American Academic Scientific Research Journal for Engineering, Technology, and Sciences
ISSN (Print) 2313-4410, ISSN (Online) 2313-4402
https://asrjetsjournal.org/index.php/American_Scientific_Journal/index

# Yield Analysis of Boost vs Non-Boost Base Trader Joe Liquidity Pools

Jinze Hu*

*Laney College, 900 Fallon St, Oakland, CA 94607, United States*
*Email: Jinzehu2023@gmail.com*

**Abstract**

This comprehensive study presents an extensive quantitative analysis of the impact of Trader Joe's Boost Incentive Program on Trader Joe's liquidity pools. The Boost Incentive Program is a liquidity initiative designed to revitalize a specific DeFi ecosystem by enhancing user engagement and competitiveness. Following the success of a previous program from mid-2021 to early 2022, this new initiative aims to reignite growth and innovation by increasing Total Value Locked (TVL), attracting new protocols, and regaining market share within the DeFi space. The ongoing program focuses on supporting both new and existing DeFi protocols through liquidity mining incentives, direct liquidity deployment, and backing for new assets and products. The strategic use of incentives is designed to maximize impact by concentrating on core primitives and top native protocols, thereby driving substantial growth in TVL. By allocating incentives to specific strategies and liquidity pools, Trader Joe aims to offer higher yields to liquidity providers, thereby attracting more participants and increasing TVL on its platform. This approach aligns with the overarching goal of the Boost program to support innovation and new protocol growth. In the below analysis, I examine how these incentives affect yields will provide insights into the effectiveness of such programs in attracting liquidity and enhancing protocol performance. By integrating detailed data from incentive_analysis.xlsx and traderjoe_base_metrics.csv, we examine how incentive allocations, fee structures, and liquidity provider participation influence liquidity provision, trading volume, fees, and yields. The analysis incorporates statistical insights and trends within the dataset, covering rewards allocation, fee structures, liquidity provider participation, and average USD values across various token pairs. The aim is to offer deep insights into the effectiveness of incentive programs in enhancing protocol performance and user engagement within the decentralized finance (DeFi) ecosystem.

***Keywords:*** Decentralized Finance; Liquidity pool; Boost Incentive Program; Trader Joe; Reward Allocations.

------------------------------------------------------------------------

*Received: 11/29/2024*
*Accepted: 1/30/2025*
*Published: 2/12/2025*

------------------------------------------------------------------------

* Corresponding author.

## 1. Introduction

Decentralized finance (DeFi) platforms rely on liquidity providers (LPs) to supply assets to liquidity pools, facilitating trading and allowing LPs to earn fees in return. Incentive programs, such as Trader Joe's Boost Incentive Program, are designed to attract additional liquidity by offering rewards to LPs. A quantitative understanding of these incentives' impact on liquidity provision, trading volume, and LP yields is crucial for optimizing pool performance and ensuring protocol sustainability. This paper provides a comprehensive quantitative analysis of the effects of Boost Incentives on Trader. Joe's liquidity pools. By integrating detailed data from incentive analysis.csv and traderjoe_base_ metrics.csv is generated from the traderjoe pool_analysis.py script—we rigorously analyze how these incentives influence pool metrics and the overall effectiveness of the Boost program. Mathematical derivations and full calculation logic are presented throughout to support the findings.

## 2. Data Description

Our analysis utilizes multiple datasets:

### *2.1. Incentive Allocation Data (incentive_analysis.xlsx)*

This dataset includes detailed information on Boost Trader Joe rewards allocated to various liquidity pools over five periods. It contains the reward amounts, fee structures, and protocol fees for each token pair.

#### *2.1.1. Established Tokens*

The data for established tokens includes reward allocations (i.e., additional liquidity injected into the pools to enhance yields) across five periods, fee settings, and protocol fees for each token pair.

For example, for the JOE - AVAX pair:

- Periodic Rewards: 7,500 AVAX per period.
- Total over the last 5 periods: $7,500 \times 5 = 37,500$ AVAX.
- Total over the entire boost duration: 120,000 AVAX.

However, the total boosted amounts are likely underestimated, as TraderJoe might not fully disclose certain boosting transactions, potentially to maintain the privacy of specific treasury wallet addresses. Therefore, we focus on the reliable aspects of the data, particularly the number of unique liquidity providers and average USD values per provider.

### *2.2. Liquidity Provider Participation Data*

This dataset contains information on:

- Number of unique liquidity providers per pool.
- Average USD value provided by each liquidity provider.

### *2.2.1. Data Extraction*

The data lists several liquidity pairs with their respective number of unique providers and the average USD value per provider, as shown in Table

**Table 1:** Unique Providers and Average USD Value per Provider

| Pair | Unique Providers | Avg USD Value |
|---|---|---|
| COQ - WAVAX | 259 | $1,485 |
| JOE - WAVAX | 209 | $3,690 |
| USDt - USDC | 164 | $19,240 |
| aUSD - USDC | 75 | $3,385 |
| BEAM - WAVAX | 48 | $3,444 |
| sAVAX - WAVAX | 48 | $139,415 |
| WAVAX - FRAX | 44 | $1,770 |
| USDC.e - USDC | 42 | $27,671 |
| SHRAP - WAVAX | 37 | $4,228 |
| QI - WAVAX | 27 | $5,903 |
| ggAVAX - WAVAX | 26 | $272,860 |
| USDT.e - USDC | 21 | $17,859 |
| DOMI - WAVAX | 21 | $1,891 |
| BLS - WAVAX | 21 | $2,157 |
| ARROW - WAVAX | 20 | $4,397 |
| USDT.e - USDt | 17 | $25,558 |
| PRIME - WAVAX | 15 | $216,443 |
| GGP - WAVAX | 14 | $6,623 |
| FXS - FRAX | 11 | $2,978 |

### *2.3. Pool Performance Data (traderjoe_base_metrics.csv)*

Generated from the traderjoe pool analysis.py script, this dataset provides timestamped snapshots of pool parameters such as liquidity, volume, fees, APRs, and the number of unique liquidity providers.

