

Sustainability of DeFi Carry Trading Using Stablecoins

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Abstract. *We investigate the sustainability of a carry trade approach on AAVE V3, in which USDC is lent and used as collateral and Wrapped Ether is obtained by borrowing. We extend the Cox-Ingersoll-Ross model by incorporating Poisson-Exponential jumps to account for abrupt rate surges which can be seen on Decentralized Finance lending platforms. Using Monte Carlo simulation with 10,000 paths, we estimate liquidation probabilities. The approach takes into account compounding interest, price fluctuations for the borrowed asset, and the liquidation mechanics of AAVE V3. We use hourly data from January 2023 to January 2026 to estimate the model parameters for USDC and WETH, more specifically variable lending and borrowing rates. Our empirical results show that the average USDC supply rate (4.98%) exceeds the average WETH borrow rate (2.86%), yielding a positive spread 76% of the time. Even with WETH price appreciation from \$1,381 to \$4,926 during the sample period, the strategy yields a low probability of liquidation and positive expected returns. The 1-year liquidation probability is approximately 6.1-7.0% at depending on starting LTV and model used, with positive mean P&L for non-liquidated paths and mostly profitable paths. Our findings demonstrate that a profitable carry trade can be carried out on DeFi platforms using stablecoins as collateral and that these positions are sustainable.*

Keywords: DeFi, carry trade, liquidation risk, CIR model, cryptocurrency, AAVE, stablecoins.

Introduction

Decentralized finance (DeFi) represents an innovation in the landscape of lending and borrowing by establishing open, trust-less, and blockchain-dependent lending pools. Within these pools, individuals can deposit assets to accrue interest, or they can secure loans by pledging a collateral. The amount of collateral required in DeFi is notable, e.g. 150% of loan value or even more. In analogy to traditional finance, this collateralization can be viewed as an alternative to evaluating creditworthiness. Opposed to traditional finance, where interest rates are decided by central banks or negotiated among financial institutions or agents, DeFi interest rates follow a kind of price formation process, being determined by algorithms based on the supply and demand within each lending pool.

The annual percentage rate (APR) can vary significantly and jump, based on the utilization rate of each token. Depending on the token, platform, and lending pool, there is an "optimal"

utilization rate which dictates the interest rate, but once this point is crossed the interest rate can go up considerably.

From a trading perspective, both creditors and debtors on these platforms must deal with ambiguity about future interest rates, which impacts their anticipated profit and loss. In addition, the sustainability of their positions is contingent upon the differential between the supply and borrow APR.

Platforms such as AAVE can be used to implement sophisticated cryptocurrency trading strategies. As of January 2026, the total value locked in DeFi platforms exceeds \$100 billion, with roughly 36 billion only in AAVE. These protocols enable traders to simultaneously hold long positions in what they deem to be promising assets while shorting/borrowing others, all while earning interest on the collateralized deposit. This represents a unique alpha generation opportunity inherent to DeFi.

The Cox-Ingersoll-Ross (CIR) model, developed by Cox, Ingersoll, and Ross in 1985, is used here to model the APRs for supply and borrowing within AAVE V3. This model is well-suited for the task because it accounts for the tendency of DeFi interest rates to a long-term mean, incorporates volatility that is tied to the interest rate itself, and the model also guarantees interest rate positivity. The parameters of the model are estimated using data collected from the AAVE protocol.

We acknowledge the limitation imposed by using a stochastic interest rate model as an approximation of the interest rate dynamics, which are a function of various factors determining the utilization rate. What exactly determines the utilization rate is a possible research direction, if cryptocurrencies (mainly Bitcoin) have become more intertwined with the general economy. Moreover, if price action is directly proportional to utilization rate is not entirely clear. Data, code and regular updates for this paper are available on [Quantlet](#), the Quantinar platform offers [further media content](#) for this research.

The rest of the paper is organized as follows: the following section presents the literature review. The one after introduces the basics of the AAVE V3 platform. After that, we present the model we used and the return dynamics. After, the methodology is described, and lastly, we present the empirical findings & discussion. The last section concludes the paper.

Literature review

Interest-rate modeling is a fundamental part of financial economics, historically based on continuous-time stochastic models like the one-factor short rate Vasicek model (Vasicek, 1977) or the Hull-White model of future interest rates (Hull and White, 1990). The CIR model is part of a category of affine term structure models that have influenced interest rate modeling since the 1980s (Duffie and Kan, 1996). Initially created for the modeling of yields of sovereign bonds, CIR and its adaptations have been applied in a few other asset classes, such as mortgage rates (Downing, Stanton, and Wallace, 2005).

Nonetheless, the emergence of decentralized finance has brought about interest rate systems that are automated and established on-chain via smart contracts. In DeFi lending markets, interest rates are mainly determined by the dynamics of supply and demand for liquidity within decentralized protocols, e.g. AAVE and Compound. Moreover, the parameters of the interest rate model can occasionally be changed by the governance of the platform, as is the case with AAVE. To our knowledge, this paper represents the first systematic application of CIR or similar models to DeFi lending rates.

The core mechanism for setting interest rates in DeFi lending protocols is utilization-based pricing: as utilization (the ratio of borrowed to supplied tokens) increases, the rates also increase in order to balance supply and demand. AAVE and Compound clearly incorporate this into their interest rate formulas in protocol whitepapers and documentation. The AAVE whitepaper describes an interest rate strategy in which the optimal utilization rate establishes a kink threshold. Under this threshold, the borrowing rate climbs slowly; beyond that point, the rate goes up sharply to prevent excessive borrowing and help maintain liquidity (AAVE, 2020).

