Decentralized Stablecoins and Collateral Risk

Roman Kozhan and Ganesh Viswanath-Natraj*

First version: June 17, 2021 (posted SSRN)

This version: September 1, 2021 (posted SSRN)

Abstract

In this paper, we study the mechanisms that govern price stability of MakerDAO's DAI token, the first decentralized stablecoin. DAI works through a set of autonomous smart contracts, in which users deposit cryptocurrency collateral, typically Ethereum, and borrow a fraction of their positions as DAI tokens. Using data on the universe of collateralized debt positions, we show that DAI price covaries negatively with returns to risky collateral. The peg-price volatility is related to collateral risk, while the stability rate has little ability to stabilize the coin. The introduction of safe collateral types has led to an increase in peg stability.

Keywords: Cryptocurrency, fixed exchange rates, monetary policy, stablecoins, collateralized debt positions.

JEL Classifications: F31, G14, G15, G18, G23

*Warwick Business School (Roman.Kozhan@wbs.ac.uk), and (ganesh.viswanath-natraj@wbs.ac.uk), respectively. For help with obtaining data for this project, we would like to thank Mike McDonald, Lou Kerner, and members from the MakerDAO team, Greg Di Prisco and Kenton Prescott. The views expressed in this paper are independent to MakerDAO. For detailed comments, we thank discussant Oliver Gloede, Adrien d'Avernas, Bruno Biais, Jonathan Chiu, Darrell Duffie, Barry Eichengreen, Pierre-Olivier Gourinchas, Brett Lyons, Rich Lyons, David Skeie, Ruslan Sverchkov,Junxuan Wang, and seminar participants at the CEBRA annual meeting. We thank Amit Chaudhary for valuable research assistance.

1 Introduction

"I expect DAI (and newer alternatives eg. RAI) to have much higher survivability than Tether long term."[1] **Vitalik Buterin, the cofounder of Ethereum**

Cryptocurrencies enable peer-to-peer transactions on a public and decentralized network without the need for intermediation. Stablecoins are a class of cryptocurrencies designed to maintain a stable peg to USD. Stablecoins come in two predominant forms based on whether they are backed by National currency or cryptocurrency collateral. For coins backed by National currency, typically the US dollar, every token in circulation is backed by a dollar in reserves. These stablecoins suffer from the drawback of having a centralized custodian of the assets. For decentralized stablecoins led by MakerDAO's DAI, on the other hand, issuance of new tokens is decentralized through using autonomous smart contracts on the Ethereum blockchain.[2] DAI tokens are generated when an investor deposits a set amount of collateral, typically Ethereum (ETH), into a collateralized debt position (CDP). Based on the value of ETH collateral, the investor can borrow a fraction of their collateral as DAI tokens. While DAI's decentralized method of issuance eliminates custodial risk, it is exposed to other risks associated with fluctuations in the price of collateral coins. In this paper we study the factors affecting stability of DAI price.

In order to answer the question about the fundamental sources of stablecoin instability in DAI, we start by developing a simple model of equilibrium price formation. In the model there are three types of agents: speculators that deposit risky ETH collateral and borrow a fraction as DAI tokens, arbitrageurs that short DAI when the peg trades at a premium, and a demand shock for DAI from investors that seek DAI to earn savings and gain utility from its use in Decentralized Finance (DeFi) applications. Speculators' beliefs about future performance of collateral follow a two-state process. The two states are a *good* and *bad* state, and reflect speculator beliefs about the expected return of ETH. In equilibrium, DAI peg-prices are dependent on the state of the collateral. Using this framework, we can investigate the importance of collateral risk on stability of the DAI stablecoin peg. We find the model generates peg premiums in the *bad* state, leading to a negative correlation between DAI prices and returns to ETH collateral. The model also generates testable implications regarding the

[1] https://twitter.com/VitalikButerin/status/1263191590543253504

[2] A smart contract is a set of instructions, written in computer code, that defines the conditions of the contract for each counterparty under different scenarios (default etc). Being managed by computer code and visible on the blockchain, it can be verified publicly by all nodes in the blockchain.

behaviour of DAI prices during periods of low and high demand, changes in ETH volatility and the interest rate on DAI borrowings, which is known as the stability rate. Peg-premiums in the *bad* state are higher in periods of high demand, high ETH volatility and when the stability rate is higher. A comparative statics exercise shows that the peg volatility increases with volatility of ETH collateral.

We then consider an extension to the model, by introducing an additional collateral type, the USDC stablecoin, that has lower volatility than ETH. Arbitrageurs have an opportunity to reduce their risk by issuing DAI with a lower volatility collateral type. To close a peg-price premium, arbitrageurs deposit collateral, borrow DAI tokens and sell it in the secondary market. We show that in equilibrium, arbitrageurs use the new collateral type to conduct arbitrage. The share of USDC collateral used by arbitrageurs increases as the USDC volatility declines. A comparative statics exercise shows that the addition of a stable collateral type causes a decline in the DAI premium in the *bad* state, and a decline in the volatility of the DAI peg. This is consistent with stable collateral leading to a decrease in the limits to arbitrage. Arbitrageurs now require lower premiums to borrow DAI and sell it in the secondary market.

We present empirical evidence to support model predictions. We use the entire history of CDP transactions made by an individual CDP, including the amounts of ETH collateral deposited, DAI borrowed, and the timestamp of each transaction. Consistent with model predictions, we find leverage, the ratio of DAI borrowing to ETH collateral for an individual CDP, responds negatively to an increase in ETH returns, volatility and the stability rate. We show that a 1 per cent increase in ETH volatility decreases leverage of an individual CDP by 25 basis points, a 1 per cent increase ETH returns decreases leverage by 23 basis points, and a 1 percent increase in annualized stability rate decreases leverage by 10 basis points. We document a significant relationship between the volatility of DAI peg price deviations and the volatility of ETH at a daily frequency, estimating an elasticity of 0.16, i.e. a 1 per cent increase in ETH volatility increases DAI volatility by 0.16 percentage points. Furthermore, consistent with our hypothesis, we document a significant negative correlation between DAI prices and ETH returns. Large drops in ETH prices can result in a substantial decline in DAI supply and significant per premiums. For example, on March 12th, 2020, known as *Black Thursday* to the cryptocurrency community, ETH crashed by up to 50% in a single day and resulted in a DAI peg-premium of 800 basis points. We estimate that on average, a 1 USD Million increase in DAI liquidations is associated with a DAI price increase of 30 basis points.

The two main stability tools used by the MakerDAO governance protocol to stabilize the peg are the stability rate and mitigation of collateral risk. The stability rate is set by the governance body and is a cost to dollar borrowings. We show that a shock to the stability rate has positive effects on the DAI price, with an elasticity of approximately 30-40 basis points with respect to a 100 basis point increase in the DAI stability rate. The leverage ratio reduces by approximately 1 percentage point. While the stability rate has the intended effect of lowering the leverage and increasing the price, it has limited scope in stability due to delays in updating rates due to the voting procedure of the MakerDAO protocol, and the existence of a lower bound on the stability rate.

To mitigate the collateral risk, MakerDAO attempted to increase the share of DAI borrowing through stable collateral types since March 2020. The introduction of USDC collateral was in direct response to the *Black Thursday* event of March 2020, to reduce the exposure of the DAI peg to mass liquidations from a risk-off event in the crypto market. Empirically, we find an increase in the share of stable collateral by 1 per cent reduces the DAI price by 1.9 basis points, and the volatility of the DAI peg by 2.1 basis points. This is consistent with the model prediction of stable collateral increasing the capacity for arbitrageurs to step in and absorb differences between the primary and secondary market rates.

In addition to depositing USDC collateral, the MakerDAO protocol introduced a peg stability module (PSM) in December 2020. Investors can directly swap DAI for USDC at a 1:1 rate.[3] By eliminating liquidation risk for investors, the PSM incentivizes arbitrage participants to swap USDC for DAI when DAI prices trade at a premium. The increase in DAI supply by arbitrageurs pushes prices toward one. We document a decline in both the magnitude of peg-price deviations and intra-day volatility of approximately 70 basis points after the introduction of PSM on December 18th, 2020. To rule out the possibility of a tighter peg due to idiosyncratic developments in the USDC stablecoin, we test a difference-in-difference (DiD) design to determine how DAI/USD prices changed relative to a control group of USDC/USD prices. The results of the test confirm the findings of an increase in peg efficiency. Relative to the USDC/USD price, we find a decline in absolute peg-price deviations of 101.8 basis points, and a 61.0 basis point decline in volatility following the PSM.

The remainder of the paper is structured as follows. In section 2 we summarize the contributions of our paper to related literature. In section 3 we summarize the properties

[3] A technical difference between the PSM and having stable collateral type is liquidation risk. For example, if investors deposit USDC collateral into a vault, there is risk of a collapse of the USDC peg which can trigger a sufficient decline in the value of collateral and a liquidation event.

of DAI and describe the data sources for our empirical work. In section 4 we introduce the model of DAI prices. We produce testable implications on the determinants of the price and a discussion of stability tools. In section 5 we conduct our empirical analysis. Section 6 concludes.

2 Related literature

The empirical research most closely related to our paper focuses on investigating properties of stablecoins (Berentsen and Schär, 2019; Bullmann et al., 2019; BIS, 2019; Eichengreen, 2019; Dell'Erba, 2019; Arner et al., 2020; Frost et al., 2020; Force et al., 2020), arbitrage in stablecoin and cryptocurrency markets (Lyons and Viswanath-Natraj, 2020; Makarov and Schoar, 2019, 2020; Borri and Shakhnov, 2018; Pernice, 2021) and intraday price changes to support the role of stablecoins as safe havens (Baur and Hoang, 2020; Baumöhl and Vyrost, 2020; Wang et al., 2020; Bianchi et al., 2020; Gloede and Moser, 2021). For example Eichengreen (2019) comments on stablecoins being backed by either national currencies or cryptocurrencies, and highlights that systems can be vulnerable to speculative attack if there is perception that the peg is under-collateralized. Lyons and Viswanath-Natraj (2020) find empirical evidence supporting an arbitrage mechanism for dollar-backed stablecoins: through which private investors deposit (withdraw) dollars when the stablecoin trades at a premium (discount), driving prices toward one. This arbitrage is central to our thesis of collateral risk: stablecoins backed by risky collateral no longer have a functioning arbitrage mechanism to stabilize the peg. Therefore collateral risk acts as a limit to arbitrage, and we find, both empirically and through our model, that the addition of stable collateral types increases the role of arbitrage in stabilizing the peg. We find empirical support for the volatility differences across stablecoin regimes in Jarno and Kołodziejczyk (2021). A comparison of volatility of dollar-backed, crypto-backed and algorithmic (un-collateralized) stablecoins reveals that peg-price deviations of crypto-collateralized stablecoins are larger and more dispersed.

Our paper contributes to an emerging literature on DeFi (Harvey et al., 2020; Schär, 2021). In addition to decentralized stablecoins, an alternative application is DeFi lending protocols, such as Compound, set interest rates and allocate funds automatically through algorithms (Gudgeon et al., 2020; Perez et al., 2020). Other DeFi applications that use the Ethereum blockchain are automated market makers, which are exchanges that trade based on algorithms without the need for a limit order book. The most common type of decentralized exchange (DEX) uses an automated market-maker constant product algorithm (Angeris and Chitra, 2020; Aoyagi and Ito, 2021; Lehar and Parlour, 2021). DAI's main use cases are as a source of savings in lending protocols and in liquidity pools for trading in decentralized exchanges. Perez et al. (2020) find lending protocols are susceptible to liquidation risk. We complement their findings by examining how liquidation events for DAI affect dynamics of the peg. In addition to understanding price-movement, we are the first paper to utilize rich data on the universe of CDP positions to shed light on the determinants of an individual CDP leverage and the probability of liquidation. We find that in the periods of positive ETH returns, high volatility, and higher interest rates reduce the leverage ratio. Liquidations are more likely in periods of extreme negative returns and high volatility of ETH collateral.

Turning to the theoretical research, recent work has modeled the price dynamics of stablecoins (Routledge et al., 2018; Klages-Mundt and Minca, 2020; Li and Mayer, 2020; d'Avernas et al., 2021). Routledge et al. (2018) adapt a model of fixed exchange rates with speculative attacks to stablecoins, and point out that centralized stablecoin regimes can collapse due to expectations of insufficient backing of dollar reserves. Klages-Mundt and Minca (2020) model over-collateralized stablecoins and show that high liquidation costs can lead to CDPs optimally creating a reserve buffer by posting excess collateral to insure against extreme negative price movements. They also model the dynamics of liquidation events on DAI peg-price premiums. Li and Mayer (2020) examine a centralized issuer of dollar-backed stablecoins that has autonomous control of token supply and maximizes the dividend of shareholders that own a governance token. Through the lens of their model, the issuer conducts open market operations to stabilize the price around its peg. Under this centralized arrangement, they consider reserve management and over-collateralization as potential solutions to avoid speculative attacks and peg discounts. d'Avernas et al. (2021) determine the equilibrium conditions in which both dollar-backed and decentralized stablecoins backed by crypto collateral can maintain parity in response to a negative demand shock or a liquidation of collateral. With respect to decentralized stablecoins, they show that a buffer reserve maintained by the governance protocol can be used as a stabilizing mechanism to restore peg stability in response to peg-discounts, similar to reserve management of a central bank. We extend existing theoretical work on stablecoins by modelling the fundamental sources of peg-instability in over-collateralized stablecoins like DAI. Our model generates a number of empirical properties: including negative correlation between DAI peg-prices and ETH returns, the positive relationship between the volatility of peg-price deviations and the volatility of collateral. We also model how stability mechanism and how multiple collateral types can diversify collateral risk and decrease limits to arbitrage, thereby increasing peg stability.

Finally, we draw on a literature on the properties of arbitrage with financial constraints

(Gromb and Vayanos, 2002, 2018; Brunnermeier and Pedersen, 2009; Nyborg and Rösler, 2019). For example, Gromb and Vayanos (2018) show that shocks to arbitrage capital can increase spreads and risk-premia, and Brunnermeier and Pedersen (2009) examine the role of funding margins on asset prices and the feedback between funding and market liquidity.[4] Nyborg and Rösler (2019) investigate the spread between unsecured and secured (repo) rates in interbank markets. They observe that risk-free rates on secured collateral are higher than unsecured rates. This spread is increasing in periods of increased volatility and negative returns of collateral, and suggests collateral risk is a limit to arbitrage in pricing interbank market rates. We contribute to this literature by focusing on an alternative limit to arbitrage: by measuring the riskiness of capital via stable and risky collateral types. We model the crucial role arbitrageurs play in the setup, and how risky collateral generates a limit to arbitrage. We show that in equilibrium, arbitrageurs can use a stable collateral type to conduct arbitrage, increasing relative supply in response to peg-price premiums and driving prices back toward one. This finds empirical support through the introduction of stablecoin collateral types in 2020, in which DAI can be swapped with USDC at a 1:1 rate. This led to a significant decline in the absolute size and intra-day volatility of peg-price deviations.

3 Definitions and Data

DAI creation process

To open a collateralized debt position (CDP), an investor deposits a set amount of collateral (eg. ETH), into a vault. The investor can borrow a fraction of their collateral as DAI tokens. The vault is regulated through a set of autonomous contracts, that update in real-time the valuation of collateral and DAI borrowings of the CDP. We outline three use cases for DAI tokens. First, DAI may be deposited as savings in the DAI savings protocol. [5] Second, DAI is a popular currency to use in decentralized finance (DeFi) protocols, such as Compound, that set interest rates and allocate funds automatically through algorithms. As of May 10th, 2021, DAI savings lent in the Compound protocol total over 4 USD Billion, and lending rates are approximately 3 per cent p.a. [6] Third, it may be used as a vehicle

[4]The liquidity spirals covered in Brunnermeier and Pedersen (2009) do not feature in our model, as we assume an exogenous process for the collateral. If, however, there are sufficient feedback effects from DAI liquidations to ETH prices, we can expect a feedback loop in which declines in ETH prices increase liquidations, causing investor losses and further declines in the ETH price. We test this empirically in Appendix E and we find liquidations do not have a statistically significant effect on ETH returns.

[5]Adjustments of the DAI savings rate is set by the MakerDAO protocol as a potential stability tool, which we discuss in more detail in a following section.

[6]See `https://compound.finance/markets` for more details.

currency to purchase other cryptocurrencies, for example BTC and ETH. To close a CDP position, an investor must first redeem all DAI tokens, by either selling the investment currency for DAI tokens in the secondary market or removing their DAI savings from the DSR or a DeFi lending protocol. Once all DAI tokens borrowed are redeemed, the smart contract is regulated to unlock their collateral, closing the CDP.[7]

Leverage Ratio

A key feature of the CDP is that investors need to over-collateralize their borrowings. The Leverage Ratio is the maximum required leverage for each collateral type before it is considered under collateralized and subject to liquidation. We calculate the leverage ratio in Equation (1). The leverage ratio is computed as the ratio of generated DAI (which has a smart contract price of 1 USD), to the collateral value in USD. If ETH prices fall, then an investor can either inject more ETH collateral, or alternatively redeem DAI to maintain their level of collateral.

$$\text{Leverage Ratio} = \frac{\text{Generated DAI}}{\text{Collateral Price} \times \text{Collateral Amount}} \times 100 \tag{1}$$

Liquidation Price

There is a limit on how much DAI one can borrow. Each vault has a maximum leverage ratio, which we define as Leverage Ratio$_{max}$. For vaults with ETH collateral, the maximum DAI that can be borrowed is equivalent to two thirds of the dollar value of the ETH collateral, so Leverage Ratio$_{max} = \frac{2}{3}$. The Maker Protocol calculates a real-time liquidation price, which is the price of collateral at which the Vault leverage is equal to the maximum leverage ratio, calculated in Equation (2). If the price of collateral falls below the liquidation price, this will trigger a liquidation event.

$$\text{Liquidation price} = \frac{\text{Generated DAI}}{\text{Collateral Amount}} \times \frac{1}{\text{Leverage Ratio}_{max}} \times 100 \tag{2}$$

Liquidation Event

In a liquidation event, the investor is required to repay the debt of DAI tokens using their remaining collateral, as well as pay a liquidation penalty. At an ETH price of 100 USD, DAI borrowings of 100 USD, and 2 ETH, gives a leverage ratio of 50 per cent. The liquidation

[7]We outline the steps in creating DAI in a schematic in Appendix A

price is calculated as $\frac{\text{DAI}}{\text{ETH}} \times \frac{1}{\text{Leverage Ratio}_{max}} \times 100 = \frac{100}{2} \times \frac{1}{66.67} \times 100 = 75\text{USD}$. Suppose in the following period, the ETH price falls below the liquidation price to 60 USD.[8] As the new ETH price is lower than the liquidation price, DAI borrowings are liquidated to zero. To pay off the DAI loan, the investor is required to cover the total value of the loan through their ETH collateral. The total value of ETH at the new price is 120 USD. Subtracting the value of the DAI loan, gives a post liquidation amount of ETH collateral equal to 20 USD, which is $\frac{1}{3}$ ETH. To pay off the loan, the smart contract forces an auction of $\frac{5}{3}$ ETH.

In addition to paying off the loan, investors are required to post penalty fees that are up to 15% of DAI borrowed. These additional fees make liquidation costly, and cause investors to post sufficient collateral as a buffer against extreme price movements. Extreme price changes in collateral can therefore cause a large liquidation, contraction in DAI borrowings and significant peg-price premiums, as evident in DAI premiums of up to 800 basis points following a 50 per cent daily decline in ETH prices on March 12th, 2020.

Liquidation auction mechanism

The system of smart contracts enforces an auction mechanism to sell the system collateral and burn DAI tokens. First, a set of agents called keepers detect an under-collateralized Vault and triggers a Liquidation. All of the collateral is put up for auction to cover the outstanding Dai and a liquidation penalty. Once the bid reaches the amount of the DAI loan including any liquidation fees, the auction reverses and bidders now compete by offering to accept less collateral for the DAI they bid in the previous phase. Once an auction settlement is reached, the bidder receives the sold collateral, and an amount of DAI equal to the loan and liquidation fees is burned from the system. The Vault owner receives leftover collateral if any remains.

The MakerDAO system incentivizes vault owners to maintain leverage low in order to prevent liquidation events. This includes setting up price alerts for the collateral asset(s) being used, or developing a rule to recapitalize when the collateral price falls below a certain level as an additional buffer. In Appendix D, we provide additional information on additional safeguards put in place by MakerDAO governance in the event liquidation auctions do not raise sufficient funds to cover the outstanding DAI and penalty fees.

DAI stability rate

The MakerDAO protocol has in place a series of tools can be used when a coin like DAI trades systematically above or below parity. One tool that is used is the stability fee on DAI,

[8] We provide a schematic of the liquidation event in Appendix A

which is analogous to an interest rate on money implemented by a central bank. A critical difference is that while central banks typically have a centralized arrangement for setting rates, DAI has a decentralized, continuous-voting procedure for approval of a stability-fee (i.e., rate) change. Voters can choose from a range of options for the future stability rate, and if the number of votes surpasses the number of votes for the prior decision, the stability rate will change. [9] The stability rate's purpose is to target the peg through changing the level of DAI borrowings, and in turn system leverage. All else equal, a higher a stability fee increases the cost of DAI borrowings, and reduces total leverage of the system.

Multiple Collateral DAI and the peg stability module

A major change to the DAI protocol occurred on November 18th, 2020 with the introduction of multiple collateral types. Users can lock alternative types of collateral, such as WBTC, which is a token pegged to BTC prices that trades on the Ethereum blockchain. On March 12th, 2020, the MakerDAO community decided to adopt stablecoin USDC as collateral. Stablecoin collateral can have a leverage ratio of one, allowing a much higher degree of leverage than with risky collateral types. To further encourage the use of stable collateral types, the Maker Protocol introduced the peg stability module (PSM) in December 2020, in which users are able to swap DAI with the USDC stablecoin. The PSM effectively anchors the DAI/USD peg to the value of USDC, by allowing users to swap USDC with DAI at a 1:1 rate without needing to create a vault and deposit collateral. In this way, there is no liquidation risk, however users need to make a one-off fee to use this. This increases the incentive for arbitrageurs to close peg-price deviations using the PSM. A technical difference between the PSM and having stable collateral type is liquidation risk. For example, if investors deposit USDC collateral into a vault, there is risk of a collapse of the USDC peg which can trigger a sufficient decline in the value of collateral and a liquidation event. In contrast, the PSM transfers the liquidation risk to the Maker Protocol, which will be willing to exchange DAI for USDC tokens at a 1:1 rate even when USDC prices are trading at a significant discount. [10]

[9] Votes are based on staking the Maker Governance token MKR, where 1 MKR locked is equal to 1 vote. Additional information on the fundamental valuation of the MKR token is provided in Appendix D.

[10] For more details on how the PSM works, we refer readers to https://community-development.makerdao.com/en/learn/governance/module-psm/

Data and summary statistics

To test the effects of collateral returns on the borrowing behavior of investors, we utilize a data set that records every transaction made by an individual CDP, including amounts of ETH collateral deposited, DAI borrowed, and the timestamp of each transaction. The actions of depositing and closing the ETH CDP is defined as "lock" and "free" respectively. The action of the investor borrowing and redeeming DAI tokens is classified as a "draw" and "wipe" respectively. The sample starts in January 1st, 2017 and ends in November 17, 2019.[11] For an individual CDP, we can trace the amounts of ETH collateral, and the amounts of DAI borrowed and redeemed at any point in time. This allows us to calculate a real-time leverage ratio, defined as the ratio of total DAI borrowed to the value of ETH Collateral.

Aggregate data on the amounts of DAI borrowed of each collateral type is obtained at https://makerburn.com/#/. The dataset also provides policy parameters, such as the stability rate on borrowings and the debt ceilings for each collateral type. For the total amounts of each type of collateral deposited in the system, we use data from Dune-Analytics, an open source platform with statistics on decentralized finance applications https://duneanalytics.com/hagaetc/maker-dao---mcd. Consolidating DAI borrowings with total collateral, we can calculate the total system leverage, as well as the leverage of each collateral type.

For price data on ETH, DAI and other collateral types, we use https://www.coinapi.io/.Coinapi offers a monthly subscription with access to their data api, which gives historical cryptocurrency OHLCV data. Where multiple cryptocurrency exchanges offer the same data, we choose the exchange that (i) has the longest time series and (ii) is one of ten exchanges that has "trusted volume" according to a report filed by the SEC.[12] We use hourly data for the pairs of ETH/USD, DAI/USD from the Bitfinex exchange from April 13th, 2018 to March 31st, 2021, and hourly data for the USDC/USD pair from the Kraken exchange available from January 8th, 2020 to March 31st, 2020.

