Decentralized Stablecoins and Collateral Risk*

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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 and borrow a fraction of their positions as DAI tokens. Using data on the universe of collateralized debt positions, we show that peg volatility is related to collateral risk. The DAI price covaries negatively with returns to risky collateral, even after controlling for safe-haven demand and the mechanical impact of collateral liquidations. 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

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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. Decentralized stablecoins led by MakerDAO's DAI have grown dramatically over the recent years with market capitalization exceeding 10 USD Billion. Their key characteristic is that 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 risks associated with fluctuations in the price of collateral coins.

In this paper we study the short-term fluctuations of the DAI peg. There are two main functions that market participants can achieve by means of trading DAI. First, speculators use DAI to take long leveraged positions in the collateral asset. Second, DAI can be used to hedge against movements of unstable coins and fulfil its "safe-haven" property. Fluctuations in either speculative or safe-haven demands coupled with limits to arbitrage can lead to DAI deviations from the peg. Changes in the relative demand for DAI, in turn, can be due to changes in the expectations of future ETH performance or liquidations of DAI by MakerDAO's protocol in response to a reduction of collateral value. Through both a model and empirical evidence, we quantify the importance of each of these channels for instability of the DAI peg.

We start by developing a simple model of equilibrium price formation. In 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. Being managed by computer code and visible on the blockchain, it can be verified publicly by all nodes in the blockchain.

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. In equilibrium, DAI peg-prices are dependent on the state of the collateral. When ETH returns increase (good state), investors collateralize ETH, borrow DAI, and then sell DAI on an exchange to buy more ETH. This puts a downward pressure on the price of DAI and generate discounts in the DAI price. In contrast, in the bad state, the decline in ETH returns cause investors to reduce their DAI borrowings. Therefore, the relative decline in DAI supply from speculators and an increase in DAI demand from the secondary market (safe-haven effect) generate peg premiums, leading to a negative correlation between DAI prices and returns to ETH collateral. The model implies that both channels – speculative beliefs and safe-haven effect – are important to generate both premia and discounts in DAI price.

The model also generates testable implications regarding the behavior of DAI prices during periods of low and high safe-haven 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 safe-haven 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 extend 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 premium to borrow DAI and sell it in the secondary market.

We present empirical evidence to support model predictions. We use the entire history of data on individual Collateralized Debt Positions (CDP), which includes the amounts of ETH collateral deposited, DAI borrowed, and the timestamp of each transaction. Consistent with model predictions, we find DAI borrowings respond positively to an increase in ETH returns.

We then test the channels through which collateral risk can generate peg-price deviations and volatility. The first channel is fluctuations in speculative beliefs on the collateral. 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. Second, extreme declines in the price of collateral result in liquidation events. The corresponding decline in supply cause peg-prices to increase, all else equal. Third, premiums can occur in periods of elevated demand, and are triggered in the bad state due to safe-haven effects.

We empirically test the contemporaneous correlation between the DAI price and ETH returns, liquidations and demand shocks. Consistent with our hypothesis, we document a significant negative correlation between DAI prices and ETH returns. Our model channel of speculative beliefs can rationalize this result; a bad state of ETH collateral causes investors to deleverage, reducing DAI supply and generating a premium. Large drops in ETH prices can result in a substantial decline in DAI supply and significant peg premiums. For example, on 12 March 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, and 10 Million USD of liquidations of ETH collateral.

We quantify the relative importance of collateral risk, liquidations and secondary market demand through an analysis of variance (ANOVA) of our explanatory variables. For peg-prices, our decomposition reveals that speculative beliefs play an important role: ETH returns is the most robust predictor of peg-price deviations explaining up to 51.1%, followed by liquidations at 30.5% and the stability fee at

13.2%. For intra-day volatility, we find liquidations is the biggest contributor at 42.9%, followed by the changes in DAI trading volume at 42.7%, and ETH volatility at 13.7%. Taken together, our model channel of speculative beliefs is therefore quantitatively significant in explaining DAI premiums and the observed negative correlation between DAI prices and ETH returns. In contrast, elevated DAI volatility can be explained by periods of high secondary market demand and liquidations.

In a robustness test, we test for the dynamic effects of ETH returns, secondary market demand changes, liquidations and the stability rate using a method of local projections in Jordà (2005) that controls for feedback through lags of the DAI price and controls. Consistent with our prior analysis, we find a negative shock to ETH returns, an increase in liquidations and secondary market demand changes have persistent effects on peg-premiums and reduce aggregate DAI borrowings. We also show that a shock to the stability rate has a long-term positive effect on the DAI price, however it has limited scope 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% reduces the DAI price and the volatility of the DAI peg by approximately 0.5 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

[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.

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 intraday 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. Following the PSM, the increased ability of arbitrageurs to short sell DAI results in a compression of peg premiums. The peg is more resilient to extreme declines in the price of collateral, with smaller premiums and a shift toward safe collateral during an extreme ETH price decline in May 2021.

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; Barthelemy et al., 2021), arbitrage in stablecoin and cryptocurrency markets (Lyons and Viswanath-Natraj, 2020; Makarov and Schoar, 2019, 2020; Borri and Shakhnov, 2018; Pernice, 2021), governance and voting behavior of decentralized stablecoin protocols (Gu et al., 2020; Zhao et al., 2022; Sun et al., 2022) 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., 2021; 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; Qin et al., 2021; Lehar and Parlour, 2022; Chiu et al., 2022). 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 (AMM) constant product algorithm, with research focusing on the design of AMMs, the role of arbitrage and liquidity provision with competing platforms of DEX and centralized exchanges. (Angeris and Chitra, 2020; Capponi and Jia, 2021; Aoyagi and Ito, 2021; Lehar and Parlour, 2021; Barbon and Ranaldo, 2021; Park, 2022). 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 and Zetlin-Jones, 2021; Klages-Mundt and Minca, 2020; Li and Mayer, 2020; d'Avernas et al., 2022). Routledge and Zetlin-Jones (2021) 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. (2022) 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). Brunnermeier and Pedersen (2009) examine the role of funding margins on asset prices and the feedback between funding and market liquidity.[4] Gromb and Vayanos (2018) show that shocks to arbitrage capital can increase spreads and risk-premia.[5] 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 (e.g., 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.[6] Second, DAI is a popular currency to use in decentralized finance (DeFi) protocols, such as Compound, that set interest rates and allocate

[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 section 5.3 and we find liquidations do not have a statistically significant effect on ETH returns.

[5]The role of collateral risk in our paper has a parallel in inter-bank repo markets. Nyborg and Rösler (2019) investigate the spread between unsecured and secured (repo) rates, and 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.

[6]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.

funds automatically through algorithms. As of 10 May 2021, DAI savings lent in the Compound protocol total over 4 USD Billion, and lending rates are approximately 3% per annum.[7] Third, it may be used as a vehicle 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.[8]

Leverage Ratio and Liquidations

A key feature of the CDP is that investors need to over-collateralize their borrowings. We calculate the leverage ratio as 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.

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

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 $\text{Ratio}_{max} = \frac{2}{3}$. 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.

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

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

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

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%. The liquidation price is calculated as $\frac{\text{DAI}}{\text{ETH}} \times \frac{1}{\text{Leverage Ratio}_{max}} \times 100 = \frac{100}{2} \times \frac{1}{66.67} \times 100 =$ 75USD. Suppose in the following period, the ETH price falls below the liquidation price to 60 USD.[9] 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.

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.

In addition to paying off the loan, investors are required to post penalty fees

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

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. We plot in Figure 1 the USD price response, the ETH price and DAI liquidations on 12 March 2020. On this day, extreme price changes in collateral caused 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% daily decline in ETH prices. 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.[10] 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. [11]

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, 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

[10]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/

[11]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/.

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.[12] 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 12 March 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

[12] 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.

when USDC prices are trading at a significant discount.[13]

3.1 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.[14] 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 DuneAnalytics, 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. DAI liquidations and governance token MKR mints and burns are available at https://www.mkranalytics.com/.

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

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

[14] 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.

filed by the SEC.[15] We use hourly data for the pairs of ETH/USD, DAI/USD from the Bitfinex exchange from 13 April 2018 to 31 March 2021, and hourly data for the USDC/USD pair from the Kraken exchange available from 8 January 2020 to 31 March 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 13 April 2018 to 31 March 2021. Figure 2 plots the time-series of DAI price, ETH price, the leverage and stability rate. DAI peg-price premium is on average of 100 basis points over the full sample. The average ETH return is 0.17%, and the standard deviation of returns is 5.8%. The large declines in ETH returns peaked on 12 March 2020, which recorded a -58.2% decline. Stability rates on borrowing DAI in ETH vaults are typically 3% on average, with periods of high interest rates of 20% 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.

[15] 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.

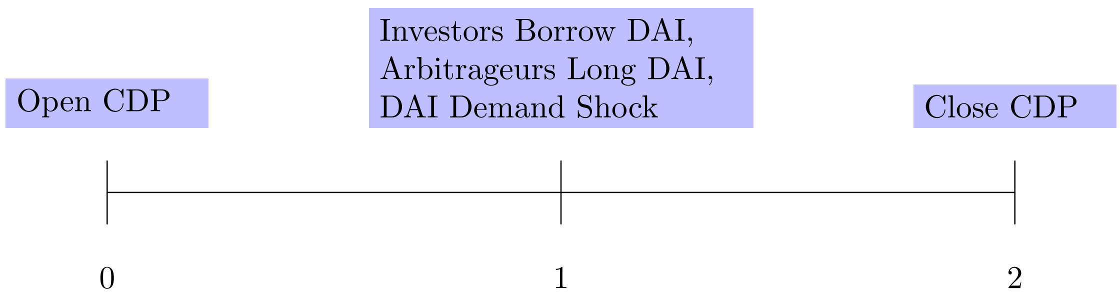
4 Model

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 safe-haven demand. Speculative investors deposit 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. Safe-haven 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 safe-haven demand. In periods of high safe-haven 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 safe-haven demand and clear the market.

4.1 Timing

We consider a model with two periods – 1 and 2. At some point of time 0 before trading starts, investors open a CDP by depositing non-stable collateral, ETH, into a MakerDAO vault. Period 1 is a trading round. In period 1, DAI tokens are borrowed (issued), and secondary market trading occurs. There are two cryptocurrencies 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 1, either ETH speculators and/or arbitrageurs borrow DAI tokens in response to a demand shock for DAI in the secondary market. Finally, in period 2, all investors close their CDPs and redeem all DAI tokens. No secondary market trading occurs in period 2. Market clearing conditions in period 1 determines DAI prices.



We denote the price of DAI in period t as p_t and its conditional on period 1 variance by $\sigma^2 = Var_1[p_2]$. DAI is liquidated in period 2 and is exchanged to USD at the risky rate p_2 with mean 1 and variance σ_2^2.[16] 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 2 is a random variable R^E with mean μ^E and variance σ_E^2.

4.2 Agents

The model includes three types of investors: ETH speculators, arbitrageurs and safe-haven DAI demand. In period 1, ETH speculators invest their wealth W_1^s in ETH optimally decide how much to further 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 $s = G$ or B which occur with probabilities π and $1 - \pi$ respectively and that $\mu(G) > \mu(B)$. The state of speculators' beliefs can, for example, depend on the

[16]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.

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 safe-haven demand as an aggregate demand D from customers who seek safety during periods of collapse of unstable coin (ETH) or have some intrinsic needs to purchase a stablecoin currency. It captures DAI's use in decentralized finance (DeFi) protocols, such as Compound, that set interest rates and allocate funds automatically through algorithms. In order to model the safe-haven effect of DAI we assume that the demand changes depending on the state of ETH collateral: $D(B) > D(G)$. In the baseline calibration, we set demand to zero in the good state and positive in the bad state. This captures in a stylized way the safe-haven component of stablecoins that typically appreciate during downturns in risky crypto asset prices (Baur and Hoang, 2020).

We describe the structure of the model and investors demands backwards starting from period 2. In period 2 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_2.

In period 1, 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 is optimally calculated by maximizing their expected utility function given their beliefs in period 1. Their wealth W_2^s evolves as shown in Equation (3):

$$W_2^s = W_1^s \left(R^E(1+\theta p_1) - \theta p_2 - \theta i^B \right). \tag{3}$$

The first term of this expression is the return earned on the leveraged position of ETH, the 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 paid by the speculators.

The arbitrageurs' wealth changes according to the following dynamics:

$$W_2^a = \begin{cases} W_1^a \left(\omega(1+i^L)p_2/p_1 + (1-\omega)(1+r) \right), & \omega \geq 0, \\ W_1^a \left(-\frac{\omega}{\theta} R^E + \omega(p_2 - p_1(1+r) + i^B) + \left(1+\frac{\omega}{\theta}\right)(1+r) \right), & \omega < 0, \end{cases} \tag{4}$$

where ω denotes the fraction of arbitrageurs' wealth invested in DAI.

The first equation corresponds to the case when arbitrageurs buy DAI in the secondary market. They invest a fraction $1-\omega$ of dollar wealth in dollars at the risk-free rate. The remaining fraction of wealth is used to purchase DAI at p_1 and earn the DAI savings rate i^L. In period 2, they re-convert DAI back to dollars at p_2. The dollar profit they make by going long in DAI is $(1+i^L)p_2/p_1$. 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 $1+\frac{\omega}{\theta}$ in dollars at the risk-free rate r. The remaining fraction of wealth is used to purchase ETH collateral. They post $\frac{|\omega|W_1^a}{\theta}$ of ETH collateral, borrowing $|\omega|W_1^a$ 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. The dollar profit they make by short-selling 1 unit of DAI is given by the term $p_1(1+r) - p_2 - i^B$.[17]

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

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

the share of DAI borrowing to be bounded between 0 and $\bar{\theta}$, which is the maximum level of leverage an investor can take:

$$U(W_2^j) = \mathbb{E}_1[W_2^j] - \frac{1}{2}\gamma Var_1[W_2^j],\ 0 \leq \theta \leq \bar{\theta},\ j = s, a. \tag{5}$$

Speculators' optimal leverage ratio for period 1 is given by

$$\theta \quad = \quad \max\left\{0, \min\left\{\frac{\frac{p_1\mu^E(s_1)-1-i^B}{\gamma W_1^s} - p_1\sigma_E^2}{p_1^2\sigma_E^2 + \sigma^2}, \bar{\theta}\right\}\right\}. \tag{6}$$

We assume that the liquidation value of DAI is independent of ETH returns and $E_1[p_2] = 1$. Although arbitrageurs know that the objective ETH returns are independent of the state s, a non-zero covariance arises endogenously due to speculators' beliefs and their corresponding actions.

Arbitrageurs' optimal DAI portfolio weight ω is:

$$\omega \quad = \quad \begin{cases} \max\left\{0, \frac{\left((1+i^L)/p_1-(1+r)\right)p_1^2}{\gamma W_1^a(1+i^L)^2\sigma^2}\right\}, & U^+(W_2^a) \geq U^-(W_2^a), \\ -\max\left\{0, \frac{\bar{\theta}\left(\mu^A-\bar{\theta}(1-p_1(1+r))+\bar{\theta}i^B\right)}{\gamma W_1^a(\sigma_E^2+\bar{\theta}^2\sigma^2)}\right\}, & U^+(W_2^a) < U^-(W_2^a), \end{cases} \tag{7}$$

where

$$U^+(W_2^a) \quad = \quad \max_{\omega_1 \geq 0} U(W_2^a) \tag{8}$$

$$U^-(W_2^a) \quad = \quad \max_{\omega_1 < 0} U(W_2^a). \tag{9}$$

Proof: See Appendix B.

4.3 Equilibrium

To clear the market, selling demand for DAI should equal to buying demand. In period 1, speculators borrow θW_1^s of DAI and sell it to convert to ETH. At the same time, arbitrageurs buy $\omega_1 W_1^a$ DAI (or short sell if $\omega < 0$) and, in addition to it, in period 1 we have safe-haven demand $D(s)$. Since there is no trading in periods 0 and 2, we focus on the market clearing condition for period 1:

$$0 \;=\; -\theta W_1^s + \omega W_1^a + D(s_1) \tag{10}$$

We solve the model numerically to from testable predictions about equilibrium prices and quantities in the model. We assign the following parameter values: $\gamma = 0.5$, $\pi = 0.5$, $W_1^s = \$350$, $\bar{\theta} = 0.66$. We calibrate the rest of the primitive parameters of the model to the sample. Specifically, we set daily rates of returns to: $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma = 0.0188$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu(G) = 1.0668$, $\mu(B) = 1.0033$. Here we take μ_A being equal to the full sample average of daily ETH return, while we take $\mu(G)$ equals to the 90-th percentile of ETH return distribution. Finally, σ_E equals to the sample standard deviation of ETH daily returns. Finally, we set $D(G) = 0$ and $D(B) = \$50$. These values are chosen to emphasize the safe-haven demand effect. Setting higher values $D(G)$ will reduce DAI peg discounts in the good state.

The choice of parameters π, γ and W_1^s is large extent arbitrary. We present in Appendix C the sensitivity analysis with respect to these parameters and demonstrate that the model's predictions are largely unaffected by this choice.

4.4 Testable implications

Baseline specification

Figure 3 plots equilibrium DAI prices for both good and bad states of nature (e.g., high and low ETH returns). In Panel A we plot DAI prices for a specification with no safe-haven demand and only speculators and arbitrageurs trading in period 1. In the bad state, speculators do not deposit ETH collateral due to their pessimistic beliefs and the supply of DAI is zero in the secondary market; DAI prices trade at par. In the good state, speculators deposit ETH collateral and borrow DAI in period 1. Market clearing requires that arbitrageurs take a long position in DAI to balance the supply of DAI by speculators. To induce a long position, arbitrageurs buy DAI at a discount.

Panel B of Figure 3 plots DAI prices for a specification with safe-haven demand

and arbitrageurs but no speculators trading in period 1. Safe-haven demand is endogenous to the state of ETH collateral, it is zero in the good state and positive in the bad state. In the good state, we assume safe-haven demand is zero and arbitrageurs do not need to supply DAI in the secondary market; DAI prices again trade at par. In the bad state, DAI prices trade at a premium as arbitrageurs have to absorb the positive safe-haven 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.

To create a two-sided distribution of stablecoin prices, we require a specification that includes speculators, arbitrageurs and safe-haven demand. We label this the full specification and plot the equilibrium DAI prices in Panel C. DAI prices in period 1 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 the positive safe-haven demand shock 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 safe-haven 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.