Gudgeon et al. (2020) present a comprehensive analysis of the interest rate mechanisms in various prominent lending protocols, such as Compound and AAVE, characterizing them as Protocols for Loanable Funds (PLFs) that utilize smart contracts to establish APRs that balance the supply and demand for funds on-chain. Qu et al. (2025) tackle static interest rates by implementing reinforcement learning for APR modifications in DeFi. Chaudhary, Kozhan, and Viswanath-Natraj (2023) examine Compound's interest rate regulations and present findings on how utilization and APR parameters differ between assets and in various market conditions.

The work of Qin et al. (2021) is rather closely related to our subject of interest, where the authors examine liquidation processes on various platforms, though they focus on profit-increasing strategy for the liquidator. Our study enhances the existing body of literature by offering a robust stochastic model for the interest rate processes on DeFi platforms, facilitating applications in trading strategies and risk management.

AAVE V3 overview

AAVE is a non-custodial liquidity protocol that enables users to deposit assets into liquidity pools and borrow against deposited collateral. Version 3, launched in 2022, introduced efficiency improvements including E-Mode for correlated assets and isolation mode for new assets (AAVE, 2024).

AAVE uses an interest rate model based on each pool's utilization. Let $U \in [0,1]$ denote the utilization rate of a lending pool, defined as Total Borrowed divided by Total Supplied. The borrowing APR r^b follows a kinked linear model:

$$r^b(U) = \begin{cases} r_0 + \frac{U}{U^*} \cdot r_1 & \text{if } U \leq U^* \\ r_0 + r_1 + \frac{U-U^*}{1-U^*} \cdot r_2 & \text{if } U > U^* \end{cases} \quad (1)$$

where U^* is the optimal utilization rate (say 80-90%), r_0 is the base APR, r_1 is the slope under optimal utilization, and r_2 is a much steeper slope, above optimal utilization aiming to incentivize deposits during high demand.

The supply APR is derived from the borrow rate accounting for the protocol reserve factor ρ :

$$r^s = r^b \cdot U \cdot (1 - \rho) \quad (2)$$

There are a few platform-specific parameters: Loan-to-Value (LTV), present also in traditional finance, which represents the maximum borrowing power relative to collateral value; Liquidation Threshold, which is actually the specific LTV level that triggers liquidation; and Liquidation Penalty, the discount offered to liquidators (say 5-15%). A position becomes eligible for liquidation when the health factor (a metric used in lending protocols to measure the safety of a borrowing position, defined as the ratio of deposited collateral value to borrowed debt) falls below 1. In AAVE, the interest rates for borrowing and supplying are designed to adhere to a mean-reverting process, ensuring stability and liquidity for the protocol. This phenomenon is influenced

by the utilization rate. The interest rate model modifies rates in accordance with utilization to either promote or deter borrowing and supplying, thus steering utilization towards a target level. When utilization is elevated, indicating that the majority of supplied assets are being borrowed, the borrowing rates are raised to make borrowing more costly and to dissuade additional borrowing. Simultaneously, supply rates may also be increased to draw in more depositors, which in turn lowers utilization. In contrast, when utilization is low, rates are lowered to encourage borrowing and render supplying less appealing, which subsequently increases utilization. This self-regulating mechanism guarantees that the system remains liquid (avoiding too high utilization) and efficient (preventing too low utilization), thus embodying mean reversion in the interest rates themselves.

Stochastic model

We model the following stochastic processes: the WETH/USDC exchange rate P_t , the USDC supply rate r_t^s , and the WETH borrow rate r_t^b . The position state variables include the USDC collateral value C_t (accruing interest), the WETH debt in native units D_t^W (accruing interest), and the WETH debt value denominated in USDC, $D_t^U = D_t^W \cdot P_t$.

Cox-Ingersoll-Ross model

We model each interest rate as a CIR process:

$$dr_t = \kappa(\theta - r_t)dt + \sigma\sqrt{r_t}dW_t \quad (3)$$

The model has some desirable properties for our case: non-negativity under the Feller condition $2\kappa\theta > \sigma^2$, and mean reversion to a long-term mean, in accordance with empirical observations in DeFi.

For the CIR process, the conditional moments are:

$$\mathbb{E}[r_t|r_0] = \theta + (r_0 - \theta)e^{-\kappa t} \quad (4)$$

$$\text{Var}(r_t|r_0) = \frac{\sigma^2}{\kappa} \left(\theta \frac{1-e^{-\kappa t}}{2} + (r_0 - \theta) \frac{e^{-\kappa t} - e^{-2\kappa t}}{1} \right) \quad (5)$$

Asymptotically, the distribution will approach a Gamma distribution:

$$r_\infty \sim \text{Gamma} \left(\frac{2\kappa\theta}{\sigma^2}, \frac{2\kappa}{\sigma^2} \right) \quad (6)$$

CIR model with jumps

To capture the sudden APR surges observed in DeFi, we extend the CIR model by incorporating a jump component:

$$dr_t = \kappa(\theta - r_t)dt + \sigma\sqrt{r_t}dW_t + J_t dN_t \quad (7)$$

where:

- N_t is a compound Poisson process with intensity λ
- $J_t \stackrel{\text{iid}}{\sim} \text{Exp}(\mu)$ are exponentially distributed jump sizes

The choice of exponential distribution ensures jumps are positive (representing APR surges) and right-skewed (small jumps are more likely than large jumps). We use a truncated exponential distribution at 65% APR based on the historical maximum.

