DAISIM: A Computational Simulator for the MakerDAO Stablecoin

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Abstract

We present a computational simulation of the single-collateral DAI stablecoin launched by the MakerDAO project in 2017. At the core of the simulation is a model of cryptocurrency investors acting as rational Markowitz mean-variance portfolio optimizers, with heterogeneous risk tolerance. The simulator, called DAISIM, incorporates automated order matching and price update mechanisms to determine the DAI price. We use the simulator to evaluate how the single-collateral DAI price, as well as portfolio allocations, vary for a given population of investors as a function of exogenous parameters such as the price of ETH and various system parameters including stability rate and transaction fee. DAISIM is being made available as open-source and may be useful in evaluating other similar projects.

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Supplementary Material *Software (Source Code)*: `https://github.com/ANRGUSC/DAISIM`

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1 Introduction

A stablecoin [11, 12] is a digital token that is designed to minimize price volatility against a peg. They are pegged to fiat currencies (most commonly the US Dollar), other assets such as gold or a basket of assets. By tying the value to an asset, stablecoins aim to mitigate the high volatility associated with other cryptocurrencies such as Bitcoin. By achieving stability, these tokens have a higher potential to be utilized as a unit of account, a store of value and a medium of exchange compared to volatile cryptocurrencies. Various methods have been developed to stabilize the value of the token. These include backing by fiat currencies, crypto-assets or using algorithmic stabilization (not backed by any asset).

One of the prominent projects is MakerDAO [6], a decentralized Stablecoin project on Ethereum blockchain launched in 2017. The Maker smart contract platform offers a crypto-asset backed Stablecoin called DAI, which has a 1:1 soft peg to the US dollar. The initial single-collateral DAI on the platform was called 'SAI' after transitioning to the new Maker Protocol with multiple collateral types. SAI officially shutdown in May 2020. Stability of single-collateral DAI was provided by Collateralized Debt Positions (CDP), Maker Governance who held the governance token called MKR and incentivized external actors.

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Our goal in this paper is to develop a computational simulation framework for modeling MakerDAO, to understand how well its underlying mechanism works under different settings. The simulation model is somewhat parsimonious, trading off some loss in realism in exchange for computational tractability, insight, and ease of exposition.

The crux of our model is to focus on the population of investors and investigate whether and when they choose to mint or burn DAI, and when they choose to buy and sell ETH or DAI. We model the investors using Markowitz's Optimal Portfolio Theory [4]. Specifically, we model them as maintaining and updating a portfolio consisting of four assets USD, ETH, DAI, and cETH (collateralized-ETH, used as collateral deposit to borrow/mint DAI), as well as a debt instrument (as interest is owed on any DAI that is borrowed), accounting also for transaction fees, in order to maximize their expected return while minimizing risk. A weight-parameter characterizes the risk-tolerance of each user. Given a population of such investors and their preferred allocations, our simulator iteratively updates the price of DAI and matches buyers and sellers to determine the market clearing or settling price. It allows us to set and modify various exogenous parameters such as return and risk associated with various assets and the price of ETH as well as system parameters such as interest rate (known as stability rate in the MakerDAO ecosystem) and transaction fees, allowing us to examine how the DAI price depends on these various parameters.

The key contributions of our work are as follows:

- We show how to model the MakerDAO ecosystem using optimal portfolio theory to model investor behavior with respect to relevant assets including USD, ETH, DAI and cETH, while accounting for transaction fees and the stability rate.
- We present our design and implementation of a computational market simulator, DAISIM, that handles order matching and price updates to determine the DAI price for a given set of parameters.
- We use the simulator to study how the DAI price and DAI supply/demand and portfolio allocation is affected by various exogenous parameters (such as risk tolerance of investors, ETH price, mean and covariance of asset returns) and system parameters (such as stability rate and transaction fees).
- The simulator itself is made available as an open-source simulation tool for use by the research community online at `https://github.com/ANRGUSC/DAISIM`.

The rest of the paper is organized as follows: in section 2, we describe the basics of the MakerDAO project with a focus on the simple single-collateral DAI launched in 2017 (extension to multi-collateral DAI is the focus of our future work). In section 3, we briefly survey the relevant prior work. In section 4, we present our simulation model and how the simulator is designed. In section 5, we present some illustrative results from the simulator to show how DAI price and investor decisions are affected by various key parameters. Finally, we present our conclusions in section 6.

2 MakerDAO – Background

At the heart of the MakerDAO is an autonomous mechanism to allow users to mint the DAI token. Before the launch of multi-collateral DAI (MCD), single-collateral DAI (SAI) could only be generated through a Collateralized Debt Position (CDP), a smart contact that required the user to lock in excess collateral above a minimum ratio called Liquidation Ratio at which the collateral is subjected to forced liquidation. After MCD, CDPs are now called "Vaults" but we call them CDPs for brevity. DAI can be used for trading, borrowing, making payments and more recently, also, saving. Some key statistics of MakerDAO can be found at [10].

