Journal Pre-proof

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PII: S2096-7209(24)00072-1
DOI: https://doi.org/10.1016/j.bcra.2024.100259
Reference: BCRA 100259

To appear in: *Blockchain: Research and Applications*

Received date: 5 May 2024
Revised date: 31 August 2024
Accepted date: 25 December 2024

Please cite this article as: I. Melnikov, I. Lebedeva, A. Petrov et al., DeFi Risk Assessment: MakerDAO Loan Portfolio Case, *Blockchain: Research and Applications*, 100259, doi: https://doi.org/10.1016/j.bcra.2024.100259.

DeFi Risk Assessment: MakerDAO Loan Portfolio Case

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Abstract

Decentralized finance (DeFi) is a rapidly evolving blockchain technology that offers a new perspective on financial services through web3 applications. DeFi offers developers the flexibility to create financial services using smart contracts, leading to a lack of standardized protocols and challenges in applying traditional finance models for risk assessment, especially in the early stages of adoption. The Maker protocol is a prominent DeFi platform known for its diverse functionalities, including loan services. This study focuses on analyzing the risk associated with Maker's loan portfolio by developing a risk model based on multiple Brownian motions passage levels with Brownian motions representing different collateral types and levels being users' collateralization ratios. Through numerical experiments using artificial and real data, we evaluate the model's effectiveness in assessing risk within the loan portfolio. While our findings demonstrate the model's potential for assessing risk within a single DeFi project, it is important to acknowledge that the model's assumptions may not be fully applicable to real-world data. This research underscores the importance of developing project-specific risk assessment models for individual DeFi projects and encourages further exploration of other DeFi protocols.

Keywords: Blockchain, Decentralized Finance, Risk Assessment, Knowledge Discovery, Smart Contract, Brownian Motion

1. Introduction

Decentralized finance (DeFi) [1, 2] refers to peer-to-peer financial services on public blockchains [3] that introduce new web3-based offerings and replicate traditional financial instruments. The lack of regulation in DeFi [4–6] has led to concerns about potential fraud, scams, and security vulnerabilities [7–10]. In traditional finance, regulations are in place to protect consumers and ensure the stability of the financial system [11]. However, in DeFi, users are responsible for their own security and must conduct thorough due diligence before participating in any protocol.

Despite these risks, DeFi has gained significant traction in recent years due to its potential for financial inclusion and innovation [12, 13]. Traditional financial services are often inaccessible to those without a bank account or credit history, but DeFi allows anyone with an internet connection to access financial services. This has the potential to revolutionize banking and finance, particularly in developing countries where traditional banking infrastructure is lacking.

In addition to providing access to financial services, DeFi also offers opportunities for individuals to earn passive income through activities such as liquidity provision and yield farming [14]. By

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providing liquidity to decentralized exchanges or lending platforms, users can earn interest on their crypto assets. Yield farming involves moving assets between different DeFi protocols to maximize returns, often through the use of governance tokens that provide additional rewards.

One of the key benefits of DeFi is its transparency and accessibility [15]. Since transactions are recorded on public blockchains, anyone can verify the integrity of the system and audit smart contracts [16]. This level of transparency is not possible in traditional finance, where transactions are often opaque and controlled by centralized institutions.

However, the rapid growth of DeFi has also led to challenges such as scalability issues and high gas fees on the Ethereum network [17]. As more users participate in DeFi protocols, the network becomes congested, leading to slower transaction times and higher fees. This has prompted developers to explore alternative blockchains and layer 2 solutions [18, 19] to improve scalability and reduce costs [20–22].

One prominent DeFi project is Maker, a blockchain protocol that enables crypto-backed loans [13, 23]. The Maker protocol is implemented through smart contracts on the Ethereum blockchain, overseen by a decentralized autonomous organization (DAO) called MakerDAO. For simplicity, we will use the terms MakerDAO and Maker interchangeably.

Transactions related to Maker are recorded on the Ethereum blockchain, making them visible to all. This includes financial data such as user operations and amounts. Although it is possible to conceal this information using zero-knowledge proofs [24–26], it would complicate the protocol, increase fees, and reduce transparency. Maker does not encrypt transaction data; only the identities of the real-world entities behind the users are hidden. This allows financial information to be extracted from the protocol, while user names remain undisclosed.

Unlike traditional financial services, DeFi protocols are largely lacking risk assessment protocols. While some qualitative and case study risk assessments have been conducted for DeFi protocols [27, 28], there have been few studies that have developed mathematical models to assess risk. For example, a specialized mathematical model was proposed in [29] to predict default likelihood in Maker lending, considering crypto-collateral and using Brownian motion for analyzing loan defaults and correlations. Similarly, a linear regression model was introduced in [30] for risk estimation in Compound and Aave lending protocols.

The goal of the current research is to evaluate the risk of MakerDAO loan portfolio. The main contributions of our work to DeFi risk assessment are as follows:

1. Extend a DeFi loan-specific mathematical model of loan default correlation to incorporate various types of collaterals.
2. Develop an artificial DeFi loan portfolio simulator.
3. Compute DeFi loan portfolio risk using both artificial and real data.

The remainder of this paper is structured as follows. Section 3 contains the literature review, while Section 2 offers background information on MakerDAO. In Section 4, an extended DeFi loan-specific mathematical model of loan default correlation that includes various types of collaterals is presented. The model is then evaluated in Section 5. Finally, Section 6 provides the conclusions of the paper.

2. MakerDAO Borrowing Protocol Background

The MakerDAO Protocol [23] is DeFi project which operates on the Ethereum blockchain, offering a sophisticated lending platform underpinned by the `DAI` stablecoin. `DAI` stands out as an ERC-20 token [31], engineered to maintain a soft peg to the United States dollar. This stability is achieved through a collateralized debt position framework, where users can lock in Ethereum and other approved cryptocurrencies as collateral in smart contracts, known as `Vaults`, to generate `DAI`. Central to the protocol's governance is the

MakerDAO, a decentralized autonomous organization composed of `DAI` holders who vote on critical decisions affecting the protocol's parameters. These parameters include the stability fee (interest rate), which influences the cost of borrowing `DAI`, and the liquidation ratio, determining the minimum collateralization required for loans, thus safeguarding the system's stability. By leveraging blockchain technology, MakerDAO facilitates a lending environment where loans are managed by smart contracts, minimizing the risk and enhancing the accessibility of financial services.

Let's consider a borrower's workflow in the Maker Protocol.

- **Creating a `Vault`:** The first step for a borrower in the Maker Protocol is to create a `Vault`. This `Vault` acts as a personal container on the blockchain where the borrower can deposit collateral. Collateral types are diverse within the Maker ecosystem, but Ethereum (ETH) is among the most commonly used. The deposited collateral serves as a security for the loan the borrower intends to take out. The concept of a `Vault` is crucial as it segregates each user's funds and activities, ensuring personalized risk management and loan details.