The long-run mean of the CIR-Jump process (7) is:

$$\lim_{t \rightarrow \infty} \mathbb{E}[r_t] = \theta + \frac{\lambda\mu}{\kappa} \quad (8)$$

Proof. Taking expectations in (7) and using the compensated Poisson property:

$$\frac{d}{dt} \mathbb{E}[r_t] = \kappa(\theta - \mathbb{E}[r_t]) + \lambda\mu \quad (9)$$

Setting the derivative to zero yields the result. Q.E.D

Return dynamics

We use a non-parametric bootstrap approach to preserve the properties of the empirical distribution of returns. Let $R_t = \log(P_t/P_{t-1})$ denote log-returns. We use block bootstrap with block size b to preserve short-term serial correlation. Future returns are drawn from the empirical distribution of historical returns, preserving temporal dependence within blocks of size $b = 5$ days. This block size was chosen because it can preserve short-term dependence (say, autocorrelation or volatility clustering corresponding to one trading week). Independent and identically distributed resampling would likely not ensure this. This block size is short enough to generate distinct blocks for diverse paths and avoid over-reusing long historical windows.

The position evolves according to:

$$dC_t = r_t^S C_t dt \quad (10)$$

$$dD_t^W = r_t^b D_t^W dt \quad (11)$$

$$D_t^U = D_t^W P_t \quad (12)$$

The loan-to-value ratio is:

$$\text{LTV}_t = \frac{D_t^U}{C_t} \quad (13)$$

The liquidation time is the first passage time to the liquidation threshold:

$$\tau = \inf\{t > 0: \text{LTV}_t \geq \bar{\ell}\} \quad (14)$$

Profit and Loss

The terminal P&L for a position with initial equity $E_0 = C_0(1 - \ell_0)$ is:

$$\text{P\&L}_T = \begin{cases} C_T - D_T^U - E_0 & \text{if } \tau > T \text{ (survived)} \\ C_\tau(1 - \pi) - D_\tau^U - E_0 & \text{if } \tau \leq T \text{ (liquidated)} \end{cases} \quad (15)$$

Methodology

We use hourly data from AAVE V3 on the main Ethereum market spanning January 27, 2023 to January 23, 2026, comprising 26,208 observations per series. The dataset includes USDC variable supply rates, WETH variable borrow rates, and WETH/USDC prices. The data was resampled to daily frequency (more specifically, 1,092 observations) for model calibration.

To implement our model we used Python, and the code is available on Quantlet.com.

CIR calibration via maximum likelihood

The CIR process has a known transition density. Given r_t , the distribution of $r_{t+\Delta t}$ is:

$$r_{t+\Delta t} | r_t \sim \frac{\sigma^2(1 - e^{-\kappa\Delta t})}{4\kappa} \cdot \chi_v^2(\lambda_{nc}) \quad (16)$$

where $\chi_v^2(\lambda_{nc})$ denotes a non-central chi-squared distribution with:

$$v = \frac{4\kappa\theta}{\sigma^2} \quad (17)$$

$$\lambda_{nc} = \frac{4\kappa e^{-\kappa\Delta t}}{\sigma^2(1-e^{-\kappa\Delta t})} \cdot r_t \quad (18)$$

The transition density can be expressed using modified Bessel functions:

$$p(r_{t+\Delta t}|r_t) = c \exp(-u - v) \left(\frac{v}{u}\right)^{q/2} I_q(2\sqrt{uv}) \quad (19)$$

where $c = 2\kappa/[\sigma^2(1 - e^{-\kappa\Delta t})]$, $q = 2\kappa\theta/\sigma^2 - 1$, $u = cr_t e^{-\kappa\Delta t}$, $v = cr_{t+\Delta t}$, and $I_q(\cdot)$ is the modified Bessel function of the first kind.

Given observations $\{r_0, r_1, \dots, r_n\}$, the log-likelihood is:

$$\mathcal{L}(\kappa, \theta, \sigma) = \sum_{i=1}^n \log p(r_i|r_{i-1}; \kappa, \theta, \sigma) \quad (20)$$

We maximize $\mathcal{L}$ subject to:

$$\Theta = \{(\kappa, \theta, \sigma): \kappa > 0, \theta > 0, \sigma > 0, 2\kappa\theta > \sigma^2\} \quad (21)$$

Lastly, we employ differential evolution, a global optimization algorithm robust to local minima (Storn and Price, 1997).

Jump detection and calibration

We use a two-stage procedure:

Stage 1: Jump Detection

Compute rate changes $\Delta r_i = r_i - r_{i-1}$ and identify jumps using robust statistics:

$$\text{Jump at } i \Leftrightarrow \Delta r_i > \text{med}(\Delta r) + k \cdot 1.4826 \cdot \text{MAD}(\Delta r) \quad (22)$$

where $\text{MAD} = \text{median}(|\Delta r - \text{med}(\Delta r)|)$ is the median absolute deviation and the factor 1.4826 ensures consistency with the standard deviation for Gaussian data. We set $k = 3$.

