Introduction

Introduction

We were tasked with evaluating the votable supply required to prevent a successful attack. This amount has been calculated by identifying the key factors that influence the value and then extensive research into them. We have utilized several methods including analysis of old data to arrive at an accurate conclusion. The ideal output would be an as-is overview of the current state, a best practice overview, and recommendations on how to get there.

We have documented our entire research in this Google Doc. Navigate through the document using the Tabs on the left-hand side to jump to specific sections.

The document includes:

- Introduction - that's this page
- Mini report
- Determining DIVS - has the method of calculating DIVS
- *d* - method of calculating price depreciation
- Market behavior analysis - contains research on market behavior with price changes
- OP token Liquidity - contains research on OP token liquidity and market depth
- Observations
- Question - detailed explanation of queries that emerged while calculating DIVS

Special Note

Meetings with the **Optimism Foundation** and **OP Labs** teams played a key role in shaping the parameters and refining the thought process behind the finalization of **DIVS**. These collaborative discussions helped align on key assumptions, validate the methodology, and ensure that the model reflects realistic governance dynamics.

Valuable contributions during the meeting & async -

Dennis
Eliza Oak
Josiah
Justine Lavande
Thomas

This report could not have been completed without their support. Sincere thanks.

Mini-Report:Decentralized Ideal Votable Supply

Mini-Report: Determining the Decentralized Ideal Votable Supply

Overview & Objectives

Decentralization Ideal Votable Supply (DIVS) represents the votable supply required to maintain decentralization and safeguard the DAO from governance attacks at the current circulating supply level.

The goal of DIVS is to identify the optimal votable supply required to safeguard the DAO from potential hostile takeovers, assuming all existing governance safeguards are removed and the DAO operates in a fully decentralized manner. If the safeguards are eliminated to enable full decentralization, it is essential to determine the appropriate votable supply necessary to ensure the DAO's treasury protection.

Framework & Methodology for DIVS

Our research focused on the treasury that is subject to voting, as well as the factors influencing the cost of an attack & The formula for **DIVS** is defined as:

$$DIVS = \frac{(200-s)(100-d)}{d \cdot t} \cdot T$$

Where:

- **T**: Number of tokens in the treasury or the tokens that the attacker is targeting via the proposal.
- **t**: Maximum turnout percentage of the votable supply in the past 180 days.
- **d**: Depreciation in OP price incurred by the attacker relative to the acquisition price.
- **s:** Percentage of tokens that the attacker acquires from outside of Votable Supply that is currently active in the DAO.

Other than DIVS there are other factors the need some exposition such as the tokens required for an attack, denoted as Ta, depend on s. The relationship between Ta and the votable supply changes based on the source of acquisition:

$$Ta = \frac{70}{(200-s)} DIVS$$

The percentage of **Ta** sourced from outside the votable supply is determined by **s**, and we introduce a new variable **Ts** to represent this:

$$Ts = \frac{s}{100} \times Ta$$

Change in Votable Supply

When the attacker acquires some part of the tokens outside of the available votable supply, for example, parts of the circulating supply that are not delegated to them, this causes a change in the votable supply. In this scenario, when $\boldsymbol{s} \neq 0$**,**

F = DIVS + Ts

Where F is the final votable supply.

Time

The time period for buying and selling tokens also influences the DIVS. We have calculated the amount of tokens an attacker can buy or sell with less than a 2% impact on the price, arriving at a value of 15 million. The following equation represents the number of days required for an attacker to acquire and sell tokens at **s = 100**. It can be found here.

$$N = \frac{(2Ts+T)}{15}$$

Here, N is the number of days to acquire and sell tokens at s = 100

At this stage we are able to calculate the cost of attack or in other words the amount an attacker would need to spend. If we want to calculate the cost of attack, then we get the following equations,

Capital Cost to Attack = $Ta \times P \times (1 + \frac{Pa}{100})$

Where,
P = price of the OP tokens
Pa = acquisition premium, which is defined in 2.2.1

Calculation Assumptions

The DIVS framework incorporates the following key assumptions:

- **Historical Voting Engagement:** Maximum voter turnout is measured over a **180-day period**.
- **Market-Driven Depreciation:** The model accounts for the anticipated depreciation of OP token price post-acquisition.
- **Treasury Vulnerability:** The formula evaluates the worst-case impact on governance security

Depreciation in the Price of OP tokens

Most of the other variables used in the formula are easily determinable, except *d.* We have explored several different approaches to calculate *d* as accurately as possible. Out of them, the most successful was a quantitative approach. It is as follows:

Quantitative Approach

In this method, we identify all the factors affecting d and formulate an equation that can give us the value by plugging information into the equation.

$$d = P_a + S + C_o + S_l$$

Where:

- **Acquisition Premium** (P_a)**:** Cost incurred when purchasing tokens in large quantities.
- **Sentiment** (S)**:** Market and community reaction to the attack.
- **Opportunity Cost** (C_o)**:** Capital cost from token acquisition to liquidation.
- **Liquidation Slippage** (S_l)**:** Impact on token price due to bulk liquidation.

Condition for Premium Application:

- If $\frac{Total\ volume\ of\ tokens}{Number\ of\ days} > 12.65\%$ of daily traded volume, a premium is applied.

Quantitative analysis is inconclusive, so we have to rely on qualitative and heuristic approaches to derive a conclusion on *d.*

Market Behaviour & Correlation with Volume

Objective

We simulated market behavior when large volumes of tokens are traded, using two models: a linear model and a logarithmic model. These models were analyzed alongside historical data to assess the impact of trading volume on price, validating our understanding of price behavior and supporting our analysis with empirical data.

Key Insights

Overall Observations:

- There was a weak correlation between price, market cap, and volume, indicating that drastic increases in trading volume do not directly drive price or market cap changes.
- Instead, liquidity, order book structure, external market sentiment, and macroeconomic conditions likely have a greater influence on market behavior.

Historical Volatility in Volume:

- Historical Volatility in Volume: **92855492.21 OP**
- Historical Volatility in Volume (%): **72.05%**

Historical Volatility in Price:

- Historical Volatility in Price: **0.832904 OP**
- Historical Volatility in Price (%): **45.56%**

Simulating Price Impact on Token Price for Large Trades:

When large volumes of a token are bought or sold in a single day, the price impact depends on market liquidity. Two models were used to estimate this impact:

- **Linear Model:** Assumes price impact increases proportionally with trade size.
- **Logarithmic Model:** Assumes diminishing price impact as trade size increases, which aligns better with market behavior.

Findings:

- The log model provides a more accurate estimate of price impact as it reflects how real markets absorb large trades through liquidity buffers.
- Larger trades cause significant price movements, but the impact slows down as trade size increases.
- Practical Implications: Traders can use the log model to estimate slippage, and market makers can optimize liquidity provision accordingly.

Thus, the log model is recommended for future price impact simulations.

Volume That Can Be Traded Without Impacting Price

Based on the analysis, the volume of daily trading that can be acquired or sold without significantly impacting the token price is:

- **Mean Tradable Volume Percentage: 12.65%** of daily volume

This indicates that, on average, up to **12.65%** of daily volume can be traded with minimal price impact. This also relates with other findings of token liquidity with market depth.

OP Token Liquidity and Market Depth

By analyzing market depth and liquidity data across both centralized exchanges (CEX) and decentralized exchanges (DEX), we determined that approximately 15 million OP tokens can be bought or sold with a price impact of no more than 2%. This finding formed the basis for calculating **N**, the number of days required for an attacker to acquire or liquidate tokens without exceeding this 2% price impact threshold.

Further Optimizations

While DIVS provides a strong baseline for securing decentralized governance, additional refinements can enhance its accuracy:

- **Improved OP Price Predictions:** More accurate forecasting of token depreciation.
- **Identification of Active Participants:** Adjusting calculations based on known voters in the votable supply.
- **Community Reaction Adjustments:** Incorporating variations in voter engagement based on proposal severity.

Overall Insights & Conclusion

The DIVS framework provides a crucial foundation for safeguarding DAOs against hostile takeovers in a fully decentralized environment. By analyzing key factors such as treasury size, voter turnout, token price depreciation, and external token acquisitions, this report sheds light on the vulnerabilities that DAOs face in an increasingly decentralized world. While the model effectively highlights the complex relationship between token liquidity, market sentiment, and the time required for attackers to acquire or liquidate tokens, it also reveals the challenges of accurately predicting token price depreciation and the nuances of market behavior.

The DIVS model offers a strong starting point, but continuous refinement is necessary to address emerging complexities. Improving price predictions, and better identifying active participants will ensure that the model evolves with the DAO ecosystem. These efforts will play a pivotal role in fortifying DAOs against future threats, ensuring that they remain resilient, secure, and true to their decentralized ideals.