- **Oracle's Role in Valuation:** The Maker Protocol utilizes Oracles to maintain a real-time price feed of the collateral assets. These Oracles are external sources of information that feed data into the system, ensuring that the valuation of collateral is current and reflects market prices. This step is critical for determining how much DAI (the stablecoin of the Maker Protocol) can be safely borrowed against the collateral.

- **Choosing a Borrowing Program:** Borrowers have options regarding the terms under which they borrow. For the collateral, there are different programs like `ETH-A`, `ETH-B`, and `ETH-C`. Each program has its own parameters, including interest rates, minimum collateralization ratios, and liquidation penalties. These programs cater to various risk tolerances and borrowing needs, the most balanced and popular of which is `ETH-A`.

- **Borrowing `DAI`:** Based on the real-time valuation of the deposited collateral and the specific parameters of the chosen borrowing program, the protocol calculates the maximum amount of `DAI` that can be borrowed. Borrowers can then generate `DAI` up to this limit. The borrowed `DAI` can be used for a range of activities, including investment, liquidity provision, or personal spending, while the collateral remains locked in the `Vault`.

- **Unlocking and Liquidation Collateral:** To regain access to their collateral, the borrower needs to repay the borrowed `DAI` along with any accumulated stability fee (interest rate). Once the repayment is complete, the borrower can withdraw their collateral. In contrast, if a `Vault`'s collateral value dips below a critical threshold, it triggers an automatic liquidation process where the system auctions the collateral to recoup the outstanding debt. During this phase, the `Vault` becomes inaccessible to the borrower, ensuring the process is swift and aims to limit losses for both the borrower and MakerDAO. The collateral auction employs a competitive bidding mechanism using `DAI`. Successful auctions that cover the debt result in any excess `DAI` being returned to the borrower. However, if the auction fails to cover the debt fully, MakerDAO might incur losses, and the borrower faces a liquidation penalty, typically ranging between 10% to 33%.

3. Related Work

Banks use various methods to keep risks at reasonable levels and improve their efficiency. They use frameworks required by regulators, like the Basel framework [11], and machine learning models [32–34]. There is also a lot of interest in research of loan portfolio data, which often uses private data not available to the public. For instance, some studies, such as those on German and Australian big banks, look at how spreading out loans to different types of borrowers affects the banks' risk and their use of capital [35, 36]. These studies had access to details from over a thousand bank portfolios across seven years. Another study compares different machine learning methods to predict loans that will not be paid back. It uses data from a bank that covers four years, 181 thousand borrowers, and many different data points [37]. Additionally, a paper used the random forest technique to identify loans likely not to be repaid in an Indonesian bank dataset, which included 3300 borrowers and 12 features [38].

Research has expanded beyond traditional finance to include decentralized finance (DeFi) and its interplay with conventional financial systems. Several studies have employed modern portfolio theory to delve into the risk models associated with DeFi money lending, as discussed in papers [39, 40]. The financial industry's response to the opportunities and challenges presented by DeFi was thoroughly analyzed in [1]. Moreover, the authors of the article [41] explored the risks and benefits of DeFi through the lens of financial intermediation and also proposed a framework for evaluating DeFi projects. In addition, the article [42] provides the analysis of Value-at-Risk, estimating the probable maximum loss from cryptocurrency investments that will not be exceeded over a specified period at a given probability. The authors of the research [43] extends this analysis by empirically examining the relationship between the S&P500 index and DeFi assets (`MKR`, `AVE`, `COMP`), offering insights into the dynamics between centralized and decentralized finance.

Data from traditional banks is often restricted due to trade secrets and privacy issues, whereas loan data from DeFi platforms is readily available on public blockchains, facilitating extensive research. Studies the platforms such as Maker, AAVE, Compound, and Spark Lend focused on data collection, economic parameters estimation, and risk management [23, 44–46]. For example, [47] provides a detailed statistical analysis using data from the decentralized Ethereum protocol Compound, leveraging a relational database for further research exploration. Another study, [44], evaluates the stability of the DAI stablecoin from the Maker project during its first year, including its response to the cryptocurrency crisis in March 2020. The issue of high collateral requirements for loans that use volatile cryptocurrencies as collateral is discussed in [48], where the authors suggest a solution to lower collateral requirements, thus enhancing loan accessibility while controlling lender risk. The distinctive characteristics of DeFi introduce complexities in developing new risk models. Although there are existing models that address the system as a whole, such as the stochastic model for collateral-based stablecoins [49], there is still a lack of models tailored to individual debts. The authors of the paper [13] categorized the in-demand usage scenarios of decentralized applications (DApps) into seven categories including finance, gaming, exchanges, security, development, healthcare, and marketplace. Their study found that the MakerDAO platform ranked third in the finance category. Moreover, the authors of the paper [29] created a unique set of data on loan portfolios from the MakerDAO project and developed a method for assessing the probability of default risk for borrowers using one asset as collateral. The dataset was initially focused on a single borrowing program, but with slight modifications to the methodology and code, it can be applied to all borrowing programs.

The study [30] presents a method for evaluating DeFi lending risk by dissecting lending and borrowing activities into synthetic borrower and lender components. This methodology, when combined with a linear regression model, offers a reliable way to pinpoint weaknesses and track fluctuations in risk levels in real-time. The effectiveness of this model was tested using data from Compound and Aave projects.

The authors of the article [50] analyze the popularity of various DeFi projects, they notes that lending is the most active subcategory in the development of applications for Web3. However, there is still no model assessing the risks of default of the users' collateral portfolio in decentralized lending. Such a model would make it possible to improve smart lending contracts and reduce risks for both lenders and borrowers.

4. Mathematical Model

This study is centered around conducting a risk assessment for the DeFi loan portfolio. In order to accurately compute this assessment, it is crucial to understand the joint distribution of borrowers' defaults. Since borrowers may possess various types of collateral, it is important to address this complexity in our analysis. The primary focus of this paper is on examining two specific types of collateral as a basic yet significant example of multiple assets. As proposed in the article [29], the cryptocurrency exchange rate can be described by Brownian motion. However, in the case of multiple assets, the task becomes more difficult, as cryptocurrency assets definitely depend on each other. In this section, we propose to describe the exchange rate of a secondary asset as a linear combination of Brownian motion for the first asset, and an independent Brownian process for the second asset. Based on this proposal, we calculate probabilities for joint defaults from both assets, as well as the covariance of these joint defaults. Additionally, we calculate the probability distribution for default amounts for a protocol.