Stage 2: Parameter Estimation

1. Remove detected jumps from the series
2. Estimate CIR parameters $(\hat{\kappa}, \hat{\theta}, \hat{\sigma})$ on filtered series via MLE
3. Estimate jump intensity: $\hat{\lambda} = n_{\text{jumps}}/T$
4. Estimate jump mean: $\hat{\mu} = \bar{f}$ (sample mean of jump sizes)

Monte Carlo simulation

We simulate $M = 10,000$ paths over horizon T with daily time steps $\Delta t = 1/365$ years. For each path, we simulate USDC supply rate and WETH borrow rate via CIR-Jump, generate WETH price paths via block bootstrap, and track position evolution including potential liquidation events.

Risk Metrics

We compute the following metrics from simulated paths:

Liquidation Probability

$$\hat{p}_{\text{liq}} = \frac{1}{M} \sum_{j=1}^M \mathbf{1}_{\{\tau^j \leq T\}} \quad (23)$$

The standard error is $\text{SE}(\hat{p}) = \sqrt{\hat{p}(1 - \hat{p})/M}$.

$$\hat{S}(t) = \frac{1}{M} \sum_{j=1}^M \mathbf{1}_{\{\tau^j > t\}} \quad (24)$$

Results

Table 1 shows descriptive statistics for the AAVE dataset. The mean USDC supply rate (4.98%) surpasses the mean WETH borrow rate (2.86%), suggesting, throughout the entire duration, a positive average spread of roughly 2.12 percentage points. The spread is favorable 76% of the time, indicating that the carry trade strategy can be profitable, depending on the price of the borrowed asset as well.



Table 1. Summary statistics of AAVE V3 data

Metric	Value
Sample Period	Jan 2023 - Jan 2026
Observations (hourly)	26,208
Average USDC variable Supply APR	4.98%
Average WETH variable Borrow APR	2.86%
Average Rate Spread	2.12pp
Spread > 0 (% of time)	76.1%
WETH Price Range	\$1,381 - \$4,926

Source: Authors' own research.

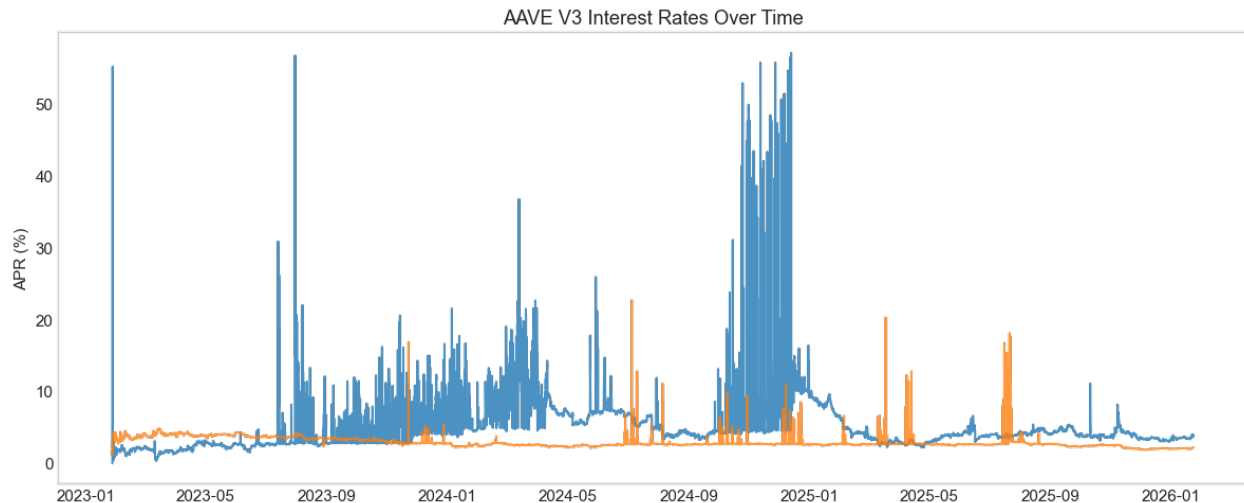
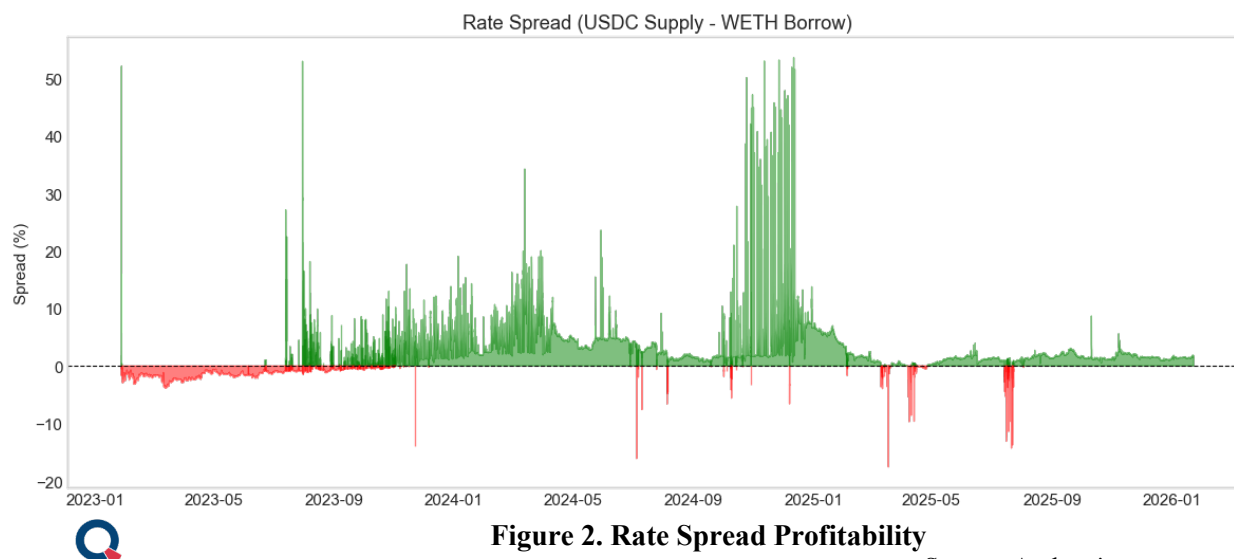


