Information Processing in a Transparent Market:
Evidence from a DeFi Protocol

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ABSTRACT

We take advantage of a rare setting in a decentralized finance market (the MakerDao Lending Protocol), where each trader's activities are freely and publicly available in real-time and recorded permanently to the blockchain, to examine traders' mimicking behavior in this extremely transparent market. We find robust evidence of cross-sectional persistence in traders' performance. Despite the public availability of all traders' past and real-time activities, investors' efficient mimicking does not happen automatically and varies with the information processing costs associated with using the publicly available information on the blockchain.

Keywords: blockchain, decentralized finance, transparency, processing costs

1. **Introduction**

Financial economists and market regulators have long debated about the optimal level of market transparency—how much market data such as prices, trades, and quotes should be made publicly available and at what frequency. Both sides of the debate assume that investors will use the market data once it is made free and publicly available. This assumption finds some support in the traditional equity market where institutional investors are found to herd with each other or mimic expert hedge funds using the mandatory positions disclosures in 13F that are filed with some delays after positions are taken (Sias 2004; Choi and Sias 2009; Shi 2017). We further test this assumption by taking advantage of a rare empirical setting—a decentralized lending market—where individual traders' activities are permanently and instantly recorded to the blockchain. We examine whether investors mimic others when all trading activities are freely and publicly available in real-time.

The free and public nature of the information recorded and published on the blockchain about other traders' activities does not guarantee that investors take advantage of it. For example, Blankespoor, deHaan, Wertz, and Zhu (2019) find that, if information processing costs are high, investors may disregard accounting information even when the information is readily available. In our setting, for investors to use the public trading data needed to engage in efficient mimicking (i.e., following superior performers and avoiding inferior performers), they first need to process historical data in order to identify the top (bottom) traders to follow (avoid). Then they need to implement a sophisticated monitoring/alerting system to be able to mimic and/or avoid certain traders' activities in real-time. Thus, whether we observe efficient mimicking in a market that features real-time trades transparency depends on the cost-benefit tradeoff investors face and thus, is an empirical question.

To examine these questions empirically, we take advantage of the decentralized lending protocol MakerDao (“Maker” for short). Established on December 18, 2017, Maker is one of the earliest DeFi (decentralized finance) platforms. It uses smart contracts (i.e., code that performs actions based on predefined criteria, for example, “pay X to C, if event A happens”) to facilitate transactions between private parties on the Ethereum blockchain, without the involvement of a centralized financial intermediary such as a bank. Users can interact with the Maker protocol by calling different functions associated with the Maker protocol smart contracts. For example, a smart contract to open an account (vault), or a smart contract to borrow or return a loan. Anyone can take out a loan on Maker—Maker performs no background or other checks. Instead, loans are overcollateralized, which means that the value of the collateral is going to be higher than the value of the loan issued. Once users open a vault, they can deposit collateral assets in the form of cryptocurrency (e.g., ETH, short for “Ether”) in their vault and borrow an amount equivalent to up to $2/3$ of their collateral in a cryptocurrency pegged to the US-dollar (called Dai). Traders can nonetheless deposit the borrowed money back again to the vault, to borrow additional Dai and repeat the cycle again; ultimately achieving an amplified exposure to the desired cryptocurrency much in the same way as leveraged (margin) trading.

The blockchain-based, decentralized lending market serves as a unique laboratory as all transactions are written to the blockchain, and thus all information is publicly available in real-time. For example, once a loan contract is initiated by a wallet, all its subsequent activities (such as borrowing, adding collateral, or making repayments) will be publicly available in real-time when these transactions are executed. In addition, the ability to leverage trade attracts informed traders (i.e., traders who are informed of price trends of cryptocurrencies and value leverage to amplify their returns) which increases the possibility that investors can find expert investors to follow.[1]

We obtain information on all loans created on Maker, from December 2017 to May 2020. First, we examine whether there is cross-sectional persistence in the performance of users on the Maker platform—if there is no performance persistence, then there is no base for investors to decide whom to follow or avoid. We calculate returns for each loan as the change in collateral value from the beginning to the end of the loan, while accounting for cash invested into the vault during the loan cycle. Our evidence is in support of cross-sectional persistence in investors' abilities to generate returns. That is, if an investor generates higher returns than others on one loan, then they are more likely to generate higher return than others in their next loan as well. Specifically, one standard deviation increase in last loan return increases next loan return by 3.2%. This result holds in various specifications and is robust to controlling for all the contemporaneous return determinants. An alternative measure of loan performance is an indicator of whether a loan is liquidated. Again, we find consistent evidence of cross-sectional persistence. Investors whose loans got liquidated in the past are more likely than others to see their next loans get liquidated—previous liquidation increases the probability of current liquidation by almost 23%. Given that previous loan performance can be a useful indicator for identifying superior and inferior performers, next we examine whether traders take advantage of the publicly available data to mimic or avoid others in real-time.

[1] We focus on leverage trading (margin trading) of cryptocurrencies in decentralized lending markets rather than cash trading in regular exchanges (Coinbase and Kraken) for two reasons. First, traders who are informed of price trends of a cryptocurrency may prefer to engage in leveraged trading, facilitated by the lending market, over trading in a regular exchange because leveraged trading amplifies return. More importantly, cryptocurrency trading on non-decentralized exchanges (e.g., Coinbase and Kraken) is not completely transparent, as most trades are done within the exchange and are thus not recorded on the blockchain. This is in contrast to decentralized exchanges (e.g., Uniswap) which started to gain popularity in mid-2020 and do not overlap with most of the period for which we have data.

To do that we define a "following" measure that, for each trader's loan cycle, counts the number of traders that mimic at least half of the borrow/repay activities in that loan cycle. Our results show that past liquidation is significantly and negatively associated with the number of a trader's future followers. However, we do not find much evidence that a trader with higher past loan returns attracts more followers. This suggests that even in a market with real-time trades transparency, investors' use of others' trading data does not occur automatically. We hypothesize that this is due to high information processing costs associated with the use of historical and real-time blockchain data. To test our hypothesis, we examine how changes in information processing costs affect investors' efficient mimicking of others in real-time.

We first use the introduction of a website that makes loans' past activity and liquidation statistics readily available to investors to study the impact of an exogenous shock that lowers the costs to acquire and integrate traders' past performance. Our evidence suggests that only when the costs to process historical performance data is sufficiently low, do investors incorporate the information (past liquidation) in their following decisions.

We next introduce three proxies to measure the complexity, and thus the processing costs, of trades undertaken in the current loan. The three proxies are designed to capture different types of complexities: (1) *number of transactions*—largely affects costs associated with monitoring when the followed trader transacts; (2) *number of smart contracts*—affects the complexity of inferring the actions taken by the followed trader and carrying out the same action; and (3) *duration*, which reflects the time it takes to monitor others' trades. We find generally consistent evidence that an increase in these costs weakens the positive (negative) relation between past returns (past liquidation) and current following. This provides further support that investors' efficient mimicking behavior is related to the costs that they need to incur to analyze and follow others in real-time.

One critique of our following measure is that it is closely related to an empirical herding measure used in the prior literature (Sias 2004, Choi and Sias 2009), and thus could also capture herding on correlated signal (i.e., investigative herding) or even coordinated trading by one trader or a group of traders. While it is always challenging to separate these underlying motives, we run different tests that taken together suggest that our results are more likely to be explained by investors mimicking others rather than trading on correlated signals or coordination. Specifically, we show that there is almost no mutual following in our sample, which is inconsistent with trading on correlated signal where trader's actions should happen around the same time resulting in mutual following. We also exclude wallets that interact with each other to test if our results are driven by coordination among multiple users or an individual investor coordinating among multiple wallets that he owns. Finally, we compare the returns of followers and non-followers and find suggestive evidence that our results are unlikely to be driven by the coordination of expert investors.

We contribute to several strands of literature. First, we contribute to a growing body of research on blockchain-based applications and crypto markets. Recent research examines the theoretical foundations of blockchain-based markets (Cong and He, 2019; Cong and Wang 2021; Saleh 2020) and how blockchain can be used by corporations and capital markets (Diri, Lambrinoudakis, and Kharoug 2021; Cao et al. 2020; Chiu and Koeppl 2019). Studies also document the existence of arbitrage opportunities and manipulation activities in decentralized exchanges (Daian, et al., 2019; Makarov and Schoar 2020; Li et al. 2020; Griffin and Shams 2020) and how cryptocurrencies are linked to criminal activities (Foley, Karlsen, and Putnins 2019; Amiram, Jorgensen, and Rabetti, 2021). In addition, there are papers that study the determinants of the pricing of cryptocurrencies (Momtaz, 2019; Liu and Tsyvinski 2018) and the success of the initial coin offering (Howell, Niessner, and Yermack 2020; Bourveau, et al. 2022; Hu, Leone, and Zhang 2020). Our paper differs from prior studies in that we are the first to collect data on, and closely examine, the decentralized crypto lending markets that allows us to examine traders' mimicking of others in a market that features real-time trades transparency that rarely exists before.

Second, we contribute to the literature on investors' information processing. Despite the SEC's efforts to improve individual investors' access to accounting information, previous literature suggests that investors may disregard accounting information even when that information is readily available (Blankespoor, deHaan, Wertz, and Zhu 2019). Similarly, the debate on market transparency has been focusing on how much transparency a marketplace should offer (and offer freely) (e.g., Gemmill, G. 1996; Jones et al. 2016).[2] Our evidence highlights that the public availability of investors' trading data, albeit necessary, does not guarantee the efficient use of the data. Whether the transparent data can be collected, understood, and processed, with relatively low costs by the average investor is a crucial factor in the determination of the value of transparency. The decentralized lending market we study provides a unique laboratory for future research aimed at separating investors' information processing ability from the availability of information (Blankespoor, deHaan, Marinovic 2020).

Third, our evidence adds to the literature on persistence, which has mixed results. For example, while some studies find evidence of persistent performance among fund managers and/or sell-side analysts (e.g., Mikhail et al. 2004), others find no evidence of systematic performance differences once other factors (such as stock returns, investment expenses, and individual

[2] On the one hand, a more transparent market enhances learning and thus information revealed in one trader's activity can be more rapidly incorporated into prices by following trades. On the other hand, if informed traders' intentions to build a position is revealed too quickly, their profits will be depleted by copycat traders, which in turn will reduce the rewards and incentives of them to collect information in the first place (e.g., Agarwal et al. 2013; Shi 2017).

characteristics) are accounted for (Carhart 1997). More recently, the persistence of other financial professionals has also been studied including hedge funds (e.g., Jagannathan et al. 2010), private equity funds (e.g., Braun et al. 2017; Kaplan and Schoar 2005), venture capitalists (e.g., Nanda et al. 2020), and activist short sellers (Hu and Walther 2021). While examining performance persistence and its asset pricing implications is not a major motivation of our paper, our unique empirical setting provides timely evidence on how investors behave and whether their cross-sectional performance persists in an environment of real-time trades transparency facilitated by the blockchain technology.

2. Decentralized Lending and the MakerDAO Protocol

A blockchain is a distributed ledger that records information in a way that is difficult, or impossible, to manipulate. That's because of the encryption used and the fact that whenever a new transaction is added to a blockchain, a record of the transaction is made public to every user of that blockchain. Perhaps the most well-known use of blockchains is to facilitate the creation and use of digital money, such as Bitcoin, Ether, and other cryptocurrencies.

More recently, blockchains have increased the use of smart contracts. Among other uses, smart contracts facilitate the buying and selling of cryptocurrencies on Ethereum and other blockchains, the raising of funds to establish new cryptocurrencies, and the borrowing and repayment of loans, such as via the MakerDAO Protocol. Established on December 18, 2017, Maker is among the leading DeFi platforms, along with Aave, InstaDapp, and Compound. The value of locked collateral on Maker totaled $16.58 billion US Dollars, as of March 23rd, 2022.The total value of locked collateral in the entire DeFi lending market was $70.42 billion US Dollars, as of March 23rd, 2022.[3]

In order to take a loan on Maker, individuals must deposit Ether ("lock ETH"), the native cryptocurrency of the Ethereum blockchain, in a digital "vault". The amount of that deposit, or collateral, determines the maximum amount of the loan. Once the deposit is made, the borrower chooses how much they want to borrow and receives the principal in Dai, a stable coin that is pegged to the US dollar. Borrowers can use the loan contract to engage in leveraged trading. To do that they first use the borrowed Dai to buy ETH. They then lock the ETH as additional collateral in the loan contract, which enables them to borrow more Dai. They repeat this process to increase their exposure to ETH. If the price of ETH keeps going up during the loan and if the appreciation in price offsets the interest expense accrued, they earn positive returns. Appendix A demonstrates the leveraging process graphically. Borrowers who do not engage in leveraged trading may decide to hold Dai or use it in other DeFi applications.

Borrowing money on Maker is different from borrowing in traditional finance markets. Unlike a human banker, smart contracts cannot verify the credit worthiness of potential borrowers. To protect lenders from the risk of default, borrowers on Maker must deposit *more* collateral than the amount they wish to borrow (i.e., loans are "overcollateralized.")

For the sample of loans used in our study, the collateralization ratio was 1.5—the standard rate in DeFi lending. This means that if an individual wants to borrow Dai equivalent of 10 ETH, they need to put down a collateral of at least 15 ETH. Since the principal is in Dai yet the collateral is in ETH, if ETH becomes less valuable in relation to Dai, the collateralization ratio may get below 1.5, in which case the loan can be liquidated, and the borrower is charged a 13% liquidation

[3] Defipulse.com publishes aggregate information on DeFi lending markets. See https://defipulse.com/defi-lending.

penalty. The remaining collateral is used to repay the loan, and the rest of the collateral is returned to the borrower. (If, on the other hand, ETH becomes more valuable in relation to Dai, the borrower could borrow *additional* Dai.) That is, the risk of liquidation incentivizes borrowers to provide adequate collateral to keep the collateralization ratio above the required 1.5 level.

