Risk Management:
DeFi Lending & Borrowing

Kashish Mittal

The author is currently working at Genpact. The views expressed in this paper are her own and do not necessarily reflect those of her employer.

2023

Table of contents

Abstract

The decentralised finance (or "DeFi") industry has only emerged in the past few years and has made possible new ways to earn both passively and actively. Although DeFi offers new and exciting financial freedoms, all that upside does not come without sizeable risks. DeFi achieves unprecedented levels of financial automation by replacing intermediaries with automated financial technology, but it also introduces new challenges and risks that are understudied.

DeFi protocols have grown significantly over the years, with DeFi lending and borrowing being a major contributor. DeFi borrowers obtain leveraged exposure to cryptocurrency assets or make portfolio adjustments, and DeFi lenders receive better returns than from bank deposits or money market funds. Price action, incredible innovation, new products, token models, and governance structures in DeFi have been pushed out at a breakneck pace. Given the quality and originality of DeFi protocols, networks, and platforms, there is good reason for optimism concerning where DeFi is headed next.

To overcome the major limitations and reduce the risks of DeFi, such as the volatility of cryptocurrency collateral used for settlement, the absence of a reliable Oracle, and trustless transactions, risk management techniques are proposed in this paper, like the VaR model for collateralised loans, the time-weighted average price approach, and DeFi score cards. This paper does not seek to universally recommend any specific actions, but rather to identify and suggest potential approaches to risk mitigation in the DeFi context.

Acknowledgement

I would like to thank my colleagues, both from Genpact and the industry at large, with whom I have discussed this subject on various occasions.

1. Introduction

DeFi refers to financial services that have neither a central authority nor someone in charge. DeFi is built on top of decentralised money like certain cryptocurrencies, which can be programmed for building lending services, insurance companies, bridges, and Dexes[1].

DeFi challenges the conventional financial infrastructure and offers several potential suggestions for its problems. DeFi platforms offer an alternative system rather than merely a plug-in to the current banking and financial systems. Since they are intended to become independent from their developers and backers and eventually be managed by a community of users whose power originates from holding the protocol's tokens, these platforms have the biggest potential to shape the future of finance.

In early 2022, the TVL (total value locked)[2] in DeFi protocols was above USD 200 billion, of which 20% was held by DeFi lending platforms. The TVL in the DeFi lending protocols increased from practically nothing in 2020 to USD 50 billion at the beginning of 2022 [1]. When the algorithmic stablecoin TerraUSD (UST) collapsed, which is regarded as the biggest crypto crash, it wiped away an estimated $60 billion across protocols [2], and caused the TVL in DeFi protocols to fall to less than USD 150 billion in early May.

DeFi lending has grown rapidly as a result of accessibility, ease of use, and yields.

Exhibit 1: Total value locked by category

USD bn

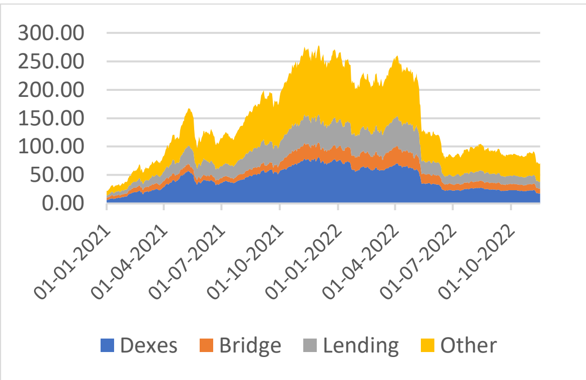
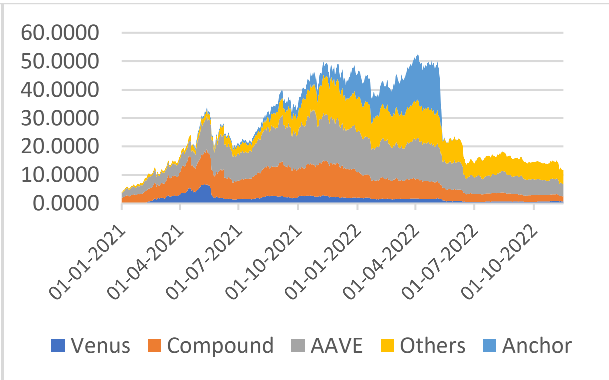


Exhibit 2: Total value locked in lending platforms

USD bn



Data accessed on November 16, 2022, for the period January 01, 2021, to November 16, 2022
Sources: DefiLlama data [1]

---

[1] "Dexes" are decentralised crypto exchanges that connect buyers and sellers of cryptocurrency for trading and swapping.
[2] "Total Value locked" represents the number of assets that are being staked in a specific protocol. See, https://coinmarketcap.com/alexandria/glossary/total-value-locked-tvl

DeFi lending protocols enable a permissionless environment for anyone to participate in the lending and borrowing setup. It needs to be developed with the aid of risk identification, assessment, and comprehensive risk management because there are plenty of opportunities but also a lot of risks.

This paper is based on the problem statement: ***"The best approaches for reducing and managing the risks associated with DeFi lending and borrowing."***

Identification and quantification of risk are done to develop a well-defined risk plan with the appropriate frameworks and form hypotheses on strategies that will help minimise the risk on DeFi lending and borrowing platforms. At last, potential strategies have been evaluated for drawing conclusions. In this paper, a few risk-management strategies have been proposed for managing risk effectively.

- **Market risk assessment for collateralised loans**: A VaR-based haircut mechanism has been proposed to be constructed for assessing market risk on collateral, and the results have been backtested to confirm the accuracy of the model. Additionally, a rating mechanism has been suggested for collateral acceptability, which can aid in lowering high liquidation issues and significant losses.

- **Mechanism for determining fair price:** Since the fair value of the collateral that the borrower is depositing determines the amount of loan that can be borrowed, a reliable mechanism can be established by incorporating the time-weighted average price with the last trading price. This would ensure fair collateral pricing and reduce the risk of price manipulation.

- **Introducing the DeFi credit score**: An effective on-chain credit score mechanism is proposed that will enable lenders to provide different interest rates and leverages based on the user profile. As a result, capital would be better utilised, counterparty risk would be reduced, and collateralised lending would be more efficient.

2. DeFi Lending vs. Traditional Lending

At a compound annual growth rate (CAGR) of 10.1%, the global lending and payments industry grew from USD 7887.89 billion in 2022 to USD 8682.26 billion in 2023 and is anticipated to grow to USD 12176.98 billion in 2027 at a CAGR of 8.8% [3].

Traditionally, the financial sector works as an intermediary between depositors and borrowers to earn a spread, where depositors keep their money in banks to earn interest, which banks then lend to borrowers and charge interest in return.

2.1 Problems with traditional lending

Banks play a major role in nearly all financial services, and their problems are becoming increasingly apparent: loan settlement takes days and requires a massive amount of human capital involved in the process; key decisions affecting billions of people are made by a privileged few people; compounded costs due to middlemen; slow transactions; delays for cross-border transactions; and inaccessibility to many sectors. Banks are hiring thousands of employees just to maintain inefficient processes and be compliant with ever-changing banking regulations [4].