Figure 1. APR Time Series for USDC & WETH

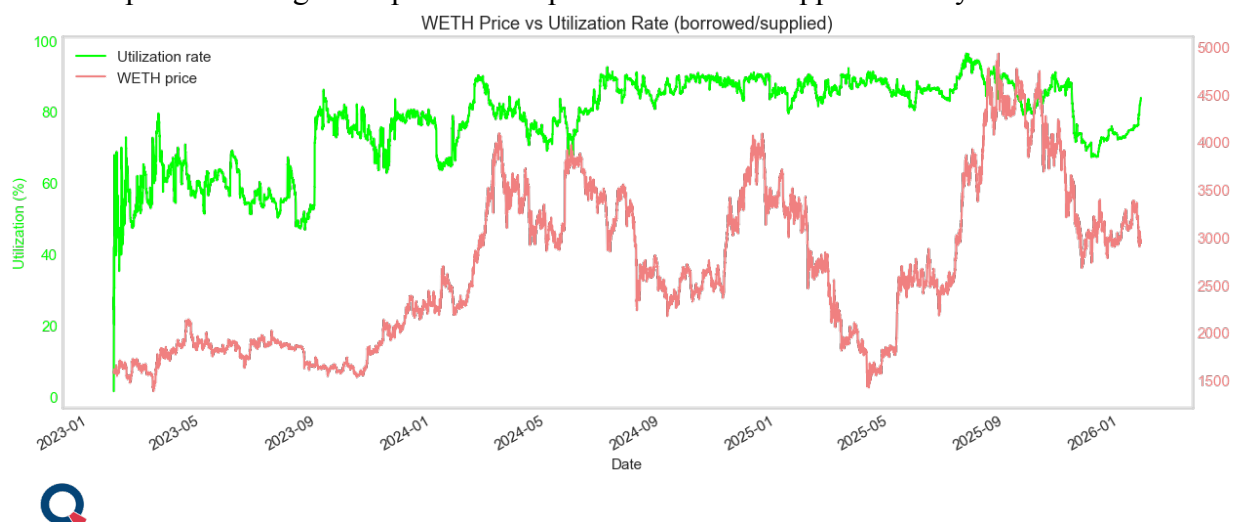
Source: Authors' own research.

Figure 1 illustrates hourly variable USDC supply APR and WETH borrowing APR over the 3 years we analyze. The series exhibit mean-reversion and jumps, with USDC experiencing more volatility and maintaining a higher average level.



Source: Authors' own research.

The interest rate spread can be seen in figure 2. Green denotes a positive spread, while red indicates periods of negative spread. The spread is favorable approximately 76% of the time.



Source: Authors' own research.

In figure 3 the time series of WETH's utilization rate and its price can be seen. Though they seem to follow similar paths, there are also timeframes where the relationship seems to be rather counterintuitive – there are periods of price fluctuation when utilization does not change too much. How much does the price determine the utilization rate remains to be seen, since the price itself is driven by a multitude of factors.

Table 2 displays the estimated parameter values for the CIR model and the enhanced CIR-Jump model. For the USDC lending APR, we have $\kappa = 28.82$, $\theta = 4.95\%$, and $\sigma = 0.823$. The Feller ratio of 4.21 guarantees positive rates. For the borrowing APR of WETH, the CIR model indicates an even quicker mean reversion ($\kappa = 50.00$) alongside a lower long-term mean

($\theta = 2.89\%$) and surprisingly lower volatility ($\sigma = 0.333$), resulting in a Feller ratio of 20.75. It is worth noting that the long-term mean of the model is very close to the historical average.

The CIR-Jump calibration identified 108 jumps in USDC APR and 87 jumps in WETH APR during the 3-year timeframe. For USDC, the jump intensity parameter $\lambda = 36.1$ jumps/year with an average size $\mu = 2.22\%$, showing that APR spikes are common but seem to be moderate. For WETH, the jump intensity is $\lambda = 29.1$ per year with a mean size of $\mu = 0.48\%$. These results show that DeFi lending rates show some irregular patterns that pure diffusion models are unable to represent.



