pool tokens so that users can use them to make trades in a decentralized way. These pools are created by users who want to profit from their usage. To pool liquidity, the amounts a user supplies must be equally divided between two coins: the primary token (sometimes called the quote token) and the base token (usually ETH or a stable coin). SushiSwap's liquidity pools allow anyone to provide liquidity. When they do so, they will receive SLP tokens (SushiSwap Liquidity Provider tokens). If a user deposited $SUSHI and $ETH into a pool, they would receive SUSHI/ETH SLP tokens. These tokens represent a proportional share of the pooled assets, allowing a user to reclaim their funds at any point. Every time another user uses the pool to trade between $SUSHI and $ETH, a 0.3% fee is taken on the trade. 0.25% of that trade goes back to the LP pool.

The value of the SLP tokens, which represent the shares of the total liquidity of each pool, is updated with each trade to add their value relative to the tokens the pool uses to trade. If previously there were 100 SLP tokens representing 100 ETH and 100 SUSHI, each token would be worth 1 ETH and 1 SUSHI (note in this example, ETH and SUSHI have the same relative value). If a user were then to trade 10 ETH for 10 SUSHI in that pool, and another user were to trade 10 SUSHI for 10 ETH, then there would now be 100.025 ETH and 100.025 SUSHI. This means each LP token would be worth 1.0025 ETH and 1.00025 SUSHI now when it is withdrawn.

Measuring Price Volatility. For the simulation purposes we neglect the accumulated fee profit, as its effect on the short term price is negligible, and instead focus on the prices of the primary and base token. Despite doing the analysis for Arbitrum L2, we take the trade information from Ethereum mainnet, as it has more historical data. We set an arbitrary initial value for the LP token which consists of an equal (in USD terms) deposit amount of primary and base token. Then, upon every trade we fetch the price ratio between the primary and base token, and use the $x \cdot y = k$ variant to reason about the new price of the LP token.

Measuring Market Liquidity. As an LP token is constructed from an equal amount of primary and base token, the available market liquidity stems from the liquidity of the two assets. For our analysis, we take the minimum liquidity among the primary and base tokens, and multiply it by 2. For example, suppose we have a SPELL/DAI LP token, and the debt token is ETH. Further, suppose that the slippage for selling 50 ETH of SPELL is 10%, and the slippage for selling 160 ETH of DAI is 10%. In this case we assume that an LP token of SPELL/DAI has 100 ETH liquidity depth for 10% slippage.

To assess the market liquidity we take a conservative approach and take into account only the available liquidity in Sushiswap for the primary and base token vs ETH [2].

4.2.1 SPELL/ETH SLP

Spell Token (SPELL) is a token that governs Abracadabra.money, a platform that lets users deposit collateral in the form of interest-bearing crypto assets (such as yvYFI, yvUSDT, yvUSDC, xSUSHI) in order to mint MIM, a stable coin that attempts to maintain a value of US $1.00. SPELL can be staked to earn sSPELL, which grants governance rights and other rewards.

The SPELL/ETH SLP is composed of equal amounts of SPELL and ETH tokens (equal in USD terms).

Price Trajectory. The STD ratio of SPELL is 2.8, and therefore the STD ratio of SPELL/ETH SLP is 1.4. The price trajectory is depicted in Figure 5.

Market liquidity. At the time of writing [3], it is possible to sell 50 ETH worth of SPELL with 10% slippage in Sushiswap over Arbitrum. Hence, the liquidity

[2] The liquidity depth of ETH vs ETH is infinite.

[3] April 7th, 2022

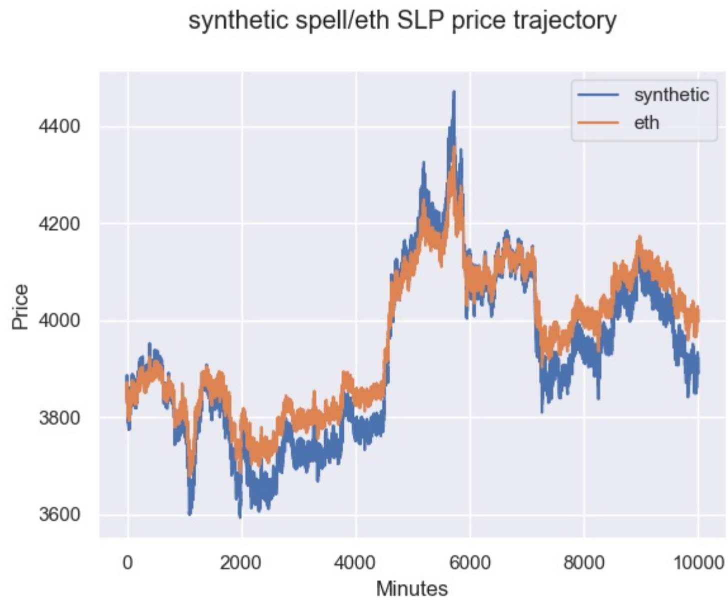

Figure 5: SPELL/ETH SLP price trajectory.