By refining these insights and tools, we can better prepare DAOs to thrive in a decentralized future.

Determining the Decentralized Ideal Votable Supply

1. Determining the Decentralized Ideal Votable Supply

1.1 Overview & Objectives

Introduction to DIVS

Decentralization Ideal Votable Supply (DIVS) represents the votable supply required to maintain decentralization and safeguard the DAO from governance attacks at the current circulating supply level.

Objective

The objective of DIVS is to determine the ideal votable supply needed to protect the DAO from hostile takeovers in a scenario where all existing governance safeguards are removed and the DAO operates fully decentralized. The current safeguards for Optimism DAO are the foundation and security council. In the event of their removal so that the DAO can be completely decentralized, we need to determine the votable supply that needs to be achieved.

What is a successful attack?	In the attack where the attacker gets the positive $ terms exit. For example, an attacker invested $500 million & was able to secure a $550 million from the attack.

1.2 Factors that Affect the DIVS

Here we have compiled a list of factors that will have an influence on the votable supply and attack. Based on assessment and reasoning we have determined how to utilize them in our calculations.

- **Token in the treasury**
  - DIVS invariably depends on the tokens left in the DAO treasury since those are the tokens that would be the target of any attacks.
  - At the time of this report, there are 1.71Bn OP tokens in the treasury i.e. about 40% of the total supply. We should note that this is not the number we are targeting. Only 138 million OP tokens are under the token house so that is where we are focusing.
  - This is important because there is a direct correlation between treasury tokens and DIVS.

- **Turnout**
  - There is never 100% participation when voting is involved. Hence the turnout is an important factor to take into account.
  - Usually, a 70% turnout rate would be considered ideal but for the sake of our calculations, we will be considering the turnout from the last 180 days.

- **Depreciation and time**
  - Depreciation is the fall in the price of OP tokens. A sudden attack on the OP is bound to cause a fall in price due to unusual changes in supply and demand. We have taken this into consideration while calculating DIVS.
  - For this, we have calculated the usual volume that is traded and taken that into consideration.
  - There is also a time factor. The period over which tokens are acquired would yield different results.

- **Acquired Tokens**
    - This parameter helps us understand how many tokens an attacker will acquire from the existing votable supply.
    - When this parameter is set to **0**, we assume that all tokens acquired by the attacker originate exclusively from the existing **votable supply**.
    - When this parameter is set to **100**, we assume that all tokens acquired by the attacker originate exclusively from the **outside** of existing **votable supply**.

1.3 Framework for DIVS

The formula for **DIVS** is defined as:

$$DIVS = \frac{(200-s)(100-d)}{d \cdot t} \cdot T \qquad \text{Eq(1)}$$

Where:

- **T**: Number of tokens in the treasury or the tokens that the attacker is targeting via the proposal.
- **t**: Maximum turnout percentage of the votable supply in the past 180 days.
- **d**: Depreciation in OP price incurred by the attacker relative to the acquisition price.
- **s:** Percentage of tokens that the attacker acquires from outside of Votable Supply that is currently active in the DAO.

As mentioned in section 1.2 we know the acquired tokens are the number of tokens that are to be acquired for an attack. This can be either from within the votable supply or outside of it.

Let us call this factor **Ta.** Then,

$$Ta = \frac{70}{(200-s)} DIVS \qquad \text{Eq(2)}$$

What percentage of Ta comes from outside of votable supply depends on *s.* Let's call this new variable **Ts**. Then it is clear that,

$$Ts = \frac{s}{100} \times Ta \qquad \text{Eq(3)}$$

Let's look at some cases,

s	Ta	Ts
0	$\frac{0.7}{2}$DIVS	0
100	$\frac{70}{100}$DIVS	Ta
50	$\frac{70}{150}$DIVS	Ta/2

Observations

- When all the required tokens are acquired from the votable supply the Ta is half of the turn out of the votable supply and Ts is zero.
- When everything is acquired from outside the attacker has to match the available votable supply and Ta becomes equal to Ts.
- We have also calculated a half and half scenario in which Ts is Ta/2.
  Similarly the value of Ta can be calculated depending on the scenario using the Eq(2)

Change in Votable Supply

When some part of the tokens are acquired by the attacker outside of the available votable supply, for example parts of the circulating supply that are not delegated to them this causes a change in the votable supply. In this scenario when $\boldsymbol{s} \neq 0$,

$$F = DIVS + Ts \qquad \text{Eq(4)}$$

Where, F is the final votable supply.

Time

The time period of buying and selling also has some influence on the DIVS. We have calculated the amount of tokens an attacker can buy or sell required to make less than a 2% impact on the price. It can be found here. We arrived at 15million.

$$N = \frac{(2Ts+T)}{15} \qquad \text{Eq(5)}$$

Here,

N is the number of days to acquire and sell token at s = 100

If we want to calculate the cost of attack then we get the following equations,

$$\text{Capital Cost to attack} = Ta \times P \times (1 + \frac{Pa}{100})$$

Where, Ta = tokens to be acquired
P = price of the OP tokens
Pa = acquisition premium which will be defined in 2.2.1

Readers can reference this table to explore different scenarios and the relationship between values like Ta, Ts, DIVS, F, N etc.

1.4 Methodology

Mental Model

The DIVS model is based on the assumption that an attacker needs to acquire at least **50% of the actively participating tokens** to manipulate governance. This model considers:

- **Malicious Proposals:** If the community identifies a governance attack, active participants will likely vote against it.
- **Attacker's Requirement:** The attacker must acquire all tokens within the votable supply to surpass the calculated DIVS threshold.
- **Worst-case scenario:** The formula assumes a scenario where the attacker attempts to drain the entire treasury.
- **Voter Response:** A treasury-draining attack may trigger **higher voter turnout**, further reducing the attack's effectiveness and increasing the likelihood of failure.

Calculation Assumptions

The DIVS framework incorporates the following key assumptions:

- **Historical Voting Engagement:** Maximum voter turnout is measured over a **180-day period**.

- **Market-Driven Depreciation:** The model accounts for the anticipated depreciation of OP token price post-acquisition.
- **Treasury Vulnerability:** The formula evaluates the worst-case impact on governance security.

1.5 Key Challenges & Further Optimization

Questions

The following are some of the queries encountered during our research. For a detailed explanation the [Questions](#) tab can be referred to.

Questions	
Why are we not considering historical Votable Supply or Circulating Supply**?**	Historically, VS has guardrails in terms of proposal filters, hence, it did not represent the number that makes the attack fail or the attacker lose. Using historical VS & CS, we have already calculated IVS, which was derived using ML Models which can help set targets.
What if the attacker gathers the token over a long period of one year?	The current methodology does not account for this factor and implicitly assumes an insider-driven attack.
What if the attacker sells the token over a long period?	The current methodology does not account for this factor and implicitly assumes an insider-driven attack.
Can we predict the exact *d* that will give us the DIVS?	We can come closer to the depreciation in OP Price that we expect, but getting the exact *d* will be impossible.

Further Optimizations

While DIVS provides a strong baseline for securing decentralized governance, additional refinements can enhance its accuracy:

- **Improved OP Price Predictions:** More accurate forecasting of token depreciation.
- **Identification of Active Participants:** Adjusting calculations based on known voters in the votable supply.
- **Community Reaction Adjustments:** Incorporating variations in voter engagement based on proposal severity.

Depreciation in Price of OP tokens

2. Depreciation in Price of OP tokens

2.1 Introduction

This section delves into calculating the change in the price of OP tokens in case of an attack. This is an important metric in calculating DIVS. For an attack to happen the attacker has to buy up a massive amount of tokens from the market. Similarly, they will have to sell them off later in order to make a profit. In both these scenarios there will be a change in the price. This price change also ultimately defines whether the attacker makes a profit or loss.
For convenience, we will call this factor *d*.

2.2 Methods of Calculating *d*

We have explored several different approaches to calculate *d* as accurately as possible. They are as follows:

2.2.1 Quantitative Approach

In this method, we identify all the factors affecting d and formulate an equation that can give us the value by plugging information into the equation. This was one of the earliest methods explored by us. We identified several factors and then narrowed them down to the following,

$$d = P_a + S + C_o + S_l$$

Where:

- **Acquisition Premium** (P_a)**:** Cost incurred when purchasing tokens in large quantities.
- **Sentiment** (S)**:** Market and community reaction to the attack.
- **Opportunity Cost** (C_o)**:** Capital cost from token acquisition to liquidation.
- **Liquidation Slippage** (S_l)**:** Impact on token price due to bulk liquidation.