Table 2. Calibrated model parameters

Parameter	USDC CIR	USDC CIR-Jump	WETH CIR	WETH CIR-Jump
κ (mean reversion)	28.82	39.93	50.00	50.00
θ (long-term mean)	4.95%	3.25%	2.89%	2.69%
σ (volatility)	0.823	0.533	0.373	0.333
λ (jumps/year)	—	36.10	—	29.08
μ (mean jump size)	—	2.22%	—	0.48%
Feller ratio	4.21	9.13	20.75	24.18
Jumps detected	—	108	—	87

Source: Authors' own research.

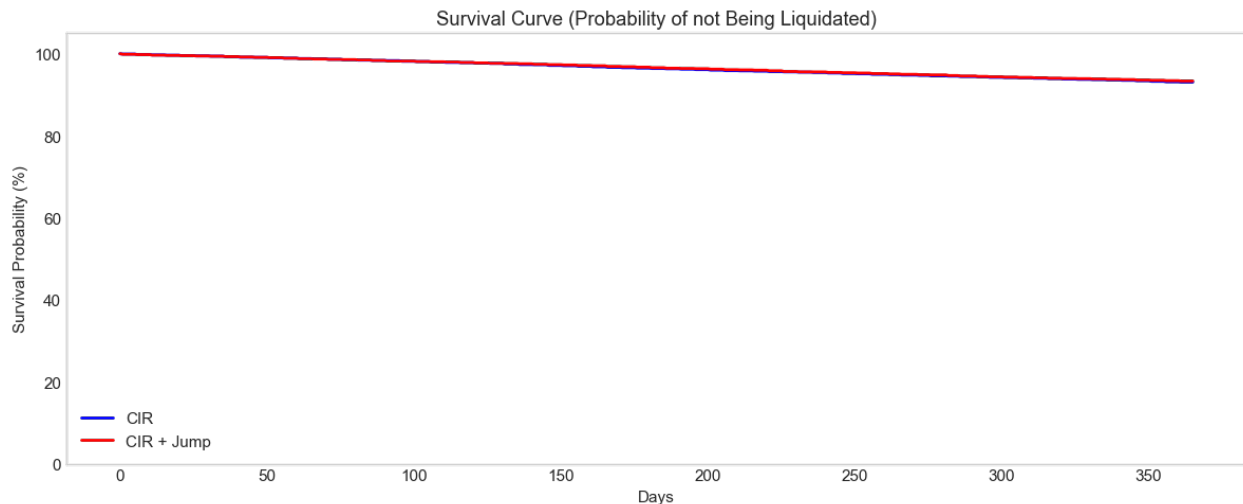


Figure 4. Survival Curve

Source: Authors' own research.

Figure 4 compares the probability of not being liquidated over a one-year period, using CIR and CIR-Jump. The curves follow an almost indistinguishable trajectory, indicating that liquidation risk is dominated rather by price dynamics than by fluctuations in the two interest rates.

Table 3 displays liquidation risk indicators for a 1-year period with an initial LTV ratio of 50%. Both models produce comparable liquidation probabilities: 6.93% for CIR and 6.65% for CIR-Jump. Incorporating jumps in the model has a positive, albeit small effect.



Table 3. Liquidation risk metrics (1-year horizon, 50% LTV)

Metric	CIR Model	CIR-Jump Model
Liquidation Probability	6.93%	6.65%
Survival Probability	93.07%	93.35%
30-day Liquidation Prob.	0.53%	0.55%
90-day Liquidation Prob.	1.64%	1.65%
180-day Liquidation Prob.	3.52%	3.28%
Mean Time to Liquidation	180 days	179 days
Median Time to Liquidation	176 days	181 days
Surviving LTV Mean	49.90%	49.74%
Surviving LTV 95th Percentile	52.08%	51.90%

Source: Authors' own research.