4.1. Basic Notations

In the context of the Maker project, when a user initiates a borrowing transaction involving the digital currency `DAI`, it is requisite for them to deposit a collateral asset. For the purposes of this discussion, and without loss of generality, this collateral will be referred to as `ETH` (Ether). The initiation of the loan occurs at time t_0 and extends to a termination point denoted as T. The termination point, T, is defined by one of three potential outcomes: the time of liquidation, the moment of complete repayment, or the maximum observed time duration in cases where the loan remains active at the point T.

At any given moment t, the quantity of collateralization assets is represented by $a(t)$. The blockchain ledger chronicles alterations to the collateral balance through a piece-wise constant function, characterized by specific update instances τ and the respective adjustments $\Delta a(\tau)$. These adjustments stem from actions such as collateral deposits or withdrawals, as well as liquidation events. The determination of the maximum permissible debt level is contingent upon both the collateral's valuation in `DAI` and the minimum required collateralization ratio, denoted as $r_{\min}(t)$. The conversion rate between `ETH` and `DAI`, $e(t)$, is supplied by oracles and is generally aligned with rates from centralized exchanges, barring instances of exceedingly high transaction costs [44]. The minimum required collateralization ratio, $r_{\min}(t)$, is defined by a piece-wise linear function featuring minimal gradients over non-uniform intervals, a measure implemented to uphold platform equilibrium. Given that the Maker project mandates a collateralization level exceeding the value of the debt, it follows that $r_{\min}(t) > 1$.

Consider the representation of debt over time as $d(t)$. Interest accrues on the outstanding debt, and the time evolution of the logarithm of the interest rate is denoted by $f(t)$. In the absence of any interventions on the debt within the interval $(t_1, t_2]$, the debt at t_2 can be expressed as:

$$d(t_2) = d(t_1) \cdot \exp\left(\int_{t_1}^{t_2} f(t)\, dt\right). \tag{1}$$

By the platform's design, the log-interest function, $f(t)$, is piece-wise constant. If $f(t)$ remains constant within the interval $(t_1, t_2]$, then the debt at t_2 simplifies to $d(t_2) = d(t_1) \cdot \exp\left(f(t_2) \cdot (t_2 - t_1)\right)$. Consequently, the collateral balance evolves in a piece-wise exponential manner. Discontinuities in this function arise due to debt repayments, further borrowings, or the liquidation process. Alterations in the log-interest rate result in derivative discontinuities without affecting the continuity of the function itself.

The current collateralization ratio, $r(t)$, for instances where $d(t) > 0$, is given as:

$$r(t) = \frac{e(t) \cdot a(t)}{d(t)}.$$

For conditions where $d(t) = 0$, it is appropriate to assign $r(t) = +\infty$. Should the collateralization ratio $r(t)$ fall beneath the minimum threshold $r_{\min}(t)$ at any point, the platform initiates a liquidation process. The verification of collateralization ratios is performed with near real-time accuracy. Moreover, the borrower is obliged to satisfy the interest payments throughout the duration of the liquidation process.

4.2. Probability of default

The probability of default (PD) is a risk assessment parameter commonly used by financial institutions. In our model, we call the default, the moment of the beginning of the liquidation of the `Value` in the MakerDAO protocol.

Theorem 1. *If*

1. *the normalized exchange rate of the first asset* $\frac{1}{\sigma_1}\ln\frac{e^1(t)}{e_0^1}$ *for a given constant* $\sigma_1 > 0$ *is a Brownian motion* $\mathtt{B}_t^1$ *with zero mean and unit variance*
2. *the normalized exchange rate of the second asset* $\frac{1}{\sigma_2}\ln\frac{e^2(t)}{e_0^2}$ *for a given constant* $\sigma_2 > 0$ *is a linear combination of Brownian motions* $\mathtt{B}_t^2 = \alpha \mathtt{B}_t^1 + \mathtt{B}_t^*$, *where* $\mathtt{B}_t^*$ *is Brownian motion with zero mean and* $\sigma_* \geq 0$
3. *the platform's interest rates* $f_1 = 0$, $f_2 = 0$ *and the minimum collateralization ratios* $r_{\min}^1 > 0$, $r_{\min}^2 > 0$ *are constant,*
4. *the first borrower has a debt* d_0^1 *and collateral* a_0^1 *at time* $t = 0$ *in the first asset and the second borrower has a debt* d_0^2, a_0^2 *in the second asset, and* $\frac{a_0^i e_0^i}{d_0^i} \geq r_{min}^i$, $i = 1, 2$
5. *the borrowers have performed no actions with debt and collateral during* $t \in (0, T]$ *in both assets*

then the probability of simultaneous default of borrowers in two assets during the time interval $(0, T]$ *are given by:*

$$\mathtt{PD}(x_{\min}^1, x_{\min}^2) = \int\limits_{-x_{\min}^2}^{0}\int\limits_{-x_{\min}^1}^{0} \frac{\partial^2 F_{1,2}(a,b)}{\partial a \partial b} da db, \quad (2)$$

where

$$F_{1,2}(a,b) = \frac{2r_0(a,b)}{\sqrt{2\pi t}} \cdot e^{-\frac{r_0(a,b)^2}{4t}} \cdot \sum_{n=1,3,\ldots} \frac{1}{n} \cdot \sin\left(\frac{n\pi\theta_0(a,b)}{\gamma}\right) \cdot \left[I_{\frac{1}{2}(\frac{n\pi}{\gamma}-1)}\left(\frac{r_0(a,b)^2}{4t}\right) + I_{\frac{1}{2}(\frac{n\pi}{\gamma}+1)}\left(\frac{r_0(a,b)^2}{4t}\right)\right]; \quad (3)$$

$$\gamma = \begin{cases} \tan^{-1}\left(-\frac{\sqrt{1-\alpha^2}}{\alpha}\right) & \textit{if } \alpha < 0 \\ \pi + \tan^{-1}\left(-\frac{\sqrt{1-\alpha^2}}{\alpha}\right) & \textit{otherwise} \end{cases};$$

$$\theta_0 = \begin{cases} \tan^{-1}\left(\frac{b}{a-\alpha Z_2}\right) & \textit{if } (.) > 0 \\ \pi + \tan^{-1}\left(\frac{b}{a-\alpha Z_2}\right) & \textit{otherwise} \end{cases};$$

$$r_0 = \frac{b}{\sigma_*}\sin(\theta_0); \quad \sigma_* = \frac{1}{\sqrt{1-\alpha^2}};$$

$$x_{\min}^i = \frac{1}{\sigma_1}\ln\left(\frac{d_0^i \cdot r_{\min}}{a_0^i \cdot e_0^i}\right), i = 1, 2,$$

$I_\mu(z)$ *is the modified Bessel function* I *with order* μ.

