



Genesis Risk Framework, Methodology, and Recommendations

A rigorous analysis of Avantis, focusing on market risk, protocol mechanics, and risk parameter analysis on a per market basis.



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Avantis Finance Genesis Parameter Recommendations

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Abstract

Avantis presents an innovative architecture explicitly designed to mitigate the risk exposures faced by liquidity providers. The platform achieves this by incorporating various skew-adapted mitigative components, including subsidized "loss protection" for skew reverting traders, skew impact positive/negative spreads, exponential dynamic margin fees, and more. Furthermore, Avantis offers support for synthetic perpetual trading, eliminating the necessity for liquidity providers and traders to hold volatile assets. While earlier perpetual exchanges such as GMX V1 improved the trading user experience by mitigating price impact on trades, they inadvertently increased liquidity providers' exposure to market skew, as observed empirically. In line with its objectives, Avantis introduces a distinct fee structure. This design aims to incentivize market neutrality, strengthen defenses against market manipulation, and ensure competitive pricing for traders—all without resorting to explicitly restrictive open interest limits. Our analysis seeks to assess the effectiveness of the proposed structure and determine optimal parameter values to minimize liquidity providers' risk while optimizing the legitimate trading user experience.

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Chapter 1

Overview

Prelaunch Risk Research

Chaos Labs has diligently worked alongside Avantis to methodically research, evaluate, and refine the impending deployment of the genesis parameterization application. Leveraging sophisticated Agent-Based Simulation Models, Chaos Labs pursues a delicate equilibrium between capital efficiency and risk exposure. Nonetheless, given the early-stage status of the protocol, our immediate focus and priority are heavily tilted toward the security and safety of the protocol. We are committed to ensuring a smooth and safe phased launch and laying a robust foundation upon which the protocol can reliably expand. The ensuing set of genesis parameter recommendations is the fruit of our rigorous research process, which involved executing millions of Monte Carlo simulations. These simulations included a wide array of variables, such as diverse price trajectories, liquidity models, levels of network congestion, and volatility levels, among others, thereby testing the system’s robustness in many potential scenarios. The forthcoming sections provide a detailed analysis, a review of the results obtained from our simulations, and, ultimately, a careful examination of our recommendations. Each proposed solution will be analyzed, comprehensively discussing its merits and potential drawbacks. This rigorous process will ensure that the proposed solutions are academically sound, practically viable, and well-suited to meet the unique challenges and requirements of the Avantis protocol. Please note that the preliminary parameter recommendations are formulated on the basis of a combination of economic-security-driven heuristics, an analysis of trader behavior observed in various external perpetual protocols, and in-depth research on empirical trading patterns found in centralized exchanges (CEX), alongside other empirical evidence.

Synthetic Perpetual Exchanges

A Synthetic Perpetual Product is a type of financial instrument often found within the realm of crypto (decentralized and centralized finance), specifically designed to emulate the price of an underlying asset or index without necessitating the ownership of the underlying asset itself. These products are termed “synthetic” because they comprise one or more derivatives that simulate an underlying asset. They’re “perpetual” because, unlike futures contracts, they do not have an expiry date and can be held indefinitely. The essence of a Synthetic Perpetual Product lies in its ability to mimic traditional financial instruments, such as futures, and facilitate unlimited exposure to various assets (like cryptocurrencies, commodities, stocks, indices, etc.) without the need for an actual asset exchange. Instead, these products are collateralized by a different asset, typically a stable cryptocurrency. Synthetic Perpetual Products are traded on what’s known as a Perpetual Swap Contract, a particular type of futures contract where, instead of settling on a predetermined date, the contract remains open until the trader decides to close it. These contracts often use a mechanism known as the “funding rate” to keep the synthetic asset’s price pegged to the real asset’s price. The ability of Synthetic Perpetual Products to offer exposure to any asset, combined with the flexibility of no expiry, makes them an attractive financial instrument in the crypto and DeFi space. This is particularly useful in jurisdictions where certain assets may be difficult to access due to various restrictions.

Chapter 2

Agent-Based Monte Carlo Simulations Architecture

1 Introduction to Agent Based Simulations

Simulations for Dynamic Systems

Introduction to Simulations

Simulations serve as a bridge between theoretical models and real-world applications, particularly in blockchain. They either interface directly with blockchain applications or emulate on-chain protocols. These simulations are grounded in mathematical assumptions derived from the interplay between protocol parameters and exogenous variables. Collectively, these assumptions form a model, facilitating a deeper comprehension of the protocol's operational dynamics.

The Rationale Behind Simulations

Analytical solutions, which employ closed-form mathematical methods or equations, are apt for models with straightforward relationships. However, the intricate nature of most real-world systems often renders such solutions impractical. In these instances, simulations emerge as the preferred tool. Through simulations, a computer numerically evaluates a model, approximating the desired real-world characteristics of the model.

Challenges in Simulation

Despite their evident utility, simulations are not ubiquitously employed. The primary deterrent is the intricacy involved in crafting high-fidelity simulations. This complexity is accentuated in the domain of Decentralized Finance (DeFi) due to its nascent stage, limited historical data, and evolving dynamics. Broadly, the challenges in simulation can be categorized into two domains: precision in modeling and scalability. The subsequent sections elucidate the system we devised to address these challenges, particularly scalability.

Chaos EVM Simulations

The Chaos simulation environment is a testament to our innovative approach. This python-based, agent-centric simulation environment commences each simulation with a data synchronization phase. This phase entails extracting and assimilating contemporary and historical mainnet data, agent elasticity, protocol liquidity, and risk parameters. Notably, Chaos simulations have demonstrated a remarkable performance, boasting a 250-fold enhancement in latency and CPU efficiency compared to on-chain simulations.

Agent-Based Simulation: A Deep Dive

In the simulation landscape, an agent is conceptualized as an autonomous entity capable of perceiving its environment and making informed decisions. These agents, over time, can adapt and refine their behaviors.

Within the DeFi simulation framework, agents mimic users, encompassing roles such as traders, arbitrageurs, and liquidity providers. The essence of agent-based simulation lies in the dynamic interactions between these agents, shaped by the ever-evolving environment.

Monte Carlo Simulations

Monte Carlo simulations adopt a probabilistic approach. For variables with inherent uncertainty, the simulation assigns a spectrum of random values, computes results for each, and subsequently aggregates these results to deduce an estimate. In the context of DeFi platforms like Avantix, each simulation iteration employs a unique, randomly generated price trajectory, with agent-based models simulating the reactions from protocol agents and secondary markets.

The Merits of Agent-Based Monte Carlo Simulations

While conventional financial models might solely rely on price dynamics, our focus extends to simulating potential protocol losses. These losses are contingent not just on price fluctuations but also on the intricate interactions between agents. By updating the actions of these entities in real-time during simulations, we can approximate the expected value of protocol losses. The subsequent sections delve deeper into the methodologies underpinning our Monte Carlo agent-based simulations and the statistical framework that ascertains the value at risk for specific parameter configurations.

2 Monte Carlo Simulation Data

Computing price trajectories

We use discrete-time random walk stochastic processes to generate price trajectories of assets.

Geometric Brownian Motion: The canonical model for generating price trajectories is geometric Brownian motion (GBM). In a simple GBM model, the price (S) changes according to a stochastic differential equation: $dSt = St(1 + \mu dt + \sigma dWt)$, where Wt is a Brownian motion, σ is a volatility scaling parameter, and μ is a forcing parameter. This stochastic DE can be integrated with Ito's formula to get that

$$S_t = S_0 e^{(\mu - \sigma^2)t} + \sigma W_t$$

This analytical solution makes it possible to sample a price trajectory's outcome without running each timestep.

Issues with GBM: Although GBM is a popular model in finance literature, it does not hold in practice at short intervals. We often see erratic price jump behavior at short timescales and short bursts of high or low volatility, which the constant- σ GBM model does not reflect. We also see times of new information that lead to a short-term jump or drop in returns, which is also not reflected in the constant- σ GBM model. To correct for these, we forego the GBM modeling and instead utilize variable volatility price trajectories.

For clear evidence of the non-normality of this data, see the distribution of price trajectories in figure 2.1. We see that the distribution of returns contains outliers that are many standard deviation events. To model returns as following a GBM process, we would either need to entirely ignore long-tail events by using the real σ , or we would need to make these long-tail events possible by increasing the σ , which would overestimate the volatility of returns in the majority of cases. A GBM with constant σ is not a suitable model for returns behavior, and this is of particular importance because long-tail returns have a significant impact on the health of GMX accounts.

Not only is the returns distribution fat-tailed, but it is also autoregressive. Figure 2.2 shows a plot of the minute log returns for over 1 month, during which several high-volatility events occurred. In some of these periods, the median across 100 minutes also elevates. This demonstrates that a minute with a significant absolute return is likely to be close to other high absolute return minutes. Assuming that the mean return

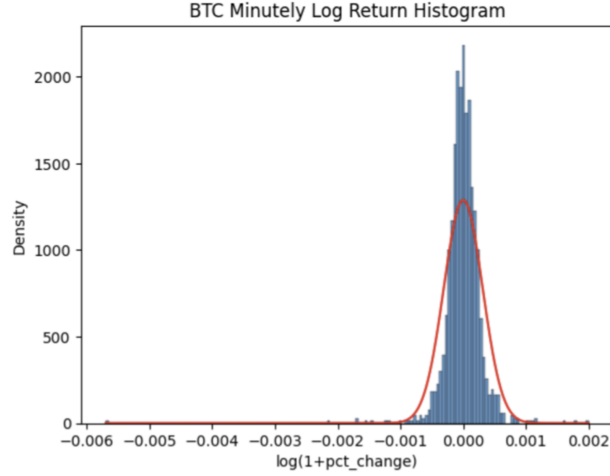


Figure 2.1: A histogram of BTC minutely log returns from 11/19/2022 to 11/20/2022. The red line is a normal distribution with the same mean and standard deviation as the log returns. That is, BTC minutely returns are lognormal.

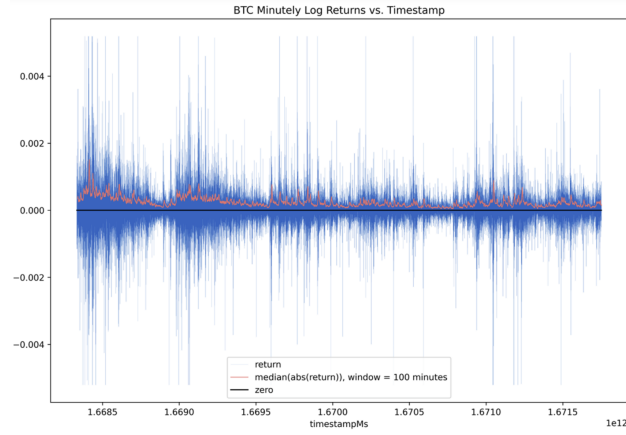


Figure 2.2: BTC log returns vs. time (blue) and BTC median of absolute log returns (red), from 11/14/2022 to 12/22/2022. The top and bottom 0.05% of values are removed for ease of viewing.

is approximately zero, the returns are simply the residuals of a time series process with a mean of 0. The variance of these residuals demonstrates autoregressive tendencies.

Modelling Volatility with GARCH. We can extend our GBM model to track more realistic volatility by modeling the autoregressive tendency of the variance of returns. Looking at historical data, we can see that a GARCH(1,1) model of the volatilities is the most fitting. From here, we can fit a GARCH model to historical data to find the baseline volatility (ω), the ARCH parameter (α), and the GARCH parameter (β). We then compute the following (assuming that the drift, μ , is equal to zero):

$$S_t = S_{t-1}(1 + \epsilon_t)$$

$$\epsilon_t = \sigma_t z_t$$

$$\sigma_t = \sqrt{\omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2}$$

The z_t term here is a white noise term with a mean of 0, and it is commonly set to $z_t \sim N(0, 1)$. This new process is quite similar to the GBM model, except it is discrete, assumes zero drift, and has a time-varying

volatility parameter σ . This process allows us to generate price paths for assets like we could for the GBM model.