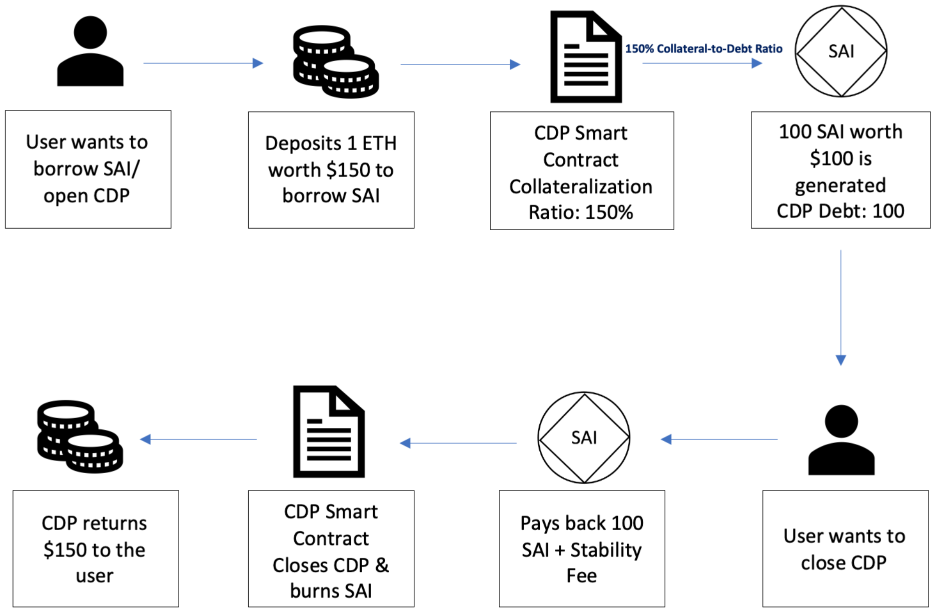


Figure 1 A sample CDP opening and closing transaction assuming that 1 ETH is equal to $150 and the minimum collateralization ratio is 150%.

Prior to the launch of multi-collateral DAI (MCD) in November 2019, DAI could only be generated through the single-collateral type, ETH[1]. MCD is now available to users at different Liquidation Ratios derived as a function of the risk pertaining the underlying collateral type determined by the Maker Risk Teams and Maker Governance.

After the user chooses a collateral-to-debt ratio (also known as the collateralization ratio) and the amount of single-collateral DAI they would like to borrow from the CDP, the smart contract deposits the collateral and returns DAI. The collateral is locked until the outstanding debt is paid in addition to the CDP Interest Rate (Stability Rate) that has accrued over time.

A CDP/Vault can be closed at any time once the debt and the CDP Interest Rate (Stability Rate) are paid. The collateralization ratio of a CDP can also be adjusted while it is active given that it is collateralized above the liquidation ratio. If a collateral becomes too risky when collateralization ratio drops to the liquidation ratio, the CDP is automatically acquired by the system and liquidated. Before MCD, liquidation was executed through a Liquidity Providing Contract whereas in MCD, an auction mechanism is used for liquidation. After the debt, Stability Rate and Liquidation Penalty have been recovered, the left-over collateral is returned to the CDP owner.

2.1 CDP and the Stability Rate

The Stability Rate acts like an interest rate on the loan. It plays a key role in maintaining stability of DAI through active governance. It is shown in DAI and paid in MKR that is removed out of circulation upon payment. When the value of DAI is below the Target Price,

[1] CDPs/Vaults can result in having more debt versus the value of collateral if there is an abrupt market crash in ETH. In this case, the collateral i.e ETH is diluted to recapitalize the system by the platform.

increasing the Stability Rate incentives users to close CDPs. Thus, it removes DAI from supply and helps restore the peg. Similarly, when the value of DAI is above the Target Price, decreasing the Stability Rate incentivizes users to open more CDPs. This increases the DAI supply and helps restore the peg. In addition to the Stability Rate, Debt Ceiling, Liquidation Ratio and Penalty Ratio are other key risk parameters for CDPs.

3 Prior work

We briefly present some relevant prior works focused on the evaluation of stablecoins, still a relatively sparse area of research. A broad survey of stablecoins is provided by Clark *et al.* [1]. Mundt and Minca [9] describe a complementary model of noncustodial stablecoins and explore different models of the liquidation structure that affects speculator decision-making and then analytically characterize the stability. Mundt and Minca [8] analyze the effects of deleveraging feedback effects that cause illiquidity during crises for non-custodial cryptocurrency-backed stable coins. Mundt et al. [7] propose a framework for relating economic mechanics of all stablecoins and formulated three classes of models for non-custodial stablecoins, for which traditional financial models are sparse. Lyons and Natraj [5] examine the efficiency and working mechanisms of stablecoins in the digital economy. They analyze how price stabilization functions in the case of stablecoins. Gudgeon *et al.* [3] investigate the feasibility of attacking the MakerDAO governance mechanism from a security perspective. Gu and Kothari [2] discuss a multiagent simulation of a generic asset-backed stablecoin with a focus on understanding demand dynamics for a stable coin in the face of exogenous price shocks.