Proof. Firstly, let's consider the results from [29]. It follows that the probability of default can be interpreted as the intersection of the passage level $x_{\min}^i(t) = \frac{1}{\sigma}\ln\left(\frac{d_0^i \cdot r_{\min}^i}{a_0^i \cdot e_0^i}\right)$ by $\mathtt{B}_t^i$, $i = 1, 2$, and from the condition of the theorem, this means that $x_{\min}^i(t) = x_{\min}^i$ and $x_{\min}^i \leq 0$. Then the probability of default in two assets for the period T is equal:

$$\begin{aligned} \mathtt{PD}(x_{\min}^1, x_{\min}^2) &= P(T_{x_{\min}^1} < T, T_{x_{\min}^2} < T) \\ &= P(\inf_{0\leq s\leq T} B_s^1 \leq x_{\min}^1, \inf_{0\leq s\leq T} B_s^2 \leq x_{\min}^2) \\ &= P(\sup_{0\leq s\leq T} B_s^1 \geq -x_{\min}^1, \sup_{0\leq s\leq T} B_s^2 \geq -x_{\min}^2), \end{aligned}$$

where $T_{C,f} = \inf\{t > 0 : \mathtt{B}_t = C\}$, and the latter equality is true due to the symmetry of Brownian motion.

Next, let us look at the results of Article [51]. In the *Main Results 1*, Chunsheng Zhou defines the probability equation for the default of at least one $P(\sup_{0\le s\le T} B_s^1 \ge -x_{\min}^1$ or $\sup_{0\le s\le T} B_s^2 \ge -x_{\min}^2)$. From here it is not difficult to understand that:

$$F_{1,2}(-x_{\min}^1, -x_{\min}^2)$$
$$= P(\sup_{0\le s\le T} B_s^1 \le -x_{\min}^1 \sup_{0\le s\le T} B_s^2 \le -x_{\min}^2)$$
$$= 1 - P(\sup_{0\le s\le T} B_s^1 \ge -x_{\min}^1 \text{ or } \sup_{0\le s\le T} B_s^2 \ge -x_{\min}^2)$$

From here we can get the necessary probability:

$$P(\sup_{0\le s\le T} B_s^1 \ge -x_{\min}^1, \sup_{0\le s\le T} B_s^2 \ge -x_{\min}^2) = \int_{-x_{\min}^2}^{0} \int_{-x_{\min}^1}^{0} \frac{\partial^2 F_{1,2}(a,b)}{\partial a \partial b} da db$$

where $F_{1,2}(a,b)$ equals (3). □

4.3. Risk assessment

The previous theorem also allows us to calculate the probability distribution for debt assets falling under liquidation.

Theorem 2. *If*

1. *there are m assets, in the kth asset there are n_k users, $k = 1..m$*
2. *the normalized exchange rate of the kth asset $\mathtt{E}_t^k = \frac{1}{\sigma} \ln \frac{e^k(t)}{e_0^k}$ for a given constant $\sigma > 0$*
3. *$x_{min,i}^k = x_i^k$ is the level passage of ith user in the kth asset at the initial moment of time, $i = 1..n_k$*
4. *$0 = x_0^k > x_1^k > x_2^k > \ldots > x_{n_k-1}^k > x_{n_k} > x_{n_k+1}^k = -\infty$, that is, users' collaterals are sorted from the most risky to the least risky*
5. *d_i^k is the debt of ith user in the kth asset*
6. *$f_k \ge 0$ is the platform's interest rate for the kth asset*
7. *The joint distribution density of $\sup_{0\le s\le T}(\mathtt{E}_s^k - f_k s)$, $k = 1..m$, is equal to $f_m(x^1, \ldots, x^m)$*

then then the probability of default a certain sum is equal:

$$P\left(\mathtt{DefaultCollaterals} : \{D_{i_k}^k, k = 1..m\}\right) = \int_{-x_{i_m}^m}^{-x_{i_m+1}^m} \cdots \int_{-x_{i_1}^1}^{-x_{i_1+1}^1} f_m(x^1, \ldots, x^m) dx^1 \ldots dx^m, \quad (4)$$

where $D_{i_k}^k = \sum_{j\le i_k} d_j^k$.

Proof. If a certain user defaults, then more and more risky users will also default. This means that the default of the first l users in the asset occurs when $\sup_{0\le s\le T}(\mathtt{E}_s^k - f_k s)$ reaches values from $-x_l^m$ to $-x_{l+1}^m$, the equation (4) follows from this.

In the case of $m = 1$, this can be written as follows:

$$P\left(\mathtt{DefaultCollaterals} : D_i\right) = \mathtt{PD}(x_i) - \mathtt{PD}(x_{i+1})$$

$m = 2$:

$$P\left(\mathtt{DefaultCollaterals} : \{D_i^1, D_k^2\}\right) = \int_{-x_k^2}^{-x_{k+1}^2} \int_{-x_i^1}^{-x_{i+1}^1} f_2(x^1, x^2) dx^1 dx^2$$

□

Note 1. *In Theorem 2, we make the assumption that all levels x_i^k within an asset $k = 1..m$ are unique. To ensure this property, we can first group loans by levels for each asset.*

Corollary 2.1. *The probability of a specific liquidation value occurring is:*

$$P\left(\mathtt{LiquidationValue} = X\right) = \sum_{i_1..i_m : \sum_{k=1}^{m} D_{i_k}^k = X} P\Big(\mathtt{DefaultCollaterals} : \{D_{i_k}^k, k = 1..m\}\Big). \quad (5)$$

Theorem 2 has been proven for the case where the joint distribution of the supremums of m assets is known. However, the theoretical distribution result has only been obtained for $m = 2$ in Theorem 1. To bridge this gap, it is feasible to estimate the joint distribution for $m > 2$ through statistical modeling.

5. Numerical Experiments

In this section, we validate theoretical results by applying them to synthetic and real data.

Duration:	100 days	3 year	For all time
Shapiro-Wilk statistics	0.959	0.942	0.909
p_{value}	0.004	$2.63 \cdot 10^{-20}$	$2.72 \cdot 10^{-35}$

Table 1: The Shapiro-Wilk test for the normality of BTC exchange rate increments for different time periods. The time series of the exchange rate from the beginning of BTC trading (2014-09-17) to the present (2024-03-29) is considered.

5.1. Synthetic data

As synthetic data, we consider the Brownian motions from Theorem 1, the coefficients for which we calculate from the exchange rates of real data.

5.1.1. Approximation

Theorem 1 suggests that two assets can be described by Brownian motion, with the second asset being a linear combination of the first asset and another independent Brownian motion. In this section, we will test the normality of the increases in the real exchange rates of BTC and calculate the coefficient $\alpha_{\texttt{BTC-ETH}}$ for the relationship between the two assets.

To test the normality of increments, we will use the Shapiro-Wilk statistical test on varying time periods. Specifically, we will analyze the BTC exchange rate over different durations. The dataset includes exchange rate values from the inception of BTC trading (2014-09-17) to the current date (2024-03-29). The results of the test are summarized in Table 1.