Correlated GARCH. Although our GARCH model improves upon the GBM model, we do not yet capture the fact that returns are correlated. For GBM models, this is typically performed by requiring the white noise term for any two assets, i and j , their Wiener process terms, dW_{ti} and dW_{tj} , to be correlated. They must satisfy $E[dW_{ti} \cdot dW_{tj}] = \rho_{i,j}$, where $\rho_{i,j}$ is the Pearson correlation coefficient of the log returns. Instead of using the independent returns white noise distribution $z_t \sim N(0, 1)$, we sample all of the white noises from a multivariate normal distribution with mean 0 and covariance matrix $\Sigma = [\rho_{i,j}]$:

$$z_t \sim N(0, [\rho_{i,j}])$$

When assets' returns have no linear correlation, our formulation is identical to the white noise distribution for independent returns. In practice, many crypto assets are correlated. See figure 2.3 for a comparison of the multivariate normal distribution that we sample for ETH and BTC returns, compared to the returns that have arisen historically. See also figure for an example of a single day's change in asset prices.

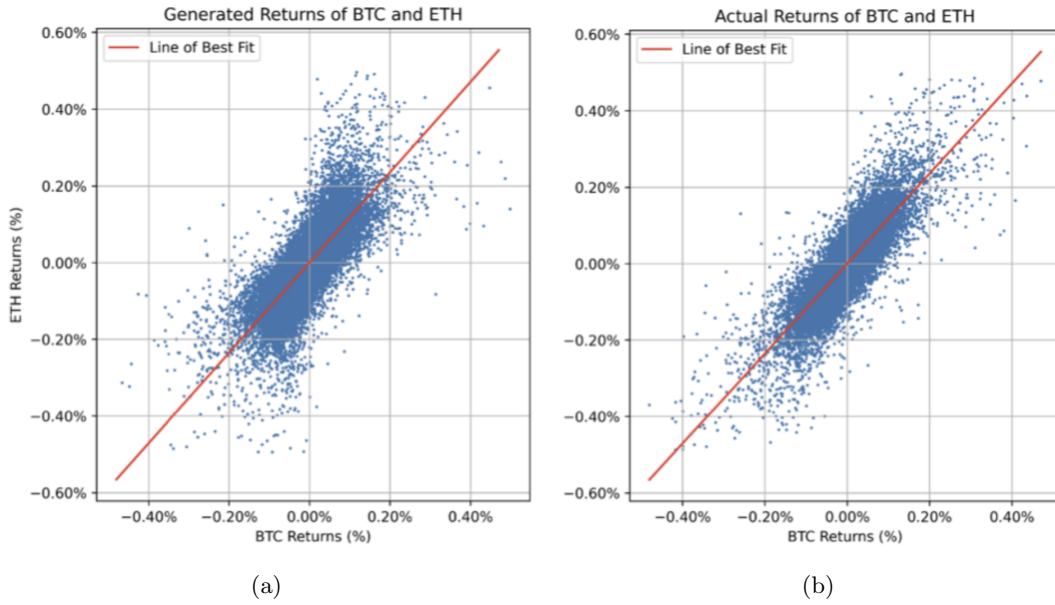


Figure 2.3: (a) Returns generated by our multivariate white noise distribution for BTC and ETH. (b) Historical returns for BTC and ETH. Each uses the same line of best fit, which was generated via historical data plotted on each.

Chapter 3

Simulations Results and Analysis

1 Dynamic Margin Fee

1.1 Introduction of the Mechanism

Maintaining a Balanced Open Interest (OI)

Achieving and sustaining a balanced open interest in financial derivatives, such as futures, options, or synthetic perpetual products, is paramount for ensuring the stability and overall health of the market. Open interest generally refers to the total number of active or outstanding contracts in the market, excluding those already settled or closed.

Several compelling reasons underscore the importance of maintaining a balanced open interest:

1. **Incentivizing Market Stability:** An imbalanced open interest can introduce price distortions. For example, if a majority of traders are taking long positions in a specific derivative contract, a sudden price drop might trigger a cascade of liquidations, exacerbating the downward pressure on prices and potentially leading to market instability or insolvency.
2. **Liquidity:** Balanced open interest correlates with robust market liquidity. When there is equilibrium between longs and shorts, executing trades becomes smoother, and opening or closing positions is less likely to cause significant price fluctuations. Conversely, an imbalance in open interest can result in liquidity challenges, making it difficult to enter or exit positions without causing substantial price swings.
3. **Risk Management:** Financial platforms offering derivative products benefit from balanced open interest, facilitating effective risk management. An excessively skewed open interest (either heavily long or short) exposes the platform to substantial risk if the market experiences a sharp movement in the opposite direction.

Balancing open interest is imperative for managing derivative products effectively, ensuring efficient market functioning, maintaining adequate liquidity, implementing robust risk management practices, and fostering fair and accurate price discovery.

Avantis' Mechanism

In contrast to its predecessors, Avantis distinguishes itself by eschewing the conventional perpetual margin fee mechanism commonly employed to maintain a balanced Open Interest (OI) skew. This traditional approach typically involves a parameterized funding fee model, where long and short traders pay or receive "funding" proportionate to the relative skew percentage at a given time (t). The skew growth leads to an exponential increase in funding in percentage terms, reflecting a scenario where a greater amount of longs/shorts pays a smaller amount of shorts/longs in absolute terms. Unlike prevalent in orderbook perpetual exchanges that incentivize platform liquidity through maker/taker incentives, Avantis employs a pool-based liquidity model.

This model necessitates direct compensation for lending out the underlying capital while minimizing relative margin requirements and general counterparty risk. Consequently, pool-based perpetual protocols tend to utilize some iteration of a rolling interest rate-equivalent mechanism, aligning the incentives of both traders and liquidity providers. The traditional factors influencing rate determination involve a combination of pool utilization rate (notional capital borrowed from the pool divided by the total capital in the pool), long/short skew, and perhaps the underlying volatility of a given asset market. The skewed portion may either pay higher fees to the pool as an interest rate or serve as an explicit funding fee.

In the case of Avantis, it adopts a distinctive perpetual margin fee akin to the latter mechanism. This unique approach exponentially imposes taxes on trades based on the linear blended utilization rate growth and skew percentage. The following section provides a detailed exploration of this component.

Mathematical Correlation Between OI Skew and Fee Incentives

The formal derivation of this total margin (mgn) fee calculation is as follows.

$$total_mgn_fee(t_i)_{HPR} = b(f)_i * [(\frac{1}{1 - blended_utilization_{t_i} * skew_{t_i}}) - 1]$$

Where $b(f)$ is the base fee in bps of a respective market i , HPR refers to the hourly periodic rate and the blended utilization rate is derived as

$$blended_utilization_{t_i} = .75 * \frac{category_OI_{t_i}}{category_max_OI_i} + .25 * \frac{asset_OI_{t_i}}{asset_max_OI_i}$$

In this context, "category" denotes a grouping of interconnected assets within a specific domain, particularly in the context of risk management. For instance, BTC and ETH can be categorized as highly liquid crypto assets with closely aligned price correlations thus the underlying exposure for liquidity providers is priced equivalently. The 75-25 allocation is designed to tactically incorporate a portion of internal market variability, ensuring adaptability in scenarios where LPs have substantial exposure to either upward or downward movements in large swaths, thus mitigating the impact of asset skew decoupling.

On the flip side, the skew for a respective market is calculated as

$$long\ skew_{t_i} = \frac{long\ OI_{t_i}}{total\ OI_{t_i}}$$

$$short\ skew_{t_i} = \frac{short\ OI_{t_i}}{total\ OI_{t_i}}$$

Thus, the element of directional variability within the total mgn fee is that of the skew differential component to incentivize skew reversion and thus mitigate liquidity provider risks. Figure 3.1 portrays a matrix with various skew and blended utilization values, which effectively account for the exponential percent amplification or deflation of the parameterized base fee:

skew/utilization	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0.1	1.01%	2.04%	3.09%	4.17%	5.26%	6.38%	7.53%	8.70%	9.89%	11.11%
0.2	2.04%	4.17%	6.38%	8.70%	11.11%	13.64%	16.28%	19.05%	21.95%	25.00%
0.3	3.09%	6.38%	9.89%	13.64%	17.65%	21.95%	26.58%	31.58%	36.99%	42.86%
0.4	4.17%	8.70%	13.64%	19.05%	25.00%	31.58%	38.89%	47.06%	56.25%	66.67%
0.5	5.26%	11.11%	17.65%	25.00%	33.33%	42.86%	53.85%	66.67%	81.82%	100.00%
0.6	6.38%	13.64%	21.95%	31.58%	42.86%	56.25%	72.41%	92.31%	117.39%	150.00%
0.7	7.53%	16.28%	26.58%	38.89%	53.85%	72.41%	96.08%	127.27%	170.27%	233.33%
0.8	8.70%	19.05%	31.58%	47.06%	66.67%	92.31%	127.27%	177.78%	257.14%	400.00%
0.9	9.89%	21.95%	36.99%	56.25%	81.82%	117.39%	170.27%	257.14%	426.32%	900.00%
1	11.11%	25.00%	42.86%	66.67%	100.00%	150.00%	233.33%	400.00%	900.00%	#DIV/0!

Figure 3.1: As skew * blended utilization rate converges to 1, the effective denominator whereby the dividend is 1 will linearly decay to 0; thus, the (quotient - 1) to be multiplied by the base fee will exponentially grow in accordance with the aggregate skew and blended utilization rate growth.

Skew $\longleftrightarrow$ Utilization Rate Relationship/Correlation

Per the above matrix, we notice the mathematical relationship between the skew and the utilization rate in base fee pct terms. However, it is noteworthy that the two linearly weighted components exhibit an inherently uncorrelated nature. Despite skew functioning as a disincentive to impede directional exposure in liquidity pools, the underlying utilization rate is intricately tied to the total borrowed amount. This introduces the possibility of scenarios where the utilization rate is low while the skew is high, rendering the relative disincentive insufficient to deter directionality.

The solution lies within the strategic role of the utilization rate. In essence, if the example above were to occur, the relative exposure concerning the notional liquidity in the pool would be subpar, and thus, directional exposure in absolute terms is mitigated. On the contrary, if the utilization rate is on the upper end while the skew is on the lower end, by proxy, the inverse OI skew traders will be paying incredibly hefty margin fees to maintain their positions, thus sufficiently disincentivizing skew reversion, in addition to generalized position repayments. Utilizing this intuition, we dive into the simulation framework for deriving appropriate base fee values.

1.2 Simulation 1: Defining Appropriate Base Fee Values

The following scenario under consideration involves the strategic actions of significantly biased traders gradually entering a specific market. These traders open positions agnostic of fee size. We will explore three sub-scenarios, each characterized by varying degrees of extremity. In these sub-scenarios, traders initiate positions with daily values equivalent to 1%, 2%, and 3% of the total Open Interest (OI) cap/2 size.

It is essential to clarify that the "total OI cap/2" element is introduced to replicate and abstract the long or short Open Interest, enhancing the realism of the biased trader's approach. For instance, if the combined long and short OI cap is \$10 million, the trader would open positions of \$50,000, \$100,000, and \$150,000 each day, respectively.

Importantly, this scenario is designed explicitly to assess the actions of various agents based on parameterization and is inherently unlikely to occur. The primary objective is to identify the "convergence value", or skew value, across different base fee values and utilization rates. This exploration aims to measure the responsiveness of (dis)incentives as the skew pressure intensifies over time.

The buying pressure remains fee-agnostic in this simulation, but the open positions are not. This implies that a new position will be initiated daily at the specified size. However, as the simulation progresses, some of these positions may close.

Setup & Assumptions

50-50 long-short relationship at $t(0)$ - i.e., explicit neutrality with respect to the skew, thus longs and shorts paying equivalently, simulated over a span of 100 days, volatility of the given underlying asset(s) implicitly factored into trader intuition.

Sweep Parameters

Range of base fee values from 1 - 7 bps per hour (87.6% - 613.2% APR), starting utilization rate from 10 - 70 %.

Parameters under examination

Base fee - we aim to match an arbitrary value (say, to derive the rate of exponentiation wrt skew/utilization changes) in accordance with the respective underlying volatility of the asset (say, BTC or ETH). In the implementation, our final results within the cells (aka, the "convergence value") will be comprised of the skew rate at the end of the simulation, which we will utilize to come up with the base fee for a given asset.