We present summary statistics in Table 1 for DAI, ETH returns and system parameters of the stability rate and leverage, over the full sample from April 13th, 2018 to March 31st, 2021. Figure 1 plots the time-series of DAI price, ETH price, the leverage and stability rate.

[11] The ending date of November 17, 2019 corresponds to the date at which users migrated from the single to multi collateral DAI system. The dataset obtained from mkr.tools.api only records investor transactions for the single collateral version.

[12] See https://www.sec.gov/comments/sr-nysearca-2019-01/srnysearca201901-5164833-183434.pdf.The report tests exchanges for fraudulent activities (e.g., suspicious variability in bid-ask spreads, systematic patterns in histograms of transaction size) and finds that the exchanges we use price data from do not have the telltale patterns in trading volume or spreads.

DAI peg price premium is on average of 100 basis points over the full sample. The average ETH return is 0.17 per cent, and the standard deviation of returns is 5.8 per cent. The large declines in ETH returns peaked on March 12th, 2020, which recorded a -58.2 per cent decline. Stability rates on borrowing DAI in ETH vaults are typically 3 per cent on average, with periods of high interest rates of 20 per cent set in 2019. The leverage ratio for ETH collateral is 0.3 over the full sample. This is much lower than the maximum leverage of two thirds. Low system leverage provides a capital buffer in the event of a collapse in collateral value. With a leverage ratio of 30%, the ETH price can crash by 50% in one day and the CDP is still sufficiently collateralized.

To understand the interaction of prices with system parameters, we provide a correlation matrix of all variables in Table 2. First, there is a negative correlation between DAI and ETH returns of -0.05. Peg-price premiums are associated with negative ETH returns. Second, we observe a negative correlation between DAI leverage and stability rate of -0.34. This indicates that high borrowing rate on DAI is associated with a decline in DAI borrowings, and system leverage. Finally, the stability rate is negatively associated with DAI price (-0.19). This is interest-rate setting of DAI borrowing in response to peg-price deviations: stability rates are increased in periods of discounts, and decreased in periods of premiums.

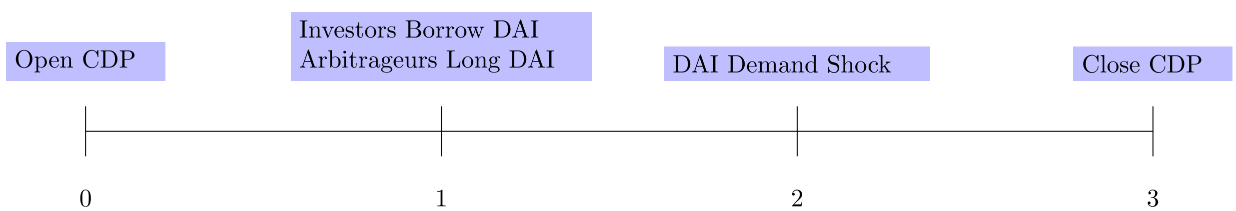
4 Model

Before turning to the empirical results, we first develop a model to structure our testable hypotheses. As a starting point, we introduce three types of agents in the model, ETH speculators, arbitrageurs, and uninformed demand. Speculative investors deposit ETH (ETH) collateral and borrow DAI tokens to invest in risky cryptocurrencies. Arbitrageurs take long or short positions in DAI based on mispricing of the peg. Uninformed demand for DAI captures the token's role in algorithmic lending and other DeFi applications, that enable users to deposit DAI and accrue savings.

The primary goal of the model is in providing testable implications on the mechanisms that govern leverage and peg stability. First, we show that peg-premiums differ conditional on the level of uninformed demand. In periods of high uninformed demand, arbitrageurs require significant peg premiums to short DAI and clear the market. We show that peg-premiums occur precisely when collateral prices are in the *bad* state, generating a negative covariance between peg-prices and returns on ETH collateral. Second, we show that in response to an increase in the volatility of collateral, the model generates a higher peg-price premium, a decline in investor borrowings and leverage, and an increase in the volatility of peg-price deviations. We then turn to a discussion of stability tools, such as the interest rate on DAI borrowings and the introduction of stable collateral types. We show that the price increases with a rise in the interest rate on DAI borrowings. Stable collateral reduces arbitrageurs' exposure to collateral risk and they require smaller premiums to absorb uninformed demand and clear the market.

Timing

We consider a model with four periods – 0, 1, 2 and 3. In period 0, investors open a CDP by depositing non-stable collateral, ETH, into a MakerDAO vault. Periods 1 and 2 are trading rounds. In period 1, DAI tokens are borrowed (issued), and secondary market trading occurs. There are two crypto-currencies traded in the market: non-stable ETH and stable DAI. Cash is in dollars and pays a constant rate of return r. We assume that the investors are small enough to affect either the Dollar rate or ETH prices, which are exogenously given. DAI is in zero-net supply. In period 2, either ETH speculators and/or arbitrageurs borrow DAI tokens in response to a demand shock for DAI in the secondary market. Finally, in period 3, all investors close their CDPs and redeem all DAI tokens. No secondary market trading occurs in period 3. Market clearing conditions in periods 1 and 2 determine DAI prices.



We denote the price of DAI in period t as p_t and its variance as σ_t^2. DAI is liquidated in period 3 and is exchanged to USD at the risky rate p_3 with mean 1 and variance σ_3^2.[13] We denote by i^B the DAI stability rate and by i^L the saving rate. We assume $i^L < i^B$. The return on ETH in the period t is a random variable R_t^E with mean μ^E and v ariance σ_E^2.

Agents

The model includes three types of investors: ETH speculators, arbitrageurs and uninformed DAI demand. ETH speculators fully invest their wealth W_t^s in ETH due to their sentiments about investing in cryptocurrency. Modelling the part of their portfolio invested

[13]This assumption is motivated by the fact that MakerDAO does not guarantee 1:1 parity of DAI to USD during the liquidation event. Moreover, it is possible that governance body can vole to change the target rate of 1 in a case of instability episodes.

in other asset classes is out of scope of this model. ETH speculators decide every period how much to leverage their position in ETH via issuing DAI. They do this by maximizing their mean-variance expected utility function. ETH speculators' beliefs about the expected return on ETH is affected by their sentiments. Specifically, they believe that the expected return on ETH depends on the state of nature $s_t = G$ or B which occur with probabilities π and $1 - \pi$ respectively and that $\mu^E(G) > \mu^E(B)$. The state of speculators' beliefs can, for example, depend on the recent past performance of ETH.

Arbitrageurs observe DAI price and step in to profit from any discrepancy between the DAI price and unity. We denote their wealth in period t by W_t^a but they can finance their positions by borrowing any amount in USD at the Dollar rate r. If the DAI is traded at a discount, arbitrageurs buy DAI in the secondary market and earn i^L on their DAI holdings. If DAI is traded at premium, arbitrageurs issue DAI tokens and put ETH collateral at highest possible leverage ratio $\bar{\theta}$. Arbitrageurs are not sentimental with respect to ETH and believe that Ethereum returns are serially uncorrelated and the expected value of ETH returns is $\mu^A = \mu^E$. Both speculators and arbitrageurs have the same mean-variance risk preferences with the risk aversion coefficient γ.

We model uninformed demand as a deterministic aggregate demand D from customers who have either some intrinsic needs to purchase a stablecoin currency.[14] The assumption on deterministic nature of the demand is for simplicity and is not essential for the model. We include it in the model to demonstrate comparative static on how additional demand can amplify the volatility and mispricing of DAI.

We describe the structure of the model and investors demands backwards starting from period 3. In period 3 there is no trading. Each investor type convert their ETH positions into USD according to the realization of the return distribution. Furthermore, DAI is being liquidated at the final liquidation price p_3.

In periods 1 and 2, speculators' demand is formed in the following way. Speculators leverage their ETH positions by borrowing DAI and converting it into ETH. Their leverage ratio θ_t is optimally calculated by maximizing their expected utility function given their beliefs at time t. Their wealth W_t^s evolves as shown in Equation (3):

$$W_{t+1}^s = W_t^s \left(R_{t+1}^E (1 + \theta_t p_t) - \theta_t p_{t+1} - \theta_t i^B \right), \text{ for } t = 1, 2. \tag{3}$$

The first term of this expression is the return earned on the leveraged position of ETH, the

[14] Uninformed demand captures DAI's use in decentralized finance (DeFi) protocols, such as Compound, that set interest rates and allocate funds automatically through algorithms.

second term is the USD price of DAI the speculators buy back to release their collateral, and the third term is the DAI borrowing fee the speculators in period t.

The arbitrageurs' wealth changes according to the following dynamics:

$$W_{t+1}^a = \begin{cases} W_t^a \left(\omega_t(1+i^L)p_{t+1}/p_t + (1-\omega_t)(1+r)\right), & \omega_t \geq 0, \\ W_t^a \left(-\frac{\omega_t}{\theta} R_{t+1}^E + \omega_t(p_{t+1} - p_t(1+r) + i^B) + \left(1 + \frac{\omega_t}{\theta}\right)(1+r)\right), & \omega_t < 0. \end{cases} \tag{4}$$

The first equation corresponds to the case when arbitrageurs buy DAI in the secondary market. They invest a fraction $1-\omega_t$ of dollar wealth in dollars at the risk-free rate. The remaining fraction of wealth is used to purchase DAI at p_t and earn the DAI savings rate i^L. In period $t+1$, they re-convert DAI back to dollars at p_{t+1}. The dollar profit they make by going long in DAI is $(1+i^L)p_{t+1}/p_t$. They typically engage in a long position to exploit mispricing when DAI traded at a discount. Theoretically, they can also buy DAI at a premium if profit earned on the saving rate i^L exceeds losses from buying DAI at premium and the risk of holding it.

The second equation corresponds to the case when arbitrageurs find it more profitable to short-sell DAI. They invest a fraction $1+\frac{\omega_t}{\theta}$ in dollars at the risk-free rate r. The remaining fraction of wealth is used to purchase ETH collateral. They post $\frac{|\omega_t| W_t^a}{\theta}$ of ETH collateral, borrowing $|\omega_t| W_t^a$ amount of DAI and selling it for dollars in the secondary market. They then invest the proceeds at the dollar risk-free rate r, and reconvert back to DAI in the next period to make a profit. The dollar profit they make by short-selling 1 unit of DAI is given by the term $p_t(1+r) - p_{t+1} - i^B$. [15]

Both types of investors maximize their corresponding mean-variance utility functions subject to the evolution of wealth in Equations (3) and (4), and constraints on the share of DAI borrowing to be bounded between 0 and $\bar{\theta}$, which is the maximum level of leverage an investor can take:

$$U_t(W_{t+1}^j) = E_t[W_{t+1}^j] - \frac{1}{2}\gamma Var_t[W_{t+1}^j],\ 0 \leq \theta_t \leq \bar{\theta},\ j = s, a. \tag{5}$$

Speculators' optimal leverage ratio for period $t = 1, 2$ is given by

$$\theta_t \quad = \quad \max\left\{0, \min\left\{\frac{\frac{p_t \mu^E(s_t) - E_t[p_{t+1}] - i^B}{\gamma W_t^s} - p_t \sigma_E^2 + c_t}{p_t^2 \sigma_E^2 + \sigma_t^2 - 2p_t c_t}, \bar{\theta}\right\}\right\}, \tag{6}$$

[15] The DAI savings and borrowing rates i^L and i^B are dollar reference rates, as the wealth of the investor is in dollars.

where $c_t = Cov_t[R^E_{t+1}, p_{t+1}]$ is the conditional covariance between the Ethereum returns and the DAI price. Given that the liquidation value of DAI is independent of Ethereum, we set $c_2 = 0$, $E_2[p_3] = 1$. Although arbitrageurs know that the objective Ethereum returns are independent of the state s_t, a non-zero covariance arises endogenously due to speculators' beliefs and their corresponding actions.

Arbitrageurs' optimal DAI portfolio weight ω_t is:

$$\omega_t = \begin{cases} \max\left\{0, \frac{\left(E_t[p_{t+1}](1+i^L)/p_t - (1+r)\right)p_t^2}{\gamma W_t^a (1+i^L)^2 \sigma_t^2}\right\}, & U_t^+(W_{t+1}^a) \geq U_t^-(W_{t+1}^a), \\ -\max\left\{0, \frac{\bar{\theta}\left(\mu^A - \bar{\theta}(E_t[p_{t+1}] - p_t(1+r)) + \bar{\theta} i^B\right)}{\gamma W_t^a(\sigma_E^2 + \bar{\theta}^2\sigma_t^2)}\right\}, & U_t^+(W_{t+1}^a) < U_t^-(W_{t+1}^a), \end{cases} \tag{7}$$

where

$$U_t^+(W_{t+1}^a) = \max_{\omega_t \geq 0} U_t(W_{t+1}^a) \tag{8}$$

$$U_t^-(W_{t+1}^a) = \max_{\omega_t < 0} U_t(W_{t+1}^a). \tag{9}$$

Proof: See Appendix B

Equilibrium

To clear the market, selling demand for DAI should equal to buying demand in each period. In period t, speculators borrow $\theta_t W_t^s$ of DAI and sell it to convert to ETH. At the same time, arbitrageurs buy $\omega_t W_t^a$ DAI (or short sell if $\omega_t < 0$) and, in addition to it, in period 2 we have uninformed demand D. Since there is no trading in periods 0 and 3, we focus on the market clearing conditions for periods 1 and 2:

$$0 = -\theta_1 W_1^s + \omega_1 W_1^a, \tag{10}$$

$$0 = -\theta_2 W_2^s + \omega_2 W_2^a + D. \tag{11}$$

We solve the model numerically to from testable predictions about equilibrium prices and quantities in the model. We assign the following parameter values: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $D = \$50$, $\bar{\theta} = 0.66$, $\sigma_3 = 0.0188$. We calibrate the rest of the primitive parameters of the model to the sample. Specifically, we set daily rates of returns to: $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. Here we take μ_A being equal to the full sample average of daily ETH return, while we take $\mu_E(G)$ equals to the 90-th percentile of ETH return distribution. Finally, σ_E equals to the sample standard deviation of ETH daily returns.

Testable Implications

Baseline Specification

Figure 2 plots equilibrium DAI prices over the three periods for both good and bad states of nature (e.g., high and low ETH returns). The model generates both discounts and premiums of DAI price over the par value of 1. Speculators deposit ETH collateral in period 0 and borrow DAI in period 1. In period 1, which is the first round of trading, market clearing requires that arbitrageurs take a long position in DAI to balance the supply of DAI by speculators. To induce a long position in period 1, arbitrageurs buy DAI at a discount. In period 2, there is public demand for DAI. We assume the demand from public is independent to the performance of ETH. DAI prices in period 2 correlate negatively with the states of nature of ETH collateral. When the market is in the bad state, speculators do not leverage ETH aggressively due to their pessimistic beliefs. As a result, arbitrageurs have to absorb positive demand shock from public investors and short sell DAI. Given shorting DAI is risky due to valuation effects of collateral, arbitrageurs charge a premium and hence are willing to short sell only at high prices. In contrast, DAI trades at discount during the good state due to excessive price pressure coming from speculators leveraging ETH and selling DAI. Speculator supply of DAI exceeds public demand; therefore arbitrageurs take a long position in DAI. To induce a long position, arbitrageurs purchase DAI at a discount in the good state. In summary, the model generates a large premium during the bad state and discount during the good state of nature.

Demand Shock

We now look at DAI prices in periods of low and high public demand. Figure 3 plots the time series of DAI prices with respect to the magnitude of public demand D. Through this exercise, we capture in a stylized way the demand for DAI due to DeFi lending protocols such as Compound. Similar to the baseline specification, we have secondary market trading in periods 1 and 2, and public demand shock occurs in period 2. Panel A features low demand and Panel B features high demand. When public demand is low, arbitrageurs do not have to short sell very aggressively. Moreover, they short sell at discounted prices because they can recover their potential losses due to small positive profits on ETH collateral. When public demand is high, arbitrageurs are required to short sell DAI to clear the market. Arbitrageurs have to absorb this demand during the bad state through a peg-price premium. Therefore, peg-premiums are higher in states of high demand.

Volatility of collateral

We next look at the stability of DAI price with respect to ETH volatility. Figure 4 presents equilibrium peg-prices with respect to ETH volatility. Panel A features a low volatility regime and Panel B features a high volatility regime. When volatility is low, speculators borrow more DAI creating an excess supply of DAI in the market. Therefore, arbitrageurs purchase DAI at a discount to induce a long position to clear the market. When volatility is high, speculators deleverage and arbitrageurs are required to short sell DAI to clear the market in the bad state of the world. Arbitrageurs have to absorb this demand through a peg-price premium. To further illustrate the effect of ETH volatility, Figure 5 presents comparative statics results for DAI prices (Panel A), period 2 DAI price volatility (Panel B) and leverage ratios (Panel C). Consistent with short-selling pressure on arbitrageurs, DAI prices in period 2 are higher in the bad state as volatility of ETH increases, increasing volatility of the peg. The channel through which DAI prices are affected is through deleveraging by speculators. In panel C, we document a decline in the leverage ratio of speculators in response to increased ETH volatility (see Panel C). To conclude, the stability of DAI deteriorates as the volatility of ETH returns increases.

Stability rate

The stability rate i^B of DAI price is set by the MakerDAO governance body to target DAI prices. Figure 6 presents comparative statics results for DAI prices in period 2 (Panel A), and the leverage ratio (Panel B). An increase in the interest rate on DAI borrowings reduces leverage. The reduction in DAI borrowings by speculators requires arbitrageurs to short sell DAI to clear the market in period 2 in the bad state of the world. Therefore, in principle, the stability rate can be used as a policy instrument to control leverage and target DAI prices. However, we note that quantitatively the stability rate has little effect in stabilizing the peg. Holding all else constant, increasing the stability fate from 0 per cent to 20 per cent increases DAI prices approximately 10 basis points based on the numerical calibration.

Model extension: multiple collateral types

We extend the model by introducing the stablecoin USDC as an additional collateral type to be used by arbitrageurs in stabilizing the peg. We assume that the expected value of USDC returns is equal to $E_t[R^U_{t+1}] = 1 + r$ given that the coin is pegged to USD and we denote by $Var_t[R^U_{t+1}] = \sigma^2_U$ the variance of its returns. Furthermore, we assume that the

USDC returns are uncorrelated with ETH and DAI returns.[16] Given our initial assumption that the speculators invest their entire wealth into ETH and choose their optimal leverage ratio θ_t, it is easy to see that they do not invest to USDC and their portfolio choice remain the same as in (6). Arbitrageurs, however, have an opportunity to reduce their risk by borrowing DAI via USDC collateral in addition to ETH. Hence, the arbitrageurs' wealth in this case changes according to the following dynamics:

$$W_{t+1}^a = \begin{cases} W_t^a \left(\omega_t(1+i^L)p_{t+1}/p_t + (1-\omega_t)(1+r)\right), & \omega_t \geq 0, \\ W_t^a \left(-\frac{\omega_t^E}{\theta} R_{t+1}^E - \omega_t^U R_{t+1}^U + (\omega_t^E + \omega_t^U)(p_{t+1} - p_t(1+r) + i^B) \right. & \\ \qquad \left. + \left(1 + \frac{\omega_t^E}{\theta} + \omega_t^U\right)(1+r)\right), & \omega_t^U, \omega_t^E < 0. \end{cases} \tag{12}$$

Here, in the first equation, $\omega_t \geq 0$ is the amount of DAI arbitrageurs purchase as a fraction of wealth, while in the second equation arbitrageurs short sell $-\omega_t$ fraction of their wealth, where $\omega_t = \omega_t^E + \omega_t^U < 0$, $\omega_t^E < 0$ is the amount of DAI arbitrageurs issue via ETH collateral and $\omega_t^U < 0$ is the amount of DAI arbitrageurs issue via USDC collateral. A negative sign indicates that arbitrageurs sell DAI after issuing it. Note that the maximum leverage ratio in USDC collateral is 1. The optimal fractions of DAI borrowing via ETH and USDC collateral in the arbitrageurs' portfolio are determined as:

$$\omega_t = \begin{cases} \max\left\{0, \frac{\left(E_t[p_{t+1}](1+i^L)/p_t - (1+r)\right)p_t^2}{\gamma W_t^a (1+i^L)^2 \sigma_t^2}\right\}, & U_t^+(W_{t+1}^a) \geq U_t^-(W_{t+1}^a), \\ \omega_t^U + \omega_t^E, & U_t^+(W_{t+1}^a) < U_t^-(W_{t+1}^a), \end{cases} \tag{13}$$

where the precise values of ω_t^E and ω_t^U are provided in Appendix B.

To demonstrate the effect of introduction of multiple collateral types on DAI prices, we calculate the equilibrium DAI price assuming the expected return on USDC is equal to $\mu^U = 1 + r = 1.015$ and the standard deviation of USD returns $\sigma^U = 0.0013$. Figure 7 plots DAI prices over the three periods for both good and bad states of nature. With the introduction of the stable collateral type, we note that premiums are smaller in the bad state relative to the baseline specification in Figure 2. The intuition is as follows. In period 2, there is public demand for DAI. When the market is in the bad state, speculators do not leverage ETH aggressively due to their pessimistic beliefs. As a result, arbitrageurs have to

[16] The assumption of zero correlation between the USDC and DAI returns can be justified by the fact that the speculators do not have sentiments about USDC as such; moreover, we show below that speculators do not use USDC as collateral which reduces the dependency of DAI on USDC fluctuations. We provide a proof that speculators only use ETH collateral instead of USDC in Appendix B

absorb positive demand and short DAI. They can now short DAI through depositing USDC collateral. An arbitrageur's risk profile is reduced due to smaller volatility of USDC as well as through diversification benefits as the two collateral types are uncorrelated. Therefore, the extra arbitrage capital implies arbitrageurs charge a smaller premium and hence are willing to short sell at lower premiums relative to the baseline equilibrium with only ETH collateral. In the good state, however, speculator supply of DAI exceeds public demand; therefore arbitrageurs take a long position in DAI. To induce a long position, arbitrageurs purchase DAI at a discount in the good state. The discount in a good state is similar to the discounts observed in an equilibrium with only ETH collateral. The reason for this asymmetry is because the addition of USDC collateral provides additional arbitrage capital for the case when arbitrageurs are required to short sell DAI, but not when they take a long position. In summary, the model with USDC collateral generates smaller premiums and peg-price deviations relative to single collateral case.

To illustrate the effect of USDC volatility, Figure 8 presents comparative statics results for the share of USDC collateral (Panel A) and DAI price volatility (Panel B). The share of stable collateral, which we define as $\frac{\omega_t^U}{\omega_t^U+\omega_t^E}$, is a decreasing function in USDC volatility. As the share of USDC collateral falls, so does the ability of arbitrageurs to provide sufficient capital to eliminate peg-price deviations, resulting in higher peg-price volatility.

5 Empirical Evidence

Individual CDP Data

We start our analysis with investigating investors' behaviour in response to changes in ETH returns, volatility and policy rates. In order to do this we use the entire history of CDP transactions for single collateral DAI. This records every transaction made by an individual CDP, including amounts of ETH collateral deposited, DAI borrowed, and the timestamp of each transaction. There are 8 types of actions an investor can execute. Actions using ETH collateral involve opening and closing the vault, depositing and withdrawing collateral, and an action to transfer ownership of the ETH vault across digital wallet addresses. Actions using DAI involve borrowing and redeeming DAI tokens, and when the vault is under-collateralized it triggers a "bite" action in which the collateral is liquidated to pay off the DAI loan.

Using each individual CDP, we calculate a real-time leverage ratio for each CDP, as illustrated in Equation (14). We take the total stock of collateral $ETH_{i,t}$ locked in a CDP i at time t, and the amount of borrowings $DAI_{i,t}$ locked in the CDP at time t. We then calculate the dollar prices of DAI borrowings and ETH collateral, $P_{DAI,t}$ and $P_{ETH,t}$ respectively, to obtain the dollar value of each component.

$$\mathrm{LR}_{i,t} = \frac{P_{DAI,t} \times DAI_{i,t}}{P_{ETH,t} \times ETH_{i,t}} \times 100 \tag{14}$$

To prevent investors from over-leveraging, the system has a "bite" action which is a liquidation event. A bite occurs when the leverage ratio calculated in Equation (14) is above the maximum allowable leverage of ETH, which is $\frac{2}{3} \times 100$ per cent.[17] Table 3 documents summary statistics of DAI borrowing, ETH collateral, the leverage ratio and liquidations. The sample contains a total of 11,718 CDPs. The average leverage is 30.55 per cent, well below the threshold leverage of 66.67 per cent. 7,097 CDPs have liquidated at least once during their lifetime, with a maximum number of liquidations of 14 for a single CDP.