Acquisition Premium (P_a)

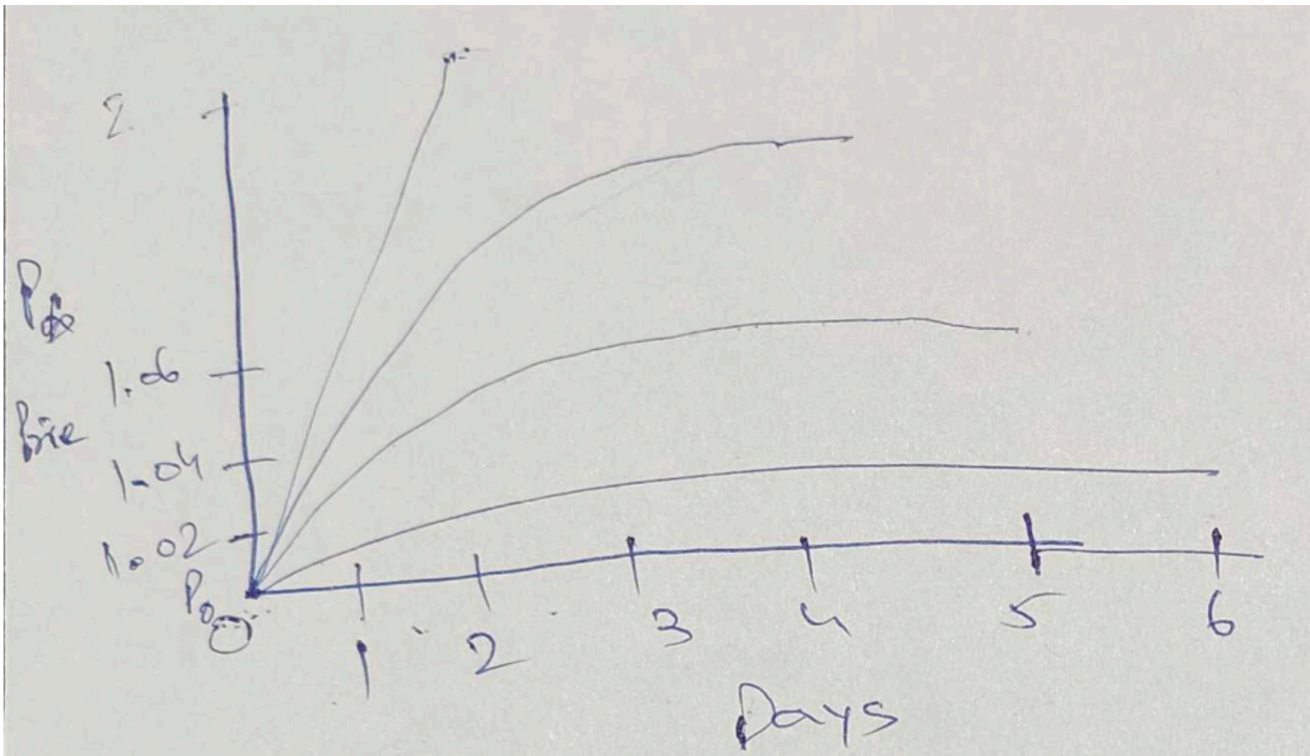
The **Acquisition Premium** represents the additional cost per token incurred by an attacker when purchasing large quantities of tokens.

- When tokens are accumulated gradually over several days, the premium remains lower.
- However, acquiring tokens in a short time frame significantly increases the premium due to **market impact** and **liquidity constraints**.

Based on our analysis, up to **12.65% of the daily trading volume** can be traded without significantly affecting the price.

Condition for Premium Application:

- If $\frac{Total\ volume\ of\ tokens}{Number\ of\ days} > 12.65\%$ of daily traded volume, a premium is applied.



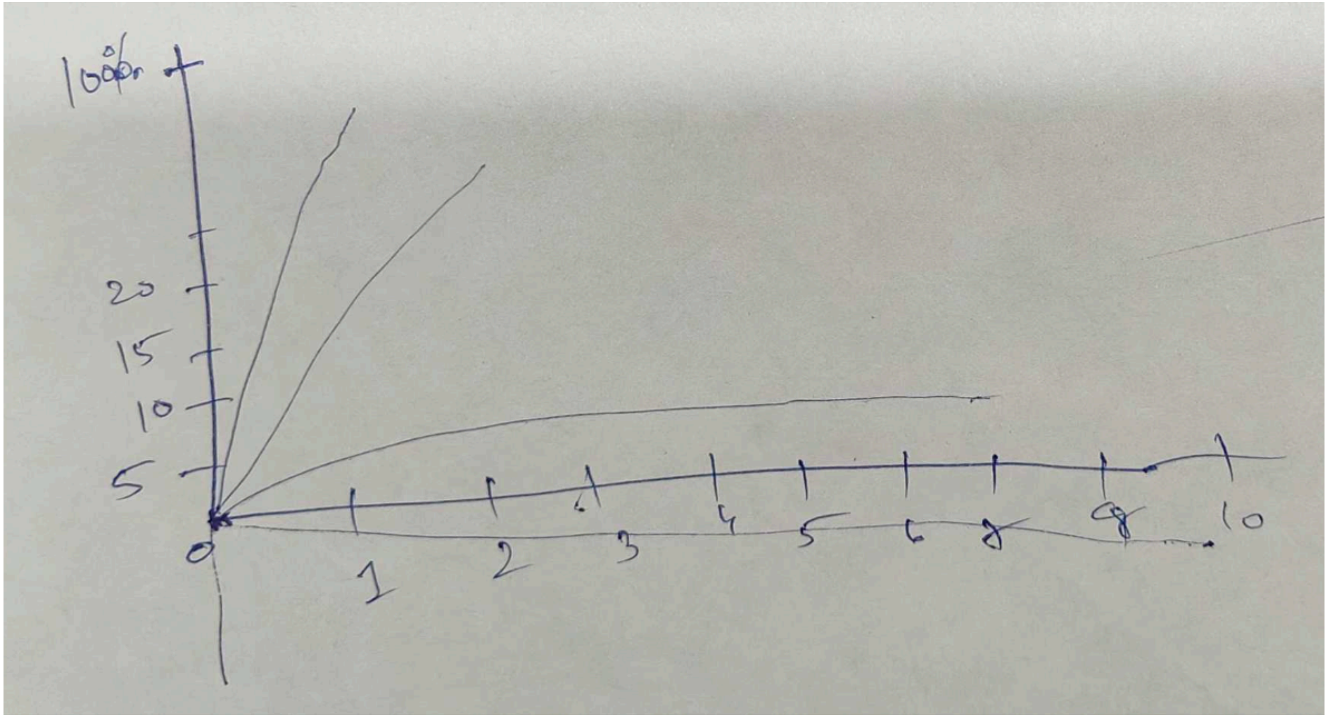
The above graph is a rough approximation of how we expect the premium to behave depending on the time period of token acquisition.

Liquidation Slippage $\left(S_l\right)$

Liquidation Slippage occurs when a seller offloads a substantial quantity of tokens to multiple buyers within a short time frame. This leads to a **lower execution price** than the prevailing market price due to increased **sell-side pressure**.

- If tokens are sold **rapidly**, the price impact is significant, causing a sharp decline in value.
- If tokens are **liquidated gradually**, the price impact can be minimized. However, this approach **incurs a higher time cost**, delaying access to capital.

Similar conditions as was for premium application, i.e., volume should be greater than 12.65% of daily traded volume.



A more comprehensive report on the correlation between price, trading volume, and market cap can be found here.

Opportunity Cost $\left(C_o\right)$

Opportunity Cost represents the time-based financial impact of capital allocation. It is defined as the duration between when an attacker starts buying tokens with fiat and when they reconvert the tokens back into fiat.

- **Assumed Opportunity Cost:** 6% per annum.
- **Impact on d:** The direct impact of time cost on **d** is minimal, but it **increases Acquisition Premium (P_a) and Liquidation Slippage (S□)**.
- **Implication:** The longer the attacker holds tokens, the greater the potential financial loss due to missed investment opportunities elsewhere.

Sentiment (S)

Sentiment during an attack consists of two key components:

1. **Market Sentiment** – The overall sentiment of the broader crypto market at the time of the attack.
2. **Community Sentiment** – The reaction of the DAO community from the proposal stage to execution when the attack becomes known.

$Sentiment = Market\,Sentiment + Community\,Sentiment$

This variable plays a significant role in determining the discount factor **d**, as shifts in sentiment can heavily influence the token price.