Simulation Agent Taxonomy & defined normalization adjustments

Agents at play:

Levered long positions $\leq t$, where $t+1$ is the timestamp of a given injection: Through the former assumptions,

the expected growth of the skew will lead to more expensive positions, thus inevitably leading to positions closing; albeit given there is no knowledge about future trades other than $\leq t$, their reactive capabilities are obviously hindered. In other words, the antics of these large-yet-gradual directional traders, specifically pertaining to the size, duration, etc., at a given $t+1$ are unknown to these position owners. As such, we create a mathematical dynamic deterrent utilizing the effective mgn fee(t), an explicit function of skew and utilization rate, to exponentially mimic trader flow.

Mathematical intuition

We begin with defining the predetermined *total_mgn_fee* calculation at t_0 ,

$$total_mgn_fee(t_0)_{DPR} = b(f) * \left[\left(\frac{1}{1 - utilization_{t_0} * .5} \right) - 1 \right]$$

Where DPR = daily periodic rate, aligning with the discrete-time series daily value - note that the .5 here comes from the 50-50 skew ratio, as both longs and shorts pay the same amount.

Thus, the given mgn fee differential equation,

$$mgn_fee_differential_t = total_mgn_fee(t)_{DPR} - total_mgn_fee(t-1)_{DPR}$$

The “t-1” timestamp here refers to t_0 at the first timestamp. So, say after the first long injection at $t+1$, the skew has now shifted to the upside for longs (>50); thus, the imbalanced values kick in (of which are a function of the base fee) as well as an increase in utilization rate, leading to increased *total_mgn_fee*($t+1$). Given we are attempting to model the amount of trades closed, we implement the relative “tax” of closing a position, i.e., multiplying the above.

$$mgn_fee_differential_t = (total_mgn_fee_t - total_mgn_fee_{t-1}) * (1 - close_fee)$$

Where *close_fee* is simply .04%, as mentioned in the documentation.

Normalization

Relative adjustment: To standardize these values for a percentage error calculation and leverage a DPR calculation, we incorporate a normalizing factor, denoted as c . The objective is to normalize the effective percentage of trade closures at a specific timestamp concerning the margin fee differential, assuming all positions are of equivalent size. The DPR differential component alone may not generate sufficient activity, given its relatively small differential. Therefore, we enhance its impact by aligning it with an estimated replication of the daily margin fee accrual and the number of trades closed daily.

By setting c to 100, we approximate the relative value of the margin fee to mirror that of the trades closing at a rate of approximately 0.274% per day, equating to a 1% decay from the margin fee every 3.65 days. This aligns with the relative decay of position values on other perpetual exchanges, particularly in extreme cases. Simultaneously, we simulate the three injection scenarios by setting c to 50, representing approximately 0.137% per day, or 1% decay every 7.29 days, resembling perp position decay in a normal setting. The final equation yields the percentage of closed trades per day or timestamp, now denoted as *% closed_trades_t*. Formally,

$$\% \text{ closed_trades}_t = mgn_fee_differential * c$$

Volatility Adjustment: The price trajectories are generated with a GARCH(1,1) model wrt underlying asset’s historical volatility conditions. Note that this specific simulation is semi-abstracting real-life price movements from parameterization recommendation, as the goal is to “stress test” in a hypothetical scenario. Regarding influencing the surrounding agents, we will integrate a price power factor equation for a given timestamp wrt total growth/decay since $t(0)$.

$$\%closed_trades_t = \begin{cases} \% \text{ closed_trades}_t * (1 - \% \text{ Price_change}_t)^\lambda & \text{if } P_t > P_{t-1} \\ \% \text{ closed_trades}_t * (1 + \% \text{ Price_change}_t)^\lambda & \text{if } P_t < P_{t-1} \end{cases}$$

Where λ is the price power factor, the motivation behind this is to create an implicit price-trajectory-specific component to the simulation, such that whilst not the main focus of this stress test, it is still important to gauge how price movements relate to trader actions. If the price at a given timestamp t is greater/smaller than the price at time $t-1$, we will deter/amplify the amount of trades closing accordingly, mimicking that of trader logic. With the $\% \text{ closed_trades}_t$ derived, we alter the long OI accordingly, and thus the skew, giving us our value to be utilized within the next timestamp.

Example:

For the example, flow with 3% injection, a base fee of 3 bps/hr (72 bps DPR), utilization rate at 50%, long + short OI cap is 12m (thus the trader will open 180k per day), a c value of 100, and a λ value of 3. 50-50 at t_0 with 50% utilization and 12m total oi cap = $12m * .5 * = 3m$ long OI + 3m short OI. Adding in our injection, we get $3m + 180k = 3.18m$ long OI and 3m short OI, or a 51.45-48.54 skew & 51.5% utilization rate to be utilized in the following formulae.

$$\text{total_mgn_fee}_{t_0} = 72\text{bps } b(f) * \left(\frac{1}{1 - .5 * .5} - 1 \right) = 24 \text{ bps}$$

$$\text{total_mgn_fee}_{t+1} = 72\text{bps } b(f) * \left(\frac{1}{1 - .515 * .5145} - 1 \right) = 25.95 \text{ bps}$$

$$\begin{aligned} \text{mgn_fee_differential} &= (\text{total_mgn_fee}_t - \text{total_mgn_fee}_{t-1}) * (1 - \text{close_fee}) \\ &= (25.95 \text{ bps} - 24 \text{ bps}) * (1 - .0004) \\ &= 1.95 \text{ bps} \end{aligned}$$

Multiplying 1.95 bps by 100 c value, we get

$$\text{closed_trades}_t = 1.95 \text{ bps} * 100 = 1.95\%$$

Normalizing through volatility: if price **decreased** 10%,

$$\text{closed_trades}_t = 1.95\% * (1 + .1)^3 = 2.60\%$$

$$\text{adjusted_long_OI}_{t+1} = 3.18m - (3.18m * 2.60\%) = \$3,097,320$$

$$\frac{\$3,097,320}{\$6,097,320} = 50.80\%, 49.20\% \text{ long/short skew}_{t+1}$$

$$\frac{\$6,097,320}{12m} = 50.81\% \text{ Utilization Rate}_{t+1}$$

to be preliminarily utilized in $t+2$ (discrete time), for which we derive the relevant values for the next timestamp (and so on, until the end of the time series).

If price **increased** 10%,

$$\text{closed_trades}_t = 1.95\% * (1 - .1)^3 = 1.42\%$$

$$\text{adjusted_long_OI}_{t+1} = 3.18m - (3.18m * 1.42\%) = \$3,134,844$$

$$\frac{\$3,134,844}{\$6,134,844} = 51.10\%, 48.90\% \text{ long/short skew}_{t+1}$$

$$\frac{\$6,134,844}{\$12,000,000} = 51.12\% \text{ Utilization Rate}_{t+1}$$

to be preliminarily utilized in $t+2$ (discrete time), for which we derive the relevant values for the next timestamp (and so on, until the end of the time series).

1.3 Simulation Results/Heat Map(s)

Running parameter sweeps for initial utilization from 30%-70% and base mng fee from 1 - 7 bps. For different normalization values ($c=50$, $c=100$), and a fixed λ of 3. See the results in 3.2.

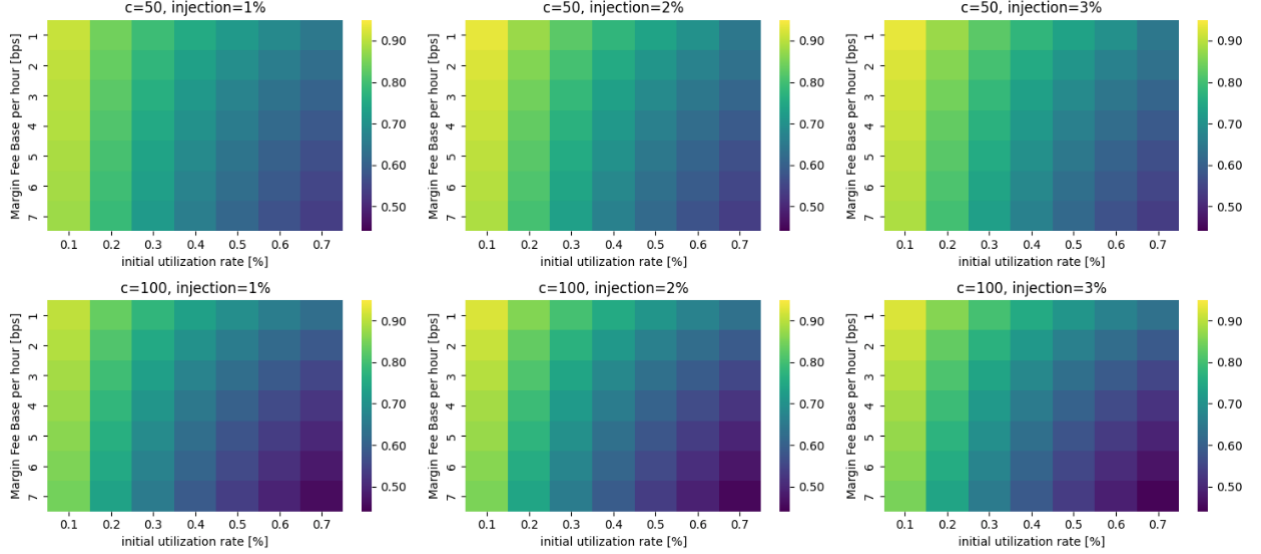


Figure 3.2: Cells denote median (P50) long skew values for both BTC and ETH at the end of the simulation time series; as we can see, in expectation, base fee higher $\rightarrow$ % of trades closed per day is higher $\rightarrow$ skew pulled down faster, of which ultimately leads to the “convergence value” within a given cell at the end of the 100 day time series.

1.4 Takeaways

We employ an aggregate mean approach across all six scenarios to establish the ultimate base fee value for both BTC and ETH markets. Subsequently, we aggregate the diverse utilization rate cell values to systematically evaluate the final skew values relative to distinct margin fees. Our conclusive inequality necessitates identifying the minimum skew value at the conclusion of the time series, leading to a skew imbalance of less than 75%. In this context, 75% corresponds to the skew value threshold which, as per the previously mentioned matrix, triggers the dynamic factor to be an aggregate mean value of $> 100\%$, to be multiplied by the base fee. Furthermore, as per the loss protection parameterization (more on that in Loss Protection: A Skew-Adjusted Safety Net for Traders), in expectation, a combination of very large subsidized trades can theoretically be realized.

Breaking it down further, we have derived values for respective sweep parameter implementations based on trader intuition on other exchanges, volatility adjustment to implicitly define trade behavior based on price movements, and different injection sizes. Therefore, we aggregate all relevant components to derive the final base fee value. This breakdown is represented on the left of table 3.1.

base fee bps/hr	avg final skew value
1	0.7676763284
2	0.7411689443
3	0.7186195589
4	0.6989980632
5	0.6813572738
6	0.6651977685
7	0.6502162088

Table 3.1: Aggregated final skew values for base fee bps/hr between 1 to 7 on the left, and 1 to 2 on the right.

base fee bps/hr	avg final skew value
1.0	0.7676763284
1.1	0.7649087481
1.2	0.7621210115
1.3	0.7593287965
1.4	0.7566217257
1.5	0.7539739296
1.6	0.7513994783
1.7	0.7487773531
1.8	0.7461858246
1.9	0.7436509304
2.0	0.7411689443

As we aim to find the aggregate value of convergence at 75% skew, we ran a more granular simulation to derive results between 1 and 2 base margin fee bps, see figure 3.3 and the aggregation in the right of table 3.1.