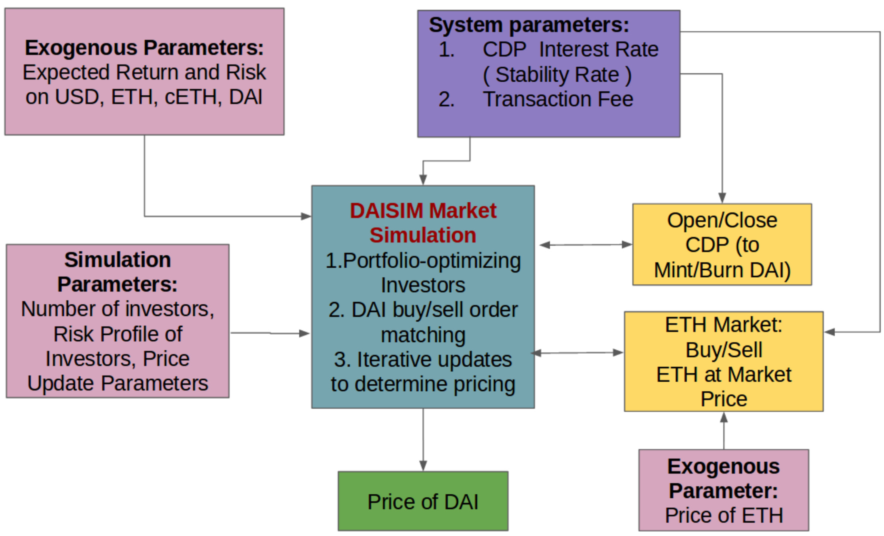


Figure 2 Overview of the DAISIM Simulator.

4 Design of the DAISIM Simulator

Considering that the Maker protocol has rapidly evolved in the last few years, this paper will assume that DAI mentioned in the subsequent sections refers to single-collateral DAI (SAI) for brevity.

4.1 System model

Our full system model for the single-collateral DAI ecosystem and our simulator is as shown in Figure 2. Exogenous inputs to the model include the price of ETH, expected return and risk (covariance) for USD, ETH, DAI and cETH. System parameters include the Stability Rate r_s and the Transaction Fees β. Additional simulation parameters include the size of the market n (number of investors), their risk profile (captured by a weight parameter λ_i for the i^{th} investor), and parameters pertaining to the price update algorithm employed in the simulation. The simulator allows investors to buy ETH on an open market as per the current ETH price P_{ETH}; it allows investors to open and close CDP's per the current stability rate; and it allows investors to buy and sell DAI from/to each other in the simulated market. All these transactions incur a constant transaction fee as specified by β. The simulator takes care of matching buy/sell orders for DAI and determining the market clearing (settling) price for DAI P_{DAI}. We describe these mechanisms in more detail below.

4.2 Price Settling Algorithm

The Price Settling Algorithm involves three steps i.e., Asset Optimization Mechanism, Order Matching Mechanism, and the Price Update Mechanism. We assume n investors each with an initial asset holdings $\mathbf{x}$ and a risk tolerance parameter λ. It is assumed that if λ is low, then the investor is risk-tolerant, and if it is high, then the investor is risk-averse. For each of these investors, we use the asset optimization mechanism to find out an optimal portfolio, x^{opt} and then use the Order Matching Mechanism to verify if all DAI Buy orders, B and the Sell Orders, S can be met. This mechanism proposes a new asset allocation of $x_{i,j}^{M}$ for the asset $j \in \{USD, ETH, DAI, cETH\}$ of the i^{th} investor based on $x_{i,j}^{opt}$. Then using the price update mechanism, we estimate the supply/demand of DAI based on the DAI bought/sold by the investors to achieve the optimal allocation and then update the DAI price, P_{DAI}. Table 1 can be referred for the details of different notations and their definitions used in this paper.

4.2.1 Asset Optimization Mechanism

For the i^{th} investor, consider the vector $\mathbf{x} = [x_{i,1}, x_{i,2}, x_{i,3}, x_{i,4}]$ which represents the i^{th} investor's holdings in each asset class: USD, ETH, DAI and cETH, respectively. We assume that the investor collateralizes at a constant safety ratio ρ that is well above the liquidation ratio of the protocol. Let r_s represents the stability rate. Let μ be the vector of expected return on investment in each of the four assets, and let $\mathbf{\Sigma}$ be the covariance matrix associated with the value of these assets. Let β be the transaction fee to buy or sell 1 USD worth of ETH/DAI and Ψ be the overall transaction fee incurred to reach the optimal allocation.
Let δ_{DAI} represents the current DAI debt for the investor. This debt corresponds to the amount of DAI minted from the CDP, and given the fixed collateralization ratio is assumed to be exactly equal to $\frac{x_{i,4}}{\rho}$. Then, it is easy to see that an optimal portfolio i.e., x^{opt} for the i^{th} investor with a total initial investment capital of $m = \Sigma x$ corresponds to one that maximizes:

$$\mathbf{x}^T\mu - \lambda \mathbf{x}\mathbf{\Sigma}\mathbf{x}^T - \frac{x_{i,4}}{\rho} r_s - \Psi \tag{1}$$

subject to the constraints:

$$\Psi = \mid x_{i,2} - x_{i,2}^{int} + x_{i,4} - x_{i,4}^{int} \mid \cdot \beta + \mid x_{i,3} - x_{i,3}^{int} \mid \cdot \beta \tag{2}$$

$$x^{int}_{i,1} \geq \Psi, x^{int}_{i,2} \geq 0, x^{int}_{i,3} \geq 0, x^{int}_{i,4} \geq 0 \tag{3}$$

$$\Sigma x^{int} = \Sigma x = m \tag{4}$$

Please note that $x^{int}_{i,j}$ is an intermediate allocation of the asset j for the i^{th} investor. It should also be noted that the transaction fees also apply to cETH as we need to buy ETH to deposit it as collateral. Constraints (2) and (3) ensure that the investors have enough USD holdings after choosing a portfolio allocation to cover any transaction fees incurred. After deducting the transaction fees Ψ, the updated asset holdings of the i^{th} investor are given as:

$$x^{opt}_{i,1} = x^{int}_{i,1} - \Psi,\ x^{opt}_{i,2} = x^{int}_{i,2},\ x^{opt}_{i,3} = x^{int}_{i,3},\ x^{opt}_{i,4} = x^{int}_{i,4}.$$

Table 1 Notations and Definitions.

Notations	Definitions
n	Number of investors participating in DAISIM
$\mathbf{x}$	Investor's initial asset's holdings
$x_{i,j}$	Initial investment of i^{th} investor in the asset j; $j \in \{USD, ETH, DAI, cETH\}$
λ_i	Risk tolerance parameter of i^{th} investor
$x^{opt}_{i,j}$	Optimal asset allocation for the i^{th} investor for asset j as suggested by the Asset Optimization Mechanism
B	Total outstanding buy order
S	Total outstanding sell order
$x^{M}_{i,j}$	Actual asset allocation for the i^{th} investor for asset j given by Order Matching Mechanism
ρ	Safety ratio
r_s	Stability rate
μ	Vector of expected return on investment in each of the four assets
$\mathbf{\Sigma}$	Covariance matrix associated with the value of the assets
β	Transaction fee to buy or sell 1 USD worth of ETH/DAI
δ_{DAI}	Current DAI debt for the investor
m	Initial investment capital
$x^{int}_{i,j}$	Intermediate allocation of the asset j for the i^{th} investor.
D^{ov}_i	DAI bought/sold by i^{th} investor to achieve optimal allocation
P_{ETH}	Price of ETH provided by the price oracle
P_{DAI}	Price of DAI determined by the price settling algorithm
D^{om}_i	DAI Bought by i^{th} investor in Order Matching Mechanism
D^{cdp}_i	DAI to be minted/returned by i^{th} investor to achieve optimal cETH allocation
π_j	Mean asset holdings for investors j; j ∈ {USD, ETH, DAI, cETH}

4.2.2 Order Matching Mechanism

We assume that the market doesn't have any external source of DAI, thus we need to make sure that the total DAI in the market is fixed during the course of the Price Settling Algorithm. Let order value, $D^{ov}_i = x^{opt}_{i,3} - x_{i,3}$ denote the amount of DAI the i^{th} investor needs to buy/sell in order to reach its optimal allocation. Let B denote the total outstanding buy order, and S represents the total outstanding sell order in the market.

$$B = \sum min(D_i^{ov}, 0) \tag{5}$$

$$S = \sum max(D_i^{ov}, 0) \tag{6}$$

If $B > S$ i. e. buy orders exceed sell orders, then all the sell orders can easily be met whereas when $S > B$ all buy orders can easily be met. In case all buy and sell orders cannot be met, the buy/sell order of an i^{th} investor is achieved in proportion to their D_i^{ov} value. The different possible scenarios of the Order Matching Mechanism can be illustrated with the help of the following examples:

▶ **Example 1.** Assume we have 4 investors with the following order values.
$D_1^{ov} = 100$, $D_2^{ov} = 120$, $D_3^{ov} = -130$, $D_4^{ov} = -190$
Total Buy orders, $B = 220$
Total Sell orders, $S = 320$
Since $S > B$, We can meet all buy orders, but not all sell orders.
Total DAI Bought in Market $= 220$
Investor 3 sells $130/320 * 220 = 89.375$
Investor 4 sells $190/320 * 220 = 130.625$
Let D_i^{om} denotes the DAI bought by i^{th} investor in the Order Matching Mechanism. Thus, $D_1^{om} = 100$, $D_2^{om} = 120$, $D_3^{om} = -89.375$, $D_4^{om} = -130.625$