In addition to that fund's custody, which is the major disadvantage of a centralised financial institution in which users trust companies with their assets and information, exchanges can only protect user funds up to a specific amount. Empowering consumers to hold their funds in ideally cold wallets significantly reduces the chance their funds will be lost to a company's insolvency, like in the recent collapse of FTX, the world's second-largest exchange, which wiped out USD 1 billion of customer funds [5]. Decentralised lending can help with some of these issues because we need something different and better to deal with them.

2.2 DeFi as a solution

DeFi is a new industry that is changing the financial landscape. Instead of relying on the conventional loan processing systems of the banks, DeFi lending enables individuals to become lenders just like a bank. Interest rates on DeFi lending are more lucrative than the rates offered by traditional banks. DeFi lending leverages the power of decentralisation and blockchain to build a new financial system that can provide access to well-known financial services in a more efficient, transparent, fair, and open way.

Exhibit 3: DeFi lending platform benefits

Efficient as DeFi loans are processed quickly. Once a loan is accepted, the amount is immediately available. It makes no difference whether the counterparties are in a different country with distinct rules and laws. Additionally, the majority of DeFi protocols can operate with little to no human interaction.

Immutability and Transparency as every transaction is visible on the blockchain, trading volume, the number of outstanding loans, and total debt can be reliably checked on the blockchain. DeFi lending ensures transparency, as the decentralised nature of the blockchain ensures that all the transactions are genuine.

Fair as the services are completely permissionless; anyone with a browser and an internet connection can access them; no documents are required; and nationality or race are irrelevant. Everyone is treated in the exact same way and is censorship-resistant, as no other party can deny us access to these services. Even multiple bad actors cannot change the rules of a sufficiently decentralised system.

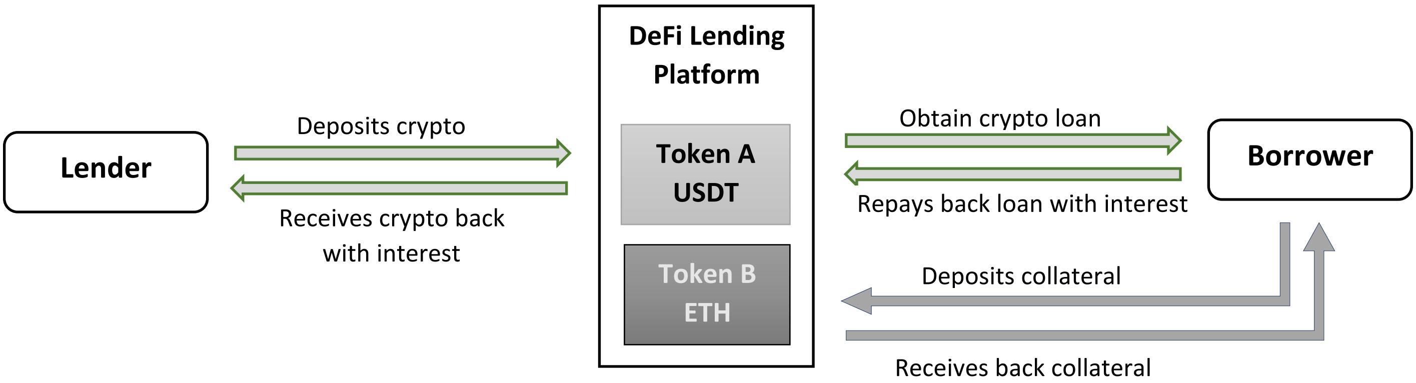
Self-custody as the use of Web3 wallets, which enable the users to be the sole custodians of their crypto assets and control their data. This means there are no limitations on how users can access their funds; there are no fees; and there is no need to get permission when users want to move assets around.

Interoperability and Programmability as use of an interconnected software stack ensures that Defi protocols and applications integrate and complement one another. Also, contracts are highly programmable and enable the development of financial instruments and digital assets.

3. Mechanics of DeFi Lending and Borrowing

Lending platforms are a crucial part of the DeFi ecosystem. DeFi lending enables users to become lenders or borrowers while preserving full custody of their coins in a completely open and permissionless manner. Smart contracts[3] that function on open blockchains like Ethereum are the foundation of DeFi lending. Users who want to become lenders submit their tokens to a particular protocol and start earning interest on their tokens according to their current supply annual percentage yield (APY).[4] The supply tokens are sent to a smart contract and become available for other users to borrow in exchange for collateral.

Exhibit 4: Crypto loans mechanism



When a borrower creates a loan on a platform, the platform's smart contracts retain custody of the collateral for the lifetime of the loan. In exchange, the platform provides a receipt token that can be exchanged for the collateral supplied along with accrued interest, which is determined by the borrow APY. These tokens, which are often pegged at a fixed rate to fiat or cryptocurrency, can be transferred between parties, but only the original party can redeem them for the associated collateral. Defi lending, while reducing much of the risk associated with centralised finance, carries its own set of risks, primarily the risk of smart contracts but also the risk of rapidly changing APYs. During mid-year 2020, the borrow APY on the bat token went up to over 30% on compound [6]. This could cause unaware users who are not tracking interest rates daily to have their loans liquidated by having to repay more than expected.

[3] "Smart contracts" are blockchain-based programmes that execute when predetermined conditions are met. See, [What are smart contracts on blockchain? | IBM]

[4] APY refers to an annualised interest rate of return earned from an investment, factoring in compound interest that accrues with the balance.

4. Managing Risk in DeFi Lending and Borrowing

Looking ahead, step-change innovation that unlocks enormous efficiency will be crucial for DeFi lending to support the real economy. This section focuses on the identification and evaluation of a number of measures to demonstrate effective risk management by overcoming the major limitations of DeFi, like the volatility of crypto collateral used for settlement, the lack of a reliable oracle, and trustless transactions, from using a VaR model for collateralised loans to, the time-weighted average price approach and credit score cards. Rather than providing an exhaustive list of DeFi mitigating variables, the purpose of this paper is to describe techniques for reducing risks and increasing the value of DeFi lending.

4.1 Market risk assessment for collateralised loans

DeFi uses a decentralised ledger to run smart contracts that automatically enforce the terms of a lending contract and safeguard the collateral. Because of the hidden identities of borrowers and lenders and the volatile nature of crypto, the DeFi lending platform relies heavily on collateral. Only assets created on blockchains can be borrowed in a decentralised manner using collateral; the borrower locks assets in the form of one token as collateral in a smart contract and receives a loan in the form of another token. Borrowers need to pledge a minimum amount of collateral to receive a loan that is determined on the basis of a haircut, or margin. To account for the volatility of crypto assets, loans are typically over-collateralised, meaning the value of the collateral must be higher than the value of the loan. For instance, if someone needs a loan of USD 100, they might be asked to keep collateral worth USD 150 in another coin. The lending platform ensures that enough collateral is locked over time, and if the collateral depreciates below a liquidation threshold, the position is said to be under-collateralised and could be liquidated. The delta between the loan-to-value and the liquidation threshold is a safety mechanism in place for lenders.