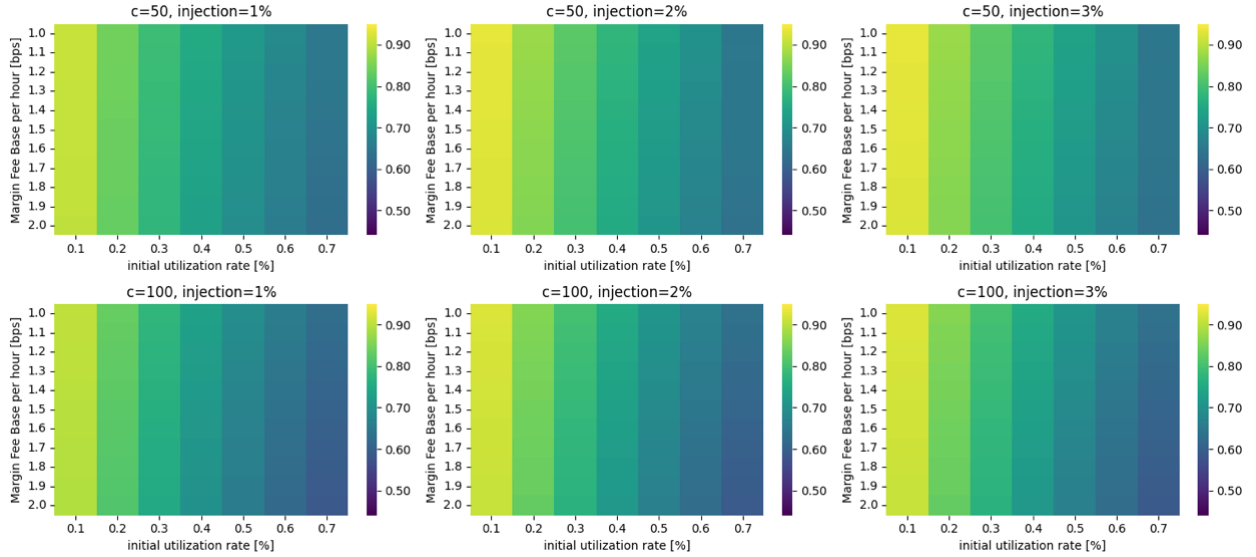


Figure 3.3: Smaller base fee range than in simulation in figure 3.3. Cells denote median (P50) long skew values for both BTC and ETH at the end of the simulation time series; as we can see, in expectation, base fee higher $\rightarrow$ % of trades closed per day is higher $\rightarrow$ skew pulled down faster, of which ultimately leads to the “convergence value” within a given cell at the end of the 100 day time series.

We recommend utilizing a base fee value of 1.6 bps/hr for BTC and ETH markets, i.e., the lowest value above the skew of 75. Plugging our base fee value into the initial matrix, we get our adjusted bps/hr with respect to skew and utilization. Using the suggested base fee value of 1.6 bps/hr, the realized margin fees for different skew and utilization values are shown in figure 3.4, where 3.4a shows the realized margin fee in bps/hr, and 3.4b the annualized values.

skew/utilization	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0.1	0.02	0.03	0.05	0.07	0.08	0.10	0.12	0.14	0.16	0.18
0.2	0.03	0.07	0.10	0.14	0.18	0.22	0.26	0.30	0.35	0.40
0.3	0.05	0.10	0.16	0.22	0.28	0.35	0.43	0.51	0.59	0.69
0.4	0.07	0.14	0.22	0.30	0.40	0.51	0.62	0.75	0.90	1.07
0.5	0.08	0.18	0.28	0.40	0.53	0.69	0.86	1.07	1.31	1.60
0.6	0.10	0.22	0.35	0.51	0.69	0.90	1.16	1.48	1.88	2.40
0.7	0.12	0.26	0.43	0.62	0.86	1.16	1.54	2.04	2.72	3.73
0.8	0.14	0.30	0.51	0.75	1.07	1.48	2.04	2.84	4.11	6.40
0.9	0.16	0.35	0.59	0.90	1.31	1.88	2.72	4.11	6.82	14.40
1	0.18	0.40	0.69	1.07	1.60	2.40	3.73	6.40	14.40	#DIV/0!

(a)

skew/utilization	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0.1	1.42%	2.86%	4.33%	5.84%	7.38%	8.95%	10.55%	12.19%	13.86%	15.57%
0.2	2.86%	5.84%	8.95%	12.19%	15.57%	19.11%	22.82%	26.70%	30.77%	35.04%
0.3	4.33%	8.95%	13.86%	19.11%	24.73%	30.77%	37.26%	44.26%	51.84%	60.07%
0.4	5.84%	12.19%	19.11%	26.70%	35.04%	44.26%	54.51%	65.96%	78.84%	93.44%
0.5	7.38%	15.57%	24.73%	35.04%	46.72%	60.07%	75.47%	93.44%	114.68%	140.16%
0.6	8.95%	19.11%	30.77%	44.26%	60.07%	78.84%	101.50%	129.38%	164.54%	210.24%
0.7	10.55%	22.82%	37.26%	54.51%	75.47%	101.50%	134.66%	178.39%	238.65%	327.04%
0.8	12.19%	26.70%	44.26%	65.96%	93.44%	129.38%	178.39%	249.17%	360.41%	560.64%
0.9	13.86%	30.77%	51.84%	78.84%	114.68%	164.54%	238.65%	360.41%	597.52%	1261.44%
1	15.57%	35.04%	60.07%	93.44%	140.16%	210.24%	327.04%	560.64%	1261.44%	#DIV/0!

(b)

Figure 3.4: (a) Margin fee (bps/hr) for a given skew and utilization value. (b) Margin fee APR for a given skew and utilization value.

2 Opening and Closing Fees

2.1 Mathematical Framework for Fixed Commodity/FX markets

Generalized Latency

Following our analysis of various pertinent Pyth price feeds, encompassing all feed updates from November 1st to December 1st, we empirically observed that 62 instances experienced a delay of more than one minute between consecutive updates ($t - t-1$). Notably, all these delayed updates, particularly those exceeding 20 seconds, were consistent across diverse feeds, irrespective of the specific underlying market. Consequently, we can reasonably deduce that the latency delay for a given feed is contingent upon the broader network state rather than the characteristics of a particular market. It is essential to note that this inference assumes the absence of any explicit user activity during the prolonged timeframe without an update, such as initiating or closing a position on a perpetual protocol. Furthermore, although one might expect a lack of timely updates to correlate with increased underlying price variability, our analysis revealed no discernible correlation between the latency and the subsequent price differential. This underscores the fact that the absence of volatility implicitly leads to a lack of dependency on the updated oracle price.

Max Price Differential Respective Update

To adequately define open/close fees, we utilize the price change of a respective market as a proxy for arbitrageur mitigation. In an efficient market, we can reasonably infer that an arbitrageur, when presented with an exploitable opportunity using outdated updates to profit based on the current effective price, will inevitably cause inherent losses for LPs at the subsequent price update, of which the arbitrageur will close his position in profit. As such, defining the open/close fee in terms of the relevant inequality or

$$\frac{\text{gas fee}}{\text{collateral size}} + \text{open_fee\%} + (1 - \text{open_fee\%}) * \text{close_fee\%} * (1 + |\frac{P_t}{P_{t-1}} - 1|) > |\frac{P_t}{P_{t-1}} - 1|$$

Where the inequality assumes possible net profit from either a long or short arbitrage trade. Nevertheless, since open/close fees are calculated linearly in relation to the notional trade size, the envisaged exploitative arbitrageurs are likely to opt for minimal leverage. Thus, the presented inequality assumes a 1x leveraged

position. Moving forward, we delve into specific markets, and table 3.2 presents various empirical P-values based on the price differentials of recent updates. The task of determining suitable open/close fees based on this inequality, in alignment with the price change values observed over the last month, rests with the team, given the considerable maximum variations in update differentials.

Normalized Confidence Percentiles

The confidence value tells how far the aggregate price might be from the true price in absolute terms. It reflects a combination of the confidence of individual quoters and how well individual quoters agree with each other. We normalize to a percent error calculation to adequately compare the relative confidence between the various price feed updates. As such, the relative differential plays a role in the conditional payoff function of an arbitrageur, whereby our underlying goal is to mitigate it altogether.

It is worth noting that we found no significant correlation between the price change and the normalized confidence values at a given time step, indicating that they're functionally irrespective of one another and estimating the total deviation from the true price ($t - t-1$) is not a straightforward process.

	USDJPY		EURUSD		GBPUSD	
	ΔP	Conf. Level	ΔP	Conf. Level	ΔP	Conf. Level
mean	0.000013	0.000221	0.000016	0.000395	0.000017	0.000512
std	0.000035	0.000355	0.000034	0.000271	0.000042	0.000624
50%	0.000000	0.000067	0.000000	0.000426	0.000000	0.000341
75%	0.000007	0.000186	0.000018	0.000587	0.000016	0.000572
90%	0.000046	0.000442	0.000047	0.000788	0.000049	0.001007
95%	0.000073	0.001343	0.000075	0.000805	0.000081	0.002633
99%	0.000159	0.001343	0.000148	0.000885	0.000179	0.002633
max	0.002743	0.003677	0.004319	0.003696	0.004517	0.004329

Table 3.2: Pyth Oracle statistics for USDJPY (left), EURUSD (center), GBPUSD (right).

2.2 Price Impact Spread

What are Price Impact Fees?

Synthetic Perpetual Exchange products leverage the concept of price impact to emulate the dynamics seen in traditional order book-based exchanges. This emulation is essential due to the inherent difference in the operating mechanism between synthetic perpetual exchanges and traditional ones. In traditional order book-based exchanges, market participants place buy or sell orders at specified prices, creating a "depth of market" where the bid-ask spread represents the difference between the highest price that a buyer is willing to pay (bid price) and the lowest price at which a seller is willing to sell (ask price). The dynamics of these exchanges involve price movement due to matching these orders, a process that influences the supply-demand balance and, ultimately, the asset price. On the other hand, Synthetic Perpetual Exchange products use a mechanism that directly interacts with a liquidity pool rather than matching individual orders. In these systems, trades result in a direct price impact, moving the asset price depending on the trade size. Therefore, the price impact mechanism is employed to simulate the behavior of price changes as observed in an order-book model. The concept of price impact allows Synthetic Perpetual Exchanges to reflect the immediate price change based on the trade's size. Larger trades significantly impact the price, emulating how larger orders would move the price in an order book model. This is akin to 'slippage' in a traditional order book context, where large market orders can end up executing at less favorable prices due to the depth of the order book. The benchmark for the order-book spread in traditional exchanges is often set by market conditions, precisely the balance of supply and demand and the overall liquidity in the market. Lower liquidity or higher volatility usually results in wider spreads as market participants demand a larger premium for taking on additional risk. This spread functions as a transaction cost and can serve as a measure of market efficiency - tighter spreads typically indicate a more efficient market. In Synthetic Perpetual Exchange products, the

spread can be considered a component of the overall transaction cost, but the specifics will depend on the individual protocol's design and mechanisms.

The Implications of Price Impact Fees

The primary objectives of integrating price impact fees are multifaceted:

Constructing safeguards to deter price manipulation

In Synthetic Perpetual Markets, price impact fees serve as a crucial lever in deterring price manipulation exploits. These fees are transaction costs that traders incur when the size of their order impacts the market price of an asset. The fees increase with larger order sizes, effectively reducing the potential profit from the trade and making manipulating the market price by placing large orders cost-prohibitive.

The rationale behind the indispensability of these fees can be articulated by delineating their impacts across three distinct pillars. It's noteworthy that while these pillars may intersect in terms of their effects, they vary in the pathways they employ to achieve their respective objectives. Thus, each pillar encapsulates a unique perspective on how these fees reinforce market stability and fairness.

- 1. Increasing Capital Requirements and Risk of Ruin for Potential Market Manipulators:**

Price impact fees can deter attempts to manipulate market prices. Without these fees, a trader with significant resources could place large buy or sell orders to artificially inflate or deflate prices and then profit from these price movements. Price impact fees make such tactics financially unviable, thus reducing the likelihood of price manipulation.

- 2. Maintaining Market Stability:** Price impact fees contribute to market stability by discouraging sudden, large trades. Large trades can cause significant price volatility, leading to a less predictable and stable market. These fees thus help maintain a more orderly and predictable market environment.

- 3. Preventing Flash Crashes and Price Spikes:** Price impact fees can help prevent flash crashes and sudden price spikes. Large sell orders can rapidly drive down prices (causing a flash crash), while large buy orders can cause a quick spike. Both situations can lead to cascading liquidations or margin calls. Price impact fees can prevent such scenarios by making large trades more expensive.

- 4. Aiding Effective Price Discovery:** Price impact fees support the fair price discovery process. They discourage 'quote stuffing' or other strategies intended to skew the price discovery process, helping ensure prices accurately reflect the balance between supply and demand.

Therefore, introducing price impact fees in Synthetic Perpetual Markets is an effective risk management tool, preserving market integrity and preventing potential price manipulation exploits.