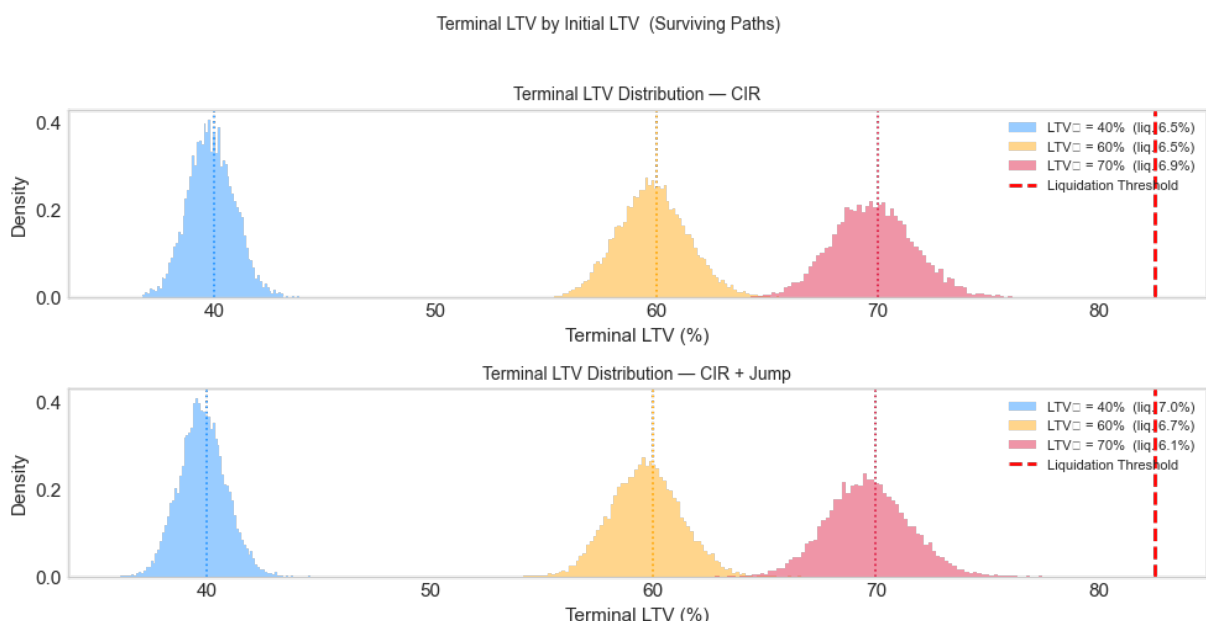


Figure 5. Terminal LTV Distributions for surviving paths – both models

Source: Authors' own research.

In figure 5, each distribution centers near its initial LTV due to modest drift, keeping the 40% starting LTV safely distant from the 82.5% liquidation threshold while 70% is visibly closer. The right tails are heavier with higher starting LTV, showing more paths passing 75%. These paths would be far more vulnerable to shocks, and in our case specifically, to stablecoin depeg events. It could be said that this starting setup range of the carry trade is quite efficient as far as survival of the two-token portfolio is considered.

Table 4 presents P&L statistics for each model. The carry trade proves to be profitable, even more so when jumps are accounted for – the r P&L, for the surviving paths, is \$2,621 for the simple model and \$2,948 for the jump model.



Table 4. P&L statistics (1-year horizon, \$100,000 collateral, 50% LTV)

Metric	CIR Model	CIR-Jump Model
Initial Equity	\$50,000	\$50,000
Mean P&L if survived	\$2,621	\$2,948
% Profitable Paths if survived	96.0%	97.9%

Source: Authors' own research.

The histograms in figure 6 show the final P&L distribution across 10,000 simulated paths. The two models present mostly profitable paths, with somewhat tight clustering and thin tails, though the left tail is visibly heavier. The inclusion of jumps improves profitability but also assigns a higher probability to experiencing losses. Jump dynamics also cause higher borrowing costs during APR spikes, which is representative of real DeFi dynamics where utilization can increase suddenly.

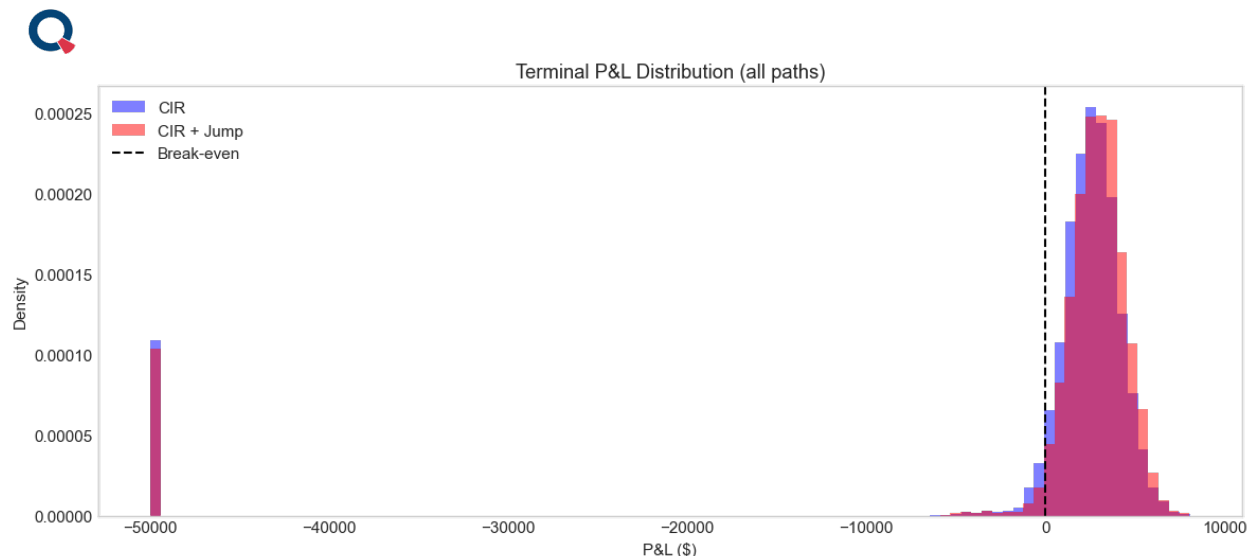


Figure 6. Terminal P&L Distribution (liquidations included)

Source: Authors' own research.