We plot the time series of the leverage ratio, DAI borrowings and ETH collateral for two individual CDPs in Figure 9. In the top panel (CDP id 5199), we plot the time series for the CDP with the maximum DAI borrowings and ETH collateral over the full sample. This CDP is an example of an investor who maintains a leverage ratio averaging 30 to 40 per cent. This is well below the threshold level of 66%. In the bottom panel of Figure 9, we have an investor (CDP id 1272) that has the maximum number of liquidation events (14) in our sample. For this CDP, we observe that the leverage ratio calculated based on end-of-day ETH and DAI prices rises above the threshold. In each case, this triggers a liquidation event, when DAI borrowings are reset to zero and the investor's ETH collateral value declines to pay off the debt. ETH collateral value declines by more due to liquidation fees, that amount up to 15% of the value of DAI borrowings.

We plot the density of leverage ratios for CDPs over the full sample from January 2017 to November 2019 in Figure 10. In the top panel, we stratify our sample based on periods of extreme positive returns (greater than +2 std) and extreme negative returns (less than -2 std). We find that periods of negative extreme events are associated with a higher leverage ratio, all else equal, with the density shifted to the right. The effects of extreme negative returns on system leverage is mechanical: negative returns result in a decline in ETH collateral, and an increase in system leverage, all else equal. In the bottom panel, we stratify the sample into high and low interest rates, where high interest rates are above 18 per cent, where the peak stability rate is 20.52 per cent. Low interest rates are below 1 per cent. Noticeably,

[17] For more details on the nomenclature of each CDP action, we refer readers to MakerDAO documentation https://docs.makerdao.com/DAI.js/single-collateral-DAI/collateralized-debt-position.

we find a bimodal distribution with high interest rates, with a much higher density toward small loans when interest rates are excessively high. This is intuitive: high DAI rates choke DAI borrowings and contract leverage.

We now formalize determinants of DAI leverage through a panel regression specification in Equation (15):

$$LR_{i,t} = \alpha_i + \beta_1 R_{ETH,t} + \beta_2 \sigma_{ETH,t} + \beta_3 SFee_t + u_t, \tag{15}$$

where the dependent variable is the leverage ratio $LR_{i,t}$ for CDP i at time t. The set of independent variables include the daily ETH return ($R_{ETH,t}$), intra-day volatility of collateral ($\sigma_{ETH,t}$) defined as the standard deviation of hourly returns, and the stability rate on DAI borrowing. Individual CDP fixed effects is captured by α_i, and controls for idiosyncratic risk preferences of an individual CDP. For example, more risk averse investors typically have a much lower leverage ratio (typically 30 per cent) to avoid liquidation events. Risk-loving investors are likely to have a leverage close to the maximum and face a much higher probability of liquidation. To create a panel with sufficient observations for all CDPs, we filter CDPs that have transactions over 30 days in the sample.[18] This gives us a total of 456 individual CDPs with at least 30 daily observations each.

The results are summarized in Table 4. The dependent variable is the leverage ratio. In column (I), a 1 per cent increase in returns reduces CDP leverage by 0.22 and 0.19 percentage points respectively. In column (II), we replace R_{ETH} variable with dummy variables R^{+}_{ETH} and R^{-}_{ETH} that capture extreme positive (>+2std) and negative (<-2std) returns in ETH. The results indicate leverage is sensitive to periods of extreme positive and negative returns, with a difference in leverage of approximately 6 percentage points between low and high return states. In column (III), a 1 per cent increase in ETH volatility reduces leverage by 0.19 percentage points. In column (IV), a 1 per cent increase in the stability rate reduces leverage by 0.11 percentage points. This elasticity is quantitatively small: a maximum stability rate of 20 percentage points in the sample leads to only a 2 percentage point decline in leverage, all else equal. In column (V), the results are robust to a specification including ETH returns, intra-day volatility and the stability rate. The CDP data allows us to measure effects on other outcome variables, including a liquidation event for an individual CDP, known as a "bite", and the total amounts of DAI borrowing and ETH collateral. We conduct a panel analysis of the determinants of CDP liquidation, borrowing and collateral in Appendix C.

[18]Statistical bias can occur due to an unbalanced panel with individual CDPs having too few observations.

Fundamentals of peg-price deviations

Figure 11 documents a scatter plot of DAI intra-day volatility and ETH intra-day volatility, and documents a relationship between peg stability is a function of collateral risk. Through the lens of the model, an increase in collateral risk reduces the capacity of arbitrageurs to deposit ETH collateral, borrow DAI tokens and sell them in the secondary market at a premium. The limits to arbitrage cause peg-price deviations to persist, and an increase in peg volatility.

A second model prediction is that DAI peg-price premiums occur precisely in periods of negative ETH returns. Declines in the price of collateral result in liquidation events. The corresponding decline in supply causes peg-prices to increase, all else equal. We empirically test the contemporaneous negative correlation between the DAI price and ETH returns in Equation (16):

$$Y_t = \beta_0 + \beta_1 R_{ETH,t} + \beta_2 \sigma_{ETH,t} + \beta_3 SFee_t + u_t \tag{16}$$

Here, the outcome variable Y_t is the DAI peg-price deviation Δ, and the intra-day volatility σ_{DAI}. Intra-day volatility is calculated as the square root of the average sum of squared hourly returns over the trading day. The explanatory variable is R_{ETH} and σ_{ETH}, which are measures of returns and intra-day volatility of ETH. All variables are measured in basis points and the stability fee is annualized and in percentage points. The results are summarized in Table 5. In columns (I) through to (IV), the outcome variable is peg-price deviations. In columns (V) through to (VIII), the outcome variable is intra-day volatility. In a specification controlling for ETH returns and intra-day volatility and the stability rate, a 1 per cent (100 basis point) increase in ETH returns is associated with a 2.3 basis point decline in DAI prices, and a 2.4 basis point increase in DAI volatility. A 1 per cent increase in ETH volatility increases DAI prices and volatility by 6.4 basis points and 15.7 basis points respectively. In columns (II) and (VI), we replace R_{ETH}, t with R^{-}_{ETH} and R^{+}_{ETH}. We estimate a more negative correlation between DAI prices and ETH returns in periods of extreme negative ETH returns. Periods of extreme negative returns are associated with a price increase of 72.4 basis points, all else equal To understand the mechanism behind extreme negative ETH returns and DAI peg-price premiums, we turn to the liquidation mechanism.

DAI liquidation mechanism

Periods of extreme negative collateral returns result in forced liquidation and a penalty. On March 12th, 2020, in an extreme crypto market event ETH collapsed by 50%. We plot in Figure 12 the USD price response, the ETH price and DAI liquidations. Congestion on the blockchain led to high gas prices, which in turn led to delays for Vault owners to attempt to add more collateral and redeem DAI tokens to their Vaults within the Protocol's one-hour window.[19] The drop in collateral value triggered liquidation auctions for around 1,200 Vaults, and led to a peak liquidation value of approximately 10 million USD on March 12th. Pressure on the DAI peg is due to the failure of the auction mechanism. Keepers, who sell DAI tokens for collateral from the auctions, did not have sufficient DAI liquidity to participate in the auctions. To burn DAI from liquidations, the governance body decided to auction MakerDAO tokens (MKR) as an effective open market operation, diluting MKR's value. [20]

To formally test the effects of liquidations on the DAI-ETH return correlation, we test the regression specification in Equation (17). The outcome variable Y_t are peg-price premiums and DAI intra-day volatility. The results are summarized in Table 6. In columns (II) and (III), the dependent variable is peg-price deviations, and in columns (IV) and (V), the dependent variable is intra-day volatility. The baseline specification regresses on the measure of liquidations, measured in millions USD. Consistent with our hypothesis: a 1 USD million increase in liquidations is associated with an increase in the DAI price of 30.5 basis points and a 42.5 basis point increase in intra-day volatility. Controlling for ETH returns, intra-day volatility and the stability rate in column (III), a 1M USD increase in DAI liquidations increases DAI prices by 28.7 basis points, all else equal. Using this estimate, the March 12th, 2020 liquidation auction of 10 USD Millions leads to an approximate 290 basis point premium. DAI prices increased from 1.02 to 1.08 USD from March 11th to March 12th. A back-of-the envelope calculation suggests that up to 50 per cent of the DAI price

[19] Gas is a measure of the amount of ether (ETH) a user pays to perform a given activity, or batch of activities, on the ETH network. These transaction costs are analogous to commissions on exchanges, however these costs are paid to the miners who authenticate the transactions on the Ethereum blockchain. These prices are denominated in GWEI which is equivalent to one-billionth of one ETH, and they are typically an average of 10 GWEI per transaction. The average gas prices temporarily spiked to over 100 GWEI per transaction from the 10 GWEI average seen just one day prior. Critically, these units of GWEI provide a proxy for transactions' latency time. Gas prices, as well as daily amounts of Ether Gas used, are provided in `https://ethgasstation.info/`. For more information see `https://blockonomi.com/ETH-gas-prices-surged/`

[20] We provide more detail on dynamics of the MKR price in Appendix D. For more details on the MakerDAO liquidations in March 2020, see MakerDAO's public release on the event `https://blog.makerdao.com/the-market-collapse-of-march-12-2020-how-it-impacted-makerdao/`.

increase on March 12th, 2020 is due to liquidations. The remaining premiums are likely due to demand-side factors for DAI, such as its role as a store of value, investor demand for safety and liquidity benefits that stablecoins provide. In Appendix C, we use the individual CDP data to conduct a panel analysis of the determinants of CDP liquidation. In Appendix E, we conduct further tests of the liquidation mechanism, including testing for the dynamic effects of liquidations on DAI prices and ETH returns.

$$Y_t = \beta_0 + \beta_1 Liquidation_t + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + u_t \tag{17}$$

Secondary market demand

We identify two sources of secondary market demand. The first source of demand we test is the demand for DAI in DeFi lending protocols such as Compound. In Figure 13, we report the total borrowing and lending of DAI on the Compound protocol, and the ratio of borrowing and lending, which is measured as the utilization rate.[21] Defining utilization D_u in Table 7, we regress the utilization rate on ETH returns and volatility. We find utilization is positively related to ETH volatility. In columns (III) and (IV), we regress peg-price deviations on the utilization rate. We find a 1 per cent change increase in utilization is associated with a 1.7 basis point increase in the DAI premium. This is robust to controlling for ETH returns and volatility. A second source of demand measures growth in aggregate trading volume in exchanges. Defining D_v as the per cent change in aggregate trading volume of DAI, in column (II) we find trading volume growth increases in periods of negative ETH returns and high ETH volatility. In column (V), we find a 1 per cent increase in trading volume is associated with a 0.19 basis point increase in the DAI premium. This effect, however, is insignificant after controlling for ETH returns and volatility.

DAI Stability rate

The stability rate, which is a cost on DAI borrowings, is implemented by the MakerDAO protocol as a way to control system leverage. We found previously that using the cross-section of CDPs that a 100 basis point increase in the stability rate reduces leverage by 10 basis points. We now estimate price effects of the stability rate using the method of local

[21] We focus on Compound as it is the largest DeFi lending protocol for DAI. The size of the borrowing and lending as a fraction of DAI tokens is significant, and total supply of DAI in compound can exceed DAI tokens in circulation due to borrowers re-depositing DAI tokens in the protocol. See https://www.coindesk.com/there-are-more-DAI-on-compound-now-than-there-are-DAI-in-the-world for more details.

projections Jordà (2005). The outcome variables include the leverage ratio, the DAI/USD price. The change in the outcome variable, $Y_{t+h} - Y_{t-1}$, is projected on the level of the interest rate $SFee$ in Equation (18).

$$Y_{t+h} - Y_{t-1} = \alpha + \beta_h SFee_t + \sum_{k=1}^{L} \delta_k SFee_{t-k} + \sum_{k=1}^{L} \gamma_k (Y_{t-k-1} - Y_{t-k-2}) + controls_t + u_t$$
$$h = 0, 1, 2, ... \tag{18}$$

The specification allows for feedback effects using lagged values of the explanatory variable and outcome variable and additional controls.[22] We use 1 lag in the baseline specification. Tracing the effects of β_h provides an impulse response of the stability rate on the DAI price and the leverage ratio. The results of a positive 100 basis point shock is presented in Figure 14. Consistent with our hypothesis, we find a positive effect on DAI prices over a long horizon, with a 100 basis point hike in the stability rate increasing DAI prices by 30-40 basis points, and reducing aggregate leverage by a peak long-run effect of 1 per cent.[23]

Multiple Collateral types and peg stability

The MakerDAO protocol introduced USDC collateral in response to the mass liquidations and peg-price stability of the ETH price collapse on March 12th, 2020. The peg stability module (PSM) was introduced on December 18th, 2020, and is indicated by the dotted line in Figure 15. In the PSM, there is a smart contract that always enforces a peg of 1 USDC=1 DAI. This allows users to swap USDC with DAI at a 1:1 rate without needing to create a vault and deposit collateral. In this way, there is no liquidation risk, however users need to make a one-off fee to use this. We hypothesize the introduction of the USDC collateral and the swap arrangement of USDC for DAI at a 1:1 rate increase peg stability through decreasing limits to arbitrage. This increases the incentive for arbitrageurs to close peg-price deviations using the PSM.[24]

---

[22] For testing price effects, we use lagged and contemporaneous values of ETH returns and the leverage ratio. For testing the leverage ratio, we use lagged and contemporaneous values of ETH returns and the DAI price.

[23] We rationalize differences between the panel regression specification and the local projections due to (i) cross-section versus aggregate system leverage and (ii) the time horizon of the effect. While the panel regression specification estimated in Equation (15) is examining the daily change in leverage, the local projections allows us to examine the long-run effects of an increase in the stability interest rate.

[24] To understand why, note that investors can swap USDC for DAI in the event of a DAI premium. However, in the case of risky ETH collateral, there is no similar arbitrage motive. This is because the realtime value of the underlying collateral that would be released or absorbed is uncertain. A risky arbitrage investor that

We test three implications of the introduction of stable collateral. First, we hypothesize that DAI volatility is strongly correlated with USDC volatility and peg-prices in the post USDC collateral period. We empirically test the muted correlation between the DAI price and ETH returns in Table 8. We divide our sample into a pre and post USDC collateral period based on the introduction of USDC collateral by the MakerDAO governance on March 12th, 2020. We run a baseline specification regressing peg-price deviations and intra-day volatility on ETH returns, ETH volatility, USDC peg-prices and USDC volatility, and the stability rate. Columns (I) and (II) are estimated for the pre USDC collateral period, and columns (III) and (IV) for the post USDC collateral period. The results suggest a high sensitivity of DAI prices and volatility to USDC volatility in the post USDC collateral period. A 1 basis point increase in USDC volatility increases DAI peg-prices and volatility by 5.04 and 7.68 basis points respectively.

Second, we hypothesize that the introduction of USDC collateral led to an increase in peg-sustaining arbitrage. Figure 15 plots the decomposition of DAI borrowing by collateral type. To construct the share of stablecoin collateral, we combine both stablecoin collateral and stablecoin borrowing via the PSM. This accounts for up to 30% of DAI borrowing over the sample of March 12th, 2020 to March 31st, 2021. The variable *share* which is equal to DAI borrowings from stable collateral types as a fraction of aggregate DAI borrowings. Stable collateral types include stablecoins USDC, TrueUSD and Tether. We also construct a variable *Ratio* which measures the per cent change in ETH volatility relative to USDC volatility. In Equation (19), we regress the share of stablecoin collateral against *Ratio*.

$$share_{stablecoin,t} = \alpha + \beta_1 Ratio_t + \beta_2 R_{ETH,t} + u_t \tag{19}$$

where

$$share_{stablecoin} = \frac{DAI_{usdc} + DAI_{usdt} + DAI_{tusd}}{DAI_{total}} \times 100, \tag{20}$$

$$Ratio = \left(\frac{\sigma_{ETH}}{\sigma_{USDC}} - 1 \right) \times 100. \tag{21}$$

In this specification, we determine the fundamentals driving the share of stablecoin collateral. The main determinant is the ratio of ETH to USDC volatility, and tests the model prediction that arbitrageurs choose to increase the share of USDC collateral in response to

borrows DAI via ETH collateral would lose money if the market value of ETH has fallen over the period. Valuation losses on their ETH collateral are larger than DAI secondary-market price deviations from the peg.

a relative increase in ETH volatility. The results are summarized in Table 9. In column (I), we run a baseline specification regressing the share on ratio. A 1 per cent change in the ratio of ETH to USDC volatility increases the share of stable collateral by 0.01 percentage points. To test the effect on peg efficiency, we run equation (22), which regresses an outcome variable Y_t on the share of stable collateral. Columns (II) through to (IV) examine the effect of the share of stable collateral on peg-price deviations, and columns (V) through to (VII) examine effects on intra-day volatility of the DAI peg. A 1 percentage point increase in the share of stable collateral reduced peg-prices by 2.1 basis points, and intra-day volatility by 2.4 basis points. These results are robust to adding controls such as returns and volatility of ETH, however, get absorbed by adding controls for USDC peg prices and volatility.

$$Y_t = \alpha + \beta_1 share_t + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + u_t. \tag{22}$$

Our final test of the effects of introducing USDC collateral is through documenting a convergence of the DAI/USD price to the USDC/USD price. Figure 16 plots the stablecoin prices and intra-day volatility for USDC and DAI. A visual inspection of Figure 16 shows that DAI peg-price deviations and intra-day volatility are larger than USDC. While the volatility decline occurred immediately after the PSM launch date, we note a decline in absolute peg-deviations began 2 to 3 months prior, which is coincident with an increase in the share of USDC collateral in September 2020. To assess the increase in peg efficiency, we test a DiD design in Equation (23), where the outcome variable Y_t is either the absolute level of peg deviations, $|\Delta|$, or the intra-day volatility of peg deviations σ_t, both measured in basis points. The indicator for treatment T_i takes on a value of 1 for DAI and 0 for USDC. The coefficient δ measures the net effect of peg stabilization relative to any trends observed in USDC.

$$Y_t = \alpha_0 + \beta T_i + \gamma post_t + \delta post_t \times T_i + u_t \tag{23}$$

The results are summarized in Table 10. In columns (I) and (II), we impose a standard structural break test by regressing the absolute size and volatility of USDC peg-price deviations on a post dummy, which takes a value of 1 on December 18th, 2020, which was the date of the PSM launch. We observe on average a 67.9 basis point decline in the absolute level of peg deviations, and a decline in intra-day volatility of 71.3 basis points. The results of our differences-in-differences analysis for the full sample are reported in columns (III) and (IV) of Table 10. There is a net convergence in the stability of peg deviations during the post PSM period, with a DiD coefficient of post × T of -83.8 basis points. Similarly, we observe a decline in intra-day volatility of 72.0 basis points relative to USDC. The results are robust to using a balanced sample, starting on January 8th, 2020. In columns (V) and (VI), we find a decline in the absolute size of peg-price deviations of 101.8 basis points, and a decline in intra-day volatility of 61.1 basis points, relative to USDC over the balanced sample. The results suggest the increase in peg efficiency is attributed to reduced limits to arbitrage. The swap arrangement enables arbitrageurs to short sell DAI when it trades at a premium through swapping USDC for DAI. In Appendix F we provide further econometric tests to show the peg is dynamically more stable in the post PSM period.

6 Conclusion

In this paper we investigate the importance of collateral risk for stability of the DAI stablecoin peg. To shed light on the fundamentals of peg-price dynamics, we introduce a model setup that has three agents: investors that deposit risky collateral and borrow a fraction as DAI tokens, arbitrageurs that short DAI when the peg trades at a premium, and a demand shock for DAI in period 1 from investors that seek DAI to earn savings and gain utility from its use in DeFi applications. In equilibrium, DAI peg-prices are dependent on investors' beliefs about the state of the collateral. The model generates peg premiums (discounts) in the *bad* (*good*) state, and a positive relationship between volatility of the peg and volatility of the collateral. Leverage of investors falls in the *bad* state, and peg-deviations are dampened through increased arbitrage capital, and an introduction of stable collateral types for arbitrageurs to borrow against.

We provide empirical evidence to support model predictions. First, we document the negative correlation between DAI prices and ETH returns. Negative correlations are higher in periods of extreme returns. Second, we find evidence of deleveraging in periods of high volatility. Using the universe of collateralized debt positions, we find that leverage is lower in periods of extreme negative returns and high volatility of collateral. Third, at the aggregate level, we find a hike in the stability rate, which is the interest charged on DAI borrowings, has effects of reducing aggregate system leverage and increasing DAI prices. Fourth, we document a trend toward peg-price stability since the advent of the peg stability module in December 2020. Stable collateral increases the capacity for arbitrageurs to step in and absorb differences between the primary and secondary market rates.

For future research, we point to implications for regulations of stablecoins with cryptocurrency collateral. Both the model and empirical evidence point to stable collateral as a necessary condition for a stable peg. While alternative tools like rates on borrowing the stablecoin can in principle induce an effective change in supply, risky collateral leads to an increased volatility of the peg. A tokenized digital version of the dollar, such as a central bank digital currency issued by the Federal Reserve, can in principle provide a dominant solution for stable collateral that minimizes custodial risk. The relationship between volatility of the peg and collateral risk can also shed light on how global stablecoins, like Facebook's Libra/Diem, should be designed. Our bottom line: stablecoins need to be backed by liquid, risk-free reserves.

References

Angeris, Guillermo and Tarun Chitra, "Improved price oracles: Constant function market makers," in "Proceedings of the 2nd ACM Conference on Advances in Financial Technologies" 2020, pp. 80–91.

Aoyagi, Jun and Yuki Ito, "Liquidity Implication of Constant Product Market Makers," *Available at SSRN 3808755*, 2021.

Arner, Douglas W, Raphael Auer, and Jon Frost, "Stablecoins: risks, potential and regulation," *Financial Stability Review. Nº 39 (Autumm 2020), p. 95-123*, 2020.

Baumöhl, Eduard and Tomas Vyrost, "Stablecoins as a crypto safe haven? Not all of them!," 2020.

Baur, Dirk G and Lai T Hoang, "A Crypto Safe Haven against Bitcoin," *Finance Research Letters*, 2020.

Berentsen, Aleksander and Fabian Schär, "Stablecoins: The quest for a low-volatility cryptocurrency," 2019.

Bianchi, Daniele, Luca Rossini, and Matteo Iacopini, "Stablecoins and cryptocurrency returns: Evidence from large bayesian vars," *Available at SSRN 3605451*, 2020.

BIS, "Investigating the impact of global stablecoins," 2019.

Borri, Nicola and Kirill Shakhnov, "Cryptomarket discounts," *Available at SSRN 3124394*, 2018.

Brunnermeier, Markus K and Lasse Heje Pedersen, "Market liquidity and funding liquidity," *The review of financial studies*, 2009, *22* (6), 2201–2238.

Bullmann, Dirk, Jonas Klemm, and Andrea Pinna, "In search for stability in crypto-assets: Are stablecoins the solution?," *ECB Occasional Paper*, 2019, (230).

d'Avernas, Adrien, Thomas Bourany, and Quentin Vandeweyer, "Are Stablecoins Stable?," *Working Paper*, 2021.

Dell'Erba, Marco, "Stable Cryptocurrencies? Assessing the Case for Stablecoins," *New York University Journal of Legislation and Public Policy, Forthcoming*, 2019.

Eichengreen, Barry, "From Commodity to Fiat and Now to Crypto: What Does History Tell Us?," Technical Report, National Bureau of Economic Research 2019.

Force, ECB et al., "Stablecoins: Implications for monetary policy, financial stability, market infrastructure and payments, and banking supervision in the euro area," Technical Report, European Central Bank 2020.

Frost, Jon, Hyung Song Shin, and Peter Wierts, "An early stablecoin? The Bank of Amsterdam and the governance of money," 2020.

Gloede, Oliver and Thomas Moser, "Crypto Havens: Are Stablecoins Safe Havens?," *Swiss National Bank Working Paper, presented at SNB-CIF Conference on Cryptoassets and Financial Innovation, 20-21 May 2021, Virtual conference, Swiss National Bank, Zurich, University of Basel, Center for Innovative Finance, Basel*, 2021.

Gromb, Denis and Dimitri Vayanos, "Equilibrium and welfare in markets with financially constrained arbitrageurs," *Journal of financial Economics*, 2002, *66* (2-3), 361–407.

_ and _ , "The dynamics of financially constrained arbitrage," *The Journal of Finance*, 2018, *73* (4), 1713–1750.

Gudgeon, Lewis, Sam Werner, Daniel Perez, and William J Knottenbelt, "DeFi protocols for loanable funds: Interest rates, liquidity and market efficiency," in "Proceedings of the 2nd ACM Conference on Advances in Financial Technologies" 2020, pp. 92–112.

Harvey, Campbell R, Ashwin Ramachandran, and Joey Santoro, "DeFi and the Future of Finance," *Available at SSRN 3711777*, 2020.

Jarno, Klaudia and Hanna Kołodziejczyk, "Does the Design of Stablecoins Impact Their Volatility?," *Journal of Risk and Financial Management*, 2021, *14* (2), 42.