depth for the SLP is 100 ETH. The price slippage is displayed in Figure 6.
Simulation results. The results are depicted in Figure 7. In the simulation, a market without a backstop could have a maximum collateral factor of 58% to avoid insolvency when the monthly liquidation volume was as the size of the collateral. A backstop with 10% of the collateral could avoid insolvency with a collateral factor of 90% when the liquidation volume ratio was 1, and a backstop with 20% would be able to handle the same factor even for x2 of the volume.

4.2.2 gOHM/ETH SLP

Olympus is an algorithmic currency protocol with the goal of becoming a stable crypto-native currency. Though sometimes called an algorithmic stablecoin, Olympus is more akin to a central bank since it uses reserve assets like DAI to manage its price. gOHM is the on-chain governance token of Olympus. It has a static balance and increasing redemption value.

The gOHM/ETH SLP is composed of equal amounts of SPELL and ETH tokens (equal in USD terms).
Price Trajectory. The STD ratio of OHM is 2.2. The price of gOHM equals the price of OHM multiplied by a rebase index. For short time durations the index does not change, hence we measure the OHM price movements, instead of the less liquid gOHM movements. Hence, we set an STD ratio of 2.2 to gOHM and 1.1 to gOHM/ETH SLP.

The price trajectory is depicted in Figure 8.

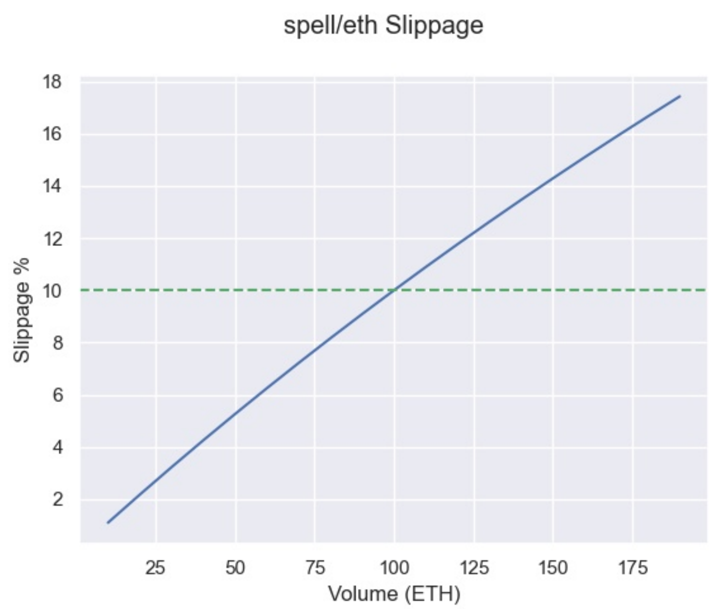

Figure 6: Price slippage of SPELL/ETH SLP token.

Market liquidity. At the time of writing [4], it is possible to sell 40 ETH worth of gOHM with 10% slippage in Sushiswap over Arbitrum.

The price slippage for gOHM/ETH SLP displayed in Figure 9.

Simulation results. The results are depicted in Figure 10. In the simulation, a market without a backstop could have a maximum collateral factor of 56% to avoid insolvency when the monthly liquidation volume was as the size of the collateral. A backstop with 10% of the collateral could avoid insolvency with a collateral factor of 90% when the liquidation volume ratio was 1, and a backstop with 20% would be able 73% collateral factor even for x2 of the volume.

4.2.3 MIM/ETH SLP

MIM is a USD soft-pegged stablecoin minted by the Abracadabra.money decentralized platform. Abracadabra uses interest-bearing tokens as collateral to mint MIM. Interest-bearing tokens able to be used as of February 2022 as collateral include liquidity provider (LP) tokens from Convex, Curve, Yearn, among others. The loan liquidation process on Abracadabra differs from other stablecoin/lending protocols like MakerDAO, in that each collateralized debt position (CDP) and its liquidation price is unique. Should the liquidation price for any specific CDP be crossed, a liquidator can purchase the position by paying off the outstanding MIM.