The findings suggest that labeling the exchange rate as a Brownian motion may be challenging. However, it serves as a fundamental concept in financial mathematics, and even with potential model inaccuracies, we can still derive meaningful insights. Future research will delve deeper into the distribution of increments in cryptocurrency exchange rates.

To calculate the coefficient α, which relates the exchange rates of two assets, we need to determine the covariance between the normalized exchange rates of these assets. Let us take BTC as the first underlying asset with the highest capitalization, and ETH as the second asset. The results for various considered periods are displayed in Table 2. It is evident from the results that, despite the varying time periods, the assets exhibit a strong correlation ranging from 0.79 to 0.84.

Duration:	100 days	3 year	For all time
$\alpha_{\texttt{BTC-ETH}}$	0.8007	0.8415	0.7922

Table 2: The coefficients of the relationship of Brownian movements in the context of BTC-ETH.

5.1.2. Default of users in different assets

In the formulation of Theorem 2, an assumption posits the interest rate to be zero, an assertion that diverges from practical scenarios. Nevertheless, it is observed that real interest rates typically range between 1% and 5% per annum. Given the temporal scope of the current investigation, which focuses on the imminent days, the effective interest rate is hypothesized to diminish further. To substantiate the validity of this assumption, a comparative analysis will be conducted. This analysis will juxtapose the theoretical outcomes derived under the zero-interest rate assumption against empirical results obtained through the application of the Monte Carlo simulation method. Specifically, the Monte Carlo simulation will incorporate Brownian motion to model exchange rates, utilizing the coefficients delineated in Section 5.1.1. The results for different interest rates f and equal the passage levels in both assets $x^1_{\min} = x^2_{\min} = x_{\min}$ are shown in Figure 1. The Root Mean Square Error (RMSE) and Mean Bias Error (MBE) metrics for the theoretical result are presented in Table 3. Based on the results, it can be seen that the zero interest rate approximation holds, as the discrepancy is negligible for the interest rates offered by the MakerDAO protocol.

5.1.3. Risk assessment

Theorem 2 and its Corollary 2.1 allow us to calculate the distribution function for the default amount $P(\texttt{LiquidationValue} \geq$

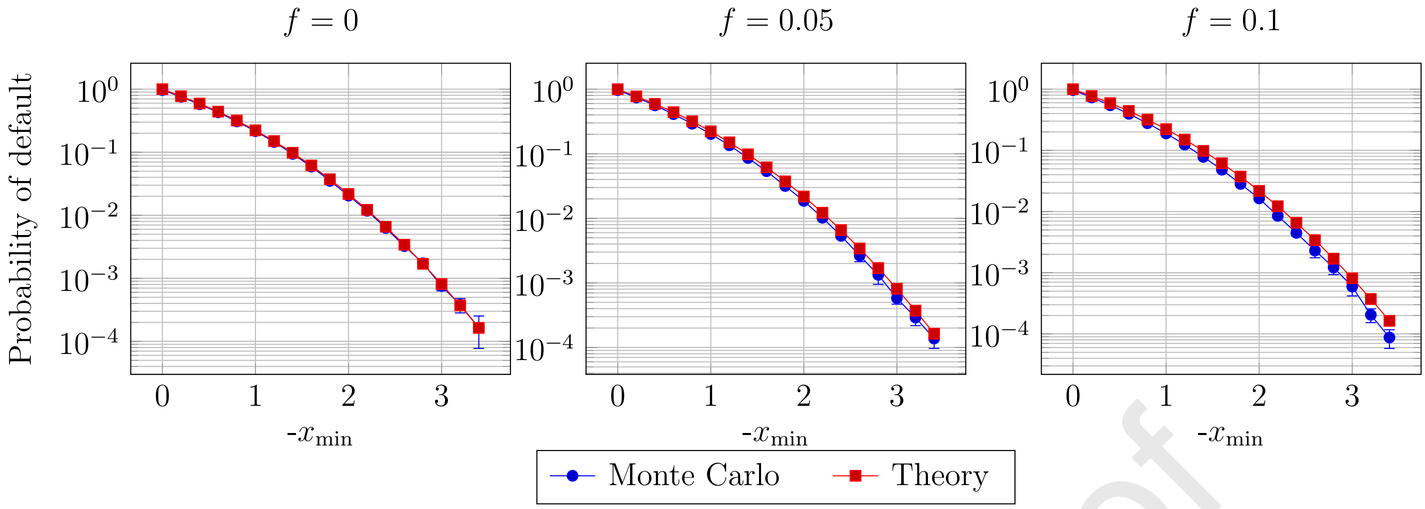

Figure 1: The results of comparing the theory with the Monte Carlo modulation method for different interest rates f, for $x^1_{\min} = x^2_{\min} = x_{\min}$ and $\alpha = 0.8$.

	$f = 0$	$f = 0.01$	$f = 0.05$	$f = 0.1$
RMSE	0.0097	0.0112	0.0171	0.0249
MBE	-0.0059	-0.0072	-0.0121	-0.0179

Table 3: RMSE and MBE for theoretical and experimental data.

`ShareOfAssets`). The result of calculating the Complementary Cumulative Distribution Function for $n = 20$ users in each of the two resources with equal levels, for $x^1_{\min} = x^2_{\min} \in \{-0.1k|k = 0..10\}$, equal the debt of each user, $f = 0.05$ and $\alpha = 0.8$ are shown in Figure 2.

5.2. Real data

5.2.1. Data structure

To illustrate the above mathematical theorems on real data, we used public data located in the Google Big Query project. Since we concentrate on various assets in this research, the assets with the largest amount of debt 3 were selected for the demonstration:

- `ETH`-Collateralized risk program A, B, C (`ETH-A`, `ETH-B`, `ETH-C` accordingly) within the MakerDAO protocol deployed on the Ethereum network debts;
- Wrapped Bitcoin `WBTC-A` – a tokenized addition to the cryptocurrency space that allows to participate in transactions within the ecosystem of decentralized finance;
- Gelato Network's Uniswap V3 token of the liquidity provider (`GUNIV3DAIUSDC2-A`).

We analyzed the data from November 2019 to July 2023 (see Figure 4). Each asset contains its own parameters common to all users. Such parameters are the log interest rate $f(t)$, exchange rate $e(t)$, and minimal collateral ratio $r_{\min}(t)$. These parameters may change over time as decided by oracles or Maker (`MKR`) token holders.

In raw data, information about user actions is determined by special functions (such as *frob*, *fork* and *grab*). If a user's action is labeled as *frob*, it means that the user generate dai/payback `DAI` or lock/unlock assets; the *fork* function is responsible for transfer assets and debt between vaults and *grab* function defines liquidation process. The data obtained from Big Query contains only information about the user's actions, the amount of borrowed `DAI` and collateral. Additional data were processed to obtain the parameters of each program. For a more detailed overview of data decoding and to obtain the final loan portfolio dataset you can refer to GitHub (https://github.com/swnirk/DeFi-Risk-Assessment-MakerDAO-Loan-Portfolio-Case).