Jordà, Òscar, "Estimation and inference of impulse responses by local projections," *American economic review*, 2005, *95* (1), 161–182.

Klages-Mundt, Ariah and Andreea Minca, "While stability lasts: A stochastic model of stablecoins," *arXiv preprint arXiv:2004.01304*, 2020.

Lehar, Alfred and Christine Parlour, "Decentralized Exchanges," *Working Paper*, 2021.

Li, Ye and Simon Mayer, "Managing Stablecoins: Optimal Strategies, Regulation, and Transaction Data as Productive Capital," *Fisher College of Business Working Paper*, 2020, (2020-03), 030.

Lyons, Richard K and Ganesh Viswanath-Natraj, "What Keeps Stablecoins Stable?," Technical Report, National Bureau of Economic Research 2020.

Makarov, Igor and Antoinette Schoar, "Price discovery in cryptocurrency markets," in "AEA Papers and Proceedings," Vol. 109 2019, pp. 97–99.

_ **and** _ , "Trading and arbitrage in cryptocurrency markets," *Journal of Financial Economics*, 2020, *135* (2), 293–319.

Nyborg, Kjell G and Cornelia Rösler, "Repo rates and the collateral spread: Evidence," 2019.

Perez, Daniel, Sam M Werner, Jiahua Xu, and Benjamin Livshits, "Liquidations: DeFi on a Knife-edge," *arXiv preprint arXiv:2009.13235*, 2020.

Pernice, Ingolf Gunnar Anton, "On Stablecoin Price Processes and Arbitrage," in "Financial Cryptography" 2021.

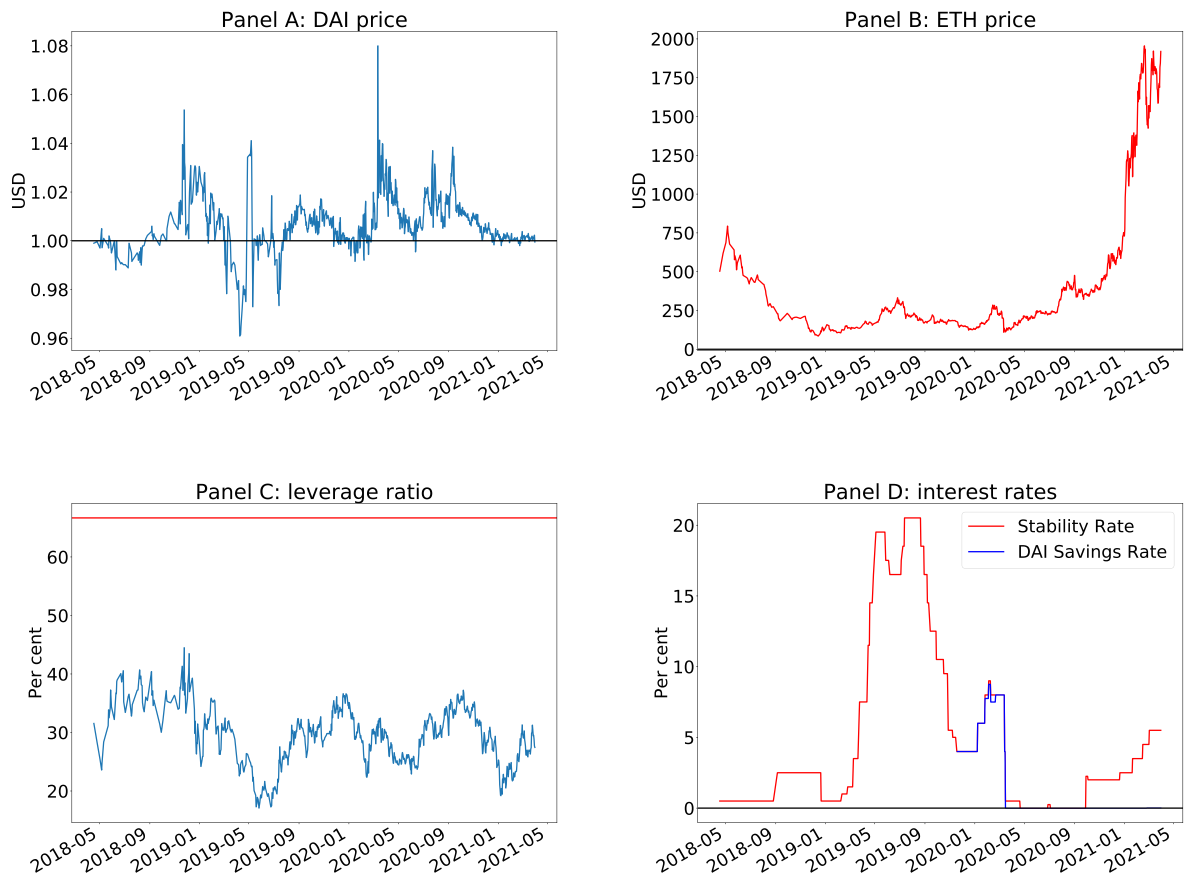
Routledge, Bryan, Ariel Zetlin-Jones et al., "Currency stability using blockchain technology," *Society for Economic Dynamics*, 2018.

Schär, Fabian, "Decentralized finance: On blockchain-and smart contract-based financial markets," *FRB of St. Louis Review*, 2021.

Wang, Gang-Jin, Xin yu Ma, and Hao yu Wu, "Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests?," *Research in International Business and Finance*, 2020, p. 101225.

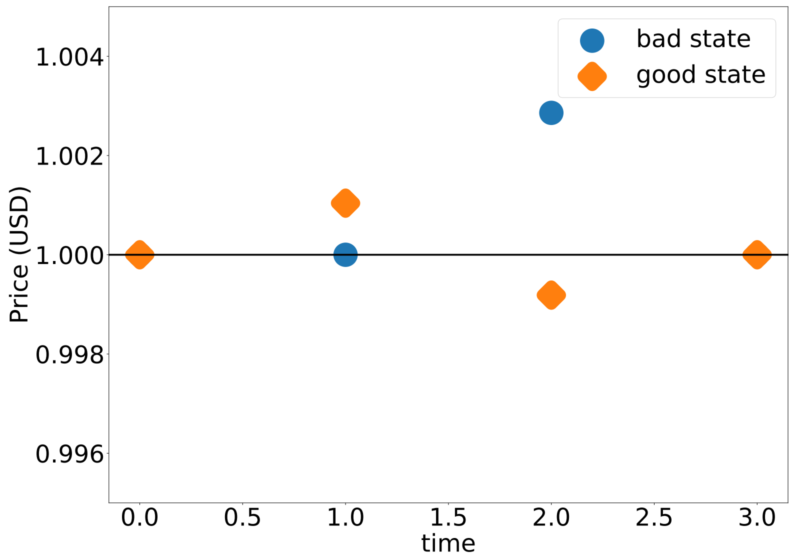
Figures

Figure 1: DAI price, ETH price, Leverage, Stability rate



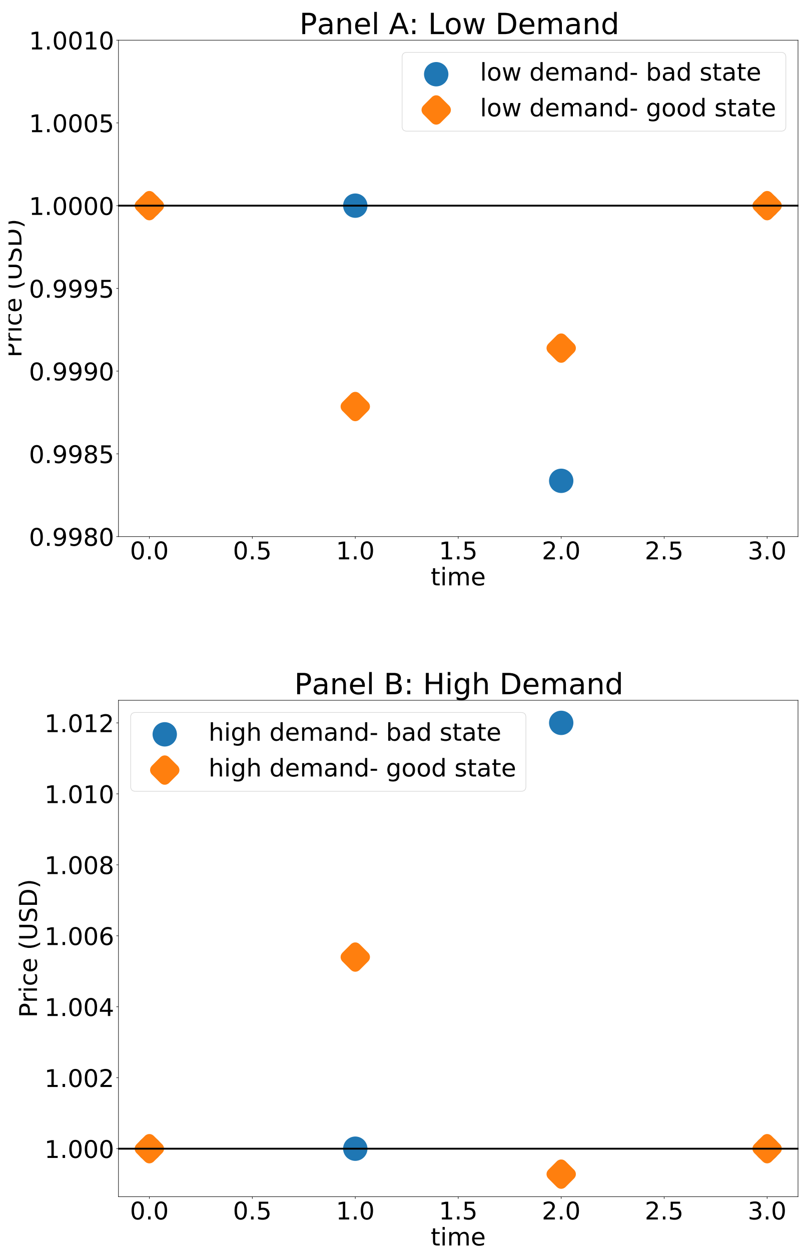
Note: This figure plots Panel A: DAI price, Panel B: ETH price Panel C: leverage in ETH vaults, and Panel D: the interest rate on DAI borrowings. Sample period is from April 13th, 2018 to March 31st, 2020.

Figure 2: DAI prices across good and bad states of ETH collateral



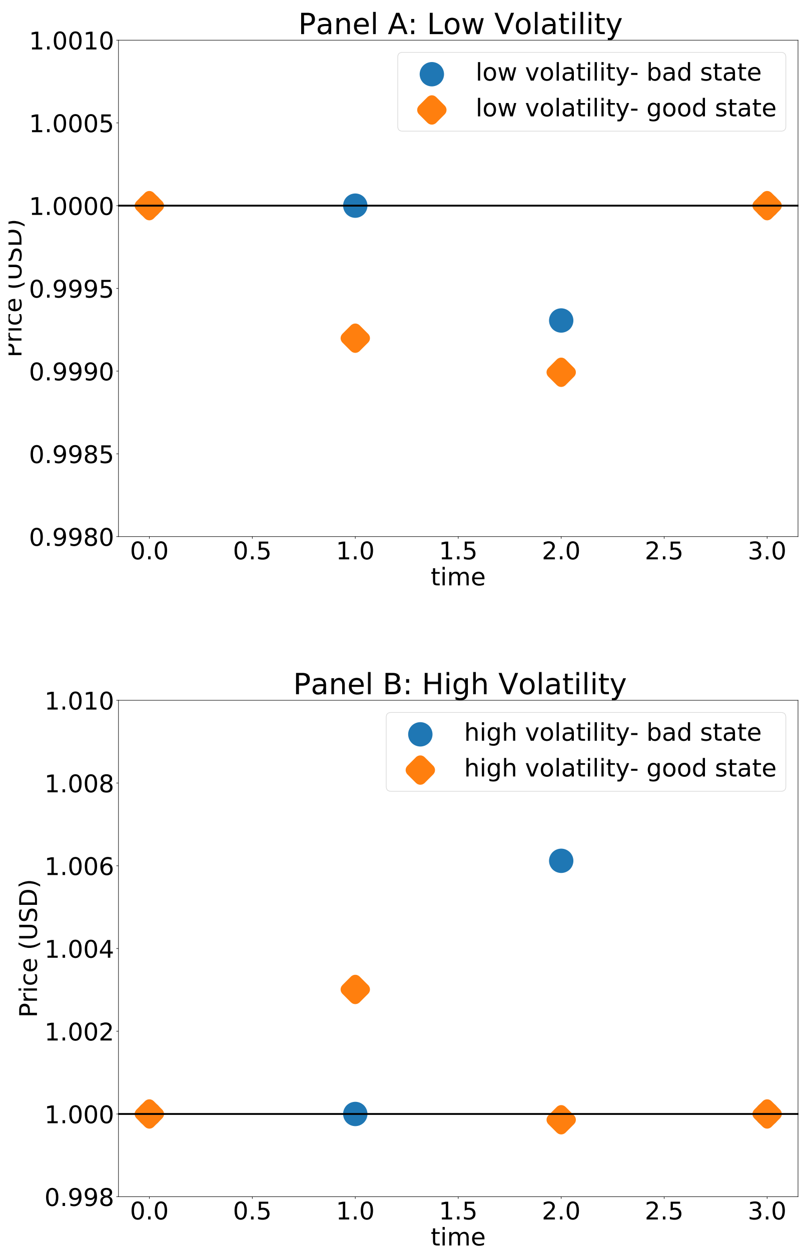
Note: This figure plots DAI prices over the three periods for both good and bad states of nature. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $D = \$50$, $\bar{\theta} = 0.66$, $\sigma_0 = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5) subject to wealth dynamics (3) and (4) and solving the model backwards in time.

Figure 3: DAI prices for low and high uninformed demand in period 2



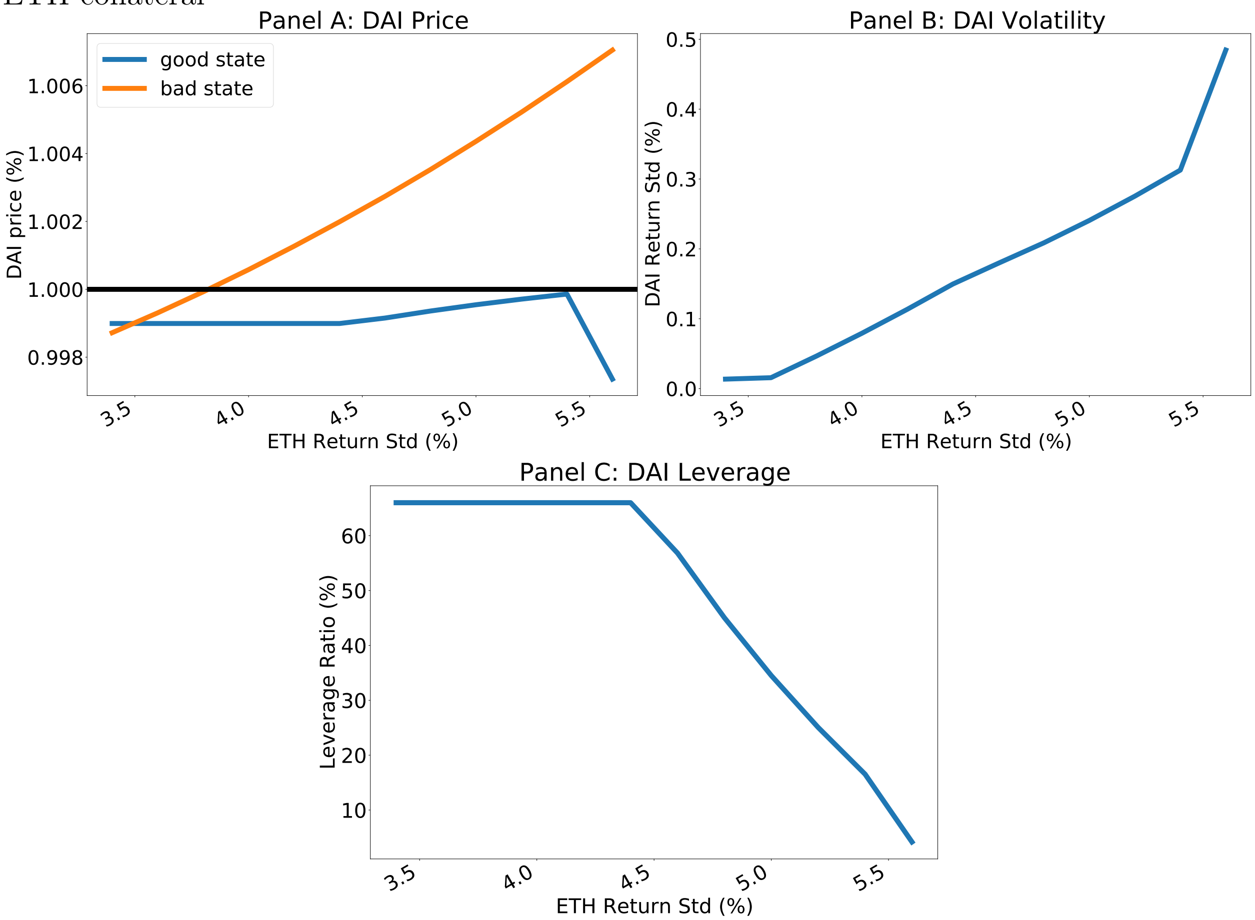
Note: This figure plots DAI prices over the three periods for both good and bad states of nature. Panel A corresponds to low demand case D = \$10, panel B corresponds to high demand case D = \$80. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $\bar{\theta} = 0.66$, $\sigma_0 = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5) subject to wealth dynamics (3) and (4) and solving the model backwards in time.

Figure 4: Peg-Price Dynamics: High and Low Volatility of Collateral



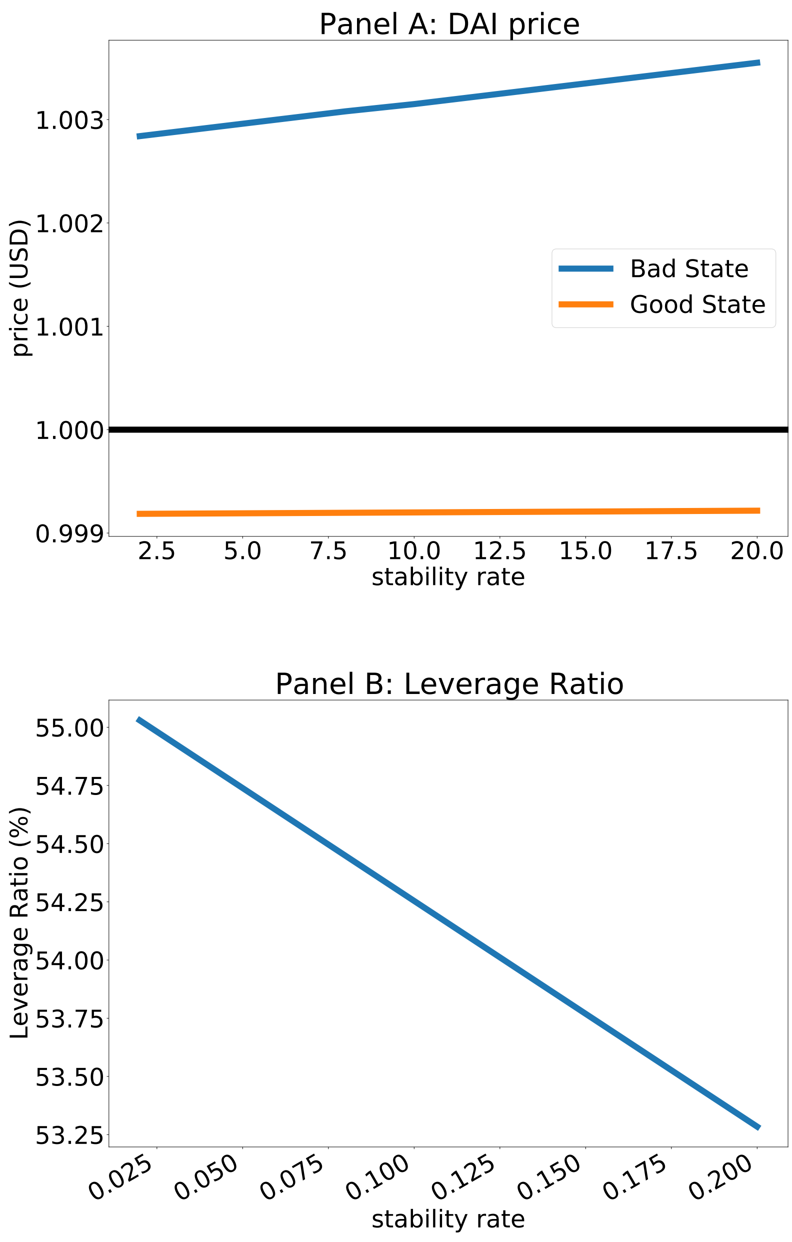
Note: This figure plots DAI prices over the three periods for both good and bad states of nature. Panel A corresponds to low volatility case $\sigma_E = 0.02$, panel B corresponds to high volatility case $\sigma_E = 0.046$. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $D = \$50$, $\bar{\theta} = 0.66$, $\sigma_0 = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5) subject to wealth dynamics (3) and (4) and solving the model backwards in time.

Figure 5: DAI prices, volatility and leverage across different parameterization of volatility of ETH collateral



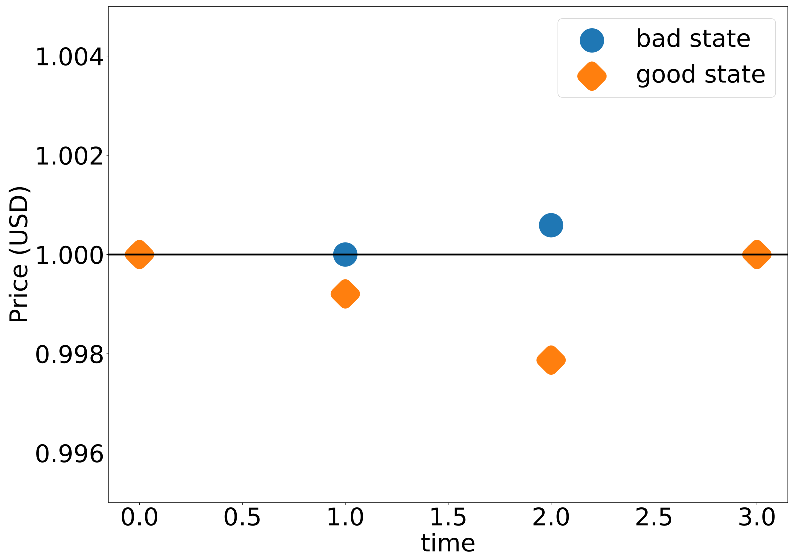
Note: This figure plots DAI prices, volatility and leverage as a function of ETH volatility, holding all other parameters constant. Panel A corresponds to DAI prices in the *good* and *bad* states respectively. Panel B corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. Panel C corresponds to DAI leverage, calculated in per cent. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $D = \$50$, $\bar{\theta} = 0.66$, $\sigma_0 = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5) subject to wealth dynamics (3) and (4) and solving the model backwards in time.