Predicting **Community Sentiment** and its impact on token price depreciation is challenging. However, insights can be drawn from past events, such as:

- **Bybit Safe Wallet Hack:** While the nature of this attack differs from a DAO governance attack, it had a noticeable negative impact on market sentiment.

- **Compound Proposal Attack (To be Investigated):** This case can provide further insights into the impact of governance-related security risks on token valuation.

2.2.2 Derivative approach

In this method, we explored the method to calculate *d* by using previous price trends. Here no factors influencing *d* are taken into account and we purely use a model to find depreciation.
One of the methods explored was the Moving average method.

There are two types of moving averages (MA):

1. **Simple Moving Average (SMA):** Assigns equal weighting to all values in the selected time period.
2. **Exponential Moving Average (EMA):** Gives more weight to recent prices, making it more responsive to new information.

To calculate EMA:

1. Compute the **SMA** over a specific period.
2. Calculate the **smoothing factor (multiplier)** using the formula:

$$\frac{2}{selected\ time\ period + 1}$$

For a 20-day moving average, this becomes:

$$\frac{2}{20 + 1} = 0.0952$$

3. Apply the EMA formula:

$$EMA_{Today} = \left[V_t \times \left(\frac{s}{1+d}\right)\right] + EMA_y \times \left[1 - \left(\frac{s}{1+d}\right)\right]$$

- V_t Represents the token price at time t
- s is the smoothing factor
- d is the depreciation factor.
- EMA_y Is the EMA from the previous period.

This approach helps capture short-term price trends and provides an alternative way to estimate d without explicitly considering external influencing factors.

2.3 Recognition Heuristics

We have analyzed and simulated several scenarios with different values of *d* to determine if our understanding of it is accurate.

Understanding these historical cases can help refine our estimation of **S** and its effect on **d**, allowing for more accurate predictions in future governance security assessments.

Scenario 1

Considering t = 70, d = 20 & s = 0, We assume that the maximum number of active participants in the past 180 days of governance will vote when they encounter a proposal that threatens the treasury. We also assume a lower bound of the discount the attacker would bear due to various factors assumed in d, which is 20%, meaning the price of OP would drop by 20%. Based on this, we conclude that the DIVS would be 1.57 billion OP. In this scenario, the proposal seeks to allocate the entire treasury for the attacker’s benefit.

Here, with the turnout for the proposal being 70%, an attacker would require 549 million OP at the time of the Voting Power snapshot. Assuming that the attacker acquires this token and manages to successfully get the entire treasury, i.e. 138 million OP, then the total tokens with the attacker at the end is

549 million + 138 million = 687 million OP

x	$\frac{200(100-x)}{x \cdot t} \cdot 138000000$
20	1.577143×10^9
25	1.182857×10^9
30	9.2×10^8
35	7.322449×10^8
40	5.914286×10^8
45	4.819048×10^8

If the discount d is 20%, which means the price at which attackers get to sell the tokens is 20% less than the cost at which they acquired the OP, then the attack can be considered a failure for the attacker, but it will have a huge impact on the Optimism ecosystem.

Scenario 2

If the amount that any proposal can pass is at max 50 million OP, then we can have much lower DIVS. Here in the screenshot at d = 20, t = 70 & s = 0, we get DIVS to be 571MN OP.

If the price impact due to the malicious proposal passing is higher, and the discount would be 45%, then DIVS can be lowered to just 174MN OP.

In the above scenario, we assume that all the tokens that the attacker acquires are acquired from the current Votable Supply. So most of these tokens are acquired due to colluding, P2salesle, existing delegators selling their OP, etc. As this is an unlikely event we can get the optimized prediction for DIVS by estimating the % of tokens that the attacker will acquire from outside of the Votable Supply. We will explore two different scenarios where the attacker acquires 50% & 75% of tokens from outside of current delegators.

x	$\frac{200(100-x)}{x \cdot t} \cdot 50000000$
20	5.714286×10^{8}
25	4.285714×10^{8}
30	3.333333×10^{8}
35	2.653061×10^{8}
40	2.142857×10^{8}
45	1.746032×10^{8}

$t = 70$

30 79

Scenario 3

T = 136, t = 70, s = 50

x	$\frac{(200-s)(100-x)}{x \cdot t} \cdot T$
20	1165.7143
25	874.28571
30	680
35	541.22449
40	437.14286

We observe that at different values of *d(x in the image),* we get DIVS which is substantially lower than when we assume that s = 0.
At *d=20* we get DIVS should be 1.165Bn, *d=25* <> DIVS = 874Mn & so on.

Scenario 4

T = 136, t = 70, s =75

x	$\frac{(200-s)(100-x)}{x \cdot t} \cdot T$
20	971.42857
25	728.57143
30	566.66667
35	451.02041
40	364.28571

In this scenario as we increase the % of tokens acquired from outside of votable supply to 75%, which could likely be from CEX, DEX, Lending or direct purchase from whale account, the DIVS required to sufficiently negate the attack lowers.

At d = 20 <> DIVS = 971Mn, d = 25 <> DIVS = 728Mn, and so on.

2.4 Key Challenges and Suggestions

Challenges

Quantitative analysis is inconclusive so we have to rely on qualitative and heuristic approaches to derive a conclusion on *d.*

Suggestions

We propose the following methods to get the required depreciation d given the lack of conclusive values from the quantitative approach.

Comparative Analysis	Case studies, historical precedents, or benchmarking against similar situations to make an informed decision.
Scenario Planning	Develop multiple possible scenarios and evaluate outcomes qualitatively to identify the most reasonable path
Logical Reasoning	Use deductive or inductive reasoning to infer conclusions based on known facts, assumptions, or patterns.

Consensus Decision-Making	Engage in discussions with relevant stakeholders and arrive at a group consensus through deliberation.
Heuristics & Rules of Thumb	Apply well-known industry heuristics or best practices that have been validated over time.

Price Correlation

3. Market behaviour & Correlation with Volume

3.1 Introduction

This section contains the internal research done by us to estimate the market behaviour when price changes drastically. We have also attempted to simulate the price impact on token prices when large trades happen and devised some models for the same.

3.1.1 Market behavior when volume increases drastically (Used data in OP)

Statistical Summary of the Price, Market-cap and Volume:

	Price	Market_cap	total_volume
count	1001.00	1001.00	1001.00
mean	1.83	7.392916e+08	1.288704e+08
std	0.83	4.205079e+08	9.290191e+07
min	0.45	0.000000e+00	2.501807e+07
25%	1.27	2.155656e+08	6.835423e+07
50%	1.64	8.796784e+08	1.031476e+08
75%	2.28	1.088409e+09	1.556587e+08
max	4.69	1.628097e+09	8.149685e+08

Here are the observations for the statistical summary provided in **OP**:

Price Analysis:

- The average price remains at **1.83 OP**, with a standard deviation of **0.83 OP**, indicating moderate fluctuations in price.
- The price ranges from **0.45 OP** (minimum) to **4.69 OP** (maximum), suggesting periods of both extreme lows and highs.
- The median price **(1.64 OP)** is slightly lower than the mean, indicating a slight right-skew in the price distribution, meaning there are some high-value outliers.

Market Capitalization Analysis:

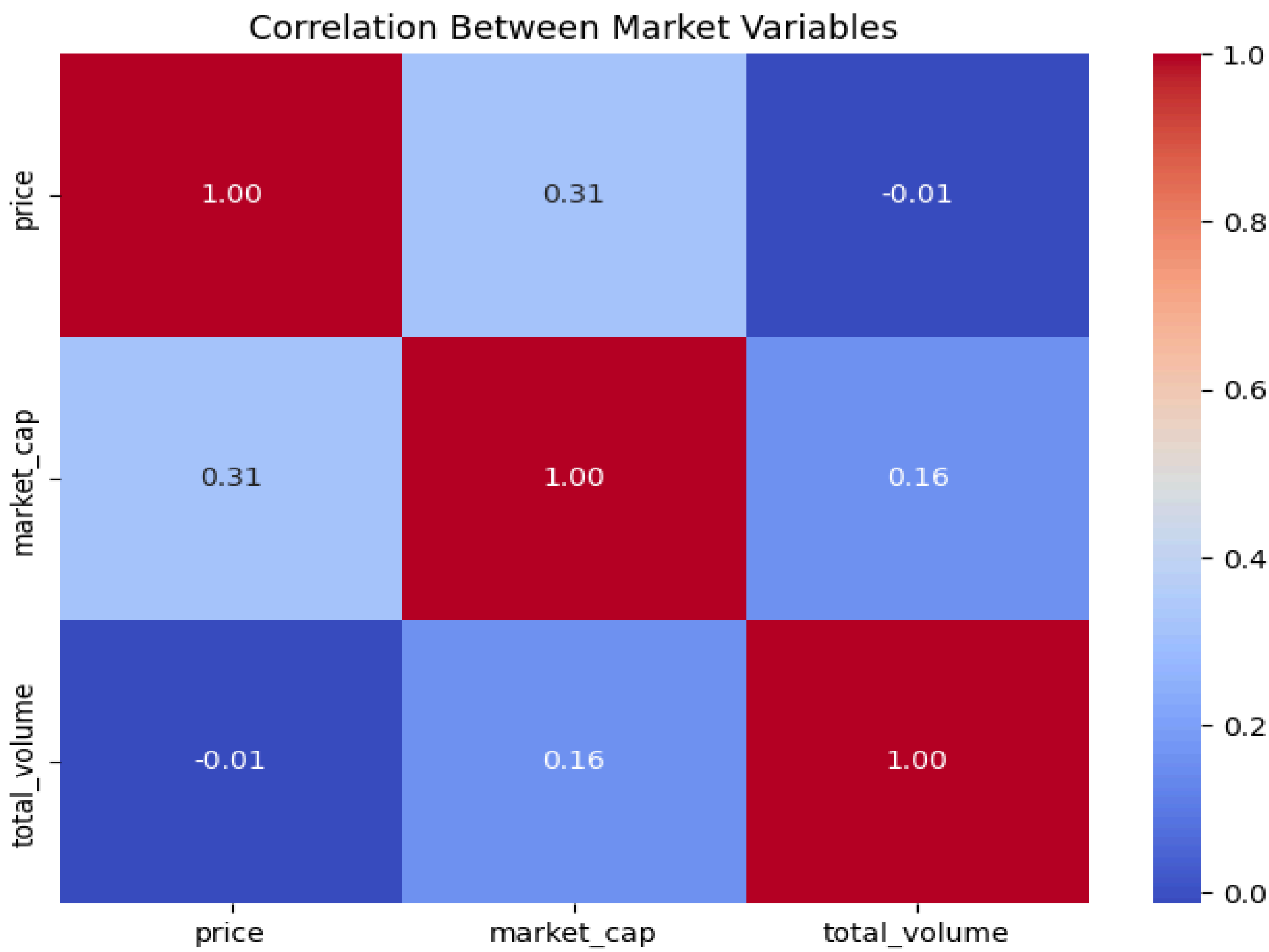
- The average market capitalization is **739.29 million OP**, with a high standard deviation of **420.51 million OP**, signifying significant variations in market cap over time.
- The minimum market cap is **0 OP**, likely indicating a data anomaly or a situation where the asset was not actively traded on certain days.
- The 75th percentile market cap (**1.08 billion OP**) is significantly higher than the median **(879.68 million OP)**, reinforcing the presence of higher-end outliers.

Trading Volume Analysis:

- The mean daily trading volume is approximately **128.87 million OP**, with a high standard deviation of **92.90 million OP**, suggesting notable volatility in liquidity.
- The volume ranges from **25.02 million OP** (minimum) to **814.97 million OP** (maximum), showing instances of extreme liquidity surges.
- The 75th percentile value **(155.66 million OP)** is significantly higher than the median **(103.15 million OP)**, indicating that on certain days, trading volumes were considerably higher than usual.

Observations from the Correlation Analysis

Absolute Values of Price, Market Cap, and Total Volume:



1. **Price & Market Cap (0.31 correlation)**
    - A weak positive correlation, meaning that as the price increases, market capitalization tends to increase, but the relationship is not very strong.
    - This is expected since market cap is calculated as the product of price and circulating supply, but the weaker correlation suggests variations in supply or other market dynamics affecting market cap.

2. **Price & Total Volume (-0.01 correlation)**
    - A near-zero correlation, suggesting that changes in trading volume do not have a significant direct impact on price.
    - This implies that other factors—such as liquidity depth, order book structure, or external market sentiment—might play a bigger role in price determination than just volume.

3. **Market Cap & Total Volume (0.16 correlation)**
    - A weak positive correlation, indicating that higher trading volumes are sometimes associated with increases in market cap, but the relationship is not strong.
    - This suggests that market cap is influenced by additional factors like token issuance, burns, or external macroeconomic conditions.

3.1.2 Historical Volatility in Volume - Source (Used data in OP)

Methodology to Calculate Historical Volatility in Volume

To measure the historical volatility in trading volume, the following steps are undertaken:

1. **Collect Historical Data:** Gather the historical trading volume data for the asset over a specific time period.
2. **Compute the Expected Volume:** Calculate the mean (average) of the historical trading volumes.
3. **Measure Deviations:** Compute the difference between each historical volume and the calculated mean.
4. **Square the Deviations:** Square each of these differences to eliminate negative values and emphasize larger deviations.
5. **Determine Variance:** Sum up all the squared deviations and divide by the total number of observations to obtain the variance.
6. **Calculate Standard Deviation:** Take the square root of the variance to determine the historical volatility in volume.
7. **Express as a Percentage:** Compute the percentage of historical volatility relative to the mean volume using the formula:

$$Historical\,Volatility\ (\%) = \left(\frac{Historical\,Volatility}{Mean\,Volume}\right) \times 100$$

Interpretation

Historical volatility in volume provides insight into the fluctuations of trading activity. Higher volatility indicates greater uncertainty or increased trading interest, while lower volatility suggests stability in market activity. This metric helps traders and analysts understand market trends and assess risk levels effectively.

- Historical Volatility in Volume: **92855492.21 OP**
- Historical Volatility in Volume (%): **72.05%**

A historical volatility in volume of **72.05%** means that the trading volume fluctuates, on average, by **72.05%** from its mean level over the observed period.
A historical volatility in volume of **92,855,492.21 OP** indicates a high degree of fluctuation in trading activity over time.

Key Insights:

1. **High Trading Activity Variability:**
   - A **72.05% volatility** suggests significant fluctuations in trading volume, indicating periods of intense buying/selling followed by calmer phases.

2. **Liquidity Considerations:**
   - If volume volatility is high but price remains stable, it may indicate deep liquidity, meaning large trades can be absorbed without impacting price significantly.
   - If both price and volume volatility are high, it suggests a more speculative asset with potential price swings.

3. **Risk and Stability:**
   - For investors, a highly volatile volume suggests unpredictability in market participation, which traders may use to identify potential entry or exit points.
   - A lower volatility percentage would indicate a more stable market with consistent trading patterns.

3.2 Simulating Price Impact on Token Price for Large Trades (Used data in OP)

3.2.1 Introduction

When large volumes of a token are bought or sold within a short period, the market price experiences an impact due to liquidity constraints. This explores two different models—**Linear** and **Logarithmic**—to simulate and analyze the price impact of large trades on the token price.

3.2.2 Methodology

The analysis is based on historical token price and trading volume data. The following steps were performed to estimate price impact:

Data Preprocessing

- The dataset contains price and trading volume information.
- Market capitalization and total volume were adjusted using token price.
- Average daily trading volume and price were calculated:
  - $Average\ Daily\ Volume = \frac{\Sigma\ Daily\ Volume}{Number\ of\ Days}$
  - $Average\ Price = \frac{\Sigma\ Daily\ Prices}{Number\ of\ Days}$
- Percentage-based trade sizes were chosen: **5%, 10%, 20%, 30%, and 50%** of the average daily volume.

Linear Model

The linear model assumes a direct proportionality between trade size and price impact. It is formulated as:

$$\triangle P = k \times Trade\ Volume$$

where k is the estimated market impact coefficient obtained using a linear regression model:

$$Price\ Change = k \times Volume\ Change$$

Estimated Market Impact Coefficient (Linear Model): k = 0.008424

Logarithmic Model

The log model assumes diminishing returns, meaning that price impact grows at a slower rate as trade volume increases. The model is:

$$\triangle P = k \times log(1 + Trade\ Volume)$$

where k is obtained via regression on log-transformed volume changes:

$$Price\ Change = k \times log(1 + Volume\ Change)$$

Estimated Market Impact Coefficient (Log Model): k = 0.017019

3.3 Results

Linear Model Results

Trade Size (% of Daily Volume)	**Price Impact**	**New Price**
5%	54,279.50	54,281.33
10%	108,559.01	108,560.84
20%	217,118.01	217,119.84
30%	325,677.02	325,678.85
50%	542,795.03	542,796.86

Observation:

- The linear model suggests **excessively high price movements** for relatively small trade sizes.
- This is **unrealistic** because markets do not respond in a strictly linear fashion.