## 3. Statistical Analysis

### *3.1. Statistical Metrics*

#### *3.1.1. Total Number of Providers*

The total number of unique liquidity providers across all pairs is calculated as:

$$Total\ Providers = \sum_{i=0}^{n} P_i \qquad (1)$$

where $P_i$ is the number of unique providers for pair i, and n is the total number of pairs.

From Table 1, we have:

Total Providers = 259 + 209 + 164 + 75 + 48 + 48 + 44
+ 42 + 37 + 27 + 26 + 21 + 21 + 21 + 20 + 17 + 15 + 14
+ 11 = 1, 119.

#### *3.1.2. Average Number of Providers per Pair*

$$Average\ Providers\ per\ Pair = \frac{Total\ Providers}{n} = \frac{1{,}119}{19} = 58.89 \qquad (2)$$

#### *3.1.3. Total Value Across All Pairs*

The total value is calculated by summing the product of the number of providers and the average USD value per provider for each pair:

$$Total\ Value = \sum_{i=1}^{n} P_i \times V_i \qquad (3)$$

where $V_i$ is the average USD value per provider for pair $i$.

Calculating the total value:

Total Value = (259 × \$1, 485) + (209 × \$3, 690) + (164 × \$19, 240) + . . . + (11 × \$2, 978)

= \$384, 765 + \$770, 810 + \$3, 155, 360 + . . . + \$32, 758

= $24, 427, 129.

### *3.1.4. Average USD Value per Provider*

$$Average\ USD\ per\ Provider\ = \frac{Total\ Value}{Total\ Providers} = \frac{\$24{,}427{,}129}{1{,}119} = \$21{,}836$$

(4)

### *3.1.5. Median Average USD Value per Provider*

1. $1,485
2. $1,770
3. $1,891
4. $2,157
5. $2,978
6. $3,385
7. $3,444
8. $3,690
9. $4,228
10. **$4,397 (10th value, median)**
11. $5,903
12. $6,623
13. $17,859
14. $19,240
15. $25,558
16. $27,671
17. $139,415
18. $216,443
19. $272,860

Thus, the median average USD value per provider is $4,397.

## *3.2. Observations*

### *3.2.1. Skewed Distribution*

The average USD value per provider is heavily skewed by pairs like ggAVAX - WAVAX and sAVAX - WAVAX, which have high average values but relatively few providers. This skewness indicates that while most providers contribute smaller amounts, a small number of providers contribute significantly larger amounts.

#### *3.2.2. Median vs. Mean*

The median average USD value per provider ($4,397) is significantly lower than the mean ($21,836), reinforcing the presence of skewness in the data. The mean is influenced by the high-value outliers, whereas the median provides a better representation of the typical provider's contribution.

#### *3.2.3. Provider Participation*

- Highest Number of Providers: COQ - WAVAX (259 providers).
- Lowest Number of Providers: FXS - FRAX (11 providers).
- Inverse Relationship: Pairs with high provider counts tend to have lower average USD values per provider, suggesting broader participation with smaller individual investments.

### *3.3. Correlation Analysis*

#### *3.3.1. Relationship Between Number of Providers and Average USD Value*

To investigate the relationship between the number of providers ($P_i$) and the average USD value per provider ($V_i$), we perform a Spearman's rank correlation analysis.

Spearman's rank correlation is a non-parametric technique that measures the strength and direction of the association between two variables based on their ordinal ranks rather than their raw values [1]. This method is particularly suited for discrete variables and data that deviate from normality. Specifically, I applied Spearman's rank correlation to examine the relationship between two key metrics derived from the incentive_analysis.xlsx and traderjoe_base_metrics.csv datasets: the number of liquidity providers in each Trader Joe pool, denoted as *Pi*, and the average USD value per provider, denoted as *Vi*. The variable *Pi* is inherently discrete, representing a count of individual participants, while *Vi* serves as a monetary measure that may not follow a continuous or normal distribution. Traditional parametric correlation methods often assume continuity and normality, which are not valid in this context. Additionally, these datasets can exhibit skewed distributions, with some pools dominated by a few large contributors and others composed of numerous smaller participants. Under such conditions, linear correlation measures may yield misleading conclusions, and exploring potential causes of non-linearity is a subject for further research.

#### *3.3.2. Spearman's Rank Correlation Coefficient*

The Spearman's rank correlation coefficient ρ is calculated using the ranks of $P_i$ and $V_i$.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \quad , \qquad (5)$$

where $d_i$ is the difference between the ranks of $P_i$ and $V_i$, and n is the number of observations.

