Liquidations: DeFi on a Knife-edge

Daniel Perez[1], Sam M. Werner[1], Jiahua Xu[2], and Benjamin Livshits[1,2,3]

[1] Imperial College London
[2] University College London, Centre for Blockchain Technologies
[3] Brave Software

Abstract. The trustless nature of permissionless blockchains renders overcollateralization a key safety component relied upon by decentralized finance (DeFi) protocols. Nonetheless, factors such as price volatility may undermine this mechanism. In order to protect protocols from suffering losses, undercollateralized positions can be *liquidated*. In this paper, we present the first in-depth empirical analysis of liquidations on protocols for loanable funds (PLFs). We examine Compound, one of the most widely used PLFs, for a period starting from its conception to September 2020. We analyze participants' behavior and risk-appetite in particular, to elucidate recent developments in the dynamics of the protocol. Furthermore, we assess how this has changed with a modification in Compound's incentive structure and show that variations of only 3% in an asset's price can result in over 10m USD becoming liquidable. To further understand the implications of this, we investigate the efficiency of liquidators. We find that liquidators' efficiency has improved significantly over time, with currently over 70% of liquidable positions being immediately liquidated. Lastly, we provide a discussion on how a false sense of security fostered by a misconception of the stability of non-custodial stablecoins, increases the overall liquidation risk faced by Compound participants.

1 Introduction

Decentralized Finance (DeFi) refers to a peer-to-peer, permissionless blockchain-based ecosystem that utilizes the integrity of smart contracts for the advancement and disintermediation of traditional financial primitives. One of the most prominent DeFi application on the Ethereum blockchain [21] are protocols for loanable funds (PLFs) [12]. On PLFs, markets for loanable funds are established via smart contracts that facilitate borrowing and lending. In the absence of strong identities on Ethereum, creditor protection tends to be ensured through overcollateralization, whereby a borrower must provide collateral worth more than the value of the borrowed amount. In the case where the value of the collateral to debt ratio drops below some liquidation threshold, a borrower defaults on his position and the supplied collateral is sold off at a discount to cover the debt in a process referred to as *liquidation*. However, little is known about the behavior of agents towards liquidation risk on a PLF. Furthermore, despite liquidators playing a critical role in the DeFi ecosystem, the efficiency with which they liquidate positions has not yet been thoroughly analyzed.

In this paper, we first lay out a framework for quantifying the state of a generic PLF and its markets over time. We subsequently instantiate this framework to all markets on Compound [16], one of the largest PLFs in terms of locked funds. We analyze how liquidation risk has changed over time, specifically after the launch of Compound's governance token. Furthermore, we seek to quantify this liquidation risk through a price sensitivity analysis. In a discussion, we highlight the existence of how the interdependence of DeFi protocols can result in agent behavior undermining the assumptions of the protocols' incentive structures.

Contributions. This paper makes the following contributions:

– We present an abstract framework to reason about the state of PLFs.
– We provide an open-source implementation[4] of the proposed framework for Compound, one of the largest PLFs in terms of total locked funds.
– We perform an empirical analysis on the historical data for Compound, from May 7, 2019 to September 6, 2020 and make the following observations: i) despite increases in the number of suppliers and borrowers the total funds locked is mostly accounted for by a small subset of participants; ii) the introduction of Compound's governance token had protocol-wide implications as liquidation risk increased as a consequence of higher risk-seeking behavior of participants; iii) liquidators became significantly more efficient over time, liquidating over 70% of liquidable positions instantly.
– Using our findings, we demonstrate how interaction between protocols' incentive structures can directly result in unexpected risks to participants.

2 Background

In this section we introduce preliminary concepts necessary for understanding how liquidations function in DeFi on Ethereum.