Due to this, the calculation of the collateral requirement becomes very critical. High collateral requirements mean inefficient use of capital and hence slower growth of DeFi lending, while low collateral requirements may lead to other risks due to liquidations. Since the collateral accepted is mostly crypto, which is highly volatile and follows a cyclical nature, the entire lending and borrowing process becomes procyclical as borrowing demand shoots up when collateral value is higher and vice versa.

Another risk with DeFi loans is the high level of interconnectedness across lending platforms. This suggests that if one protocol suffers an operational shutdown or a run-on deposit, the issue could quickly affect multiple DeFi protocols due to a lack of transparency in funding sources, as it is unclear whether the collateral is fully owned by the depositor or if it is a debt owed to another protocol. This cascading impact can be seen in the recent collapse of the algorithmic stablecoin TerraUSD (UST). Terra was accepted as collateral on multiple protocols; its collapse led to the largest crypto crash, with an estimated USD 60 billion wipeout across protocols, shaking the global digital currency market [2].

4.1.1 Collateral Acceptability

The lending platform shall specify the list of eligible cryptocurrencies that shall qualify for collateral contribution for a borrow position in spite of taking any token as collateral, which would otherwise cause liquidation issues and huge losses. It can also adopt a rating mechanism based on multiple factors, primarily liquidity, to determine which tokens qualify to be used as collateral.

In the rating mechanism, weights can be assigned to the tokens based on multiple factors, like the total value locked on the token, the number of users, past trading activity on the token, and volatility. Liquidity is another significant one, as in the event of the liquidation of an illiquid, large, or concentrated token, market prices of the token could be depressed, bid/ask spreads could widen, and some of it might have to be sold at a steep discount. In simple terms, liquidity can be referred to as how easy or difficult it would be to sell a token without impacting the price. Liquidity can be calculated either by various liquidity ratios or the bid-ask spread and volume of a particular token. Since the bid-ask price must meet for a transaction to occur, consistently large bid-ask spreads imply low volume in a cryptocurrency, while consistently small bid-ask spreads imply high volume. Although stablecoins are considered the safest cryptocurrencies and many lending platforms accept stablecoins as collateral, as mentioned earlier, the collapse of the Terra blockchain has shaken confidence in stablecoins too. So, a lending platform should develop a safe and efficient rating mechanism to access the liquidity and quality of a cryptocurrency to qualify as collateral.

4.1.2 Collateral limits

Lending platforms may, at their discretion, specify the maximum amount a single token may deposit by way of collateral contribution, as a large concentration of a cryptocurrency can cause a sudden fall in the price in the event of liquidation. Similarly, a lending platform can define limits for borrowing, such as the maximum amount of an asset that can be borrowed because large borrowings of an illiquid token may lead to price exploits and protocol insolvency.

4.1.3 Collateral valuation

Due to the highly volatile nature of cryptocurrencies, collateral must be valued at regular intervals, which may be every minute. Valuations are subject to parametrised checks of Oracle prices and assessments of their robustness. Large movements in the prices should be highlighted by exception, and the liquidator should take cautious measures in such events.

4.1.4 Collateral haircut methodology

Haircut, a discount on the market value of securities taken in as collateral, to make sure the lender is sufficiently covered with collateral in case the value of the loan assets declines. In this paper, VaR-based haircut mechanism have been constructed for collateral market risk. Typically, lending platforms use a simple moving average (MA) approach for capturing volatility risk or peak volatility percentages. Here exponentially weighted moving average (EWMA) measure has been suggested rather than MA, as EMWA smooths the volatility curve and gives more weight to recent data than to historical data, making it more relevant for future forecasts.

We are using Ethereum/USD historical price data from January 01, 2021, to November 25, 2022, to compute one-day VaR at a 99% confidence interval.

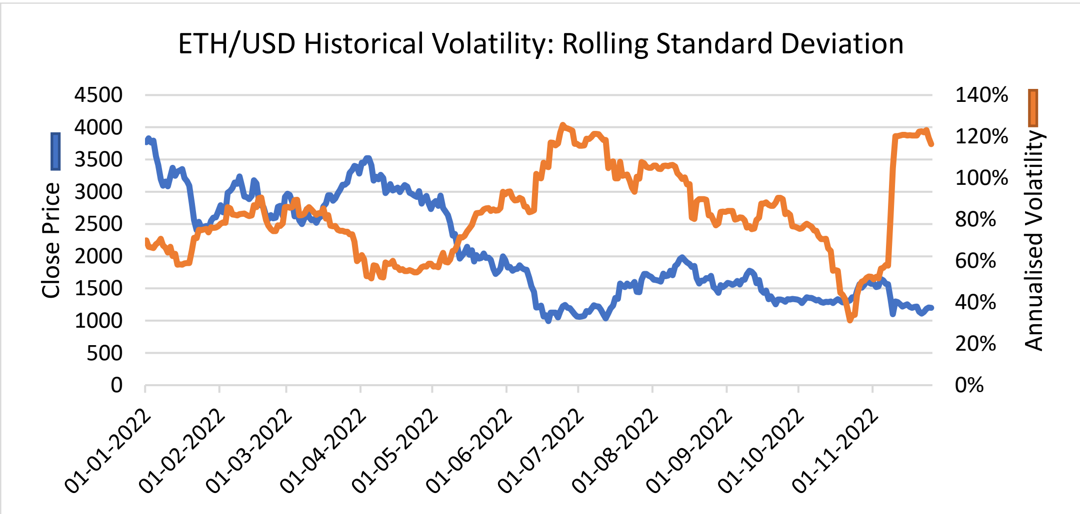
To calculate volatility, we first calculate the continuously compounded daily returns for the Ethereum price from January 01, 2021, to November 25, 2022, using the below formula.

$$r_j = \ln (P_j / P_{j-1})$$

Where,
r is the log return
P is the price
$_j$ is the time instant. For daily returns, there are 24 hours between $_j$ and $_{j-1}$.

The volatility of the token can be seen in the graph below. At the start of the year, volatility was around 60%, and it shot up to 126% due to the cryptocurrency market crash in June 2022. During this period, the ETH price dropped from USD 4000 to USD 993. The global crypto market cap shrank below USD 1 trillion after touching the USD 3 trillion mark in 2021 due to a massive sell-off by investors amid heightened inflation fears and the pausing of withdrawals by crypto lending service Celsius [7].

Exhibit 5: ETH/USD historical volatility computed from a 30-day rolling standard deviation



Data accessed on November 25, 2022, for the period January 01, 2022, to November 25, 2022
Sources: finance.yahoo [8]*; authors' calculations*
Annualised volatility is computed from the standard deviation of the logarithmic daily return where the last 30-day rolling period was considered for calculation.