### *3.3.3. Calculation*

First, we assign ranks to $P_i$ and $V_i$.

Table 2: Ranks of Providers and Average USD Value

| Pair | $P_i$ | Rank $P_i$ | $V_i$ | Rank $V_i$ |
|---|---|---|---|---|
| COQ - WAVAX | 259 | 1 | $1,485 | 1 |
| JOE - WAVAX | 209 | 2 | $3,690 | 8 |
| USDt - USDC | 164 | 3 | $19,240 | 13 |
| aUSD - USDC | 75 | 4 | $3,385 | 6 |
| BEAM - WAVAX | 48 | 5 | $3,444 | 7 |
| sAVAX - WAVAX | 48 | 5 | $139,415 | 17 |
| WAVAX - FRAX | 44 | 7 | $1,770 | 2 |
| USDC.e - USDC | 42 | 8 | $27,671 | 15 |
| SHRAP - WAVAX | 37 | 9 | $4,228 | 9 |
| QI - WAVAX | 27 | 10 | $5,903 | 11 |
| ggAVAX - WAVAX | 26 | 11 | $272,860 | 19 |
| USDT.e - USDC | 21 | 12 | $17,859 | 12 |
| DOMI - WAVAX | 21 | 12 | $1,891 | 3 |
| BLS - WAVAX | 21 | 12 | $2,157 | 4 |
| ARROW - WAVAX | 20 | 15 | $4,397 | 10 |
| USDT.e - USDt | 17 | 16 | $25,558 | 14 |
| PRIME - WAVAX | 15 | 17 | $216,443 | 18 |
| GGP - WAVAX | 14 | 18 | $6,623 | 16 |
| FXS - FRAX | 11 | 19 | $2,978 | 5 |

Now, calculate the differences $d_i$ and $d_i^2$.

**Table 3:** Differences in Ranks and Squared Differences

| Pair | Rank $P_i$ | Rank $V_i$ | $d_i$ = Rank $P_i$ − Rank $V_i$ |
|---|---|---|---|
| COQ - WAVAX | 1 | 1 | 0 |
| JOE - WAVAX | 2 | 8 | -6 |
| USDt - USDC | 3 | 13 | -10 |
| aUSD - USDC | 4 | 6 | -2 |
| BEAM - WAVAX | 5 | 7 | -2 |
| sAVAX - WAVAX | 5 | 17 | -12 |
| WAVAX - FRAX | 7 | 2 | 5 |
| USDC.e - USDC | 8 | 15 | -7 |
| SHRAP - WAVAX | 9 | 9 | 0 |
| QI - WAVAX | 10 | 11 | -1 |
| ggAVAX - WAVAX | 11 | 19 | -8 |
| USDT.e - USDC | 12 | 12 | 0 |
| DOMI - WAVAX | 12 | 3 | 9 |
| BLS - WAVAX | 12 | 4 | 8 |
| ARROW - WAVAX | 15 | 10 | 5 |
| USDT.e - USDt | 16 | 14 | 2 |
| PRIME - WAVAX | 17 | 18 | -1 |
| GGP - WAVAX | 18 | 16 | 2 |
| FXS - FRAX | 19 | 5 | 14 |

and sum:

$d^2_i = 0^2 + (-6)^2 + (-10)^2 + (-2)^2 + (-2)^2 + (-12)^2 + 5^2 + (-7)^2 + 0^2 + (-1)^2 + (-8)^2 + 0^2 + 9^2 + 8^2 + 5^2 + 2^2 + (-1)$

= 0+36+100+4+4+144+25+49+0+1+64+0+81+64+25+4+1+4+196

= 802.

Now, compute $\rho$:

$$\rho = 1 - \frac{6 \times 802}{19(19^2 - 1)}$$

$$= 1 - \frac{4{,}812}{19(360)}$$

$$= 1 - \frac{4{,}812}{6{,}840}$$

$$= 1 - 0.7035$$

$$= 0.2965$$

### ***3.3.4. Interpretation***

A Spearman's ρ of approximately 0.2965 suggests a weak positive correlation between the number of providers and the average USD value per provider. This indicates that there is not a strong relationship between these two variables.

Ranking $Pi$ and $Vi$ using Spearman's Rank Correlation allows us to determine whether an increase in the number of providers corresponds to a systematic increase (or decrease) in the relative standing of the average investment size per provider. The calculated Spearman's coefficient was approximately 0.30, which indicates that as the count of providers increases, there is a slight but not pronounced tendency for the average per-provider investment to rank somewhat higher relative to other pools. This means that pools with more participants do not strongly or consistently align with either larger or smaller average contributions per liquidity provider. While there is a modest incline—pools with higher provider counts may, on average, have somewhat larger per-provider investments than those with fewer participants—this relationship is not indicative of a strong correlation. When applying this to our model

$$L_i = \alpha + \beta R_i + \varepsilon_i$$

, the weak monotonic association detected through Spearman's correlation implies that more complex or non-linear models may be required to fully capture the determinants of liquidity provision and investment size. The model predicted that higher rewards should lead to increased liquidity, and while the correlation exists, we see if a pool manages to attract more participants, it does not necessarily follow that incentives alone will boost total liquidity in a linear or uniform fashion.

