Safer & Smarter Looping Strategy

We will involve re-investing borrowed assets back into lending platforms to create a leverage loop with the aim of amplifying potential returns.

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Contents

1 Introduction

In the dynamic realm of DeFi, investors relentlessly pursue high returns, often at the cost of embracing excessive risks. Amidst a rising bullish sentiment, unchecked optimism fuels over-leverage, setting the stage for familiar pitfalls.

*"The volume of loans liquidated on Ethereum lending markets **has hit its highest monthly value since June 2022** (Terra crash), **despite April not even being half over**." - The Block Data*

These **lending markets**, pivotal in the leverage play, enable strategies that amplify returns through *"leverage loops"*, where borrowed assets are reinvested to enhance potential gains. However, the allure of these looping strategies also brings heightened risks of liquidation.

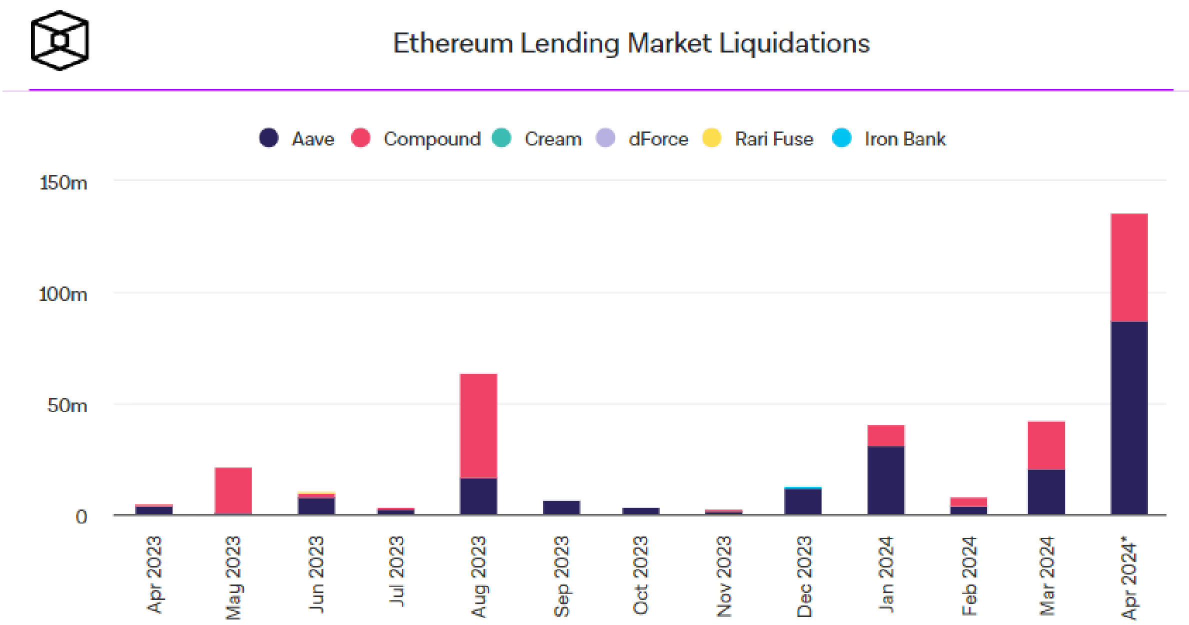

Figure 1: **Source:** theblock.co **Date:** APR-21 2024*
The amount of monthly liquidations in USD, grouped by lending markets. Liquidation occurs when a liquidator sells collateralized assets at a discount to repay the debt. Only Ethereum data is included.

As DeFi evolves, the sophistication of investment strategies must also advance.
The challenge lies in mastering these looping strategies to maximize gains while safeguarding against the volatile whims of the market. This delicate balance is at the heart of the issues we are tackling.

2 Problem

The central problem this model aim to address is:

What is the optimal looping strategy that maximizes expected returns while mitigating the risk of liquidation?