[4] April 5th, 2022

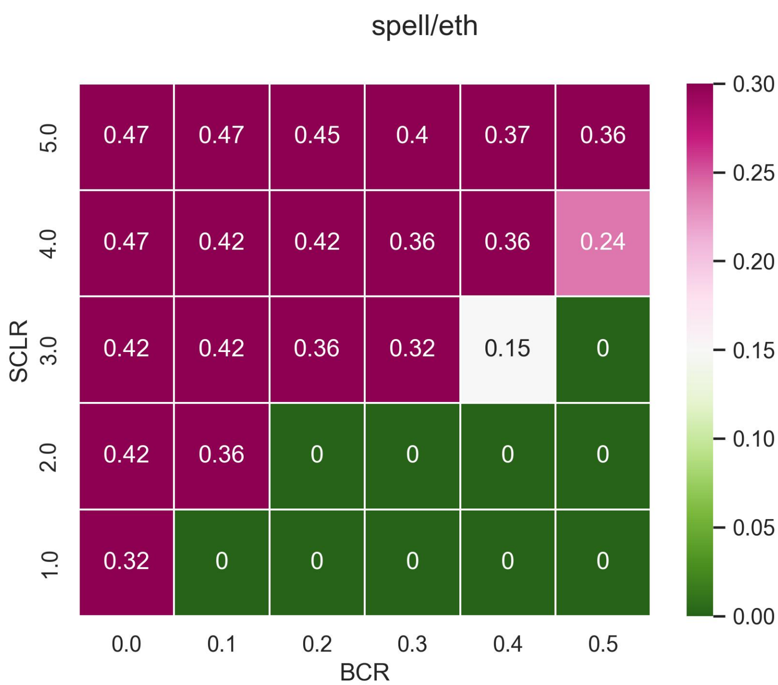

Figure 7: Simulation results for SPELL/ETH SLP. The x axis is the ratio between the backstop size and total market supply. The y axis is the ratio between monthly liquidation volume, and total market supply. The result is the maximum max drop during the 12 month simulation.

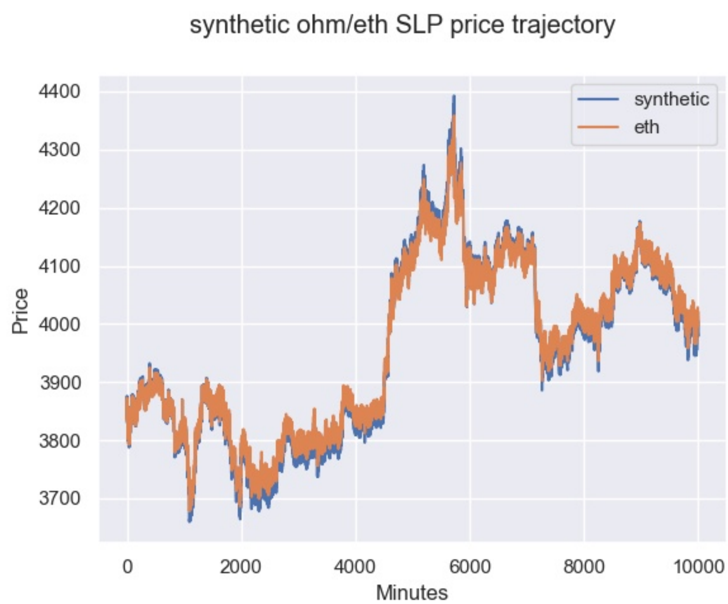

Figure 8: gOHM/ETH SLP price trajectory.

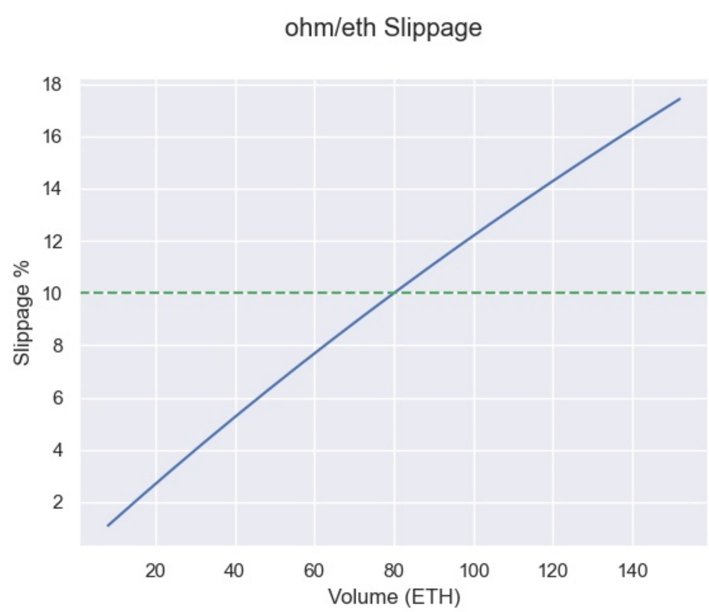

Figure 9: Price slippage of gOHM/ETH SLP token.