Volatility of collateral

We next look at the stability of DAI price with respect to ETH volatility. Arbitrageurs have to absorb this demand through a peg-price premium. To further illustrate the effect of ETH volatility, Figure 4 presents comparative statics results for period 1 DAI prices (Panel A), the expected DAI price (Panel B), DAI price volatility (Panel C) and leverage ratios (Panel D). 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. Consistent with short-selling pressure on arbitrageurs, DAI prices in period 1 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 D, we document a decline in the leverage ratio of speculators in response to increased ETH volatility. 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 5 presents comparative statics results for period 1 DAI prices (Panel A), the expected DAI price (Panel B), DAI price volatility (Panel C) and leverage ratios (Panel D). As the stability rate increases, the reduction in DAI borrowings by speculators requires arbitrageurs to short sell DAI to clear the market in the bad state of the world. Arbitrageurs charge a premium and hence are willing to short sell only at high prices, and increase peg volatility. 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 rate from 0% to 20% increases the expected DAI price by approximately 5 basis points based on the numerical calibration.

Safe-haven demand shock

We now look at DAI prices in periods of low and high safe-haven public demand. Figure 6 presents comparative statics results for period 1 DAI prices (Panel A), the expected DAI price (Panel B), DAI price volatility (Panel C) and leverage ratios (Panel D). Through this exercise, we capture in a stylized way the demand for DAI due to its use in decentralized finance protocols and its role as a safe-haven. Arbitrageurs have to absorb this demand during the bad state through a peg-price premium. When public demand is low, arbitrageurs do not have to short sell very aggressively. Therefore, peg-premiums and volatility are higher in states of high demand.

Finally, we show the comparative statics are robust to changes in system parameters in Appendix C. The probability of the good state π amplifies the slope of comparative static figures, but does not change the sign (see Figures A3 - A5). Coefficients γ and W_1^s amplify premia and discounts of DAI price deviations (see Figure A6) and we choose their values in the baseline specification to approximately reflect the magnitude of DAI price deviations in th edata.

4.5 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 $E[R^U] = 1 + r$ given that the coin is pegged to USD and we denote by $Var[R^U] = \sigma_U^2$ the variance of its returns. Furthermore, we assume that the USDC returns are uncorrelated with ETH and DAI returns.[18] Given our initial assumption that the speculators invest their entire wealth into ETH and choose their optimal leverage ratio θ_1, 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:

$$W_2^a = \begin{cases} W_1^a \left(\omega(1+i^L)p_2/p_1 + (1-\omega)(1+r)\right), & \omega \geq 0, \\ W_1^a \Big(-\frac{\omega^E}{\theta} R^E - \omega^U R^U + (\omega^E + \omega^U)(p_2 - p_1(1+r) + i^B) & \\ \qquad + \left(1 + \frac{\omega^E}{\theta} + \omega^U\right)(1+r)\Big), & \omega^U, \omega^E < 0. \end{cases} \tag{11}$$

Here, in the first equation, $\omega \geq 0$ is the amount of DAI arbitrageurs purchase as a fraction of wealth, while in the second equation arbitrageurs short sell $-\omega$ fraction

[18]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.

of their wealth, where $\omega = \omega^E + \omega^U < 0$, $\omega^E < 0$ is the amount of DAI arbitrageurs issue via ETH collateral and $\omega^U < 0$ 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:

$$\omega = \begin{cases} \max\left\{0, \frac{\left((1+i^L)/p_1-(1+r)\right)p_1^2}{\gamma W_1^a(1+i^L)^2\sigma^2}\right\}, & U^+(W_2^a) \geq U^-(W_2^a), \\ \omega^U + \omega^E, & U^+(W_2^a) < U^-(W_2^a), \end{cases} \tag{12}$$

where the precise values of ω^E and ω^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 two 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. The intuition is as follows. 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 public 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 period 1 DAI prices (Panel A), the expected DAI price (Panel B), DAI price volatility (Panel C), leverage ratio of speculators (Panel D) the share of USDC collateral (Panel E). The comparative statics with respect to USDC volatility are qualitatively similar to comparative statics with respect to ETH volatility. The difference is now that the capacity of *arbitrageurs*, as opposed to speculators, change with the volatility of stable collateral. When USDC volatility is low, arbitrageurs 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, arbitrageurs are required to short sell DAI to clear the market in the bad state of the world. Consistent with short-selling pressure on arbitrageurs, DAI prices in period 1 are higher in the bad state as volatility of USDC increases, increasing volatility of the peg. In panel D, the speculators always leverage to the maximum in the good state. The share of stable collateral in panel E is defined as $\frac{\omega^U}{\omega^U+\omega^E}$, and 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

5.1 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.

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. To prevent investors from over-leveraging, the system has a "bite" action which is a liquidation event. A bite occurs when the leverage ratio is above the threshold $\frac{2}{3} \times 100$ per cent, at which positions are liquidated.[19] 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%, well below the threshold leverage of 66.67%. 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%. 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

[19] 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.

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%, where the peak stability rate is 20.52%. Low interest rates are below 1%. Noticeably, 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 CDP positions through a panel regression specification in Equation (13):

$$Y_{i,t} = \alpha_i + \beta_1 R_{ETH,t} + \beta_2 \sigma_{ETH,t} + \beta_3 sfee_t + u_{i,t}, \tag{13}$$

where the dependent variable is one of the following variables: the amount of DAI borrowing ($DAI_{i,t}$) by CDP i on day t, the amount of ETH collateral ($ETH_{i,t}$) by CDP i on day t, a dummy variable $Bite_{i,t}$ indicating a "bite" liquidation event for CDP i at time t. The set of independent variables include the daily contemporaneous 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 ($sfee_t$). Individual CDP fixed effects is captured by α_i, and controls for idiosyncratic risk preferences of an individual CDP. To create a panel with sufficient observations for all CDPs, we filter CDPs that have transactions over 30 days in the sample.[20] This gives us a total of 456 individual CDPs with at least 30 daily observations each.

Independent variables $\sigma_{ETH,t}$ and $sfee_t$ are designed to capture contemporaneous effects of collateral risk and the changes of stability rate respectively. We use $R_{ETH,t}$ as a proxy for speculators beliefs about the state of future ETH returns. We do not use lagged return as a measure of future expected returns because the speculators

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

in our model are not assumed to be rational, hence we cannot rely on the rational expectations hypothesis. We treat speculators more as short-term momentum or positive feedback traders who react to contemporaneous changes in ETH to form their speculative positions. Hence, positive contemporaneous returns are considered as a signal to the good state while negative returns indicate the bad state.

Table 4 summarizes the results. A 1% increase in ETH returns increases DAI borrowing and ETH collateral by 442 USD and 3,300 USD respectively (see columns (1) and (2)). This matches the model mechanism: investors deposit more ETH collateral and borrow more DAI in the good state, and borrow less DAI in the bad state. A 1% increase in the stability fee reduces DAI borrowing and ETH collateral by 620 USD and 1600 USD respectively. To estimate the effect of a change in the explanatory variable on the probability of liquidation, we use a panel probit specification in Column (3). A 1% increase in ETH returns reduces the probability of liquidation by 0.075 percentage points. A 1% increase in ETH volatility and stability rate increases the probability of liquidation by 0.13 and 0.02 percentage points respectively.

5.2 Fundamentals of peg-price deviations

The model tests the channels through which collateral risk can generate peg-price deviations and volatility. The first channel is speculative beliefs on the collateral. 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. The prediction is that DAI peg-price premiums occur precisely in periods of negative ETH returns. Second, declines in the price of collateral result in liquidation events. The corresponding decline in supply causes peg-prices to increase, all else equal. Third, premiums can occur in periods of elevated demand, and are triggered in the bad state due to safe-haven effects. We empirically test the contemporaneous correlation between the DAI price and ETH returns, liquidations and demand shocks in Equation (14):

$$Y_t = \beta_0 + \beta_1 R_{ETH,t} + \beta_2 \sigma_{ETH,t} + \beta_3 sfee_t + \beta_4 L_t + \beta_5 D_t + u_t. \tag{14}$$

Here, the outcome variable Y_t is the DAI peg-price deviation $\Delta_{DAI,t}$, and the intra-day volatility $\sigma_{DAI,t}$. 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 $R_{ETH,t}$ and $\sigma_{ETH,t}$, which are measures of contemporaneous returns and intra-day volatility of ETH. Similarly to the specification in Equation (13), we use contemporaneous return to capture the model assumption of extrapolative beliefs of speculators and to proxy signals about the good and bad states of future ETH returns. To control for the effect of lagged returns, we test for feedback effects in Section 5.3 and negative ETH returns cause persistent peg-premiums. $sfee_t$ is the stability rate on DAI borrowings (annualized). L_t measures aggregate liquidations of ETH collateral in USD Million, and D_t measures the per cent change in aggregate secondary market trading volume of DAI, and measures growth in aggregate trading volume in exchanges. All variables are measured in basis points.

The results for peg-price deviations are summarized in Table 5. We first test the effect of ETH returns, ETH volatility, and the stability fee in columns (3) to (6). In the specification in column (3), a 1% (100 basis point) increase in ETH returns is associated with a 3.7 basis point decline in DAI prices. This supports the first model channel of speculative beliefs on collateral. The negative correlation observed between DAI prices and ETH returns is due to the extrapolative beliefs of speculators. In the bad state, investors reduce ETH collateral and DAI borrowings. The reduction in supply of DAI pushes DAI prices up. In the good state, investors increase ETH collateral and DAI borrowings. The increase in DAI supply reduces the price, generating the negative correlation between ETH returns and DAI prices in the data. In column (4), we find a 1% (100 basis point) increase in intra-day volatility of ETH increases DAI prices by 0.5 basis points.

The second channel is liquidation events, which are triggered in extreme states of collateral. Column (1) shows that liquidations are more likely to occur in periods of negative ETH returns, and in periods of increased ETH volatility. The specification in column (6) regresses DAI price deviations 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 17.7 basis points. Using this estimate, the 12 March 2020 liquidation auction of 10 USD Millions leads to an approximate 180 basis point premium. DAI prices increased to 1.08 USD on 12 March. Therefore liquidations alone cannot account for the large premiums on *Black Thursday*.

The third channel is that DAI premiums exhibit safe-haven properties (Baur and Hoang, 2020). In specification (2), we find trading volume growth increases in periods of negative ETH returns and high ETH volatility. The specification in column (7) regresses DAI price deviations on the measure of demand. Consistent with our hypothesis: a 1% increase in secondary market trading volume is associated with an increase in the DAI price of 0.3 basis points. Specification (10) includes all explanatory variables. We find the three key variables of ETH returns, liquidations and safe-haven demand remain statistically significant.

In addition to peg-prices, the model predicts a positive relationship between peg volatility and collateral risk. 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. The results for intra-day volatility are summarized in Table 6 respectively. In contrast to our analysis on peg-prices, ETH volatility is a stronger predictor of DAI volatility. In column (3), a specification which controls for ETH returns, intra-day volatility and the stability rate, a 1% (100 basis point) increase in ETH volatility increases DAI volatility by 2.1 basis points, all else equal. ETH returns and the stability fee have insignificant effects. Turning to liquidations, column (4) regresses DAI volatility on liquidations. Consistent with our hypothesis: a 1 million USD increase in liquidations results in 10.5 basis point increase in volatility. We test the effect of change in DAI secondary market trading volume on DAI volatility in columns (6) and (7). A 1% (100 basis point) increase in DAI trading volume increases DAI peg volatility by 0.2 basis points. Finally, in column (8) which includes all variables, we find trading volume is the only statistically significant variable that corresponds to periods of elevated DAI volatility.

Decomposition of Channels

We have shown that each channel, speculative beliefs on the state of collateral, liquidations and secondary market trading volume can explain peg-prices and intra-day volatility. We can estimate the relative importance of each channel through an analysis of variance (ANOVA) of our explanatory variables. In Figure 12, we breakdown the decomposition of peg-price deviations and intra-day volatility into 5 explanatory variables, stating the per cent contribution to the explanatory sum of squares of each variable. For peg-prices, speculative beliefs play an important role: ETH returns is the most robust predictor of peg-price deviations explaining up to 51.1%, followed by liquidations at 30.5% and the stability fee at 13.2%. For intra-day volatility, we find liquidations is the biggest contributor at 42.9%, followed by trading volume at 42.7%, and ETH volatility at 13.7%. Taken together, our model channel of speculative beliefs is therefore quantitatively significant in explaining DAI premiums and the observed negative correlation between DAI prices and ETH returns. In contrast, elevated DAI volatility can be explained by periods of high secondary market trading volume and liquidations.

5.3 Dynamic effects of ETH returns, liquidations, trading volume and stability rate

In this section we test for the dynamic effects of ETH returns, liquidations, demand and the stability rate on DAI prices and leverage using local projections (Jordà, 2005). The outcome variables include the DAI/USD price, aggregate liquidations, ETH returns 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 (15). The specification allows for feedback effects using lagged values of the explanatory variable and outcome variable and additional controls C_t. 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 on the outcome variables.

$$Y_{t+h} = \alpha + \beta_h X_t + \sum_{k=1}^{L} \delta_k X_{t-k} + \sum_{k=1}^{L} \gamma_k Y_{t-k-1} + C_t + u_t, \qquad h = 0, 1, 2, ... \qquad (15)$$

The results are presented in Figure 13. In panel A we test the effect of a *negative* 100 basis point shock to ETH returns. We observe DAI premiums, and an initial positive increase in liquidations and a decrease in DAI borrowings. This is consistent with the empirical results using individual CDP data, where we find negative ETH returns increase the probability of liquidation, and decrease DAI borrowings. Panel B tests the effect of a 1 million USD shock in liquidations. The liquidation event on 12 March 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 and a liquidation spiral, which is put forward theoretically in Klages-Mundt and Minca (2020). We observe contemporaneous DAI premiums and a negative ETH return but that dissipates within one day. 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 market capitalization of ETH at the end of the sample on 12 March 2020 is approximately 12.4 USD Billion, and the market capitalization of DAI is 0.11 USD Billion. The ratio of DAI to ETH market capitalization is less than 1%.

Panel C tests the effect of a 1% increase in aggregate secondary market trading volume of DAI. We test for the feedback effects from a demand shock to DAI prices, ETH returns and DAI borrowings. Our measure of demand is the growth in aggregate trading volume of DAI in the secondary market. We observe weakly positive DAI premiums and an increase in DAI borrowings, with insignificant effects on ETH returns.

In Panel D, we trace the impulse response of the stability rate on the DAI price and the leverage ratio.[21] The stability rate, which is a cost on DAI borrowings, is

[21] We use the specification (15) with $X_t = sfee_t - sfee_{t-1}$, which is the change in the stability rate.

implemented by the MakerDAO protocol as a way to control system leverage and DAI prices. 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 approximately 5 basis points over the long-term, and reduces DAI borrowings by 8 million USD over a horizon of 30 days.[22]

5.4 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 12 March 2020. The peg stability module (PSM) was introduced on 18 December 2020, and is indicated by the dotted line in Figure 14. 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.[23]

We test four implications of the introduction of stable collateral that are directly related to our model predictions. First, we hypothesize that the introduction of USDC collateral led to an increase in peg-sustaining arbitrage. Second, we hypothesize that the introduction of stable collateral attenuated correlations between the risky ETH collateral and DAI prices, and increased the sensitivity of DAI to USDC volatility. Third, we hypothesize that peg-prices are dynamically more stable following the PSM. Fourth, we hypothesize the PSM attenuates the response of DAI prices

[22] 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.

[23] 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 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.

to periods of extreme ETH returns and liquidation events.

Determinants of share of stable collateral

In this section we hypothesize that the share of stable collateral increases in response to a relative increase in ETH volatility. Figure 14 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 12 March 2020 to 31 March 2021. We define the variable $share_t$ to be equal to DAI borrowings from stable collateral types as a fraction of aggregate DAI borrowings. Stable collateral types include stablecoins USDC, TrueUSD and Tether.

In order to determine the fundamentals driving the share of stablecoin collateral, we estimate the following regression model:

$$share_t = \alpha + \beta_1 R_{ETH,t} + \beta_2 \sigma_{ETH,t} + \beta_3 \sigma_{U,t} + u_t. \tag{16}$$

In an alternative specification, we substitute $\sigma_{ETH,t}$ and $\sigma_{U,t}$ with thier ratio $\sigma_{ETH,t}/\sigma_{U,t}$.

The estimation results are summarized in Table 7. A 1% increase in USDC volatility reduces the share of stable collateral by 1.7 basis points. While intra-day volatility is insignificant in column (2), after controlling for intra-day volatility of USDC in column (4) we find it is significant and positively associated with the share of stable collateral. A 1% increase in the ratio of ETH to USDC volatility (see columns (3) and (5)) increases the share of stable collateral by 0.14%. The results support the model prediction that arbitrageurs choose to increase the share of USDC collateral in response to an increase in ETH volatility (see Panel E of Figure 8).

ETH-DAI correlations Pre and Post USDC

Our second test is on whether the channels of DAI peg-prices become muted following the introduction of stable collateral. We hypothesize that (i) the correlation between ETH returns and DAI prices is attenuated and (ii) DAI volatility is more strongly correlated with USDC volatility in the post USDC collateral period.

To test this, we divide our sample into a pre and post USDC collateral period based on the introduction of USDC collateral by the MakerDAO governance on 12 March 2020. We run the following baseline specifications:

$$\Delta_{DAI,t} = \beta_0 + \beta_1 \Delta_{DAI,t-1} + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + \beta_4 \Delta_{U,t} + \beta_5 \sigma_{U,t} + \beta_6 sfee_t + u_t,$$
$$\sigma_{DAI,t} = \beta_0 + \beta_1 \sigma_{DAI,t-1} + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + \beta_4 \Delta_{U,t} + \beta_5 \sigma_{U,t} + \beta_6 sfee_t + u_t,$$

where $\Delta_{U,t}$ denotes the daily peg-price deviations of USDC prices (in basis points).

The estimation results are presented in Table 8. Columns (1) and (2) are estimated for the pre-USDC collateral period, and columns (3) and (4) for the post-USDC collateral period. Consistent with our hypothesis, we observe an attenuation in the correlation between ETH returns and DAI prices from -0.054 to -0.012 in the post USDC collateral period. This confirms the model prediction that the correlation between bad and good states of ETH returns is weakened after the introduction of stable collateral.[24] We find USDC is a more significant predictor of DAI peg prices and volatility than ETH in the post period. A 1 basis point increase in USDC volatility increases DAI peg-prices and volatility by 0.8 and 2.2 basis points respectively in the post-period.