This finding implies that the number of LPs in a pool does not necessarily predict the average amount of capital each LP provides. Several factors may contribute to this observation:

- Market Segmentation: Different pools may attract LPs with varying investment capacities. Some pools may be more appealing to large institutional investors, while others attract retail investors. When evaluating liquidity pools, two main factors typically guide an investor's decision: liquidity and volatility. As discussed in [2,3] institutional investors and investors with larger capital allocations—are often drawn to high-liquidity pools such as BTC.b – AVAX, because they can move significant sums in and out of the liquidity pool with minimal price slippage. A high level of liquidity can also attract investors with low-risk profiles as it signals that many participants trust the protocol or the token pair. Low-liquidity pools such as ZRO – AVAX can exhibit higher volatility and slippage, making them riskier especially to larger investors. However, each LP's share of rewards can be larger, attracting smaller investors with a higher risk tolerance. As noted in [4] pools with high volatility are also suitable for short-term traders and speculators who thrive on price swings. Conversely, pools with low volatility would have lower impermanent loss which is critical for investors concerned about protecting their principal. Low volatility pools are more attractive to long-term investors who seek consistency—often looking to park funds for extended periods.
- Token Characteristics: According to [5] the nature of the tokens in the pair (e.g., established tokens vs. newer tokens) can influence LP behaviour. Established tokens with a proven track record, solid market capitalization, and widespread recognition tend to attract larger investments per LP. This is primarily due to the perceived stability and lower risk associated with such tokens. In contrast, newer tokens, while potentially offering higher yields or growth prospects, often come with greater uncertainty and volatility. As a result, LPs may either invest smaller amounts or approach such tokens with heightened caution [6].
- Risk Appetite: LPs' risk tolerance can affect their investment size. LPs with a higher risk profile may be more willing to allocate larger amounts of capital to pools with higher risk, due to the potential of earning substantial yields or taking advantage of market volatility. On the other end, we have low-risk investors who prioritize capital preservation and stable returns over the possibility of high yield [7]. These individuals typically gravitate toward well-established tokens or pools with high liquidity and low volatility, where the chances of impermanent loss or sudden market swings are minimized. In between, risk-neutral investors tend to balance potential rewards and risks by diversifying their portfolios across a variety of pools. This group could include investors with quantitative strategies to monitor market conditions and adjust their allocations dynamically, aiming to optimize returns without overexposing themselves to volatility.
- Incentive Structures: Variations in incentive programs and expected returns can influence both the number of LPs and the average investment size [8]. For example, the base fee which is the percentage distributed directly to LPs plays a significant role in determining the type of investors it attracts. A higher base fee or incentive often indicates that a pool is low in liquidity, volatile, and high in risk, which appeals to risk-tolerant LPs seeking higher yields. Conversely, a lower base fee and incentive typically suggest a steady and predictable income stream, attracting LPs with larger liquidities and a lower risk tolerance.

Overall, the weak correlation suggests that other factors beyond the simple number of LPs and average investment size play significant roles in liquidity provision.

### *3.4. Fee Structures and Protocol Settings*

Although the data provided includes columns for "Disc Settings," "Base Fee," and "Protocol Fee," inconsistencies and misalignments in the dataset make it challenging to perform a reliable analysis. However, general observations can be made.

#### *3.4.1. General Observations*

- Fee Variations: Fees vary across different pairs, ranging from as low as 1 basis point (bp) to as high as 50 bps. This variation indicates strategic differentiation in fee structures across pools.
- Protocol Fees: Protocol fees, which represent the portion of fees allocated to the protocol itself, are generally set around 20% to 25%. Lower protocol fees are observed in pools with lower base fees.
- Impact on Liquidity Provision: Higher fees might deter traders due to increased transaction costs, potentially reducing trading volume and, consequently, fee earnings for LPs. Conversely, lower fees may encourage trading activity but generate less revenue per trade.

## 4. Mathematical Framework

To analyze the impact of incentives and fees on liquidity pools, we establish a mathematical framework that models the relationships between variables.

### *4.1. Liquidity Provision Model*

Let $L_i$ represent the average liquidity in pool i, and $R_i$ denote the total rewards (i.e., additional liquidity injected into the pools to enhance yields) allocated to pool i. We hypothesize that liquidity is a function of rewards:

$$L_i = \alpha + \beta R_i + \varepsilon_i \qquad (6)$$

where α is the intercept, β is the coefficient measuring the impact of rewards on liquidity, and $\varepsilon_i$ is the error term.

### *4.2. Trading Volume Model*

Let $V_i$ be the average trading volume in pool $i$, and $F_i$ represent the base fee percentage for pool i. We model trading volume as a function of the fee:

$$V_i = \gamma + \delta F_i + \eta_i, \qquad (7)$$

where $\gamma$ is the intercept, $\delta$ is the coefficient measuring the impact of fees on volume, and $\eta_i$ is the error term.

### *4.3. Liquidity Provider Yield Model*

The yield for LPs in pool i, denoted as $Y_i$, is derived from both trading fees and incentives. The total yield can be expressed as:

$$Y_i = Y_{f,i} + Y_{r,i}, \quad (8)$$

where $Y_{f,i}$ is the yield from fees, and $Y_{r,i}$ is the yield from rewards.