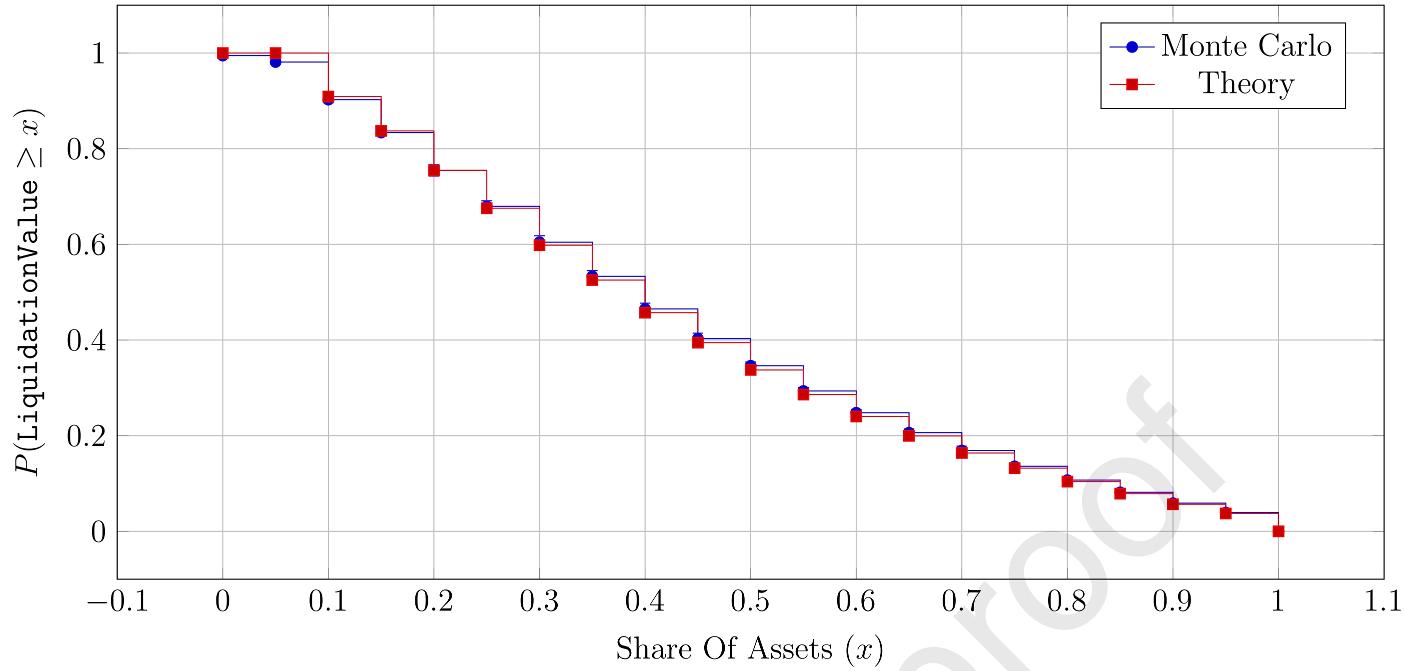

Figure 2: Complementary Cumulative Distribution Function for $n = 20$ users in each of two assets with equal levels, for $x^1_{\min} = x^2_{\min} \in \{-0.1k|k = 0..10\}$, $f = 0.05$ and $\alpha = 0.8$.