▶ **Example 2.** Assume we have 4 investors with the following order values.
$D_1^{ov} = 500$, $D_2^{ov} = 120$, $D_3^{ov} = -130$, $D_4^{ov} = -190$
Total Buy orders, $B = 620$
Total Sell orders, $S = 320$
Since $B > S$, We can meet all sell orders.
Total DAI Sold in Market $= 320$
Investor 1 buys $500/620 * 320 = 258.06$
Investor 2 buys $120/620 * 320 = 61.93$
$D_1^{om} = 258.06$, $D_2^{om} = 61.93$, $D_3^{om} = -130$, $D_4^{om} = -190$

At the end of the Order Matching Mechanism, we have $x_{i,1}^M = x_{i,1} - \Psi$, $x_{i,2}^M = x_{i,2}^{opt}$, $x_{i,3}^M = x_{i,3} + D_3^{om}$, $x_{i,4}^M = x_{i,4}^{opt}$. The transaction fees in this step of the algorithm is,

$$\Psi = \mid x_{i,2}^M - x_{i,2} + x_{i,4}^M - x_{i,4} \mid \cdot \beta + \mid x_{i,3}^M - x_{i,3} \mid \cdot \beta$$

4.2.3 Price Update Mechanism

It is evident from the above discussion that the Asset Optimization Mechanism estimates the market's demand for DAI whereas the Order Matching Mechanism tries to fulfill the demand keeping total DAI in the market constant. The Price Update Mechanism updates P_{DAI} based on the supply and demand of DAI in the market. We assume that DAI minted by CDPs as another indicator for P_{DAI}. Let $D_i^{cdp} = \frac{(x_{i,4}^{opt} - x_{i,4}) * P_{ETH}}{P_{DAI} * \rho}$ be the DAI to be minted/returned by i^{th} investor to achieve optimal cETH allocation.

$$\sum_{i=1}^{n} (D_i^{ov} - D_i^{cdp}) \geq 0 \Rightarrow High\, Demand$$

$$\sum_{i=1}^{n} (D_i^{ov} - D_i^{cdp}) < 0 \Rightarrow High\, Supply$$

If we are in a high demand zone, we raise the price, else we reduce it. At the end of each iteration we fix the asset allocation $x_{i,j} = x_{i,j}^M$.

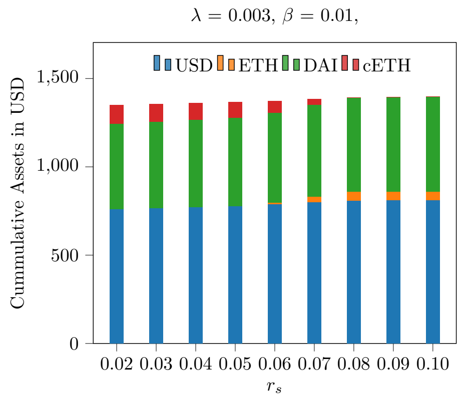


Figure 3 Investor Asset Holdings vs. r_s.

5 Simulation Results

We present here some results illustrating the DAISIM Market simulation model which allows us to show the impact of various parameters on the investors' optimal portfolio. Purely as an illustrative example, we assume that the return rates on the four assets i.e., [USD, ETH,DAI, cETH] are given by $\mu = [0.08, 0.22, 0.18, 0.16]$ and that their covariance matrix is given as follows:

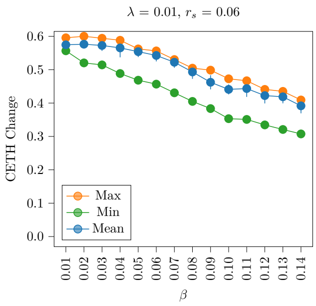
$$\mathbf{\Sigma} = \begin{bmatrix} 0.04 & 0 & 0 & 0 \\ 0 & 0.64 & 0.048 & 0.36 \\ 0 & 0.048 & 0.09 & 0.015 \\ 0 & 0.36 & 0.015 & 0.25 \end{bmatrix} \tag{7}$$

These parameters have been chosen arbitrarily for illustration, but intuitively encode the following assumptions. The returns and variance in increasing order are USD $<$ cETH $<$ DAI $<$ ETH. Returns on USD is assumed to be uncorrelated with other assets while DAI is weakly correlated with ETH and cETH. ETH and cETH are relatively highly correlated with each other.

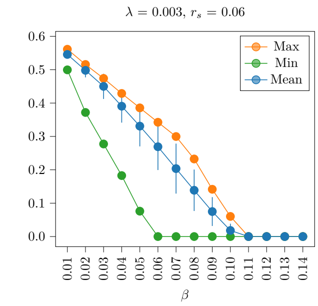
5.1 Baseline parameters and portfolio

Considering our baseline model with parameters $n = 10$, $\pi_{USD} = \$1000$, $\pi_{DAI} = \$1000$, $\pi_{eth} = \$0$, $\pi_{ceth} = \$0$, $r_s = 0.06$, $\beta = 0.01$, we analyze how does the transaction fee β, Stability Rate r_s and risk preference λ affect the P_{DAI} and the optimal portfolio of an investor. We fix $\lambda = 0.01$ for a risk-averse investor and $\lambda = 0.003$ for a risk-tolerant investor.