And this problem has mainly two rationales:

1. **Maximizing Returns:**
    - Efficient use of looping strategies can significantly boost DeFi participants' gains. The crucial factor is finding the right number of loops for maximum yield in bullish markets, requiring a system that simplifies DeFi lending dynamics and operates autonomously.
2. **Minimizing Liquidation Risk:**
    - Seeking higher returns entails higher risks, especially in volatile markets where collateral values can rapidly decline. Our project addresses this by analyzing market data to predict liquidation occurrences and incorporating a liquidation penalty into the expected return formula.

2.1 Why Is This Problem Worth Solving?

Addressing this problem is critical for several reasons:

- **Democratizing Access to Advanced DeFi Strategies & Leverage Risk**
    - This model simplifies and automates looping strategies, making advanced yield optimization accessible to all, not just sophisticated investors.
    - By showcasing liquidation occurrence probability, we aim to educate people to take more responsible financial decisions
- **Fostering Innovation in Financial Engineering:**
    - The development of a looping strategy optimization model represents a leap forward in financial engineering within the blockchain space. It showcases the potential for innovative algorithms and mathematical models to solve complex financial challenges, paving the way for future breakthroughs in DeFi finance.

3 Looping Optimization Model

We aim to build a model that identifies **the optimal looping strategy involving long positions in ETH by supplying ETH and borrowing USDC, and aiming to avoid liquidation over a 7 week period using the last two years of data**. This process involves several steps, from data acquisition and preprocessing to model training and evaluation.

3.1 Utilizing GIZA Datasets

The GIZA datasets serve as the foundation of our optimization model. These comprehensive datasets, encompassing historical token price, supply/borrow APYs and loan-to-value (LTV) ratios provide the raw materials for our analysis. By analyzing trends and patterns in these data, we can construct a model that not only identifies optimal looping strategies but also adapts to changing market conditions.

3.2 Datasets Used for Analysis

- *GIZA Tokens daily information:* This dataset contains daily historical price, market cap, and 24-hour volumes data for various cryptocurrencies, sourced from the CoinGecko API. It includes data fields such as price, market_cap, volumes_last_24h, and token for each day.
- *GIZA Daily Deposits & Borrows v3:* This dataset provides the aggregated daily borrows and deposits made to the AAVE v3 Lending Pools. Only the pools in Ethereum L1 are taken into account and the contract_address feature can be used as an unique identifier for the individual pools. The dataset contains all the pool data from 25.01.2023 to 25.01.2024, and individual rows are omitted if there were no borrows or deposits made in a given day.
- *GIZA Daily Exchange Rates & Indexes v3:* This dataset provides the average borrowing rates (variable & stable), supply rate, and liquidity indexes of AAVE v3 Lending Pools. Only the pools in Ethereum L1 are considered, and the contract_address feature can be used as a unique identifier for the individual pools. The dataset contains all the pool data from 27.01.2023 to 23.01.2024, and individual rows are omitted if there were borrows executed on the pool.

4 7-Days Liquidation Occurrence by Looping level - Descriptive Model

With the aim of understanding how the ***liquidation event*** occurs for a ***selected leverage rate***, we designed the following model that generates 9 different loops and evaluate the frequency of the liquidation event by looking at ETH 7-days price change between 27.01.2023 to 23.01.2024, sourced from GIZA Tokens Daily information. We'll use these observed frequencies by loop level later on, as the probability of liquidation by leverage rate, for our Expected Return maximization model.

4.1 Looping Model

Our Looping Model defines initially an ETH amount and a leverage rate amount, which we call as looping level. At the same moment, it gathers variables from GIZA such as Max Loan-to-Value (LTV), ETH Supply APY, USDC Borrow APY, ETH and USDC Price. With this information, we calculate initial ETH supply and initial USDC borrow amount in t_0.