PSM and peg efficiency

We now test the introduction of the PSM on peg efficiency. Figure 15 plots the stablecoin prices and intra-day volatility for USDC and DAI. A visual inspection of Figure 15 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 Difference-in-difference (DiD) design in Equation (17), where the outcome variable $Y_{j,t}$ is either the absolute level of peg deviations, $|\Delta_{j,t}|$, or the intra-day volatility of peg deviations $\sigma_{j,t}$ for $j = DAI, U$,

[24] We refer readers to Figure 7 which plots the model peg-prices before and after the introduction of stable collateral. The introduction of stable collateral weakens the link between the bad ETH state and DAI peg-premiums. The stable collateral type makes it easier for arbitrageurs to short sell DAI at smaller premiums.

both measured in basis points. More specifically, we estimate

$$Y_{j,t} = \alpha_0 + \beta\ T_j + \gamma\ post_t + \delta\ post_t \times T_j + u_{j,t}, \tag{17}$$

where the indicator for treatment T_j takes on a value of 1 for DAI and 0 for USDC, and $post_t$ take on a value 0 for t prior to 18 December 2020 (the date of the PSM launch) and 1 afterwards. The coefficient δ measures the net effect of peg stabilization relative to any trends observed in USDC.

The results are summarized in Table 9. 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 (3) and (4) of Table 9. There is a net convergence in the stability of peg deviations during the post PSM period, with a DiD coefficient of $post)t \times T_j$ 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 8 January 2020. In columns (5) and (6), 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 5.4 we provide further econometric tests to show the peg is dynamically more stable in the post PSM period.

Asymmetric increase in peg efficiency

We have shown an increase in the efficiency of the peg following the PSM. Our model shows that this increase is asymmetric: peg premiums are compressed in an equilibrium with stable collateral as arbitrageurs can now diversify risk when short-selling DAI. Histograms of the distribution of peg-price deviations is plotted in Figure 16, and shows the distribution is skewed toward peg premiums in the pre-PSM but becomes more symmetric in the post-PSM. In Table 10, 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.[25]

To test the stabilizing properties of the pre and post-PSM periods, we conduct a self-exciting threshold auto-regressive (SETAR) analysis. In Equation (18), peg-price deviation $\Delta_{DAI,t}$ 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.

$$\Delta_{DAI,t} = \begin{cases} \rho_L \Delta_{DAI,t-1} + \epsilon_t, & \Delta_{DAI,t-1} < \Delta_L \\ \rho_M \Delta_{DAI,t-1} + \epsilon_t, & \Delta_L \leq \Delta_{DAI,t-1} \leq \Delta_U \\ \rho_U \Delta_{DAI,t-1} + \epsilon_t, & \Delta_{DAI,t-1} > \Delta_U \end{cases} \tag{18}$$

We estimate the SETAR for the sub-samples pre and post PSM. Our results are presented in Table 11. 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 increased ability of arbitrageurs to short sell DAI in the post PSM, leading to a compression of peg premiums and an increase in peg stability.

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

PSM and liquidations

Our model predicts that post PSM, the peg is more resilient to periods of extreme collateral returns. We present a comparative case study of the DAI price, liquidations and the ETH price during the 19 May 2021 crypto crash, in which cryptocurrencies like ETH dropped by approximately 30%. We plot in Figure 17 the USD price response, the ETH price and DAI liquidations. Compared to the *Black Thursday* crash on 12 March 2020, DAI exhibits much smaller premiums, with a peak of 40-50 basis points in May 2021, in contrast to 800 basis points in March 2020 (see Figure 1 for plots of DAI, ETH prices and liquidations during March 2020). Liquidations of ETH are correspondingly smaller in the latter period at 0.4 USD million compared to 10 USD million. Panel C of Figure 17 confirms our hypothesis: the decline in ETH returns and increased volatility triggered a rebalancing of DAI creation through investors swapping USDC for DAI via the PSM. The rebalancing was quantitatively significant: DAI borrowing via ETH collateral fell from a peak of 2.75 to 1.75 USD Billion over the month of May 2021, and borrowing via the PSM increased from 1 to 2 USD Billion over this period. The PSM reduced limits to arbitrage and consequently increased stability of the peg.

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. Peg-deviations are dampened through the introduction of stable collateral types for arbitrageurs to borrow against. The model highlights importance of both channels to generate realistic discounts and premia of DAI price: state-dependent speculative behaviour and safe-haven demand.

We provide empirical evidence to support model predictions. Using the universe of collateralized debt positions, we find that DAI borrowings and ETH collateral deposited by speculators are lower in periods of extreme negative returns and high volatility of collateral. Second, we turn to fundamental determinants of DAI prices. We find DAI peg-prices are determined through three channels: speculative beliefs on the state of collateral, liquidations and safe-haven demand. Consistent with our channel of speculative beliefs, we observe a negative correlation between DAI prices and ETH returns. A decomposition analysis reveals that the state of ETH collateral, via ETH returns, is the most important determinant for DAI prices, whereas liquidations and demand contribute more to the volatility of the peg. Third, 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 should be designed. Our bottom line: stablecoins need to be backed by liquid, risk-free reserves.

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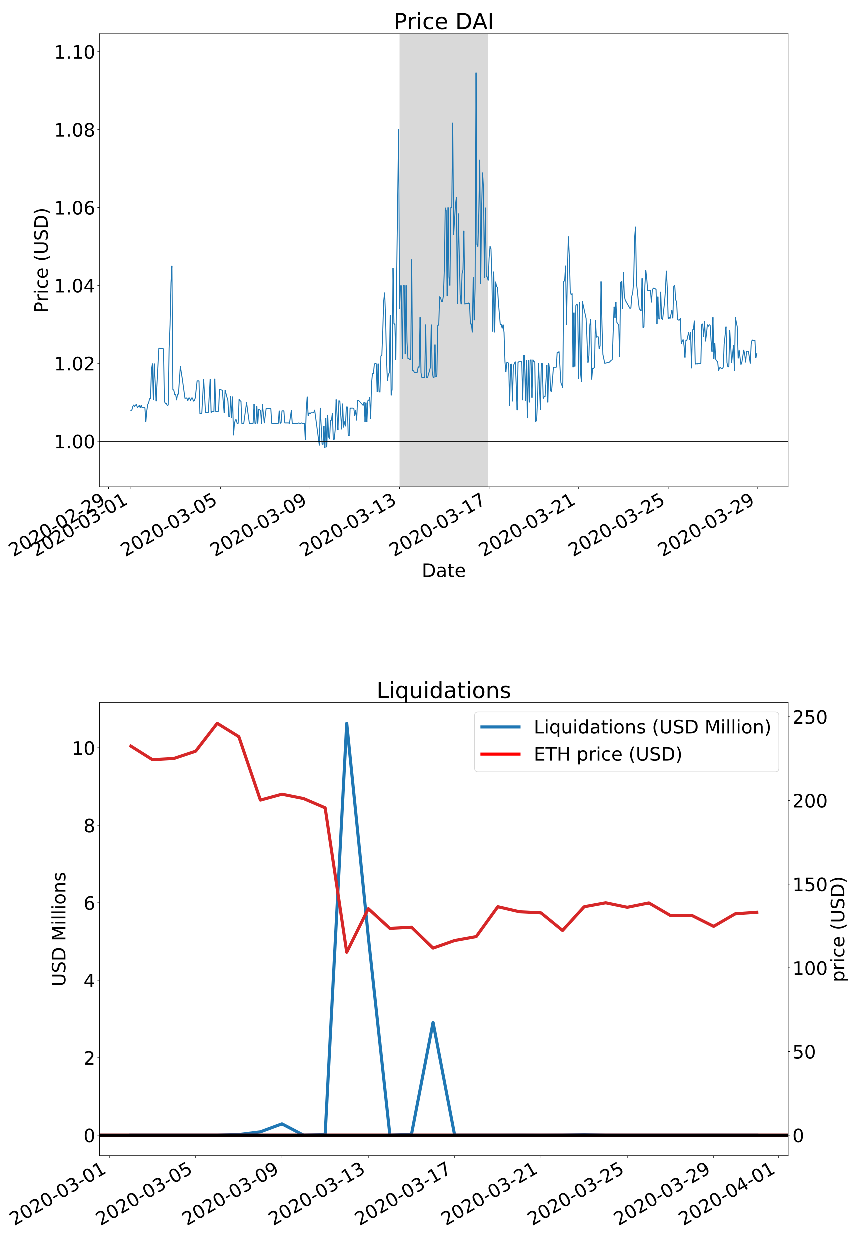
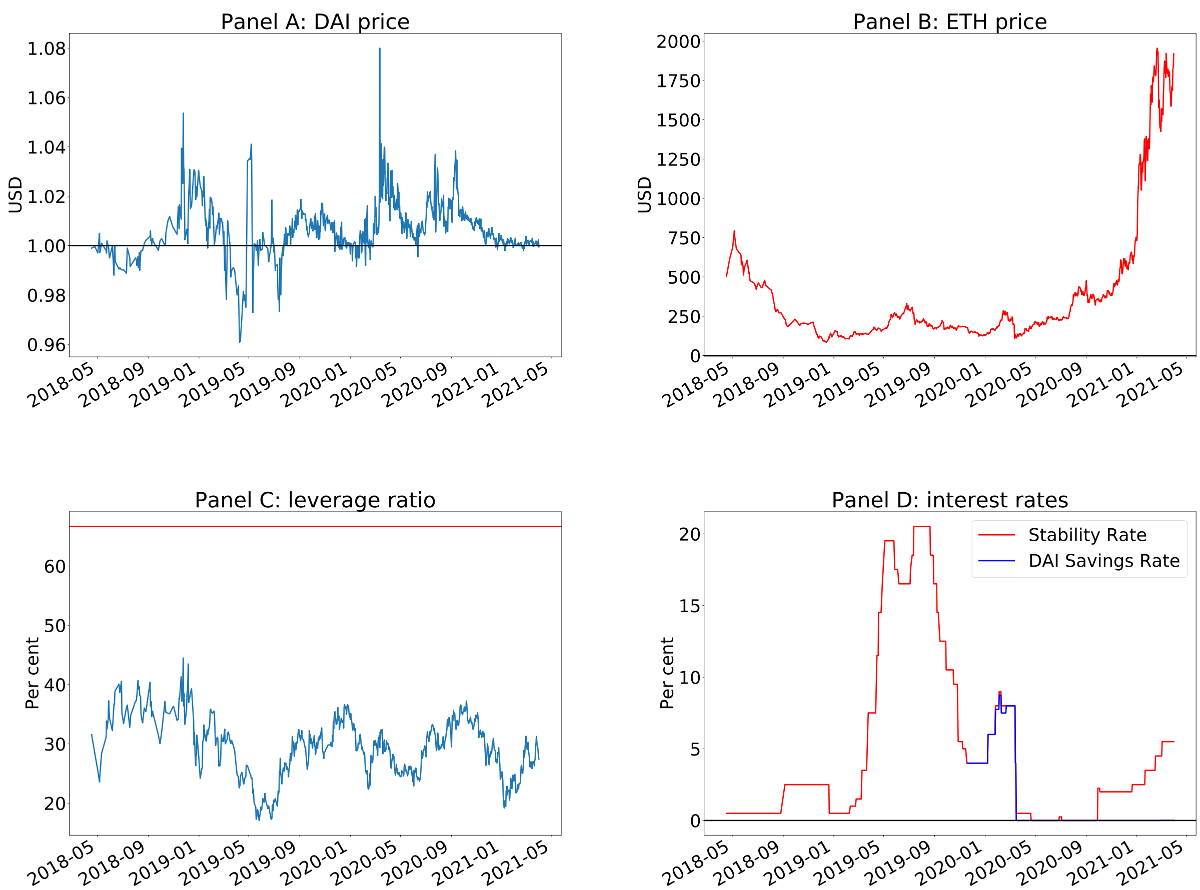
Figures

Figure 1: DAI price and liquidations response to negative price shock of ETH in March 2020



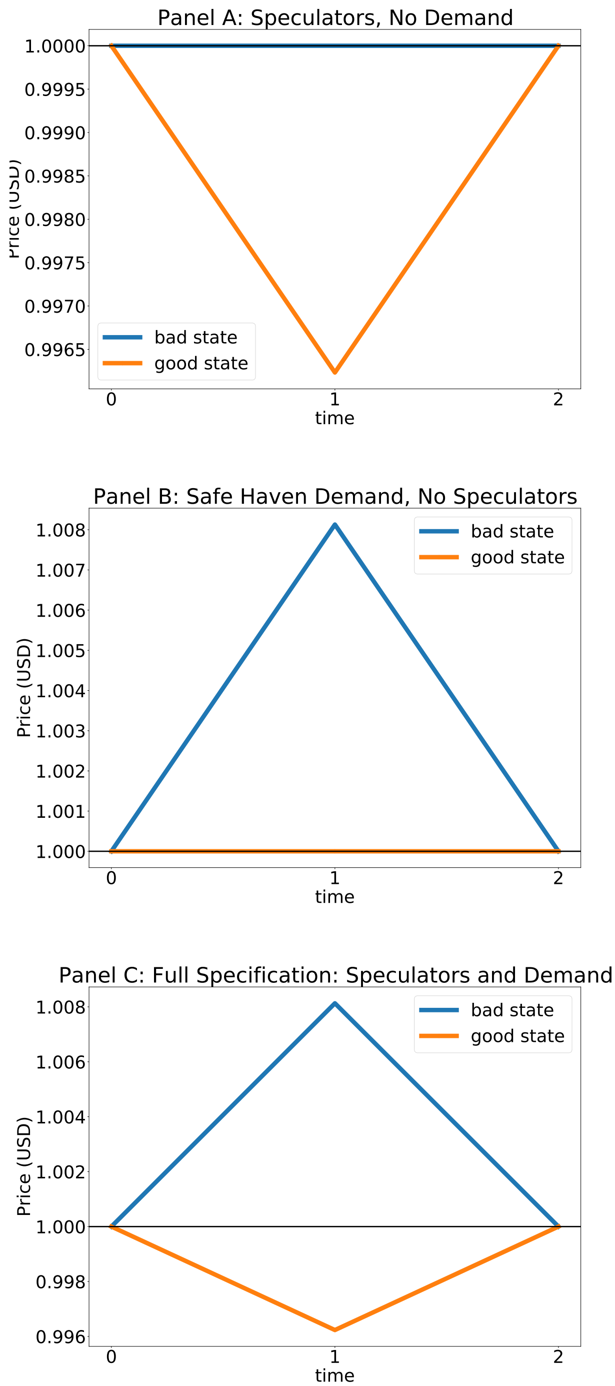
DAI price in USD, ETH price in USD and DAI liquidations during the month of March 2020. Shaded areas indicate the period when the price of ETH fell approximately 50% from 12 March 2020 to 13 March 2020.

Figure 2: DAI price, ETH price, Leverage, Stability rate



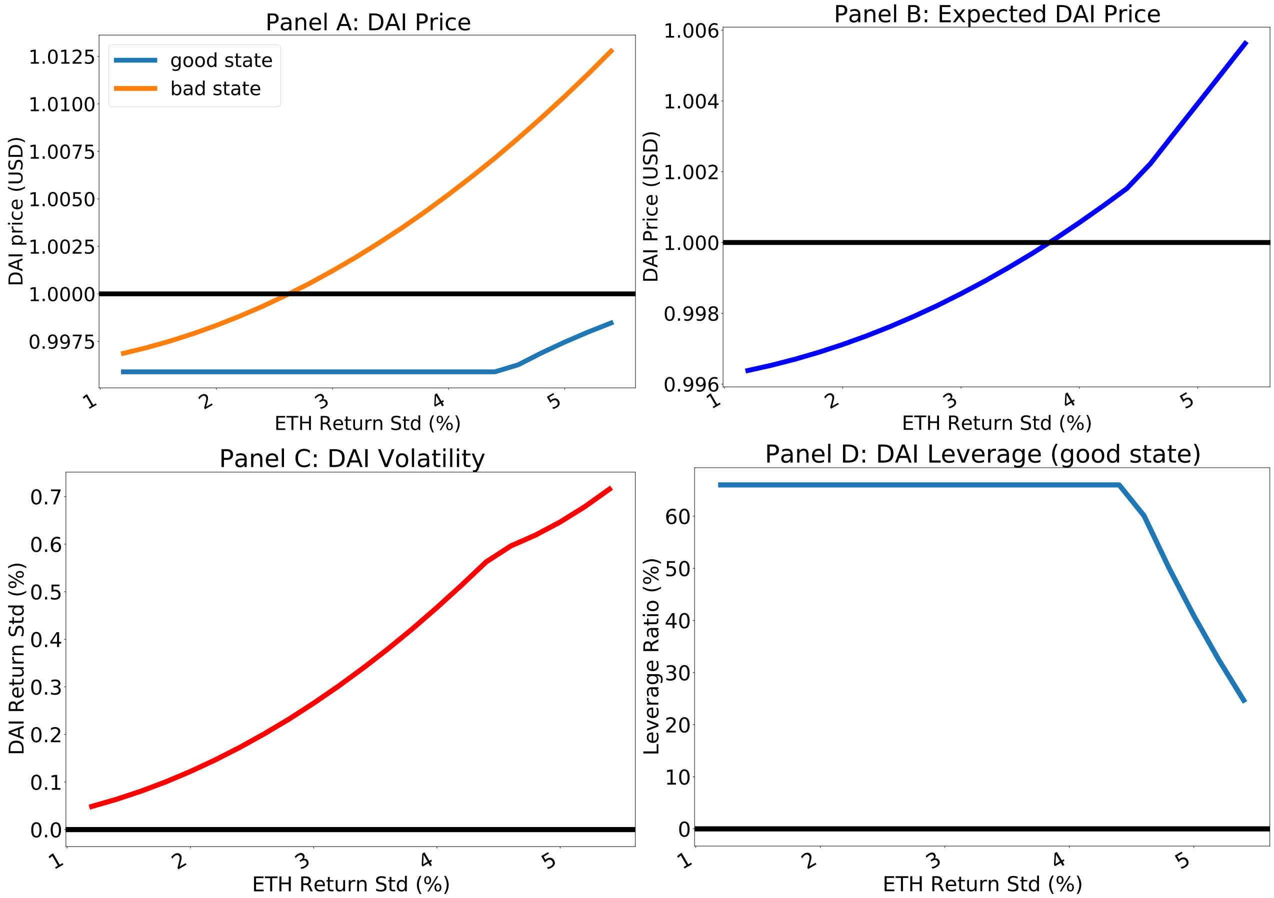
This figure plots Panel A: DAI price, Panel B: ETH price Panel C: leverage in ETH vaults, and Panel D: the interest rate on DAI borrowings. Sample period is from 13 April 2018 to 31 March 2020.