Loans on Maker do not have a pre-determined duration and can be held indefinitely. So, whenever borrowers decide to pay off their loans, they simply pay back the loan plus interest expenses. The Dai that was created for the loan is then destroyed by the software code and the borrower's collateral is returned to the borrower's wallet.[4]

Interest rate on Maker (a.k.a. the "stability fee") is compounded continuously and is also used to keep the value of Dai stable at 1 US Dollar. For example, when more investors want to borrow Dai, demand for Dai increases, creating upward pressure on the price of Dai relative to the dollar. To push the price of Dai back down to its desired dollar peg, Maker community members can vote to increase the stability fee, which reduces borrowing and, thus, the demand for Dai. During the period we study, the lowest stability fee was 0.50% (which was the fee when Maker first launched). Throughout the period, the stability fee was adjusted 13 times, mostly upwards. The fee peaked at 19.50% in May 2019. (In Appendix B, we chart the changes to the stability fee, including the corresponding transaction hashes)

Since every Maker transaction is executed on the Ethereum blockchain, and all trade information on the blockchain is publicly available as soon as it is executed, investors can observe the execution of all transactions in real-time, as well as trace transaction histories of other investors. This is in contrast to traditional financial markets where investors' activities are typically

[4] When investors decide to pay back the loan, they can also pay it back in installments. For example, an investor unlocks some collateral by paying back some Dai. The investor then uses the unlocked ETH collateral to trade for more Dai, which is then used to pay back the loan and unlock more Ether.

unobservable to other investors. And even when they *are* observable, they are rarely observable in real-time.

In May 2020, Maker replaced the original version of its Dai stablecoin, the "Single Collateral Dai", where only ETH could be placed as collateral, with an upgraded version, the "Multi-Collateral Dai" which allows other cryptocurrencies to be used for collateral. In this paper, we evaluate all loan contracts under the original version during December 2017–May 2020 period.

3. Hypotheses Development

While seminal research has proposed crypto pricing models (Momtaz, 2019; Liu and Tsyvinski 2018), the complete pricing mechanisms of crypto assets are still more or less a black box to many, with ongoing debate about what constitutes their fundamentals and future cash flows. Despite the uncertainties in pricing and the highly unregulated nature of the space, prior research found that in the initial coin offering (ICO) market, investors use both disaggregated information (e.g., white paper disclosures provided by the ICO project team) and aggregated information (e.g., ratings offered by the rating agencies) in their funding decisions (Bourveau, et al. 2022). While both types of information in the ICO setting are provided voluntarily and written in human language, the public availability of DeFi market data is a default feature of blockchain-based markets, and the processing of the data may require a deep understanding of the protocol and big data techniques. We examine whether investors use others' trades that are publicly, permanently, and instantly recorded to the blockchain to mimic their trading strategies

For investors to be able to mimic other traders as closely as possible, they need to be in a fully transparent market where others' trading activities are made publicly available in real-time. While this is almost unthinkable in traditional equity/debt markets and in cryptocurrency markets hosted by traditional centralized exchanges, the real-time public availability is one key feature of blockchain-based decentralized lending markets such as the Maker protocol we study. Real-time transactions transparency, however, may not be sufficient for efficient mimicking to happen.[5] Specifically, just like with traditional accounting data, processing information hosted on the blockchain involves different types of costs.[6] If investors believe these costs are higher than the benefits of using the information, they may be reluctant to incur the costs to process the information, and vice versa. This leads us to our first hypothesis (stated in the null form):

HYPOTHESIS 1: *Investors do not incorporate traders' past performance in their following decisions.*

Next, we consider the two steps that investors need to take in order to mimic expert investors and develop hypotheses regarding the processing costs involved in each step. First, investors need to process *historical* data and calculate traders' performance in order to identify superior ones to follow and inferior ones to avoid. In terms of historical data, there are many websites that provide detailed information on all transactions made on the Ethereum blockchain. For example, etherscan.io provides for each transaction information about the transacting wallets, the type of transaction (e.g., buy, sell, borrow, repayment, swap, etc.), the amount transacted, the time of the transaction, the currencies involved, etc. However, one must still acquire, organize, and analyze the trading activity data, in order to rank wallets into top and bottom performers. That is, incorporating other's historical performance in trading decisions requires a deep understanding of

[5] We do not have enough evidence to make any statement about the efficiency of the crypto market or the defi market we study. By efficient mimicking, we only refer to the behavior of following investors with superior past performance who are more likely to have better future performance relative to others, while avoiding investors with inferior past performance who are more likely to perform worse in the future.

[6] Blankespoor et. al (2019) decompose the processing costs into awareness costs, acquisition costs, and integration costs. They regard the awareness and acquisition costs to be low when a piece of information is "readily available." In our setting, all the trading data are hosted on a public blockchain in real-time. Still monitoring when a transaction happened may be costly. Moreover, information hosted on a blockchain might still need to be acquired before they can be integrated into decisions. For this reason, we do not draw strict lines between different components as in Blankespoor et. al (2019) framework. We use processing costs to refer to all costs that need to be incurred to process publicly and freely available information.

the protocol and the structure of past loan data hosted on the blockchain, as well as an API to download the data. These potential processing costs, associated with the identification of superior performers to follow, and inferior performers to avoid, lead to our second hypothesis (stated in the alternative form).

HYPOTHESIS 2*: If acquisition and integration costs are a barrier to investors' ability to process historical data, then a reduction in these costs, for example by providing free, aggregated and easily digestible information on traders' past activity, would increase the likelihood that traders use other traders' past performance in their following decisions.*

The second step—to actively follow other traders—requires one to follow a certain trader in real-time. The following trader needs to monitor real-time data, acquire the needed information, and process it to understand the actions needed to be performed on the Maker protocol. Monitoring and acquiring real-time data are very difficult to do without the development of some automated alerting system (i.e., a bot), which may be a significant barrier to many investors. Moreover, even once one automates these processes, there is still the need to analyze the functions executed in the smart contracts in order to understand the interaction required with the Maker protocol. Our third hypothesis (stated in the alternative form) is then:

HYPOTHESIS 3*: If data awareness, acquisition, and integration costs are a barrier to investors' ability to mimic other traders in real-time, then an increase in these costs would decrease the ability of investors to efficiently mimic others.*

4. Data and Empirical Design

Below we detail our data and main variable construction. Section 4.1 discusses the source of the data and the sample selection process. In section 4.2, we explain our empirical design, especially how we calculate main variables such as loan return and the measure for following traders. We discuss descriptive statistics and time trends at the end of the section.

4.1 Data and Sample Selection

We download all our data from MakerDao's official Dai 1.0 API.[7] We obtain information on every loan ever created using the platform's Single Collateral Dai smart contracts from December 2017 to May 2020. A Maker loan contract is typically referred to as a Collateralized Debt Position (CDP).[8] We start from a sample of 155,406 CDPs and delete CDPs that have zero principal (no borrowing activities at all) and CDPs that are still open and not closed, arriving at 31,279 CDPs with 57,941 loan cycles. We then delete loans that use relayer wallets, which are third-party wallets that execute transaction on users' behalf, resulting in a sample of 34,454 loans. Since our research question focuses on the persistence of returns and efficient mimicking over time, we restrict the sample to a set of users who have at least two complete loans cycles. Furthermore, because we focus on traders that use Maker for a substantial leveraged investment strategy, we further reduce the sample to include only loans of at least $1 US dollar.[9]After implementing the last two filters, we reach our final sample of 8,062 loans representing 2,545 unique wallets.

We use the Ethereum wallet as the unique identifier to identify investors. While wallet addresses do not reveal the real identity of traders, they allow individual wallets' activities to be

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[7] For more information, and access to the API, please visit the following link: https://developer.makerdao.com/dai/1/graphql

[8] Users can open a CDP and make borrowing or repayment transactions as often as they wish. Therefore, users can hold multiple loans within a CDP. We split the transactions associated with a given CDP into different loans. Specifically, the start of the loan is marked by a transaction that increases the outstanding loan balance of the CDP from zero to any positive amount. The end of a loan is marked by a transaction that completely pays off the outstanding balance. The number of loans a CDP has is just the number of times the outstanding debt is completely paid off.

[9] In untabulated tests, we replicate our results on the sample without this restriction, our results remain robust.

tracked in real-time; as the process involved in building a leveraged position requires repeated borrow-and-redeposit cycles that use the same wallet. This makes the wallet address very different from the masked trader identifier in traditional equity markets where buying and selling a security is a one shot action and the masked identifier leaves no opportunity to observe a trader's action in sequence. Consequently, we believe that using wallet addresses to identify traders still improves on using random trader tags in traditional equity markets. In addition, we implement a test in the spirit of Bertrand and Schoar (2003) in the Internet Appendix A. We find that adding wallet fixed effects to explain the returns of loans significantly increases the adjusted R square, from 0.259 to 0.392, which indicates that individual wallets have significant explaining power over loan cycle performance. The F-test for the joint significance of the wallet fixed effects is highly significant with $p<0.001$. This test demonstrates that either traders are not intentionally using multiple wallets to hide their behavior, or they cannot do it well enough to completely wipe out the explanatory power of individual wallets on return. Furthermore, to mitigate the possibility that our results are due to one trader holding multiple wallets, we run our tests on a restricted sample that excludes wallets that interact with each other and find robust results.

4.2 Empirical Design and Measurement

For each user, we obtain every transaction executed for every loan taken. These transactions include opening of a loan contract, borrowing in Dai, locking collateral in ETH, repaying of the loan in Dai, unlocking of the ETH once a portion of the loan is paid back, closing of the loan contract, and the liquidation of a loan. Recall that over the life cycle of the loan, users may borrow, lock collateral, or repay, more than once. For each of these transactions, we have the exact timestamp of the transaction, the transaction hash, and the amount in Dai or ETH associated with the transaction. In Appendix C, we present an example of an actual loan including all the executed transactions.

In this simple example, the loan was opened on March 2nd, 2019. The investor initially put in 133 ETH, which was worth approximately 17,529.07 Dai (also USD). The investor borrowed 6,000 Dai and then used 5,815.3 Dai out of it to place an additional 44 ETH as collateral; thereby, borrowing an additional 1,000 Dai. Next, the trader used 964.82 out of the 1,000 borrowed Dai to add 7.3 ETH as collateral. About two hours after opening the loan contract, at 19:19:48 on March 2nd, 2019, the investor injected 2,269 USD from external sources to add more collateral to the loan. After that the investor repeated the borrow-and-add-collateral cycle three more times (the first one was taken about three minutes later, the second was after around ten days, and the third was twenty days later). The loan was finally paid back in full on Juley 18th, 2019.

This example clearly illustrates leveraged trading where the investor was able to gain more exposure to ETH with the Dai they borrowed from Maker (starting with 133 ETH plus the externally added 19 ETH and leveraged all the way up to 243 ETH eventually). If ETH prices go up during this period and what the investor gains from the appreciation of ETH is higher than the interest expenses, the investor would be making a positive return.

We calculate the return by simply looking at how much value in ETH or Dai users have at the end of the loan and subtracting the amount they invested into the loan contracts (including the amount needed to pay back the loan and the interest expense). In particular, we use the following equation:

$$Return = \frac{Ending\ collateral\ value\ +\ Ending\ cash\ balance\ -\ Cash\ used}{Cash\ used}$$

where *ending collateral value* is the value of collateral in US dollars that is returned to the user's Ethereum address when the loan is paid back in full.

To calculate *ending cash balance*, for each investor, we create a cash account that tracks the use of funds borrowed from Maker. When the investor takes out a loan, we add the loan amount to their cash balance. When the investor repays the loan, we subtract the corresponding amount from the cash balance. We assume that the investor will use their Maker funds to repay the loan before they use their own external capital. When the investor places more collateral, we also assume that they use the cash balance associated with their Maker funds first and subtract the corresponding amount from this cash balance. If the investor's existing Maker cash balance is not enough to repay in full or pay for the collateral they placed, we first deplete the cash balance associated with Maker funds and then add external cash to complete the transaction. The last component, *cash used* is simply the total external cash needed to facilitate the transactions of the loan contract as well as the value of the initial collateral placed to open the loan contract. This calculation also works for loan returns in the event of liquidation. When a loan is not liquidated, the repayment amount comes from either the cash balance associated with Maker funds or external cash injected into the loan, or both. When a loan is liquidated, the repayment of the loan (plus the interest) and the 13% liquidation penalty will be paid from the loan's collateral. Therefore, instead of reducing the cash balances to make the repayment, we reduce the value of the final collateral returned to the investor.

We further illustrate the calculation of return using the example in Appendix C. The calculation on the cash balance and external cash is presented in Appendix D. The final value of the collateral returned to the user is 55,082.81 USD, this amount represents the US dollar value equivalent of 242.84 ETH on July 18th, 2019, at 19:02:52 EST. The ending cash balance is zero. External cash injected into the loan is 32,737.32 USD, which is the sum of the initial deposit, the externally injected deposit, the loan repayment amount and the interest expense. The return for this loan is then (55,082.81 + 0 – 32,737.32)/32,737.32=68.26%.