Figure 6: DAI price and leverage ratio across different parameterization of stability rate on DAI borrowings



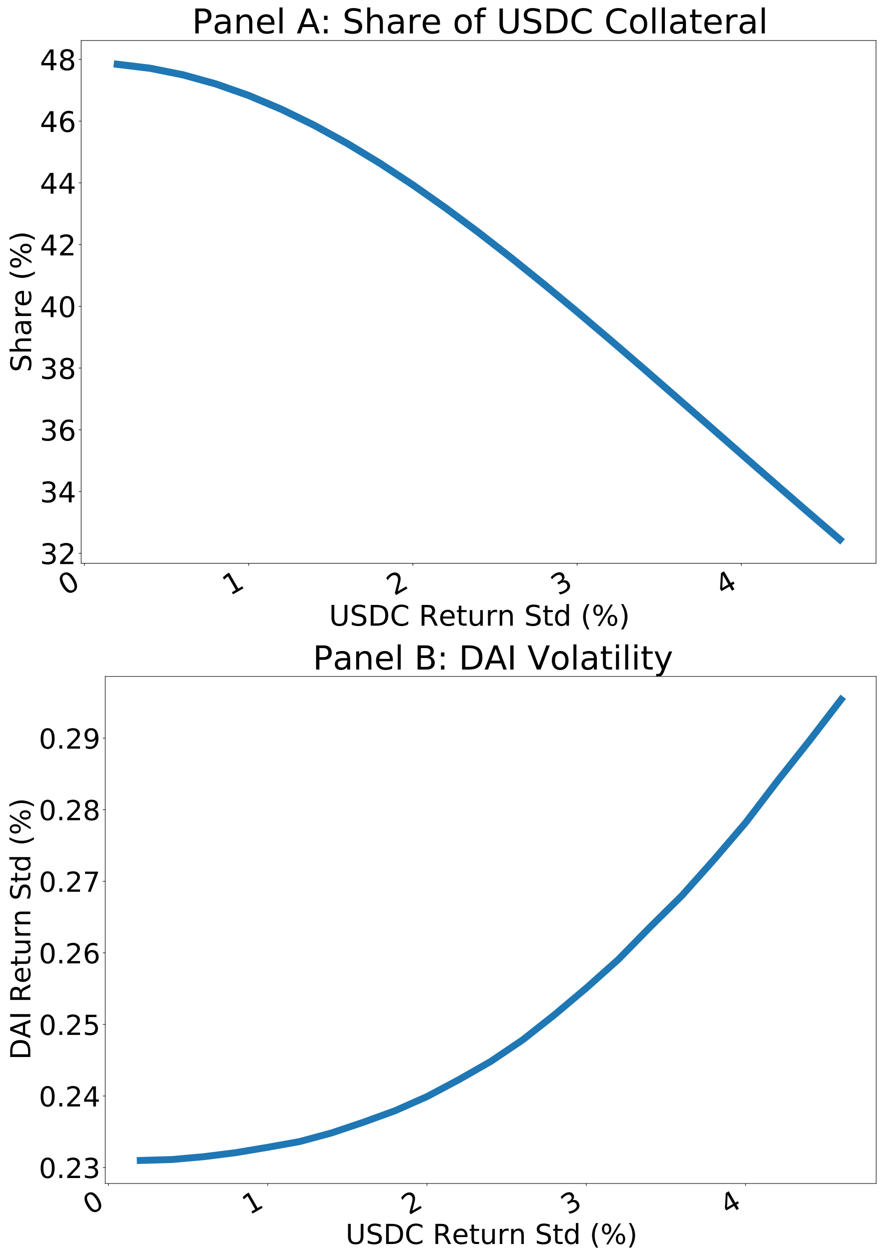
Note: This figure plots DAI prices and leverage as a function of the interest rate on DAI borrowings. Panel A corresponds to DAI prices in the *good* and *bad* states respectively. Panel B corresponds to DAI leverage, calculated in per cent. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $D = \$50$, $\bar{\theta} = 0.66$, $\sigma_0 = 0.0188$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5) subject to wealth dynamics (3) and (4) and solving the model backwards in time.

Figure 7: DAI price for Multiple Collateral System



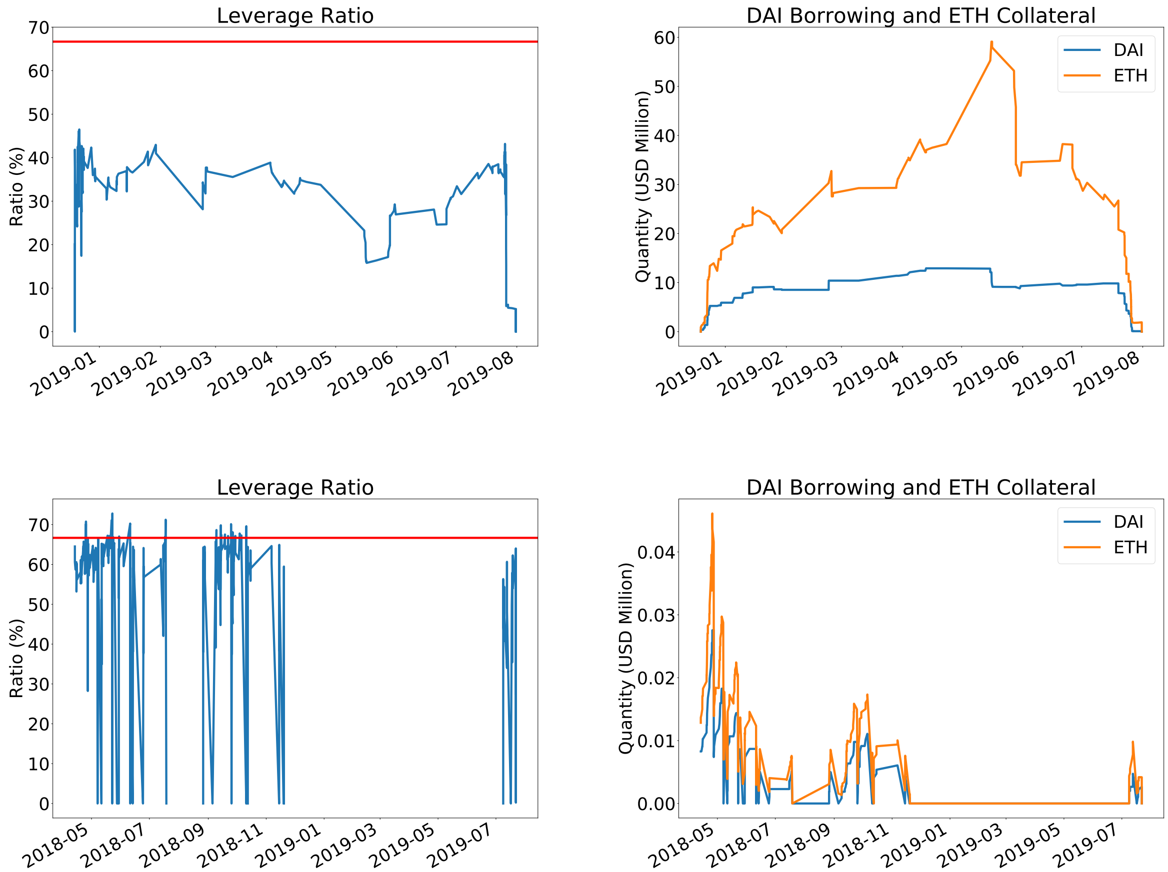
Note: This figure plots DAI prices over the three periods for both good and bad states of nature. In addition the ETH collateral, arbitrageurs now have access to USDC collateral, with volatility $\sigma_U = 0.0013$. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $D = \$50$, $\bar{\theta} = 0.66$, $\sigma_0 = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5) subject to wealth dynamics (3) and (4) and solving the model backwards in time.

Figure 8: Comparative statics with respect to USDC volatility: Panel A: Share of stable Collateral used by arbitrageurs Panel B: Volatility of DAI peg



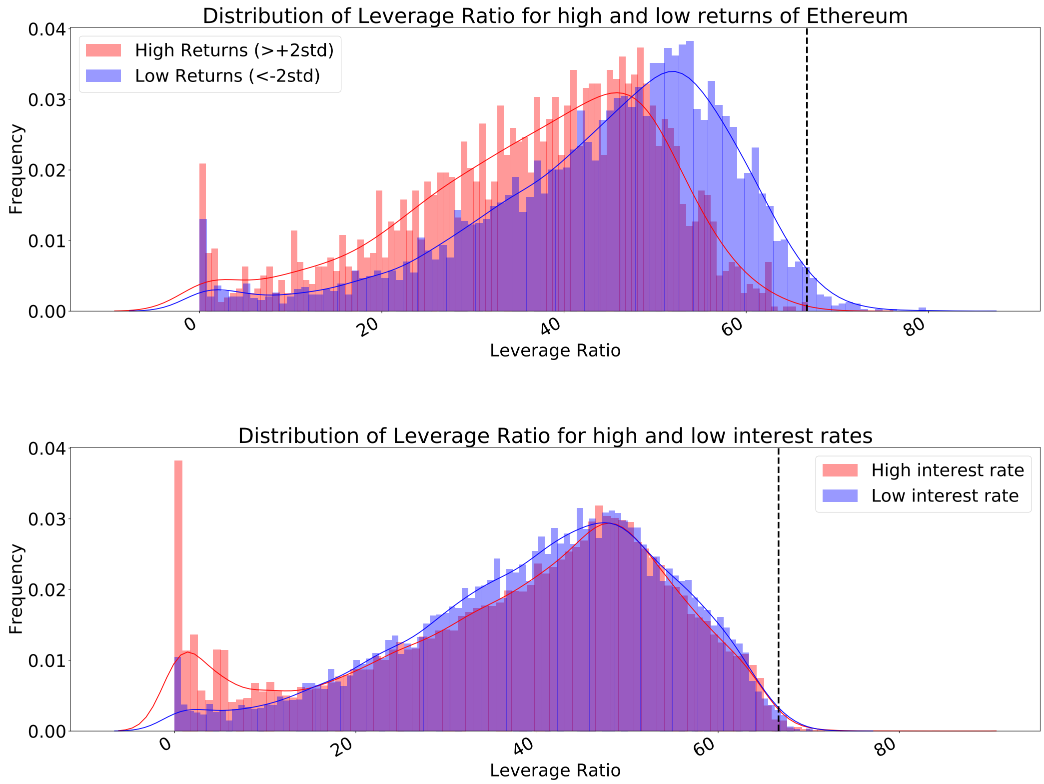
Note: This figure plots the share of USDC collateral and the DAI volatility as a function of the USDC volatility. Panel A corresponds to the share of USDC collateral deposited by the arbitrageur. Panel B corresponds to DAI volatility. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_0^s = \$350$, $D = \$50$, $\bar{\theta} = 0.66$, $\sigma_0 = 0.0188$, $\sigma_U = 0.0013$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5) subject to wealth dynamics (3) and (4) and solving the model backwards in time.

Figure 9: Time Series of Leverage Ratio, DAI borrowings and ETH collateral for two CDPs. Top panel: CDP id: 5199. Bottom panel: CDP id: 1272



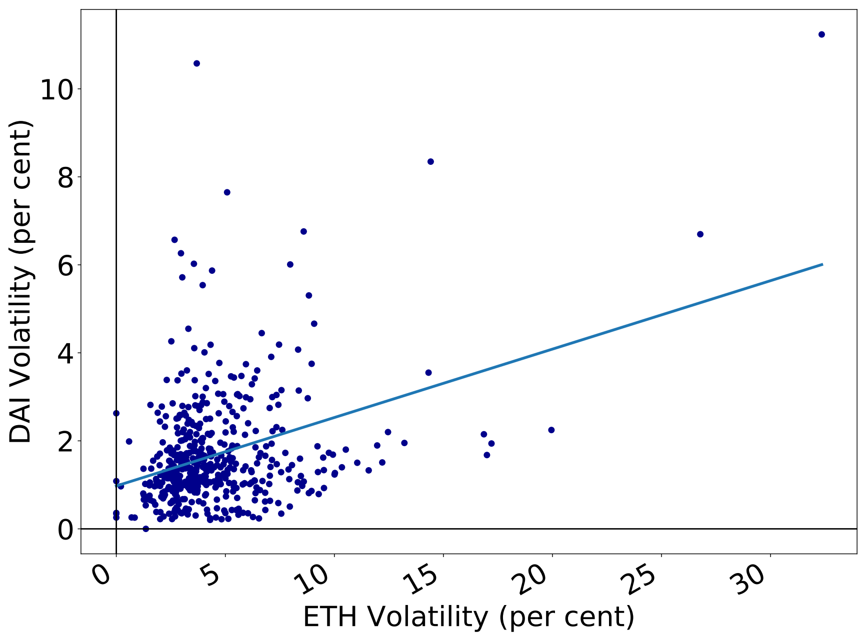
Note: Top panel: Time series of leverage ratio (left) and DAI borrowings and ETH collateral for CDP 5199. Bottom panel: Time series of leverage ratio (left) and DAI borrowings and ETH collateral for CDP 1272. CDP transactions are aggregated to a daily frequency, with sample period from April 13th, 2018 to November 18th, 2019.

Figure 10: Distribution Conditional on ETH Returns



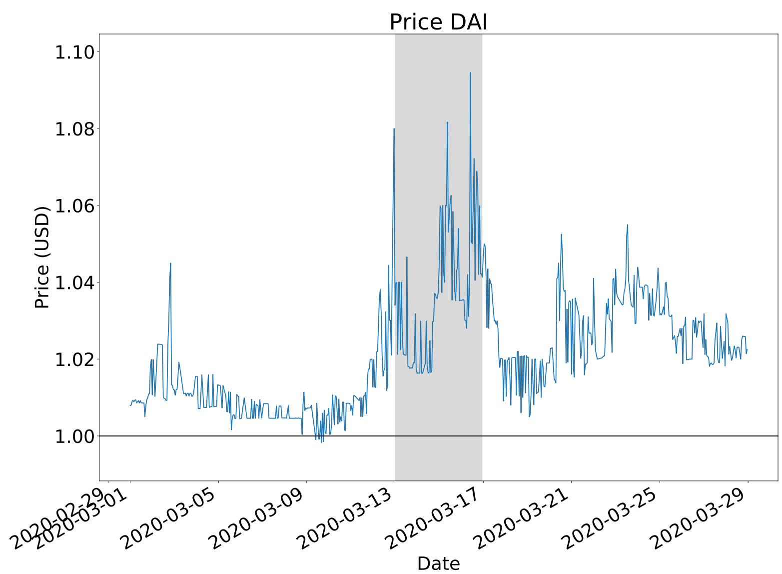
Note: This figure plots the kernel density of the leverage ratio for all CDPs. Top panel: Distributions are conditioned on periods of high and low returns of ETH, where high returns corresponds to returns that exceed +2std of ETH returns, and low returns corresponds to returns that are less than -2 std of ETH returns. Bottom panel: Distributions are conditioned on periods of high and low interest rates. High interest rates correspond to the distribution of CDP leverage when the DAI stability rate reached its peak of 19.0%. Low interest rates correspond to the distribution of CDP leverage when the DAI stability rate is at the floor of 0%. CDP liquidations, when the action is "bite" and DAI borrowings are zero, are excluded from the sample. CDP transactions are aggregated to a daily frequency, with sample period from April 13th, 2018 to November 18th, 2019.

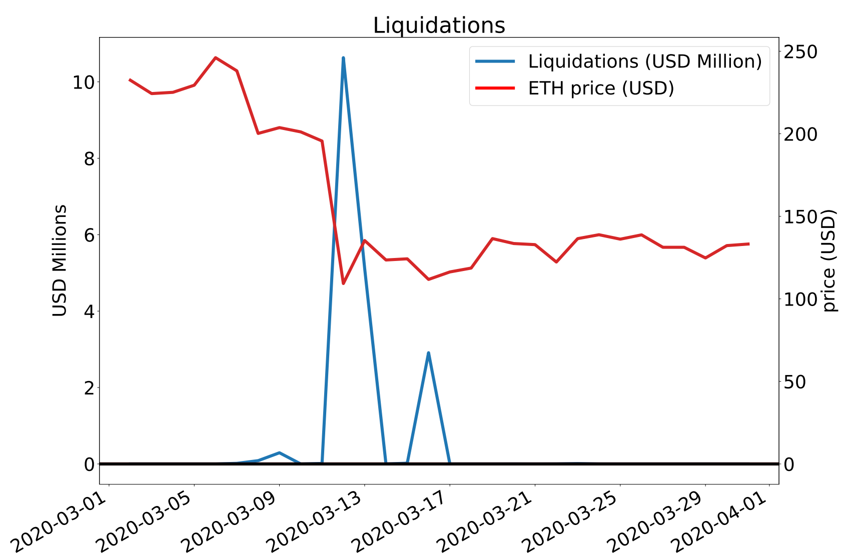
Figure 11: DAI and ETH intra-day volatility



Note: This figure plots a scatter plot of intra-day volatility of DAI and ETH. Intra-day volatility is measured in basis points. Price data for currencies obtained from coinapi and use intra-day prices from the Bitfinex exchange. Sample period is from November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI.

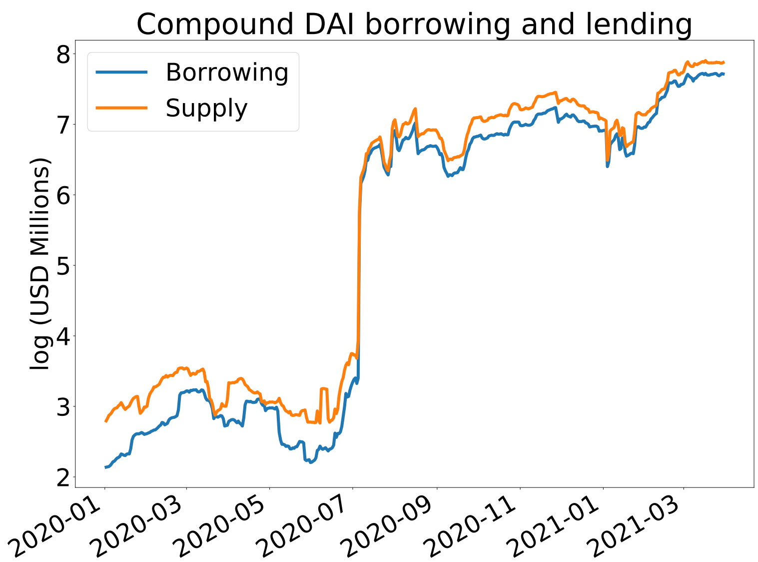
Figure 12: DAI price and liquidations response to negative price shock of ETH in March 2020

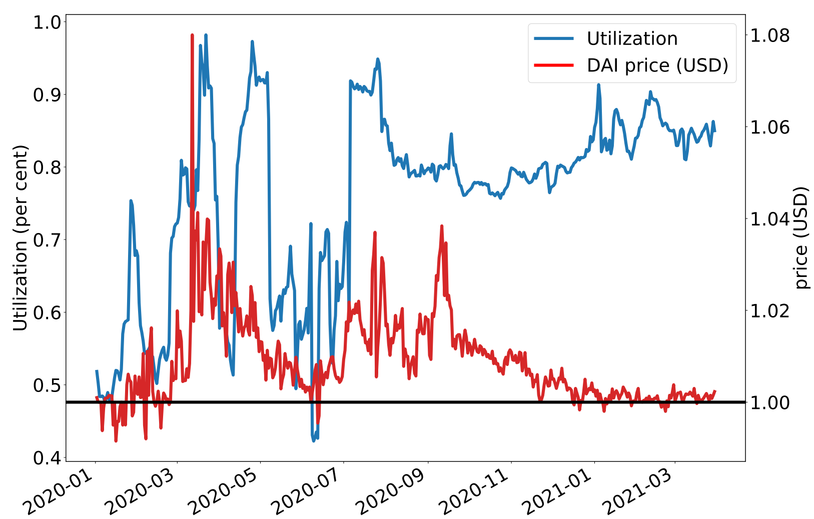




Note: DAI price in USD, ETH price in USD and DAI liquidations during the month of March 2020. Shaded areas indicate the period when the price of ETH fell approximately 50% from March 12th to March 13th.

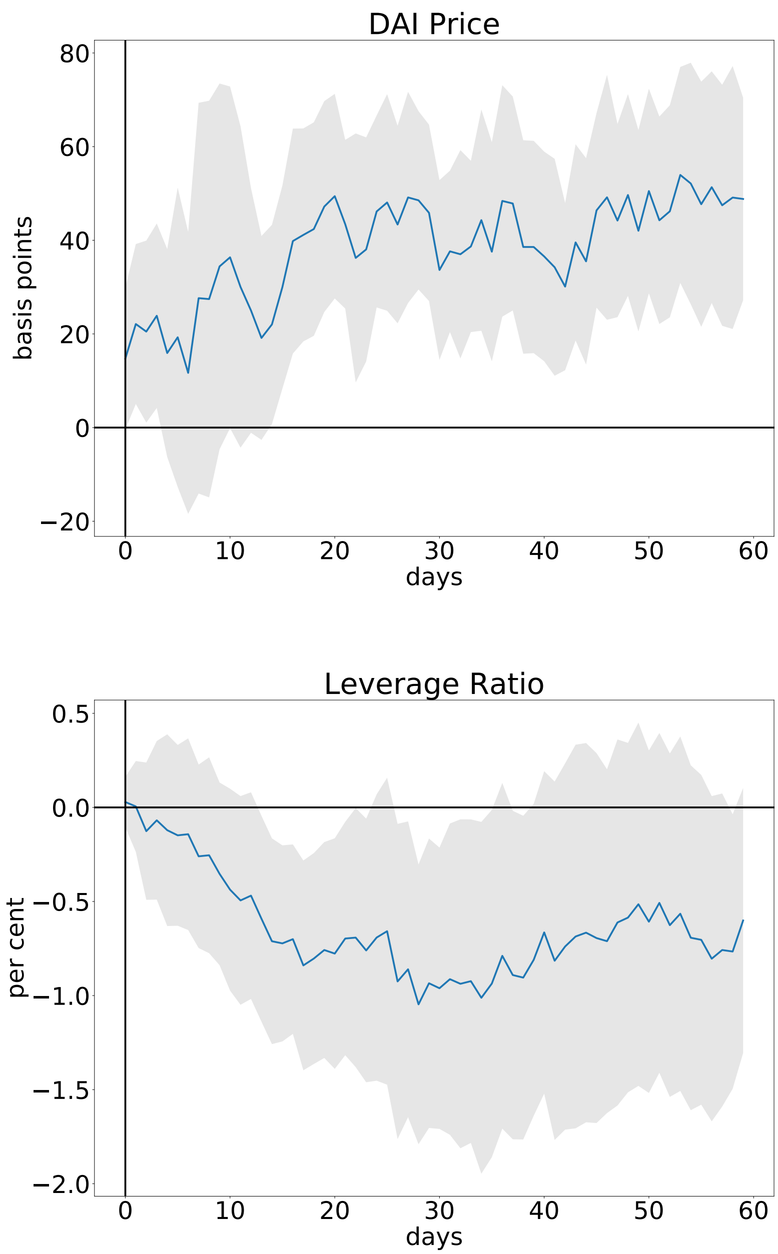
Figure 13: DAI borrowing and lending in Compound Protocol





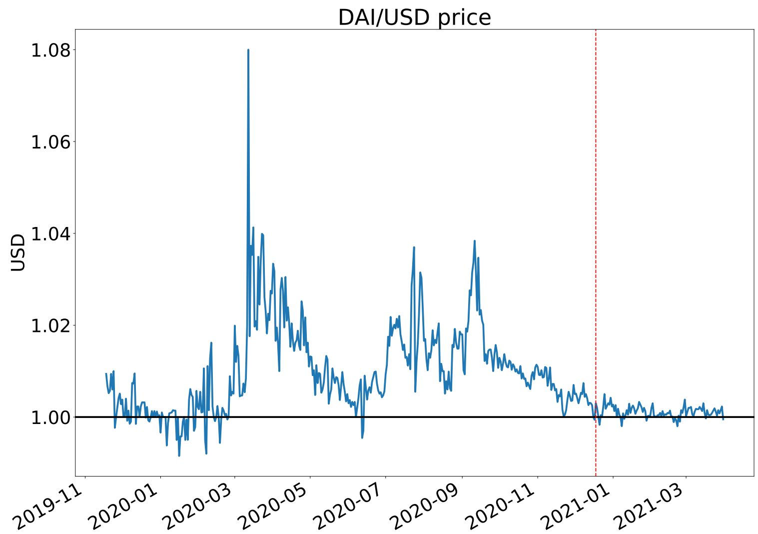
Note: Total DAI borrowing, lending and utilization rate in DeFi protocol Compound. Utilization rate is defined as the ratio of total borrowing to total lending. Sample period is from January 1st, 2020 to March 31st, 2021.

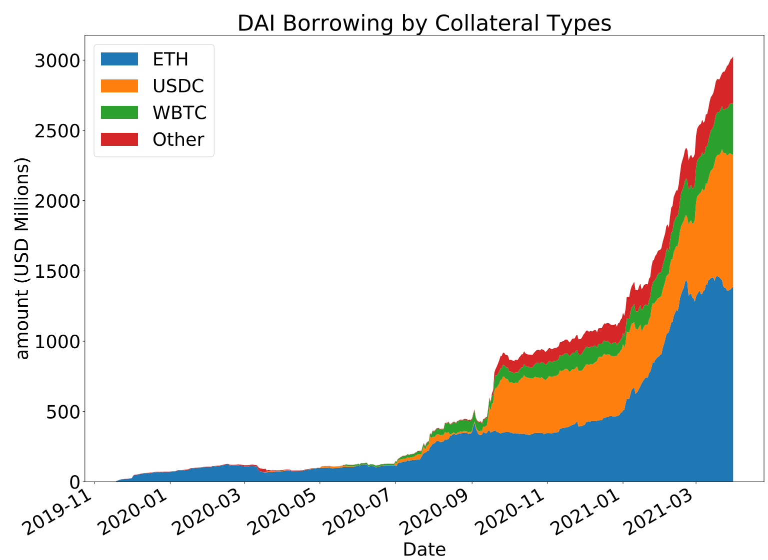
Figure 14: Local Projections of a 100 basis point shock to the stability rate on the DAI price and the leverage ratio



Note: This figure illustrates the response of aggregate system leverage and the DAI price to a positive 100 basis point shock to the stability rate, using the method of local projections. Leverage ratio is based on aggregate measures of DAI borrowings and ETH collateral. Stability rate is cost of borrowing DAI from ETH vaults. Sample period is from November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI. 1 lag is included in the baseline specification. Gray area denotes 95% confidence interval using White heteroscedasticity-robust standard errors.