2.1 Ethereum

On Ethereum, smart contracts are programs written in a Turing-complete language, typically in Solidity, that define a set of rules that may be invoked by any network participant. These programs rely on the Ethereum Virtual Machine (EVM), a low-level stack machine which executes the compiled EVM bytecode of a smart contract [21]. Each instruction has a fee represented in a unit called "gas", and the total gas cost of a transaction is the sum of all instructions' gas and a fixed base fee [5,18]. The sender of a transaction must then set a gas price, which is the amount of money he is willing to pay per unit of gas to execute the transaction. The total fee of the transaction is given by the gas price multiplied with the gas cost [20,19]. Within a transaction, smart contracts can store data in logs, which are metadata specially indexed as part of the transaction. This metadata, commonly referred to as *events*, is typically used to allow users to monitor the activity of a contract externally.

[4] Anonymized for blind-review

2.2 Collateralization

Given the pseudonymity of agents in Ethereum, borrow positions need to be overcollateralized to reduce the default risk. Thereby, the borrower of an asset is required to supply collateral, where the total value of the supplied collateral exceeds the total value of the borrowed asset. For example, in order to borrow 100 USD worth of `DAI` with `ETH` as collateral at a collateralization ratio of 150%, a borrower would have to lock 150 USD worth of `ETH` to collateralize the borrow position. Thus, the protocol does not face monetary risk from defaulted borrow positions, as the underlying collateral of a defaulted position can be sold off to recover the debt.

2.3 Liquidation

The process of selling a borrower's collateral to recover the debt value upon default is referred to as liquidation. A borrow position can be liquidated once the value of the collateral falls below some fixed liquidation threshold, i.e. the minimum acceptable collateral to debt ratio. Any network participant may liquidate these positions by purchasing the underlying collateral at a discount. Hence, liquidators are incentivized to actively monitor borrowers' collateral to debt ratios. Note that in practice, there may exist a maximum amount of liquidable collateral that a single liquidator can purchase.

2.4 Protocols for Loanable Funds

In DeFi, asset borrowing and lending is achieved via so-called *protocols for loanable funds* (PLFs), where smart contracts act as trustless intermediaries of loanable funds between borrowers and lenders in markets of different assets. Unlike traditional peer-to-peer lending, deposits are pooled and instantly available to borrowers. On a DeFi platform, the aggregate of tokens that the PLF smart contracts hold, which equals the difference between supplied funds and borrowed funds, is termed locked funds [10]. Borrowers are charged interest on the debt at a floating rate determined by a market's underlying interest rate model. A small fraction of the paid interest is allocated to a pool of reserves, which is set aside in case of market illiquidity, while the remainder is paid out to suppliers of loanable funds. Interest in a given market is generally accrued through market-specific, interest-bearing derivative tokens that appreciate against the underlying asset over time. Hence, a supplier of funds receives derivative tokens in exchange for supplied liquidity, representing his share in the total value of the liquidity pool for the underlying asset. The most prominent PLFs are Compound [7] and Aave [4], with 749m USD and 1.39bn USD in total funds locked, respectively, at the time of writing [10]. For a more in-depth explanation of the workings of PLFs, we direct the reader to [12].

2.5 Oracles

One of the major challenges smart contracts face concerns access to off-chain information, i.e. data that does not natively exist on-chain. Oracles are data feeds into smart contracts and provide a mechanism for accessing off-chain information through some third party. In DeFi, oracles are commonly used for price feed data to determine the real-time price of assets. For instance, via the Compound Open Price Feed [8], vetted third party reporters sign off on price data using a known public key, where the resulting feed can be relied upon by smart contracts.

2.6 Liquidity Incentives

As the total liquidity in DeFi is fragmented across protocols, a constant competition over deposits persists, commonly referred to as *liquidity mining*. Apart from earning interest on deposited funds on PLFs or liquidity provider fees on automated market makers, liquidity providers may also earn rewards by receiving protocol-specific tokens, as seen for automated market makers [1,2], PLFs [7], and yield aggregators [3]. While these tokens are typically intended for participation in protocol governance, they are also tradable on the open market and thus provide further financial incentive to liquidity providers.

2.7 Stablecoins

An alternative to volatile cryptoassets is given by stablecoins, which are priced against a peg and can be either custodial or non-custodial. For custodial stablecoins (e.g. `USDC` [6]), tokens represent a claim of some off-chain reserve asset, such as fiat currency, which has been entrusted to a custodian. Non-custodial stablecoins (e.g. `DAI` [17]) seek to establish price stability via economic mechanisms specified by smart contracts. For a thorough discussion on stablecoin design, we direct the reader to [14].