The calculation of return depends on two key assumptions. The first assumption is that if investors lock in additional collateral (i.e., engage in leveraged trading), they use the money they borrow from Maker first before accessing their own cash reserves. We believe this is reasonable as it assumes that investors are rational and should maximize returns whenever they can.[10] Our second assumption is that users' funds stay within the Maker platform. To validate the second assumption that most users stay within the Maker platform, we examine a subsample of 4,000 loans in more detail. (Our final sample has roughly 8,000 loans.) We extract data from borrowers' Ethereum "wallets" during the time they hold Maker loans. Next, we inspect the unique smart contract addresses—including those used by Maker, as well as those used by other popular DeFi platforms, such as Kyber, Compound, and dYdx—those users interact with. We manually tag the 108 most used addresses. We find that roughly 54% of Maker users in the subsample only interact with smart contracts on Maker, which means most of them do not move their borrowed Dai funds from Maker to use on other platforms.[11,12] Given the above, and that the cost to follow borrowers' every transaction on Ethereum is prohibitively high, we believe our measure of investors' returns is a reasonable proxy for the actual returns that Maker users earn.[13] To confirm that our results

[10] Investors who are engaging in leveraged trading are minimizing the denominator of the return calculation – cash used – to maximize their return.
[11] We believe this number is a lower-bound as many users write their own custom smart contracts that only interact with the Maker protocol. We were unable to look through and tag all these smart contracts manually as the cost of doing that is prohibitive given our sample size.
[12] Our return calculation also works for a user who just borrows from the platform once (i.e., they are pledging ETH collateral to borrow Dai). If they are just borrowing from the platform without engaging in leveraged trading and locking in additional collateral, we do not need to make the first assumption.
[13] We observe some users using Dai to purchase and hold Bitcoin but do not observe many cases where users purchase and hold other cryptocurrencies. This is likely because currencies other than ETH could not be used on Maker's Single Collateral Dai protocol—limiting the ability to leverage up.

are not due to our assumptions, we also use an alternative performance measure, loan liquidation, that does not rely on any assumptions on investors' strategies.

With the return measure constructed, we first investigate what loan characteristics are correlated with the return on a loan by running the following model:

$$Return_{i,t} = b_0 + b_1{}'LoanCharacteristics_{it} + b_2'controls_{it} + \ monthYearFE_t + e_{it} \qquad (1)$$

where variables included in $LoanCharacteristics$ are defined as follows. *Order* is the order of the loan in the sequence of all loan cycles held by the wallet. Specifically, order = n if the loan is the trader's n^{th} loan, and measures the wallet's experience level with the Maker protocol. *Principal* is the natural logarithm of the total principal amount borrowed during the loan plus 1, which proxies for the size of the loan. *Duration* is the duration of the loan in days, and represents the length of the loan. *Collateralization* is the minimum total collateral to total principal ratio in the duration of a loan. *Leverage* is the total principal amount borrowed in a loan divided by the total external cash injected into the loan. Both these measures reflect a combination of traders' strategy choices and the platform's minimum requirement that collateral-to-borrowed-funds ratio needs to be higher than 1.5. Traders, however, can choose to keep their collateralization ratio close to the required 1.5 level or deposit additional ETH to keep a higher collateralization level and thereby reduce the probability of liquidation as a result of a drop in the price of ETH.

The $control$ variables include concurrent ETH market returns (*Eth_return*) and various wallet level characteristics. To build wallet-level controls, we download wallet-level transaction data from the Ethereum blockchain using the Web3.py interface. Specifically, we download the full transaction history for every Ethereum wallet in our final sample. With this data, we calculate

Age, which is the number of days since the wallet's earliest Ethereum transaction till the beginning date of the loan. It captures the trader's experience with the Ethereum blockchain. *NA_trading_hour (NA_regular_hour)*, is an indicator variable that equals 1 if the average time of the trader's transactions is between 9:30am to 4pm EST (7 am to 10 pm EST); and 0 otherwise. These two variables proxy for the geographical location of the trader, because other geographic information is not available. *Num_txhash* is the average number of the traders' daily transactions; calculated as the wallet's total number of Ethereum transactions over the wallet's *Age*. This measure seeks to capture how active the investor is in general on the Ethereum blockchain. We also include year-month fixed effects to control for other variables that may vary month to month such as stability fees.

Once we understand how loan returns are associated with various loan characteristics, we study whether past loan returns predict future loan returns by adding past loan returns as an independent variable to model (1).

$$Return_{i,t} = b_0 + b_1 Return_{it-1} + b_2' \, LoanCharacteristics_{it} + b_3' controls_{it} + \, monthYearFE_t + e_{it} \qquad (2)$$

If a trader who earns higher past return in the previous loan cycle also earns higher return in their current loan cycle, then $b_1>0$. In our main model, we include current loan cycle characteristics to make sure past loan returns have explanatory power beyond current loan characteristics. We find consistent results in a model with no control variables or in a model that controls for past loan characteristics.

To alleviate the concerns that our assumptions on traders' strategy introduce measurement errors in our loan return measure that might bias our results, we use liquidation events as an alternative loan performance proxy. Specifically, we repeat our regression models in (1) and (2) by replacing *Return* with *Liquidated*, which is an indicator that equals 1if a loan is liquidated, and 0 otherwise.

To study mimicking behavior, we construct our *following* measure. The following measure of loan Z is defined as the number of investors who followed at least half of Z’s borrowing and repayment transactions. A following transaction X’ is said to have followed transaction X if: (1) transaction X’ and X are of the same type of transaction, and (2) transaction X’ occurred within 15 minutes after transaction X. We note that this is a strict definition, as users need to not only follow traders’ positions but rather follow more than half of the borrowing and repayment transactions that lead to that position.

We highlight that our following measure aims to capture the degree to which an investor’s actions in a loan is mimicked by another investor in real-time. In our running example in Appendix C, there are five borrowing transactions and one repayment transaction. In this case, a trader needs to mimic at least three of these six transactions to be considered a follower of the loan by our definition. Next, we describe the steps a follower goes through to mimic a successful users’ loan transactions. First, the follower needs to identify the successful trader by examining the trader’s past performance. Then, when he decides to follow the successful trader, he simply needs to wait for the successful user to build another position. That is, he waits for the successful trader to make another borrowing transaction. The follower then mimics the trader’s move and borrows at the same time. When the successful trader uses the borrowed funds to leverage the ETH investment, as we saw in the running example, the follower observes these transactions, and he can borrow again at around the same time. Finally, when the successful trader decides to cover the position and repay the loan, the follower observes the repayment transaction and repays his loan as well.

By following the timings of the borrowing and repayment transactions of the successful trader, the borrower can earn a similar return on their investment.

Our following measure is closely related to investors herding (see Bikhchandani and Sharma, 2000, for a review), which prior literature defines as "a group of investors following each other into (out of) the same securities over some period of time." (Sais 2004, p166). The empirical literature examines several different measures for investors' herding (e.g., Lakonishok et. al, 1992, Warmers, 1995, Sias, 2004). These measures mostly assess correlation between investors' positions and holding of different stocks. For example, Sias (2004) and Choi and Sias (2009) use cross-sectional temporal dependence of institutional demand of individual stocks or stocks in certain industries over adjacent quarters as a measure of institutional investors' herding. Unlike studies of the stock market that look at quarterly or annual data, our setting allows us to study real-time mimicking as we can look at much shorter time windows. In addition, our data allows us to see mimicking of an investor's "course of actions" rather than only position outcomes. For example, the same leveraged exposure to a crypto could be achieved by various action paths. If a trader ends up with the same leveraged positions to a cryptocurrency with another trader but takes actions in a completely different order, then they will not be counted as followers in our setting. This is in contrast to traditional equity markets where the buy (sell) actions are mapped one-to-one to an increase (decrease) in the outcome position of a security. Given the above, we believe that our following measure is more likely to capture mechanical mimicking of others, which is closer to herding due to informational cascades (i.e., investors inferring information from others' trades) than to investigative herding on correlated signals or coordinated trading.

To study what past loan characteristics investors base their mimicking decisions on, and specifically whether the decision incorporates past loan performance we run the following model:

$$Following_{i,t} = b_0 + b_1 Return_{it-1} + b_2' LoanCharacteristics_{it-1} + b_3' controls_{it} + monthYearFE_t + e_{it} \quad (3)$$

$$Following_{i,t} = b_0 + b_1 Liquidated_{it-1} + b_2' LoanCharacteristics_{it-1} + b_3' controls_{it} + monthYearFE_t + e_{it} \quad (4)$$

If wallets with higher loan returns attract more followers, then we would observe $b_1 > 0$ in model (3). By the same logic, we would observe $b_1 < 0$ in model (4), because liquidation indicates poor performance.

We control for traders' previous loan's characteristics to ensure that the mimicking decisions are driven by previous loan performance, rather than other omitted previous loan characteristics that are observable at the start of the current loan. In addition, we include the innate wallet level variables such as wallet location, experience level, and activity level as in model (1). Most importantly, we believe the inclusion of concurrent ETH market return as a control mitigates concerns that our results are due to coordinated trading on ETH returns.

To examine how information processing costs of historical loan data and of real-time on-chain trades affect investors' efficient mimicking, we augment models (3) and (4) by interacting past loan performance with proxies for historical and real-time information processing costs (*PC*).

$$Following_{i,t} = b_0 + b_1 Return_{it-1} \times PC + b_2 \mathrm{PC} + b_3 Return_{it-1} + b_4' LoanCharacteristics_{it-1} + b_5' controls_{it} + monthYearFE_t + e_{it} \quad (5)$$

$$Following_{i,t} = b_0 + b_1 Liquidated_{it-1} \times PC + b_2\text{PC} + b_3 Liquidated_{it-1} + b_4' LoanCharacteristics_{it-1} + b_5' controls_{it} + monthYearFE_t + e_{it} \quad (6)$$

If the *PC* proxy increases investors information processing costs, then the positive relation between past return and future following should be weakened, b1<0 in model (5), or the negative relation between past liquidation should be weakened, b1>0 in model (6). On the other hand, if the *PC* proxy decreases investors information processing costs, then we should observe the opposite.

4.3 Descriptive Statistics

We present summary statistics of these variables in Table 1 Panel B. Return is on average negative and is equal to -6.4%, indicating that investors on average cannot time the ETH market well for leverage (margin) trading. We further present the time trends of loan returns in Appendix E Panel A. For each month, we first find all loan contracts that started in that month, then compute the average return for all loans (in blue). We then find loans that are in the 90th percentile in loan return (good performing loans), and loans that are in the bottom 10th percentile in return (bad performing loans). We compute the average returns for these two groups of loans for each month in our sample. The average returns of the good performing loans are represented by the orange line, and those of the bad performing loans the grey line. We find that while the overall average return hovers around 0, the good performing loans earned substantial profit. These loans earned a return as high as 100% on average in December 2018. Moreover, in 12 of the 30 months, top performing loans earn an average return of more than 50%. Contrary to good performing loans whose average return is positive every month, bad performing loans earn significantly negative return. In 20 of the 30 months, bad performing loans earn an average return that is below -50%.

The average borrower uses \$35.89 thousand dollars to facilitate the transactions of the loan, which is lower than the portfolio size of \$54.9 thousands for margin traders in Barber et. al (2020). On average, collateralization ratio is 2.36, which means that most investors are conservative. They put in more money than necessary to avoid the possibility of liquidation. The average principal amount borrowed is 20.64 thousand dollars, which is slightly higher than the average loan size of \$13-15 thousand on marketplace lending platforms like Prosper (peer-to-peer) and Lending Club.[14] The average duration of a loan from the date it is opened to the date it is fully paid back is 54 days. The average age of investor's wallet is 227, which suggests that most of them are experienced. This also suggests that investors in our sample are not constantly using new accounts or wallet addresses to open loan contracts. The majority of wallet users are based in North America--71% of wallets transact during North American trading hours. Furthermore, on average, traders in our data perform 7.36 daily transactions on the Ethereum blockchain—much higher than the average of fewer than one Ethereum daily transactions per user—again indicating that they are more active and experienced investors.[15] In our sample, around 28% of the loans are liquidated.

The *following* measure indicates that most wallets are not being actively followed by other investors. On average, the number of followers each loan has is 0.05. We present in Appendix E Panel B, trends in the percentage of following and followed loans over our sample period. The percentage of following loans (the orange line) is the number of loans that followed at least one loan divided by the total number of loans in that month. The percentage of followed loan (the blue line) is the number of loans that have at least one follower divided by the total number of loans in

[14] Prosper and Lending Club are marketplace lenders providing unsecured loans and open for retail and institutional investors to participate.

[15] On average, Ethereum users in our sample period perform fewer than one transaction per day. This number is based on a simple calculation that divides the total number of daily transactions on the Ethereum blockchain by the total number of wallets

the month. As the graph shows, the percentages of followed and following loans increase once Maker launched the website with stats on loans in December 2018. They peak in late 2019 and then wane off. The timing of the decline reflects the launch of the Multi-Collateral Protocol in November 2019 that allows investors to deposit other cryptocurrencies (in addition to ETH) as collateral and drives more and more investors to migrate to the new protocol.[16]

We present the correlation matrix in Table 1 Panel C. Loan *Return* is negatively correlated with liquidation with a statistically significant coefficient of -0.49. The sign and magnitude of the correlation is expected as *Liquidated* is used as an alternative loan performance proxy that captures the negative loan outcome. *Return* is also positively correlated with *Eth_return*, which is the average daily ETH return during the time of the loan. The relation is intuitive as loan return should be higher if the price of ETH goes up. Next, we look at variables that are significantly correlated with liquidation. *Liquidated* is correlated with *Leverage* with a correlation coefficient of 0.34, which means that the more money a user borrows relative to the amount of cash they put down, the more likely the loan to be get liquidated. *Liquidated* is also correlated with *duration* with a coefficient of 0.27, which means if the loan lasts longer, it may be more likely to trigger a liquidation event where the value of the collateral falls below 1.5 times the dollar amount of the principal. *Collateralization* and *Leverage* are negatively correlated with a coefficient of -0.37. The relation is expected since total principal is the denominator of *Collateralization* and the numerator of *Leverage*. But a correlation of -0.37 also suggests that these variables capture different types of information. We therefore include them both in our regression designs.

[16] The single Dai protocol that we examine is no longer in operation since May 2020.