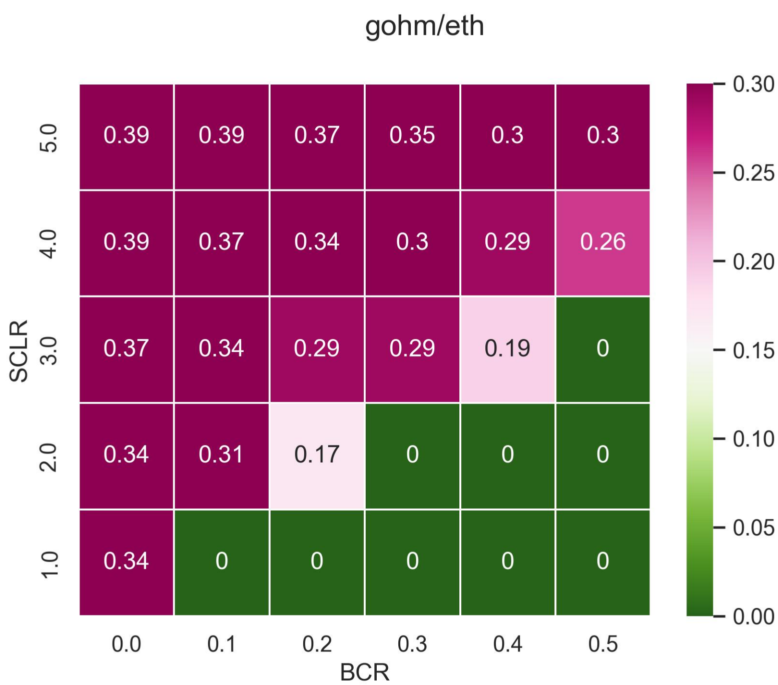

Figure 10: Simulation results for gOHM/ETH SLP. The x axis is the ratio between the backstop size and total market supply. The y axis is the ratio between monthly liquidation volume, and total market supply. The result is the maximum max drop during the 12 month simulation.

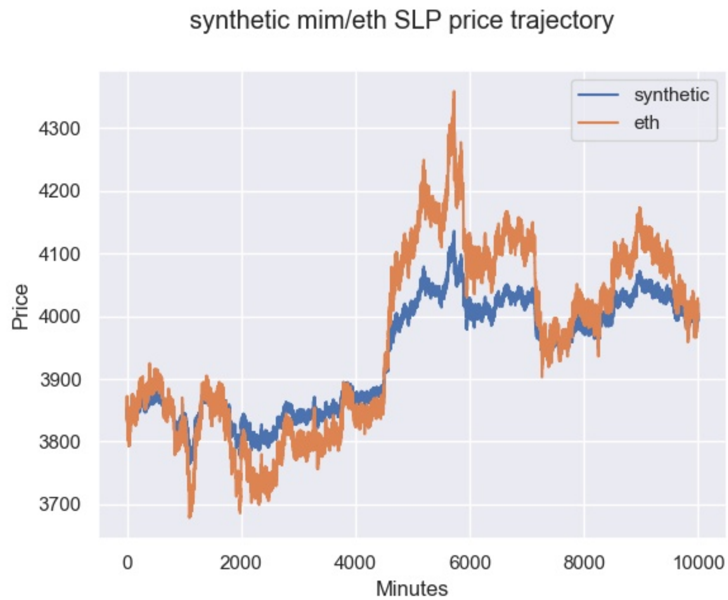

Figure 11: MIM/ETH SLP price trajectory.

Price Trajectory. The STD ratio of MIM is 1, as the volatility of ETH vs USD is identical to the volatility of MIM vs ETH. Hence, the STD ratio of MIM/ETH SLP is 0.5.

The price trajectory is depicted in Figure 11.

Market liquidity. At the time of writing [5], it is possible to sell 500 ETH worth of MIM with 10% slippage in Sushiswap over Arbitrum. The price slippage of MIM/ETH SLP displayed in Figure 12.