## 5. Data Preparation and Calculation Logic

### *5.1. Incentive Allocation Data Processing*

From incentive_analysis.xlsx, we extract the total rewards $R_i$ for each pool over the five periods. We ensure data consistency by verifying the sum of rewards across periods for each pool.

### *5.2. Pool Performance Data Processing*

Using traderjoe_base_metrics.csv, we extract the following variables for each pool:

- Average liquidity $L_i$
- Average trading volume $V_i$
- Base fee $F_i$
- Average fees earned per hour $F_{e,i}$
- Average APR $A_i$

We calculate the average values over the relevant time frames to smooth out short-term fluctuations.

### *5.3. Calculations of LP Yields*

#### *5.3.1. Yield from Fees*

The yield from fees for pool i is calculated as:

$$Y_{f,i} = \frac{F_{e,i} \times 24 \times 365}{L_i} \times 100\% \quad (9)$$

where $F_{e,i}$ is the average fees earned per hour, and $L_i$ is the average liquidity.

### *5.3.2. Yield from Rewards*

Assuming that the rewards are distributed proportionally to the liquidity provided, the yield from rewards is:

$$Y_{f,i} = \frac{R_i \times P_{AVAX}}{L_i} \times 100\% \tag{10}$$

where $R_i$ is the total rewards allocated over the period in AVAX, $P_{AVAX}$ is the price of AVAX in USD, and $L_i$ is in USD.

### *5.3.3. Total Yield Calculation*

Using Equation (8), we compute the total yield:

$$Y_{f,i} = \frac{F_{e,i} \times 24 \times 365}{L_i} + \frac{R_i \times P_{AVAX}}{L_i} \times 100\% \tag{11}$$

## 6. Analysis and Results

### *6.1. Impact of Rewards on Liquidity*

Using Equation (6), we perform a linear regression analysis to estimate the coefficientsα and β.

### *6.1.1. Regression Calculation*

Let n be the number of pools analyzed. We compute the following sums:

$$\sum_{i=1}^{n} R_i \ , \sum_{i=1}^{n} L_i \, , \sum_{i=1}^{n} R_i L_i \, , \sum_{i=1}^{n} R_i^2 \tag{12}$$

The estimates of β and α are given by:

$$\beta = \frac{\sum_{i=1}^{n} R_i L_i - \sum_{i=1}^{n} R_i \sum_{i=1}^{n} L_i}{\sum_{i=1}^{n} R_i^2 - \left(\sum_{i=1}^{n} R\right)^2} \tag{13}$$

$$\alpha = \frac{\sum_{i=1}^{n} L_i - \beta \sum_{i=1}^{n} R_i}{n} \tag{14}$$

***6.1.2. Sample Calculation***

Assuming we have data for n = 5 pools:

**Table 4:** Sample Data for Regression Analysis

| Pool | $R_i$ (Rewards in AVAX) | $L_i$ (Liquidity in USD) |
|---|---|---|
| JOE – AVAX | 37,500 | $5,000,000 |
| COQ – AVAX | 31,000 | $3,500,000 |
| ggAVAX – AVAX | 25,000 | $2,000,000 |
| sAVAX – AVAX | 25,000 | $2,500,000 |
| Qi – AVAX | 37,500 | $4,500,000 |

First, calculate the sums:

$R_i$ = 37,500 + 31,000 + 25,000 + 25,000 + 37,500 = 156,000

$L_i$ = 5,000,000 + 3,500,000 + 2,000,000 + 2,500,000 + 4,500,000 = 17,500,000 $R_i^2 = (37{,}500)^2 + (31{,}000)^2 + (25{,}000)^2 + (25{,}000)^2 + (37{,}500)^2 = 4{,}781{,}250{,}000$

$R_iL_i$ = (37,500 × 5,000,000) + (31, 000 × 3,500,000)+

(25,000 × 2,000,000) + (25,000 × 2,500,000) + (37,500 × 4,500,000)

= 187,500,000,000 + 108,500,000,000 + 50,000,000,000 + 62,500,000,000 + 168,750,000,000
= 577,250,000,000

Now, calculate β:

$$\beta = \frac{5 \times 570{,}250{,}000{,}000 - 156{,}000 \times 17{,}500{,}000}{5 \times 4{,}781{,}250{,}000 - (156{,}000)^2}$$

$$= \frac{2{,}886{,}250{,}000{,}000 - 2{,}730{,}000{,}000{,}000}{23{,}906{,}250{,}000 - 24{,}336{,}000{,}000}$$

$$= \frac{156{,}250{,}000{,}000}{-429{,}750{,}000}$$

$$= -363.6516$$

Now, calculate $\alpha$:

$$\alpha = \frac{17{,}500{,}000 - (-363.6516) \times 156{,}000}{5}$$

$$= \frac{17{,}500{,}000 + 56{,}726{,}457.6}{5}$$

$$= \frac{74{,}226{,}457.6}{5}$$

$$= 14{,}845{,}291.52$$

Therefore, the estimated model is:

$$L_i = 14{,}845{,}291.52 - 363.6516\, R_i \qquad (15)$$

#### *6.1.3. Interpretation*

The negative value of β obtained from the regression analysis suggests an inverse relationship between the total rewards allocated to a pool ($R_i$) and the average liquidity in that pool ($L_i$). This finding is counterintuitive, as one would generally expect that higher rewards would incentivize more liquidity provision, leading to higher liquidity levels.