Logarithmic Model Results

Trade Size (% of Daily Volume)	Price Impact	New Price
5%	0.2668	2.0951
10%	0.2786	2.1069
20%	0.2904	2.1187
30%	0.2973	2.1256
50%	0.3060	2.1342

Observation:

- The log model provides a **more reasonable price impact**, showing that **larger trades still move the price but at a decreasing rate**.
- This aligns with real-world market behavior, where liquidity buffers prevent extreme price swings.

3.4 Interpretation & Conclusion

3.4.1 Key Findings

1. The **linear model overestimates price impact**, making it impractical for predicting actual trading effects.
2. The **log model better represents reality**, where price impact is significant but follows a diminishing returns pattern.
3. In real markets, liquidity providers and arbitrageurs mitigate extreme price swings, further supporting the log model.

3.4.2 Practical Implications

- **For traders:** The log model should be used to estimate price slippage when executing large trades.
- **For market makers:** Understanding the diminishing impact can help optimize liquidity provision.
- **For researchers:** This study reinforces that non-linear models are preferable for market impact estimation.

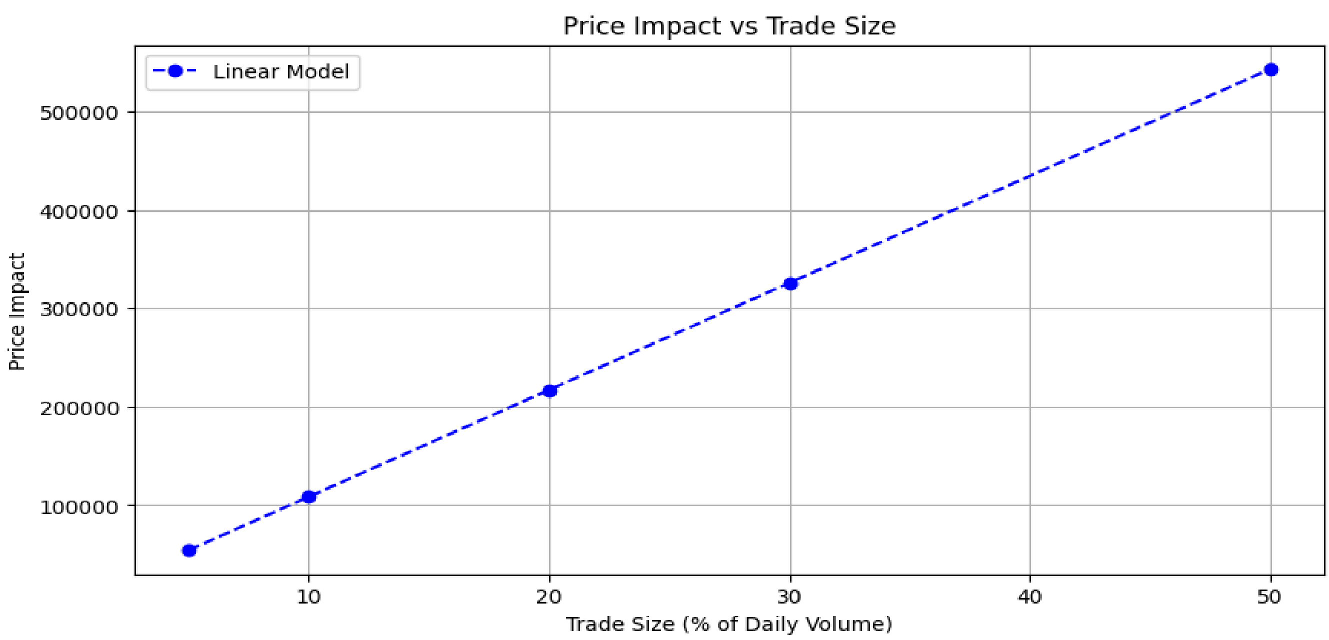
3.4.3 Final Recommendation

Given the findings, the **log model should be used** for simulating price impact in future analyses, as it more accurately represents market behavior.

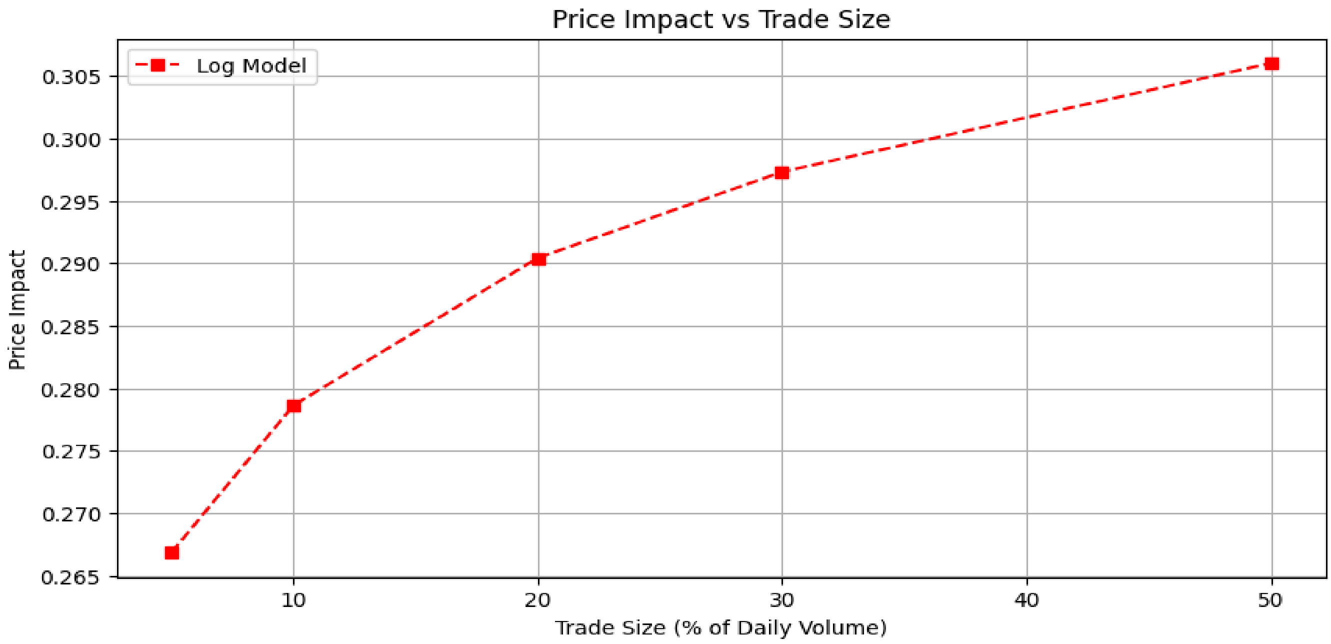
3.5 Visualizations

3.5.1 Price Impact vs Trade Size

- The linear model shows a sharp increase in price impact, which is unrealistic.