Simulation results. The results are depicted in Figure 13. In the simulation, a market without a backstop could have a maximum collateral factor of 79% to avoid insolvency when the monthly liquidation volume was as the size of the collateral. A backstop with 10% of the collateral could avoid insolvency with a collateral factor of 90% when the liquidation volume ratio was 1, and a backstop with 20% would be able to handle a similar factor even for x3 of the volume.

5 Conclusion

In this work we developed a theoretical framework to simulate lending market liquidation events. Our main contribution is removing the need to guess the borrowers reaction to price changes, and instead we fix the liquidation events, and extrapolate the price trajectory from a reference asset.

[5] April 8th, 2022

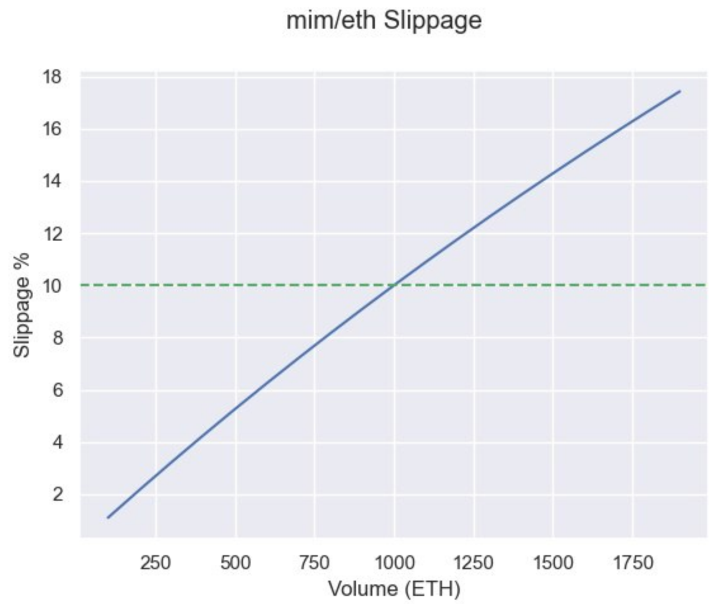

Figure 12: Price slippage of MIM/ETH SLP token.

We implemented the framework and ran a simulation for a market that consists of ETH, gOHM/ETH SLP, MIM/ETH SLP, and SPELL/ETH SLP on the supply side, and only ETH on the borrow side, on Arbitrum L2.

In future work, we plan to refine the price trajectory and market liquidity model, and introduce stochastic modeling for the liquidation sizes.

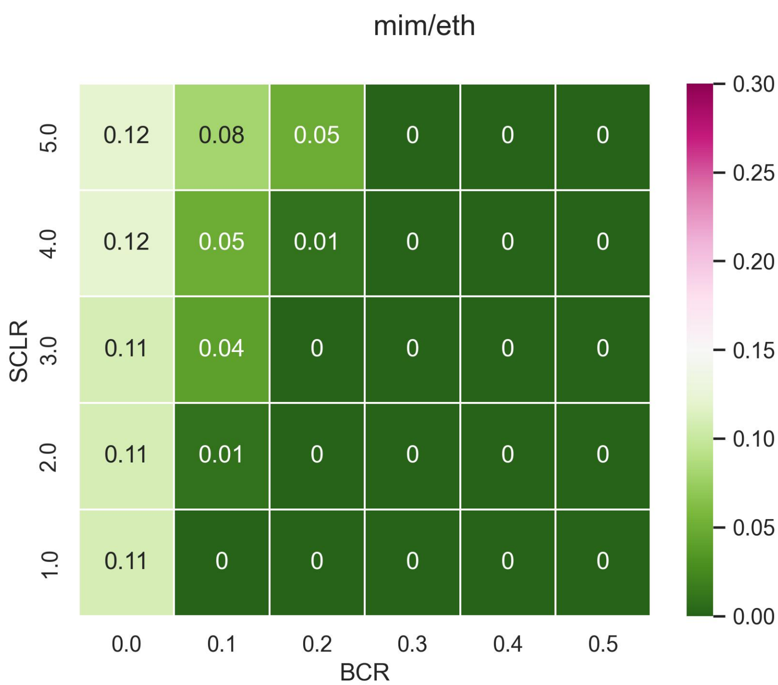

Figure 13: Simulation results for MIM/ETH SLP. The x axis is the ratio between the backstop size and total market supply. The y axis is the ratio between monthly liquidation volume, and total market supply. The result is the maximum max drop during the 12 month simulation.

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