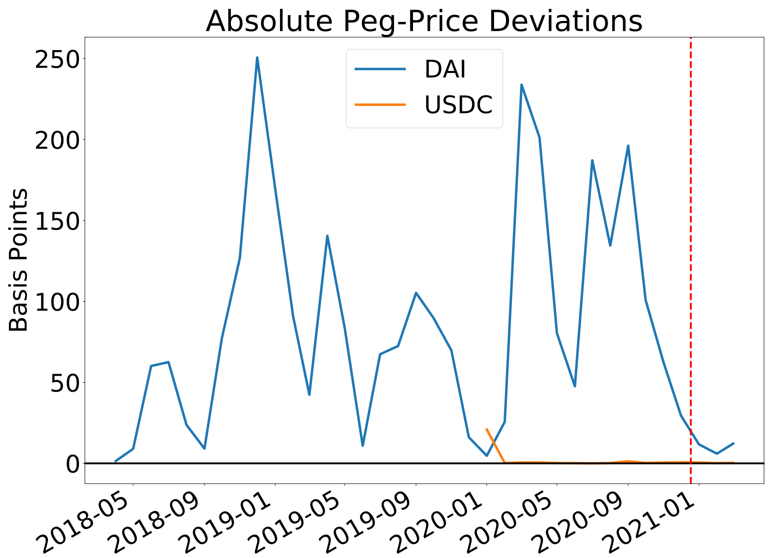
Figure 15: DAI/USD Prices

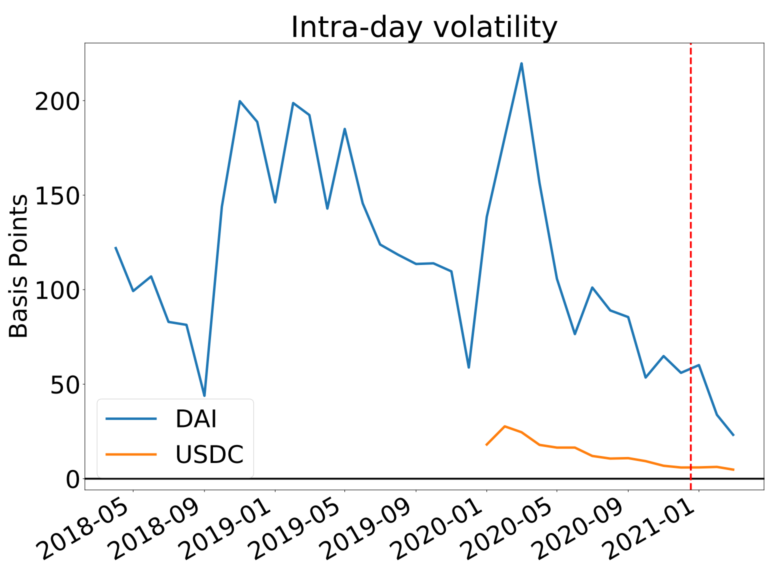




Note: Left: This figure plots the deviations of the DAIUSD peg from parity. A positive deviation indicates DAIUSD trades at a premium. Sample period is from 11/19-03/21. Right: This figure plots the breakdown of total DAI borrowing by Vault. DAI borrowing is denominated in USD Million. Vault types include ETH, USDC, WBTC (synthetic BTC) and other. Sample period is from 18th November, 2019 to March 31st, 2020

Figure 16: DAI vs. USDC: Absolute peg-price deviations and volatility





Note: This figure plots average monthly stablecoin prices and intra-day volatility for the treatment (DAI) and the control group stablecoins. The treatment stablecoin is DAI. The control stablecoin is USDC. The red dotted line indicates the date of structural change of December 18th, 2020 used in the baseline specification. Sample is April 13th, 2018 through to March 31st, 2021.

Tables

Table 1: Summary statistics

	count	mean	std	min	25%	50%	75%	max
R_{ETH}(%)	798.0	0.17	5.80	-58.22	-2.34	0.11	3.02	23.31
Δ (USD)	798.0	0.01	0.01	-0.04	0.00	0.01	0.01	0.08
Stability Rate (%)	798.0	3.24	6.34	0.00	0.02	0.04	2.50	20.52
Leverage Ratio (%)	798.0	29	5	17	26	30	33	44

Note: This table presents summary statistics of key variables in empirical analysis. R_{ETH} measures daily returns in ETH in per cent. Δ measures deviations from the peg and are expressed in USD (1 USD=100 basis points). The stability rate is an interest rate on DAI borrowing and is expressed in per cent (annualized). The leverage ratio is the ratio of total DAI borrowings to total ETH collateral. Sample period is from April 13th, 2018 to March 31st, 2021.

Table 2: Correlation matrix

	R_{ETH}	Δ	Stability Rate	Leverage Ratio
R_{ETH}	1.000	-0.044	-0.015	-0.209
Δ	-0.044	1.000	-0.190	0.250
Stability Rate	-0.015	-0.190	1.000	-0.340
Leverage Ratio	-0.209	0.250	-0.340	1.000

Note: This table presents pairwise correlation of key variables in empirical analysis. R_{ETH} measures daily returns in ETH in per cent. Δ measures deviations from the peg and are expressed in USD (1 USD=100 basis points). The stability rate is an interest rate on DAI borrowing and is expressed in per cent (annualized). The leverage ratio is the ratio of total DAI borrowings to total ETH collateral. Sample period is from April 13th, 2018 to March 31st, 2021.

Table 3: CDP Summary Statistics

	count	mean	std	min	25%	50%	75%	max
DAI (USD Million)	11,718	.015	0.16	0.00	0.00	0.00	0.002	7.87
ETH (USD Million)	11,718	0.04	0.50	0.00	0.00	0.00	0.005	24.96
Leverage Ratio (%)	11,718	30.55	19.01	0.00	13.43	33.02	44.79	84.49
Liquidations	7,097	1.06	0.40	1	1	1	1	14

Note: This table presents summary statistics of key variables of individual CDP data. DAI and ETH measure the total DAI borrowings and ETH collateral of each individual CDP, measured in USD million. The leverage ratio is the ratio of total DAI borrowings to total ETH collateral. Liquidations measures the number of times a CDP leverage ratio is above the threshold governed by the liquidation price. Only CDPs with at least 30 days of observations are included in the sample. Sample period is from April 13th, 2018 to November 17th, 2019, which corresponds to the period of single collateral DAI.

Table 4: Determinants of CDP Leverage

	I	II	III	IV	V
	LR	LR	LR	LR	LR
R_{ETH}	-0.22***				-0.23***
	(0.02)				(0.02)
R^+_{ETH}		-3.84***			
		(0.36)			
R^-_{ETH}		2.07***			
		(0.55)			
σ_{ETH}			-0.19***		-0.25***
			(0.05)		(0.05)
SFee				-0.11**	-0.10**
				(0.05)	(0.05)
Intercept	40.90***	41.01***	42.01***	41.95***	43.13***
	(0.42)	(0.43)	(0.55)	(0.51)	(0.56)
R-Squared	0.010	0.006	0.002	0.003	0.016
Observations	24,977	25,002	25,002	25,002	24,977
Number of id	456	456	456	456	456
id Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note: This table regresses the leverage ratio on ETH returns, intra-day volatility and the stability fee on DAI. The dependent variable in columns (I) through to (V), LR measures the leverage ratio of an individual CDP, and is the ratio of DAI borrowing to ETH collateral in per cent. Explanatory variables include R_{ETH}, which is daily ETH returns measured in per cent. Dummy variables R^+_{ETH} and R^-_{ETH} which take a value of 1 when ETH returns are greater (less) than 2 standard deviations respectively. σ_{ETH} measures daily intra-day volatility of ETH returns in per cent. $SFee$ is the interest rate on DAI borrowings (per cent per annum). The sample runs from April,13th 2018 to November 17th, 2019, which corresponds to the period of single collateral DAI. White heteroscedasticity-robust standard errors are reported in parentheses, and are clustered at the individual CDP level. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 5: DAI ETH Return correlations

	I	II	III	IV	V	VI	VII	VIII
	Δ	Δ	Δ	Δ	σ_{DAI}	σ_{DAI}	σ_{DAI}	σ_{DAI}
R_{ETH}	-0.024***		-0.021**	-0.023***	0.014		0.024**	0.024**
	(0.008)		(0.008)	(0.007)	(0.011)		(0.010)	(0.010)
R^{+}_{ETH}		35.61				182.4***		
		(28.99)				(38.52)		
R^{-}_{ETH}		72.39**				89.21**		
		(33.89)				(45.04)		
σ_{ETH}			0.045***	0.064***			0.160***	0.157***
			(0.014)	(0.012)			(0.018)	(0.018)
SFee				-17.89***				2.72
				(1.43)				(2.09)
Intercept	84.87***	81.48***	64.31***	102.1***	166.8***	162.1***	93.94***	88.20***
	(4.278)	(4.340)	(7.715)	(7.360)	(5.837)	(5.766)	(9.870)	(10.81)
R-squared	0.02	0.01	0.04	0.27	0.00	0.05	0.14	0.14
Observations	498	499	498	498	498	499	498	498

Note: This table regresses peg-price deviations and intra-day volatility on ETH returns, intra-day volatility and the stability rate. The dependent variable in columns (I) through to (IV), Δ measures the DAI peg-price deviation $p_{DAI} - 1$ in basis points. The dependent variable in columns (V) through to (VIII) σ_{DAI} measures the intra-day volatility of DAI prices in basis points. Explanatory variables include R_{ETH}, which is daily ETH returns measured in basis points. Dummy variables R^{+}_{ETH} and R^{-}_{ETH} which take a value of 1 when ETH returns are greater (less) than 2 standard deviations respectively. σ_{ETH} measures daily intra-day volatility of ETH returns in basis points. $SFee$ is the interest rate on DAI borrowings (per cent per annum). The sample runs from November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 6: DAI ETH Return correlations: Liquidations

	I	II	III	IV	V
	Liquidation	Δ	Δ	σ_{DAI}	σ_{DAI}
Liquidation		30.57***	28.71***	42.53***	15.09
		(5.89)	(6.39)	(7.96)	(9.56)
R_{ETH}	-0.0003***		-0.013*		0.029***
	(0.0000)		(0.007)		(0.011)
σ_{ETH}	0.0012***		0.029*		0.139***
	(0.0001)		(0.014)		(0.022)
SFee	0.012		-18.26***		2.439
	(0.010)		(1.398)		(2.090)
Intercept	-0.483***	80.62***	115.9***	163.6***	95.30***
	(0.0507)	(4.192)	(7.845)	(5.671)	(11.731)
R-squared	0.37	0.05	0.30	0.05	0.15
Observations	499	500	499	500	499

Note: This table regresses peg-price deviations and intra-day volatility on ETH returns, intra-day volatility and the stability rate. The dependent variable in column (I) is *Liquidation*, which is the value (in millions USD) of liquidations, which is when a CDP 'bite' is called and DAI debt is paid off through a reduction in collateral. The dependent variable in columns (II) and (III) Δ measures the DAI peg-price deviation $p_{DAI} - 1$ in basis points . The dependent variable in columns (III) and (IV) σ_{DAI} measures the intra-day volatility of DAI prices in basis points. Explanatory variables include R_{ETH}, which is daily ETH returns measured in basis points. σ_{ETH} measures daily intra-day volatility of ETH returns in basis points. $SFee$ is the interest rate on DAI borrowings (per cent per annum). *Liquidation* is the value (in millions USD) of liquidations, which is when an individual CDP 'bite' is called. The sample runs from November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 7: DAI peg and Demand Shocks: DeFi Lending Protocol and Secondary Market Volume

	I	II	III	IV	V	VI
	D_u	D_v	Δ	Δ	Δ	Δ
D_u			1.71***	1.63***		
			(0.35)	(0.35)		
D_v					0.19*	0.11
					(0.10)	(0.10)
R_{ETH}	0.001	-0.0095**		-0.025***		-0.022***
	(0.001)	(0.004)		(0.008)		(0.008)
σ_{ETH}	0.006***	0.026***		0.027*		0.035**
	(0.002)	(0.007)		(0.015)		(0.015)
Intercept	72.82***	-3.313	9959***	9955***	10088***	10074***
	(1.077)	(3.829)	(27.189)	(27.092)	(4.647)	(8.302)
R-squared	0.02	0.05	0.05	0.08	0.01	0.04
Observations	454	454	454	454	454	454

Note: Table presents regressions of DAI peg-price premiums and intra-day volatility on the share of stable collateral. The variable D_u measures the utilization of DAI on the DeFi lending protocol Compound. It is the ratio of total borrowing in DAI to total lending in DAI. The variable D_v measures aggregate growth in secondary market volume across major exchanges. In columns (I) and (II), we test determinants of Compound utilization and secondary market growth. The dependent variable in columns (III) to (VI) is the DAI premium Δ, which measures the DAI peg-price deviation $p_{DAI} - 1$ in basis points. In columns (III) and (IV), the DAI premium is regressed on D_u and controls for ETH returns and volatility. In columns (V) and (VI), DAI premium is regressed on D_v and controls for ETH returns and volatility. The sample runs from January 1st, 2020 to March 31st, 2021. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 8: DAI ETH Return correlations in the Pre and Post USDC Collateral Periods

	I	II	III	IV
	Δ	σ_{DAI}	Δ	σ_{DAI}
R_{ETH}	-0.061***	0.072**	0.002	0.021***
	(0.012)	(0.029)	(0.007)	(0.008)
σ_{ETH}	0.133***	0.259***	0.011	0.135***
	(0.026)	(0.067)	(0.013)	(0.013)
Δ_{USDC}			-0.54	-3.10**
			(1.49)	(1.55)
σ_{USDC}			5.04***	7.68***
			(0.643)	(0.672)
SFee	3.639	29.13***	-19.70***	-12.72***
	(3.155)	(7.94)	(2.486)	(2.597)
Intercept	-47.44**	-67.00	5490	31042**
	(18.63)	(46.91)	(14889)	(15555)
R-squared	0.56	0.30	0.41	0.54
Observations	115	115	183	183
Pre USDC	Yes	Yes	No	No
Post USDC	No	No	Yes	Yes

Note: This table regresses peg-price deviations and intra-day volatility on ETH returns, intra-day volatility and the stability rate. The dependent variable in columns (I) and (III), Δ measures the DAI peg-price deviation $p_{DAI} - 1$ in basis points. The dependent variable in columns (II) and (IV) σ_{DAI} measures the intra-day volatility of DAI prices in basis points. Explanatory variables include R_{ETH}, which is daily ETH returns measured in basis points. σ_{ETH} measures daily intra-day volatility of ETH returns in basis points, Δ_{USDC} and σ_{USDC} which measure daily peg-price deviations and intra-day volatility of USDC in basis points. $SFee$ is the interest rate on DAI borrowings (per cent per annum). The sample is divided into the Pre-USDC Collateral and Post-USDC Collateral period. The Pre-USDC Collateral sample runs from November 18th, 2019 to March 11th, 2020. The Post-USDC Collateral sample runs from March,12th 2020 to March 31st, 2021. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 9: Determinants and peg efficiency effects of an increase in the stable collateral share

	I	II	III	IV	V	VI	VII
	share	Δ	Δ	Δ	σ_{DAI}	σ_{DAI}	σ_{DAI}
share		-2.121***	-2.071***	-0.448	-2.436***	-2.376***	-0.405
		(0.247)	(0.244)	(0.286)	(0.279)	(0.244)	(0.271)
$\frac{\sigma_{ETH}}{\sigma_{USDC}}$	0.010***						
	(0.002)						
R_{ETH}	0.002		-0.021**	-0.022***		0.015*	0.013*
	(0.002)		(0.008)	(0.008)		(0.008)	(0.007)
σ_{ETH}			0.032**	0.008		0.154***	0.123***
			(0.014)	(0.013)		(0.014)	(0.0124)
Δ_{USDC}	-0.0401			-1.209			-3.139**
	(0.379)			(1.684)			(1.595)
σ_{USDC}				7.214***			8.765***
				(0.802)			(0.759)
Intercept	421.0	150.5***	135.9***	12117	212.0***	137.9***	31396**
	(3787)	(7.427)	(9.978)	(16845)	(8.376)	(9.993)	(15954)
R-squared	0.05	0.16	0.19	0.33	0.17	0.36	0.53
Observations	385	385	385	385	385	385	385

Note: This table regresses peg-price deviations and intra-day volatility on the share of stable collateral, ETH and USDC returns and intra-day volatility. The variable *share* measures the share of total stable collateral deposited in vaults: this includes stablecoins USDC, Tether and TrueUSD. In column (I), the dependent variable is the share of stable collateral. $\frac{\sigma_{ETH}}{\sigma_{USDC}}$ is measured as the per cent change in the ratio of intra-day volatility of ETH to DAI. The dependent variable in columns (II) through to (IV), Δ measures the DAI peg-price deviation $p_{DAI} - 1$. The dependent variable in columns (V) through to (VII) σ_{DAI} measures the intra-day volatility of DAI prices. Explanatory variables include R_{ETH}, which is daily ETH returns measured in basis points. σ_{ETH} measures daily intra-day volatility of ETH returns in basis points, Δ_{USDC} and σ_{USDC} which measure daily peg-price deviations and intra-day volatility of USDC in basis points. The sample runs from March,12th 2020 to March 31st, 2021. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 10: Tests of a structural break in DAI peg deviations

	I	II	III	IV	V	VI
	$\|\Delta\|$	σ_{DAI}	$\|\Delta\|$	σ_{DAI}	$\|\Delta\|$	σ_{DAI}
post	-67.86***	-71.30***	-2.73***	-9.29***	-2.73***	-9.29***
	(2.63)	(2.89)	(0.59)	(0.55)	(0.59)	(0.55)
T			96.64***	108.29***	114.63***	97.36***
			(3.10)	(2.71)	(5.14)	(4.17)
post $\times T$			-83.84***	-72.00***	-101.83***	-61.07***
			(3.26)	(3.47)	(5.23)	(4.70)
Intercept	74.99***	95.12***	3.45***	14.97***	3.45***	14.97***
	(2.54)	(2.37)	(0.59)	(0.49)	(0.59)	(0.49)
R-squared	0.07	0.08	0.26	0.37	0.47	0.48
Observations	1532	1532	1532	1532	897	897
Sample	Full	Full	Full	Full	Balanced	Balanced

Note: Table presents regressions of the absolute level and volatility of deviations of the peg. The absolute level of deviations is denoted by $|\Delta|$, which measures the absolute size of DAI peg-price deviation $|p_{DAI} - 1|$, and σ_t is calculated based on a measure of intra-day volatility of the price, both measured in basis points. The post dummy $Post_t$ takes a value of 1 from December 18th, 2020, which is the launch date of the PSM (swap arrangement in which USDC is swapped with DAI at a 1:1 rate). The Treatment dummy T takes a value of 1 for DAI/USD, and 0 otherwise. Control-group currency is USDC/USD. Full sample for columns (I) through to (IV) is November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI. Balanced panel for columns (V) and (VI) is from January 8th 2020 to March 31st 2021. White heteroscedasticity-robust standard errors are used in estimation. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Online Appendix to

"Decentralized Stablecoins and Collateral Risk"

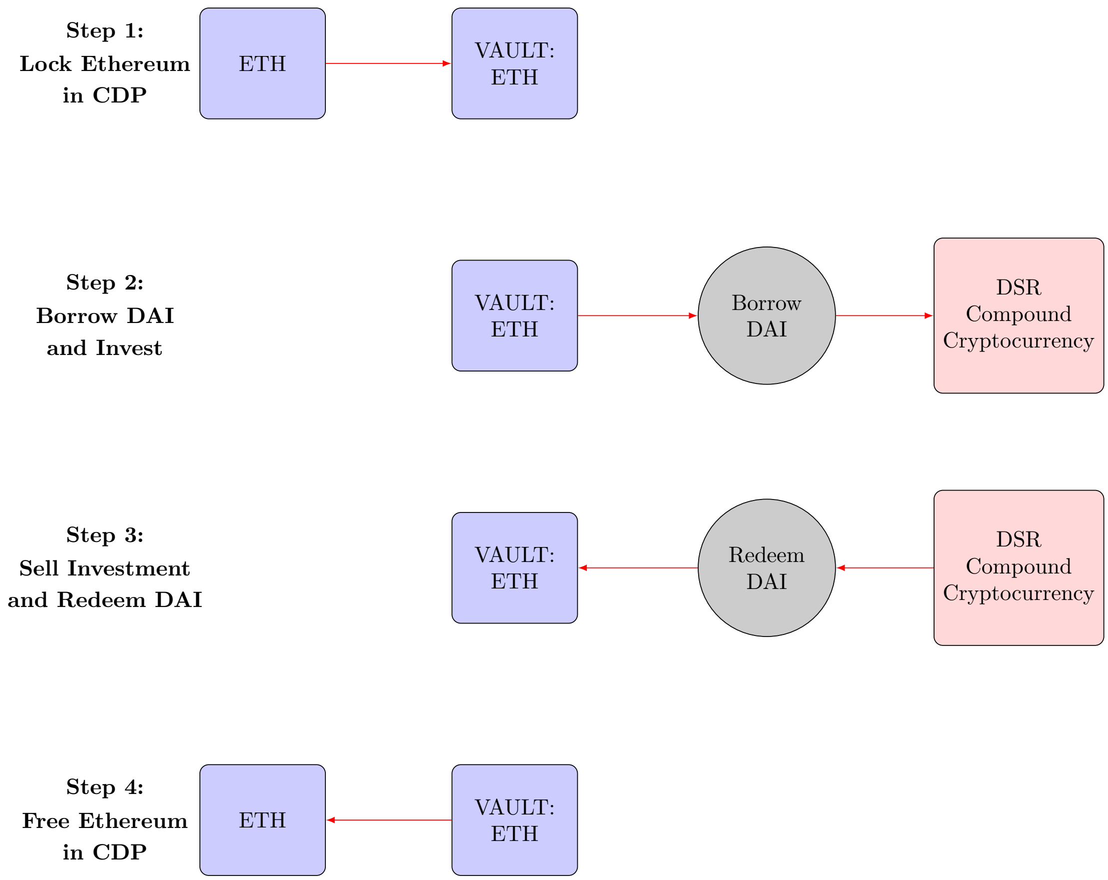
(Not for publication)

We provide a roadmap of each section of our appendix.

1. Appendix A provides supplementary Figures on DAI creation and liquidation dynamics.
2. Appendix B provides model proofs.
3. Appendix C provides supplementary analysis using individual CDP data, including determinants of the probability of liquidation, total DAI borrowings and ETH collateral.
4. Appendix D provides details on the MKR governance token supply and price dynamics.
5. Appendix E provides additional analysis on the effects of liquidations on DAI prices, ETH returns and leverage.
6. Appendix F provides additional evidence on the arbitrage mechanism using a self-exciting auto regressive model (SETAR) to identify an asymmetry in the arbitrage process.

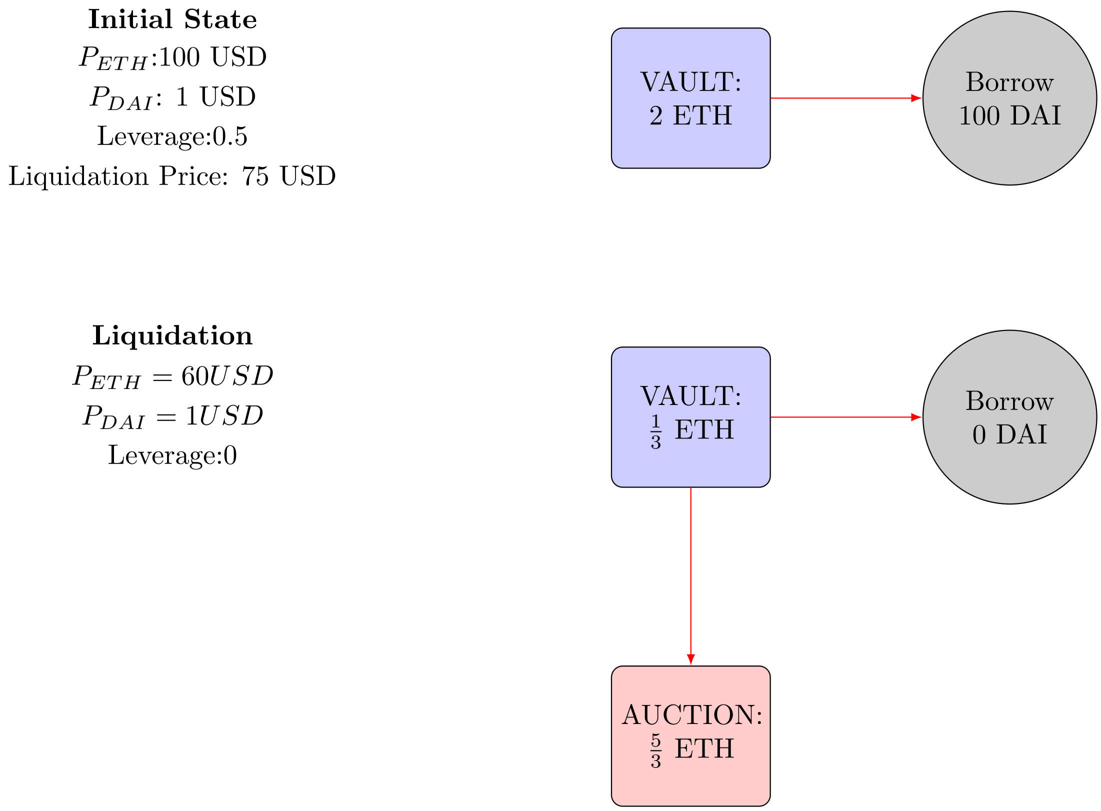
Appendix A: Definitions: CDP and Liquidation Process

Figure A1: Process of DAI creation



Note: This figure illustrates the steps of depositing dollar wealth into a collateralized debt position (CDP) to create DAI tokens. In borrowing a fraction of ETH collateral as DAI to invest in an alternative currency. At the conclusion of the investment horizon, the investor sells investment for DAI tokens, redeems their DAI tokens and frees their ETH collateral.