Possible explanations for this unexpected result include:

- Data Limitations: The sample size is small (n = 5 pools), which may not be sufficient to capture the true relationship between rewards and liquidity. Small samples are susceptible to random variations and may not be representative of the larger population.
- Outliers and Influential Points: There may be outlier pools where high rewards are associated with low liquidity, possibly due to other confounding factors, such as low token popularity or high perceived risk.
- Reverse Causality: It is possible that pools with lower liquidity are allocated higher rewards in an effort to boost liquidity. In this case, the causality runs from liquidity levels to reward allocation, rather than the other way around.
- Unobserved Variables: Other factors not included in the model may be influencing liquidity, such as market sentiment, LPs' expectations, or alternative investment opportunities.

• Lagged Effects: The impact of rewards on liquidity may not be immediate. LPs might take time to adjust their positions in response to changes in incentives.

Given these considerations, the negative β suggests that the relationship between rewards and liquidity is more complex than a simple linear association. It highlights the need for a more comprehensive model that includes additional variables and possibly explores non-linear relationships or lagged effects.

Furthermore, this result underscores the importance of carefully designing incentive programs and monitoring their effectiveness, as higher rewards alone may not suffice to increase liquidity if other barriers or disincentives are present

### *6.2. Impact of Fees on Trading Volume*

Using Equation (7), we perform a similar regression analysis to estimate γ and δ.

#### *6.2.1. Regression Calculation*

Assuming sample data for n = 5 pools with base fees and trading volumes:

**Table 5:** Sample Data for Fee Impact on Volume

| Pool | $F_i$ (Base Fee %) | $V_i$ (Volume in USD) |
|---|---|---|
| JOE – AVAX | 0.25% | $10,000,000 |
| COQ – AVAX | 0.80% | $2,500,000 |
| ggAVAX – AVAX | 0.01% | $20,000,000 |
| sAVAX – AVAX | 0.01% | $18,000,000 |
| Qi – AVAX | 0.25% | $9,000,000 |

Calculate the sums:

$\Sigma F_i = 0.25 + 0.80 + 0.01 + 0.01 + 0.25 = 1.32\%$

$\Sigma V_i = 10,000,000 + 2,500,000 + 20,000,000 + 18,000,000 + 9,000,000 = 59,500,000$

$\Sigma F_i^2 = (0.25)^2 + (0.80)^2 + (0.01)^2 + (0.01)^2 + (0.25)^2 = 0.7127$

$\Sigma F_i V_i = (0.25 \times 10,000,000) + (0.80 \times 2,500,000)+$

$(0.01 \times 20,000,000) + (0.01 \times 18,000,000) + (0.25 \times 9,000,000)$

$= 2,500,000 + 2,000,000 + 200,000 + 180,000 + 2,250,000$

= 7, 130, 000

Calculate δ:

$$\delta = \frac{5 \times 7{,}130{,}000 - 1.32 \times 59{,}500{,}000}{5 \times 0.7127 - (1.32)^2}$$

$$= \frac{35{,}650{,}000 - 78{,}540{,}000}{3.5635 - 1.7424}$$

$$= \frac{-42{,}890{,}000}{1.8211}$$

$$= -23{,}556{,}676.3$$

Calculate $\gamma$:

$$\gamma = \frac{59{,}500{,}000 - (-23{,}556{,}676.3) \times 1.32}{5}$$

$$= \frac{59{,}500{,}000 + 31{,}092{,}825.92}{5}$$

$$= \frac{90{,}592{,}825.92}{5}$$

$$= 18{,}118{,}565.18$$

Estimated model:

$$V_i = 18{,}118{,}565.18 - 23{,}556{,}676.3\, F_i \qquad (16)$$

### *6.2.2. Interpretation*

The negative coefficient δ indicates a negative relationship between the base fee percentage ($F_i$) and the average trading volume ($V_i$). Specifically, the model suggests that for each percentage point increase in the base fee, the average trading volume decreases by approximately $23,556,676.

This finding aligns with economic theory and market expectations for several reasons:

- Transaction Cost Sensitivity: Traders are sensitive to transaction costs. Higher fees increase the cost of trading, making it less attractive for traders to execute trades, particularly for high-frequency or low-margin strategies [9].
- Market Competition: In the DeFi space, traders have access to multiple platforms offering similar services. If one platform has higher fees, traders may switch to competitors with lower fees, reducing trading volume on the higher-fee platform [10, 11].
- Price Elasticity of Demand: The demand for trading services is price elastic; small changes in fees can lead to larger proportional changes in trading volume [11].

However, it’s essential to consider that:

- Optimal Fee Strategy: While lower fees can increase trading volume, they also reduce the revenue per trade. Platforms need to find an optimal fee level that maximizes overall revenue and provides sufficient incentives for LPs.
- Non-Fee Factors: Trading volume is also influenced by factors such as market volatility, token popularity, and external events. The model isolates the effect of fees but does not account for these other variables.
- Causality Direction: The relationship may be influenced by reverse causality. Pools with lower trading volumes may increase fees to compensate LPs, or fees may be adjusted in response to changes in trading activity.

Overall, the negative δ supports the hypothesis that higher fees discourage trading activity. Platforms should carefully consider their fee structures to balance the trade-off between attracting trading volume and generating sufficient fee revenue.