3 Methodology

In this section, we describe our methodology for the different analyses we perform with regard to leveraging on a PLF. To be able to quantify the extent of leveraged positions over time, we first introduce a state transition framework for tracking the borrow and supply positions across all markets on a given PLF. We then describe how we instantiate this framework on the Compound protocol using on-chain events data.

3.1 Definitions

Throughout the paper, we use the following definitions in the context of PLFs:

Market A smart contract acting as the intermediary of loanable funds for a particular cryptoasset, where users supply and borrow funds.

Supply Funds deposited to a market that can be loaned out to other users and used as collateral against depositors' own borrow positions.

Borrow Funds loaned out to users of a market.

Collateral Funds available to back a user's aggregate borrow positions.

Locked funds Funds remaining in the PLF smart contracts, equal to the difference between supplied and borrowed funds.

Supplier A user who deposits funds to a market.

Borrower A user who borrows funds from a market. Since a borrow position must be collateralized, a borrower must also be a supplier.

Liquidator A user who purchases a borrower's supply in a market when the borrower's collateral to borrow ratio falls below some threshold.

3.2 States on a PLF

In this section, we provide a formal definition of the state of a PLF. We note $\mathfrak{P}_t$ to be the global state of a PLF at time t. For brevity, in the following definitions, we assume that all the values are at a given time t. We define the global state for the PLF as

$$\mathfrak{P} = (\mathcal{M}, \mathit{\Gamma}, \mathcal{P}, \mathit{\Lambda})$$

where $\mathcal{M}$ is the set of states of individual markets, $\mathit{\Gamma}$ is the price the Oracle used, $\mathcal{P}$ is the set of states of individual participants and $\mathit{\Lambda}$ is the close factor of the protocol, which specifies the upper bound on the amount of collateral a liquidator may purchase.

We define the state of an individual market $m \in \mathcal{M}$ as

$$m = (\mathcal{I}, \mathcal{B}, \mathcal{S}, \mathcal{C})$$

where $\mathcal{I}$ is the market's interest rate model, $\mathcal{B}$ is the total borrows, $\mathcal{S}$ is the total supply of deposits, and $\mathcal{C}$ is the collateralization ratio.

$\mathcal{P}^m$ is the state of all participants in market m and the positions of a participant P in this market is defined as

$$P^m = (B^m, S^m)$$

where B^m and S^m are respectively the total borrows positions and total supplied deposits of a market participant in market m.

For a given market m, the total deposits supplied $\mathcal{S}^m$ is thus given by:

$$\mathcal{S}^m = \sum_{P^m \in \mathcal{P}^m} S^m \tag{1}$$

Similarly, the market's total borrows $\mathcal{B}^m$ is given by:

$$\mathcal{B}^m = \sum_{P^m \in \mathcal{P}^m} B^m \tag{2}$$

Event	Description	State variables affected
`Borrow`	A new borrow position is created.	$\mathcal{B}$
`Mint`	cTokens are minted for new deposits.	$\mathcal{S}$
`RepayBorrow`	A borrow position is partially/fully repaid.	$\mathcal{B}$
`LiquidateBorrow`	A borrow position is liquidated.	$\mathcal{B}$, $\mathcal{S}$
`Redeem`	cTokens are used to redeem deposits of the underlying asset.	$\mathcal{S}$
`NewCollateralFactor`	The collateral factor for the associated market is updated.	$\mathcal{C}$
`AccrueInterest`	Interest has accrued for the associated market and its borrow index is updated.	$\mathcal{B}$
`NewInterestRateModel`	The interest rate model for the associated market is updated.	$\mathcal{I}$
`NewInterestParams`	The parameters of the interest rate model for the associated market are updated.	$\mathcal{I}$
`NewCloseFactor`	The close factor is updated.	Λ

Fig. 1: The events emitted by the Compound protocol smart contracts used for initiating state transitions and the states affected by each event.