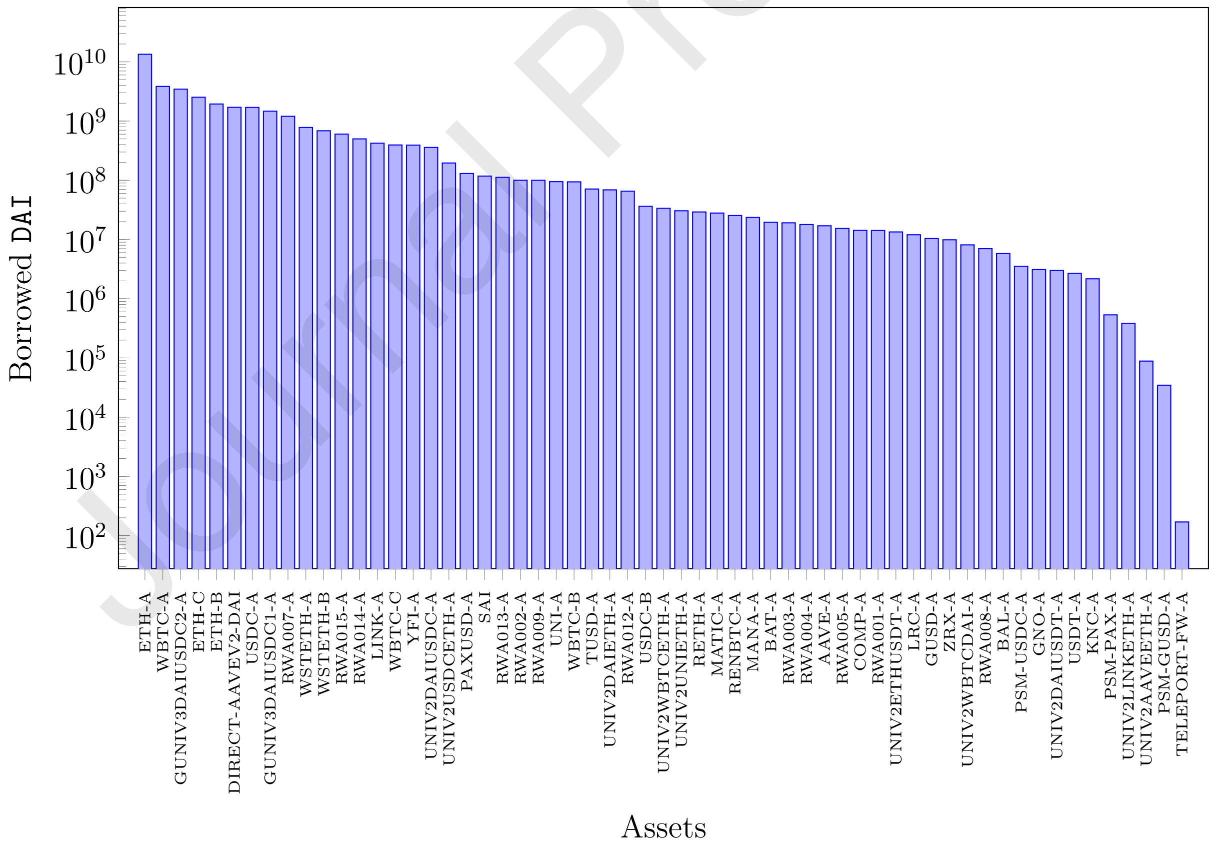

Figure 3: The total number of borrowed `DAI` for asset

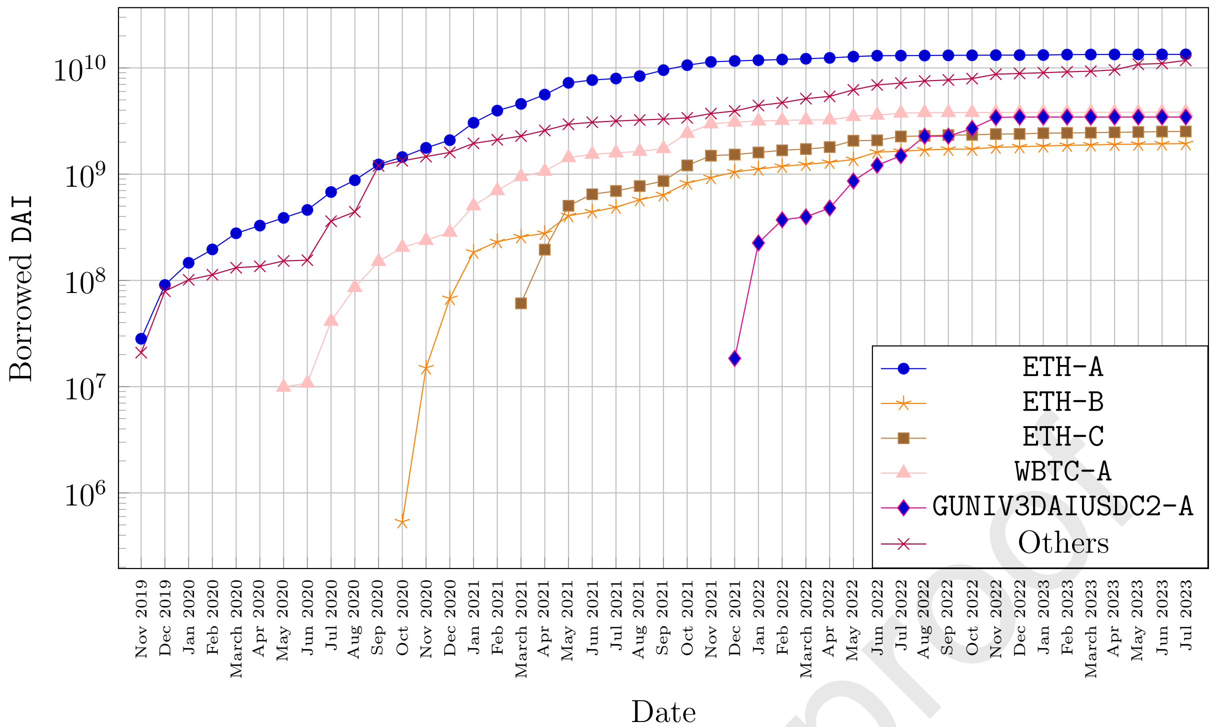

Figure 4: Dependence of borrowed DAI on date for each asset

5.2.2. Default of one users in one asset

We conducted a series of experiments to assess how well theoretical considerations suited for real-life data analysis. In order to check it, we calculated the actual number of defaults a day ahead together with the predictions from the Brownian motion mathematical model. To calculate it we used the results from the article [29]:

$$\mathtt{PD}_B(T) = e^{\frac{2fx_{min}}{\sigma^2}} \cdot \left[1 - \Phi\left(\frac{x_{min} + fT}{\sigma\sqrt{t}}\right)\right] + \left[1 - \Phi\left(\frac{x_{min} - fT}{\sigma\sqrt{t}}\right)\right],$$

where x_{min} is the passage level of the definite user and f is a log interest rate at the current time moment (the day before the time moment T). For comparison, we also considered the Poisson model since it is a baseline in classical finance. This model assumes all debts are independent and have an exponential distribution with an unknown parameter $\lambda > 0$. Thus the probability of default for a single debt during time T, $\mathtt{PD}_P(T) = 1 - e^{-\lambda T}$. The assumptions are also taken from the article [29].

To compare the fit of models to the real data, we use following metrics:

- Mean Squared Error (MSE) and Mean Absolute Error (MAE) are mean of squared and absolute differences between the observed and predicted values.
- Total Variation (TV): measures the discrepancy between two probability distributions. It is defined as half the sum of the absolute differences between the corresponding probabilities in the two distributions.
- Kullback-Leibler divergence (KL): measures the discrepancy between two probability distributions. It determines the amount of information lost by using one distribution to approximate the other.

The results of calculating default probabilities for the Poisson and Brownian motion models were taken as predicted data, while the true values were obtained by comparing the collateral-to-debt ratio r for definite user with the minimal collateral ratio r_{min}. In the case of $r < r_{min}$ user is marked as defaulted. For the each metric, a smaller value indicates a better fit of the theoretical model to the empirical data. Let us compare the obtained results.

The table 4 shows the result of comparing two mathematical models for different assets. For each asset, the best results are highlighted in bold. As can be seen that in most cases the Brownian motion model gives more accurate and reliable forecasts. This result can be explained by the fact that in the case of the Poisson model, all debts are assumed to be independent. However, for the Maker data, this assumption is incorrect because all debts of the same asset are based on the same type of collateral but with different collateralization ratios. In the case of `WBTC-A`, the Poisson model shows better result, this may be due to the fact that the Poisson model more effectively captures the likelihood of sudden, discrete price jumps that are characteristic of Bitcoin's volatility.

5.2.3. Default of users in different assets

As it was shown in the previous paragraph 5.2.2, the Brownian motion model most accurately describes the behavior of users in real life, so we chose this model for further experiments. To calculate the probability of default of a share x in two assets, we used the corollary 2.1. The Figure 5 shows the probability of a random process to reach threshold x for different time intervals such as one day, one month and one year. For the experiment, portfolios of different users at the same moment in time were taken from the `ETH-A` and `WBTC-A` assets. As the time horizon increases, the probability of default of share x increases, which is consistent with real logical considerations. Since, the exchange rate and the annual interest rate usually increase, the default probability of the user will also increase day by day, in case they stop replenishing their balance, securing himself against liquidation.

Thus, we estimated the default risks of two programs at once, using real loan portfolios. In reality, the default risk is even smaller due to the presence of more users and other programs. The proposed method of risk assessment is not sufficient to use it in real life, but it serves as a good tool to prevent dangerous situations for the platform.