Figure 3: DAI prices across good and bad states of ETH collateral



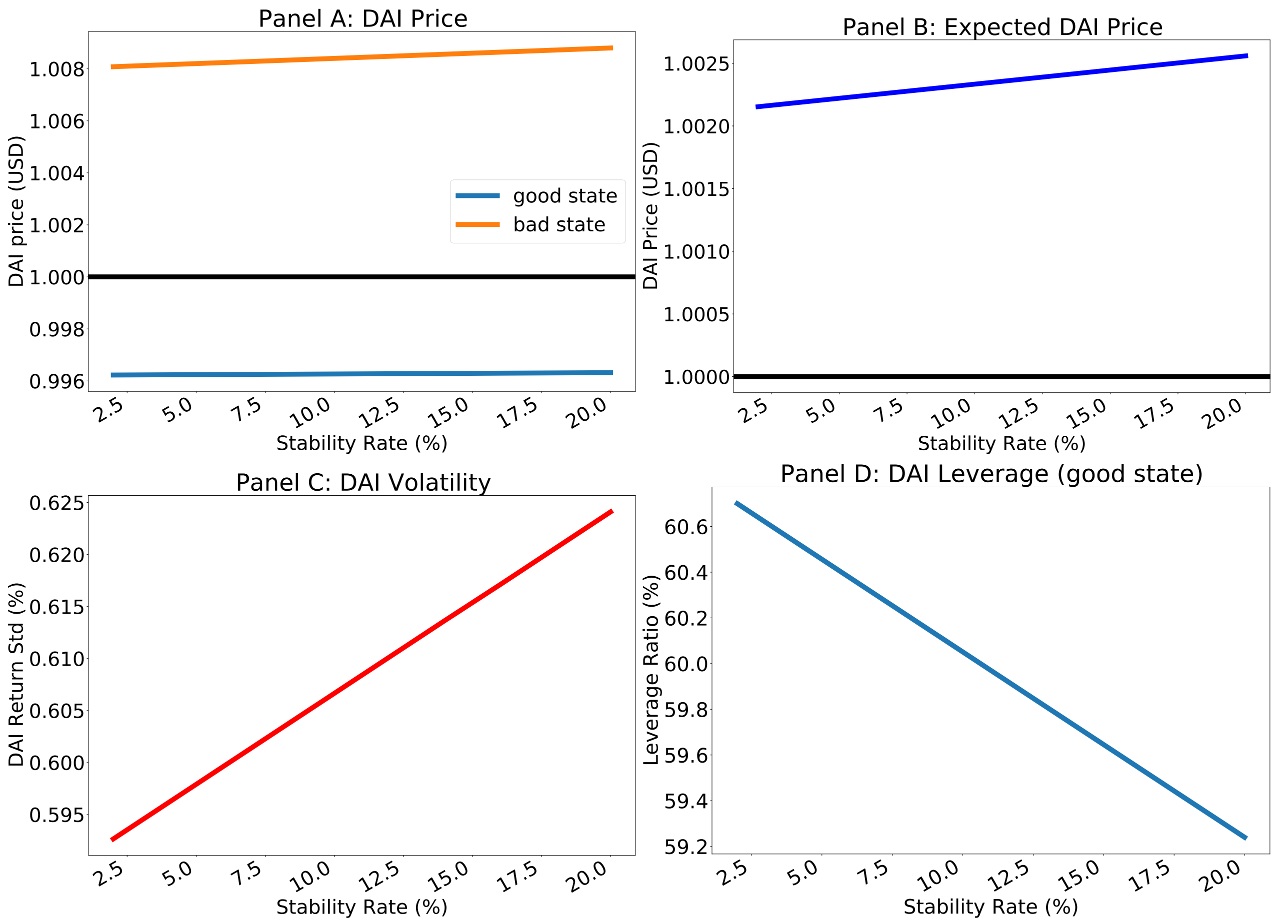
This figure plots DAI prices for both good and bad states of nature. Panel A plots DAI prices for a specification with no safe-haven demand ($D(G) = D(B) = 0$) and only speculators and arbitrageurs trading in period 1. Panel B plots DAI prices for a specification with safe-haven demand ($D(B) = \$50$, $D(G) = \$0$) and arbitrageurs but no speculative trading in period 1 ($\mu_E(G) = \mu_E(B) = \mu_A$). Panel C plots DAI prices for the full specification with safe-haven demand, speculative beliefs and arbitrageurs present. The rest of the primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_1^s = \$350$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure 4: DAI prices, volatility and leverage across different values of ETH volatility



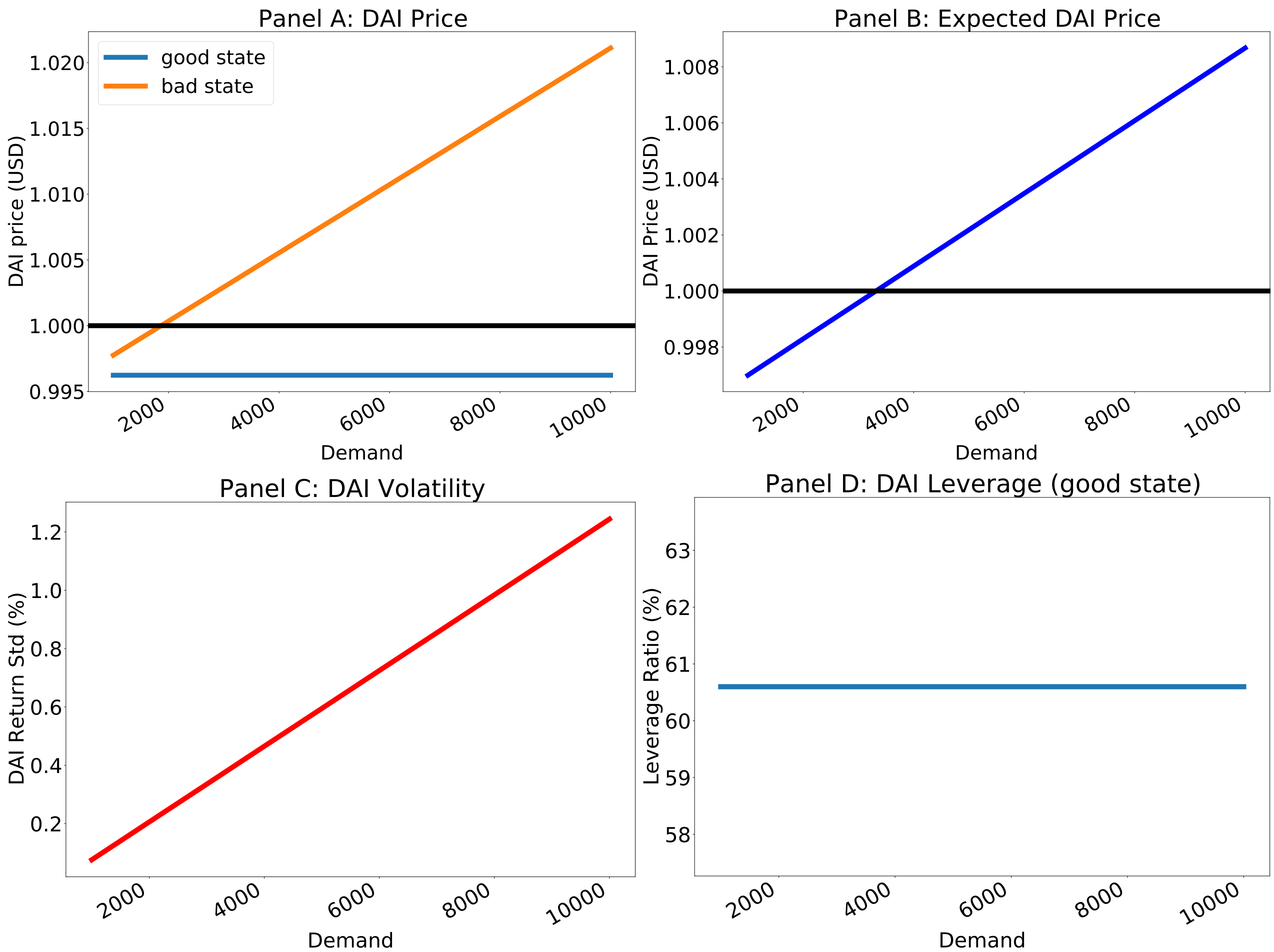
This figure plots DAI prices, volatility and leverage as a function of ETH volatility, holding all other parameters constant. Panel A corresponds to DAI prices in the good and bad states respectively. Panel B corresponds to the expected DAI price, with the good and bad states occurring with probability 0.5. Panel C corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. Panel D corresponds to DAI leverage, calculated in per cent. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_1^s = \$350$, $D(B) = \$50$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure 5: DAI prices, volatility and leverage across different values of stability rate



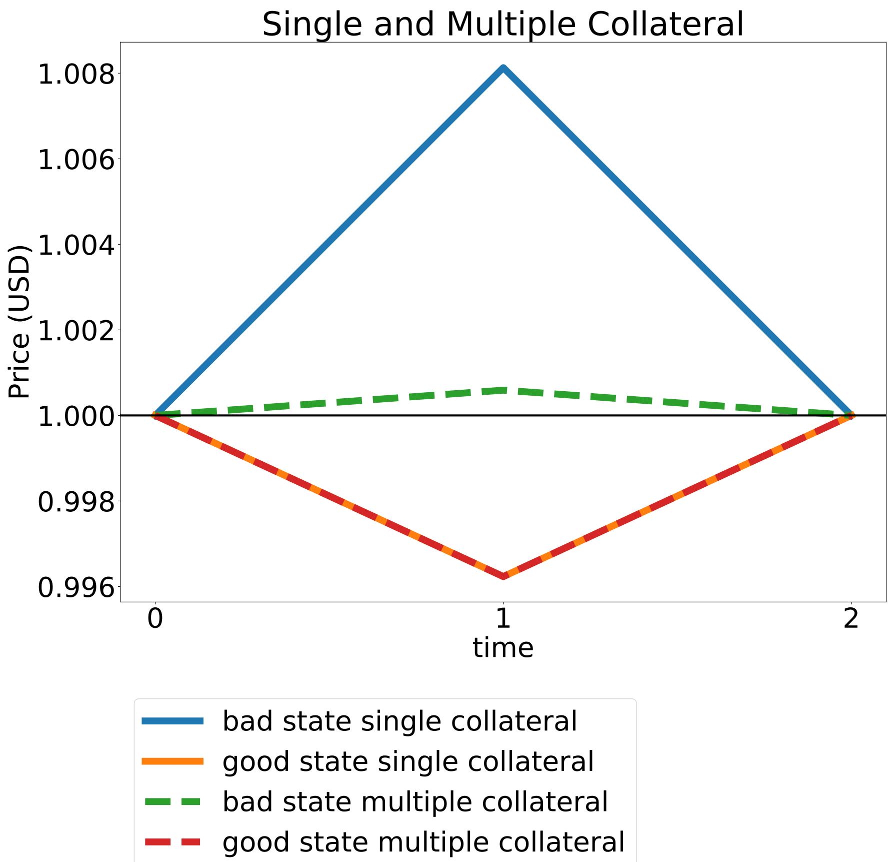
This figure plots DAI prices, volatility and leverage as a function of the interest rate on DAI borrowings, holding all other parameters constant. Panel A corresponds to DAI prices in the good and bad states respectively. Panel B corresponds to the expected DAI price, with the good and bad states occurring with probability 0.5. Panel C corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. Panel D corresponds to DAI leverage, calculated in per cent. The primitive parameters are f follows: $\gamma = 0.5$, $\pi = 0.5$, $W_1^s = \$350$, $D(B) = \$50$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $\sigma_E = 0.0459$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure 6: DAI prices, volatility and leverage across different values of safe-haven demand



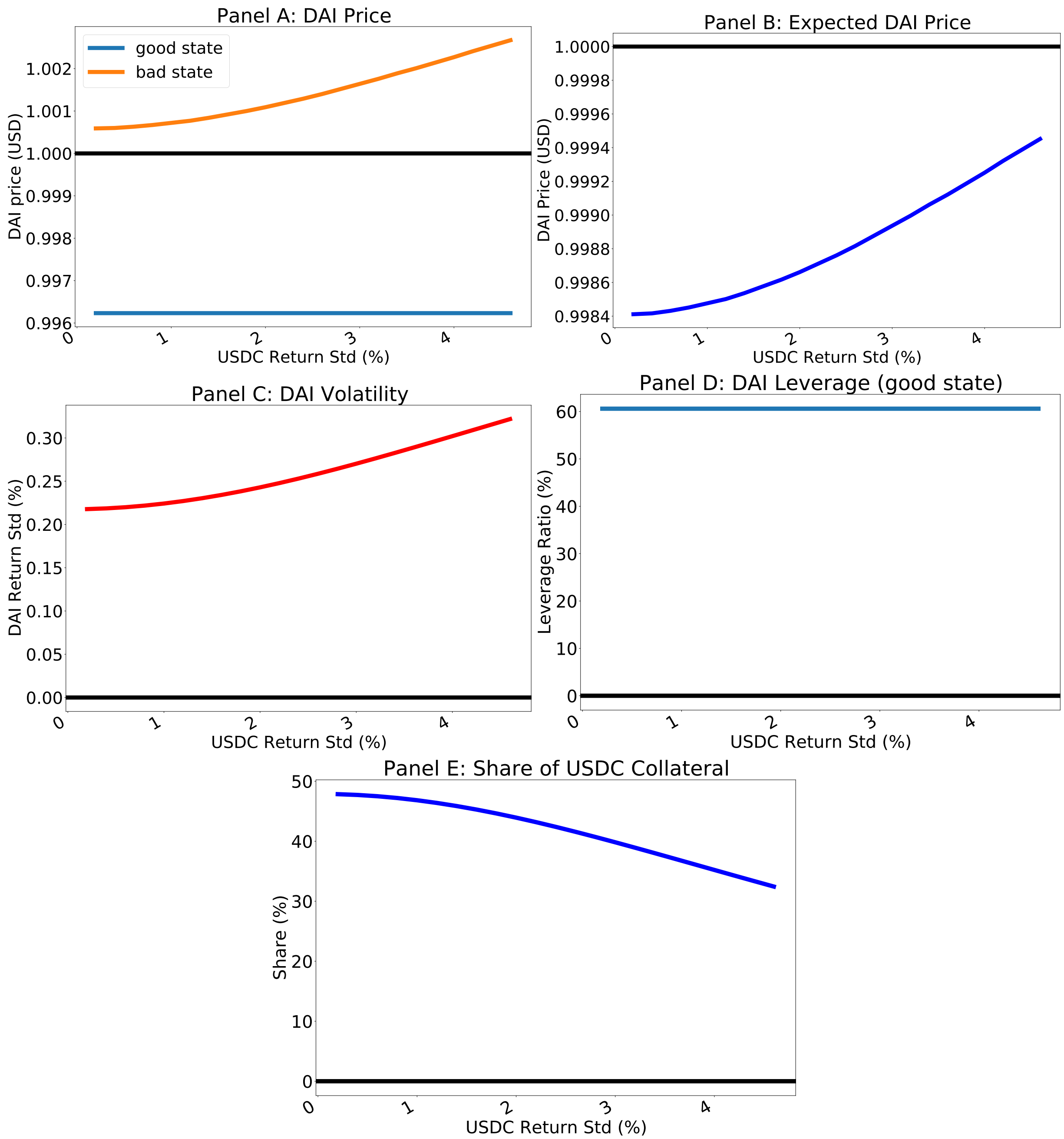
This figure plots DAI prices, volatility and leverage as a function of safe-haven demand, holding all other parameters constant. Panel A corresponds to DAI prices in the good and bad states respectively. Panel B corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. Panel C corresponds to DAI leverage, calculated in per cent. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_1^s = \$350$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $\sigma_E = 0.0459$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure 7: DAI price for single and multiple collateral system



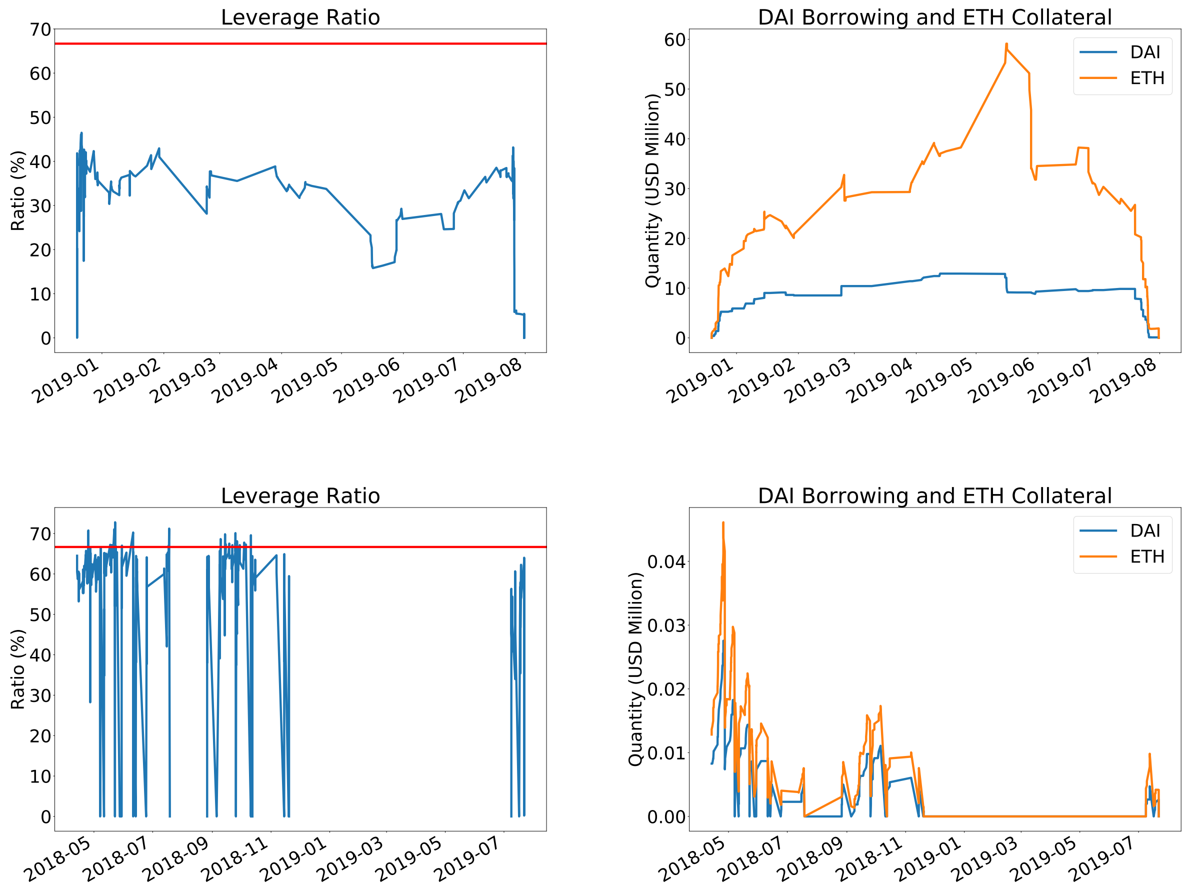
This figure plots DAI prices for both good and bad states of nature. Solid lines is for the specification with only unstable (ETH) collateral, and is a full specification with safe-haven demand and when speculators and arbitrageurs are both present. Dotted line indicates a specification with multiple collateral. In this case, while speculators have access to ETH collateral, arbitrageurs have access to USDC collateral with volatility $\sigma_U = 0.0013$. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_1^s = \$350$, $D(B) = \$50$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\sigma_E = 0.0459$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure 8: DAI prices, volatility, leverage and share of USDC collateral versus USDC volatility