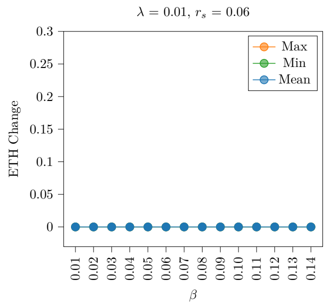
In a population of n investors with 2 possible risk values i.e., $\lambda \in \{0.003, 0.01\}$, we have 2^n different risk profiles for n investors. When $n = 10$, we have $2^{10} = 1024$ different risk profiles for an investor population. Also, when we fix λ for a single investor, we have 512 different risk profiles for the remaining 9 investors. In each of these 512 risk profiles, we find the assets bought or sold by the investor and we call the mean of this value as Mean Asset Change. For example, Mean cETH Change (Δ cETH) refers to the mean cETH bought or sold by an investor when we change λ for the other 9 investors. Mean DAI Settling Price is also similarly defined.



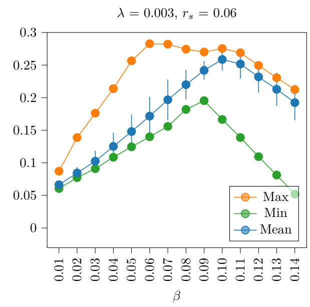
(a) Δ cETH vs. β (Less Risky).



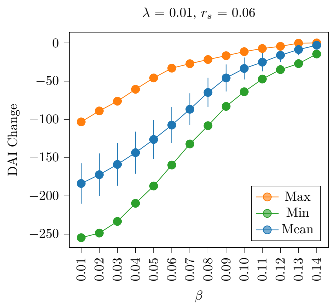
(b) Δ cETH vs. β (More Risky).



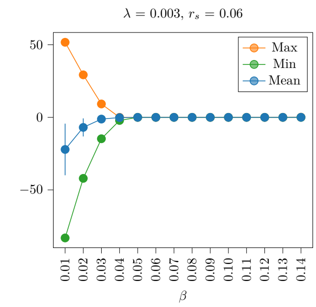
(c) Δ ETH vs. β (Less Risky).



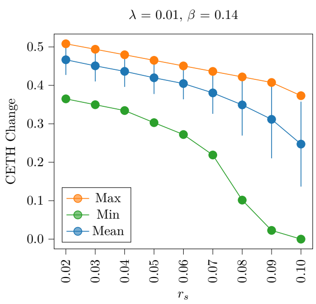
(d) Δ ETH vs. β (More Risky).



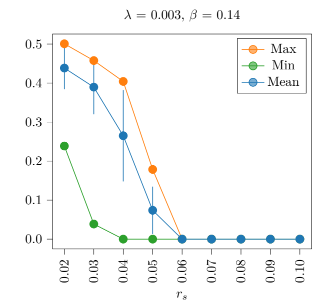
(e) Δ DAI vs. β (Less Risky).



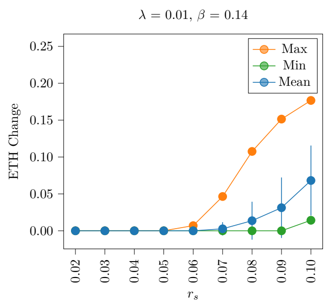
(f) Δ DAI vs. β (More Risky).



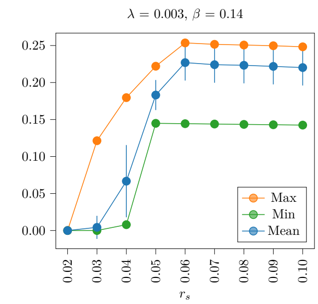
(g) Δ cETH vs. r_s (More Risky).



(h) Δ cETH vs. r_s (More Risky).

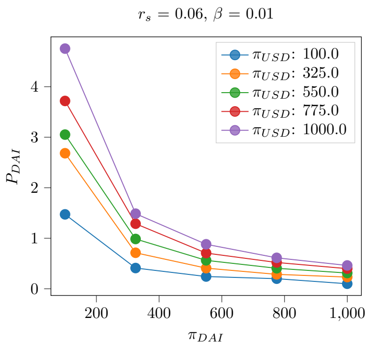


(i) Δ ETH vs. r_s (Less Risky).

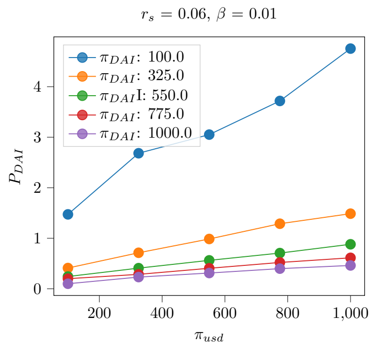


(j) Δ ETH vs. r_s (More Risky).