6. Conclusions

Decentralized finance (DeFi) presents a new frontier in the financial world, offering innovative web3-based products as well as mimic for traditional financial instruments. However, the lack of regulation in DeFi has raised concerns about potential risks such as fraud, scams, and security vulnerabilities. While some qualitative risk assessments have been conducted on DeFi protocols, there is a need for more robust mathematical models to evaluate risk.

One prominent DeFi project is Maker, a blockchain protocol that facilitates crypto-backed loans. The objective of our current research is to evaluate the risk associated with MakerDAO's loan portfolio. In order to accomplish this, we have expanded upon a mathematical model specifically designed for DeFi loans to incorporate a variety of collateral types, as outlined in Theorems 1 and 2. Theorem 1 enables the calculation of the joint distribution of default probabilities for two borrowers, each with their own type of collateral. Theorem 2 provides a way to determine the probability of a certain portion of the portfolio defaulting.

We tested our theoretical models using artificial data generated by our simulator, which is based on Brownian motion modeling. Subsequently, we applied these Theorems to real data from MakerDAO, spanning from its launch in November 2019 to July 2023. Our findings indicate that there is a potential for the loan portfolio to default within a reasonable timeframe.

The research has several limitations that prevent its real-life application. Firstly, Maker is not solely focused on loans, so its operational stability is influenced by various factors, including the stability of the loan portfolio. Secondly, the proposed model is based on strong assumptions, such as the collateral price following an unshifted Brownian motion and borrowers not taking any actions to avoid defaults during the specified period. These assumptions are unlikely to hold true,

Asset	**Poisson model**				**Brownian model**			
	MSE	MAE	TV	KL	MSE	MAE	TV	KL
ETH-A	0.048	0.113	0.057	0.744	**0.047**	**0.005**	**0.024**	**0.046**
ETH-B	**0.167**	0.217	0.108	0.794	0.173	**0.181**	**0.090**	**0.175**
ETH-C	**0.049**	0.091	0.046	0.818	0.050	**0.050**	**0.025**	**0.050**
WBTC-A	**0.004**	**0.061**	**0.031**	0.769	0.115	0.116	0.058	**0.115**
GUNIV3DAIUSDC2-A	**0.004**	0.031	0.016	0.872	**0.004**	**0.004**	**0.002**	**0.004**

Table 4: Performance metrics for different mathematical models

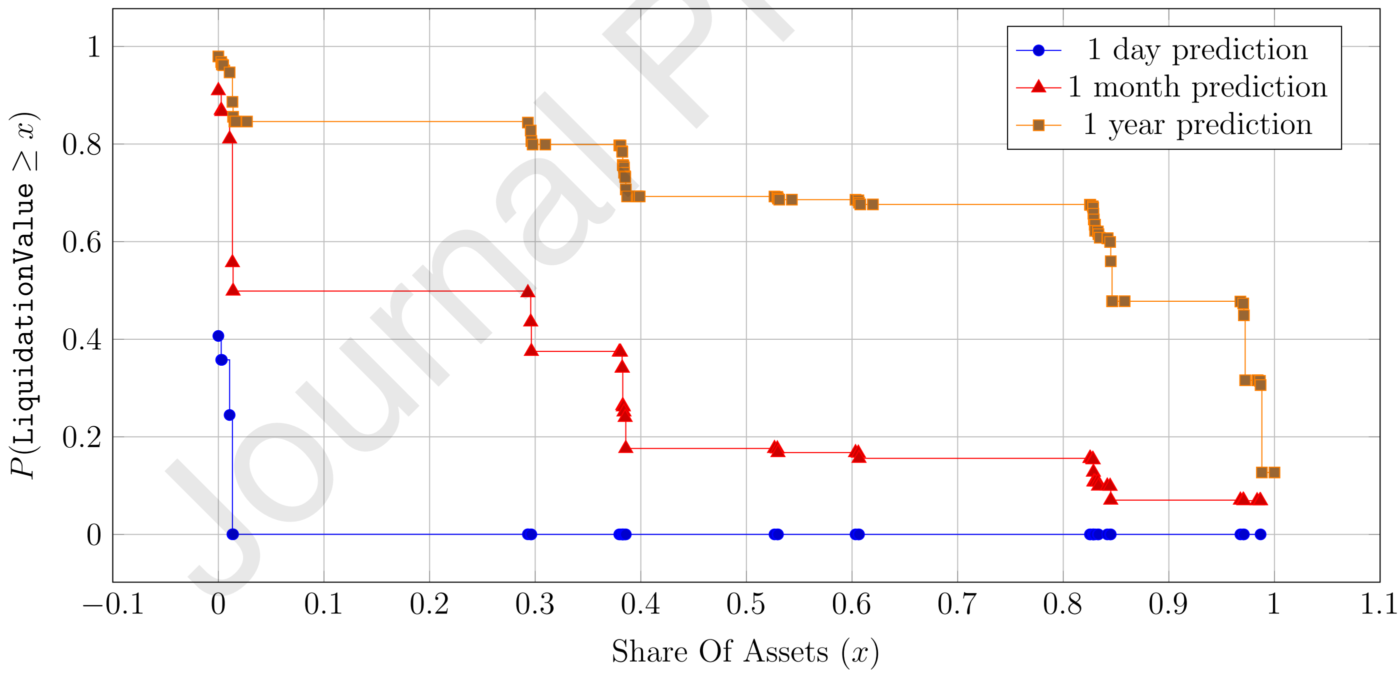

Figure 5: Probability of default of a share $\geq x$ of two assets (`ETH-A` and `WBTC-A`)

as evidenced by statistical testing and user operation history. However, our model has the potential to offer quantitative insights into the protocol's risk. Additionally, incorporating models of Brownian motion with jumps could enhance the model's accuracy and may be considered for future work, although obtaining theoretical results for such a model will be challenging.

Our model draws inspiration from Maker's loan portfolio and is evaluated using its data. However, it's important to note that other DeFi projects such as AAVE, Compound, and Spark Lend also have loan portfolios. Although the operational principles of DeFi lending are similar, the specific details and smart contracts may vary depending on different protocols. This presents a challenge for data collection and model transfer when analyzing other protocols in future research.

The Brownian motion model, while parametric and interpretable, lacks certain crucial aspects such as user activity. With DeFi usage data being publicly available, data-driven machine learning models hold promise for providing more accurate default probability predictions.

Our research underscores the importance of conducting thorough risk assessments in DeFi projects and emphasizes the need for further exploration of risk evaluation methodologies across a range of DeFi protocols.

Acknowledgments

We acknowledge ChatGPT for enhancing the English language and readability of the paper.

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Declaration of interests

v The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for *[Journal name]* and was not involved in the editorial review or the decision to publish this article.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Ignat Melnikov: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization

Irina Lebedeva: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization

Artem Petrov: Conceptualization, Validation, Writing - Review & Editing

Yury Yanovich: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Supervision