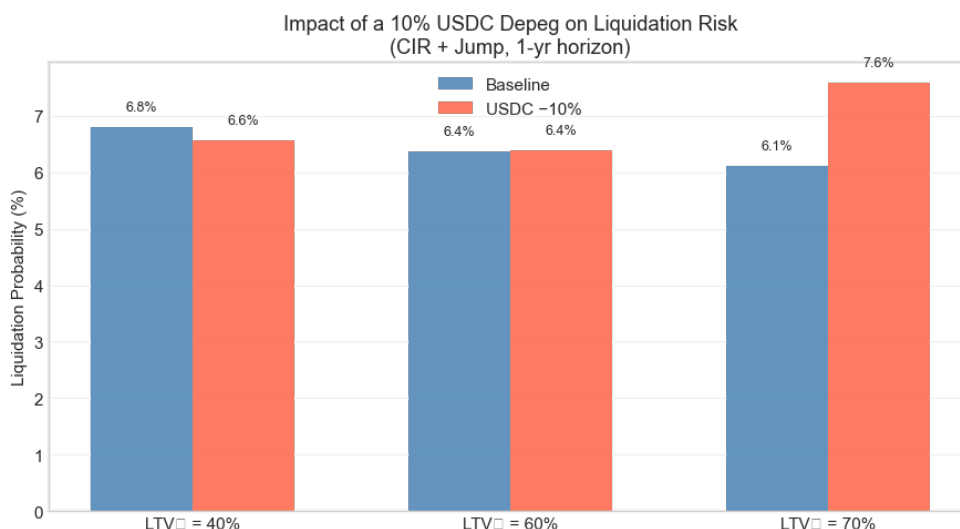


Figure 7. Sensitivity Analysis for depeg risk

Source: Authors' own research.

Figure 7 illustrates the non-linear escalation of liquidation risk in the event of a 10% depeg of USDC. The disparity between the blue (baseline) and orange (shocked) bars expands significantly as the initial loan-to-value (LTV) ratio rises — at 40%, liquidation probability very slightly decreases, likely an artifact of the simulation, whereas at 70%, the likelihood of liquidation spikes, indicating the diminishing buffer to the 82.5% threshold. Though rare, this scenario is not theoretical — USDC reached around \$0.87 during the Silicon Valley Bank incident in March 2023.

The findings highlight two main recommendations: 1) Keep LTV significantly below the maximum limits set by the protocol to maintain a buffer against collateral shocks, and 2) Static LTV targets are inadequate — it is necessary to monitor the stability of the stablecoin peg, at least to protect against such rare/extreme events.

Discussion

Our study uncovers a potential use case for carry trades backed by stablecoins in a DeFi setting: the interest rate differential can prove to be a source of profit, strong enough that it offsets the outstanding debt incurred by the occasional price appreciation in the short asset and the accumulated interest left to be paid.

It will be interesting to see how such a strategy would play out in the future, since ETH has experienced a serious drawdown over the last months and cryptocurrencies are in a bear market.

One noteworthy aspect is the sensitivity of the starting LTV. A value of 40% would likely keep a large amount of “idle” collateral, while starting with 70% would increase the liquidation probability and create a too fragile portfolio, where large negative price movements in the collateral would result in quick liquidation.

There are some limitations of our work which must be mentioned. First, we do not necessarily assume a functional form between a token’s APR and its price. The reason we have chosen to do so is because the strength and direction of this relationship is not clear, moreover it might vary depending on the specific assets used. Second, active rebalancing of the portfolio would likely be better for practical considerations. One more aspect that would be important is the inclusion of gas fees and slippage. Though we did mention the stablecoin depegging risk, quantifying this could prove challenging. Lastly, there are also platform-specific risks (e.g. smart contract vulnerabilities) which can pose a serious threat to a trading strategy.

Conclusion

We introduce a quantitative framework to assess the sustainability of leveraged carry trades on AAVE V3, augmenting the CIR model with Poisson-Exponential jumps to better capture DeFi interest rate dynamics. Using three years of hourly block data and 10,000 Monte Carlo simulations over a 1-year period, we show that a USDC deposit / WETH borrow strategy can yield positive expected returns, with a positive average interest rate spread of 2.12% and relatively healthy LTV ratio, with a small probability of liquidation.

Our simulations show a 6.5–6.9% one-year liquidation probability for a starting LTV range of 40-70% using the CIR model. Using the CIR+Jump model the probability of liquidation appears to be a monotonically decreasing function of the starting LTV: increasing the LTV results in decreasing the liquidation probability. Though this seems to be profitable on average, the portfolio is more fragile to volatile price movements in the two tokens.

In this USDC /WETH setup, a stablecoin-collateralized “carry trade” is quite profitable, even with WETH appreciating occasionally. In order for the position to survive, the expected supply-borrow spread must be greater than the expected WETH appreciation plus a liquidation-risk premium. For future improvements, some next steps can include testing hedged variants, dynamic LTV/risk rebalancing, and alternative asset pairs with better price-rate dynamics—though robust crypto opportunities remain very rare.

Acknowledgements

This paper is supported through the project “IDA Institute of Digital Assets”, CF166/15.11.2022, contract number CN760046/23.05.2023; the project “AI for Energy Finance (AI4EFin)”, CF162/15.11.2022, contract number CN760048/23.05.2023; the project “Accountable Governance and Responsible Innovation in Artificial Intelligence”, CF158/15.11.2022, contract number CN760047/23.05.2023, financed under the Romania’s National Recovery and Resilience Plan, Apel nr. PNRR-III-C9-2022-I8; and the Marie Skłodowska-Curie Actions under the European Union's Horizon Europe research and innovation program for the Industrial Doctoral Network on Digital Finance, acronym: DIGITAL, Project No. 101119635.

This paper was co-financed by The Bucharest University of Economic Studies during the PhD program.

During the preparation of this work, the authors utilized ChatGPT 5 and DeepSeek to enhance readability and language clarity. Following the use of this tool, the authors meticulously reviewed and revised the content as necessary and assume full responsibility for the final content of the publication.

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