Looping works as the following sequence:

$$Loop_1 : \text{USDC Borrow L1} = \frac{\text{ETH initial amount L0} \times \text{ETH initial price} \times \text{LTV\%}}{\text{USDC initial price}}$$

With the above $Loop_1$, we go to AAVE and borrow USDC. With that borrowed USDC, we buy more ETH as following:

$$Loop_1 : \text{ETH Buy L1} = \frac{\text{ETH initial price}}{\text{USDC Borrow L1}}$$

Having bought ETH at t_0, we can set it as Supply again in AAVE protocol and define an ETH Balance for $Loop_1$ as the following:

$$Loop_1 : \text{ETH Balance L1} = \text{ETH initial amount L0} + \text{ETH Buy L1}$$

Following the same logic, we can define $Loop_2$ as:

$$Loop_2 : \text{USDC Borrow L2} = \frac{\text{ETH Balance L1} \times \text{ETH initial price} \times \text{LTV\%}}{\text{USDC initial price}} - \text{USDC Borrow L1}$$

With the above $Loop_2$, we go to AAVE and borrow USDC. With that borrowed USDC, we buy more ETH as following:

$$Loop_2 : \text{ETH Buy L2} = \frac{\text{ETH initial price}}{\text{USDC Borrow L2}}$$

Having bought ETH at t_0, we can set it as Supply again in AAVE protocol and define an ETH Balance for $Loop_1$ as the following:

$$Loop_2 : \text{ETH Balance L2} = \text{ETH initial amount L1} + \text{ETH Buy L2}$$

This sequence can be followed till the LTV% gets that much closer to the Max LTV, where a really minor ETH price change liquidates the position.

After defining the Looping level/Leverage ratio with the previous model, we can **evaluate our position at t_1 by looking if the same was liquidated or not** with the following logic: We can define the **Liquidation Ratio** for a position:

$$LiquidationRatio = \frac{(\text{USDC Borrow} + \text{USDC Accrued Interest Balance}) \times (\text{USDC Highest Day}_1 \text{ Price})}{(\text{ETH Supply} + \text{ETH Accrued Interest Balance}) \times \text{ETH Lowest Day}_1 \text{ Price}}$$

Then, if Liquidation Ratio > Liquidation LTV Threshold, the position is considered as liquidated, hence, the liquidation flag is equal to 1. On the other hand, if Liquidation Ratio < Liquidation LTV Threshold we accrued daily interest, which are defined as -

USD Accurred Interest:

$$USDCAccurredInterestDay_1 = \frac{\text{USDC Borrow} + \text{USDC Accrued Interest Balance}}{\text{USDC Borrow APY} \times \frac{1}{365}}$$

ETH Accurred Interest:

$$ETHAccurredInterestDay_1 = \frac{\text{ETH Supply} + \text{ETH Accrued Balance}}{\text{ETH Supply APY} \times \frac{1}{365}}$$

With both ETH & USDC accured interest formulas defined, we can compute the interest balance in USDC as:

$$\text{USDC Accrued Balance Day}_1 = \text{USDC Accrued Balance Day}_0 + \text{USDC Accrued Interests Day}_1$$

Now, in t_2, we re-define an ETH initial Supply, we have the ETH Accured Interests Day_1, we have a ETH Supply APY, we re-define a USDC Initial Borrow, we have USDC Accurred Interest Day_1, we have a USDC Borrow APY and, again, a Liquidation LTV% Threshold. With this information, we need to see if, at t_2, Liquidation Ratio > Liquidation LTV Threshold and follow the sequence.

The final output for this descriptive analysis will conclude with a Liquidation frequency vector which will show the event occurence frequency %, considered later as the $p(liquidation)$, by level of loop.

4.2 Historical Liquidation Simulation Model by Loop Level

While looking at *Figure 2*, we can understand the **Liquidation Frequency** as the observed probability, $p(liquidation)$, of a position being liquidated **by each level of Loop** during 27-01-2023 to 23-01-2024. We understand that during this data period there wasn't a significant amount of external events that made the ETH price decrease that much that it liquidated the opened positions. That's why we have developed our Looping model in such a way that if we receive an extended dataset that compiles bigger data periods we can update the frequency of liquidation to reflect more accurate results.