2.3 Methodology Behind Depth-Quoting: Mimicking CLOB Spreads

We note that this need not apply for metals/fx, whereby a constant spread is implemented solely due to obvious non-manipulability within incredibly liquid external spot markets. Specifically, we will focus on the two crypto-related markets that will be live at launch - BTC and ETH.

Traditional on-chain perpetual protocols employ one of two design iterations pertaining to the derivation of an effective spread to price a given trade size accordingly.

1. Through the utilization of a traditional orderbook model, whereby there is some ideation around incentivizing market makers through rebates, funding rates to maintain skew, dynamic margin requirements, etc. - similar to that of a centralized exchange
2. A pool-based liquidity model, which prices a respective trade in accordance with the available notional liquidity, skew impact, leveraged utilized, and other minor components. Here, the liquidity pool effectively acts as the generalized counterparty for all trades on the platform, generating protocol revenue whilst bearing the inverse PnL.

In Avantis' case, they will be utilizing a combination of the two designs: a pool-based synthetic liquidity counterparty model which attempts to price the underlying spread with respect to orderbook liquidity residing on centralized exchanges, yet also provides additional (dis)incentives for a given trade based on the relative skew impact. As such, to synthetically mimic the spot central-limit-order-book (CLOB) in a pooled-liquidity-friendly way, Avantis will be implementing an exponential dynamic spread “slippage” calculation based on the cumulative 1% orderbook depth, i.e., from all important centralized exchanges (CEXs).

$$1\%_{orderbook_depth} = \sum_{i=1}^n 1\%_{bid_or_ask_depth_i}$$

Where i is a given Centralized exchange being utilized within the API aggregation. Note that the “bid or ask” component simply refers to the directionality of a given cumulative sum of liquidity.

The spread we are trying to replicate is calculated as the following:

$$Price_impact_spread = \max\left(\frac{e^{\left(\frac{ordersize}{b \cdot 1\%_{orderbook_depth}}\right)} - 1}{100}, 1\%_{linear_extrapolation}\right)$$

where b is a scaling parameter, and

$$1\%_{linear_extrapolation} = \frac{\frac{ordersize}{1\%_{depth_volume}}}{100}$$

Ultimately, our goal here is to find the optimal dynamic impact spread function with respect to scaling parameter b , such that we can empirically align the proposed function with that of the spot market to deter contract mispricing.

Importantly, we use this “1% linear extrapolation” component to sufficiently parameterize b ; say, there exists some point along the exponential dynamic spread function whereby the spread % can reside below the spot market liquidity spread, thus forcing a reparameterization of b . Conversely, this reparameterization would lead to pricing the underlying spread too aggressively due to the “mispriced” point on the function being relatively close to the midpoint. We utilize a maximum calculation to minimize unnecessary risk adversity and maximize capital efficiency.

2.4 Skew Impact Spread Adjustment Parameter

An additional component is the skew impact spread, which rewards/taxes traders based on whether their trade is correcting or making the skew worse, with an amplification parameter.

$$Skew_impact_spread = \frac{1}{100} * skew_param * \left(e^{\frac{skew_after_trade}{100}} - e^{\frac{skew_before_trade}{100}} + e^{\left(\frac{100 - skew_after_trade}{100}\right)} - e^{\left(\frac{100 - skew_before_trade}{100}\right)} \right)$$

where $skew_param$ is the amplification parameter, which can thus lead to a positive/negative impact in the event of a skew de/correction event

In figure 3.5, we examine the effective dynamic skew impact spread with the sweep parameters as aforementioned sensitivity and skew starting/ending point [55, 100], with the fixed assumption being the inverse ending/starting value of 50-50 such that we can derive the $\pm$ spread. Note that $\pm$ values imply a positive/negative skew impact for traders, as seen in the heat map in figure 3.5.

For example, say we have a 90-10 pre-trade skew in favor of shorts, \$10m total OI, and a skew spread sensitivity of 5.

For a given post-price_impact_spread adjusted long trade size of \$8m, skew is transformed from 90-10 to 50-50, or \$9m long and \$9m short, thus the skew impact spread returns.

Skew starting point (reverting to 50-50)	Skew Sensitivity Parameter									
	1	2	3	4	5	6	7	8	9	10
55	-0.0041%	-0.0082%	-0.0124%	-0.0165%	-0.0206%	-0.0247%	-0.0289%	-0.0330%	-0.0371%	-0.0412%
60	-0.0165%	-0.0330%	-0.0495%	-0.0660%	-0.0825%	-0.0990%	-0.1155%	-0.1320%	-0.1485%	-0.1650%
65	-0.0372%	-0.0743%	-0.1115%	-0.1487%	-0.1858%	-0.2230%	-0.2602%	-0.2973%	-0.3345%	-0.3717%
70	-0.0662%	-0.1323%	-0.1985%	-0.2647%	-0.3308%	-0.3970%	-0.4632%	-0.5294%	-0.5955%	-0.6617%
75	-0.1036%	-0.2072%	-0.3107%	-0.4143%	-0.5179%	-0.6215%	-0.7251%	-0.8287%	-0.9322%	-1.0358%
80	-0.1495%	-0.2990%	-0.4485%	-0.5980%	-0.7475%	-0.8970%	-1.0465%	-1.1960%	-1.3455%	-1.4950%
85	-0.2040%	-0.4081%	-0.6121%	-0.8162%	-1.0202%	-1.2242%	-1.4283%	-1.6323%	-1.8363%	-2.0404%
90	-0.2673%	-0.5347%	-0.8020%	-1.0693%	-1.3367%	-1.6040%	-1.8713%	-2.1387%	-2.4060%	-2.6733%
95	-0.3395%	-0.6791%	-1.0186%	-1.3582%	-1.6977%	-2.0372%	-2.3768%	-2.7163%	-3.0558%	-3.3954%
100	-0.4208%	-0.8417%	-1.2625%	-1.6834%	-2.1042%	-2.5250%	-2.9459%	-3.3667%	-3.7876%	-4.2084%

Figure 3.5: For example, we can see that a given trader correcting the skew from 95% to 50% with a skew sensitivity param value of 7 will lead to a positive slippage impact of 2.38%, and vice versa.

$$\begin{aligned}
Skew_impact_spread &= \frac{1}{100} * 5 * (e^{\frac{50}{100}} - e^{\frac{90}{100}} + e^{\frac{100-50}{100}} - e^{\frac{100-90}{100}}) \\
&= \frac{1}{100} * 5 * (1.649 - 1.105 + 1.649 - 2.4596) \\
&= -1.33\% \text{ price impact}
\end{aligned}$$

or positive for the trader due to correcting the skew.

2.5 Total Spread Calculation

Consolidating the various components to derive our total dynamic spread calculation

$$Total_dynamic_Spread = Constant_Spread + Price_Impact_Spread + Skew_Impact_Spread$$

where Constant Spread equates to a fixed spread for a given asset irrespective of trade size; this will generally be trivial for highly liquid assets. However, it will be parameterized such that we are not effectively granting any arbitrageur free lunch in the event of a stale oracle update in times of volatility. We elaborate more on this in the Mathematical Framework for Fixed Commodity/FX Asset Spreads section.

2.6 Simulation 2: Formulating the Relevant Spread Parameterization through Stress-Testing

As previously defined, the core reliance of the dynamic spread calculation is that of the 1% depth calculation at a given time t , of which is then extrapolated to derive the relative exponentiation. Thus, given the effective goal of replicating the concavity of a central limit order book with respect to orderbook depth distribution (i.e., the amount of liquidity on an orderbook decreases the further away the tick from the midpoint), it is imperative that we utilize the above formulae to simulate that of very large trade scenarios in varying skew states, such that we can gauge a traders ability to realize a decreased spread with respect to spot markets. If this is indeed a viable vector, a given large trader can lead to great losses for LPs. This is especially important, given the lack of an underlying correlation between total counterparty liquidity in Avantis pool and trader spreads, such that relative mispricing is inherently amplified if total liquidity in the pool is low. In addition, the notional size of a given trade, or the ability for a trader to utilize leverage, can further amplify this, as the relative cost of “exploitation” is mitigated. Through this data, we now formulate stress test scenarios with different skew starting points, hopefully deterring inadvertent positive slippage due to skew correction.

Setup

1. Scrape daily cumulative 1% median depth value across relevant major exchanges over the last 365 days, where the term “median” here implies the median of the per day cumulative depth value, such

that in aggregation, we realize a fixed daily value.

2. Find the annual P10 (10th percentile) value based on the daily cumulative 1% orderbook depth median value over the last year to create an ordersize/1% orderbook depth value.
3. Similar to (2), we find the annual P10 value of the daily median depth distribution, which we will utilize for our spot market comparison

We use P10 here as it effectively acts as the inverse (P90) in our case; say, by setting the integrated 1% depth to P10, we can derive a “stress test” with respect to a relatively lower depth value to get a sense of how the trader can interact with the synthetic order-book-equivalent function in edge-cases/times when liquidity depth is low.

Scenario Implementation

We implement 3 distinct scenarios for both longs and shorts, each assuming an initial OI of \$10m:

1. Skew at 90-10, 9m long/short + 1m short/long
2. Skew at 75-25, 7.5m long/short + 2.5m short/long
3. Skew at 50-50, 5m + 5m

All in favor of longs/shorts, whilst a very short/long trader wants to create a very large leveraged position with respect to the annual 1% aggregate depth.

Sweep Parameters

$$b \in [1, 3]$$

$$skew_param \in [1, 10]$$

The presented values within this matrix will be in the form of a minimum trade size whereby it is believed that it can present an issue pertaining to this vector, with n/a being placed if the following inequality is false.

Formally,

$$\forall x \in \mathbb{R}^+ :$$

$$\begin{aligned} & orderbook_depth_percentage - (error * orderbook_depth_percentage) \\ & > constant_spread + \max(price_impact_spread, 1\%linear_extrapolation) + skew_impact_spread \end{aligned}$$

where

$$orderbook_depth_percentage = \sum_{i=.001}^n tick_i$$

where $tick_i \in [.001, 1]$ and n is the last tick of which gets utilized with respect to a given trade size, such that,

$$tick_n \approx \arg \min_n \left(\frac{ordersize}{\sum_{i=1}^n tick_liquidity_i} = 1 \right)$$

Where

$$\max(orderbook_depth_size) = \sum_{i=1}^N tick_liquidity_i$$

where $tick_liquidity_i \in [.001, 1]$ and $tick_liquidity\ N$ indicates the final tick liquidity on the orderbook.

Dynamic Error Adjustment:

To account for minute oscillations around the spot market function, which would otherwise be deemed insufficient if there existed a point whereby the spot market depth outpaced the dynamic spread, we integrate an error component to create an effective buffer. Formally,

$$error_{t_i} = (e^{(\frac{1\%_{depth_liquidity}}{10\%_{orderbook_depth_size}} - \frac{order_size_t}{(\frac{10\%_{orderbook_depth_size}}{2})})} * \frac{1\%_{depth_liquidity}}{10\%_{orderbook_depth_size}}) - .01$$

we can assume a competitive edge for a given trader with varying error values to account for slight oscillations along the function. In other words, the further along the curve (I.e., the larger the trade size), the smaller the error component gets (and vice versa) as the error in dollar terms increases. As we see, the starting point of this exponentially decaying error solely relies on the 1% depth size with respect to cumulative size. This is important as the greater the relative 1% depth size, the more we can assume smaller trades to be sufficiently priced, & thus allow for more error, in accordance with Avantis's dynamic spread function. For example, the max error of a trade size of 500k assuming a 1m 1% depth liquidity and 10m 10% orderbook depth size,

$$e^{(\frac{1m}{10m} - \frac{500,000}{\frac{10,000,000}{2}})} * \frac{1m}{10m} - .01 = 9\% \text{ max_error}$$

will be greater than that of a \$5m trade size,

$$e^{(\frac{1m}{10m} - \frac{5,000,000}{\frac{10,000,000}{2}})} * \frac{1m}{10m} - .01 = 3.06\% \text{ max_error}$$

due to the mispricing of a larger trade being of more importance to fine-tune vs a smaller trade size, given the theoretical dollar value if mispriced.