The recursive equation of the EWMA model can be written as:

$$\text{EWMA Variance} = \sigma_j^2 = \lambda^*(\sigma_{j-1})^2 + (1 - \lambda)\, r_{j-1}^2$$

Where,
σ_j^2 is the estimated variance on day j
σ_{j-1} is denoted as the variance on day j-1

r is the return on day j-1

$_j$ is the time horizon

λ is the decay factor used to reduce each subsequent weight the further back into history we go; its value could change between 0 and 1, 1 − λ is the highest weight assigned to the most recent return. In times of high market uncertainty, it may make sense to tune the value of the Lambda to a lower value to put more weight on recent events and consequently have a more adaptive measure of volatility and minimise the forecast error. Here, we are using the lambda as suggested by RiskMetrics which is 0.94 [9].

For this study, we follow a simple estimation procedure: using the EWMA variance formula to calculate volatility from January 1, 2022, to November 25, 2022, where the first variance is calculated by utilising the excel variance function "VAR.P" of the previous 365 days' logarithmic return. For the next day's calculation, i.e., from January 2, 2022, onward, we are using the EMWA variance formula:

i.e., EMWA variance for January 02, 2022 = lambda *(Previous day's variance, January 1, 2022) + (1-lambda) *(Today's squared return, January 2, 2022) = 0.94*0.0031 + (1-0.94)*$(0.0234)^2$.

The daily EMWA volatility, i.e., standard deviation, is derived by taking the square root of the EMWA variance previously calculated, which is represented as:

$$\text{EMWA Volatility} = \sigma_j = \sqrt{\text{EMWA Variance}}$$

Value at risk (VaR) is a function of the volatility or standard deviation at the desired confidence level[5]; here we have considered a 99% confidence interval.

VaR = standard deviation (σ_j) * z-value of the standard normal cumulative distribution corresponding with 99%.

We use the Excel function "NORMSINV(0.99)" to calculate the z-value, and the resulting z-value is 2.326. The table below represents the daily VaR at a 99% confidence interval for Ethereum/USD for the first 15 days of the period.

Exhibit 6: Daily VaR at 99% confidence interval for the daily returns of ETH/UST using EMWA approach

(fig. in ETH/USD)

Date	Close Price	Daily Returns	EWMA 0.94	SD = SQRT(EWMA)	VaR 0.99
01-01-2022	3769.70	0.0234	0.0031	0.0561	-
02-01-2022	3829.56	0.0158	0.0030	0.0547	12.72%
03-01-2022	3761.38	-0.0180	0.0028	0.0531	12.36%
04-01-2022	3794.06	0.0086	0.0027	0.0517	12.03%
05-01-2022	3550.39	-0.0664	0.0025	0.0502	11.68%
06-01-2022	3418.41	-0.0379	0.0026	0.0513	11.93%
07-01-2022	3193.21	-0.0681	0.0026	0.0506	11.77%
08-01-2022	3091.97	-0.0322	0.0027	0.0518	12.05%

[5] VaR is an estimation of the potential loss in value of a portfolio as a result of changes in market prices over a specified time period with a specified level of confidence.

Date	Close Price	Daily Returns	EWMA 0.94	SD = SQRT(EWMA)	VaR 0.99
09-01-2022	3157.75	0.0211	0.0026	0.0509	11.83%
10-01-2022	3083.10	-0.0239	0.0025	0.0496	11.53%
11-01-2022	3238.11	0.0491	0.0023	0.0484	11.26%
12-01-2022	3372.26	0.0406	0.0023	0.0485	11.27%
13-01-2022	3248.29	-0.0375	0.0023	0.0480	11.17%
14-01-2022	3310.00	0.0188	0.0023	0.0475	11.04%
15-01-2022	3330.53	0.0062	0.0021	0.0462	10.76%

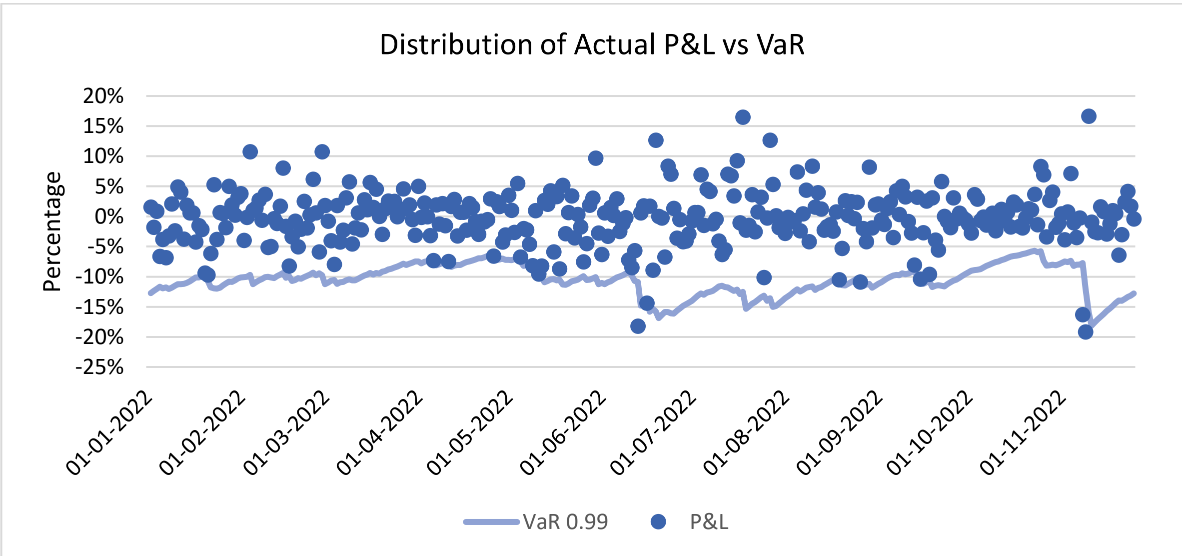
Data accessed on November 25, 2022, for the period January 01, 2021, to November 25, 2022.
Sources: finance.yahoo [8]*; authors' calculations*
Note: From January 1, 2022, to November 25, 2022, we calculated daily VaR and presented the first 15 observations for the reader's understanding.

4.1.5 Result and Interpretation

As a result, in the last column of the table, VaR is determined at a 99% confidence interval and considered the haircut for the collateral, allowing the platform to measure volatility risk where collateral value can be determined after subtracting the haircut percentage.

To check whether the VaR model's prediction of losses is reasonably accurate, backtesting is done, where actual daily profit and loss (P&L) are compared to the predicted level of losses by the model at a given level of confidence. This identifies instances where VaR has been underestimated, meaning the loss experienced is greater than the original VaR estimate. In our example, we will compare the actual P&L as compared to the predicted losses by the VaR model on a daily basis. An exception is recorded whenever the actual loss is greater than the predicted loss. The number of exceptions in the VaR context falling outside of the confidence level should not exceed one minus the confidence level. In this example, exceptions should occur less than 1% of the time at a 99% confidence level, i.e., 329 days (from January 1, 2022, to November 25, 2022), *1%, which equals 3.29 exceptions.

Exhibit 7: Chart of ETH/USD daily P&L vs. calculated VaR losses



Data accessed on November 25, 2022, for the period January 01, 2022, to November 25, 2022.
Sources: finance.yahoo [8]*; authors' calculations*

In the chart above, the jagged line running across the bottom of the chart indicates the one-day 99% VaR. An exception is recorded when instances of a P&L fall below that line. We would expect a 99% VaR measure to experience approximately 3.29 exceptions in 329 days. In this chart, we count 3. Therefore, the haircuts calculated above via a VaR-based approach are stable and in sync with the estimated volatility. The overall behaviour is expected and relatively stable.