5. Loan Performance and Persistence

Below we discuss our empirical results for loan- and user-level characteristics that are associated with loan performance, and study whether loan performance is persistent.

5.1 Loan Performance

We first investigate what factors affect loan returns by running loan returns on various wallet level and loan level characteristics as specified in model (1) in section 4.2. Our results are presented in Table 2. In the first two columns, we find that *Principal* and *Collateralization* are positively associated with loan returns, while *Duration* is significantly negative. This suggests that bigger loans are associated with better performance while longer loans are associated with lower returns. Moreover, keeping collateral level high is associated with higher returns. This is most likely due to Maker's requirement that the loan will be liquidated if the collateralization ratio falls below 1.5. Thus, to keep collateralization low and close to the minimum requirement runs a higher risk of being liquidated. Similarly, *Volatility* is significantly negative indicating that loans taken during periods with higher ETH price volatility, face higher risks of being liquidated and may generate lower returns. Our results hold also after we include the concurrent ETH market return along with other wallet level characteristics as additional controls. As expected, in the last two columns of Panel A of Table 2, concurrent ETH market return is highly significant and positive. None of the wallet level characteristics are significantly associated with returns.

In Panel B of Table 2, we use liquidation as an alternative proxy for loan performance. Since liquidation is indicator variable, we use a logit regression. We find that all variables that are significant in Panel A of Table 2 are also significant in Panel B of Table 2 but with an opposite sign. This is because liquidation is a negative outcome. Traders' locations and activity level become significant in Panel B. Both *Num_txhash* and *NA_regular_hours* are significantly negative, suggesting that traders who are more active and more likely to locate in the US are less likely to be liquidated. *Leverage* becomes significantly positive in Panel B, suggesting a higher leverage is associated with a higher likelihood of liquidation. Overall, results based on loan returns and liquidation are largely consistent with each other. While liquidation might miss some information as it is only a zero-or-one indicator, it does not need any assumptions about traders' strategies to evaluate their outcome.

5.2 Persistence in Loan Performance

Next, we study whether previous loan performance from the same trader (wallet) predicts current loan performance. This is an important step to ensure that investors indeed have the information needed to identify investors with better returns to mimic.

The results for loan return (Panel A) and liquidation (Panel B) are presented in Table 3. In both specifications (Columns I & II), we find that previous loan return (return(-1)) is significantly and positively associated with current loan return, while past liquidation is a significant predictor for the current liquidation. More specifically, under the most stringent specifications, a one standard deviation increase in previous loan return (return(-1)) increases current loan returns by 3.20% (based on the coefficient in Panel A Column II). Moreover, if the previous loan of a user is liquidated, it increases the chance that the next loan is liquidated by 23% (based on the coefficient in Panel B Column II). These results suggest that past performance (positive and negative) is a good indicator for current performance. Inferences about concurrent ETH returns and other loan characteristics are consistent with Table 2.

In untabulated analyses, we replace all current loan characteristics with previous loan characteristics and find robust results. Taken together, we find robust results that a trader's past loan performance predicts their current loan (margin trading) performance in the decentralized cryptocurrency market.[17]

6 Information Processing Costs and Mimicking of Superior Performers

In this section we study whether investors in this market take advantage of this real-time transparency to identify and follow investors whose superior past performance likely leads to superior future performance. Most importantly, we examine and discuss how their following decisions are affected by costs associated with the processing of free and publicly available trade data.

We first investigate whether investors incorporate others' past performance in their mimicking decisions by running models (3) and (4). Results are presented in Table 4. In all specifications, past return is not significantly associated with the *following* measure, suggesting that investors do not use the persistence in returns and the transparency offered by the blockchain to identify superior performers to follow. In contrast, as the table shows, past liquidation is negatively associated with current following. This indicates that inferior investors are less likely to be followed and is consistent with superior performers attracting more followers.

The mixed evidence of our first hypothesis suggests that even in a transparent market in which others' trading activities are published and recorded by the blockchain in real-time, efficient mimicking does not happen automatically. Investors likely still need to incur costs to process (e.g., to monitor, acquire, and integrate) the public data hosted on the blockchain. Next, we more directly

[17] It is worth noting that while we assume in our returns' calculations that traders use only a leverage investment strategy in ETH, this strategy may still generate drastically different returns due to the differences in the timing in terms of when to leverage and when to de-leverage. The persistence in returns we find, thus, likely implies a persistent skill in timing the ETH market. Furthermore, our analysis of liquidation does not make assumption on the investment strategy. This suggests that the assumption that all loans use the same leveraged trading strategy is not required to find performance persistence.

examine how investors' efficient mimicking is affected by information processing costs involved in two steps of the efficient mimicking. To do so, we study how changes in costs associated with processing historical and real-time data affect mimicking behavior.

6.1 Information processing costs of historical data

We start with examining how a reduction in costs involved in processing historical performance data affects efficient mimicking. We use the launch of a website, https://mkr.tools, which provides both aggregate and transaction-level data for each Maker CDP as an event that reduces the cost of processing historical data for investors.[18] Before the launch of the website, users who wanted to access individual loan information could obtain the data using Maker's API.[19] The Maker API provides transaction-level data on every CDP of the Maker Single Collateral Dai protocol. However, the API does not provide aggregate level information (such as total principal) or data processing capacities (such as sorting CDP by total principal). For users to process the information using the API, they need to use advanced big data processing techniques. On December 6th, 2018, the Maker foundation launched a website to provide investor with information that is easier to process. The website offers summary data for each CDP, such as total principal, collateral amount, collateral to loan ratio, and liquidation price (which is the ETH price that will trigger a liquidation event). The website also had information on the wallet holder of the CDP, the duration of the CDP, and the number of transactions. We present more detailed description and a screenshot of the archived version of the website in Appendix F Panel A. Most importantly, the website also offered transaction-level information for every Maker loan. Specifically, it recorded every transaction that

[18] We were able to access the website while writing the paper in May 2021. The website is currently not maintained anymore and largely replaced by the Maker Business Analytics website (https://www.mkranalytics.com).
[19] Of course, users can also obtain the information directly from the Ethereum blockchain. But to do that, they will most likely need to run a full Ethereum node and then filter out all transactions that are related to Maker. This approach incurs significantly higher processing cost than obtaining data directly using the Maker API.

took place in a loan. In Panel B, we reconstruct this portion of the website for our running example. In Panel C, we also reconstruct the portion of the website for a CDP that is liquidated. Although the website provided information on whether or not a CDP is liquidated, it did not provide information on the return of the loan. Users could use the information on the website to calculate the return themselves and incur higher information processing cost. We use the launch of this website as a natural experiment to study whether a reduction in the costs associated with compiling all wallets/traders' historical activities into one place reduces investors' processing costs of traders' historical performance, thereby making it easier and more likely for investors to incorporate traders' past performance in their mimicking decisions.

We create an indicator variable *post* that equals 1 if the loan begins after the launch of the website and 0 otherwise. We run models (5) and (6) with the *Post* indicator serving as the *PC* proxy. Table 5 presents the results. The coefficients of interest are the interaction term *post* × *return(-1)* and *post* × *liquidated(-1)*. As shown in Columns I and II, the coefficient on *post* × *return(-1)* is positive and significant while the coefficient on *post* × *liquidated(-1)* is negative and significant. Interestingly, the coefficient on *liquidated(-1)* is not significant, suggesting that our previous result that investors use liquidation in their following decisions is mainly driven by the later part of our sample period when the website made information on past liquidations more readily available.

To test whether our results are due to changes in other observable loan characteristics or wallet characteristics pre- and post-website introduction, we repeat our analyses in a fully interacted model in which we further control for the interaction terms between *Post* and all other loan level and wallet level controls. Results are presented in Panel B of Table 5. In column I, both *return(-1)* and *post* × *return(-1)* lose significance. Results with liquidation in columns II are consistent with what we find in Panel A of Table 5.[20]

Overall, our analyses in Table 5 show that providing a website that compiles all wallets' past activities including liquidation status makes it easier for investors to use that information in their mimicking decisions. That is, the costs to process wallets' historical performance is nontrivial in investors mimicking decisions and provides support for our second hypothesis.

6.2 Information processing costs of real-time data

After separating expert investors from others, actively mimicking these investors' strategies requires one to monitor and acquire real-time blockchain data as well as integrate this information to understand what actions need to be performed. Ex ante, loans that are more complex, longer, and with more transactions would generally be more difficult to follow in real-time. In Table 6, we use the number of smart contracts, duration, and number of Maker transactions of the current loan cycle as three different processing costs proxies (*PC*) for the costs involved in the processing of real-time information and estimate model (5) and (6).

These three variables capture slightly different types of information processing costs. Specifically, each Maker transaction may be composed of one, or more, smart contracts. For example, traders can in one transaction call only the Maker smart contract that executes "add collateral to Maker account" or choose in the same transaction to also call the Maker smart contract that executes "borrow from Maker." Moreover, while Maker has its own standard smart contracts, traders can code their own smart contracts that, for example, upon activation would execute certain

[20] We acknowledge the possibility that our results could be biased by confounding events. To the best of our knowledge, the only other event that occurred around the time of the website introduction is the launch of Uniswap in November 2018.We do not think it confounds our results. Most importantly, the volume on Uniswap was minimal till July 2020 when Uniswap introduced V2. In other words, over our entire sample period, activities on Uniswap are stably low.

actions if the price of ETH reaches a predefined level. Consequently, while the number of transactions would affect the cost of monitoring when a trader transacts with the Maker protocol, the number of smart contracts more closely relates to the complexity of understanding the activity. Finally, duration is a more mechanical measure of monitoring transactions on the blockchain over a certain period of time.

In Table 6 Panel A, we use past return to measure historical performance and estimate *following* on *return(-1), PC,* and an interaction term of *PC*× *return(-1),* along with other loan-level and wallet-level controls. We find that across all specifications, the coefficient on *PC* is negative and significant. The coefficient on *return(-1)* is weakly significant and positive for specifications using the number of smart contracts and duration, with *PC*× *return(-1)* being negatively significant for both. These results imply that the information costs of processing current loan cycle information in real-time is nontrivial in investors' mimicking decisions. The results in the specification with smart contracts suggests that the costs are not limited to monitoring and acquiring the information—which can be mitigated by bots—but rather also hold for the integration of the information into a coherent investment strategy. Since investors can code their own smart contracts, automating this part is more complex and thus requires more manual intervention.

Panel B of Table 6 presents results with liquidation as the performance measure. The results are largely consistent with the above. An increase in PC proxies weakens the negative relation between past liquidation and current following.[21] Overall, Table 6 shows that the relationship

[21] We caution readers against interpreting the negative relation between past liquidation and current following as only about investors avoiding bad performers. Similar to the positive relation between post return and current loan following, the negative relation between past liquidation and current loan following could also result from investors mimicking better performed investors. When better performed users attract more followers to mimic them, worse performers and liquidated users see relatively fewer followers.

between past performance and current loan following weakens when processing costs increase. This is consistent with our third hypothesis that processing costs of real-time information affect investors' efficient mimicking of expert investors.

7 Additional Analyses and Robustness Tests

In section 7.1, we examine the returns traders would have enjoyed had they chosen to mimic expert investors. We also compare the actual loan returns of followers and the loan returns of non-followers. Furthermore, we assess the possibility that our following measure is driven by trading on correlated signals or coordination by one investor or a group of investors. We discuss numerous robustness checks of our main results in section 7.2.

7.1 Additional Analyses

The transaction transparency of the market raises the question: what would the returns be, if traders chose to mimic expert investors? To answer this question, we build a mimicking strategy and examine the time series of the strategy returns. Starting from December 2017, we use each of the 6-month data as historical data to identify wallets that rank in the top decile in terms of their Sharp Ratio (average loan returns/standard deviation of loan returns). We then follow the loans they take in the next 6 months. As Table 7 shows, this strategy of following the top 10 percent investors generates significant positive returns of 12.8% per loan, on average, for all periods before the launch of the website that made wallet statistics readily available. This is in stark contrast to the average loan return (to proxy for the return of an independent strategy) in our data which generates a significant negative return of -8.4% during the same time periods. The difference between mimicking experts and trading independently is at 20%, and is statistically significant. When the processing costs are lowered by a website that compiles traders' past activities, the difference between the mimicking and the independent strategy shrinks and becomes no longer significant.[22]

In the above test, we evaluate an ideal situation in which investors can perfectly identity and follow superior performers. Investors may or may not be able to do so in reality. We next study the actual return of investors who followed and did not follow other investors. In Table 8, we examine the differences in return distributions and liquidation frequencies between these two types of investors. We define a user as a follower if they followed another loan at least once. Non-followers are then traders that did not follow any loan. The non-follower group of traders likely includes very skilled or very unsophisticated traders who've implemented an independent strategy. We find that the average return of a follower is -0.02, while the average return for a non-follower is -0.07. The difference in means is significant at 1%. Interestingly, this better performance is mainly driven by the avoidance of incurring huge losses. The 25th percentile and median returns of followers are less negative than the corresponding values for non-followers. However, the 75th percentile return of followers is less positive than that of non-followers (with average return of 0.01 vs 0.05). Taken together, these suggest that, compared to good performers who implement their own strategies, followers are better at avoiding large losses. However, they are not as successful at earning better returns. If our following measure was mainly capturing coordination (within one expert or among a group of experts), then followers should have performed better than non-followers throughout the entire distribution and should particularly be better at generating more positive returns. That is not what we observe in the data.

[22] We find some weak evidence of increased reliance on past returns in mimicking decisions post the website introduction in Table 5, implying that top performers are more likely to be mimicked if they take loans. This could contribute to a lower return of the mimicking strategy.