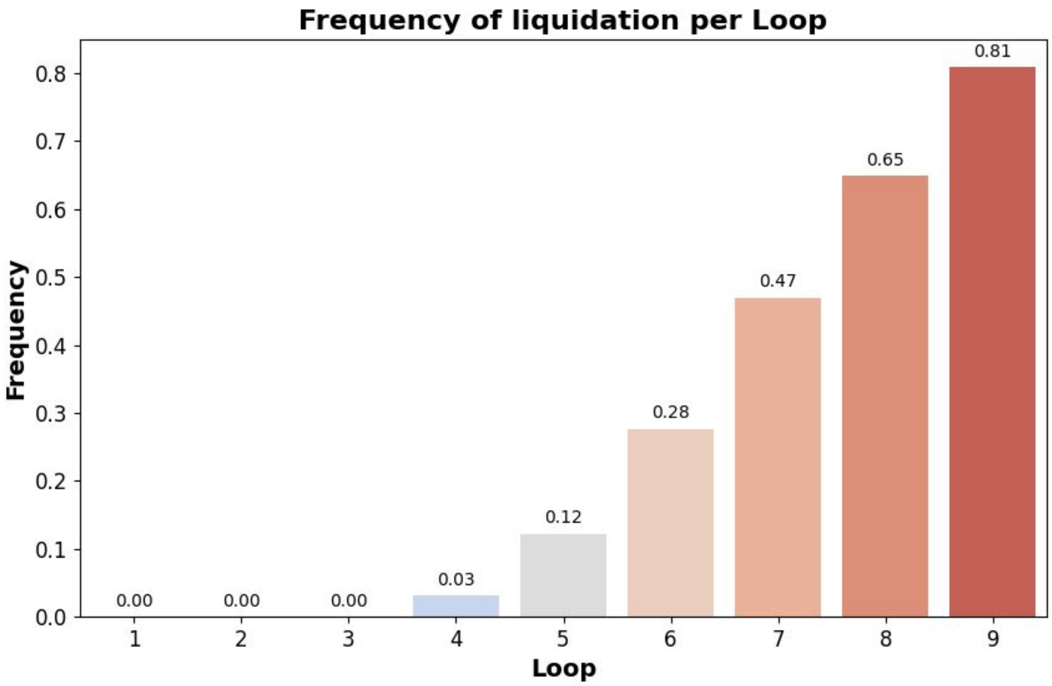

Figure 2: **Source:** GIZA **Date:** 27-01-2023 to 23-01-2024

Figure 3: **Source:** GIZA **Date:** 27-01-2023 to 23-01-2024

5 7-Days Price Variation - LR Predictive Model

5.1 Data Selection & Manipulation

We estimated the expected price of ETH at the end of a seven-day period, Δp_w, using a linear regression model to explain the movement of the price of ETH over a one-week period. We used the GIZA datasets described in section 3.1 of this article. We processed daily data on prices, bid and ask rates, deposits, and loans from 27-01-2023 to 23-01-2024. Based on this information, we computed moving averages at 7, 14, and 21 days plus the minimal price to capture lags in the variables and understand the effect of the lowest price for the week, with the aim of inferring the expected price change, as part of the variable selection process. We took the natural logarithm of the price ratio as the y-variate for our regression.

It's important to highlight that we selected the previously mentioned time frame for this analysis because these are the dates for which we have supply & borrow rates. If at some time in the future we are able to get more information, our model is designed in such a way that we can expand our analysis temporal horizon to include the extra data and capture more events that might give a better prediction and, hence, more robust results in terms of liquidation frequency and expected price change.

The data analysis phase consisted of a process with a total of 15 regressions that were executed to test several hypotheses about the price movement before reaching our last concluding model that allows us to estimate Δp_w with a reasonable fit. Initially, we considered a very basic model with ETH price & volume metrics plus their 7, 14 and 21 MA which described that 1 or 2 lags variables could add level of significant information to our predictive model. Secondly, we analyzed the effect of daily ETH and USDC deposits & borrow for themselves and with their respective MA. This information suggested that neither ETH or USDC deposits and borrows would explain the changes on the weekly price of ETH. Last but not least, we took a similar approach as we took for ETH & USDC deposits and borrows with ETH & USDC Supply and Borrow Rates, including their MA. This last model showed us that the information about these rates could end up explaining a significant part of the ETH 7-days Price change, Δp_w.