### *6.3. Calculation of LP Yields*

Using Equations (9) and (10), we calculate the yields for each pool.

### *6.3.1. Sample Calculation for Pool 1*

Given:

- $F_{e,1}$ = $500 per hour

- $L_1$ = $5,000,000
- $R_1$ = 37, 500 AVAX(Assuming AVAX price is $10,total rewards in USD is $375,000)

Calculate yield from fees:

$$Y_{f,i} = \frac{\$500 \times 24 \times 365}{\$5{,}000{,}000} \times 100\%$$

$$= \frac{\$4{,}380{,}000}{\$5{,}000{,}000} \times 100\%$$

$$= 87.6\%$$

Yield from rewards:

$$Y_{f,i} = \frac{\$375{,}000}{\$5{,}000{,}000} \times 100\%$$

$$= 7.5\%$$

Total yield:

$$Y_1 = 87.6\% + 7.5\% = 95.1\%$$

#### *6.3.2. Interpretation*

For Pool 1, the total annual yield for LPs is calculated to be 95.1%, with 87.6% coming from trading fees and 7.5% from rewards.

This result provides several insights:

- Significance of Trading Fees: The majority of the yield is generated from trading fees, highlighting the importance of trading volume in providing returns to LPs. Active pools with high trading volumes can offer substantial fee-based earnings.
- Effectiveness of Incentives: The rewards contribute an additional 7.5% to the yield. While this is smaller than the fee-based yield, it can still be a meaningful enhancement, making the pool more attractive to LPs.
- Competitive Returns: A total yield of 95.1% is highly competitive in the DeFi space, potentially attracting more LPs to the pool. High yields can compensate LPs for risks such as impermanent loss and market volatility.
- Sustainability Considerations: Reliance on trading fees for the bulk of the yield may be more sustainable than rewards, which are often time-limited or subject to change. LPs should consider the long-term prospects of both yield components.

This analysis underscores the importance of both trading activity and incentive programs in generating attractive yields for LPs. It also highlights the need for LPs to assess the sources of yield and associated risks when choosing where to provide liquidity.

## 7. Integrated Analysis of Pool Performance

### *7.1. Liquidity and Incentives*

The regression analysis on the impact of rewards on liquidity yielded a negative coefficient, suggesting that higher rewards are associated with lower liquidity. This counterintuitive result indicates that the relationship between incentives and liquidity provision is not straightforward.

Possible explanations include:

- Ineffective Incentives: The incentive program may not be effectively encouraging LPs to provide more liquidity, perhaps due to insufficient reward amounts relative to LPs' expectations or alternative opportunities.
- Market Saturation: LPs may have reached a saturation point where additional rewards do not significantly influence their decisions.
- Risk Factors: LPs may be deterred by risks associated with certain pools, such as impermanent loss, token volatility, or smart contract vulnerabilities, which rewards cannot fully offset.

This suggests that while incentives are important, they must be part of a broader strategy that addresses LPs' concerns and market dynamics.

### *7.2. Trading Volume and Fees*

The negative relationship between fees and trading volume highlights the sensitivity of traders to transaction costs. Key takeaways include:

- Fee Optimization: Protocols need to carefully set fees to balance revenue generation and trading activity. Lower fees can stimulate trading volume, but too low fees may not adequately compensate LPs.
- Market Competitiveness: In a competitive market, maintaining fees at a reasonable level is crucial to retain traders who might otherwise switch to platforms with more favorable fee structures.
- Segmented Fee Structures: Implementing differentiated fee structures based on pool characteristics or trader profiles could optimize both volume and revenue.

Understanding the fee elasticity of trading volume is essential for protocols aiming to maximize their overall performance.

### *7.3. LP Yields and Impermanent Loss*

LPs earn yields from both trading fees and incentives but face the risk of impermanent loss, which occurs when the price of the pooled tokens diverges [12]. Implications include:

- Yield Adequacy: The total yield must be sufficient to compensate LPs for the risk of impermanent loss and other potential costs.
- Token Volatility: Pools involving highly volatile tokens may present higher impermanent loss risk, requiring higher yields to attract LPs.
- Risk Management: LPs should consider strategies to mitigate impermanent loss, such as providing liquidity to stablecoin pairs or using tools that hedge price movements.

Protocols can enhance LP participation by offering tools and information to help LPs manage these risks effectively.

## 8. Conclusion

This comprehensive analysis reveals that while Trader Joe's Boost Incentive Program has the potential to impact liquidity provision in Trader Joe's pools, the relationship is complex and influenced by multiple factors. Key findings include:

- Incentives and Liquidity: The expected positive relationship between rewards and liquidity was not observed in the sample, suggesting that incentives alone may not drive liquidity provision effectively.
- Fees and Trading Volume: Higher fees are associated with lower trading volumes, underscoring the importance of fee structures in influencing trader behavior and, consequently, LP earnings.
- LP Yields: LPs derive significant earnings from trading fees, with incentives providing additional, though smaller, contributions to total yield.
- Provider Behavior: The weak correlation between the number of providers and average investment suggests that other factors, such as risk preferences and market conditions, play significant roles.

Balancing incentives, fees, and trading activity is crucial for optimizing pool performance and attracting LP participation. Protocols should adopt a holistic approach that considers the interplay of these factors to enhance their platforms' competitiveness and sustainability.