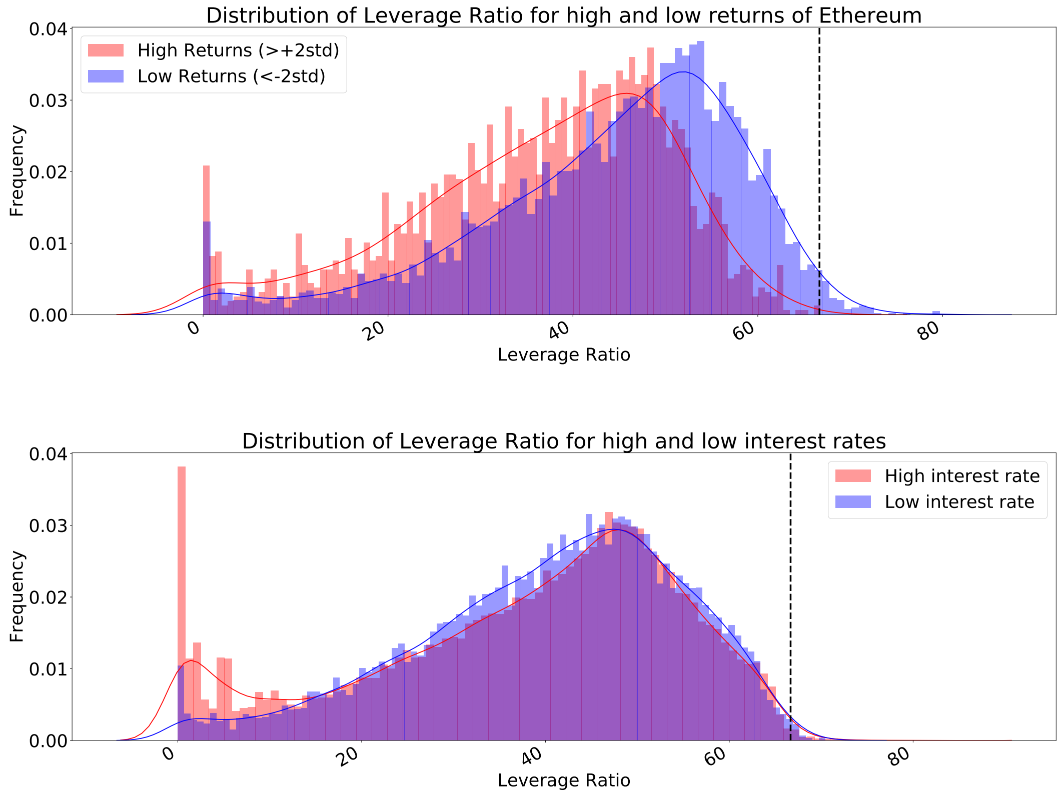
This figure plots DAI prices, volatility, leverage and the share of USDC collateral as a function of USDC volatility, holding all other parameters constant. Panel A corresponds to DAI prices in the good and bad states respectively. Panel B corresponds to the expected DAI price, with the good and bad states occurring with probability 0.5. Panel C corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. Panel D corresponds to DAI leverage, calculated in per cent. Panel E corresponds to the share of stable collateral as a ratio to total collateral deposited by both speculators and arbitrageurs. The primitive parameters are as follows: $\gamma = 0.5$, $\pi = 0.5$, $W_1^s = \$350$, $D(B) = \$50$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $\sigma_E = 0.0459$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure 9: Time Series of Leverage Ratio, DAI borrowings and ETH collateral for two CDPs



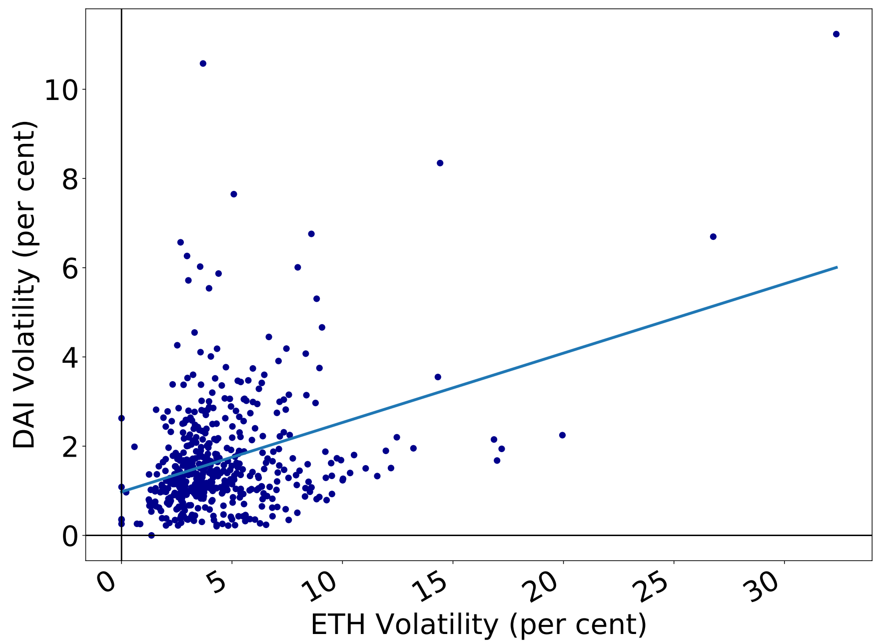
Top panel: Time series of leverage ratio (left) and DAI borrowings and ETH collateral for CDP #5199. Bottom panel: Time series of leverage ratio (left) and DAI borrowings and ETH collateral for CDP #1272. CDP transactions are aggregated to a daily frequency, with sample period from 13 April 2018 to 18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

Figure 10: Distribution Conditional on ETH Returns



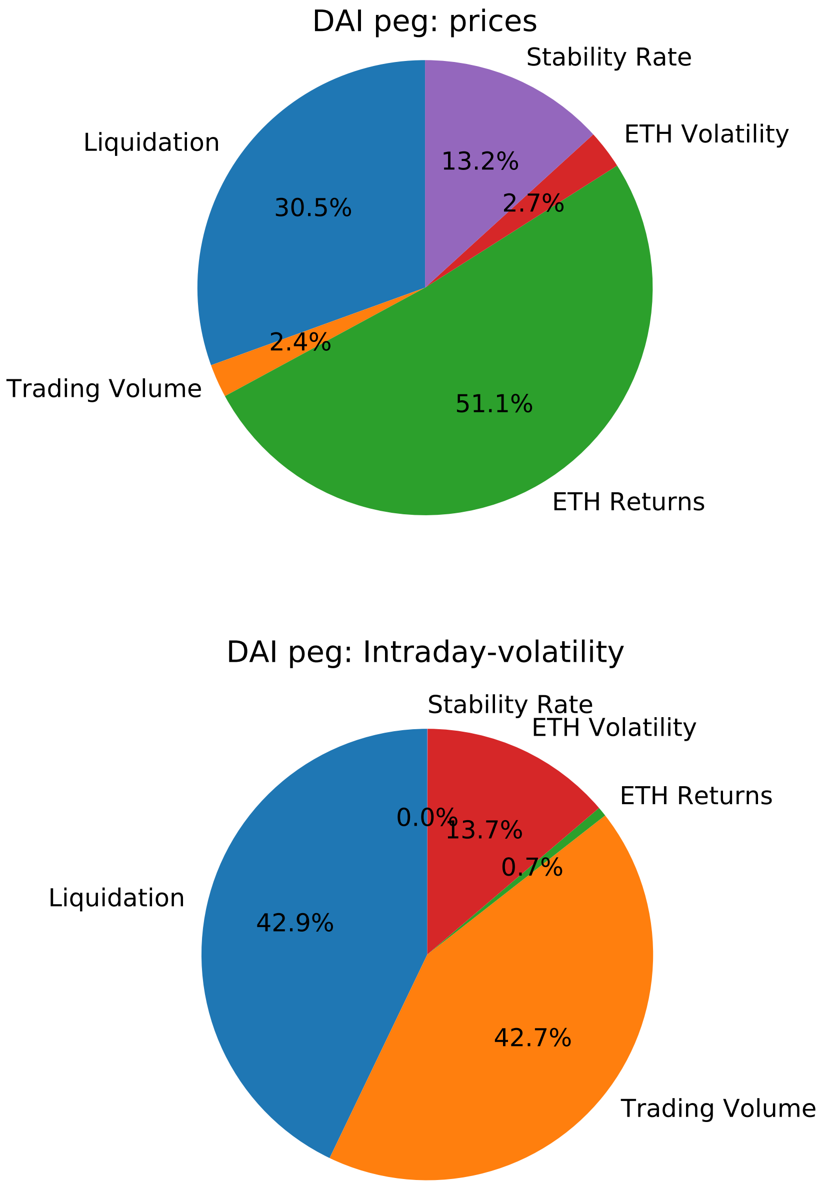
This figure plots the kernel density of the leverage ratio for all CDPs. Top panel: Distributions are conditioned on periods of high and low returns of ETH, where high returns corresponds to returns that exceed +2std of ETH returns, and low returns corresponds to returns that are less than -2 std of 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 13 April 2018 to 18 November 2019.

Figure 11: DAI and ETH intra-day volatility



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 18 November 2019 to 31 March 2021, corresponding to the period of Multi Collateral DAI.

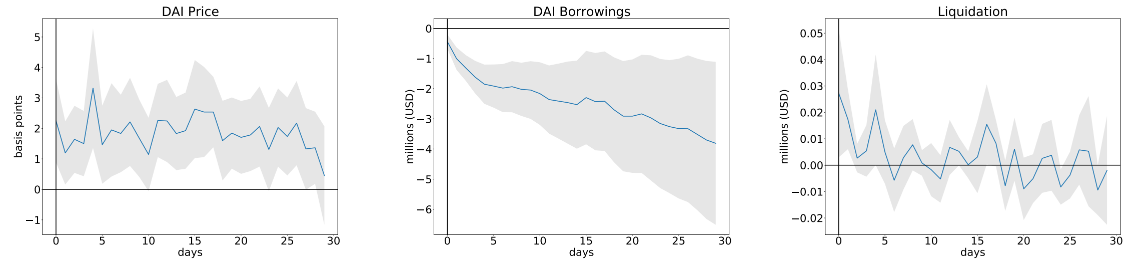
Figure 12: Contribution of fundamentals to peg-rice and volatility



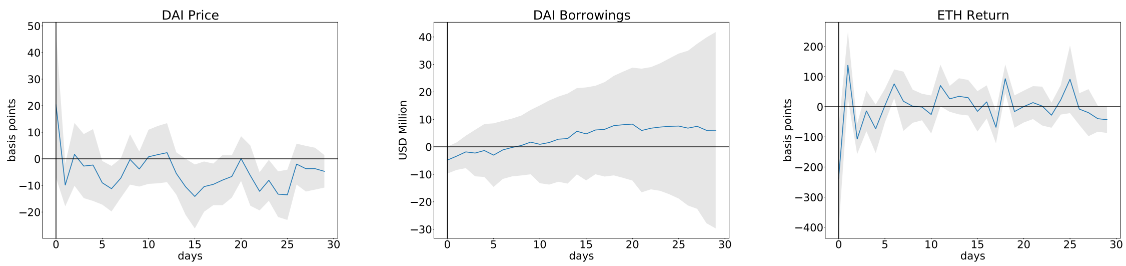
This figure plots a pie chart showing the contribution of fundamentals to peg-price and volatility. Variables include ETH returns and volatility, the stability rate, liquidations of ETH collateral and demand (measured by the per cent change in secondary market trading volume of DAI). The decomposition is based on an ANOVA, which reports the sum of squares explained by each variable. In calculations, the percentage contribution is the sum of squares contribution of each variable.

Figure 13: Effect of ETH returns, liquidations, DAI trading volume and stability rate on DAI

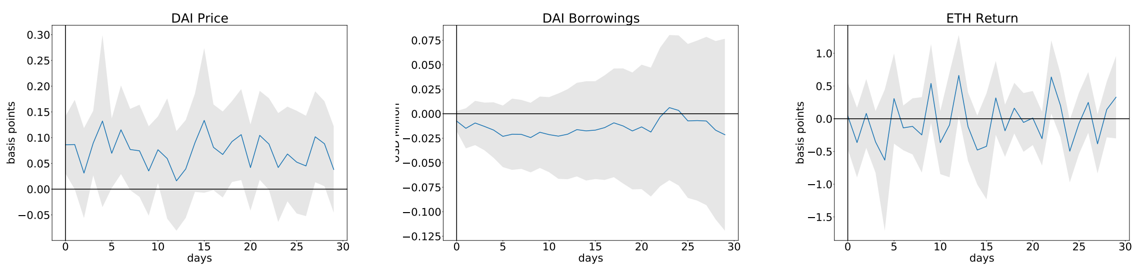
Panel A: ETH returns



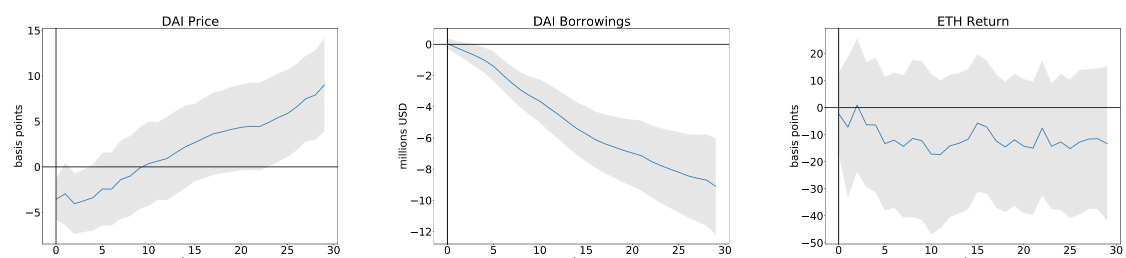
Panel B: Liquidations



Panel C: DAI trading volume

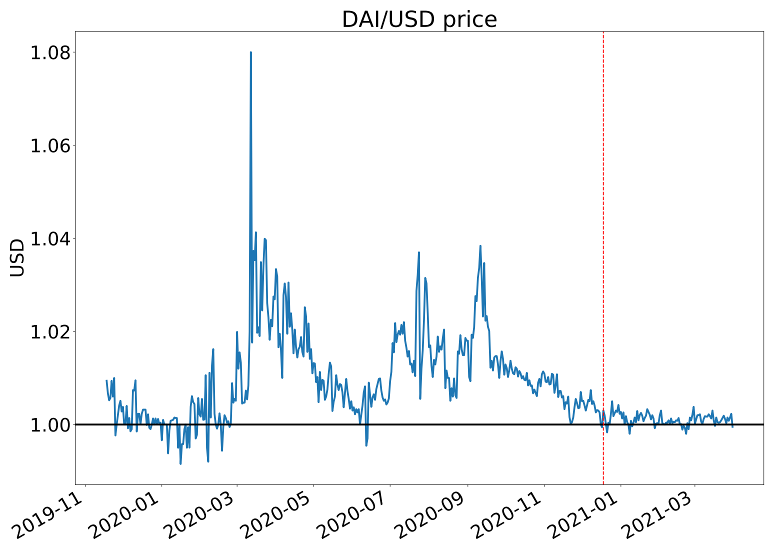


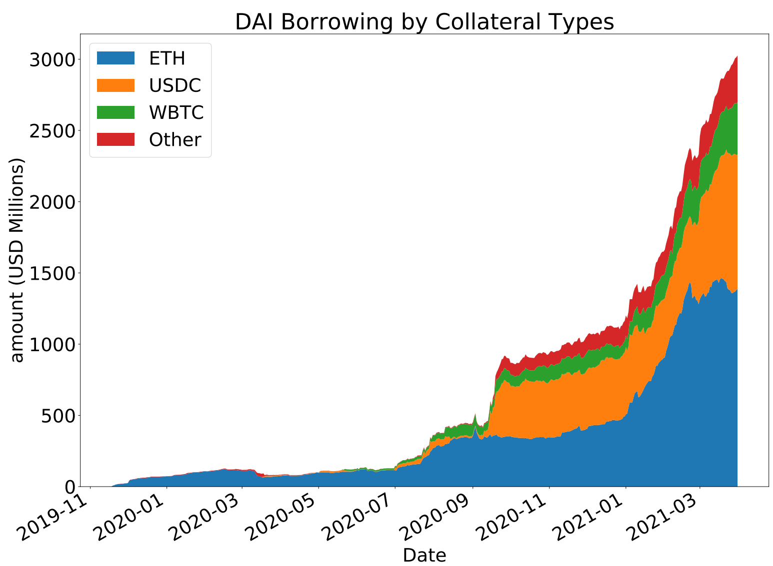
Panel D: Stability rate



This figure illustrates the response of DAI price and leverage to: Panel A: A negative 100 basis point shock to ETH returns, Panel B: 1 million USD Liquidations, Panel C: 1% change in DAI trading volume, Panel D: 1% change in stability rate fee, using the method of local projections. Leverage ratio is based on aggregate measures of DAI borrowings and ETH collateral. Sample period is from 18 November 2019 to 31 March 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.