Based on the described data analysis phase, we were able to infer our last model which included 10 out of the total analyzed variables to explain Δp_w. These variables are *avg_stableBorrowRate_eth*, *avg_supplyRate_eth*, *weekly_change_usdc*, *ma_7_stableBorrowRate_eth*, *ma_7avg_supplyRate_eth*, *eth_daily_deposits_borrows_ma_21*, *price_eth*, *ma_14_price_eth*, *eth_daily_deposits_borrows_ma_14* & *ma_21_price_eth.*

We then look at the results of the model, which, with an R^2 of 83% and an MSE of 0.1%, allows us to compute a linear function to estimate the expected change in ETH at the end of 7 days.

The same Linear Regression model allows us to assess the significance of each of the estimated β coefficients through the p-values. All of them are significant at a 95% confidence level used in the analysis.

These results (please refer to "Table 1: Regression Results") will be used in the next section to infer an estimated Δp_w function.

Table 1: Regression Results

Metric	Name	β	p-value	Low CI 95%	High CI 95%
MSE	-	0.1%	-	-	-
R^2	-	83.0%	-	-	-
avg_stableBorrowRate_eth	X_1	8.34	0.9%	2.06	14.62
avg_supplyRate_eth	X_2	-8.82	0.6%	-15.05	-2.59
weekly_change_usdc	X_3	0.97	1.2%	0.21	1.73
ma_7_stableBorrowRate_eth	X_4	-8.96	0.8%	-15.57	-2.35
ma_7avg_supplyRate_eth	X_5	9.30	0.7%	2.62	15.97
eth_daily_deposits_borrows_ma_21	X_6	0.00	0.1%	0.00	0.00
price_eth	X_7	0.00	0.0%	0.00	0.00
ma_14_price_eth	X_8	0.00	0.0%	0.00	0.00
eth_daily_deposits_borrows_ma_14	X_9	0.00	0.0%	0.00	0.00
ma_21_price_eth	X_{10}	0.00	0.0%	0.00	0.00

5.2 Data Analysis Conclusions

From the above LR Model we can conclude that with our predictive model we can explain the 83% of the Δp_w variation with an 95% confidence level. In addition to that, the results shows that the 83% Δp_w variation is mainly explained by movements on *avg_stableBorrowRate_eth*, *avg_supplyRate_eth*, *weekly_change_usdc*, *ma_7_stableBorrowRate_eth*, *ma_7avg_supplyRate_eth*. Also, ETH Borrow rates and ETH MA(7) Borrow rates generates opposite movements in similar magnitudes to our final estimated output, same as ETH Supply rates and it's MA(7).

5.3 Final Δp_w Definition & Validation

With the results from the data analysis section, we were able to compute our Δp_w, based on each significant variable's β, as the following:

$$\Delta p_w = \sum_{i=1}^{10} \beta_i \times X_i \; + \overline{\alpha} \;\; with\, \overline{\alpha}\, constant$$

While replacing β_i with the detailed in *Table 1*,

$$\Delta p_w = 8.34 \times X_1 - 8.82 \times X_2 + 0.97 \times X_3 - 8.96 \times X_4 + 9.30 \times X_5 + \sum_{i=6}^{10} \beta_i \times X_i + \overline{\alpha}$$

As β_i for i between $6\,\&\,10$ is equal to cero, and assuming $\overline{\alpha} = 0$, we can express the above equation as:

$$\Delta p_w = 8.34 \times X_1 - 8.82 \times X_2 + 0.97 \times X_3 - 8.96 \times X_4 + 9.30 \times X_5$$

We'll use the Δp_w formula to estimate the ETH price change at 7-days. The same will be included as part of the next section's **Expected Return Model**

Below we can conclude the fit of our model:

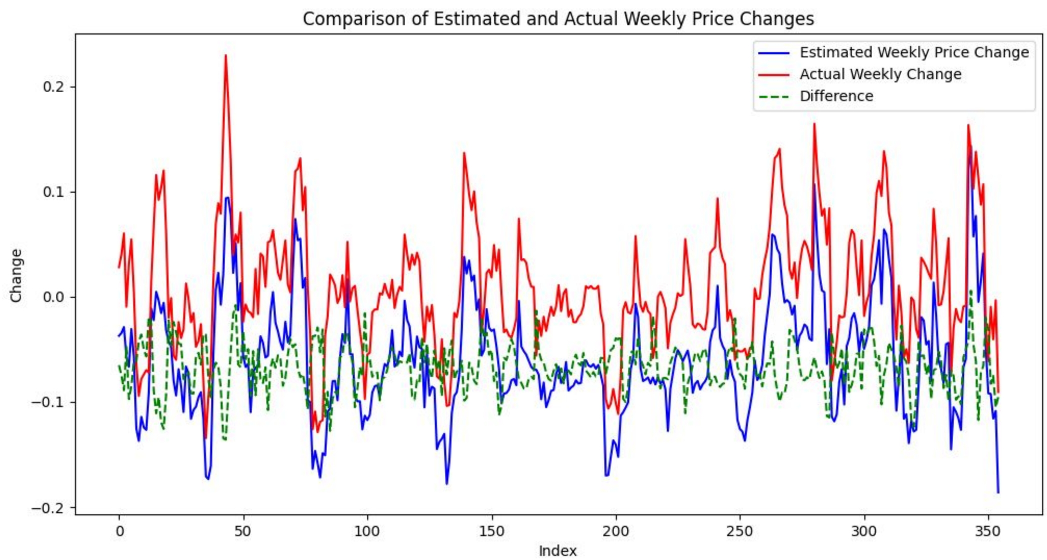

Figure 4: **Source:** GIZA **Date:** 27-01-2023 to 23-01-2024

As we can observe from *Figure 2*, our Δp_w doesn't captures the price change positive spikes but it really captures the events where the ETH weekly price changes is negative. Meaning that we are confident that we can minimize the liquidation event for a given position.

6 Expected Return - Predictive Model

6.1 Variable definition

For this section of the analysis, we'll define the 5 variables that will end up building the Expected Return Model later, based on the predicted 7-Days ETH Price % change. We call the previously defined Liquidation Event Occurrence as the observed probability of having the position liquidated for each level of Looping.

- $p(liquidation) \rightarrow$ this is the main output from our Looping Model. Defined from the observed frequency of the liquidation event.
- $L^* \rightarrow$ Optimal Leverage Rate. This variable is defined from the Loop level, the same is selected based on the predicted Δp_w at a given time.
- $\Delta p_w \rightarrow$ expected change of ETH price at the end of the week time frame. We estiamte the same based on our LR Model described in section 5 of the article.
- $\overline{c} \rightarrow$ Liquidation cost. For this case, this is defined by AAVE Protocol.
- $\delta_c \rightarrow$ Loopig Cost incurred from the observed difference between supply & borrow rates.

6.2 Formula Definition

We define r_e as the Expected return for an expected ETH 7-Days Price change Δp_w. The following formula represents how the expected return is calculated based on the $p(liquidation)$, the Δp_w, the $\bar{c}$ & δ_c.

$$r_e = \overbrace{[1 - p(liquidation)] \times \Delta p_w \times L^*}^{Earnings_e} - \overbrace{p(liquidation) \times L^* \times \bar{c} - \delta_c}^{Costs_e}$$

$$r_e = L^* \times [[1 - p(liquidation)] \times \Delta p_w - p(liquidation) \times \bar{c}]$$

Model Assumptions:

- **Assumption 1**: $p(liquidation)$ gathered from the Looping Model. The same is defined for each level of Loop at a given expected price change for the week.
- **Assumption 2**: $\bar{c} = 5\%$.
- **Assumption 3**: $\delta_c = 0$ for the weekly time frame.

Now, with all set up, the next challenge consist on defining an Optimal Leverage ratio L^* that maximizes the Expected Return r_e. This phase demands a maximization exercise that will allow the user to find which Looping level is the healthiest one that maximizes their return in a weekly time lapse. The next figure will show how the expected return curve changes by moving Δp_w for each level of loop L^*.

Then, above described formula will define, for a predicted ETH price 7-days change, Δp_w, the leverage level L^* that, considering the $p(liquidation)$, maximizes r_e.

7 On-Chain Strategy - GIZA Agent

With this complete ***Safe & Smarter Looping Strategy Model***, we aim to make it available for the entire DeFi public while working with a GIZA Agent. This proposal is part of the GIZA Hackaton taking place at Buenos Aires Apr-24. You can find the proposal, code architecture, description of our various modules and installation & usage instructions at the following link: README.md