Next, we further address concerns that our following measure mainly captures coordination within one trader (i.e., same users using multiple wallets to obfuscate their activities in real-time). If traders use multiple wallets to interact with the Maker protocol, it is likely that they need to transfer funds between these wallets. Therefore, we look at all wallets' transactions between the time they started transacting on the Ethereum blockchain and their last loans on Maker. We define any two wallets as linked if the two wallets ever interacted on the Ethereum blockchain during that time. Linked wallets are more likely to belong to the same user than non-linked wallets. We test the robustness of our results on the subset of non-linked wallets (see Internet Appendix B). All our results are robust, and inferences remain unchanged.

Finally, we note that our following measure is designed to capture the mimicking of an investor's "course of actions" rather than only traders' position outcomes. Given that we require traders to not only follow traders' positions but rather follow more than half of the borrowing and repayment transactions that lead to that position, we believe that our following measure is less likely to capture investigative herding on correlated signals or coordinated trading. Indeed, among the 432 traders who either follow others or are being followed, only two mutually follow each other. All the other pairs reflect following in one direction, which is inconsistent with trading on correlated signals or coordinated trading that would lead to more mutual following. Moreover, as we show in the Internet Appendix C, the average number of followers per loan is relatively low (no more than 3) and thus more consistent with mimicking than trade coordination.

7.2 Robustness Tests

Because some of our controls are correlated, we first replicate our results with regression specifications that do not include loan- or wallet-level controls. Our results are robust to these alternative specifications (see Internet Appendix D). Second, we also check the robustness of our results to alternative return measure--defining *return(-1)* as the average past loan return of the investor (Internet Appendix E). All our inferences hold. To confirm that our results are not driven by extremely small loans, we limit the sample to loans that have borrowed more than 100 USD (Internet Appendix F). Results and inferences hold for this subsample as well.

Appendix E Panel C graphs the daily closing ETH price during our sample period. We observe that during the first few months (from December 2017 to April 2018), the price of ETH drops significantly from a high of $1,400 USD in January 2018 to $400 in April 2018. The price of ETH continues to decline in months after April 2018 and remains at around $200 for the rest of our sample period. The overall bear market raises the concern that our persistence result is mostly driven by investors earning negative returns. To study whether there are investors who can still earn positive profit consistently, we first explore if we could identify a group of investors with persistent *positive* returns. We find that 262 investors in our data—accounting for more than 10% of the entire sample of investors (262/2,545)—earn persistently positive returns (i.e., 100% of their loans generated positive returns). These investors earn sizable returns—average return of 20.28% (and a standard deviation of 0.25), which is statistically different from 0.

We further test whether high performing investors' returns are persistent, by restricting the sample to only investors who have at least three loans and whose first two loans earned positive returns. Our results are consistent (see Internet Appendix G). To exclude the possibility that our results are driven by the drop in ETH prices in the beginning of our sample period or by other market-wide events that drove down the price of ETH, we test our results on subsamples that exclude loans that started in the first 3 or 6 months of the sample period. In both subsamples, our results remain robust (see Internet Appendix H and I), and inferences remain the same.

8. Conclusion

In this paper, we study whether a market that features real-time trades transparency facilitates users' mimicking of transactions made by other users. We study one of the first and most popular decentralized lending protocol, MakerDao's Single Collateral Dai, and examine users' leverage trading strategies. We find that both lagged loan returns and lagged liquidation can significantly predict current loan returns and liquidation. Moreover, we hypothesize that if loan performance is persistent, then users who intend to earn better returns can mimic the transactions of investors with superior past performance. However, we do not find that an investor's past return is positively associated with the degree to which the investor is being followed by others in the current loan. Nonetheless, we find that lagged liquidation event is negatively associated with how much an investor is being followed by others in the current loan. Further analyses indicate that the significant negative relation between past liquidation events and the number of future followers is mainly driven by a period of our sample after the introduction of a website founded by the Maker foundation that gathers past liquidation events and makes them publicly available and easy to process. This suggests that the costs to process historical performance data hinder investors' ability to incorporate the information into their mimicking decisions. In addition, we find that an increase in the processing costs of current loan cycle activities in real-time also reduces efficient mimicking. Overall, this evidence provides support that it is probably the information collecting and processing costs that prevent investors from avoiding inferior investors and following superior investors.

Our study has important implications for practitioners and regulators. Our results suggest that even when a market that publishes trades information in real-time, investors may still lack the sophistication to process the information and take advantage of it. Therefore, transparency alone is not sufficient to ensure efficient mimicking. Regulators should not only aim at transparency but also require data to be aggregated and presented in a way that is accessible for the average investor. introduction. We caution our readers that our evidence on investors information processing of publicly available trading data is based on the specific DeFi market we investigate. Future research could investigate whether our results hold in other markets where traders' activities are traceable in real-time, if more such markets emerge

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Table 1. Summary Statistics

Table 1 presents summary statistics of our measures of loan-level and wallet-level characteristics. Our sample period is from December 2017 to May 2020, the entire period that MakerDao's Single Collateral Dai is in operation. Our sample includes all loans opened with MakerDao. We restrict the sample to a set of loans that are repaid, have total borrowed principal of strictly greater than 1 US dollars, and to a set of wallet holders that have at least two loans. This sample selection process yields a total number of 8,062 loans. Panel A presents the main variables. *Following* is the number of followers of the loan, where number of followers are defined as anyone who followed more than half of the borrowing and repayment transactions of a loan. *Return* is calculated for each loan as (the ending collateral value of the loan + ending cash balance - cash used), divided by cash used. *Cash* is the amount of cash used to facilitate the transaction in the loan. *Collateralization* is the minimum total collateral to total principal ratio across all the times that the wallet holder borrows money from the loan. *Leverage* is total principal borrowed during the loan divided by the total amount of cash used. *Principal* is the natural logarithm of one plus the amount borrowed. *Duration* is the duration of the loan in number of days. *Volatility* is the standard deviation of daily Ethereum returns over the duration of the loan. *Volatility_missing* is an indicator variable that is equal to 1 if the loan opens and closes on the same day, which results in *Volatility* having a zero value. *Eth_return* is the average daily Ethereum return over the duration of the loan. *Age* is the number of days between the earliest transaction of the wallet to the beginning time of the loan. *NA_trading_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American trading hours, from 9.5 am to 16 pm EST; 0 otherwise. *NA_regular_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American hours, from 7 am to 22 pm EST, 0 otherwise; *Num_txhash* measures the average number of transactions per day for the wallet holder of the loan since its first crypto transaction to the start time of the MakerDao loan. *Liquidated* is an indicator variable that is equal to 1 if the loan is liquidated; 0 otherwise. Panel A outlines the sample construction process and data filters we use to arrive at the final sample. Panel B presents the summary statistics table. Panel C presents the correlation matrix of the main variables. Bold numbers in Panel C indicate the correlation coefficients are significant at the 5% level.

Panel A. Sample construction

Total number of MakerDao CDPs	155,406
Delete CDPs with zero principal	(9,270)
Delete all open CDPs	(114,857)
Total number of closed CDPs	31,279
Total number of loans based on the total number of closed CDPs	57,941
Delete loans that use relayer wallets	(23,487)
Total number of loans that do not use proxy wallets	34,454
Delete loans whose wallet holder has fewer than 2 loans during the sample period	(23,798)
Delete loans whose total principal is less than 1 USD	(2,594)
Final sample of loans	8,062

Panel B. Summary statistics

	mean	sd	p25	p50	p75	count
following	0.048	0.33	0.00	0.00	0.00	8062
return	-0.064	0.34	-0.18	-0.01	0.04	8062
cash (in thousand dollars)	35.89	338	0.08	1.21	9.42	8062
collateralization	2.36	1.34	1.66	2.01	2.47	8062
leverage	0.61	0.50	0.33	0.48	0.68	8062
principal	6.02	3.07	3.43	6.22	8.41	8062
principal (in thousand dollars)	20.65	262.18	0.03	0.5	4.5	8062
duration	54.44	92.05	1.54	13.96	64.35	8062
volatility	0.04	0.03	0.03	0.04	0.05	8062
volatility_missing	0.17	0.37	0.00	0.00	0.00	8062
eth_return	-0.00	0.03	-0.01	-0.00	0.01	8062
age	227.45	250.42	16	136	379	8062
NA_trading_hours	0.71	0.45	0.00	1.00	1.00	8062
NA_regular_hours	0.95	0.23	1.00	1.00	1.00	8062
num_txhash	7.36	7.30	3.23	4.78	8.00	8062
liquidated	0.28	0.45	0.00	0.00	1.00	8062

Panel C. Correlation matrix. Bold numbers indicate the correlation coefficients are significant at the 5% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) following	1.00														
(2) return	0.01	1.00													
(3) order	0.00	0.00	1.00												
(4) collateralization	0.00	**0.05**	**0.04**	1.00											
(5) leverage	**-0.03**	**0.03**	**-0.09**	**-0.37**	1.00										
(6) principal	**-0.09**	-0.02	**0.11**	**-0.11**	**0.20**	1.00									
(7) duration	**-0.06**	**-0.08**	**-0.10**	-0.02	**0.06**	**0.22**	1.00								
(8) volatility	**-0.13**	**-0.11**	**-0.08**	**-0.06**	**0.10**	**0.25**	**0.20**	1.00							
(9) volatility_missing	**0.19**	**0.06**	**0.16**	**0.08**	**-0.11**	**-0.27**	**-0.27**	**-0.70**	1.00						
(10) eth_return	**-0.03**	**0.24**	0.01	**0.04**	0.00	0.00	0.03	**-0.05**	-0.03	1.00					
(11) age	**-0.04**	**0.07**	**0.16**	**0.10**	**-0.10**	**0.20**	**0.03**	**0.06**	**-0.04**	0.01	1.00				
(12) NA_trading_hours	**-0.04**	0.02	**0.06**	0.00	0.02	**0.20**	**0.06**	**0.07**	**-0.11**	-0.01	**0.13**	1.00			
(13) NA_regular_hours	**-0.04**	0.02	**0.05**	**0.04**	-0.00	**0.11**	**0.06**	**0.07**	**-0.10**	0.02	**0.11**	**0.37**	1.00		
(14) num_txhash	**0.07**	0.02	**0.41**	**-0.07**	**0.07**	**0.12**	**-0.17**	**-0.18**	**0.27**	-0.00	**-0.12**	0.00	-0.02	1.00	
(15) liquidated	**-0.05**	**-0.49**	**-0.10**	**-0.20**	**0.34**	0.01	**0.27**	**0.20**	**-0.18**	**-0.15**	**-0.09**	-0.02	**-0.03**	**-0.10**	1.00

Table 2. Characteristics that Associate with Contemporaneous Loan Return

Table 2 investigates which features impact the return of the loan return. Specifically, it presents results from regressing return variables, such as *return* or *liquidated* on day t on loan features on day t.

$$Y_{i,t} = b_0 + b_1 loanCharacteristics_i + b_2' controls_{it} + \ monthYearFE_t + e_{it}$$

where *order* is order of the loan in the sequence of all loans held by the wallet, specifically order = n if the loan is the user's nth loan. *Following* is the number of followers of the loan, where number of followers are defined as anyone who followed more than half of the borrowing and repayment transactions of a loan. *Collateralization* is the minimum total collateral to total principal ratio across all the times that the wallet holder borrows money from the loan. *Leverage* is total principal borrowed during the loan divided by the total amount of cash used. *Principal* is the natural logarithm of one plus the amount borrowed. *Duration* is the duration of the loan in number of days. *Volatility* is the standard deviation of daily Ethereum returns over the duration of the loan. *Volatility_missing* is an indicator variable that is equal to 1 if the loan opens and closes on the same day, which results in *Volatility* having a zero value. *Eth_return* is the average daily Ethereum return over the duration of the loan. *Age* is the number of days between the earliest transaction of the wallet to the beginning time of the loan. *NA_trading_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American trading hours, from 9.5 am to 16 pm EST; 0 otherwise. *NA_regular_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American hours, from 7 am to 22 pm EST, 0 otherwise; *Num_txhash* measures the average number of transactions per day for the wallet holder of the loan since its first crypto transaction to the start time of the MakerDao loan. Month-year fixed effects are included in the regressions. Robust standard errors are clustered at the wallet level. In Panel A, we examine the determinants of *return*. In Panel B, we examine the determinants of whether a loan is *liquidated* using contemporaneous loan-level characteristics using logit regressions.