4.1.6 Currency Haircut

In the above example, we have assumed that the collateral currency and the loan in the form of cryptocurrency both have the same underlying currency. That's why we have calculated a haircut based on volatility. When exposure and collateral are held in different currencies, there is a currency mismatch. Then, an additional downward adjustment must be made to the volatility-adjusted collateral amount to take into account possible future fluctuations in exchange rates.

4.1.7 Collateral haircut setting process

Collateralisation parameters cannot be something static, fixed in the smart contracts, but need to be continuously recalculated. Collateral haircuts need to be checked daily due to the volatile nature of crypto. If any material change is noticed, it needs to be adjusted accordingly. Haircuts should be backtested on an hourly basis to check for appropriateness, and whenever significant breaches are observed, haircuts should be immediately recalculated. However, in extreme and stressful scenarios, haircuts need to be revisited on a minute-by-minute basis.

4.2 Mechanism for Determining the Fair Price

DeFi has exploded from a niche market into a billion-dollar industry. Dune Analytics reports a 4 million user increase in DeFi applications such as DeFi lending over the last two years. That is nearly 40 times larger than the 2020 user pool [10]. However, in parallel with the growth of investments in DeFi, Oracle manipulation and hack rates are also increasing, with over USD 154 million stolen only in 2020 [11]. The decentralised platforms utilise oracles, which act as an intermediary bridging real-world (off-chain) services and blockchain (on-chain) protocols. Oracles retrieve off-chain data and publish this real-time data on the blockchain to be then used by smart contracts. If oracles are poorly selected or managed, the funds of a rising number of investors are inevitably in danger. Oracles in lending pools are important as they determine the price of assets and those held as collateral. The value of a deposited digital asset determines the amount of a loan that can be borrowed and, for lenders, the interest to be accrued.

So far, many cases have been documented in which attackers exploited a vulnerability in a DeFi platform by using Oracle prices. In mid-October 2022, attackers exploited Mango markets, the DeFi lending platform on Solana, and stole more than USD 110 million worth of cryptocurrencies off the network [12].

The attacker began their mission by funding an account on the site with USD Coin for USD 5 million, then artificially inflating the price of the illiquid MNGO token, the platform's native cryptocurrency, from USD 0.03 to USD 0.091 by taking out a large position in Mango's perpetual futures contracts. They then used their significant unrealised profits as collateral to borrow assets belonging to the protocol and eliminated all of the liquidity in Mango markets, which resulted in a steep drop in the price of MNGO to USD 0.02, draining over USD 110 million from its treasury. A similar instance of pump-and-dump was recorded with the Ethereum-based lending protocol Inverse Finance (INV), where attackers stole USD 15.6 million worth of cryptocurrency [13].

4.2.1 Time-Weighted Average Price for lending oracles

To prevent oracle price manipulation by artificially inflating a token price by making huge purchase orders to push the price, there needs to be a more robust system of calculating the fair value of the collateral that the borrower is giving. One such way to reduce dependencies and validate the oracle price is to incorporate a time-weighted average price (TWAP) so that any noise can be avoided and the fair value of collateral can be assessed for borrowing.

4.2.2 Calculating TWAP

TWAP is a pricing methodology that calculates the mean price of an asset during a specified period of time. For example, a "one-hour TWAP" means taking the average price over an hour. It is used to regulate artificial price movements and to eliminate short-term price fluctuation or manipulation. TWAP is calculated using the following formula: the price **P** multiplied by how long it lasts **T** is continuously added to a cumulative value [14].

$$TWAP = \frac{\sum_j P_j . T_j}{\sum_j T_j}$$

Where,

$_j$ is each individual measurement that occurs over a specified period

P_j denotes the current security price at the time of measurement $_j$

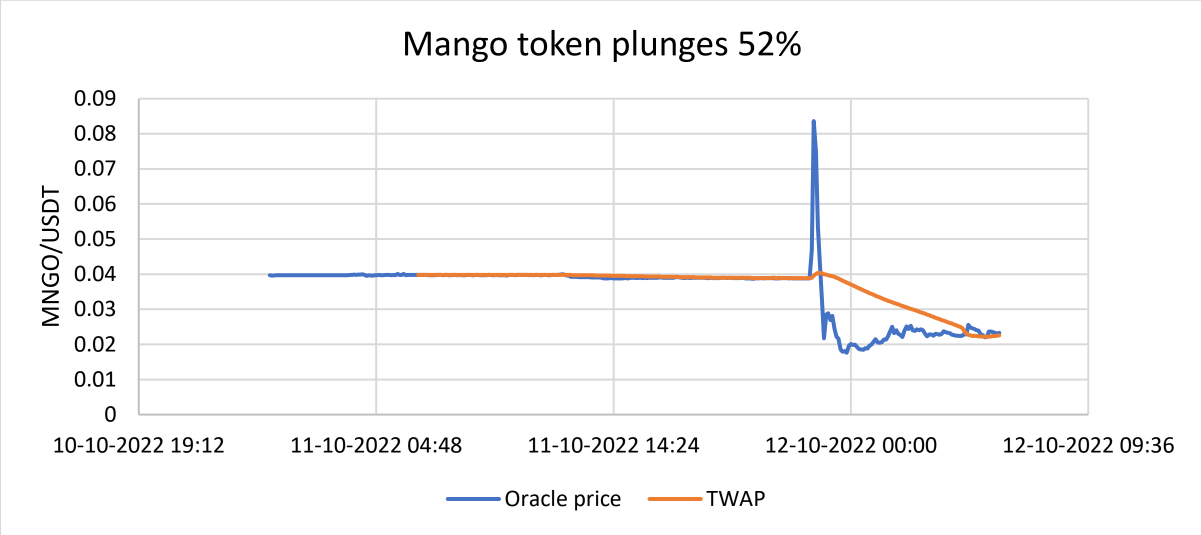
T_j is a change of time since the previous price measurement

4.2.3 Approach

Because TWAP is an average price over time, it is slow to react to price changes; lenders should deploy some accepted tolerance level between the last trading price (LTP) and the TWAP. This helps to keep a fine balance between risk and a fair collateral assessment. Also, as TWAP is flatter and slower to react when the prices are going down, this might lead to extra risk if the prices are indeed plunging. So, lenders need to develop a method to consider TWAP plus some threshold as the limit when LTP is more than TWAP and only consider the LTP and not TWAP when the LTP is lower than TWAP; otherwise, it can cause an understatement of risk.

The following is a case study of Mango market prices on October 11th and 12th, 2022, and how the USD 110 million Mango market hack could have been avoided with this TWAP approach. For this case study, we have considered the threshold at 10%.

Exhibit 8: Dynamics of TWAP in response to short-term fluctuations in Mango prices



Data accessed on November 23, 2022 *Sources: 6gate.io* [15]*; TWAP: authors' calculations.*
As the graph depicts, TWAP is flatter than Oracle Price and reacts very little to a sudden artificial price increase in Mango. It also reacts slowly when prices start plunging.