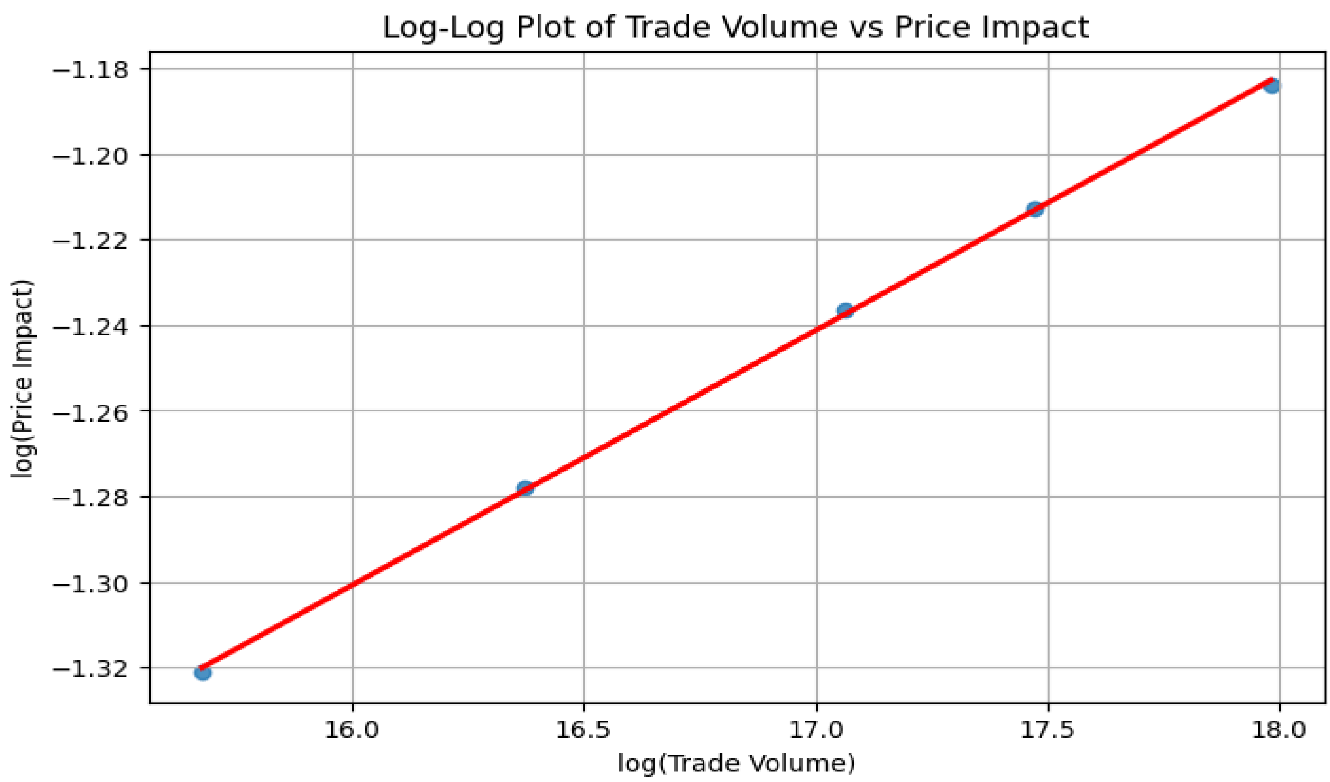


- The log model shows a gradual increase, aligning with expected market behavior.



3.5.2 Log-Log Plot of Trade Volume vs Price Impact

- Confirms the validity of the log model in capturing the relationship between trade volume and price change.



This analysis answers the question, **"Simulate price impact on token price if large volume is bought or sold in a day"** by:

a. Defining the Relationship Between Trade Size and Price Impact

- The study estimates how the price of the token changes when large trade volumes occur within a single day.
- Two models (Linear and Log) were used to quantify the price impact:

    - **Linear Model:** Assumes a constant relationship between trade size and price impact.
    - **Log Model:** Assumes diminishing price impact as trade size increases, which aligns better with real market conditions.

b. Simulating Different Trade Sizes and Their Price Impact

- Various trade sizes (5%, 10%, 20%, 30%, 50% of daily volume) were simulated.
- The price impact was calculated using both models.
- The results showed how the price would change under different trade sizes, helping estimate potential slippage for large trades.

c. Results Interpretation

- **Linear Model Findings:** Predicts very high price changes, which are unrealistic because real markets have liquidity providers and arbitrageurs who absorb some of the impact.
- **Log Model Findings:** Predicts a more reasonable, non-linear price change, showing that as trade size increases, price impact slows down.
- **Real-World Implications:** The log model is a better fit because, in real markets, large transactions don't always move prices proportionally due to liquidity providers and market stabilization mechanisms.

d. Practical Application

- **Traders and investors** can use these findings to **estimate potential price slippage** before executing large orders.
- **Governance and DeFi protocols** can use this information to design better trading mechanisms, reducing adverse price impacts.

Conclusion

This simulation provides a **quantitative estimate of price impact** for different trade sizes, helping answer the original question. It shows that:

1. Larger trades cause bigger price movements.
2. The log model better represents how actual markets behave.
3. Market participants should consider liquidity constraints to minimize slippage.

3.6 What daily volume can be acquired or sold without an impact on price?

Methodology for Estimating Tradable Daily Volume Without Price Impact (Used data in OP)

This methodology estimates the **percentage of daily trading volume that can be transacted without significantly impacting the price** of OP tokens. The approach is based on the **Amihud Illiquidity Ratio**, a widely used measure of market liquidity.

a. Compute the Daily Price Change Percentage

The daily price change percentage is calculated to measure the relative change in price compared to the previous day:

$$Price\ Change\ \%_t = \frac{Price_t - Price_{t-1}}{Price_{t-1}} \times 100$$

Where:

- $Price_t$ is the price of the token on day t.
- $Price_{t-1}$ is the price of the token on the previous day.

To handle missing values, the first day's price change is set to 0.

b. Compute the Amihud Illiquidity Ratio

The Amihud Illiquidity Ratio (A_t) measures the price impact of trading volume and is computed as:

$$A_t = \frac{\left|Price\ Change\ \%_t\right|}{Total\ Volume_t}$$

Where:

- $\left|Price\ Change\ \%_t\right|$ is the absolute daily price change percentage.
- $Total\ Volume_t$ is the total trading volume on day t.

A higher Amihud ratio indicates a more illiquid market, where price movements are more sensitive to trading volume.

c. Compute the Maximum Tradable Volume Without Price Impact

To estimate the maximum volume that can be traded without significantly affecting the price, we assume a threshold where trading should not move the price by more than 0.1%.

$$V_{tradable,\,t} = \frac{0.1}{A_t}$$

Where:

- $V_{tradable,\,t}$ represents the estimated tradable volume on day t.
- A_t is the Amihud ratio from Step 2.
- 0.1 represents the price impact threshold (0.1%).

d. Compute the Percentage of Daily Volume That Can Be Traded Without Impact

Finally, we compute the percentage of total daily volume that can be traded without significantly affecting the price:

$$\%V_{tradable,\,t} = \left(\frac{V_{tradable\,,\,t}}{Total\ Volume_t}\right) \times 100$$

Where:

- $\%V_{tradable,\,t}$ is the percentage of daily volume that can be safely traded.
- $V_{tradable\,,\,t}$ is the tradable volume from Step 3.
- $Total\ Volume_t$ is the daily trading volume.

Key Assumptions

- ➢ The **0.1%** price impact threshold is an arbitrary choice; different thresholds may yield different results.

Questions and Answers

1. Market Behavior when Volume increases drastically:

When trading volume increases drastically, the market exhibits the following behaviors:

Price Behavior:

- The average price is 1.83 OP, with moderate fluctuations (standard deviation of 0.83 OP).
- The correlation between price and volume is -0.01, indicating that trading volume spikes do not significantly impact price movements.
- The median price (1.64 OP) is slightly lower than the mean, suggesting the presence of occasional high-value outliers.

Market Capitalization:

- The average market cap is 739.29 million OP, with notable variations over time (standard deviation of 420.51 million OP).
- The correlation between market cap and volume is 0.16, showing a weak positive relationship.
- This suggests that changes in trading activity do not strongly influence market cap, and other factors such as token issuance, burns, or broader economic conditions may play a more significant role.

Trading Volume:

- The mean daily trading volume is 128.87 million OP, with significant fluctuations (standard deviation of 92.90 million OP).
- The 75th percentile trading volume (155.66 million OP) is much higher than the median (103.15 million OP), indicating periods of extreme liquidity surges.

Overall Observations:

- The weak correlations between price, market cap, and volume indicate that drastic increases in trading volume do not directly drive price or market cap changes.
- Instead, liquidity, order book structure, external market sentiment, and macroeconomic conditions likely have a greater influence on market behavior.

2. Historical Volatility in Volume:

- Historical Volatility in Volume: **92855492.21 OP**
- Historical Volatility in Volume (%): **72.05%**

2. Historical Volatility in Price:

- Historical Volatility in Price: **0.832904 OP**
- Historical Volatility in Price (%): **45.56%**

3. Simulating Price Impact on Token Price for Large Trades:

When large volumes of a token are bought or sold in a single day, the price impact depends on market liquidity. Two models were used to estimate this impact:

- **Linear Model:** Assumes price impact increases proportionally with trade size. However, it overestimates price changes, making it unrealistic for real-world scenarios.
- **Logarithmic Model:** Assumes diminishing price impact as trade size increases, which aligns better with market behavior.

Findings:

- The log model provides a more accurate estimate of price impact, as it reflects how real markets absorb large trades through liquidity buffers.
- Larger trades cause significant price movements, but the impact slows down as trade size increases.
- Practical Implications: Traders can use the log model to estimate slippage, and market makers can optimize liquidity provision accordingly.

Thus, the log model is recommended for future price impact simulations.

4. Volume That Can Be Traded Without Impacting Price

Based on the analysis, the volume of daily trading that can be acquired or sold without significantly impacting the token price is:

- **Mean Tradable Volume Percentage: 12.65%** of daily volume
- **Median Tradable Volume Percentage: 3.11%** of daily volume

This indicates that, on average, up to **12.65%** of daily volume can be traded with minimal price impact, but in more typical scenarios, the safe threshold is around **3.11%**.

OP Token Liquidity

4. Report on OP Token Liquidity and Market Depth

4.1 Objective

The purpose of this report is to determine the volume required to create a 2% impact on the price of the OP token. This analysis is based on market data retrieved from CoinGecko, which includes liquidity depth metrics from various centralized and decentralized exchanges.