Figure A2: DAI Liquidation Mechanism



Note: This figure illustrates the steps of liquidation for a hypothetical CDP. In the initial state, the investor deposits 2 ETH in a vault, and borrows 100 DAI tokens. At prices of $P_{ETH} = 100$ USD and $P_{DAI} = 1$ USD, the leverage of the CDP is 0.50. In the liquidation period, the price of ETH declines to 60 USD. This triggers liquidation as the price is less than the liquidation price of 75 USD. DAI borrowings are forced to zero. Keepers auction off 100 USD worth of collateral to pay off the DAI loan, this is equal to $\frac{5}{3}$ ETH at the new price of 60 USD. The new amount of ETH in the vault is $\frac{1}{3}$ ETH. This example is a simplified setting as it ignores additional liquidation costs, such as a liquidation penalty or the potential for fire sale auction prices of ETH.

Appendix B: Model

Derivation of speculators' demand

To solve the speculators' optimization problem in Equation (5), we specify the following Lagrangian function:

$$\begin{aligned} L(\theta_t) &= E_t[W^s_{t+1}] - \frac{1}{2}\gamma Var_t[W^s_{t+1}] + \lambda_1\theta_t + \lambda_2(\bar{\theta} - \theta_t) \\ &= W^s_t \left[\mu^E(s_t)(1+\theta_t p_t) - \theta_t E_t[p_{t+1}] - \theta_t i^B\right] \\ &- \frac{\gamma W^{s2}_t}{2}\left[\sigma^2_E(1+\theta_t p_t)^2 + \theta^2_t\sigma^2_t - 2\theta_t(1+\theta_t p_t)c_t\right] + \lambda_1\theta_t + \lambda_2(\bar{\theta} - \theta_t), \end{aligned} \tag{24}$$

for $\lambda_1, \lambda_2 \geq 0$. The first order conditions are:

$$\begin{aligned} 0 &= W^s_t\left[\mu^E(s_t)p_t - E_t[p_{t+1}] - i^B\right] - \gamma W^{s2}_t\left[\sigma^2_E(1+\theta_t p_t)p_t + \theta_t\sigma^2_t - (1+2\theta_t p_t)c_t\right] \\ &+ \lambda_1 - \lambda_2, \end{aligned} \tag{25}$$

$$0 = \lambda_1\theta_t, \tag{26}$$

$$0 = \lambda_2(\bar{\theta} - \theta_t). \tag{27}$$

We consider the following cases of variable and Lagrange multipliers values:

1. $\theta_t = 0$.

   Condition $\theta_t = 0$ implies that $\lambda_1 \geq 0$ and $\lambda_2 = 0$. The first-order condition (25) becomes $\lambda_1 = -W^s_t\left[\mu^E(s_t)p_t - E_t[p_{t+1}] - i^B\right] - \gamma W^{s2}_t\left[\sigma^2_E - c_t\right]$. Hence, $\lambda_1 \geq 0$ is equivalent to

   $$\mu^E(s_t)p_t - E_t[p_{t+1}] - i^B \leq \gamma W^s_t\left[\sigma^2_E - c_t\right].$$

2. $0 < \theta_t < \bar{\theta}$

   In this case, $\lambda_1 = \lambda_2 = 0$ and the first-order condition (25) becomes

   $$\theta_t = \frac{\frac{p_t\mu^E(s_t) - E_t[p_{t+1}] - i^B}{\gamma W^s_t} - p_t\sigma^2_E + c_t}{p^2_t\sigma^2_E + \sigma^2_t - 2p_t c_t}. \tag{28}$$

   In order to satisfy the initial restriction $0 < \theta_t < \bar{\theta}$, it should hold:

   $$p_t\sigma^2_E - c_t < \frac{\mu^E(s_t)p_t - E_t[p_{t+1}] - i^B}{\gamma W^s_t} < p_t\sigma^2_E - c_t + \bar{\theta}\left(p^2_t\sigma^2_E + \sigma^2_t - 2p_t c_t\right).$$

3. $\theta_t = \bar{\theta}$.

In this case $\lambda_1 = 0$ and the first-order equation (25) implies

$$\lambda_2 = W_t^s \left[\mu^E(s_t)p_t - E_t[p_{t+1}] - i^B\right] - \gamma W_t^{s2}\left[\sigma_E^2(1+\bar{\theta}p_t)p_t + \bar{\theta}\sigma_t^2 - (1+2\bar{\theta}p_t)c_t\right] \geq 0$$

which holds whenever

$$\frac{\mu^E(s_t)p_t - E_t[p_{t+1}] - i^B}{\gamma W_t^s} \geq p_t\sigma_E^2 - c_t + \bar{\theta}\left(p_t^2\sigma_E^2 + \sigma_t^2 - 2p_tc_t\right).$$

Combining the three cases, we get Equation (6).

Q.E.D.

Derivation of arbitrageurs' demand: single collateral

To solve the arbitrageurs' optimization problem in Equation (5), we optimize the expected utility function in each region $\omega_t \geq 0$ and $\omega_t \leq 0$ separately.

1. $\omega_t \geq 0$.

   For this case we specify the following Lagrangian function:

$$\begin{aligned} L(\omega_t) &= E_t[W_{t+1}^a] - \frac{1}{2}\gamma Var_t[W_{t+1}^a] + \lambda_1\omega_t \\ &= W_t^a\left[\omega_t(1+i^L)\frac{E_t[p_{t+1}]}{p_t} + (1-\omega_t)(1+r)\right] - \frac{\gamma W_t^{a2}}{2p_t^2}\omega_t^2(1+i^L)^2\sigma_t^2 + \lambda_1\omega_t, \qquad (29) \end{aligned}$$

   for $\lambda_1 \geq 0$. The first order conditions are:

$$0 = W_t^a\left[(1+i^L)\frac{E_t[p_{t+1}]}{p_t} - (1+r)\right] - \frac{\gamma W_t^{a2}\omega_t(1+i^L)^2\sigma_t^2}{p_t^2} + \lambda_1, \qquad (30)$$

$$0 = \lambda_1\omega_t. \qquad (31)$$

   We consider the following cases of values of ω_t:

   a). $\omega_t = 0$.

   Condition $\omega_t = 0$ implies that $\lambda_1 \geq 0$. The first-order condition (30) becomes

$$\lambda_1 = -W_t^a\left[\frac{(1+i^L)E_t[p_{t+1}]}{p_t} - (1+r)\right].$$

   Hence, $\lambda_1 \geq 0$ is equivalent to

$$(1+i^L)E_t[p_{t+1}] \leq (1+r)p_t.$$

b). $\omega_t > 0$ In this case, $\lambda_1 = 0$ and the first-order condition (30) becomes

$$\omega_t = \frac{\left(E_t[p_{t+1}](1+i^L)/p_t - (1+r)\right) p_t^2}{\gamma W_t^a (1+i^L)^2 \sigma_t^2}. \tag{32}$$

In order to satisfy the initial restriction $\omega_t > 0$, it should hold:

$$E_t[p_{t+1}](1+i^L) > (1+r)p_t.$$

Now we consider the maximum of the expected utility function of the short-selling region.

2. $\omega_t \leq 0$.

For this case we specify the following Lagrangian function:

$$\begin{aligned} L(\omega_t) &= E_t[W_{t+1}^a] - \frac{1}{2}\gamma Var_t[W_{t+1}^a] - \lambda_1 \omega_t \\ &= W_t^a \left(-\frac{\omega_t}{\bar{\theta}}\mu_A + \omega_t(E_t[p_{t+1}] - p_t(1+r) + i^B) + \left(1 + \frac{\omega_t}{\bar{\theta}}\right)(1+r)\right) \\ &- \frac{\gamma W_t^{a2}\omega_t^2}{2}\left[\frac{\sigma_E^2}{\bar{\theta}^2} + \sigma_t^2 - \frac{2c_t}{\bar{\theta}}\right] - \lambda_1\omega_t, \end{aligned} \tag{33}$$

for $\lambda_1 \geq 0$. The first order conditions are:

$$\begin{aligned} 0 &= W_t^a\left[-\frac{\mu_A}{\bar{\theta}} + (E_t[p_{t+1}] - p_t(1+r) + i^B) + \frac{1+r}{\bar{\theta}}\right] \\ &- \gamma W_t^{a2}\omega_t\left[\frac{\sigma_E^2}{\bar{\theta}^2} + \sigma_t^2 - \frac{2c_t}{\bar{\theta}}\right] - \lambda_1, \end{aligned} \tag{34}$$

$$0 = -\lambda_1\omega_t. \tag{35}$$

We consider the following cases of values of ω_t:

a). $\omega_t = 0$.

Condition $\omega_t = 0$ implies that $\lambda_1 \geq 0$. The first-order condition (34) implies

$$\lambda_1 = W_t^a\left[-\frac{\mu_A}{\bar{\theta}} + (E_t[p_{t+1}] - p_t(1+r) + i^B) + \frac{1+r}{\bar{\theta}}\right].$$

Hence, $\lambda_1 \geq 0$ is equivalent to

$$\mu_A \leq \bar{\theta}(E_t[p_{t+1}] - p_t(1+r) + i^B) + 1 + r.$$

b). $\omega_t < 0$

In this case, $\lambda_1 = 0$ and the first-order condition (34) implies

$$\omega_t = -\bar{\theta}\frac{\left[\mu_A - (1+r) - \bar{\theta}(E_t[p_{t+1}] - p_t(1+r) + i^B)\right]}{\gamma W_t^a(\sigma_E^2 + \bar{\theta}^2\sigma_t^2 + c_t\bar{\theta})}. \tag{36}$$

In order to satisfy the initial restriction $\omega_t < 0$, it should hold:

$$\mu_A > \bar{\theta}(E_t[p_{t+1}] - p_t(1+r) + i^B) + 1 + r.$$

Combining the cases and comparing the maxima values of the expected utility function in each region, we get Equation (7).

Q.E.D.

Derivation of arbitrageurs' demand: two types of collateral

To solve the arbitrageurs' optimization problem in the case of two collateral, we optimize the expected utility function in $\omega_t \leq 0$ region and compare it with the maximum of the expected utility in $\omega_t \geq 0$ region (the latter case is the same as in the single collateral case). Denote by $N_t = E_t[p_{t+1}] - p_t(1+r) + i^B$ and $M = \frac{\mu_A - (1+r)}{\bar{\theta}}$. In order to simplify the calculations we make the following assumptions about the parameter values that are justified by the sample estimations in the main body of the paper and are verified in the equilibrium above: $\sigma_E^2 > \sigma_t^2$, and $c_t > 0$.

For this case we specify the following Lagrangian function:

$$\begin{aligned} L(\omega_t^E, \omega_t^U) &= E_t[W_{t+1}^a] - \frac{1}{2}\gamma Var_t[W_{t+1}^a] - \lambda_1\omega_t^E - \lambda_2\omega_t^U \\ &= W_t^a\left[-\frac{\omega_t^E}{\bar{\theta}}\mu_A - \omega_t^U(1+r) + (\omega_t^E + \omega_t^U)N_t + \left(1 + \frac{\omega_t^E}{\bar{\theta}} + \omega_t^U\right)(1+r)\right] \\ &- \frac{\gamma W_t^{a2}}{2}\left[\frac{\omega_t^{E2}}{\bar{\theta}^2}\sigma_E^2 + \omega_t^{U2}\sigma_U^2 + (\omega_t^E + \omega_t^U)^2\sigma_t^2 - \frac{2\omega_t^E(\omega_t^E + \omega_t^U)c_t}{\bar{\theta}}\right] - \lambda_1\omega_t^E - \lambda_2\omega_t^U, \end{aligned} \tag{37}$$

for $\lambda_1, \lambda_2 \geq 0$. The first order conditions are:

$$0 = W_t^a[N_t - M] - \gamma W_t^{a2}\left[\frac{\omega_t^E}{\bar{\theta}^2}\sigma_E^2 + (\omega_t^E + \omega_t^U)\sigma_t^2 - \frac{(2\omega_t^E + \omega_t^U)c_t}{\bar{\theta}}\right] - \lambda_1, \tag{38}$$

$$0 = W_t^a N_t - \gamma W_t^{a2}\left[\omega_t^U\sigma_U^2 + (\omega_t^E + \omega_t^U)\sigma_t^2 - \frac{\omega_t^E c_t}{\bar{\theta}}\right] - \lambda_2, \tag{39}$$

$$0 = -\lambda_1\omega_t^E \tag{40}$$

$$0 = -\lambda_2\omega_t^U. \tag{41}$$

We consider the following cases of values of ω_t^E and ω_t^U:

a). $\omega_t^E = \omega^U = 0$.

Conditions $\omega_t^E = 0$ and $\omega_t^U = 0$ imply that $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$. The first-order conditions (38) and (39) become

$$\lambda_1 = W_t^a [N_t - M],$$

$$\lambda_2 = W_t^a N_t.$$

Hence, $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$ are equivalent to $N_t \geq M$ and $N_t \geq 0$.

b). $\omega_t^E = 0$ and $\omega^U < 0$

Conditions $\omega_t^E = 0$ and $\omega^U < 0$ imply that $\lambda_1 \geq 0$ and $\lambda_2 = 0$. The first-order conditions (38) and (39) become

$$\lambda_1 = W_t^a [N_t - M] - \gamma W_t^{a2} \omega_t^U \left[\sigma_t^2 - \frac{c_t}{\bar{\theta}}\right],$$

$$\omega_t^U = \frac{N_t}{\gamma W_t^a (\sigma_U^2 + \sigma_t^2)}.$$

Inequality $\lambda_1 \geq 0$ is equivalent to

$$\frac{N_t}{\sigma_U^2 + \sigma_t^2} \geq \frac{M}{\sigma_U^2 + \frac{c_t}{\theta}}$$

and $\omega_t^U < 0$ is equivalent to $N_t < 0$.

c). $\omega_t^E < 0$ and $\omega^U = 0$

Conditions $\omega_t^E < 0$ and $\omega^U = 0$ imply that $\lambda_1 = 0$ and $\lambda_2 \geq 0$. The first-order conditions (38) and (39) become

$$\omega_t^E = \frac{N_t - M}{\gamma W_t^a \left[\frac{\sigma_E^2}{\theta^2} + \sigma_t^2 - \frac{2c_t}{\theta}\right]},$$

$$\lambda_2 = W_t^a EE - \gamma W_t^{a2} \omega_t^E \left[\sigma_t^2 - \frac{c_t}{\bar{\theta}}\right].$$

Inequality $\lambda_2 \geq 0$ is equivalent to

$$\frac{N_t}{\sigma_t^2 - \frac{c_t}{\theta}} \geq \frac{M}{\frac{\sigma_E^2}{\theta^2} - \frac{c_t}{\theta}}$$

and $\omega_t^E < 0$ is equivalent to $N_t < M$.

d). $\omega_t^E < 0$ and $\omega^U < 0$

In this case, $\lambda_1 = \lambda_2 = 0$ and the first-order conditions (38) and (39) become

$$\omega_t^E = \frac{\frac{N_t}{\sigma_t^2+\sigma_U^2} - \frac{M}{\sigma_U^2+\frac{c_t}{\theta}}}{\gamma W_t^a \left(\frac{\frac{\sigma_E^2}{\theta^2}+\sigma_U^2}{\sigma_U^2+\frac{c_t}{\theta}} - \frac{\sigma_U^2+\frac{c_t}{\theta}}{\sigma_t^2+\sigma_U^2} \right)}.$$

$$\omega_t^U = \frac{\frac{N_t}{\sigma_t^2-\frac{c_t}{\theta}} - \frac{M}{\frac{\sigma_E^2}{\theta^2}-\frac{c_t}{\theta}}}{\gamma W_t^a \left(\frac{\sigma_U^2+\frac{c_t}{\theta}}{\frac{\sigma_E^2}{\theta^2}-\frac{c_t}{\theta}} + \frac{\sigma_t^2+\sigma_U^2}{\sigma_t^2-\frac{c_t}{\theta}} \right)}.$$

In order to satisfy the initial restrictions $\omega_t^U < 0$ and $\omega_t^E < 0$, it should hold:

$$\frac{N_t}{\sigma_t^2+\sigma_U^2} < \frac{M}{\sigma_U^2+\frac{c_t}{\theta}}.$$

and

$$\frac{N_t}{\sigma_t^2-\frac{c_t}{\theta}} < \frac{M}{\frac{\sigma_E^2}{\theta^2}-\frac{c_t}{\theta}}$$

Simple calculations verifies the following summary of the results:

- If $N_t \geq 0$ and $N_t \geq M$ then

$$\omega_t^E = 0, \tag{42}$$
$$\omega_t^U = 0. \tag{43}$$

- If $N_t < 0$ and $M \leq \delta N_t$ then

$$\omega_t^E = 0, \tag{44}$$
$$\omega_t^U = \frac{N_t}{\gamma W_t^a(\sigma_U^2+\sigma_t^2)}, \tag{45}$$

where

$$\delta = \frac{\sigma_U^2+\frac{c_t}{\theta}}{\sigma_U^2+\sigma_t^2}.$$

- If $N_t \geq 0$ and $N_t < M \leq \Delta N_t$ then

$$\omega_t^E = \frac{N_t - M}{\gamma W_t^a \left[\frac{\sigma_E^2}{\theta^2}+\sigma_t^2-\frac{2c_t}{\theta}\right]}, \tag{46}$$
$$\omega_t^U = 0, \tag{47}$$

where

$$\Delta = \frac{\frac{\sigma_E^2}{\theta^2} - \frac{c_t}{\theta}}{\sigma_t^2 - \frac{c_t}{\theta}}.$$

- If $N_t \geq 0$ and $M > \Delta N_t$ or $N_t < 0$ and $M > \delta N_t$ then

$$\omega_t^E = \frac{\frac{N_t}{\sigma_t^2+\sigma_U^2} - \frac{M}{\sigma_U^2+\frac{c_t}{\theta}}}{\gamma W_t^a \left(\frac{\frac{\sigma_E^2}{\theta^2}+\sigma_U^2}{\sigma_U^2+\frac{c_t}{\theta}} - \frac{\sigma_U^2+\frac{c_t}{\theta}}{\sigma_t^2+\sigma_U^2} \right)}, \tag{48}$$

$$\omega_t^U = \frac{\frac{N_t}{\sigma_t^2-\frac{c_t}{\theta}} - \frac{M}{\frac{\sigma_E^2}{\theta^2}-\frac{c_t}{\theta}}}{\gamma W_t^a \left(\frac{\sigma_U^2+\frac{c_t}{\theta}}{\frac{\sigma_E^2}{\theta^2}-\frac{c_t}{\theta}} + \frac{\sigma_t^2+\sigma_U^2}{\sigma_t^2-\frac{c_t}{\theta}} \right)}. \tag{49}$$

Q.E.D.

Appendix C: Additional Panel CDP Regression Specifications

In this section, we provide supplementary regressions using the individual CDP data.

$$Y_{i,t} = \alpha_i + \beta_1 R_{ETH,t} + \beta_2 \sigma_{ETH,t} + \beta_3 SFee_t + u_t, \tag{50}$$

In regression 50 where the dependent variable $Y_{i,t}$ is a dummy variable indicating a "bite" (liquidation event), the amount of DAI borrowings and ETH collateral for a CDP at time t. The set of independent variables include the daily ETH return ($R_{ETH,t}$), intra-day volatility of collateral ($\sigma_{ETH,t}$) and the stability rate on DAI borrowing. Intra-day volatility is calculated as the square root of the average sum of squared hourly returns over the trading day. Individual CDP fixed effects is captured by α_i, and controls for idiosyncratic risk preferences of an individual CDP.

In Table A1, the dependent variable is a dummy variable indicating a liquidation event. We use a panel probit specification to estimate the effect of a change in the explanatory variable on the probability of liquidation. In column (I), a one percentage point increase in ETH returns reduces the probability of liquidation by 0.08 percentage points. In column (II), the results indicate the probability of liquidation is higher in extreme negative states to ETH collateral. In column (III), a one percentage point increase in intra-day ETH volatility increases the probability of liquidation by 0.10 percentage points. In column (IV) a 1 per cent increase in the stability rate increases the probability of liquidation by 0.01 percentage points. In column (V), the results are robust to a specification including ETH returns, intra-day volatility and the stability rate.

In Tables A2 and A3, we extend our outcome variables to the amount of DAI borrowing and ETH collateral of each position. To control for serial correlation, we include the first lag as a control. For both DAI borrowings and ETH collateral, robust predictors include ETH returns and the DAI stability. For example, a 1 per cent increase in ETH returns increases DAI borrowing and ETH collateral by 442 USD and 3,300 USD respectively. A 1 per cent increase in the stability fee reduces DAI borrowing and ETH collateral by 620 USD and 1600 USD respectively.