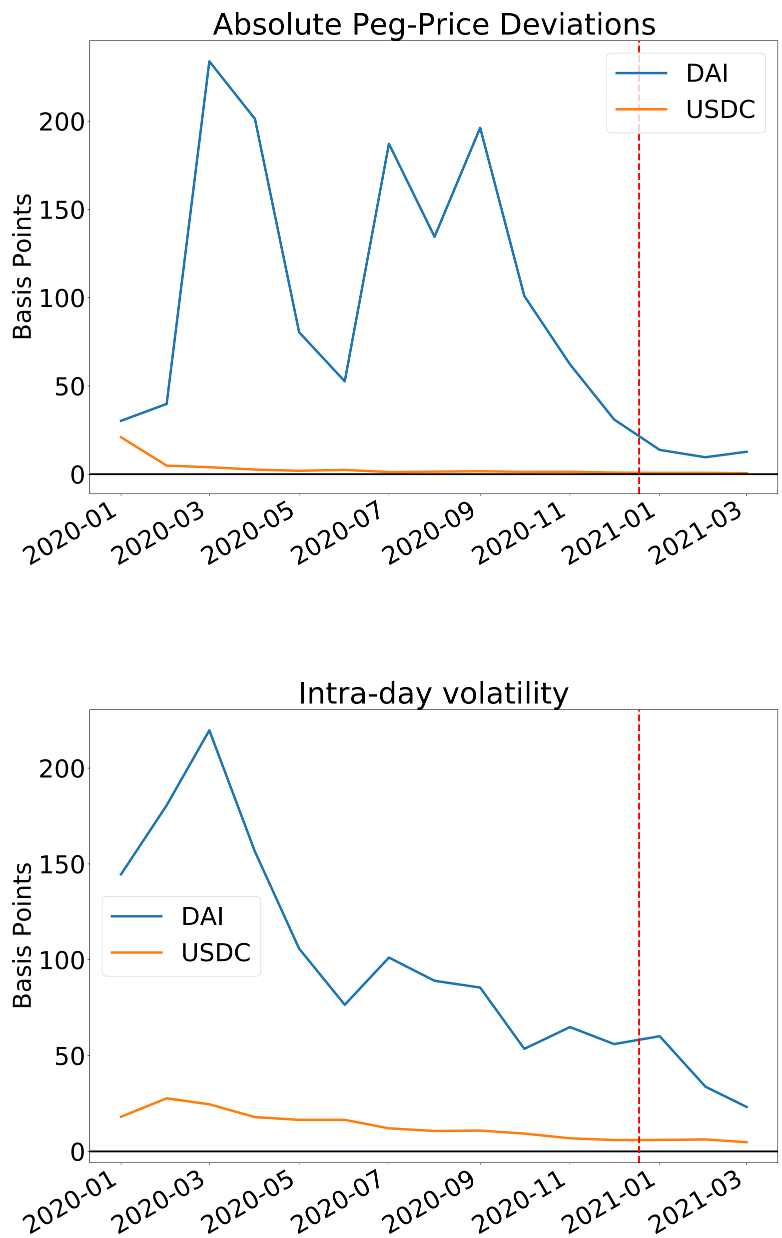
Figure 14: DAI/USD prices





Left panel: This figure plots the deviations of the DAI/USD peg from parity. A positive deviation indicates DAI/USD trades at a premium. Sample period is from 18 November 2019 to 31 March 2020. Right panel: 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 18 November 2019 to 31 March 2020.

Figure 15: DAI vs. USDC: Absolute peg-price deviations and volatility



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 18 December 2020 used in the baseline specification. Sample is 13 April 2018 through to 31 March 2021.

Figure 16: Distribution of peg-price deviations, pre- and post-PSM

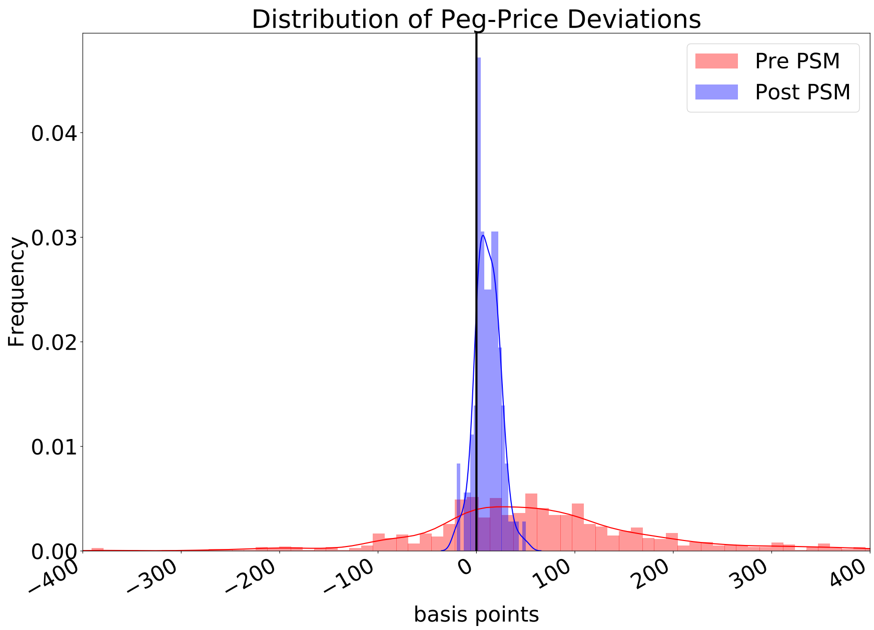
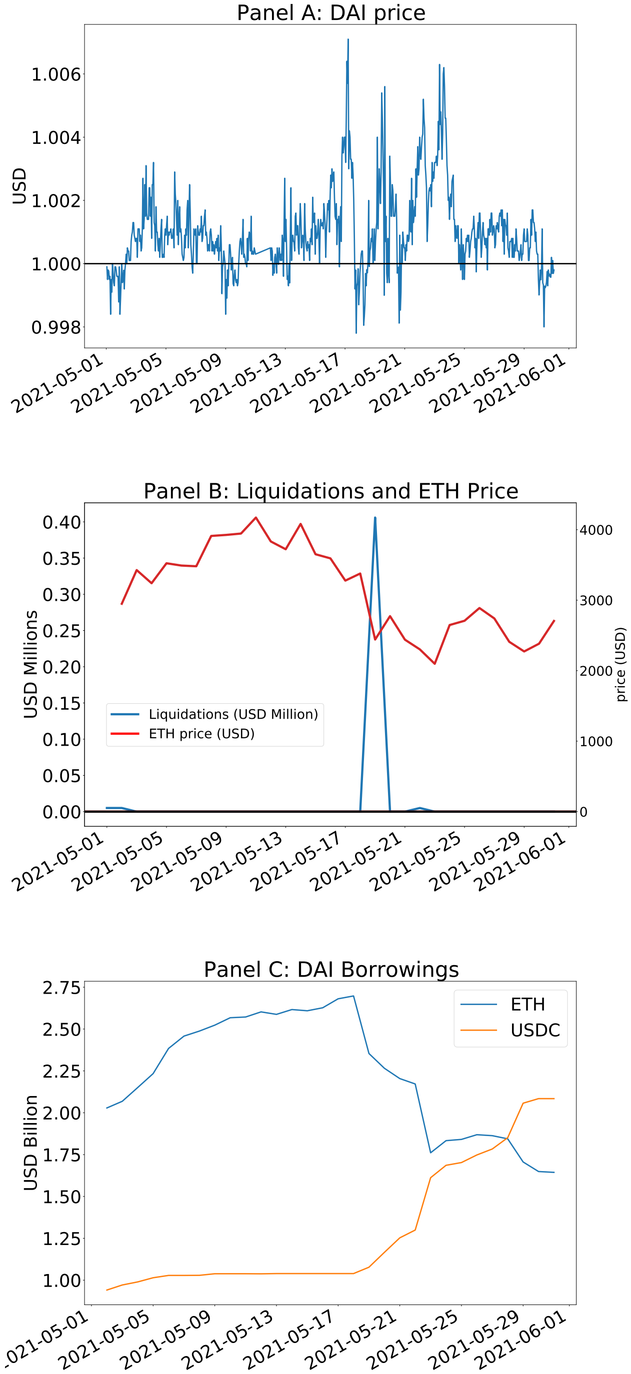


Figure plots a histogram of deviations of the DAI/USD price from parity for sub-samples corresponding to pre and post PSM. A positive deviation indicates DAI/USD trades at a premium. The pre PSM sample is from 18 November 2019 to 18 December 2020. The post PSM sample is from 18 December 2020 to 31 March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

Figure 17: DAI price, liquidations and source of collateral in response to negative price shock of ETH in May 2021



DAI price in USD, ETH price in USD and DAI liquidations and DAI borrowing by collateral type during the month of May 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_{DAI} (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

This table presents summary statistics of key variables in empirical analysis. R_{ETH} measures daily returns in ETH in per cent. Δ_{DAI} 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 13 April 2018 to 31 March 2021.

Table 2: Correlation matrix

	R_{ETH}	Δ_{DAI}	Stability Rate	Leverage Ratio
R_{ETH}	1.000	-0.044	-0.015	-0.209
Δ_{DAI}	-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

This table presents pairwise correlation of key variables in empirical analysis. R_{ETH} measures daily returns in ETH in per cent. Δ_{DAI} 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 13 April 2018 to 31 March 2021.

Table 3: CDP summary statistics

	count	mean	std	min	25%	50%	75%	max
DAI (USD Million)	11,718	0.015	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

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 13 April 2018 to 17 November 2019, which corresponds to the period of single collateral DAI.

Table 4: Determinants of CDP DAI borrowing, ETH collateral, leverage and liquidation event

	$DAI_{i,t}$	$ETH_{i,t}$	$Bite_{i,t}$
$DAI_{i,t-1}$	0.993***		
	(0.005)		
$ETH_{i,t-1}$		0.976***	
		(0.004)	
$R_{ETH,t}$	0.460**	3.434**	-0.075***
	(0.221)	(1.441)	(0.006)
$\sigma_{ETH,t}$	-0.254	0.260	0.126***
	(0.347)	(1.952)	(0.011)
$sfee_t$	-0.632*	-1.684**	0.019***
	(0.332)	(0.735)	(0.005)
Intercept	9.178***	24.311**	-4.09***
	(2.633)	(11.248)	(0.129)
Nr. obs.	11,197	11,197	25,125
Nr. ids.	456	456	456
id FE	Yes	Yes	Yes

This table presents the estimation results of the following panel regression:

$$Y_{i,t} = \alpha_i + \beta_1 R_{ETH,t} + \beta_2 \sigma_{ETH,t} + \beta_3 sfee_t + u_{i,t},$$

where the dependent variable $Y_{i,t}$ is one of the following variables: $DAI_{i,t}$ (the individual DAI borrowing at time t of CDP i in thousands of USD), $ETH_{i,t}$ (the individual ETH collateral of CDP i in thousands of USD), and $Bite_{i,t}$ (a dummy variable indicating a "bite", which is a liquidation event at time t of CDP i). Explanatory variables include daily ETH returns $R_{ETH,t}$ (in per cent), daily intra-day volatility of ETH returns $\sigma_{ETH,t}$ (in per cent), the interest rate on DAI borrowings $sfee_t$ (in per cent per annum). The sample runs from 13 April 2018 to 17 November 2019, which corresponds to the period of single collateral DAI. For $Bite_{i,t}$ dependent variable we use a panel probit specification. White heteroscedasticity-robust standard errors are reported in parentheses, and are clustered at the individual CDP level. All specifications include CDP fixed effects. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5: DAI peg-price fundamentals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	L_t	D_t	$\Delta_{DAI,t}$					
$\Delta_{DAI,t-1}$			0.818***	0.796***	0.758***	0.786***	0.809***	0.765***
			(0.027)	(0.028)	(0.031)	(0.028)	(0.028)	(0.030)
$R_{ETH,t}$	-0.312***	-0.943**	-0.037***					-0.029***
	(0.111)	(0.385)	(0.005)					(0.005)
$\sigma_{ETH,t}$	1.532***	3.641***		0.013				-0.015
	(0.134)	(0.749)		(0.010)				(0.011)
$sfee_t$	0.102	-0.243			-0.035***			-0.038***
	(0.104)	(0.784)			(0.011)			(0.011)
L_t						0.018***		0.014***
						(0.004)		(0.004)
D_t							0.003***	0.002***
							(0.001)	(0.0006)
Intercept	-538.4***	-659.5	19.03***	12.39**	30.13***	17.40***	14.88***	35.81***
	(53.20)	(409.7)	(3.491)	(5.393)	(5.483)	(3.621)	(3.677)	(6.269)
R-sq.	40.5%	6.2%	68.5%	64.3%	65.0%	66.0%	65.8%	70.6%
Nr. obs.	454	454	454	454	454	454	454	454

This table presents the estimation results of the following regression models:

$$
\begin{aligned}
L_t &= a_0 + a_1 R_{ETH,t} + a_2 \sigma_{ETH,t} + a_3 sfee_t + u_t, && \text{Column (1)},\\
D_t &= b_0 + b_1 R_{ETH,t} + b_2 \sigma_{ETH,t} + b_3 sfee_t + u_t, && \text{Column (2)},\\
\Delta_{DAI,t} &= \beta_0 + \beta_1 \Delta_{DAI,t-1} + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + \beta_4 sfee_t + \beta_5 L_t + \beta_6 D_t + u_t, && \text{Columns (3)-(8)},
\end{aligned}
$$

where the dependent variables in columns (1) and (2) are L_t (value of liquidations in thousands of USD) and D_t (the aggregate growth in DAI trading volume across major exchanges in basis points) respectively. The dependent variable in columns (3) to (8) is $\Delta_{DAI,t}$ (the DAI peg-price deviation $p_{DAI,t} - 1$, in basis points). Explanatory variables include daily ETH returns $R_{ETH,t}$ (in basis points), daily intra-day volatility of ETH returns $\sigma_{ETH,t}$ (in basis points), the interest rate on DAI borrowings $sfee_t$ (in per cent per annum), the value of liquidations L_t (in thousands of USD) and aggregate growth in DAI secondary market trading volume D_t (in basis points). The sample runs from 18 November 2019 to 31 March 2021, corresponding to the period of Multi Collateral DAI. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6: DAI volatility fundamentals

	(1)	(2)	(3)	(4)	(5)	(6)
			$\sigma_{DAI,t}$			
$\sigma_{DAI,t-1}$	0.642***	0.624***	0.633***	0.634***	0.646***	0.635***
	(0.036)	(0.037)	(0.037)	(0.036)	(0.036)	(0.037)
$R_{ETH,t}$	-0.007					-0.002
	(0.005)					(0.005)
$\sigma_{ETH,t}$		0.023**				0.004
		(0.010)				(0.012)
$sfee_t$			0.013			0.010
			(0.010)			(0.010)
L_t				0.010***		0.007
				(3.524)		(4.554)
D_t					0.002***	0.002***
					(0.0006)	(0.0006)
Intercept	34.74***	25.72***	31.77***	34.03***	32.24***	29.07***
	(4.365)	(5.583)	(4.786)	(4.329)	(4.362)	(6.206)
R-sq.	40.9%	41.4%	40.9%	41.8%	42.1%	42.5%
Nr.obs.	454	454	454	454	454	454

This table presents the estimation results of the following regression models:

$$\sigma_{DAI,t} = \beta_0 + \beta_1 \sigma_{DAI,t-1} + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + \beta_4 sfee_t + \beta_5 L_t + \beta_6 D_t + u_t,$$

where the dependent variable $\sigma_{DAI,t}$ measures the daily intra-day volatility of DAI prices (in basis points). Explanatory variables include daily ETH returns $R_{ETH,t}$ (in basis points), daily intra-day volatility of ETH returns $\sigma_{ETH,t}$ (in basis points), the interest rate on DAI borrowings $sfee_t$ (in per cent per annum), the value of liquidations L_t (in thousands of USD) and aggregate growth in DAI secondary market trading volume D_t (in basis points). The sample runs from 18 November 2019 to 31 March 2021, corresponding to the period of Multi Collateral DAI. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7: Determinants of the share of stable collateral share

	(1)	(2)	(3)	(4)	(5)	(6)
			$share_t$			
$R_{ETH,t}$	0.002				0.001	0.002
	(0.002)				(0.001)	(0.002)
$\sigma_{ETH,t}$		-0.002			0.005**	
		(0.003)			(0.0025)	
$\sigma_{U,t}$			-1.727***		-1.766***	
			(0.110)		(0.112)	
$\frac{\sigma_{ETH,t}}{\sigma_{U,t}}$				0.0014***		0.0014***
				(0.0002)		(0.0002)
Intercept	23.41***	24.47***	42.86***	15.93***	40.83***	15.76***
	(0.961)	(1.703)	(1.438)	(1.335)	(1.702)	(1.341)
R-sq.	0.28%	0.11%	39.1%	13.2%	39.9%	13.6%
Nr. obs.	385	385	385	385	385	385

Table presents the estimation results of the regression of the share of stable collateral on ETH returns and ETH and USDC intra-day volatility:

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

where the dependent variable $share_t$ measures the share of total stable collateral deposited in vaults: this includes stablecoins USDC, Tether and TrueUSD (in percent). The explanatory variables include daily ETH returns $R_{ETH,t}$ (in basis points), daily intra-day volatility of USDC ($\sigma_{U,t}$) and ETH ($\sigma_{ETH,t}$) returns (in basis points) as well as the ratio of these volatilties. The sample runs from 12 March 2020 to 31 March 2021. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8: DAI-ETH return correlations in the pre- and post-USDC collateral periods

	(1) $\Delta_{DAI,t}$	(2) $\Delta_{DAI,t}$	(3) $\sigma_{DAI,t}$	(4) $\sigma_{DAI,t}$
$\Delta_{DAI,t-1}$	0.605***	0.707***		
	(0.092)	(0.031)		
$\sigma_{DAI,t-1}$			0.221**	0.469***
			(0.086)	(0.042)
$R_{ETH,t}$	-0.054***	-0.012**	0.045***	-0.003
	(0.010)	(0.005)	(0.015)	(0.004)
$\sigma_{ETH,t}$	0.130***	-0.021**	0.177***	0.016*
	(0.023)	(0.010)	(0.033)	(0.008)
$\Delta_{U,t}$		0.728		-1.505*
		(0.969)		(0.816)
$\sigma_{U,t}$		0.802*		2.227***
		(0.461)		(0.396)
$sfee_t$	0.785	-7.658***	9.863**	-5.562***
	(2.579)	(1.760)	(4.098)	(1.459)
Intercept	-39.25**	40.913***	-21.85	20.433***
	(15.02)	(6.685)	(21.86)	(5.695)
R-sq.	70.7%	44.7%	41.1%	57.8%
Nr. obs.	115	383	115	383
Pre USDC	Yes	No	Yes	No
Post USDC	No	Yes	No	Yes