The attacker started pumping up the Mango-USDT prices in the illiquid market and pumped the price from USD 0.03 to USD 0.09 within a few minutes. Since oracle considered LTP for collateral value calculation, he was able to take a loan at 3x prices. After obtaining the loan, the attacker immediately sold the tokens, resulting in liquidations and a loss of approximately USD 110 million to the Mango Treasury and its users. Using the TWAP method for Oracle pricing would have avoided this incident. As shown in the table below, at 10.30 UTC, the oracle using the TWAP method would have reported a price of 0.0396 instead of 0.0836, hence a lower loan amount would have been approved.

Exhibit 9: Price (LTP or TWAP) to be considered for collateral value assessment of Mango tokens.

(fig. in MNGO/USDT)

Time (a)	LTP (b)	TWAP (c)	TWAP*1.10 (d)	Is (b<d)	Considered Price
11-10-2022 22:20	0.0388	0.0389	0.0428	Yes	0.0388
11-10-2022 22:25	0.0469	0.0390	0.0429	No	0.0390
11-10-2022 22:30	0.0836	0.0396	0.0436	No	0.0396
11-10-2022 22:35	0.0748	0.0401	0.0441	No	0.0401
11-10-2022 22:40	0.0535	0.0403	0.0443	No	0.0403
11-10-2022 22:45	0.0417	0.0403	0.0444	Yes	0.0417
11-10-2022 22:50	0.0322	0.0403	0.0443	Yes	0.0322
11-10-2022 22:55	0.0217	0.0400	0.0440	Yes	0.0217
11-10-2022 23:00	0.0285	0.0399	0.0439	Yes	0.0285
11-10-2022 23:05	0.0288	0.0397	0.0437	Yes	0.0288
11-10-2022 23:10	0.0269	0.0396	0.0435	Yes	0.0269
11-10-2022 23:15	0.0281	0.0394	0.0434	Yes	0.0281
11-10-2022 23:20	0.0244	0.0392	0.0431	Yes	0.0244

Time (a)	LTP (b)	TWAP (c)	TWAP*1.10 (d)	Is (b<d)	Considered Price
11-10-2022 23:25	0.0222	0.0390	0.0429	Yes	0.0222
11-10-2022 23:30	0.0217	0.0388	0.0426	Yes	0.0217
11-10-2022 23:35	0.0185	0.0385	0.0423	Yes	0.0185
11-10-2022 23:40	0.0179	0.0382	0.0420	Yes	0.0179
11-10-2022 23:45	0.0181	0.0379	0.0417	Yes	0.0181

Data accessed on 23 November 2022; Data Source: 6gate.io [15]*; TWAP and final price: authors' calculations*
*Note: The criteria have been defined as when LTP is greater than TWAP*1.10, TWAP is accepted (marked in blue), and in all other cases, the real-time LTP price is considered.*

4.3 Introducing DeFi credit score

The key foundation of efficient and mature capital markets is reputational-based credit. It helps build trust and relationships and allows for capital efficiency [16]. The core mechanism of global credit markets is a lender's efficient evaluation of a counterparty's credit risk and the subsequent pricing of their overall cost of capital. Despite the importance of reputational credit, DeFi uses trustless transactions on the blockchain, which maintains the anonymity of borrowers and lenders as no user data is collected. Because of hidden identities, risk assessment and asset recovery become very difficult for on-chain debt markets. Building an efficient on-chain credit score would represent a step-change innovation for the DeFi lending industry.

The total value locked in uncollateralised lending was more than USD 140 million in November 2022 [1]. These protocols require users to fund an initial margin amount, after which they may borrow up to the platform's determined leverage. These lending protocols built for individual users enforce repayment via an immutable smart contract and enable users to leverage positions via recursive borrowing: users supply ETH to borrow USDT, purchase more ETH, and borrow more USDT against their ETH loan. This process leverages against a diminishing amount of collateral. On-chain credit scores based on the user's profile would allow lenders to offer different interest rates and leverages. This would result in increased capital utilisation and efficient collateralised lending.

By utilising credit scores to increase transparency, minimise counterparty risk, and improve liquidation mechanisms, it will become far easier to identify and mitigate the following risks before they become systemic.

Exhibit 10: Risks mitigated by using DeFi credit score

Credit risk	▪ Credit scores enable lenders to assess a borrower's creditworthiness and assist lenders in granting better interest rates and lowering collateral requirements to participants with better and more consistent track records. ▪ Provides a credit risk assessment for individual wallet addresses based on historical on-chain borrowing activity and thereby reduces default risk. ▪ It allows lenders to supply liquidity preferentially based on the credit risk of individual borrowers which results in the formation of a credit spread between different risk profiles. ▪ Creates a user profile for borrowers, which in turn helps to obtain loans in a reasonable time or at a reasonable cost.

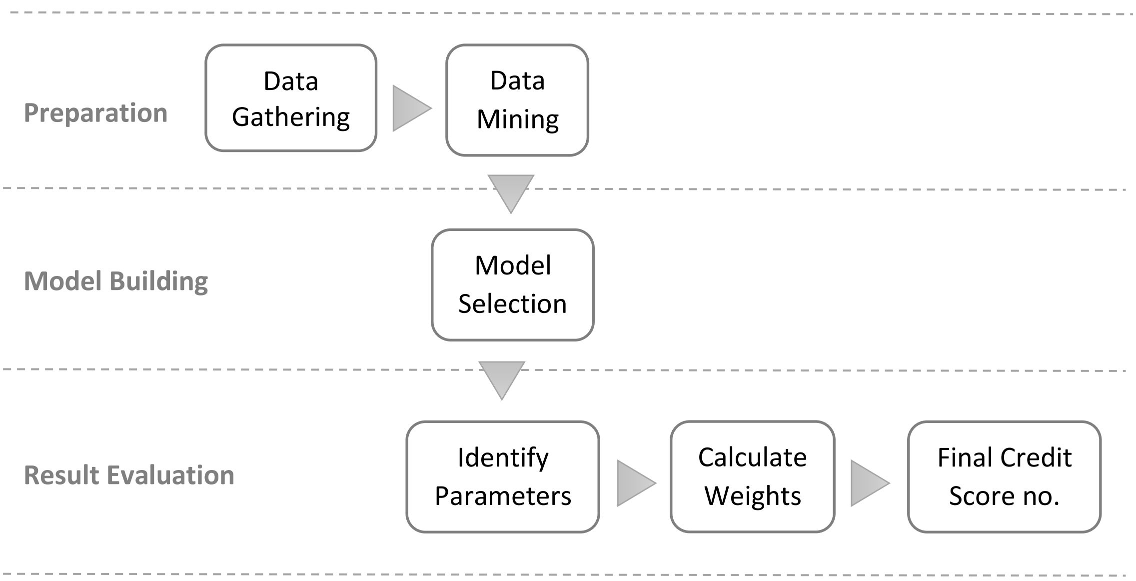
Capital inefficiency	▪ Allows creditworthy borrowers to unlock greater capital efficiency on their crypto-collateralised loans and get more leverage. ▪ Furthermore, platforms' loss provision capital buffers may be reduced as their credit scores enable an efficient collateral mechanism. ▪ Crypto credit scores would enable a diversified approach to collateral handling and reduce locked capital as current lending protocols impose high collateral requirements (over-collateralisation) to overcome the volatile nature of crypto collateral. ▪ As a potential borrower's historical credit history allows the lender to decide the leverage percentage, it helps stabilise the under-collateralised (or unsecured) DeFi market.