As such, the flow of the simulation will look something like this:

1. Derive aforementioned dynamic spread & skew formulae taken into account for each sub-scenario utilizing P10 1% depth, with respect to trade sizes.
2. Utilize P10 depth distribution to derive a function of trade size with respect to the cumulative orderbook ask liquidity, with the y value being the aforementioned orderbook depth percentage.
3. Find the minimum value of a given b & skew param, accounting for error, whereby $\forall x \in \mathbb{R}^+ : spot_market_spread > dynamic_spread$ with the aforementioned relevant formulae.

Applying to Execution

Given the abovementioned data, it's important to aggregate the relevant spread metrics for the defined parameterization to mathematically present the relative impact for a given trade on Avantis. Similar to an $xy = k$ slippage calculation, the maximum market spread $\neq$ net execution is alternatively the integrated value between 0 and the maxima. Formally,

$$Net\ Execution_{shorts} = \int_{i=1}^n (tick_liquidity_i - tick_liquidity_{i-1}) + ((tick_liquidity_i - tick_liquidity_{i-1}) * price_impact_spread_i) dx$$

Conversely, for longs,

$$Net\ Execution_{longs} = \int_{i=1}^n (tick_liquidity_i - tick_liquidity_{i-1}) + ((tick_liquidity_i - tick_liquidity_{i-1}) * (\frac{1}{1 + price_impact_spread_i} - 1)) dx$$

Where $tick_liquidity_i - tick_liquidity_{i-1}$ is a given infinitesimally small and ever-increasing differential along the function, as the larger “i” is, the greater the spread at the given point on the function - note that here we replicated it as the tick liquidity differential of the orderbook, however, this can be interpolated accordingly as with traditional AMMs. Thus, by proxy, we can find the net execution percentage, otherwise known as the net price impact spread.

$$Net\ Execution\ Percentage = 1 - \frac{Net\ execution}{tick_liquidity_n}$$

Scenario Results: Defining Spread Parameters through Leveraging Spot Market Liquidity Distribution

2.7 ETH Results/Parameterization

Figure 3.6a shows the median orderbook execution size for ETH. Figure 3.6b shows that, as expected, the value of the 1% depth with respect to the cumulative orderbook size leads to that of an error function that begins at about 22% and decays according to the tick liquidity distribution. We now dynamically integrate this into the aforementioned function to allow for oscillation as Avantis’ synthetic spread grows wrt the 1% depth to derive the relevant inequality.

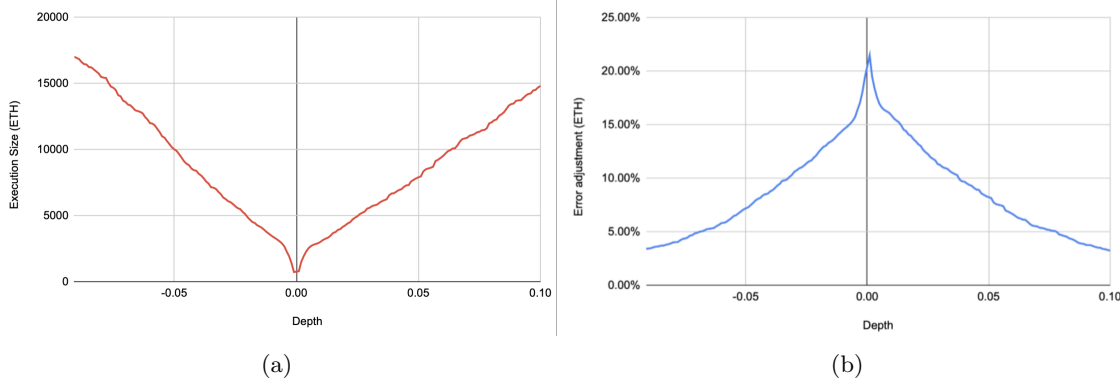


Figure 3.6: Orderbook ETH: (a) Annual daily median P10 orderbook execution size, extrapolated to 10% bid/ask depth from midpoint. (b) Error function.

Figure 3.7 shows the inequality matrix. Here, “N/A” implies that the inequality is false or that Avantis dynamic spread function is deemed sufficient, as there is no overlap along the function, accounting for error. On the flip side, “TRUE” indicates that the error-adjusted depth is greater than Avantis at some point on the function and thus is insufficient. Based on the minimum value that fails to satisfy this inequality, we propose parameterizing the ETH market with a recommended b value of 1.2 and a skew parameter value of 2. The ensuing presentation outlines the pertinent details. It’s important to note that we have opted for the minimum matrix value between bid and ask derivations, given the lack of functional differentiation in the context of skew reversion between the binary trade types. However, we can clearly deduce that the bid side distribution has a much more pronounced 1% depth size with respect to the cumulative orderbook.

Figure 3.8a shows the aforementioned net execution size - at no point along this function does the Avantis execution size outpace that of the spot market, ensuring sufficient pricing. Figure 3.8b shows the execution percentage - here we derive the final “slippage” exponential function recommendation for both longs and shorts; we elaborate on key benchmarks in the tables in figure 3.7. Figure 3.8c shows the Price Impact Spread in absolute terms, in accordance with the initial exponential function for which we indicate a spread value for a given trade size.

		B Value (ETH longs)									
		1	1.2	1.4	1.6	1.8	2	2.2	2.4	2.6	2.8
Skew Impact Spread	1	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	2	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	3	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	4	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	5	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	6	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	7	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	8	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	9	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	10	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

(a)

		B Value (ETH shorts)									
		1	1.2	1.4	1.6	1.8	2	2.2	2.4	2.6	2.8
Skew Impact Spread	1	#N/A	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	2	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	3	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	4	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	5	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	6	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	7	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	8	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	9	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
	10	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

(b)

Figure 3.7: Inequality matrix for ETH: (a) longs. (b) shorts.

2.8 BTC Results/Parameterization

As shown in figure 3.9a BTC cumulative orderbook distribution. Evidently, this distribution is quite linear, with the 1% depth equivalent to just about 10% of the 10% ask depth. This will thus impact our dynamic spread calculations, as the 1% depth value effectively acts as the backbone of our function. The error starting point in Figure 3.9b is down due to lackluster 1% depth.

Our BTC simulation results in the matrix shown in figure 3.10, whereby longs and shorts returned the same value. As the 1% depth is relatively small with respect to the cumulative, we return 1.4 as our b value due to the 1% linear extrapolation (accounting for error and skew adjustment) returning relatively similar values at the start of the oscillating function. In addition, our skew impact spread recommendation of 2 is directly aligned with the ETH recommendation.

In figure 3.11c, we see that as per the recommended 1.4 b value, the lack of sufficient 1% depth liquidity results in rampant exponentiation, as the size of a trade with respect to the 1% depth will absolutely be larger. Thus, we notice that post-6-7% orderbook depth, the raw spread becomes that of >100% for longs.

2.9 A few caveats to note

1. These are sample spread sizes with respect to the chosen parameterization assuming P10 historical 1% liquidity depth. In implementation, these spreads will generally be improved due to greater 1% liquidity depth. However, we have effectively shown and parameterized according to a “worst-case scenario” stress test.
2. Given the orderbook in bid/ask terms assumes linearity between the underlying percent depth, thus would imply an effective skew to the downside based on the extrapolation, we normalize it to equivalent price percentage movements. This is done by dividing $1/(1+\text{bid depth})$, or 9.09% adj. maximum bid depth, assuming our 10% maximum bid depth.
3. The above-portrayed price impact graphs assume the abstraction of the skew impact spread and its parameterization. It is rather simply a product of the stress testing.

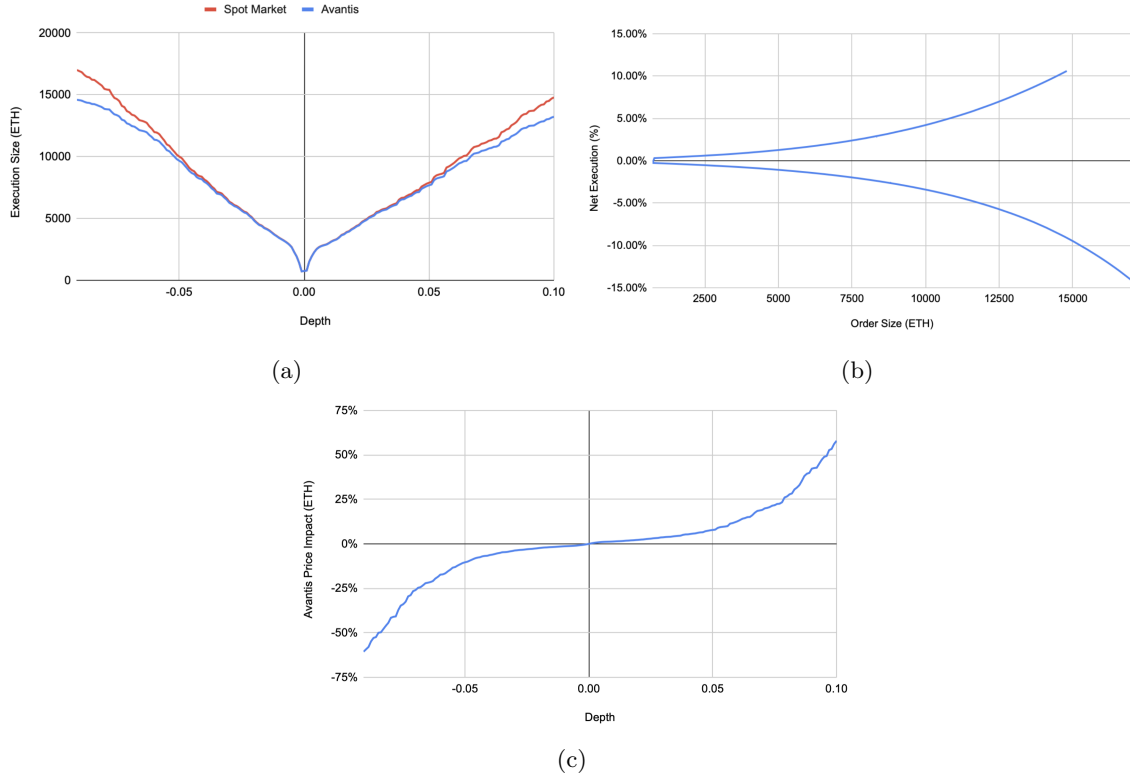


Figure 3.8: ETH: (a) Execution Size. (b) Execution percentage. (c) Price Impact Spread.

4. In the initial conceptualization of our stress testing, we meticulously addressed the mitigation of exploitative scenarios, ensuring that the order book spread never exceeds the value of the underlying liquidity along the price impact spread. However, the underlying liquidity is inherently synthetic, mirroring the distribution of spot market liquidity, specifically the 1% depth value. Theoretically, a trader could strategically break down order sizes into exceptionally small trades, facilitating a "net execution" that aligns with the artificially narrow spreads. Importantly, these meticulously planned trade executions would not introduce any variance to the price impact spread at $t + 1$ on the spot market itself, thereby requiring further optimization around this spread mechanism.

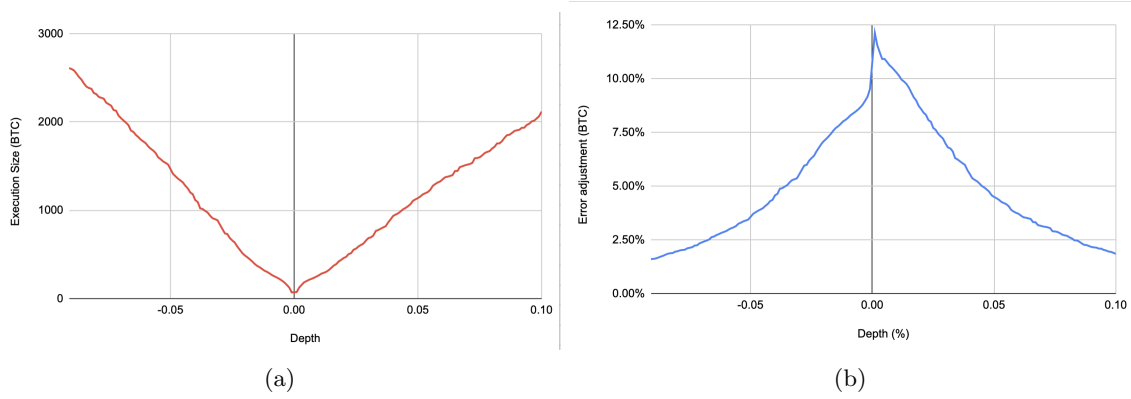


Figure 3.9: Orderbook BTC: (a) Annual daily median P10 orderbook execution size, extrapolated to 10% bid/ask depth from midpoint. (b) Error function.

skew/b	1	1.2	1.4	1.6	1.8	2	2.2	2.4	2.6	2.8
1	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
2	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
3	#N/A	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
4	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
5	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
6	#N/A	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
7	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
8	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
9	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
10	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

Figure 3.10: Inequality matrix for BTC.