This table presents the estimation results of the following regression models:

$$\Delta_{DAI,t} = \beta_0 + \beta_1 \Delta_{DAI,t-1} + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + \beta_4 \Delta_{U,t} + \beta_5 \sigma_{U,t} + \beta_6 sfee_t + u_t, \quad \text{Columns (1) and (2),}$$
$$\sigma_{DAI,t} = \beta_0 + \beta_1 \sigma_{DAI,t-1} + \beta_2 R_{ETH,t} + \beta_3 \sigma_{ETH,t} + \beta_4 \Delta_{U,t} + \beta_5 \sigma_{U,t} + \beta_6 sfee_t + u_t, \quad \text{Columns (3) and (4),}$$

where the dependent variables in columns (1) and (2) is $\Delta_{DAI,t}$ (the DAI peg-price deviation $p_{DAI,t} - 1$, in basis points) and in columns (3) and (4) is the daily intra-day volatility of DAI prices $\sigma_{DAI,t}$ (in basis points). Explanatory variables include daily ETH returns $R_{ETH,t}$ (in basis points), daily intra-day volatility of ETH returns $\sigma_{ETH,t}$ (in basis points), daily peg-price deviations of USDC prices $\Delta_{U,t}$ (in basis points), the daily intra-day volatility of USDC per-price deviations $\sigma_{U,t}$ (in basis points), the interest rate on DAI borrowings $sfee_t$ (in per cent per annum). The sample is divided into the Pre-USDC Collateral (columns (1) and (3)) and Post-USDC Collateral period (columns (2) and (4)). The Pre-USDC Collateral sample runs from 18 November 2019 to 11 March 2020. The Post-USDC Collateral sample runs from 12 March 2020 to 31 March 2021. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 9: Tests of a structural break in DAI peg deviations

	(1)	(2)	(3)	(4)
	$\|\Delta\|$	σ	$\|\Delta\|$	σ
$post_t$	-53.73***	-39.90***	-2.732***	-9.295***
	(3.439)	(3.250)	(0.595)	(0.546)
T_i			114.63***	97.356***
			(5.139)	(4.173)
$post_t \times T_i$			-101.83***	-61.07***
			(5.234)	(4.702)
Intercept	60.85***	63.71***	3.454***	14.97***
	(3.374)	(2.794)	(0.592)	(0.489)
R-sq.	7.75%	6.15%	46.4%	47.9%
Nr.obs.	897	897	897	897

Table presents estimation results of the following difference-in-difference regression:

$$Y_{j,t} = \alpha_0 + \beta T_j + \gamma\ post_t + \delta\ post_t \times T_j + u_{j,t},$$

where the outcome variable $Y_{j,t}$ is either the absolute level of peg deviation $|\Delta_{j,t}|$ (columns (1) and (3)), or the intra-day volatility of peg deviations $\sigma_{j,t}$ (columns (2) and (4)) for $j = DAI, U$, both measured in basis points. The post dummy $post_t$ takes a value of 1 from 18 December 2020, which is the launch date of the PSM (swap arrangement in which USDC is swapped with DAI at a 1:1 rate) and 0 otherwise. The Treatment dummy T_j takes a value of 1 for DAI/USD, and 0 for USDC/USD (control-group currency). The sample is based on the balanced panel from 8 January 2020 to 31 March 2021. White heteroscedasticity-robust standard errors are used in estimation. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 10: Summary statistics of peg deviations pre- and post-PSM periods

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

Table presents summary statistics of peg deviations in basis points. A positive deviation indicates DAI/USD trades at a premium. The pre PSM sample is from 18 November 2019 to 18 December 2020. The post PSM sample is from 18 December 2020 to 31 March 2021.

Table 11: SETAR of peg deviations pre- and post-PSM periods

period	ρ_L	ρ_M	ρ_U	Δ_L	Δ_U
Pre-PSM	0.84	1.011	0.759	24bps	290bps
Post-PSM	-0.228	0.913	0.412	1bps	27bps

Table presents results of SETAR analysis:

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

where Δ is peg-price deviations (measured in basis points), the auto-regressive parameter is ρ and 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 pre PSM sample is from 18 November 2019 to 18 December 2020. The post PSM sample is from 18 December 2020 to 31 March 2021.

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.

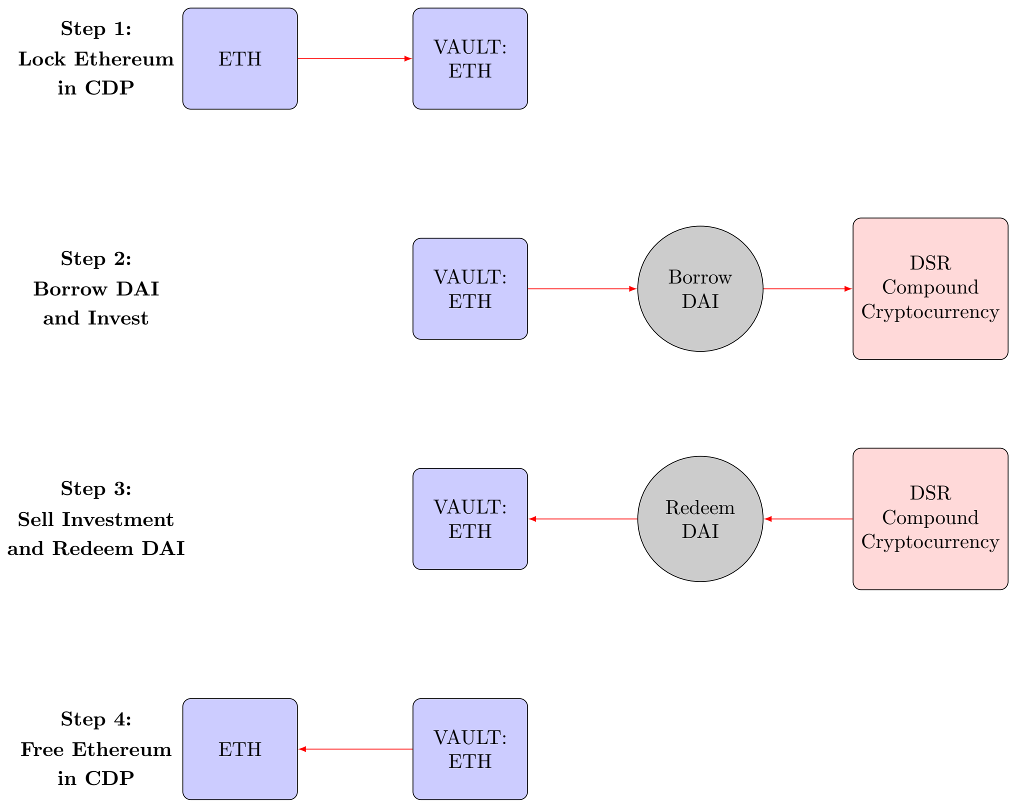
2. Appendix B provides model proofs.

3. Appendix C presents sensitivity analysis with respect to model parameters.

4. Appendix D provides details on the MKR governance token supply and price dynamics.

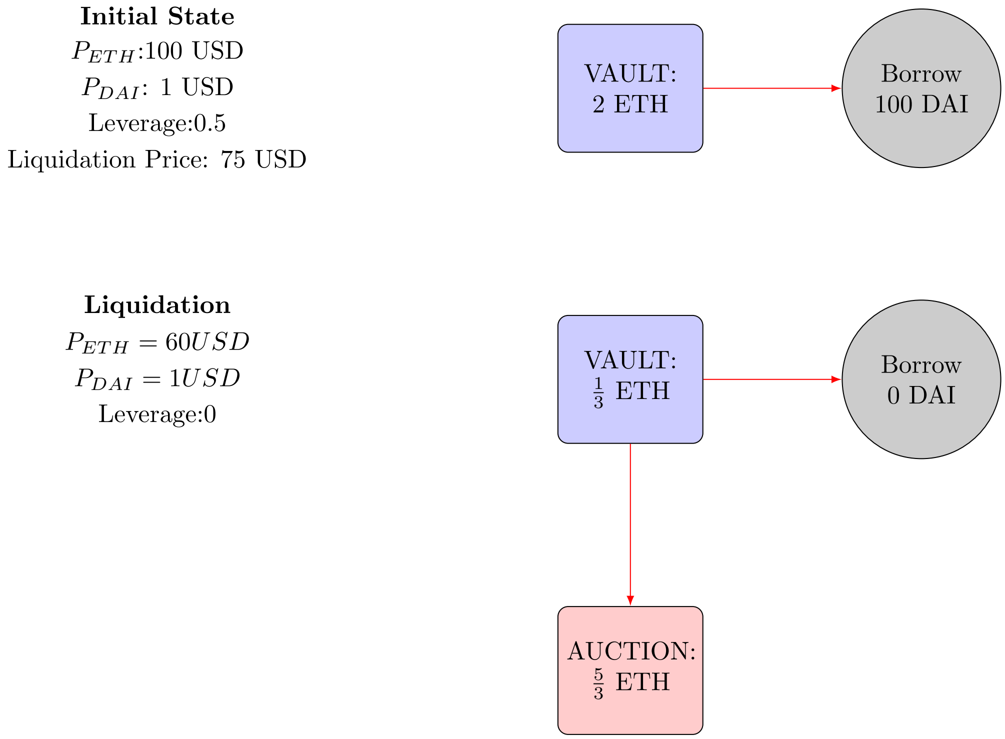
Appendix A: Definitions: CDP and liquidation process

Figure A1: Process of DAI creation



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



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:

$$
\begin{aligned}
L(\theta) &= \mathbb{E}_1[W_2^s] - \frac{1}{2}\gamma Var_1[W_2^s] + \lambda_1\theta + \lambda_2(\bar{\theta} - \theta) &(19)\\
&= W_1^s\left[\mu^S(s)(1+\theta p_1) - \theta - \theta i^B\right] - \frac{\gamma W_1^{s2}}{2}\left[\sigma_E^2(1+\theta p_1)^2 + \theta^2\sigma^2\right] + \lambda_1\theta + \lambda_2(\bar{\theta} - \theta),
\end{aligned}
$$

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

$$0 = W_1^s\left[\mu^S(s)p_1 - 1] - i^B\right] - \gamma W_1^{s2}\left[\sigma_E^2(1+\theta p_1)p_1 + \theta\sigma^2\right] + \lambda_1 - \lambda_2, \tag{20}$$

$$0 = \lambda_1\theta, \tag{21}$$

$$0 = \lambda_2(\bar{\theta} - \theta). \tag{22}$$

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

1. $\theta = 0$.

   Condition $\theta = 0$ implies that $\lambda_1 \geq 0$ and $\lambda_2 = 0$. The first-order condition (20) becomes $\lambda_1 = -W_1^s\left[\mu^S(s)p_1 - 1 - i^B\right] - \gamma W_1^{s2}\sigma_E^2$. Hence, $\lambda_1 \geq 0$ is equivalent to

   $$\mu^S(s)p_1 - 1] - i^B \leq \gamma W_1^s\sigma_E^2.$$

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

   In this case, $\lambda_1 = \lambda_2 = 0$ and the first-order condition (20) becomes

   $$\theta = \frac{\frac{p_1\mu^S(s)-1-i^B}{\gamma W_1^s} - p_1\sigma_E^2}{p_1^2\sigma_E^2 + \sigma^2}. \tag{23}$$

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

   $$p_1\sigma_E^2 < \frac{\mu^S(s)p_1 - 1 - i^B}{\gamma W_1^s} < p_1\sigma_E^2 + \bar{\theta}\left(p_1^2\sigma_E^2 + \sigma^2\right).$$

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

   In this case $\lambda_1 = 0$ and the first-order equation (20) implies

$$\lambda_2 = W_1^s \left[\mu^S(s)p_1 - 1 - i^B\right] - \gamma W_1^{s2} \left[\sigma_E^2(1 + \bar{\theta}p_1)p_1 + \bar{\theta}\sigma^2\right] \geq 0$$

   which holds whenever

$$\frac{\mu^S(s)p_1 - 1 - i^B}{\gamma W_1^s} \geq p_1\sigma_E^2 + \bar{\theta}\left(p_1^2\sigma_E^2 + \sigma^2\right).$$

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 $\omega \geq 0$ and $\omega \leq 0$ separately.

1. $\omega \geq 0$.

   For this case we specify the following Lagrangian function:

$$\begin{aligned} L(\omega) &= \mathbb{E}_1[W_2^a] - \frac{1}{2}\gamma Var_1[W_2^a] + \lambda_1\omega \\ &= W_1^a\left[\frac{\omega(1+i^L)}{p_1} + (1-\omega)(1+r)\right] - \frac{\gamma W_1^{a2}\omega^2(1+i^L)^2\sigma^2}{2p_1^2} + \lambda_1\omega, \quad (24) \end{aligned}$$

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

$$0 = W_1^a\left[\frac{1+i^L}{p_1} - (1+r)\right] - \frac{\gamma W_1^{a2}\omega(1+i^L)^2\sigma^2}{p_1^2} + \lambda_1, \quad (25)$$

$$0 = \lambda_1\omega. \quad (26)$$

   We consider the following cases of values of ω:

   a). $\omega = 0$.

   Condition $\omega = 0$ implies that $\lambda_1 \geq 0$. The first-order condition (25) becomes

$$\lambda_1 = -W_1^a\left[\frac{1+i^L}{p_1} - (1+r)\right].$$

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

$$1 + i^L \leq (1 + r)p_1.$$

b). $\omega > 0$

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

$$\omega = \frac{\left((1 + i^L)/p_1 - (1 + r)\right) p_1^2}{\gamma W_1^a (1 + i^L)^2 \sigma^2}. \tag{27}$$

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

$$1 + i^L > (1 + r)p_1.$$

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

2. $\omega \leq 0$.

For this case we specify the following Lagrangian function:

$$\begin{aligned} L(\omega) &= \mathbb{E}_1[W_2^a] - \frac{1}{2}\gamma Var_1[W_2^a] - \lambda_1 \omega \\ &= W_1^a \left(-\frac{\omega}{\bar{\theta}} \mu^A + \omega(1 - p_1(1 + r) + i^B) + \left(1 + \frac{\omega}{\bar{\theta}}\right)(1 + r) \right) \\ &- \frac{\gamma W_1^{a2} \omega^2}{2} \left[\frac{\sigma_E^2}{\bar{\theta}^2} + \sigma^2 \right] - \lambda_1 \omega, \end{aligned} \tag{28}$$

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

$$0 = W_1^a \left[-\frac{\mu^A}{\bar{\theta}} + (1 - p_1(1 + r) + i^B) + \frac{1 + r}{\bar{\theta}} \right] - \gamma W_1^{a2} \omega \left[\frac{\sigma_E^2}{\bar{\theta}^2} + \sigma^2 \right] - \lambda_1, \tag{29}$$

$$0 = -\lambda_1 \omega. \tag{30}$$

We consider the following cases of values of ω:

a). $\omega = 0$.

Condition $\omega = 0$ implies that $\lambda_1 \geq 0$. The first-order condition (29) implies

$$\lambda_1 = W_1^a \left[-\frac{\mu^A}{\bar{\theta}} + (1 - p_1(1+r) + i^B) + \frac{1+r}{\bar{\theta}} \right].$$

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

$$\mu^A \leq \bar{\theta}(1 - p_1(1+r) + i^B) + 1 + r.$$

b). $\omega < 0$

In this case, $\lambda_1 = 0$ and the first-order condition (29) implies

$$\omega = -\bar{\theta} \frac{\left[\mu^A - (1+r) - \bar{\theta}(1 - p_1(1+r) + i^B)\right]}{\gamma W_1^a(\sigma_E^2 + \bar{\theta}^2 \sigma^2)}. \tag{31}$$

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

$$\mu^A > \bar{\theta}(1 - p_1(1+r) + i^B) + 1 + r.$$

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 $\omega \leq 0$ region and compare it with the maximum of the expected utility in $\omega \geq 0$ region (the latter case is the same as in the single collateral case). Denote by $N = 1 - p_1(1+r) + i^B$ 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: $\sigma_E^2 > \sigma^2$.

For this case we specify the following Lagrangian function:

$$\begin{aligned}
L(\omega^E,\omega^U) &= \mathbb{E}_1[W_2^a]-\frac{1}{2}\gamma Var_1[W_2^a]-\lambda_1\omega^E-\lambda_2\omega^U \\
&= W_1^a\left[-\frac{\omega^E}{\bar{\theta}}\mu^A-\omega^U(1+r)+(\omega^E+\omega^U)N+\left(1+\frac{\omega^E}{\bar{\theta}}+\omega^U\right)(1+r)\right] \\
&- \frac{\gamma W_1^{a2}}{2}\left[\frac{\omega^{E2}}{\bar{\theta}^2}\sigma_E^2+\omega^{U2}\sigma_U^2+(\omega^E+\omega^U)^2\sigma^2\right]-\lambda_1\omega^E-\lambda_2\omega^U, \qquad (32)
\end{aligned}$$

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

$$\begin{aligned}
0 &= W_1^a[N-M]-\gamma W_1^{a2}\left[\frac{\omega^E}{\bar{\theta}^2}\sigma_E^2+(\omega^E+\omega^U)\sigma^2\right]-\lambda_1, \qquad (33)\\
0 &= W_1^aN-\gamma W_1^{a2}\left[\omega^U\sigma_U^2+(\omega^E+\omega^U)\sigma^2\right]-\lambda_2, \qquad (34)\\
0 &= -\lambda_1\omega^E \qquad (35)\\
0 &= -\lambda_2\omega^U. \qquad (36)
\end{aligned}$$

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

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

Conditions $\omega^E=0$ and $\omega^U=0$ imply that $\lambda_1\geq 0$ and $\lambda_2\geq 0$. The first-order conditions (33) and (34) become

$$\lambda_1=W_1^a[N-M],$$

$$\lambda_2=W_1^aN.$$

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

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

Conditions $\omega^E=0$ and $\omega^U<0$ imply that $\lambda_1\geq 0$ and $\lambda_2=0$. The first-order conditions (33) and (34) become

$$\lambda_1=W_1^a[N-M]-\gamma W_1^{a2}\omega^U\sigma^2,$$

$$\omega^U=\frac{N}{\gamma W_1^a(\sigma_U^2+\sigma^2)}.$$

Inequality $\lambda_1 \geq 0$ is equivalent to

$$\frac{N}{\sigma_U^2 + \sigma^2} \geq \frac{M}{\sigma_U^2}$$

and $\omega^U < 0$ is equivalent to $N < 0$.