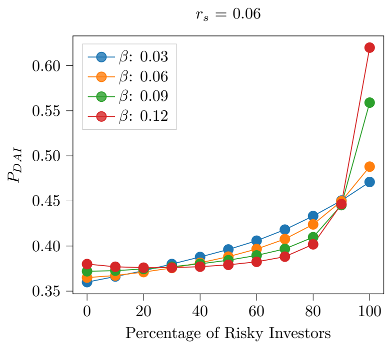
Figure 4 Investor Asset Trends.



(a) P_{DAI} vs. π_{DAI}.

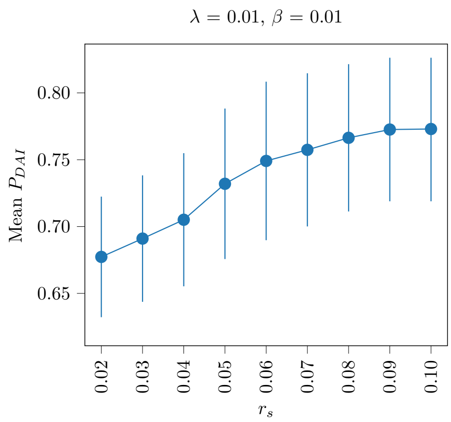


(b) P_{DAI} vs. π_{USD}.

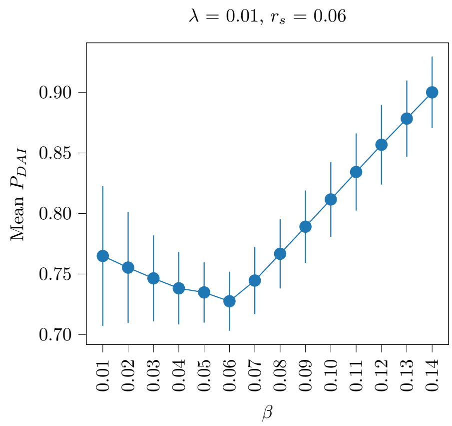


(c) P_{DAI} vs. Percentage of risky investors.

Figure 5 P_{DAI} v/s Investor population aggregates.



(a) Mean P_{DAI} vs. r_s.

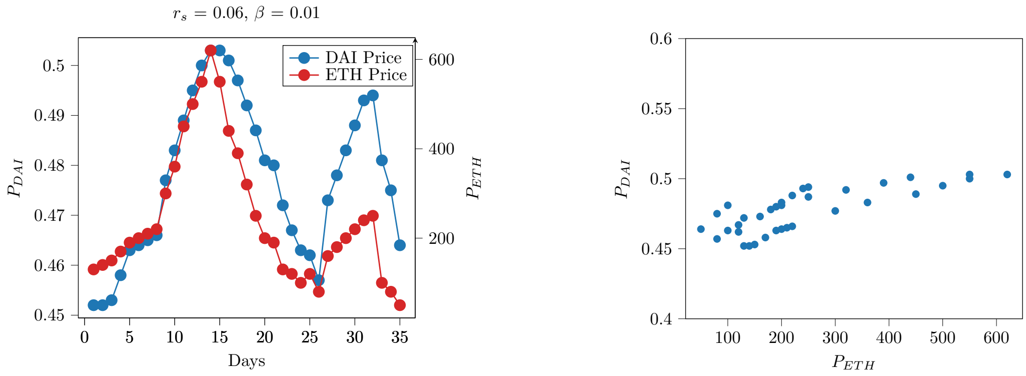


(b) Mean P_{DAI} vs. β.

Figure 6 Mean P_{DAI} vs. r_s & β.

5.2 Investor Assets

In this section, we describe how does risk preference λ, transaction fee β & stability rate r_s impact an investor's asset allocation. In Figure 3, we analyze the impact of change in r_s on the distribution of an investor's assets. It is observed that once the value of r_s increases from 0.02 to 0.1, the distribution of different assets (shown in different colors) changes. An increase in r_s makes it costlier to open a CDP and therefore disincentivizes an investor from



(a) P_{DAI} & P_{ETH} over 35 days.

(b) Correlation of P_{DAI} & P_{ETH}.

Figure 7 Relationship b/w P_{DAI} & P_{ETH}.

holding cETH. At the same time, as β remains constant, the cost of holding ETH remains the same. It is evident from Figure 3 that an investor reduces its cETH holdings and increases its ETH holdings as r_s increases. This is because holding ETH becomes cheaper and more profitable given its high return rate.