4.2 Data Overview

The dataset comprises trading pairs, exchange names, liquidity depth at ±2% price movement, 24-hour trading volume, and trust scores. The key parameters relevant to this analysis are:

- **+2% Depth ($):** The total amount of buy orders required to push the price up by 2%.
- **-2% Depth ($):** The total amount of sell orders required to push the price down by 2%.

4.3 Findings

Based on the aggregated market data as of March 19, 2025:

- **Total Buy Liquidity (+2% Depth):** $18,999,228.34
- **Total Sell Liquidity (-2% Depth):** $21,927,707.69

This indicates that:

- A **buy volume of approximately $18.99 million** would be required to increase the OP token price by 2%.
- A **sell volume of approximately $21.93 million** would be necessary to decrease the OP token price by 2%.

4.4 Conclusion

The OP token market demonstrates significant liquidity, with approximately $19 million required to push the price up by 2% and $21.93 million to bring it down by 2%. We can consider around 10-20million OP can be bought or sold at a 2% price impact.

Data: CoinGecko (as of March 19, 2025, 10:07 UTC)
Dataset: Google Sheet

Observations

5. Observations with few constraints.

Different Scenarios with varied levels of turnout and treasury tokens

Scenario	T	t	DIVS	Range of s & d
1	136	70	200	s(0,100) =>d(66,50)
2	50	70	200	s(0,100) => d(41,26)
3	136	70	400	s(0,100) => d(49,32)
4	50	70	400	s(0,100) => d(26,15)
5	136	90	400	s(0,100) => d(43,27)
6	50	90	400	s(0,100) => d(21,12)
7	136	70	600	s(0,100) => d(39,24)
8	136	90	600	s(0,100) => d(33,20)
9	50	70	600	s(0,100) => d(32,19)

Key Observations & Recommendations:

1. **Feasibility of DIVS at 400 Million (With Withdrawal Cap of 50M)**

• If all tokens are acquired from the votable supply (VS), the attacker would require a **26% price loss** to be in deficit.

• If all tokens are acquired from the market, a **15% price loss** would lead to an attack failure.

• **Key Insight:** Keeping a **withdrawal cap of 50M** allows **DIVS to be set at 400 million**, ensuring economic security while maintaining decentralization.

2. **Feasibility of DIVS at 600 Million (Without Withdrawal Cap)**

• If **maximum tokens are withdrawn from the treasury**, the required **price loss for an attack failure ranges from 39% to 24%** with a **decent voter turnout** (t = 70%).

• Acquiring the necessary **213M tokens** would take **at least 37 days** with a **2% price impact**, making it highly difficult given current volume and holdings data.

• With a **90% voter turnout**, the required price loss drops to **33% to 20%**, making an attack nearly impossible.

• **Key Insight:** At **600M DIVS**, an attack attempt is highly unlikely due to the long accumulation period and required price loss conditions.

3. **Impact of Lower DIVS Values**

- **Lower DIVS values** reduce the accumulation period, making it easier to acquire the required tokens with **minimal price impact** from just a few large holders.

- Even with a withdrawal cap, if **DIVS is set at 200M**, the **required price loss is only 33%**, which is **unlikely to deter attacks**, as tokens could be acquired in **less than 20 days**.

- **Key Insight:** A **cap on proposal withdrawals is necessary** to prevent easy token accumulation and governance manipulation.

TL;DR

If there is no cap on the maximum amount a proposal can ask, **DIVS should be 600M.** We estimate that the immediate post-attack price depreciation falls within the 24% to 39% range that doesn't allow a successful attack.

If a withdrawal cap of 50M is enforced, **DIVS should be set at 400M**, maintaining a strong balance between security and accessibility.

This ensures that governance remains **resilient to attacks** while **keeping proposal funding sustainable**.

The assessment is informed by observational data and contextual indicators, and while we believe it to be directionally accurate, we currently lack a formal, objective methodology to substantiate it.

Questions

Questions

What does a successful attack mean?

In the attack where the attacker gets the positive $ terms exit.
For example, an attacker invested $500 million & was able to secure a larger amount from the attack.

Considering that we have 138 million OP tokens under the TokenHouse Treasury, with the different VS, what could be the maximum profit considering zero discount? (s = 0)

Votable Supply(in millions)	**Tokens required for a successful attack at 70% turnout (in millions)**	**Gain(%)**
100	35	394.29
200	70	197.14
300	105	131.43
400	140	98.57
500	175	78.86
600	210	65.71
700	245	56.33
800	280	49.29
900	315	43.81
1000	350	39.43
1100	385	35.84
1200	420	32.86
1300	455	30.33
1400	490	28.16
1500	525	26.29

Why are we not considering historical Votable Supply or Circulating Supply?

Factors that influenced not considering them are:-

1. Historically, VS has guardrails in terms of proposal filters, hence, it did not represent the number that makes the attack fail or the attacker lose.
2. Circulating Supply provides the upper cap that Votable Supply can have; the current method of constructing DIVS doesn't cross this threshold. Also, in case it crosses the threshold(highly unlikely), we can increase VS by delegating from locked tokens/treasury/RPGF, etc.

3. Using historical VS & CS, we have already calculated IVS, which was derived using ML Models which can help set targets.

What if the attacker gathers the token over a long period of one year?

The current methodology does not account for this factor and implicitly assumes an insider-driven attack, given that the attacker has been exposed to prolonged price volatility risk.

What if the attacker sells the token over a long period?

The outcome aligns with the findings in **Q.4**, and this scenario may not qualify as a deliberate attack. Additionally, risk mitigation measures for such cases are beyond the scope of this methodology.

How do we know that the DIVS formula gives the right value?

Let's consider the treasury has 100 tokens & you can gain these 100 tokens by having control of,

Scenario 1:

Controlling 50 tokens grants a majority required to pass a proposal, enabling access to the full supply of 100 tokens. Post-execution, the attacker holds a total of 150 tokens. The breakeven point occurs if the token price declines by **66.66%**, which corresponds to our discount factor (**d**).

Scenario 2:

Controlling 100 tokens grants a majority required to pass a proposal, enabling access to the full supply of 100 tokens. Post-execution, the attacker holds a total of 200 tokens. The breakeven point occurs if the token price declines by **50%**, which corresponds to our discount factor (**d**).

Scenario 3:

Controlling 150 tokens grants a majority required to pass a proposal, enabling access to the full supply of 100 tokens. Post-execution, the attacker holds a total of 250 tokens. The breakeven point occurs if the token price declines by **40%**, which corresponds to our discount factor (**d**).

Likewise, we can put these into a formula and reverse calculate to arrive at **d** in the formula of DIVS. This ensures that the necessary things are captured in the simple DIVS formula with three independent variables.

Can we predict the exact *d* that will give us the DIVS?

We can come closer to the depreciation in OP Price that we expect, but getting the exact *d* will be impossible.

What are the current holdings of OP by CEX?

Currently based on the query results we got that around **301 million OP** are held by different CEXes, this **does not include** the accounts which are marked as Coinbase on Optimistic Etherscan.

What are the total holdings by Coinbase tagged accounts on Optimistic Etherscan?

These are around 280 different addresses with holdings in the range of 300 to 165 million, & a total of **990 million OP**

Why do we need the variable *s*?

We understand that for an attack to succeed, the attacker must acquire tokens either by purchasing or collaborating with holders of tokens that are **not currently delegated**. To model this dynamic, we introduce ***s*** as a variable representing the **percentage of tokens acquired from outside the current votable supply**. This allows us to better capture and control for the source of tokens used in the attack.

What is Final Votable Supply?

When the attacker acquires a token from the market it results in increasing present Votable Supply, to represent this we have separately presented **F** which will be the **sum of DIVS & Ts**(Tokens acquired from the market).

Sources

Sources

Data Source:

CoinGecko (as of March 19, 2025, 10:07 UTC)

OP Token Holders Dataset

[PUBLIC] OP Token Unlock (Estimated)

Derived Formulae with DIVS & its parameters

Historical Volatility in Volume - Source (Used data in OP)

Mural - Link(Password required)

Experiments & Observations

Desmos

- DIVS
- DIVS with s = 0
- Predict d for other constants
- Scenario based graphs
  - DIVS 600, T 136 & t 70
  - DIVS 600, T 136 & t 90
  - DIVS 600, T 50 & t 70
  - DIVS 400, T 136 & t 70
  - DIVS 400, T 50 & t 70
  - DIVS 400, T 136 & t 90
  - DIVS 400, T 50 & t 90
  - DIVS 200, T 50 & t 70
  - DIVS 200, T 136 & t 70