The state of a participant P is liquidable if the following holds:

$$\sum_{m \in \mathcal{M}} \Big\{ [S^m \cdot \mathcal{C} + \mathcal{I}(S^m)] \cdot \Gamma(m) \Big\} - \sum_{m \in \mathcal{M}} \Big\{ [B^m + \mathcal{I}(B^m)] \cdot \Gamma(m) \Big\} < 0 \quad (3)$$

where $\Gamma(m)$ returns the price of the underlying asset denominated in a predefined numéraire (e.g. USD), $\mathcal{I}(S^m)$ returns the interest earned with supply S^m and $\mathcal{I}(B^m)$ returns the interest accrued with borrow B^m.

The transition from a state of a market m from time t to $t+1$ is given by some state transition σ, such that $m_t \xrightarrow{\sigma} m_{t+1}$.

3.3 States and the Compound PLF

For our analysis, we apply our state transition framework to the Compound PLF. Therefore, we briefly present the workings of Compound in the context of our framework.

State Transitions We initiate state transitions via events emitted from the Compound protocol smart contracts. We provide an overview of the state variables affected by Compound events in Table 1.

Funds Supplied Every market on Compound has an associated "cToken", a token that continuously appreciates against the underlying asset as interest accrues. For every deposit in a market, a newly-minted amount of the market's associated cToken is transferred to the depositor. Therefore, rather than tracking the total amount of the underlying asset supplied, we account the total deposits of an asset supplied by a market participant in the market's cTokens. Likewise, we account the total supply of deposits in the market in cTokens.

Funds Borrowed A borrower on Compound must use cTokens as collateral for his borrow position. The borrowing capacity equals the current value of the supply multiplied by the collateral factor for the asset. For example, given an exchange rate of 1 `DAI` = 50 `cDAI`, a collateral factor of 0.75 for `DAI` and a price of 1 `DAI` = 1 USD, a holder of 500 `cDAI` (10 `DAI`) would be permitted to borrow up to 7.50 USD worth of some other asset on Compound. Therefore, as funds are borrowed, an individual's total borrow position, as well as the respective market's total borrows are updated.

Interest The accrual of interest is tracked per market via a borrow index, which corresponds to the total interest accrued in the market. The borrow index of a market is also used to determine and update the total debt of a borrower in the respective market. When funds are borrowed, the current borrow index for the market is stored with the borrow position. When additional funds are borrowed or repaid, the latest borrow index is used to compute the difference of accrued interest since the last borrow and added to the total debt.

Liquidation A borrower on Compound is eligible for liquidation should his total supply of collateral, i.e. the value of the sum of the borrower's cToken holdings per market, weighted by each market's collateral factor, be less than the value of the borrower's aggregate debt (Equation (3)). The maximum amount of debt a liquidator may pay back in exchange for collateral is specified by the close factor of a market.

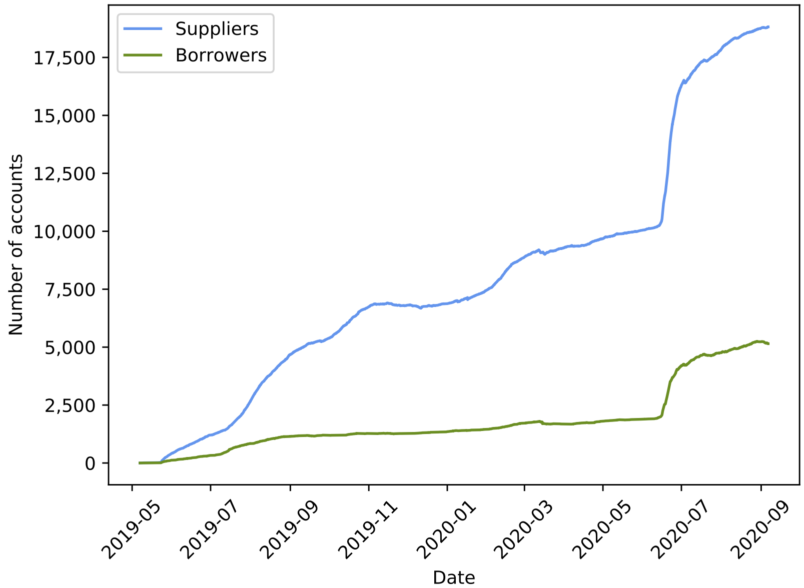
4 Analysis

In this section, we present the results of the analysis performed with the framework outlined in Section 3. We analyze data from the Compound protocol [16] over a period ranging from May 7, 2019—when the first Compound markets were deployed on the Ethereum main network—to September 6, 2020. The full list of contracts considered for our analysis can be found in Appendix A. When analyzing a single market, we choose the market for `DAI`, as it is the largest by one order of magnitude.