Panel A. Characteristics that associate with contemporaneous loan return

Regressions	I		II	
	return	tstat	return	tstat
order	-0.001	-0.69	-0.001	-1.04
collateralization	0.013	3.92	0.012	3.86
leverage	0.003	0.26	0.003	0.22
principal	0.006	3.38	0.005	2.67
duration	-0.000	-2.69	-0.000	-2.60
volatility	-1.033	-3.67	-1.029	-3.69
volatility_missing	-0.000	-0.00	-0.003	-0.21
eth_return			1.986	13.32
age			0.000	0.68
NA_trading_hours			0.007	0.62
NA_regular_hours			0.021	1.33
num_txhash			0.001	1.41
Observations	8062		8062	
R-squared	0.259		0.259	
Month-year FE	Yes		Yes	
Clustering	Wallet		Wallet	

Panel B. Characteristics that associate with liquidation

Regressions	I		II	
	liquidated	tstat	liquidated	tstat
order	-0.034	-1.74	-0.016	-0.80
collateralization	-0.568	-4.53	-0.581	-4.74
leverage	1.837	14.21	1.939	15.03
principal	-0.210	-12.09	-0.197	-10.87
duration	0.008	14.02	0.007	13.55
volatility	11.322	5.87	11.366	5.81
volatility_missing	-1.005	-5.80	-0.860	-4.83
eth_return	-19.842	-11.24	-20.189	-11.21
age			-0.000	-0.47
NA_trading_hours			-0.093	-0.82
NA_regular_hours			-0.351	-2.03
num_txhash			-0.048	-4.68
Observations	8062		8062	
Pseudo R-squared	0.316		0.323	
Month-year FE	Yes		Yes	
Clustering	Wallet		Wallet	

Table 3. The Persistence of Loan Returns

Table 3 investigates whether past loan returns can predict future return. Specifically, it presents results from regressing performance variables, such as *Return* or *Liquidated* of the current loan on *Return* or *Liquidated* of a trader's previous loan as well as loan features on day t-1.

$$Y_{i,t} = b_0 + b_1 Y_{i,t-1} + b_2 loanCharacteristics_{i,t} + b_3' controls_{it} + monthYearFE_t + e_{it}$$

where o*rder* is order of the loan in the sequence of all loans held by the wallet, specifically order = n if the loan is the user's nth loan. *Following* is the number of followers of the loan, where number of followers are defined as anyone who followed more than half of the borrowing and repayment transactions of a loan. *Collateralization* is the minimum total collateral to total principal ratio across all the times that the wallet holder borrows money from the loan. *Leverage* is total principal borrowed during the loan divided by the total amount of cash used. *Principal* is the natural logarithm of one plus the amount borrowed. *Duration* is the duration of the loan in number of days. *Volatility* is the standard deviation of daily Ethereum returns over the duration of the loan. *Volatility_missing* is an indicator variable that is equal to 1 if the loan opens and closes on the same day, which results in *Volatility* having a zero value. *Eth_return* is the average daily Ethereum return over the duration of the loan. *Age* is the number of days between the earliest transaction of the wallet to the beginning time of the loan. *NA_trading_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American trading hours, from 9.5 am to 16 pm EST; 0 otherwise. *NA_regular_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American hours, from 7 am to 22 pm EST, 0 otherwise; *Num_txhash* measures the average number of transactions per day for the wallet holder of the loan since its first crypto transaction to the start time of the MakerDao loan. Month-year fixed effects are included in the regressions. Robust standard errors are clustered at the wallet level. In Panel A, we examine the persistence of *return*. In Panel B, we examine the persistence *liquidation* using current loan-level characteristics and logit regressions. The number of observations in these regressions is 5,517 because we drop the first loan of every user since return(-1) for these observations are zero.

Panel A. Persistence in return

Regressions	I		II	
	return	tstat	return	tstat
return(-1)	0.094	4.69	0.094	4.70
order	-0.000	-0.32	-0.001	-0.70
collateralization	0.008	2.43	0.008	2.42
leverage	-0.010	-0.75	-0.010	-0.78
principal	0.005	2.76	0.005	2.13
duration	-0.000	-2.10	-0.000	-1.99
volatility	-1.353	-4.11	-1.352	-4.16
volatility_missing	-0.014	-1.06	-0.017	-1.23
eth_return	1.747	10.28	1.745	10.22
age			0.000	0.33
NA_trading_hours			0.009	0.63
NA_regular_hours			0.019	1.03
num_txhash			0.001	1.17
Observations	5517		5517	
R-squared	0.272		0.272	
Month-year FE	Yes		Yes	
Clustering	Wallet		Wallet	

Panel B. Persistence in liquidation

Regressions	I		II	
	liquidated	tstat	liquidated	tstat
liquidated(-1)	2.253	21.71	2.231	21.41
order	-0.045	-2.95	-0.032	-2.01
collateralization	-0.424	-5.26	-0.434	-5.31
leverage	1.531	12.19	1.598	12.53
principal	-0.215	-11.46	-0.201	-10.19
duration	0.008	13.35	0.008	13.00
volatility	13.674	5.00	14.200	5.14
volatility_missing	-0.856	-3.78	-0.697	-3.03
eth_return	-18.477	-8.09	-18.883	-8.31
age			-0.000	-1.27
NA_trading_hours			-0.120	-1.01
NA_regular_hours			0.013	0.06
num_txhash			-0.036	-3.90
Observations	5517		5517	
Pseudo R-squared	0.425		0.429	
Month-year FE	Yes		Yes	
Clustering	Wallet		Wallet	

Table 4. The Determinants of Following Score

Table 4 investigates the determinants of the following score. We estimate
$Following_{i,t} = b_0 + b_1 Y_{i,t-1} + b_2 LoanCharacterstics_{i,t-1} + b_3' controls_{i,t} + monthYearFE_t + e_{it}$
where *Y* is either *Return* or *Liquidated*, or both. *Following* is the number of followers of the loan, where number of followers are defined as anyone who followed more than half of the borrowing and repayment transactions of a loan. *Return* is calculated for each loan as (the ending collateral value of the loan + ending cash balance - cash used), divided by cash used. *Liquidated* is an indicator variable that is equal to 1 if the loan is liquidated; 0 otherwise. *Collateralization* is the minimum total collateral to total principal ratio across all the times that the wallet holder borrows money from the loan. *Leverage* is total principal borrowed during the loan divided by the total amount of cash used. *Principal* is the natural logarithm of one plus the amount borrowed. *Duration* is the duration of the loan. *Volatility* is the standard deviation of daily Ethereum returns over the duration of the loan. *Volatility_missing* is an indicator variable that is equal to 1 if the loan opens and closes on the same day, which results in *Volatility* having a zero value. *Eth_return* is the average daily Ethereum return over the duration of the loan. *Age* is the number of days between the earliest transaction of the wallet to the beginning time of the loan. *NA_trading_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American trading hours, from 9.5 am to 16 pm EST; 0 otherwise. *NA_regular_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American hours, from 7 am to 22 pm EST, 0 otherwise; *Num_txhash* measures the average number of transactions per day for the wallet holder of the loan since its first crypto transaction to the start time of the MakerDao loan. Month-year fixed effects are included in the regressions. Robust standard errors are clustered at the wallet level. We examine the determinants of following score with lagged return (Column I) and with lagged liquidation (Column II). The number of observations in these regressions is 5,517 because we drop the first loan of every user.

Panel A. Determinants of following with return and other variables

Regressions	I		II	
	following	tstat	following	tstat
return(-1)	0.009	0.90		
liquidated(-1)			-0.020	-2.26
collateralization(-1)	0.002	0.34	0.001	0.27
leverage(-1)	-0.015	-1.99	-0.009	-1.15
principal(-1)	-0.004	-1.81	-0.004	-1.92
duration(-1)	0.000	1.41	0.000	1.79
volatility(-1)	0.510	2.51	0.531	2.59
volatility_missing(-1)	0.081	3.94	0.081	3.94
eth_return	-0.365	-1.32	-0.378	-1.36
age	-0.000	-1.26	-0.000	-1.27
NA_trading_hours	0.007	0.60	0.007	0.59
NA_regular_hours	-0.061	-1.64	-0.062	-1.66
num_txhash	0.003	2.60	0.002	2.53
Observations	5517		5517	
R-squared	0.034		0.034	
Month-year FE	Yes		Yes	
Clustering	Wallet		Wallet	

Table 5. Differential following behavior of loans opened before or after the introduction of the MakerDao website

Table 5 examine the effects of MakerDao website introduction on users' following behavior. We estimate

$$Following_{i,t} = b_0 + b_1 Y_{i,t-1} + b_2 Post_{i,t} + b_3 Y_{i,t-1} \times Post_{i,t} + b_2 loanCharacterstics_{i,t-1} + b_3' controls_{i,t} + monthYearFE_t + e_{i,t}$$

where *Y* is either *ret* or *liquidated*, or both. *Following* is the number of followers of the loan, where number of followers are defined as anyone who followed more than half of the borrowing and repayment transactions of a loan. *Post* is an indicator variable that is equal to 1 if the loan began and ended after December 6th, 2018; 0 if the loan began and ended before December 6th, 2018. *Return* is calculated for each loan as (the ending collateral value of the loan + ending cash balance - cash used), divided by cash used. *Liquidated* is an indicator variable that is equal to 1 if the loan is liquidated; 0 otherwise. *Collateralization* is the minimum total collateral to total principal ratio across all the times that the wallet holder borrows money from the loan. *Leverage* is total principal borrowed during the loan divided by the total amount of cash used. *Principal* is the natural logarithm of one plus the amount borrowed. *Duration* is the duration of the loan. *Volatility* is the standard deviation of daily Ethereum returns over the duration of the loan. *Volatility_missing* is an indicator variable that equals 1 if the loan opens and closes on the same day, which results in *Volatility* having a zero value. *Eth_return* is the average daily Ethereum return over the duration of the loan. *Age* is the number of days between the earliest transaction of the wallet to the beginning time of the loan. *NA_trading_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American trading hours, from 9.5 am to 16 pm EST; 0 otherwise. *NA_regular_hours* is an indicator variable that equals 1 if the average hour of transactions made by the wallet occurs within regular North American hours, from 7 am to 22 pm EST, 0 otherwise; *Num_txhash* measures the average number of transactions per day for the wallet holder of the loan since its first crypto transaction to the start time of the MakerDao loan. Month-year fixed effects are included in the regressions. Robust standard errors are clustered at the wallet level. In Panel A, we examine the determinants of following score with lagged return (Column I) and with lagged liquidation (Column II). Next, we use a fully interacted model where all control variables are interacted with *Post*. We present abbreviated version of this test in Panel B. The number of observations in these regressions is 5,207, instead of 5,517 because we drop loans that began before December 6th, 2018, but ended after December 6th, 2018.

Panel A. Examining the effect of introducing MakerDao website on users' following behavior.

Regressions	I		II	
	following	tstat	following	tstat
post	0.030	1.36	0.037	1.61
return(-1)	-0.021	-2.21		
post*return(-1)	0.041	2.47		
liquidated(-1)			0.009	1.21
post*liquidated(-1)			-0.051	-3.88
collateralization(-1)	0.002	0.40	0.002	0.37
leverage(-1)	-0.013	-1.68	-0.001	-0.12
principal(-1)	-0.004	-2.03	-0.005	-2.25
duration(-1)	0.000	0.95	0.000	1.82
volatility(-1)	0.539	2.57	0.580	2.73
volatility_missing(-1)	0.085	4.01	0.086	4.03
eth_return	-0.387	-1.35	-0.404	-1.40
age	-0.000	-1.20	-0.000	-1.26
NA_trading_hours	0.012	0.95	0.013	1.00
NA_regular_hours	-0.062	-1.61	-0.063	-1.64
num_txhash	0.003	2.59	0.002	2.45
Observations	5207		5207	
R-squared	0.034		0.035	
Month-year FE	Yes		Yes	
Clustering	Wallet		Wallet	

Panel B. Fully interacted model

Regressions	I		II	
	following	tstat	following	tstat
post	0.040	0.78	0.044	0.85
return(-1)	0.000	0.01		
post*return(-1)	0.020	1.35		
liquidated(-1)			0.000	0.07
post*liquidated(-1)			-0.041	-3.05
Observations	5207		5207	
R-squared	0.034		0.035	
Fully Interacted Controls	Yes		Yes	
Month-year FE	Yes		Yes	
Clustering	Wallet		Wallet	

Table 6. Information Processing Cost

Table 6 examine the effects of real-time information processing cost on users' following behavior. We estimate

$$Following_{i,t} = b_0 + b_1 Y_{i,t-1} + b_2 Processing\_cost_{i,t} + b_3 Y_{i,t-1} \times Processing\_cost_{i,t} + b_2 loanCharacterstics_{i,t-1} + b_3' controls_{i,t} + monthYearFE_t + e_{i,t}$$

where *Y* is either *return* or *liquidated. Following* is the number of followers of the loan, where number of followers are defined as anyone who followed more than half of the borrowing and repayment transactions of a loan. *Processing cost* are proxies that measure the complexity of the trades of the loan. The more complex the loan, the higher the processing cost for the follower. We use three proxies for processing cost. We use the *duration* of the loan, which is the number of days a loan is opened on MakerDao (Column I); *num_smart_contracts*, which is the number of smart contracts used in the loan (Column II); and *num_makerdao_tx,* which is the number of transactions occurred in the loan (Column III). In Panel A, we examine the relation between following and return interacted with three processing cost proxies. In Panel B, we examine the relation between following and liquidation interacted with three processing cost proxies. We include lagged loan-level, and wallet-level controls that are the same as the ones used in Table 4 and Table 5. Month-year fixed effects are included in the regressions. Robust standard errors are clustered at the wallet level.