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

Conditions $\omega^E < 0$ and $\omega^U = 0$ imply that $\lambda_1 = 0$ and $\lambda_2 \geq 0$. The first-order conditions (33) and (34) become

$$\omega^E = \frac{N - M}{\gamma W_1^a \left[\frac{\sigma_E^2}{\bar{\theta}^2} + \sigma^2\right]},$$

$$\lambda_2 = W_1^a N - \gamma W_1^{a2} \omega^E \sigma^2.$$

Inequality $\lambda_2 \geq 0$ is equivalent to

$$\frac{N}{\sigma^2} \geq \frac{M}{\frac{\sigma_E^2}{\bar{\theta}^2}}$$

and $\omega^E < 0$ is equivalent to $N < M$.

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

In this case, $\lambda_1 = \lambda_2 = 0$ and the first-order conditions (33) and (34) become

$$\omega^E = \frac{\frac{N}{\sigma^2 + \sigma_U^2} - \frac{M}{\sigma_U^2}}{\gamma W_1^a \left(\frac{\frac{\sigma_E^2}{\bar{\theta}^2} + \sigma_U^2}{\sigma_U^2} - \frac{\sigma_U^2}{\sigma^2 + \sigma_U^2}\right)}.$$

$$\omega^U = \frac{\frac{N\sigma_E^2}{\bar{\theta}^2} - M\sigma^2}{\gamma W_1^a \left(\sigma^2 \sigma_U^2 + \frac{\sigma_E^2}{\bar{\theta}^2}(\sigma^2 + \sigma_U^2)\right)}.$$

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

$$\frac{N}{\sigma^2 + \sigma_U^2} < \frac{M}{\sigma_U^2} \qquad \text{and} \qquad \frac{N\sigma_E^2}{\bar{\theta}^2} < M\sigma^2.$$

Simple calculations verifies the following summary of the results:

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

$$\begin{aligned} \omega^E &= 0, \quad (37) \\ \omega^U &= 0. \quad (38) \end{aligned}$$

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

$$\begin{aligned} \omega^E &= 0, \quad (39) \\ \omega^U &= \frac{N}{\gamma W_1^a(\sigma_U^2 + \sigma^2)}, \quad (40) \end{aligned}$$

  where

$$\delta = \frac{\sigma_U^2}{\sigma_U^2 + \sigma^2}.$$

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

$$\begin{aligned} \omega^E &= \frac{N - M}{\gamma W_1^a \left[\frac{\sigma_E^2}{\bar{\theta}^2} + \sigma^2\right]}, \quad (41) \\ \omega^U &= 0, \quad (42) \end{aligned}$$

  where

$$\Delta = \frac{\sigma_E^2}{\bar{\theta}^2 \sigma^2}.$$

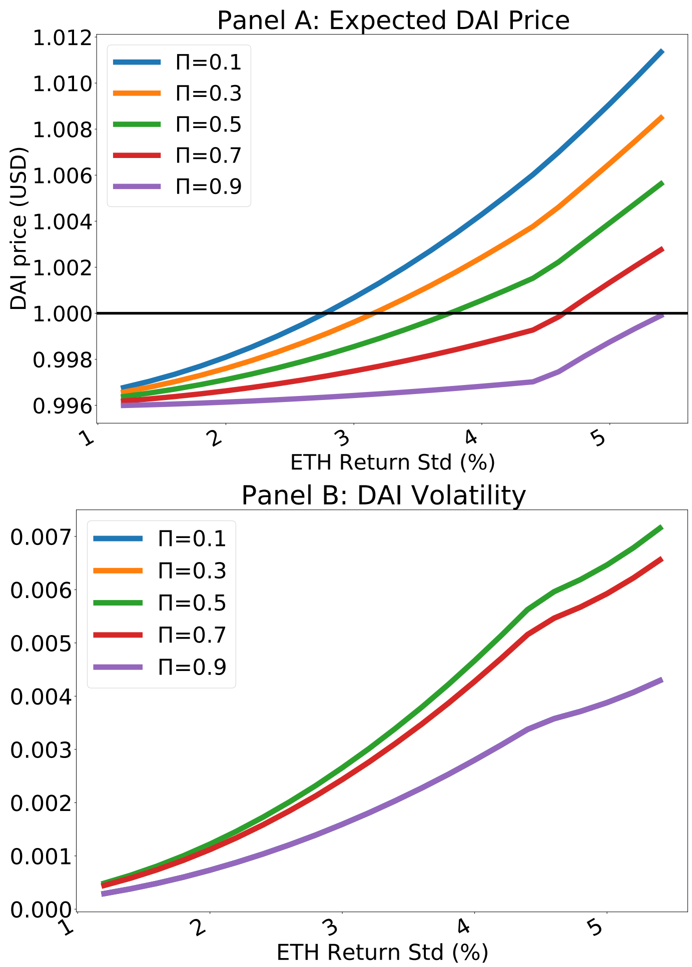
- If $N \geq 0$ and $M > \Delta N$ or $N < 0$ and $M > \delta N$ then

$$\begin{aligned} \omega^E &= \frac{\frac{N}{\sigma^2+\sigma_U^2} - \frac{M}{\sigma_U^2}}{\gamma W_1^a \left(\frac{\frac{\sigma_E^2}{\bar{\theta}^2}+\sigma_U^2}{\sigma_U^2} - \frac{\sigma_U^2}{\sigma^2+\sigma_U^2} \right)}, \quad (43) \\ \omega^U &= \frac{\frac{N\sigma_E^2}{\bar{\theta}^2} - M\sigma^2}{\gamma W_1^a \left(\sigma^2\sigma_U^2 + \frac{\sigma_E^2}{\bar{\theta}^2}(\sigma^2 + \sigma_U^2) \right)}. \quad (44) \end{aligned}$$

Q.E.D.

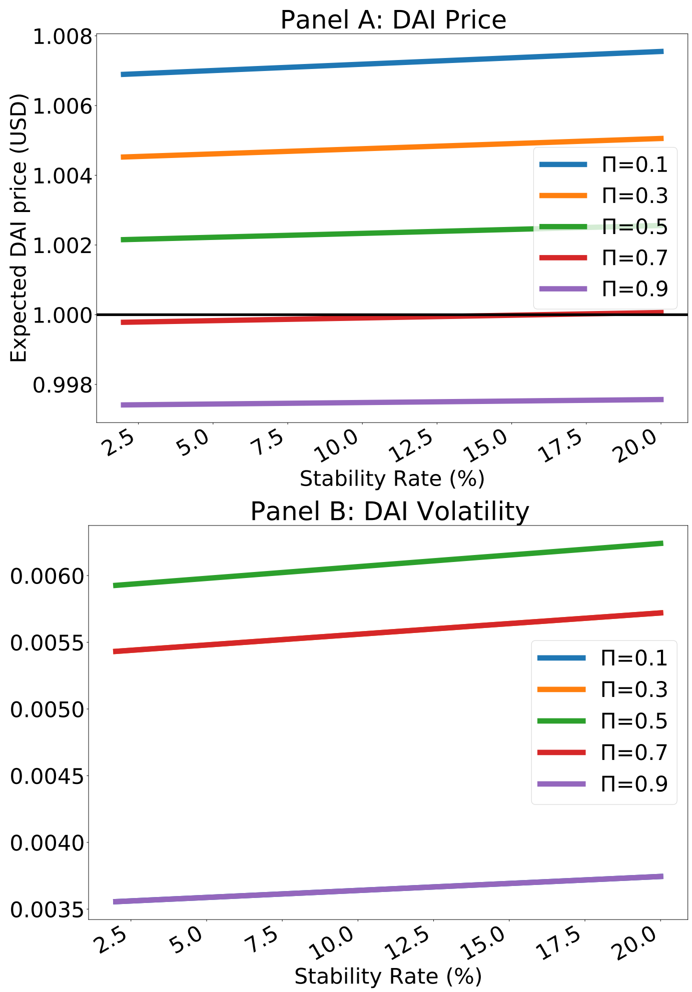
Appendix C: Model sensitivity analysis

Figure A3: DAI prices, volatility sensitivity analysis across different values of ETH volatility



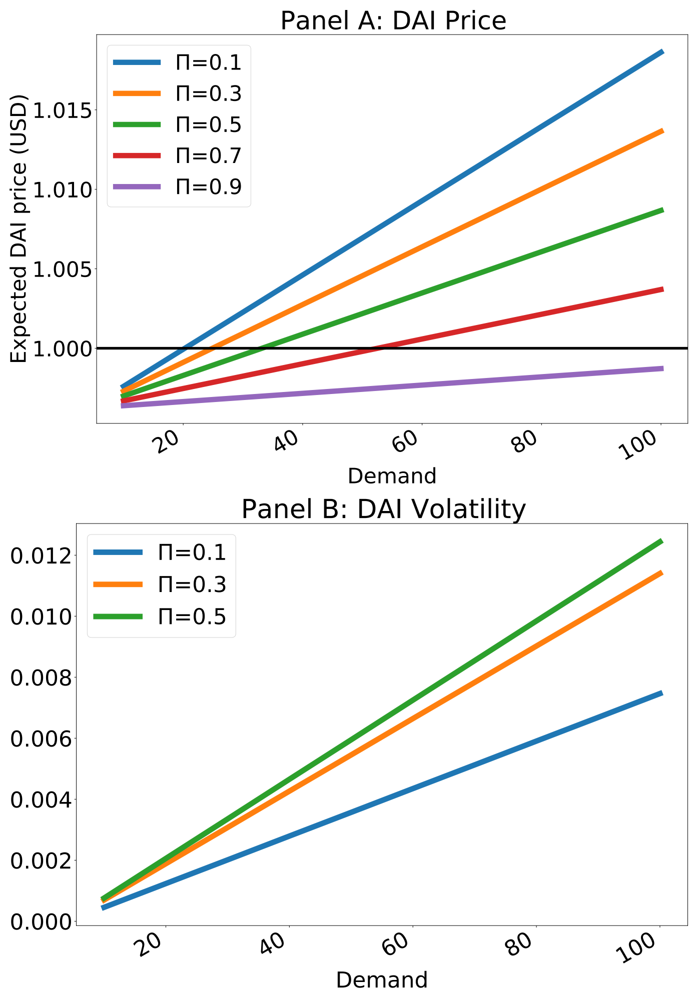
This figure plots the expected DAI prices and volatility as a function of ETH volatility, for different values of probability π of the good state of ETH returns. All other parameters are held constant. Panel A corresponds to the expected DAI price. Panel B corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. The primitive parameters are as follows: $\gamma = 0.5$, $W_1^s = \$350$, $D(B) = \$50$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure A4: Sensitivity analysis: DAI prices and volatility across different values of interest rate on DAI borrowing



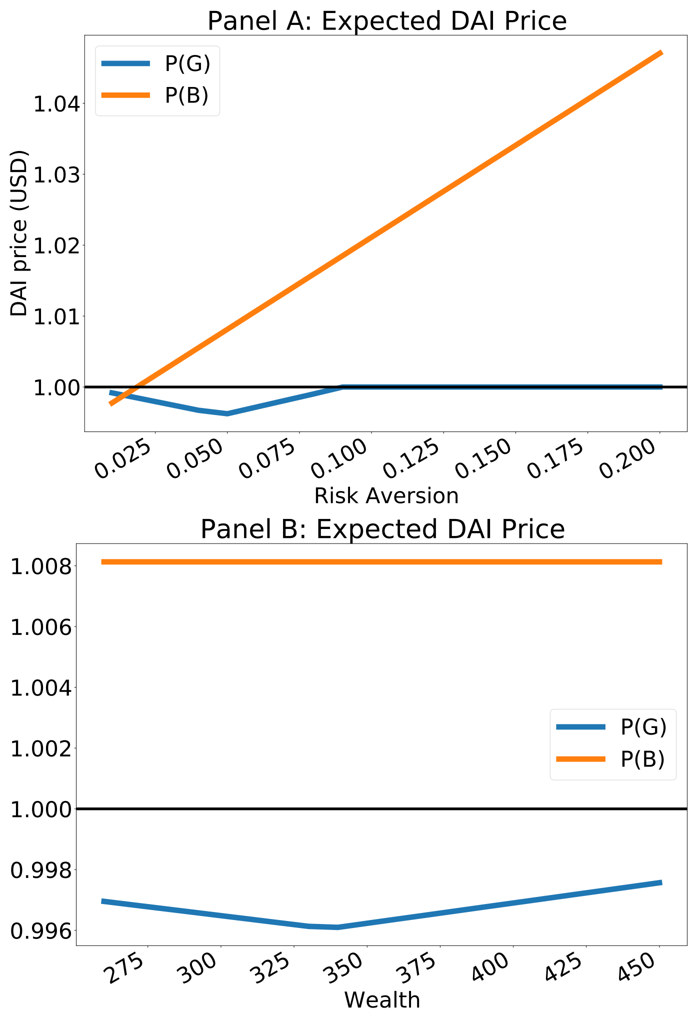
This figure plots the expected DAI prices and DAI volatility as a function of the DAI stability rate, for different values of probability π of the good state of ETH returns. All other parameters are held constant. Panel A corresponds to the expected DAI price. Panel B corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. The primitive parameters are as follows: $\gamma = 0.5$, $W_1^s = \$350$, $D(B) = \$50$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $\sigma_E = 0.0459$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure A5: Sensitivity analysis: DAI prices and volatility across different values of safe-haven demand



This figure plots the expected DAI prices and DAI volatility as a function of the DAI safe-haven demand in the bad state, for different values of probability π of the good state of ETH returns. All other parameters are held constant. Panel A corresponds to the expected DAI price. Panel B corresponds to peg-price volatility, calculated as the standard deviation of peg-prices across the two states of collateral. The primitive parameters are as follows: $\gamma = 0.5$, $W_1^s = \$350$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $\sigma_E = 0.0459$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

Figure A6: Sensitivity analysis: DAI prices and volatility across different values of wealth and risk aversion



This figure plots the DAI prices during the good and bad states as a function of the risk average coefficient γ (Panel A) and the wealth of speculators W_1^s (Panel B). All other parameters are held constant. The primitive parameters are as follows: $D(B) = \$50$, $D(G) = \$0$, $\bar{\theta} = 0.66$, $\sigma = 0.0188$, $\sigma_E = 0.0459$, $i^B = 0.0324/252$, $i^L = 0.0139/252$, $r = 0.015/252$, $\mu_A = 1.0033$, $\mu_E(G) = 1.0668$, $\mu_E(B) = 1.0033$. For panel A we assume $W_1^s = \$350$ and for Panel B we assume $\gamma = 0.5$. The rest of the parameters in the models are computed numerically by optimizing the expected utilities (5).

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.

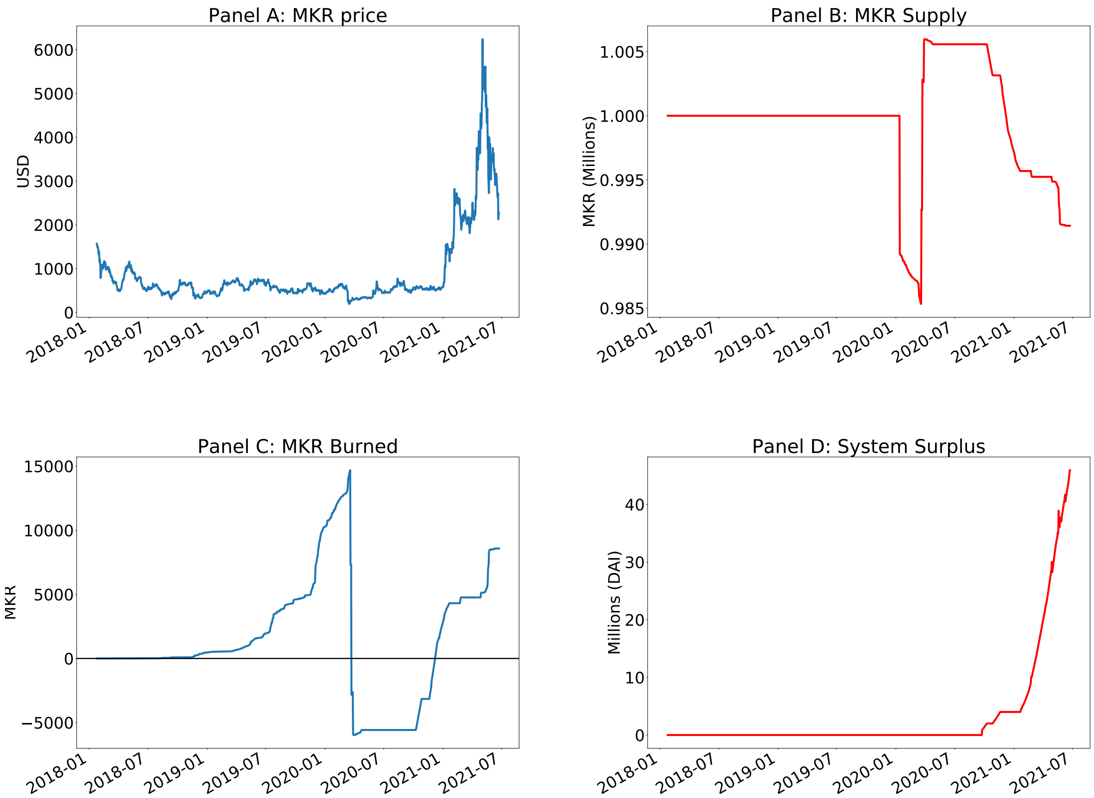
For example, consider an extreme price movement in ETH, such as the Black Thursday crash on 12 March 2020. This triggered a liquidation event, which requires collateral to be auctioned off to pay off the DAI loan and penalty fees. If the sale of collateral is not sufficient to pay off the DAI loans triggered 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. [26] 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

[26] 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.

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.

Figure A7 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 A7: MKR price, MKR Supply, Burned/Minted Tokens and System Surplus



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