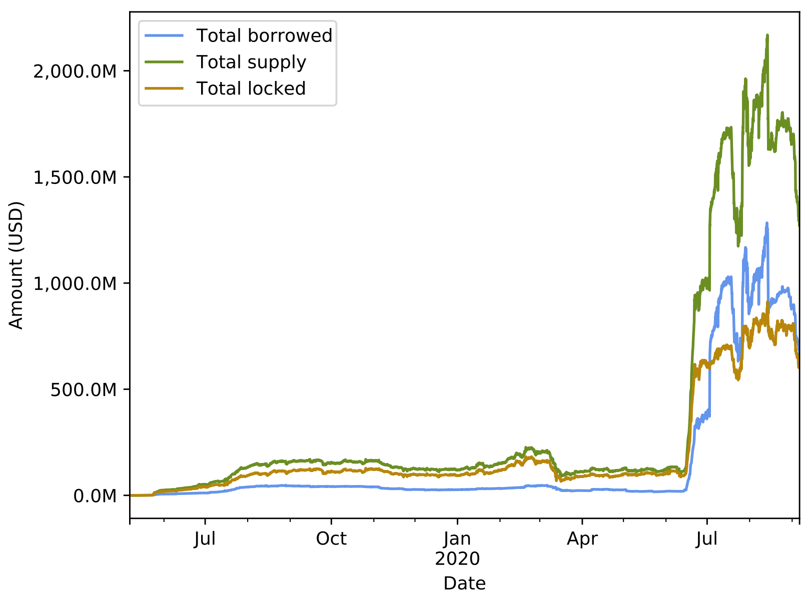
4.1 Borrowers and Suppliers

We first examine the total number of borrowers and suppliers on Compound by considering any Ethereum account that, at any time within the observation period, either exhibited a non-zero cToken balance or borrowed funds for any Compound market. The change in the number of borrowers and suppliers over time is displayed in Figure 2a.

We see that the total number of suppliers always exceeds the total number of borrowers. This is because on Compound, one can only borrow against funds he supplied, which automatically makes the borrower also a supplier. Interestingly,

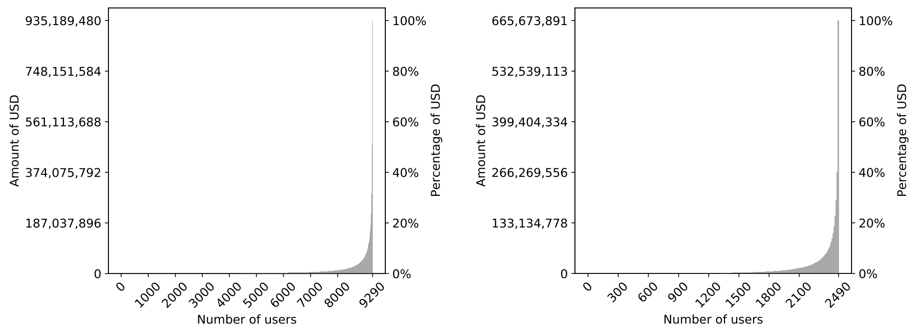


(a) Number of suppliers and borrowers.



(b) Amount of funds supplied, borrowed and locked.

Fig. 2: Number of active accounts and amount of funds on Compound over time.



(a) Distribution of supplied funds. (b) Distribution of borrowed funds.

Fig. 3: Cumulative distribution of funds in USD. Accounts are bucketed in bins of 10, i.e. a single bar represents the sum of 10 accounts.

the number of suppliers has become increasingly bigger relative to the number of borrowers over time. There is notable sudden jump in both the number of suppliers and borrowers in June 2020.