Panel A. Examining the relation between following and return with three processing cost proxies.

	pc = duration		pc = number of smart contracts		pc = number of Makerdao transactions	
Regressions	I		II		III	
	following	tstat	following	tstat	following	tstat
processing cost	-0.0001	-2.81	-0.0243	-3.71	-0.0003	-4.41
return(-1)	0.0215	1.66	0.0416	1.71	0.0120	1.08
processing cost * return (-1)	-0.0002	-2.22	-0.0222	-1.96	-0.0002	-1.39
Observations	5517		5517		5517	
R-squared	0.034		0.035		0.034	
Controls	Yes		Yes		Yes	
Month-year FE	Yes		Yes		Yes	
Clustering	Wallet		Wallet		Wallet	

Panel B. Examining the relation between following and liquidation with three processing cost proxies.

	pc = duration		pc = number of smart contracts		pc = number of Makerdao transactions	
Regressions	I		II		III	
	following	tstat	following	tstat	following	tstat
processing cost	-0.0002	-3.34	-0.0256	-3.10	-0.0005	-4.84
liquidated(-1)	-0.0340	-3.16	-0.0397	-2.12	-0.0256	-2.64
processing cost * liquid.(-1)	0.0002	3.74	0.0165	1.66	0.0004	3.45
Observations	5517		5517		5517	
R-squared	0.035		0.035		0.035	
Controls	Yes		Yes		Yes	
Month-year FE	Yes		Yes		Yes	
Clustering	Wallet		Wallet		Wallet	

Table 7. Returns of a Mimicking Strategy

Table 7 examines the time series of a strategy return *Ret_Mimic* that ranks investors into deciles based on each six-months data in the past and follows the loans of those that rank in the top decile in the next six months. We compare the mimicking strategy returns to the average loan returns *Ret_Avg* during the same time periods that is to capture how well investors perform if they trade independently. We investigate whether *Ret_Mimic*, *Ret_Avg* and the difference between the two change before and after the introduction of the website that makes traders' past performance easier to process, by regressing them on *Post. Post* is an indicator variable that is equal to 1 if the loan began and ended after December 6^{th}, 2018; 0 if the loan began and ended before December 6^{th}, 2018. ***p<0.01, ** p<0.05, * p<0.1

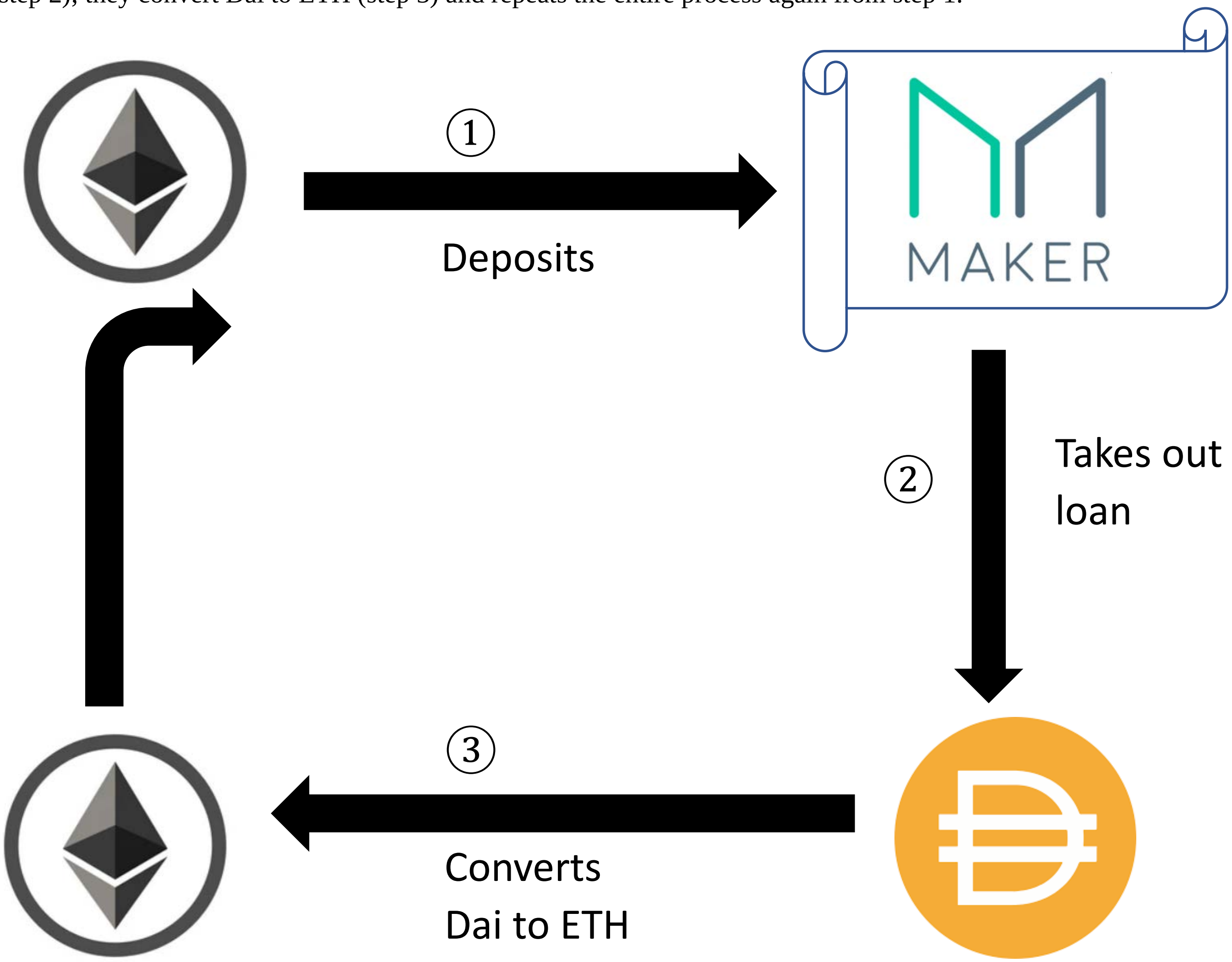
	(1)	(2)	(3)	(4)	(5)	(6)
	Ret_Mimic		Ret_Avg		Diff	
VARIABLES	coef	tstat	coef	tstat	coef	tstat
Constant (pre-period)	0.128*	1.78	-0.084***	-3.42	0.201**	2.84
Post	-0.174*	-1.94	0.066**	2.16	-0.231**	-2.63
Constant+Post (post-period)	-0.045	0.77	-0.017	-2.42	-0.03	-0.52

Table 8. Comparing following and non-following wallet return.

Table 8 examines the differences in return distributions and liquidation frequencies between users that follow another user (wallet) and users that do not (i.e., users who are implementing independent strategies). We define a following user as any wallet that has at least one following loan. A loan is identified as a following loan if at least 50% of the transactions in the loan occurred within 15 minutes after the transactions of another loan. *Return* is the average return for a user across all his loans. *Percentage of liquidated loans* is calculated as the number of liquidated loans of a user divided by the total number of their loans. *, **, *** represent significance at the 10%, 5%, and 1% level (two-tailed), respectively.

	Following Users						Non-following Users						Difference in means
	mean	sd	p25	p50	p75	count	mean	sd	p25	p50	p75	count	
return	-0.02	0.16	-0.05	-0.00	0.01	212	-0.07	0.25	-0.21	-0.04	0.05	2333	0.05***
percentage of liquidated loans	0.19	0.32	0.00	0.00	0.33	212	0.32	0.38	0.00	0.00	0.50	2333	-0.13***

Appendix A. Graphic representation of leveraged trading strategy using MakerDao loans:
Appendix A gives a simple graphic representation of leveraged trading strategies. Here, the investor deposits ETH (step 1) to take out a loan in Dai (step 2); they convert Dai to ETH (step 3) and repeats the entire process again from step 1.[23]



[23] When they decide to pay back the loan, they can also pay it back in installments. For example, the investor unlocks some collateral by paying back Dai. They use the unlocked collateral to trade for more Dai, which they then use to pay back the loan and unlock ETH.

Appendix B. Interest fee change schedule for the Maker Protocol

In this table, we present historic interests rates used by the MakerDao protocol. There are 13 changes to the interest rate. We also present the beginning time and ending time where each interest rate is in effect as well as the transaction has that is used to make the change.

Begin Time	End Time	Interest Rate	TxHash used to facilitate the change
Dec-18-2017 20:15:01	Aug-30-2018 20:15:01	0.50%	
Aug-30-2018 20:15:01	Dec-21-2018 19:11:50	2.50%	0x9012d9a877dfce00501208ecb536045fc6d4540408868a377f9fc78f41d9170d
Dec-21-2018 19:11:50	Feb-09-2019 20:19:26	0.50%	0x644f94010bf0a5a077f0a05568e4319565f480fb307587e7b096462278b1c8a9
Feb-09-2019 20:19:26	Feb-23-2019 19:24:23	1%	0x7fb069a649d73166dbd6428fec7a28493f5502beda20038a7b78784c6ed00e75
Feb-23-2019 19:24:23	Mar-09-2019 02:27:42	1.50%	0x9cfeb1dde25706f868c34c34ce6cc8c8c7686bed13e736f26b1169dc1723bcc9
Mar-09-2019 02:27:42	Mar-22-2019 22:58:39	3.50%	0x0332973a529c1d68556ea1399ea807f19805b1b6461972bbbfddd66d26f94c2a
Mar-22-2019 22:58:39	Apr-14-2019 23:39:09	7.50%	0xee9f25fbb05d8f91580c0f81bc7eb38dcb92f35117055e6976076b5b0320441c
Apr-14-2019 23:39:09	Apr-19-2019 19:56:33	11.50%	0x121af46b6eb05157327b43324ae54ac7612e8b3ca375fe631d280d3bdcd37f8d
Apr-19-2019 19:56:33	Apr-28-2019 04:04:21	14.50%	0x04c73f2e1664b50c2d0d3458f237adecae71a26f1d9bb43bc6fb8c9fce9982f4
Apr-28-2019 04:04:21	May-03-2019 20:23:23	16.50%	0xe063598c19bb7c5ec52f9c82cfd8c986b8141351f7dfe3d05677ba3d262e204f
May-03-2019 20:23:23	May-28-2019 21:06:19	19.50%	0xfecb046baeeb49d39d2fe00333c94903132e87a0372cd5ee62953b9c06d396fa
May-28-2019 21:06:19	Jun-05-2019 13:12:18	17.50%	0x694006c530c902d441e38a17f29b41a1a66f2a136e931778c71109d884e35db7
Jun-05-2019 13:12:18	Jun-05-2021 13:12:18	16.50%	0xf0b6a4187fde63b239a85764cdfe5e1246c8e6f3ec2e2f09965003ea16544f02

Appendix C. Example of a MakerDao loan contract

Appendix C gives an example of a MakerDao loan. The unique MakerDao CDP identifier for this loan is 15256. In the table below, we present every single transaction of the loan. Transaction-level data include the following: the timing of the transaction, the type of the transaction, amount in Dai or ETH associated with each transaction, and the transaction hash that executes the transaction on the Ethereum blockchain.

Transaction Time (EST)	Collateral (Dai)	Collateral (ETH)	Principal (Dai)	Repayment (Dai)	Transaction Type	Transaction Hash
2019-03-02 18:53:37					Opening CDP	0x5c369fa56dbba6446354c349cf707373e84dc87c9ad1020532d6e302d3070bdf
2019-03-02 18:53:37	17,529.07	133			Place collateral	0x5c369fa56dbba6446354c349cf707373e84dc87c9ad1020532d6e302d3070bdf
2019-03-02 18:53:37			6,000		Borrow loan	0x5c369fa56dbba6446354c349cf707373e84dc87c9ad1020532d6e302d3070bdf
2019-03-02 19:05:51	5,815.37	44			Place collateral	0x1ff809a19c47c1558b1d179bc76333d2427d56179193110b8657954d03a3bf34
2019-03-02 19:10:16			1,000		Borrow loan	0x74c382295230404dd88c734911039ef0ab6c1aada7046eb7170e84f60c7805df
2019-03-02 19:13:12	964.82	7.3			Place collateral	0x82467a6c4a0b1ff6091b92a578fbc227447b1e252fe29726cfc1517cbd0c8b2f
2019-03-02 19:19:48	2,489.36	18.67			Place collateral	0x6b1ca0c0d85ac6492e1e4a8dc36fcb396d9db3d72717cde1bc81001f8b9a68ea
2019-03-02 19:22:48			1,500		Borrow loan	0x4a533f1262c39e8d5c1ff7e5e02b4ea8b20b92e12c80152374659d0c7139bb06
2019-03-02 19:25:55	1,447.28	10.85			Place collateral	0x9debd0c4ee70652aa92581ddaff265d20bcac56fbcd420ae18a721889d72a234
2019-03-12 18:00:47			2,000		Borrow loan	0xc93b03def37d8f7d680c1bd65adc38da58226d8930bfe5dfb62db09e86431308
2019-03-12 18:06:12	1,959.27	14.87			Place collateral	0xcbce2e60486148d48221c8bf7b32b2ddb8a276c249c62618cd10e97f7af19a05
2019-03-31 11:56:40			2,000		Borrow loan	0xbb480205d65e2f0fb60f6c229bcfe92d63cb7ebece9a9d65979811b5c11c4636
2019-03-31 12:06:12	1,922.18	13.624			Place collateral	0x6ffad7d8c54679db481f6b800c35f90193fb4e0e81d2148803c9325a5d69f202
2019-07-18 19:02:52				12,500	Repay loan	0xbeeae7fd6ff8fe2b9596374bad5e9f9d642c20078b906589feba18149bdaab8e
2019-07-18 19:02:52				609.97	Interest Expense	0xbeeae7fd6ff8fe2b9596374bad5e9f9d642c20078b906589feba18149bdaab8e
2019-07-18 19:02:52	55,082.81	242.84			Return Collateral	0xbeeae7fd6ff8fe2b9596374bad5e9f9d642c20078b906589feba18149bdaab8e

Appendix D. Calculating loan return

Appendix D gives an example of a MakerDao loan and how we calculate its return. In addition to transaction-level information of the loan, we compute two additional columns – cash balances (associated with MakerDao funds), and (external) cash used. Cash balances records the flow of Dai, assuming that the investor will use the Dai he borrows to place collateral or repay the loan. It is only when the cash balance is depleted will he use his external cash. External cash used records all his own capital injected into the loan to facilitate its transactions.