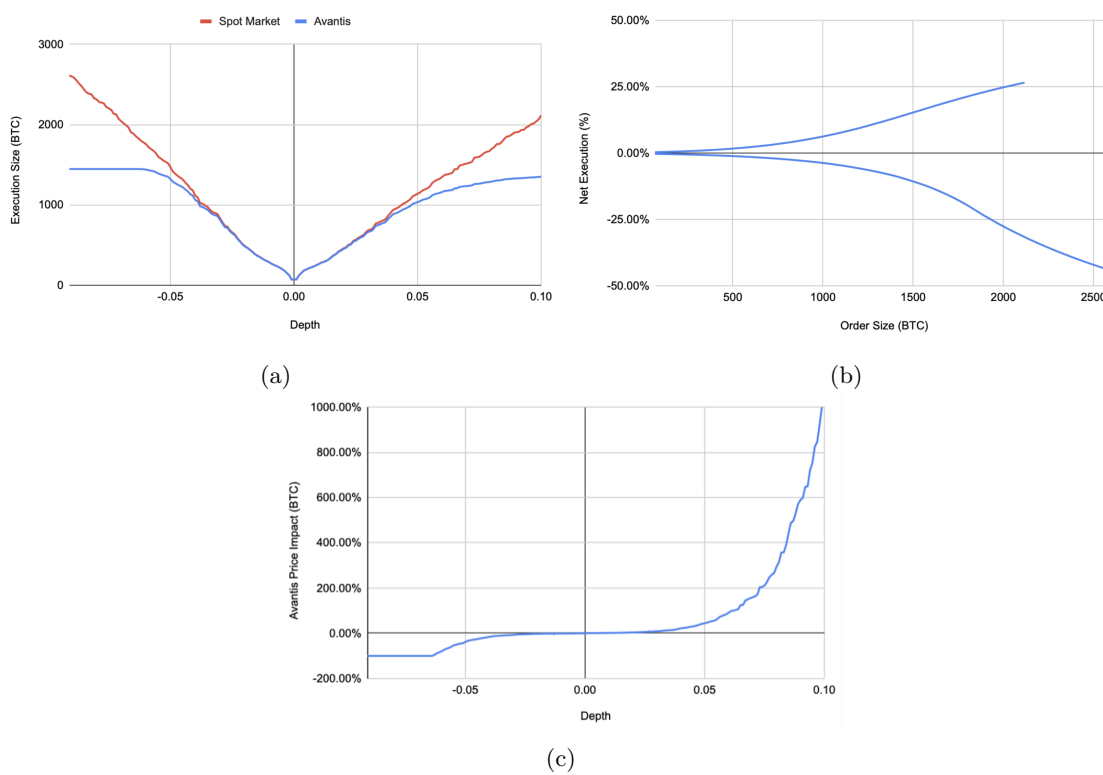


Figure 3.11: BTC: (a) Execution Size. (b) Execution percentage. (c) Price Impact Spread.

3 Loss Protection: A Skew-Adjusted Safety Net for Traders

3.1 Introduction of the Mechanism

To further incentivize corrective actions in skew management, Avantis has introduced a "loss protection mechanism," statically rewarding traders with a percentage rebate in the event of liquidation or position drawdown, as illustrated in figure 3.12.

For instance, if a trader initiates a short position with a skew of 75-25 in favor of longs, they receive a 20% conditional rebate, irrespective of the skew's post-trade changes.

Important Metrics to Look At

In the pursuit of understanding the impact of this mechanism, we aim to synthetically replicate its effects and gauge its influence on:

1. **Relative LP net impact:** Examining the additional net and normalized LP losses in parallel with trader subsidies
2. **Total percentage of positions with loss protection at the end of the simulation timeframe:** Analyzing whether traders with rebates are likely to hold positions longer and if they leverage this buffer to amplify their positions, and its subsequent impact on LPs.

3.2 Simulation 3: Stress Testing the Loss Protection Mechanism

Simulation Setup: Maximizing Effective Skew Volatility while Utilizing GMX v2 Trader Flow

To authentically capture the dynamics of trader behavior and position adjustments involving loss protection, it is essential to modify the inherent intuition of a trader before initiating a trade in response to a specific

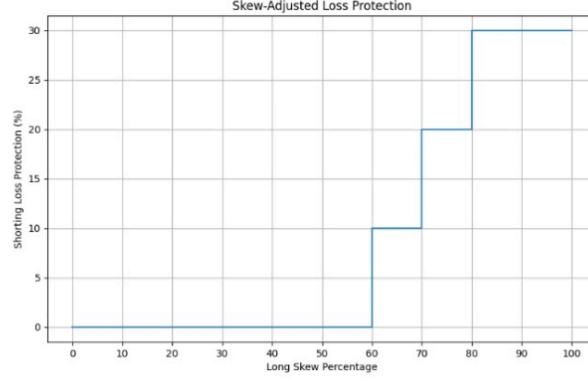


Figure 3.12: Loss Protection levels for different skews.

adjustment. By understanding this underlying intuition, we can accurately gauge how different types of traders would adapt, abstracting and categorizing them based on associated respective risk, as well as providing protection. This categorization allows us to estimate the adjustments a trader would make to their position, ensuring that the simulated adjusted positions closely mirror real-life scenarios.

To stress-test the loss protection mechanism effectively, we simulate a highly volatile environment. This is done by utilizing the ETH price volatility from Aug 4th, 2021, to Mar 15th, 2022, as our GARCH maximum likelihood estimation (MLE) input parameters, during a remarkable ETH price volatility period. We then relay a given price differential as a proxy for GMX v2 relative OI skew changes, with some exponentiation (lambda) to amplify its effect. Formally,

$$adjusted_skew_calculation_t = initial_skew_calculation_{GMX_t} * \left(\frac{P_t}{P_{t-1}}\right)^\lambda$$

This `adjusted_skew_calculation` effectively acts as the baseline component for which we dictate the underlying actions by the various agents, and thus, as well as the loss protection mechanism being utilized at a given time t .

$$protection_{t_0} = \begin{cases} 0.1 & \text{if adj skew calculation } x \notin [40, 60] \\ 0.2 & \text{if adj skew calculation } x \notin [30, 70] \\ 0.3 & \text{if adj skew calculation } x \notin [20, 80] \end{cases}$$

Defining Trader Agents: What can be implied through trader risk tolerance?

By modifying the inherent trader intuition to simulate their awareness of loss protection at t_0 , we categorize agents into a binary adjustment, considering the median relative leverage on GMX. This entails grouping all traders into a collective category regardless of protection status. This grouping assumes that traders will leverage their subsidy to magnify their position tendencies on GMX.

$$P_{leverage_t} = \begin{cases} P_j * (1 + protection_t) & \text{if } > P50_{j,t} \\ P_i * (1 + protection_t) & \text{if } < P50_{j,t} \end{cases}$$

Where $P_{leverage}$ denotes a given position in accordance with its leverage percentile, i = collateral size and j = trades wrt leverage used as such from GMX v2 since genesis, in order to gauge the composition of trader tendencies. We now elaborate on the various trader adjustments in our simulation, or “agents”.

Simply put, if a trader’s leverage percentile is greater than P50 at a given time t (bearing in mind that the relative median fluctuates with new positions being initiated or closed), we can infer that the trader is less risk-averse than the average trader. Conversely, if the leverage percentile is less than P50, we can assume the trader is more risk-averse than the average, prompting them to utilize loss protection to allocate more capital as collateral while keeping leverage constant.

Highly Leveraged Trader Conditional adjustment(s)

Conventional wisdom assumes that highly leveraged traders are generally indifferent to skew changes and their potential long-term effects on the profitability of a position. However, introducing a loss protection mechanism, coupled with the anticipation of increased volatility, may intuitively prompt these traders to become more aggressive, driven by the expectation of a rebate.

As such, we will integrate the values accordingly; say, a given function for which the loss protection mechanism will be utilized for a given high-leverage trader can look like this:

If $adjusted_skew_calculation_t < .4$:

$$Long_adj_{j,t} = Long_{j,t} * (1 + protection_t)$$

i.e., increasing the amount of leverage used, and vice versa, if $adjusted_skew_calculation_t > .6$

$$Short_adj_{j,t} = Short_{j,t} * (1 + protection_t)$$

We then apply these amplified values according to the P-value(s) of a given trade, in this case the leverage element, such that

$$adj_leverage_ratio_t = init_leverage_ratio_{j,t} * Long/Short_adj_{j,t}$$

As an arbitrary example, say the adj. skew is 75-25 in favor of longs, with a given high leverage short trader leverage value of 10x, with 3k collateral in his account. Ignoring the margin fees/spread, we get

$$Short_adj_{j,t} = 10x * (1 + .2) = 12x \text{ leverage}$$

$$12x \text{ leverage} * \$3,000 = \$36,000 \text{ notional_position_value}$$

and thus will maintain a liquidation price as if his notional was \$30,000. Whilst any >P50-j trader will realize equivalent loss protection in pct terms, these traders undoubtedly present the most risk to the LPs in terms of net PnL competitive edge due to the amplification as it relates to the absolute leverage value (and thus notional position value).

Risk Averse Trader Conditional adjustment(s)

This agent effectively treats the loss protection mechanism as a “free” competitive edge wrt the collateral component of the trade, as doing so would allow for a “free” collateral buffer. We assume that the <P50 leverage traders will be implementing this, of which we can expect an increase in trade longevity (thus collateral), not trade exposure/leverage.

For example, a given basis trader may implement the following strategy:

1. Price of ETH is P_{t_0}
2. Trader holds y ETH spot
3. skew is 90-10 in favor of longs, the trader gets 30% rebate if liquidated or closed in red
4. Trader opens 2x leverage ETH short with x ETH_{t_0} worth of collateral, where $x > y$, thus notional value of position is $P_{t_0} * 2x$ and total value of portfolio is $P_{t_0} * (x + y)$
5. If the price jumps Δ , the trader loses and/or is liquidated. However, portfolio is worth $y * (1 + \Delta(P_t)) + (30\% * (x - \Delta(P_t)))$
6. If price dumps Δ , port value is now $2x * P_{t_0} - 2x * (1 - \Delta(P_t)) + y * (1 - \Delta(P_t))$

With these traders, psychologically, we don't expect them to alter their leverage ratios. However, we expect the collateral size to increase due to their risk-averse nature.

$$Long_adj_{i,t} = Long_{i,j,t} * (1 + protection_t)$$

$$Short_adj_{i,t} = Short_{i,j,t} * (1 + protection_t)$$

As such, the dynamic margin fee component is incredibly important in terms of this long vol/basis strategy viability, or:

$$total_mgn_fee_t = b(f) * \left[\frac{1}{1 - utilization_t * skew_t} - 1 \right]$$

These (non-liquidated) traders are expected to keep their positions open for the simulation or when dynamic mgn fee accrual > protection. Thus, we must factor in the real-time skew changes into the daily mgn fee calculation.

$$adj_position = \begin{cases} closed & \text{if } \int_{t_0}^{\tau} total_mgn_fee \, dt > protection_{t_{open}} \\ open & \text{otherwise} \end{cases}$$

On the condition that the stopping times τ follow the inequality,

$$\tau_{adj_position} > \tau_{init_closed_position}$$

We monitor the low-leverage traders by focusing on the percentage of traders retaining their positions amid collateral size growth, influencing overall position health. Our strategy involves mitigating the relative loss of a low-leveraged position by preventing liquidation, ensuring positions persist even when closing in the red. Upon conclusion of the time series, assess the relative Profit and Loss (PnL) for these forcibly maintained positions.