## 9. Future Work

Future direction of expanding this would involve collecting more extensive data across additional pools and time periods to improve the robustness of the analysis. This would allow for econometric modeling of relationship between both users that deploy in boosted pools and non-boosted pools, particular looking at LP and trader behaviors in such pools. From a risk standpoint, analyzing the impact of impermanent loss and other risks on LP participation and designing mechanisms would also show interesting correlations between boosted and non-boosted pools.

## Acknowledgements

I would like to express my heartfelt gratitude to my mentor, Eddie Huang, for his invaluable guidance, insightful feedback, and unwavering support throughout the course of my learning and the research process. His expertise and encouragement were instrumental in shaping my understanding and approach to this work. This research would not have been possible without his mentorship, which provided both direction and inspiration at every step.

**References**

[1]. T. D. Gauthier. (2001, Dec.). “Detecting Trends Using Spearman's Rank Correlation Coefficient,” *ScienceDirect*. [Online]. pp. 1. Available: https://www.sciencedirect.com/science/article/abs/pii/S1527592201900618. [Accessed: Sept. 1, 2024].

[2]. Fidelity Digital Assets. (2024, Apr.). “Exploring Institutional Interest in Blockchain Applications and Digital Asset Uses.” *Fidelity Digital Assets*. [Online]. pp. 8. Available: https://www.fidelitydigitalassets.com/sites/g/files/djuvja3256/files/acquiadam/1075436.1.0%20Fidelity%20Digital%20Assets_Institutional%20Investor%20Study%20Whitepaper_fnl.pdf [Accessed: Sept. 2, 2024].

[3]. D. Miori, M. Cucuringu. (2024, Jan). “Clustering Uniswap v3 traders from their activity on multiple liquidity pools, via novel graph embeddings.” *Digital Finance*. [Online]. Vol. 6, pp. 115. Available: https://link.springer.com/article/10.1007/s42521-024-00105-4 [Accessed: Sept. 6, 2024].

[4]. A. Kalacheva, P. Kuznetsov, I. Vodolazov, and Y. Yanovich. (2024, Oct.). “Detecting Rug Pulls in Decentralized Exchanges: The Rise of Meme Coins.” *SSRN*. [Online]. pp. 3. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4981529 [Accessed: Dec. 6, 2024].

[5]. L. Heimbach, Y. Wang and R. Wattenhofer. (2021, May.). “Behavior of Liquidity Providers in Decentralized Exchanges.” arXiv. [Online]. pp. 12. Available: https://arxiv.org/pdf/2105.13822 [Accessed: Sept. 20, 2024].

[6]. A. Brini and J. Lenz. (2024, Apr.). “A Comparison of Cryptocurrency Volatility-benchmarking New and Mature Asset Classes,” *arXiv preprint arXiv:2404.04962*, 2024. [Online]. Available: https://arxiv.org/pdf/2404.04962. [Accessed: Sept. 29, 2024].

[7]. H. Park. (2021, Apr.). “Influence of Risk Appetite on Investment Decisions: A Malliavin Calculus Approach,” *arXiv preprint arXiv:2104.00911*, 2021. [Online]. Available: https://arxiv.org/pdf/2104.00911. [Accessed: Oct. 2, 2024].

[8]. A. Lehar, C. Parlour, and M. Zoican. (2024, May). “Fragmentation and optimal liquidity supply on decentralized exchanges,” *arXiv preprint arXiv:2307.13772*, 2023. [Online]. Available: https://arxiv.org/pdf/2307.13772. [Accessed: Oct. 9, 2024].

[9]. J. R. Jensen, V. V. Wachter , and O. Ross. (2021, Mar.). “An Introduction to Decentralized Finance (DeFi),” *Computer Science and Information Technologies Quarterly*, vol. 26, pp. 4, 2021. [Online]. Available: https://journals.rtu.lv/index.php/CSIMQ/article/viewFile/csimq.2021-26.03/2570. [Accessed: Oct. 11, 2024].

[10]. J. Hasbrouck, T. J. Rivera, and F. Saleh. (2022, Aug.). “The Need for Fees at a DEX: How Increases in Fees Can Increase DEX Trading Volume,” *The American Finance Association Journal of Finance*. [Online]. Available: https://afajof.org/management/viewp.php?n=43204. [Accessed: Oct. 20, 2024].

[11]. C. Liu and M. A. Sustik. (2021, Jun.). “Elasticity Based Demand Forecasting and Price Optimization for Online Retail,” *arXiv preprint arXiv:2106.08274*, 2021. [Online]. Available:

https://arxiv.org/pdf/2106.08274. [Accessed: Oct. 21, 2024].

[12]. A. A. Aigner and G. Dhaliwal. (2021, Jun.). “Uniswap: Impermanent Loss and Risk Profile of a Liquidity Provider,” *arXiv preprint arXiv:2106.14404*, 2021. [Online]. Available: https://arxiv.org/pdf/2106.14404. [Accessed: Oct. 22, 2024].

[13]. “LFJ Dex API (1.0.0).” Internet: https://lfj.dev/ [Accessed: May. 15, 2024].

[14]. “LFJ Documentation.” Internet: https://docs.lfj.gg/ [Accessed: April. 26, 2024].