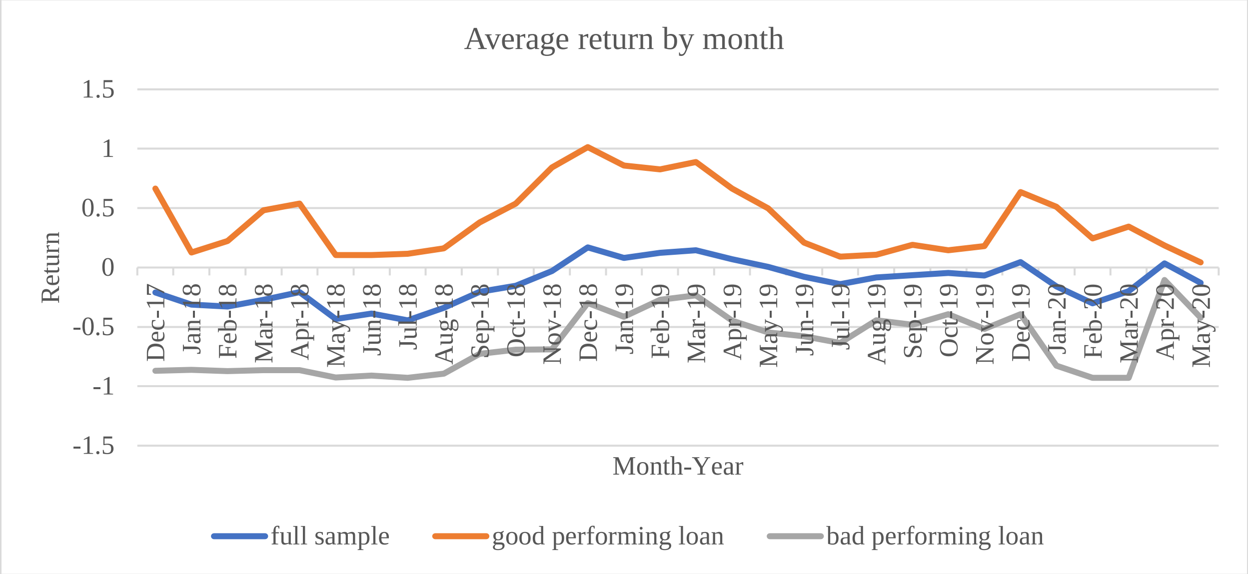
Transaction Time (EST)	Collateral (Dai)	Collateral (ETH)	Principal (Dai)	Repayment (Dai)	Transaction Type	Cash Balance (MakerDao Funds	External Cash Used
2019-03-02 18:53:37					Opening CDP		
2019-03-02 18:53:37	17,529.07	133			Place collateral		17,529.07
2019-03-02 18:53:37			6,000		Borrow loan	6,000	
2019-03-02 19:05:51	5,815.37	44			Place collateral	184.63	
2019-03-02 19:10:16			1,000		Borrow loan	1,184.63	
2019-03-02 19:13:12	964.82	7.3			Place collateral	219.81	
2019-03-02 19:19:48	2,489.36	18.67			Place collateral		2,269.55
2019-03-02 19:22:48			1,500		Borrow loan	1,500	
2019-03-02 19:25:55	1,447.28	10.85			Place collateral	52.72	
2019-03-12 18:00:47			2,000		Borrow loan	2,052.72	
2019-03-12 18:06:12	1,959.27	14.87			Place collateral	93.45	
2019-03-31 11:56:40			2,000		Borrow loan	2,093.45	
2019-03-31 12:06:12	1,922.18	13.624			Place collateral	171.27	
2019-07-18 19:02:52				12,500	Repay loan		12,329
2019-07-18 19:02:52				609.97	Interest Expense		609.97
2019-07-18 19:02:52	55,082.81	242.84			Return Collateral		

Return Calculation: Ending collateral value for this loan is \$55,082.81. Total cash used, which is the sum of all entries in the "external cash used" column, is \$32,737.32 Ending cash balance on MakerDao is 0. The total return for this loan is therefore (55,082.81 + 0 – 32,737.32)/32,737.32 = 68.26%.

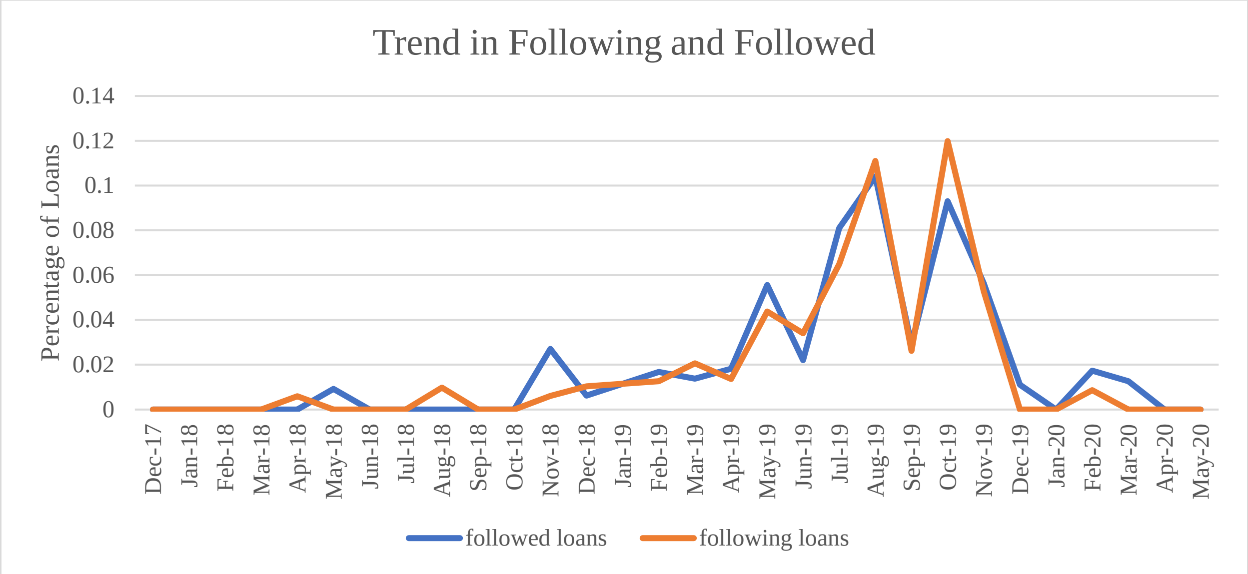
Appendix E. Additional Graphs

In Panel A, we graph the average loan returns for loans whose start time belong to the same month. We also graph the top 10 percent and bottom 10 percent loan return over time. In Panel B, we graph the percentage of loans that are following another loan and the percentage of loans that are being followed by another loan. In Panel C, we graph daily ETH closing price in USD for the days in our sample period. Source of this data is from coinmarketcap.com.

Panel A. Average loan return over time. Good performing loans are those whose returns are in the top 10 percent of the month. Bad performing loans are those whose returns are in the bottom 10 percent of the month.



Panel B. Percentages of following and followed loans.[24]



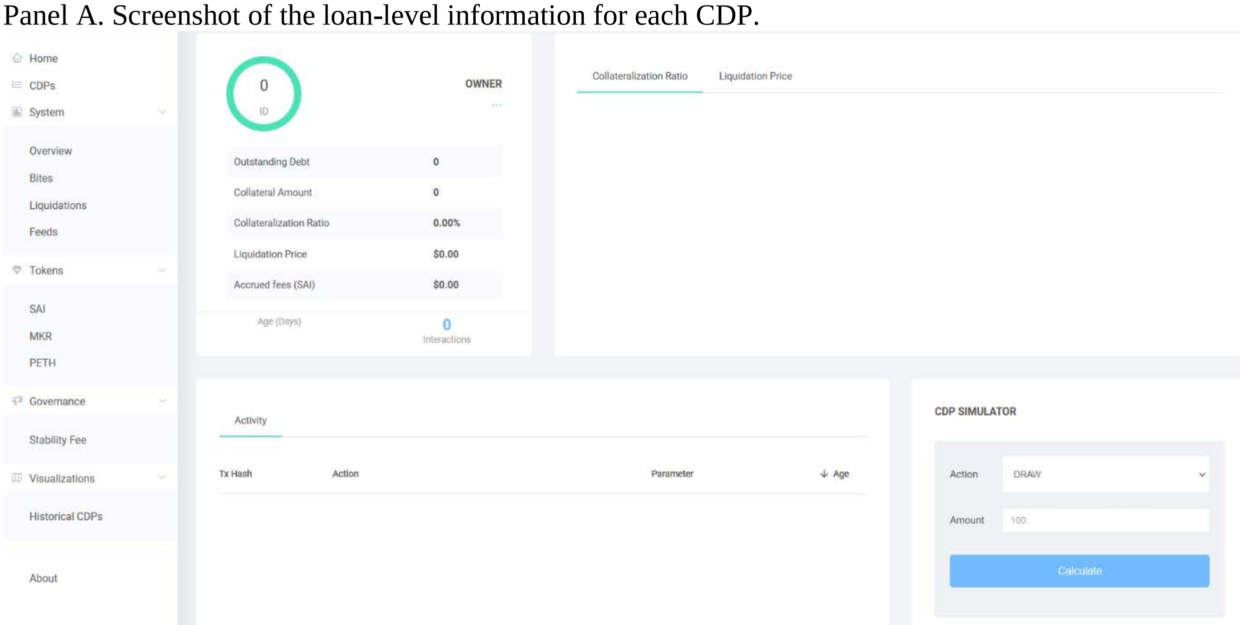
[24] We believe that the drop in percentage of followed and following loans in September 2019 is due to a pre-launch bug found in the Multi-Collateral protocol; though acknowledge it might be also due to data error in the Maker API.

Panel C. Daily ETH closing price over time

Appendix F. Information about the MakerDao website

In Appendix F Panel A, we present a screenshot of the CDP level loan information from mkr.tools, the website that MakerDao launched in December 2018 to provide users with more information. The website has since been discontinued. But we were able to find an archived version of the website using Wayback Machine (https://archive.org). The screenshot below looks at how the website presents loan-level information for one CDP. On the upper left-hand corner of the webpage, the website presents summary information of the loan. It has information on the CDP number, the owner of the CDP. Information on total principal (Outstanding Debt), total collateral (Collateral Amount), current level of collateralization ratio (Collateralization Ratio), the ETH price that will trigger a liquidation event (Liquidation Price), and the interest expense accrued on the CDP in USD (Accrued Fees). Moreover, the bottom line of this panel has information on the duration of the CDP (Ages) and the number of transactions. In the upper right-hand corner, the website shows graphs that tracks the CDP's collateralization ratio and liquidation price over time. The bottom left-hand corner has information on each transaction that took place in the CDP. In Panel B, we reconstruct this portion of the website for our running example (CDP 15256) using the MakerDao's Single Collateral Dai API, which is also the API that feeds data into mrk.toools. In Panel C, we also reconstruct this portion of the website for a CDP that was liquidated (CDP 14141). The bottom right-hand corner has a CDP simulator that allow any user to see how the upper panels change if an action were taken. There are four actions that users can simulate: borrowing loan (draw), repaying loan (wipe), placing collateral (lock), and returning collateral (free). The website has a page like the one shown in Panel A for every CDP on the single collateral Dai protocol.

Panel A. Screenshot of the loan-level information for each CDP.



Panel B. Reconstruction of the transaction level information for a loan and a non-liquidated loan (CDP 15256). Age is the how many days ago the transaction occurred. We used March 15th, 2022, as the bench date to calculate *Age*, which is the number of days that have elapsed between the date of the transaction and the benchmark date. In the “Actions” column, open is opening the CDP; lock is placing collateral; draw is borrowing loan; wipe is repaying loan; free is returning collateral.

Activity			
Tx Hash	Action	Parameter	Age
0x5c369fa56dbba6446354c349cf707373e84dc87c9ad1020532d6e302d3070bdf	OPEN	-	1109
0x5c369fa56dbba6446354c349cf707373e84dc87c9ad1020532d6e302d3070bdf	LOCK	133	1109
0x5c369fa56dbba6446354c349cf707373e84dc87c9ad1020532d6e302d3070bdf	DRAW	6000	1109
0x1ff809a19c47c1558b1d179bc76333d2427d56179193110b8657954d03a3bf34	LOCK	44	1109
0x74c382295230404dd88c734911039ef0ab6c1aada7046eb7170e84f60c7805df	DRAW	1000	1109
0x82467a6c4a0b1ff6091b92a578fbc227447b1e252fe29726cfc1517cbd0c8b2f	LOCK	7.3	1109
0x6b1ca0c0d85ac6492e1e4a8dc36fcb396d9db3d72717cde1bc81001f8b9a68ea	LOCK	18.67	1109
0x4a533f1262c39e8d5c1ff7e5e02b4ea8b20b92e12c80152374659d0c7139bb06	DRAW	1500	1109
0x9debd0c4ee70652aa92581ddaff265d20bcac56fbcd420ae18a721889d72a234	LOCK	10.85	1109
0xc93b03def37d8f7d680c1bd65adc38da58226d8930bfe5dfb62db09e86431308	DRAW	2000	1099
0xcbce2e60486148d48221c8bf7b32b2ddb8a276c249c62618cd10e97f7af19a05	LOCK	14.87	1099
0xbb480205d65e2f0fb60f6c229bcfe92d63cb7ebece9a9d65979811b5c11c4636	DRAW	2000	1080
0x6ffad7d8c54679db481f6b800c35f90193fb4e0e81d2148803c9325a5d69f202	LOCK	13.624	1080
0xbeeae7fd6ff8fe2b9596374bad5e9f9d642c20078b906589feba18149bdaab8e	WIPE	12500	971
0xbeeae7fd6ff8fe2b9596374bad5e9f9d642c20078b906589feba18149bdaab8e	FREE	242.84	971

Panel C. Reconstruction of the transaction level information for a loan for a liquidated loan (CDP 14141). Age is the how many days ago the transaction occurred. We used March 15th, 2022, as the bench date to calculate *Age*, which is the number of days that have elapsed between the date of the transaction and the benchmark date. In the “Actions” column, open is opening the CDP; lock is placing collateral; draw is borrowing loan; wipe is repaying loan; free is returning collateral; bite is liquidating CDP.

Activity			
Tx Hash	Action	Parameter	Age
0x28e58df653ab4c503cd99257c78047e0e8a99b0dace2c1f7372249bc81f75855	OPEN	-	1140
0x28e58df653ab4c503cd99257c78047e0e8a99b0dace2c1f7372249bc81f75855	LOCK	1	1140
0x28e58df653ab4c503cd99257c78047e0e8a99b0dace2c1f7372249bc81f75855	DRAW	50	1140
0x43739dc4fde31a0c693125b4da0b7322d075fe303e020636649807b7dd641dae	BITE	0	672