If a position was closed by a given subsidized trader in the red, we decay his liquidation price_t accordingly,

$$liquidation_price_t = \frac{notional_{i,t_0} \pm long/short_adj_{i,t}}{\frac{notional_{t_0}}{price_{t_0}}} * (1 \pm \int_{t_0}^t total_mgn_fee \, dt)$$

Where “ $\pm$ ” indicates a long or short directional trade of which inversely dumps or pumps - however, the relevant position theoretical value is still that of the init. leverage ratio, thus the position-adjusted loss when in the red is that of,

$$trader_adj_loss_t = collateral_{i_{GMX},t} * \frac{notional_{i,t_0} * |1 - (1 \pm \Delta(P_{t-t_0}))|}{long/short_adj_{i,t}} * (1 + \int_{t_0}^t total_mgn_fee \, dt)$$

$$Forced_adj_PnL = \max(trader_adj_PnL_{\tau}, GMX_init_loss_{t_c})$$

This adjusted position mitigates the initial position's adverse aspects, particularly in terms of liquidation price and calculated profit and loss (PnL), while preserving the notional upside equivalent to the initial position. If the adjusted position were to revert and experience a positive price movement from the time of the initial closing, we would employ the logistics of the initial position to compute the profit, of which would result in a net loss for liquidity providers (LPs) compared to GMX from the time of closing. On the contrary, by altering the core behavior of this trader with regard to safeguarding their investments, the maximum drawdown of the modified position is explicitly determined by the GMX_init_loss , as indicated in the formula above. This measure guarantees the absence of any theoretical scenario where the adjusted total Profit and Loss (PnL) could generate greater gains for Liquidity Providers (LPs) than the original GMX PnL for any given agent. In instances where a trader with a negative position would have closed their position on GMX, our simulation mandates the position to persist, thereby constraining potential trader losses to align with those incurred on GMX, resulting in a net zero outcome if applicable.

As an arbitrary example, say the leverage size of a given low leveraged long position is 1.5x with \$15,000 of collateral, whilst the skew is 90-10 in favor of shorts.

$$Long_adj_{t_i} = 15,000 * (1 + .3) = \$19,500 \text{ collateral}$$

If liquidated through traditional market flow according to the initial position liquidation price,

$$\$19,500 - \$15,000 = \$4,500 \text{ rebate to trader}$$

thus, the PnL differential between the GMX PnL and our protection adjustments for this given trader is 4.5k due to the trader being effectively refunded from the liquidity pool.

If the trader closed in the red, we revert the close to fit that of the updated collateral size and thus update the relative liquidation price in accordance with the perpetual margin fee accrual.

In our case,

$$liquidation_price_t = \frac{22,500 - 19,500}{\frac{22,500}{price_{t_0}}} * (1 + \int_{t_0}^t total_mgn_fee \, dt)$$

Whereby the relative decay of the position of which has decayed 50% is calculated as:

$$trader_adj_loss_t = 15,000 * \frac{22,500 * .5}{19,500} * (1 + \int_{t_0}^t total_mgn_fee \, dt)$$

$$trader_adj_loss_t = \$8,653 * (1 + \int_{t_0}^t total_mgn_fee \, dt)$$

Whilst an equivalent non-adjusted position of which is nominally still open,

$$trader_init_loss_t = 22,500 * .5 * (1 + \int_{t_0}^t total_mgn_fee \, dt)$$

$$trader_init_loss_t = \$11,250 * (1 + \int_{t_0}^t total_mgn_fee \, dt)$$

3.3 Results

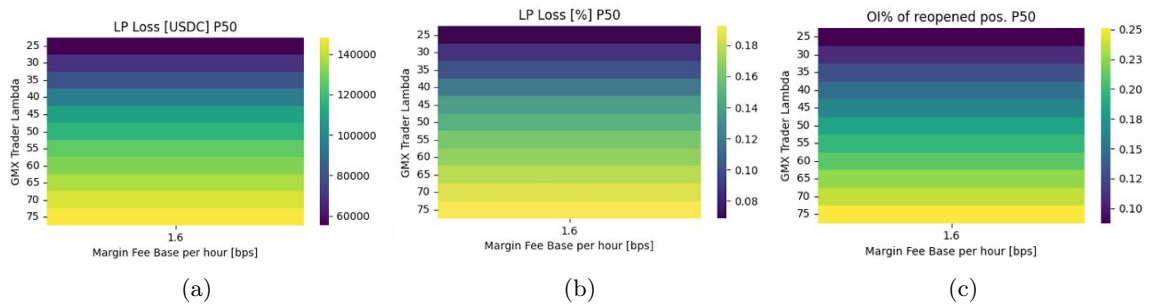


Figure 3.13: Results of the loss protection simulation. Using the 1.6 bps/hr base margin fee as proposed in section 1. (a) Expected LP PnL Loss differential in USDC. (b) Relative LP PnL Differential (c) % of Protected Positions.

Expected LP PnL Differential

The Expected LP Pnl Differential is calculated as follows,

$$Net\ LP\ Loss\ Differential = \sum_{i=1}^n PnL_{adj_i} - \sum_{i=1}^n PnL_{GMX_i}$$

where i refers to a given trader.

In the graphic representation in figure 3.13a, we present a consistent chart depicting the median net loss differential experienced by Liquidity Providers (LPs) between our adjusted longs/shorts flow and the GMX V2 positions. This analysis spans a week-long timeframe and varies according to different λ values. Naturally, higher λ values result in more trades receiving protection, thereby introducing theoretical adjustments to our net calculation. In a real-world context, based on our initial assumptions, this suggests that within our specified timeframe, LPs might incur losses ranging from \$55k to \$148k weekly. This trade-off is made in exchange for the potential inclusion of an additional skew reversion component, acting as a disincentive for LPs to engage in directional exposure.

Our analysis implies that the positions that remained open after the week-long timeframe solely include positions that were opened and closed during the week. This is due to the otherwise inability to adequately compare the loss protection adjustment against positions that did not realize the protection at opening (i.e., before the week), as well as the subsidy only being realized at position close (i.e., positions open post-week).

Relative LP PnL Differential

When working with net Profit and Loss (PnL), employing the relative differential in a net calculation may yield non-normalized outcomes, given that the effective differential is influenced by one or more values that can be relatively low in a net context. To address this, we employ a calculation that accounts for relevant loss and gain weights. Subsequently, we extrapolate the results by considering cumulative profit and absolute cumulative loss differentials, as formulated below.

$$Loss_weight = \frac{|\sum_{i=1}^n Loss_{GMX_i} + \sum_{i=1}^n Loss_{adj_i}|}{\sum_{i=1}^n Profit_{adj_i} + \sum_{i=1}^n Profit_{GMX_i} + |\sum_{i=1}^n Loss_{adj_i} + \sum_{i=1}^n Loss_{GMX_i}|}$$

$$Gain_weight = 1 - Loss_weight$$

$$Relative\ LP\ Loss\ Differential = Gain_weight * (\frac{\sum_{i=1}^n Profit_{adj_i}}{\sum_{i=1}^n Profit_{GMX_i}} - 1) + Loss_Weight * (|\frac{\sum_{i=1}^n Loss_{GMX_i}}{\sum_{i=1}^n Loss_{adj_i}}| - 1)$$

The numerical results are shown in figure 3.13b, where the color schema implies varying % differentials per the values on the right-hand side. Unlike the above net PnL differential, this relative calculation will be uniform irrespective of the time series length in expectation. In other words, by employing a loss protection mechanism to incentivize skew reversion, we can reasonably deduce that LPs are giving up 6.87%-19.2% of theoretical revenue that would otherwise flow to them.

% of Protected Positions

$$\% \text{ of } OI \text{ with Protection} = \frac{\sum_{i=1}^n protected_notional_i}{total_OI_{GMX_\tau}}$$

Where τ refers to the end of the time series, similarly, this % of OI with protection gives us a range which, based on our assumptions, leads to an inherent competitive edge for traders as a collective unit. It remains an open question as to how traders (particularly of the <P50 flavor) adapt to this over a longer timeframe; however, this adequately paints a preliminary aggregate picture.

The % of Protected Positions that stayed open until the end of our simulation is shown in 3.13c.

Chapter 4

Conclusion

In its preliminary stages, Avantis unveils unprecedented risk mitigation strategies, prompting our investigative approach to rely significantly on a nuanced blend of implicit and explicit conjectures firmly grounded in empirical data. For instance, in our loss protection simulation, we integrate agents whose behavior and risk inclinations are extrapolated from observations in GMX V2. Additionally, we leverage generalized historical orderbook data to calculate both the price impact spread and skew impact spreads. The ultimate validation of our refined binary assumptions, encompassing trader intuition, skew trajectories, and the orderbook's adaptability over time, especially in highly bullish or bearish markets, awaits implementation. Nevertheless, our cautiously implemented approximations align with a rigorous "stress test" approach, ensuring robust resilience in varied market conditions.

Additionally, we generate synthetic data by simulating price trajectories and liquidity landscapes based on historical market price oscillations. While considering our scenario approximations suitable adaptations, we anticipate that empirically observed behavior may deviate, given the unique dynamics yet to be implemented. While powerful, synthetic data synthesis has inherent limitations as it assumes that all future market movements or scenarios hinge on historically discerned conditions. Recognizing the recurrence of unexpected 'Black Swan' incidents in the crypto realm in various forms, extending the operational period of the system would augment the data set, thereby improving the accuracy of our models.

From a rigorous economic standpoint, integrating utilization rate/skew-correlative exponential margin fees, skew impact spreads, skew-scaled open/close fees, and dynamic loss protection has been meticulously parameterized to align with our assumptions to the best of our ability. Post-launch, these intricately interwoven mechanisms require collective monitoring, specifically emphasizing translating components from this research paper into practical optimization efforts over time. Our empirical optimal approximations center on ascertaining whether the foundational liquidity providers effectively sacrifice net revenue through assertive subsidization in the context of methodically adapted skew-neutralizing intuition. By proxy, it raises the question of whether pertinent trader execution and user experience will surpass that of competing perpetual exchanges. This requires careful observation to gauge these economic strategies' real-world impact and efficacy, ensuring that skew mitigation aligns harmoniously with traders' and liquidity providers' financial interests and strategic choices.

Furthermore, our evaluation of fixed spreads for commodity/fx assets is influenced by the historical uncertainty associated with Pyth price feeds; our portrayed historical data has shown occasional inconsistencies and outliers. Recognizing the importance of accurate and reliable price information in our risk assessment, we acknowledge the need for ongoing monitoring and validation of Pyth feeds to ensure their consistency and adherence to infinitesimal market dynamics, such that adequate fixed spread parameterization is employed. As Avantis progresses through its launch and operational phases, continuous vigilance over Pyth price feeds will be integral to refining and optimizing risk management.

Regarding OI cap recommendations, determining a precise absolute value to distinguish among diverse genesis markets, all highly liquid with comparable risk structures, is mainly theoretical and introduces unnecessary inefficiencies. This generally pertains to relevant utilization rate calculation and its underlying effect on users of a given respective market, as it thus becomes unclear how to divvy up absolute max OI numbers from an economic point of view. Instead, consider a relative maximum percentage of total OI

values, derived granularly from the asset class percentage of total and specific asset percentage of total, as outlined in the initial documentation. This approach encompasses implicit risk assumptions related to theoretical directionality for a given asset.

Given these considerations, our methodology and initial genesis suggestions are provisional and mandate successive iterations as more data surfaces. At Chaos Labs, we place the highest emphasis on a secure and methodical launch, prompting us to adopt a prudent stance regarding specific modeling parameters.

Appendix A

About Chaos Labs

[Chaos Labs](#) is a cloud-based platform that develops risk management and economic security tools for decentralized finance (DeFi) protocols. The platform leverages sophisticated and scalable simulations to stress test protocols in adverse and turbulent market conditions. By partnering with DeFi protocols, Chaos Labs aims to create innovative solutions that enhance the efficiency of DeFi marketplaces.

The Chaos Labs team exhibits exceptional talent and represents diverse expertise, encompassing esteemed researchers, engineers, and security professionals. Chaos Labs has garnered its experience and skills from renowned organizations, including Google, Meta, Goldman Sachs, Instagram, Apple, Amazon, and Microsoft. Additionally, the team boasts members who have served in esteemed cyber-intelligence and security military units, further contributing to their unparalleled capabilities.

You can explore our past and ongoing projects for customers like Aave, GMX, Benqi, dYdX, Uniswap, Maker, and more in the [Research](#) and [Blog](#) sections of our website.