4.3.1 Evaluation of the on-chain credit score

As DeFi is transparent, the data of on-chain users' transactions are easily accessible. There is enough data available to review for sophisticated machine-learning models to make predictions. Data cleansing is done using statistical and machine learning techniques to correct irregularities and outliers.

Model selection is an exploratory process involving the continuous evaluation of multiple machine learning models, as default prediction is highly complicated and dependent on the unique credit risk characteristics of a given wallet address. Models should be empowered to tailor the financial products, including varying the collateral requirements for a DeFi loan. To decrease collateral requirements while still maintaining safe liquidity levels in the lending protocols, the score must accurately reflect whether a borrower is likely to repay their loan.

Exhibit 11: Workflow of Credit Score Model



A credit score breaks down into two main parts, which are attributes and weights. In this paper, we have evaluated two main parameters for calculating credit scores.

4.3.1.1 Utilisation reward

This parameter assesses borrow usage as a percentage of total debt at a given level of collateral. For example, if the borrowing usage is 37.02%, the available liquidity to borrow further is 62.98%. Borrowing usage is defined in equation 1.

$$\text{Borrow Usage} = \frac{\sum \text{Value of total Debt}_j}{\sum \text{BC}} \tag{1}$$

where $_j$ represents the index of collateral or debt if the borrower owns collateral or owes a debt in multiple cryptocurrencies.

Liquidation Threshold (LT): The percentage at which the collateral value is counted towards the borrowing capacity. For example, if a collateral has a liquidation threshold of 65%, the loan will be liquidated when the debt value rises above 65% of the collateral value.

Borrowing capacity (BC): The total amount that a borrower can seek from a lending pool given the value of the collateral [17]. Equation 2 defines a borrower's borrowing capacity for each collateral asset $_j$.

$$\text{BC} = \sum \text{Value of Collateral}_j \times \text{LT}_j \tag{2}$$

Calculation of Weighted Average Usage:

The most recent 365-day borrow usage data was collected to calculate the utilisation reward. Then, weights need to be assigned based on lambda (which must be less than one), which determines the rate at which "older" data enters the calculation. It acts as a variance that is weighted or biased toward more recent data. For this calculation, we are applying a low decay factor of 0.994 due to the volatile nature of crypto, as volatility is very unstable here. Normalised weights were then calculated by dividing lambda weights by their total, which was 13.467. Weighted average usage is calculated as 56.4%, which is the sum of all weighted usage values ((a)*(c)). The below table represents 14 days of sample data; likewise, 365 days of data can be taken for calculating weighted average usage.

Exhibit 12: Weighted average usage calculated from 14 days of sample data

Day	Borrow usage (a)	Weights with lambda = 0.994 (b)	Normalised weights (c) = (b)/13.467	Weighted average usage (d) = (a) * (c)
01-Nov-22	30.01	1	0.074256192	2.228428331
31-Oct-22	25.99	0.994	0.073810655	1.918338927
30-Oct-22	40.23	0.988036	0.073367791	2.951586241
29-Oct-22	50.00	0.982107784	0.072927584	3.646452151
28-Oct-22	75.67	0.976215137	0.072490019	5.485319735
27-Oct-22	60.89	0.970357846	0.072055079	4.387433751
26-Oct-22	62.06	0.964535699	0.071622748	4.444907764
25-Oct-22	61.01	0.958748485	0.071193012	4.343485655
24-Oct-22	60.87	0.952995994	0.070765854	4.307517522

Day	Borrow usage (a)	Weights with lambda = 0.994 (b)	Normalised weights (c) = (b)/13.467	Weighted average usage (d) = (a) * (c)
23-Oct-22	57.13	0.947278018	0.070341259	4.018596109
22-Oct-22	46.76	0.94159435	0.069919211	3.269422313
21-Oct-22	70.45	0.935944784	0.069499696	4.896253575
20-Oct-22	72.38	0.930329115	0.069082698	5.00020566
19-Oct-22	80.22	0.924747141	0.068668202	5.508563126
Total		**13.46689036**		**56.40651086**

Note: This sample data only covers 14 days; for an accurate calculation, the most recent 365 days of data should be used.

The multiplier will be determined by the model based on the calculated weighted average usage. The more a borrower uses its liquidity, the higher will be the borrow usage, and the more its impact on lowering the score will be proportionate to this parameter's weight or multiplier. Ideally, 60% can be considered the optimum borrow usage; lower than 60% is more conservative, and higher is more aggressive.

4.3.1.2 Liquidation History

By assessing account attributes and analysing borrower past liquidation behaviour with machine learning, a factor score is generated to predict the likelihood of future liquidation for a single address. For accessing creditworthiness, the health factor can be calculated and monitored.

Health Factor (HF): The health factor measures a position's collateralisation status, which is defined as the ratio of borrowing capacity to outstanding debts in Equation 3. If HF is less than 1, the collateral becomes eligible for liquidation [17].

$$HF = \frac{BC}{\sum \text{Value of total Debt}_j} \tag{3}$$

If HF < 1, the position may be liquidated to maintain solvency

The historical records of the health factor dataset, which includes the frequency of liquidations a borrower experiences and the density of liquidations of an on-chain wallet address, will be used to analyse past transaction records from multiple blockchains with the aid of artificial intelligence (AI).

Crucially, if a position's HF falls below 1 due to a decrease in the value of its collateral or an increase in the value of its debt, it is eligible for liquidation. In this event, a liquidator may repay up to a specified sum of the account's debt in exchange for an equivalent amount of its collateral plus a liquidation penalty. If the position is not repaid, it is eligible for liquidation (HF < 1), implying delinquency, or not (HF ≥ 1), implying responsible financial behaviour.

Liquidation Penalty: The liquidation penalty is a fee levied on the value of the collateral's assets when liquidators buy them as part of the liquidation of a loan that has breached the liquidation threshold.

The model predicts the probability ŷ = p(y|X) ∈ [0, 1] based on historical account attributes, such as liquidation history. Here, y = 1 denotes delinquency, termed a "bad" account, while y = 0 denotes repayment, termed a "good" account. This prediction ŷ is then converted to an integer credit score, such as {b ∈ N: 0.2 ≤ b ≤ 1}. These scores are then scaled to the final score range of 0.2 to 1.

Likewise, historical data of an on-chain wallet, like the number of times a loan was taken, weighted borrow usage, liquidation count, liquidation density, liquidation percentage, average loan tenure, average borrowing amount, etc., were collated from on-chain network sources. These data were factored into the model to compute individual attribute weights, which act as probability. These scores are then "scaled to the final score."