5.2.1 Impact of Risk Preference

A risk-tolerant investor is more likely to invest in ETH as compared to a risk-averse investor given that ETH is the riskiest asset. In Figures 4a through 4j, we make the following observations,

- In Figures 4a, 4b the cETH holdings of a risk-tolerant investor quickly reach 0. It appears that a risk-tolerant investor is very sensitive to β.
- In Figures 4c, 4d, we see that a risk-tolerant investor invests in the riskiest asset i.e., ETH, while a risk-averse investor doesn't invest in ETH at all. For the risk-tolerant investor as β increases, we observe that ETH holdings first increase and then decrease. We believe that an investor prefers to convert its cETH to ETH as it offers a better return rate but once its cETH holdings reach 0, the taxation from β comes into the picture which causes a decline in ETH Holdings.
- In Figures 4e, 4f, we see that a risk-tolerant investor prefers to hold DAI vs. a risk-averse investor that wants to minimize total DAI held. At lower β's an investor is very sensitive to the risk parameters of other $n-1$ investors.
- In Figures 4g, 4h, we see that the cETH holdings of a risk-tolerant investor are also very sensitive to r_s. And from Figures 4i, 4j, we see that a risk-tolerant investor holds more ETH than a risk-averse investor.

5.2.2 Impact of Transaction Fee

In Figures 4a, 4b we see that as β goes up, the mean cETH change decreases. In Figure 4e, 4f we see that as we increase β, the absolute mean DAI Change also reduces to 0. Similarly, an investor is also less likely to buy/sell ETH. These trends are easy to explain because a transaction fee on buying/selling of any asset is similar to a tax. A higher β disincentivizes an investor from buying and selling assets.

In Figure 6b, we see that as β increases from 0.01 to 0.14 with π_{USD} = \$325 & π_{DAI} = \$300, mean P_{DAI} first decreases and then increases. An increase in β has two side effects i.e., reduction in DAI demand and reduction in DAI supply. We believe that, when DAI demand reduces more than DAI supply we see a decrease in P_{DAI} and when DAI supply reduces more than DAI demand we see an increase in P_{DAI}.

5.2.3 Impact of Stability Rate

In Figures 4g, 4h we see that as r_s increases from 0.02 to 0.1, with all parameters matching the baseline, the mean cETH change for an investor decreases because it becomes costlier to open a CDP for minting DAI. In Figures 4i, 4j it is also seen that the mean ETH change for an investor increases initially and then flattens out. The Stability Rate r_s doesn't affect the mean ETH change directly but as r_s increases, it becomes prohibitively expensive to hold cETH, and as a result, the investor converts its cETH to ETH which causes an increase in mean ETH change. As all of the cETH is converted to ETH, a further increase in r_s does not affect the mean ETH change. Also, a change in r_s does not directly affect an investor's willingness to buy/sell DAI.

5.3 DAI Settling Price

In this section we analyze the impact of stability rate r_s, transaction fee β, mean USD holdings for the investor population π_{USD}, mean DAI holdings for the investor population π_{DAI}, price of ETH P_{ETH} and investor risk preference on the DAI Settling Price P_{DAI}.

5.3.1 Impact of mean DAI and USD holdings

In Figure 5a, we see that as π_{DAI} in the market increases, P_{DAI} decreases because an increase in DAI supply while keeping the demand constant drives down P_{DAI}. Similarly in Figure 5b, we see that as π_{USD} in the market increases P_{DAI} increases because as investors have more money to spend, they want to invest more in stable assets such as DAI. An increase in demand for DAI while keeping supply constant drives up the P_{DAI}.

5.3.2 Impact of Investor Risk Preference

In Figure 5c, as we increase the percentage of risk-tolerant investors in the market, P_{DAI} increases. As a risk-tolerant investor prefers to hold more DAI than a risk-averse investor, we can say that a risk-tolerant investor has a tendency to buy DAI and a risk-averse investor has a tendency to sell DAI. As we increase the number of risk-tolerant investors in the market, two things occur. Firstly, with more risk-tolerant investors we have more investors with a higher DAI demand which increases the total DAI demand in the market. Secondly, with less risk-averse investors we have fewer investors willing to sell DAI which reduces the total DAI supply in the market. These two factors are sufficient to drive up P_{DAI}.

5.3.3 Impact of stability rate

In Figure 6a, we see that as r_s increases from 0.02 to 0.1, with π_{USD} = \$325 & π_{DAI} = \$300, mean P_{DAI} increases. This is because with an increase in r_s, people are less likely to open a CDP to mint DAI which reduces the DAI supply keeping DAI demand constant. This directly leads to an increase in P_{DAI}.

5.3.4 Impact of ETH price

In Figure 7a, we observe how P_{DAI} changes as we perform the market simulation over multiple days with an external ETH price feed. We observe that the P_{DAI} closely mirrors the changes in P_{ETH}. From Figure 7b we see that the P_{DAI} is highly correlated to P_{ETH}. We also observe that P_{DAI} varies slightly with large P_{ETH} changes showing that the P_{DAI} is resistant to rapid P_{ETH} changes.

6 Conclusions

We have presented DAISIM, the first open-source computational simulation of the single-collateral DAI stablecoin from MakerDAO. The simulation models investors as rational portfolio optimizers and simulates DAI trading on a market to determine the DAI price as a function of various relevant parameters. In future work this simulation could be used to develop automated mechanisms to steer or control the price of DAI by modifying relevant control parameters. We also plan to extend DAISIM to handle the newer multi-collateral version of DAI that has been introduced more recently.

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