Table A1: Determinants of CDP Probability of Liquidation

	I	II	III	IV	V
	liquidation	liquidation	liquidation	liquidation	liquidation
R_{ETH}	-0.08***				-0.05***
	(0.01)				(0.01)
R^+_{ETH}		-0.45			
		(0.31)			
R^-_{ETH}		1.03***			
		(0.19)			
σ_{ETH}			0.10***		0.10***
			(0.01)		(0.02)
SFee				0.01***	0.01
				(0.00)	(0.01)
Intercept	-2.80***	-2.68***	-3.38	-2.91***	-3.46
	(0.33)	(0.30)	(0.00)	(0.06)	(0.00)
Observations	26,047	26,047	26,074	26,074	26,047
Number of id	456	456	456	456	456
id Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note: This table regresses the probability of liquidation on ETH returns, intra-day volatility and the stability fee on DAI. The dependent variable in columns (I) through to (V), *Liquidation* is a dummy variable that is equal to 1 when an individual CDP calls a "bite" action, which requires the CDP to liquidate all DAI borrowings. Explanatory variables include R_{ETH}, which is daily ETH returns measured in per cent. Dummy variables R^+_{ETH} and R^-_{ETH} which take a value of 1 when ETH returns are greater (less) than 2 standard deviations respectively. σ_{ETH} measures daily intra-day volatility of ETH returns in per cent. $SFee$ is the interest rate on DAI borrowings (per cent per annum). The sample runs from April,13th 2018 to November 17th, 2019, which corresponds to the period of single collateral DAI. A panel probit specification is used. White heteroscedasticity-robust standard errors are reported in parentheses, and are clustered at the individual CDP level. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A2: Determinants of CDP DAI Borrowing

	I	II	III	IV	V
	DAI	DAI	DAI	DAI	DAI
L.DAI	0.99***	0.99***	0.99***	0.99***	0.99***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R$_{ETH}$	442.06**				460.24**
	(206.40)				(221.49)
R$^{+}_{ETH}$		16,778.53			
		(10,661.00)			
R$^{-}_{ETH}$		-8,314.51*			
		(4,516.87)			
σ_{ETH}			-332.40		-254.01
			(337.44)		(347.49)
SFee				-620.10*	-631.95*
				(328.90)	(331.98)
Intercept	2,106.81***	1,840.59***	3,880.99**	7,658.53**	9,178.37***
	(744.43)	(623.40)	(1,585.24)	(3,504.92)	(2,633.46)
R-Squared	0.90	0.90	0.90	0.90	0.90
Observations	11,197	11,197	11,197	11,197	11,197
Number of id	456	456	456	456	456
id Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note: This table regresses DAI borrowing on ETH returns, intra-day volatility and the stability fee on DAI. The dependent variable in columns (I) through to (V), DAI measures the individual DAI borrowing of a CDP in USD. Explanatory variables include R_{ETH}, which is daily ETH returns measured in per cent. Dummy variables R^{+}_{ETH} and R^{-}_{ETH} which take a value of 1 when ETH returns are greater (less) than 2 standard deviations respectively. σ_{ETH} measures daily intra-day volatility of ETH returns in per cent. $SFee$ is the interest rate on DAI borrowings (per cent per annum). The sample runs from April,13th 2018 to November 17th, 2019, which corresponds to the period of single collateral DAI. A panel probit specification is used. White heteroscedasticity-robust standard errors are reported in parentheses, and are clustered at the individual CDP level. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A3: Determinants of CDP ETH Collateral

	I	II	III	IV	V
	ETH	ETH	ETH	ETH	ETH
R_{ETH}	3,338.61**				3,434.18**
	(1,347.09)				(1,441.33)
R^{+}_{ETH}		83,445.08*			
		(46,078.92)			
R^{-}_{ETH}		-39,218.78***			
		(12,894.32)			
σ_{ETH}			-379.54		259.77
			(1,796.75)		(1,952.28)
SFee				-1,600.66**	-1,684.43**
				(702.25)	(734.62)
Intercept	10,615.95***	9,089.49***	12,415.87	24,702.44***	24,310.62**
	(3,189.50)	(2,511.30)	(9,987.61)	(9,095.06)	(11,248.10)
R-Squared	0.86	0.86	0.86	0.86	0.86
Observations	11,197	11,197	11,197	11,197	11,197
Number of id	456	456	456	456	456
id Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note: This table regresses ETH collateral on ETH returns, intra-day volatility and the stability fee on DAI. The dependent variable in columns (I) through to (V), ETH measures the individual ETH collateral of a CDP in USD. Explanatory variables include R_{ETH}, which is daily ETH returns measured in per cent. Dummy variables R^{+}_{ETH} and R^{-}_{ETH} which take a value of 1 when ETH returns are greater (less) than 2 standard deviations respectively. σ_{ETH} measures daily intra-day volatility of ETH returns in per cent. $SFee$ is the interest rate on DAI borrowings (per cent per annum). The sample runs from April,13th 2018 to November 17th, 2019, which corresponds to the period of single collateral DAI. A panel probit specification is used. White heteroscedasticity-robust standard errors are reported in parentheses, and are clustered at the individual CDP level. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Appendix D: MakerDAO Auctions and Governance

The Maker Governance protocol is in charge of adding new collateral types, the regulation of the smart contracts enforcing collateralized debt positions, and adjusting risk parameters of the protocol, such as the liquidation ratio, debt ceilings and the stability and savings rate.

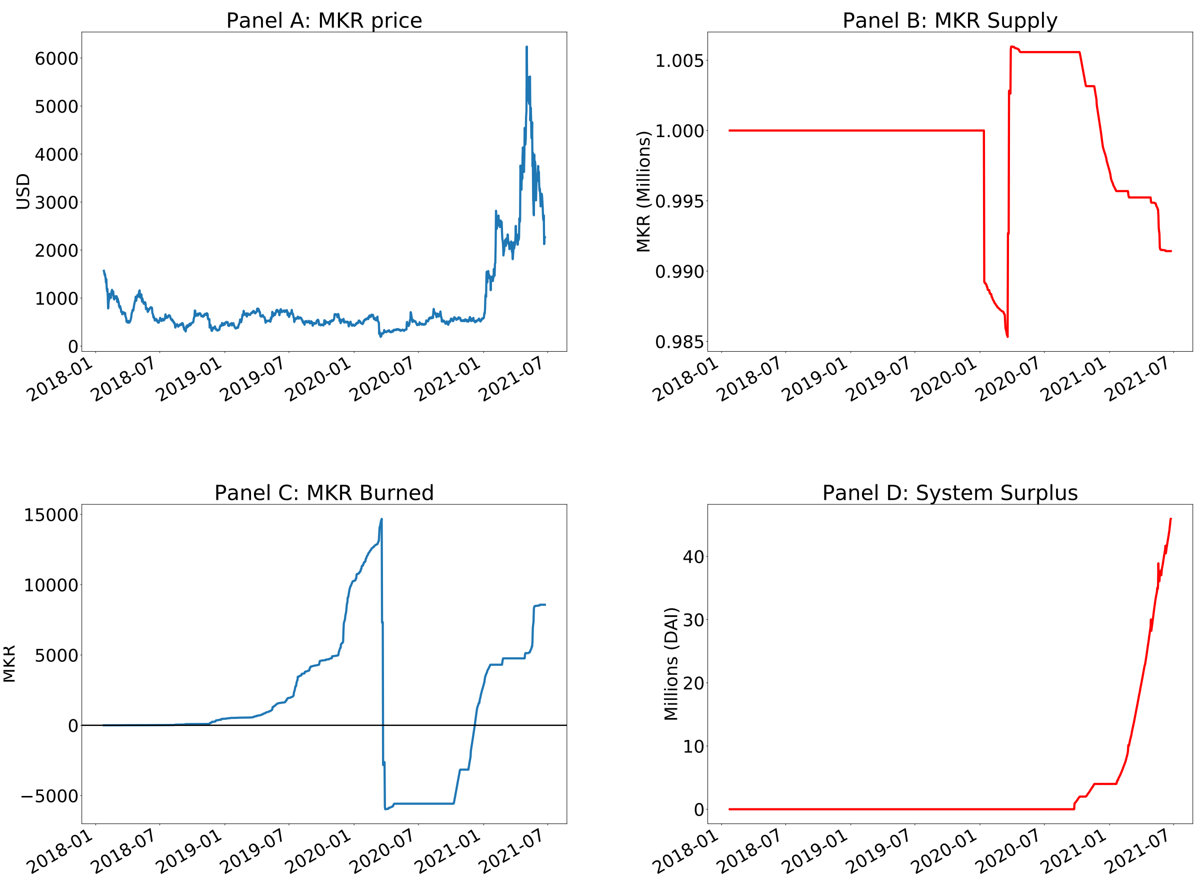
The MKR governance token is used for voting on the management of the protocol and DAI. For example, to change the stability rate, each user places a vote on their preferred stability rate by staking their MKR tokens. Each MKR token equals one vote when locked in a voting contract. Users commit their Maker tokens to a proposal, with the outcome being decided by the number of MKR tokens it receives. MakerDAO token launched with a supply of 1 million MKR, but the supply will change as MKR are minted or burned by the Maker ecosystem based on the success of the DAI peg.

For example, consider an extreme price movement in ETH, such as the Black Thursday crash on March 12th, 2020. This triggered a liquidation event, which requires collateral to be auctioned off to pay off the DAI loan and penalty fees. If the sale of collateral is not sufficient to pay off the DAI loans triggered in liquidation, the Protocol triggers a MKR Debt Auction. MKR is minted by the system, increasing the amount of MKR in circulation, and then sold to bidders for DAI. [25] As well as minting MKR tokens to pay off DAI loans during liquidation, the MKR tokens are burned by the system in response to growth in the system Surplus, which is the amount of DAI generated from system fees, including Stability Fees and Liquidation Fees set by Maker governance. For example, the MakerDAO governance sets a safety buffer in DAI as a contingency against a significant devaluation of the DAI peg. When the system surplus exceeds the safety buffer, any additional DAI is auctioned off for MKR, the governance token of the Maker Protocol, in lots of 10,000 DAI in a Surplus Auction. The system then burns the MKR it receives in the Surplus Auction, reducing the total supply. The economics of the MKR governance token is that it appreciates in value when MKR tokens are burned due to growth in the system surplus, and it depreciates in value when MKR tokens are minted in response to MKR debt auctions to cover losses on liquidating DAI loans. Therefore, the valuation of the MKR token is analogous to a dividend that is paid to MKR stakeholders for supporting the governance protocol in maintaining the DAI peg.

[25] An additional safeguard of Maker Governance is a process called global settlement. When global settlement is triggered, the entire system freezes and all holders of DAI and CDPs are returned the underlying collateral. A global settlement can be triggered by a select group of trusted individuals who hold the global settlement keys. If these signatories see something going horribly wrong, they will enter their keys initiate the process ofÂ winding down the system.

Figure A3 documents the MKR price, total supply in circulation, MKR tokens burned and system surplus. The MKR token features some of the dynamics of mints and burns. During the March 12th Black Thursday Crypto crash, MKR tokens were minted to pay off the DAI debt triggered by liquidations. In 2021, strong growth in the system surplus due to stability and liquidation fees has led to a net reduction of MKR tokens through surplus auctions. Strong growth in the system surplus has also coincided with appreciation of the MKR token.

Figure A3: MKR price, MKR Supply, Burned/Minted Tokens and System Surplus



Note: This figure plots Panel A: MKR price, Panel B: MKR Supply Panel C: MKR Burned, and Panel D: System Surplus. Sample period is from April 13th, 2018 to March 31st, 2020.

Appendix E: Liquidation Mechanism

In this section we provide supplementary tests to understand the liquidation mechanism and how it determines DAI and ETH return correlations. In Table A4, we test the regression specification in Equation (16), and condition our sample for days with positive and zero liquidations. In columns (I) and (II), we run on the sample of positive liquidations. We observe a significant negative correlation between DAI premiums and ETH returns. In columns (III) and (IV), we condition on a sub-sample of zero liquidations. We find the correlation is still negative, but insignificant. This suggests that the liquidation mechanism is quantitatively significant in accounting for the observed negative correlation between ETH returns and DAI peg-premiums.[26]

To identify the dynamic effects of ETH returns and volatility on DAI prices, liquidations and leverage, we use the method of local projections Jordà (2005). The outcome variables include the DAI/USD price, aggregate liquidations and the leverage ratio. The change in the outcome variable, $Y_{t+h} - Y_{t-1}$, is projected on the explanatory variable X_t, in Equation (51). The specification allows for feedback effects using lagged values of the explanatory variable and outcome variable and additional controls, including the stability rate and ETH volatility. We use 1 lag in the baseline specification. Tracing the effects of β_h provides an impulse response of a shock to the explanatory variable ETH returns on the DAI price and the leverage ratio. The results of a *negative* 100 basis point shock to ETH returns is presented in Figure A4. We observe DAI premiums, and an initial positive increase in liquidations and a decrease in the leverage ratio. This is consistent with the empirical results in the main body of the paper using individual CDP data, where we find negative ETH returns increase the probability of liquidation, and decrease leverage.

$$\begin{aligned} Y_{t+h} - Y_{t-1} &= \alpha + \beta_h X_t + \sum_{k=1}^{L} \delta_k X_{t-k} + \sum_{k=1}^{L} \gamma_k (Y_{t-k-1} - Y_{t-k-2}) + controls_t + u_t \\ h &= 0, 1, 2, ... \end{aligned} \tag{51}$$

We can also test for the feedback effects from a liquidation shock to DAI prices, ETH returns and leverage. The liquidation event on March 12th, 2020 led to a fire-sale of ETH collateral to pay off the DAI debt. If the ETH collateral is a substantial fraction of total ETH in circulation, then fire sales of ETH collateral would cause further declines in ETH prices

[26] Based on the two subsamples, we observe a correlation of DAI prices and ETH returns of -0.14 over the sample with positive liquidation, and a correlation of -0.04 over the sample with zero liquidation.

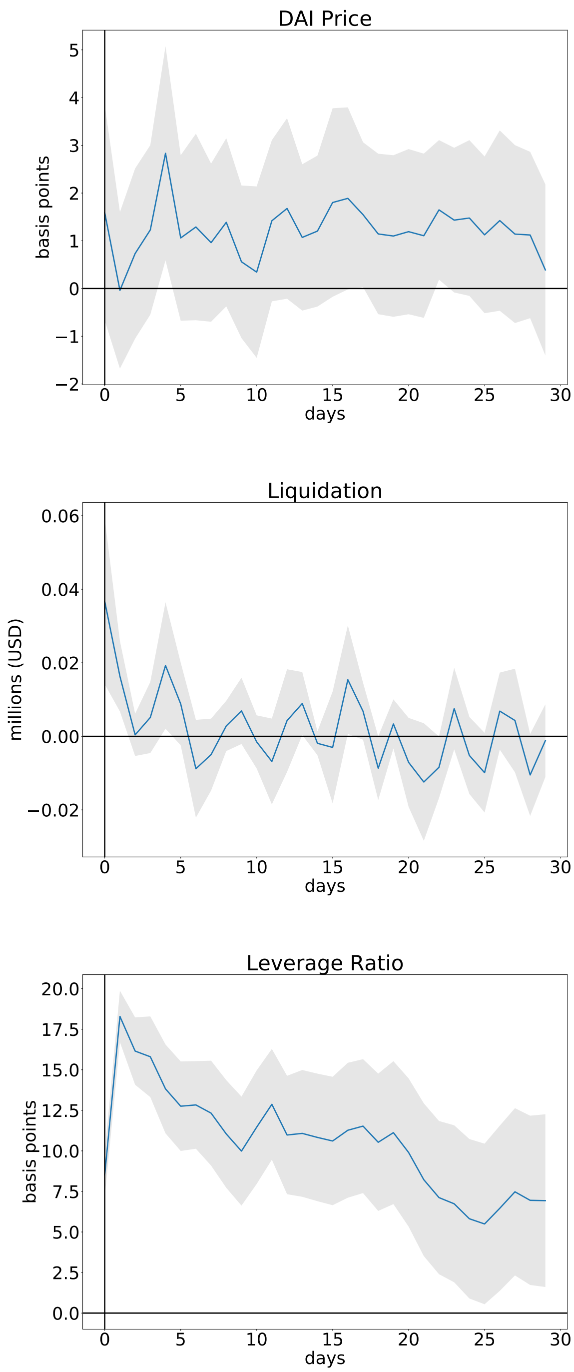
and a liquidation spiral, which is is put forward theoretically in Klages-Mundt and Minca (2020). Using aggregate liquidations as the explanatory variable in equation 51, the results of a 1 million USD positive shock to liquidations presented in Figure A5. We observe DAI premiums, a contemporaneous negative ETH return but that dissipates within one day. We also observe an increase in leverage of about 20 basis points that gradually dissipates over a 30 day horizon. Based on the results, we find weak evidence for a liquidation spiral. The lack of persistent effects of liquidations on ETH returns is due to DAI in circulation being a small fraction of the market cap of ETH. For example, based on data from `coinmarketcap.com`, the marketcap of ETH at the end of the sample on March 12th, 2020 is approximately 12.4 USD Billion, and the marketcap of DAI is 0.11 USD Billion. The ratio of DAI to ETH marketcap is less than 1 per cent.

Table A4: DAI ETH Return correlations: Liquidations

	I	II	III	IV
	Δ	σ_{DAI}	Δ	σ_{DAI}
R_{ETH}	-0.040***	0.028	-0.001	0.016
	(0.014)	(0.018)	(0.014)	(0.017)
σ_{ETH}	0.055***	0.174***	-0.049*	0.021
	(0.021)	(0.026)	(0.029)	(0.035)
R^{-}_{ETH}	-56.04	-51.13	0.00	0.00
	(47.88)	(60.98)	(0.00)	(0.00)
R^{+}_{ETH}	95.43**	65.97	0.063	87.44
	(47.16)	(60.06)	(44.26)	(54.21)
Intercept	61.30***	103.82***	90.19***	119.62***
	(11.15)	(14.19)	(11.77)	(14.41)
R-squared	0.07	0.18	0.02	0.04
Observations	305	305	194	194
Liquidations	Yes	Yes	No	No

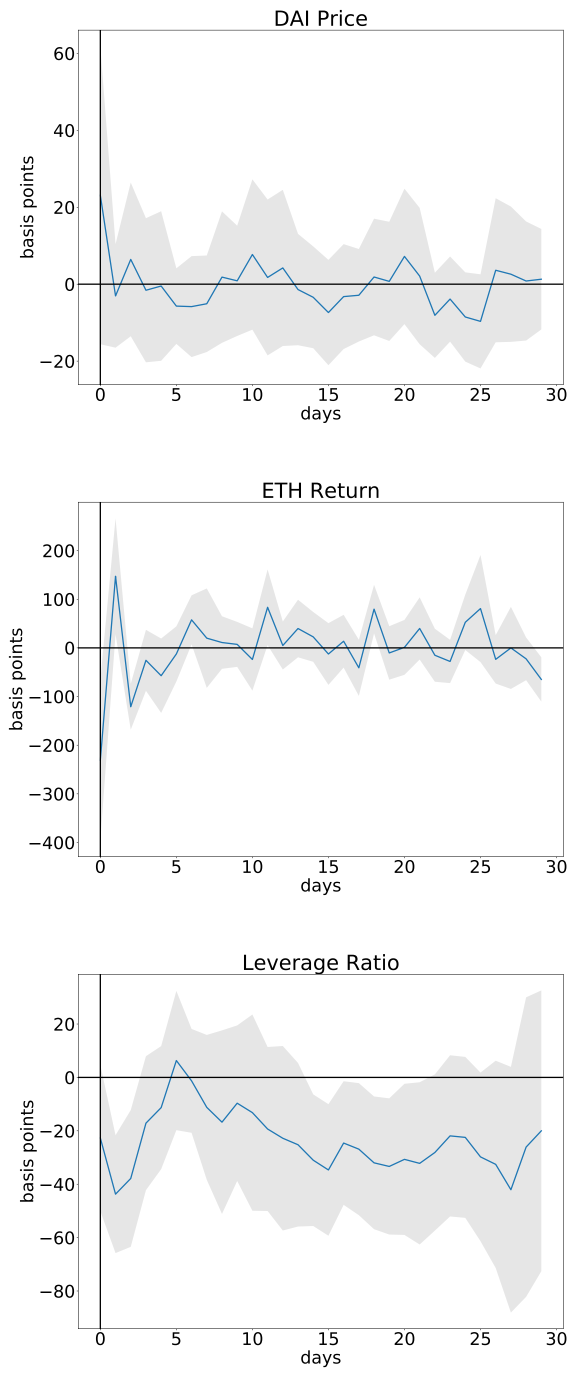
Note: This table regresses intra-day DAI returns and volatility on ETH returns, volatility and the interaction of ETH returns with volatility. The dependent variable in columns (I) and (III), Δ measures the individual DAI borrowing of a CDP in USD. The dependent variable in columns (II) and (IV) σ_{DAI} measures the intra-day volatility of DAI prices. Columns (I) and (II) are estimated for the sub-sample of days with a positive amount of liquidations. Columns (III) and (IV) are for the sub-sample of days with zero liquidations. The sample runs from November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Figure A4: Effect of ETH returns on the DAI peg, liquidation and leverage



Note: This figure illustrates the response of the DAI price, aggregate liquidations and leverage, to a negative 100 basis point shock to ETH returns, using the method of local projections. Leverage ratio is based on aggregate measures of DAI borrowings and ETH collateral. Sample period is from November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI. 1 lag is included in the baseline specification. Gray area denotes 90% confidence interval using White heteroscedasticity-robust standard errors.

Figure A5: Effect of Liquidations on DAI Price, ETH returns and leverage



Note: This figure illustrates the response of aggregate system leverage, ETH returns and the DAI price to a positive 1 million USD shock liquidation, using the method of local projections. Leverage ratio is based on aggregate measures of DAI borrowings and ETH collateral. Sample period is from November 18th, 2019 to March 31st, 2021, corresponding to the period of Multi Collateral DAI. 1 lag is included in the baseline specification. Gray area denotes 90% confidence interval using White heteroscedasticity-robust standard errors.

Appendix F: Testing Peg Arbitrage Mechanism

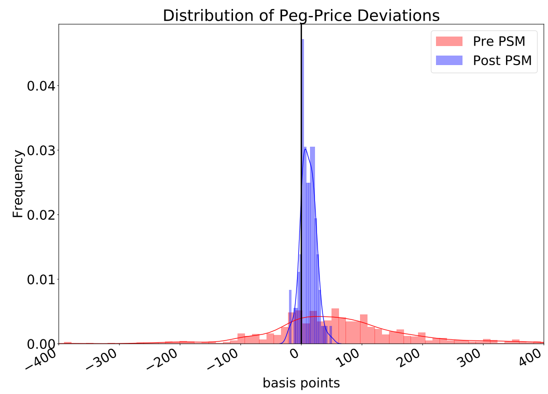
In this section we document additional properties of the DAI peg following the peg stability mechanism (PSM) introduced on December 18th, 2020. The PSM is an arrangement in which MakerDAO is willing to swap USDC for DAI at a 1:1 rate. In Table A5, we document summary statistics of peg-price deviations. The distribution is much more compact in the post peg stability mechanism (PSM) period. This is evident in a lower range of peg-price deviations, ranging from -20 to 50 basis points in the post PSM period, in contrast to a range of -84.8 to 800 basis points during the pre PSM period. The half-life of peg-price deviations has reduced from 5.95 days to 1.76 days.[27] The declining half-life is attributable to the PSM facilitating arbitrage and making it easier to short sell DAI when it trades at a premium. Histograms of the distribution of peg-price deviations is plotted in Figure A6. As well as being more compact, it is notable that there is right skew in peg-price deviations with most of the density occurring at premiums.

Table A5: Summary statistics

period	count	mean	std	min	25%	50%	75%	max	half-life (days)
Pre-PSM	396.0	101.95	98.83	-84.8	33.75	85.5	153.5	800.0	5.95
Post-PSM	103.0	11.27	12.38	-20.0	3.0	11.0	20.0	50.0	1.76

[27] To measure the half-life, we run an auto-regressive process of order 1 on the deviations, $\Delta = \rho\Delta_{t-1} + u_t$. The half-life, or the time it takes for a shock to dissipate by 50%, is $T = \frac{log(0.5)}{log(\rho)}$.

Figure A6: Distribution of Peg-Price Deviations, Pre and Post PSM



Note:Figure plots a histogram of deviations of the DAI/USD price from parity for sub-samples corresponding to pre and post PSM. A positive deviation indicates DAI/USD trades at a premium. The pre PSM sample is from November 18th, 2019 to December 18th, 2020. The post PSM sample is from December 18th, 2020 to March 31st, 2021.

To test the stabilizing properties of the pre and post-PSM periods, we conduct a self-exciting threshold auto-regressive (SETAR) analysis. In equation 52, peg-price deviation Δ is characterized by three auto-regressive processes. Each process is based on a low,middle and high regime, where the low regime is given by the threshold of deviations ranging from $[-\infty,\, \Delta_L]$, the middle regime is $[\Delta_L, \Delta_U]$ and the high regime is $[\Delta_U, \infty]$. The middle regime can be interpreted as a band of inaction in which peg-price deviations are sufficiently small compared to transaction costs and the risk of conducting arbitrage. We estimate the SETAR for the sub-samples pre and post PSM in equations 53 and 54. There is a large band of inaction for peg-premiums ranging from 24 to 290 basis points, in which peg deviations are persistent and approximate a random walk. This is consistent with a significant risk in short selling DAI in response to peg-price premiums. Once premiums exceed 290 basis points, the model estimates a half-life of 2.51 days. In the post-PSM sample, the band of inaction is much smaller, $[\Delta_L, \Delta_U]$ is now between 1 and 27 basis points. The addition of a swap arrangement with USDC facilitates a risk-free arbitrage opportunity by swapping USDC for DAI when DAI trades at a premium. Therefore for deviations in excess of 27 basis points, the half-life is only 0.78 days. In summary, we observe an increase in peg efficiency and the ability to short sell DAI as we proceed from the pre to post PSM.

$$\Delta_t = \begin{cases} \rho_L \Delta_{t-1} + \epsilon_t, & \Delta_{t-1} < \Delta_L \\ \rho_M \Delta_{t-1} + \epsilon_t, & \Delta_L \leq \Delta_{t-1} \leq \Delta_U \\ \rho_U \Delta_{t-1} + \epsilon_t, & \Delta_{t-1} > \Delta_U \end{cases} \tag{52}$$

$$\Delta_t = \begin{cases} 0.840 \Delta_{t-1} + \epsilon_t, & \Delta_{t-1} < 24bps \\ 1.011 \Delta_{t-1} + \epsilon_t, & 24bps \leq \Delta_{t-1} \leq 290bps \\ 0.759 \Delta_{t-1} + \epsilon_t, & \Delta_{t-1} > 290bps \end{cases} \tag{53}$$

$$\Delta_t = \begin{cases} -0.228 \Delta_{t-1} + \epsilon_t, & \Delta_{t-1} < 1bps \\ 0.913 \Delta_{t-1} + \epsilon_t, & 1bps \leq \Delta_{t-1} \leq 27bps \\ 0.412 \Delta_{t-1} + \epsilon_t, & \Delta_{t-1} > 27bps \end{cases} \tag{54}$$