Exhibit 13: Historical on-chain wallet data for various parameters

Wallet	Total Loan count (no.)	Weighted Borrow Usage (%)	Liquidation count (no.)	Liquidation density (USD)	Liquidation (%)	Average Loan tenure (days)	Average borrowing amount (USD)	Credit score
x6b1	12	56.4	7	89,453	9%	15	10,00,000	0.63
e894	19	67.9	5	78,62,376	15%	252	5,20,00,000	0.67
4952	9	24.6	2	3,455	7%	5	50,000	0.85
498b	3	57.13	6	1,10,420	2%	60	72,00,000	0.92
47dc	22	46.76	9	7,20,00,672	17%	435	42,00,00,000	0.81
a952	6	70.45	2	61,989	83%	152	75,000	0.42

We have defined credit scores (0.7, 1.0) for low-risk categories (marked with green color), credit scores (0.5, 0.7) for medium-risk categories (marked with yellow color), and credit scores (0.2, 0.5) for high-risk categories (marked with red color).

Note: We have only considered a few parameters; more attributes can be tested and incorporated for building the DeFi credit score model.

Because there will be no history for new users, a default credit score will be assigned. Subsequently, it will be changed depending on the establishment of the credit history.

In the future, credit score models can be designed to incorporate on and off-chain information that represents borrower behaviour and financial responsibility to develop wallet-level predictive analytics modes. Attributes such as traditional banking activity or employment status can be incorporated. Moreover, the adoption of off-chain data unlocks the real identities of the users, which in turn helps the platform fall under the regulatory umbrella. By abandoning anonymity and using real names, borrowers and lenders can take financial and legal recourse in the event of toxic liquidations and asset recovery.

5. Concluding Remarks and Recommendations

On a concluding note, DeFi has the potential to become a standard way to obtain financial services in the long term. However, the limitations of DeFi lending block elements of genuine innovation. Acknowledging and managing risk in DeFi lending platforms paves the way for widespread use of the platform's products and its growth. To recognise and reduce risks, lending platforms must proactively establish a well-defined risk plan with the proper frameworks and tools. Platforms can accomplish this by incorporating an organised framework for risk assessment.

Regulators around the globe are researching more on DeFi projects to identify potential regulatory issues, discuss possible solutions, and develop a plan to operate legally. Enforcing a clear mechanism for regulating a stateless DeFi entity has various challenges due to many reasons, most specifically the anonymous nature of the DeFi blockchains. Bringing DeFi under regulatory purview is very essential for DeFi's growth, and it will also help in reducing fraud because participants can take legal recourse in the event of unfair practices, resolving fragmentation, and creating markets that are efficient, resilient, fair, and equally accessible to all [18].

To ensure mass and institutional adoption of DeFi, lending protocols need to implement risk management strategies like haircut mechanisms, market risk assessment for collateralised loans, on-chain credit scores, and fair collateral pricing. These strategies can support the platform through better risk management, help remove many obstacles to further expansion, and support well-informed investment decisions in the space.

About the Author

Kashish Mittal is a member of Genpact's market risk model validation team. She has more than five years of industry experience. Throughout her career, she has worked in the market risk and treasury risk divisions of corporate and investment banking, where she developed in-depth knowledge of credit products. She has also contributed to numerous Basel, FRTB, and regulatory projects. She holds an FRM certification and is a chartered accountant, a member of the Institute of Chartered Accountants of India.

Kashish Mittal
E: Kashish.mittal@genpact.com

6. References

[1] "DefiLlama - DeFi Dashboard," DefiLlama (data assessed on November 16, 2022). https://defillama.com/.

[2] "What Really Happened To LUNA Crypto?" Forbes. https://www.forbes.com/sites/qai/2022/09/20/what-really-happened-to-luna-crypto/?sh=1de3a1df4ff1.

[3] "Lending And Payments Global Market Report 2022," Globenewswire (May 20, 2022). Lending And Payments Global Market Report 2022 (globenewswire.com).

[4] Jakub "DeFi – The Future of Finance," Finematics (Feb 02, 2021). DeFi – The Future Of Finance – Finematics.

[5] "Client funds worth at least $1 billion missing at failed crypto firm FTX," Business Today. https://www.businesstoday.in/crypto/story/client-funds-worth-at-least-1-billion-missing-at-failed-crypto-firm-ftx-352747-2022-11-14.

[6] ANTÓNIO MADEIRA "How Did Basic Attention Token (BAT) Become the Most Used DeFi Token?," Cointelegraph (July 10, 2020). https://cointelegraph.com/news/how-did-basic-attention-token-bat-become-the-most-used-defi-token.

[7] Rajeev Kumar "Crypto crash reason: Why cryptocurrency markets crashed this month," Financial Express (June 28, 2022). https://www.financialexpress.com/blockchain/crypto-crash-reason-6-13-why-is-crypto-crashing-today/2558313/.

[8] Data source: historical prices of ETH/USD, Yahoo Finance (January 01, 2021, to November 25, 2022). https://finance.yahoo.com/quote/ETH-USD/history/.

[9] "The RiskMetrics 2006 methodology," RiskMetrics Group https://www.msci.com/documents/10199/d0905614-2771-46dc-b000-1a033146586a.

[10] "The Rise of DeFi Lending and How to Get Involved," Hedera. The Rise of DeFi Lending and How to Get Involved | Hedera.

[11] Patrick Thompson. "The DeFi hacks of 2020," Coingeek (December 31, 2020). https://coingeek.com/the-defi-hacks-of-2020/.

[12] Anthony Clarke. "How low liquidity led to Mango Markets losing over $116 million," Cointelegraph (November 03, 2022). https://cointelegraph.com/news/how-low-liquidity-led-to-mango-markets-losing-over-116-million.

[13] Sam Kessler. "DeFi Lender Inverse Finance Exploited for $15.6M," Coindesk (April 02, 2022, updated April 05, 2022). https://www.coindesk.com/tech/2022/04/02/defi-lender-inverse-finance-exploited-for-156-million/.

[14] TWAP formula. https://en.wikipedia.org/wiki/Time-weighted_average_price.

[15] MNGO/USDT prices on 11th and 12th October 2022, the time interval of 5min, Gate.io. (Data accessed on November 23, 2022). Buy/Sell Bitcoin, Ethereum | Cryptocurrency Exchange | Gate.io.

[16] Hugh "Introducing ARCx Credit and the DeFi Credit Score," (August 23, 2022). https://arcx.substack.com/p/introducing-arcx-credit-and-the-defi#:~:text=The%20DeFi%20Credit%20Score%20is,Curve%E2%80%9D%20on%20a%20daily%20basis.

[17] "An Empirical Study of DeFi Liquidations: Incentives, Risks, and Instabilities," Arxiv (October 01, 2021). https://arxiv.org/pdf/2106.06389.pdf.

[18] Caroline A. Crenshaw "Statement on DeFi Risks, Regulation and Opportunities," U.S. Securities and Exchange Commission (November 09, 2021) https://www.sec.gov/news/statement/crenshaw-defi-20211109.