In terms of total deposits, a very similar trend is observable in Figure 2b, which shows that at the same time, the total supplied deposits increased, while the total borrows followed shortly after. Furthermore, the total funds borrowed exceeded the total funds locked for the first time in July 2020 and have remained so until the end of the examined period. We discuss the reasons behind this in the next part of this section.

Despite the similarly increasing trend for the number of suppliers/borrowers and amount of supplied/borrowed funds, we can see in Figure 3 that the majority of funds are borrowed and supplied only by a small number of accounts. For instance, for the suppliers in Figure 3a, the top user and top 10 users supply 27.4% and 49% of total funds, respectively. For the borrowers shown in Figure 3b, the top user accounts for 37.1%, while the top 10 users account for 59.9% of total borrows.

4.2 The `COMP` Governance Token

The sudden jumps seen in Figures 2a and 2b can be explained by the launch of Compound's governance token, `COMP`, on June 15, 2020. The `COMP` governance token allows holders to participate in voting, create proposals, as well as delegate voting rights. In order to empower Compound stakeholders, new `COMP` is minted every block and distributed amongst borrowers and suppliers in each market.

Initially, `COMP` was allocated proportionally to the accrued interest per market. However, the `COMP` distribution model was modified via a governance vote on July 2, 2020, such that the borrowing interest rate was removed as a weighting mechanism in favor of distributing `COMP` per market on a borrowing demand basis, i.e. per USD borrowed. The distributed `COMP` per market is shared equally

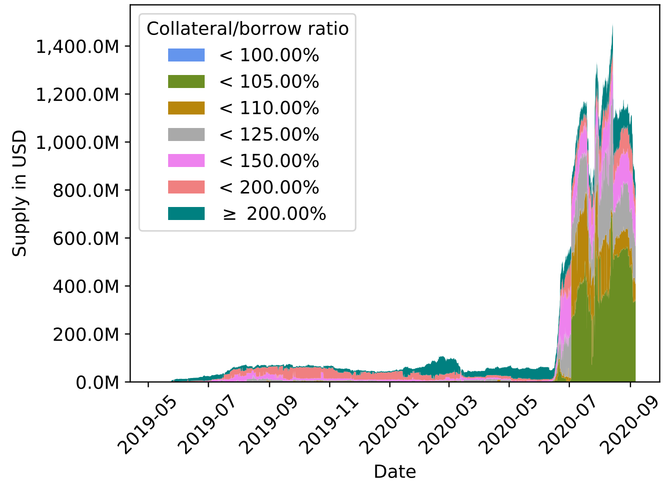


Fig. 4: Collateral locked over time, showing how close the amounts are from being liquidated. Positions can be liquidated when the ratio drops below 100%.

between a market's borrowers and suppliers, who receive `COMP` proportionally to their borrowed and supplied amounts, respectively. Hence, a Compound user is incentivized to increase his borrow position as long as the borrowing cost does not exceed the value of his `COMP` earnings, which presumably explains why the total borrows surpass the total amount locked after the `COMP` launch, as seen in Figure 2b.

4.3 Liquidation Risk

Given the high increase in the number of total funds borrowed and supplied, as well as the decrease in liquidity relative to total borrows, we seek to identify and quantify any changes in liquidation risk on Compound since the launch of `COMP`. Figure 4 shows the total USD value of collateral on Compound and how close collateral amounts are from liquidation. In addition to the substantial increase in the total value of collateral on Compound since the launch of `COMP`, the risk-seeking behavior of users has also changed. This can be seen by examining collateral to borrow ratios, where since beginning of July, 2020, a total of approximately 350m to 600m USD worth of collateral has been within a 5% price range of becoming liquidable. However, it should be noted that the likelihood of the amount of this collateral becoming liquidable highly depends on the price volatility of the collateral asset.

In order to examine how liquidation risk differs across markets, we measure for the largest market on Compound, namely `DAI`, the sensitivity of collateral becoming liquidable given a decrease in the price of `DAI`. Figure 5 shows the amount of aggregate collateral liquidable at the historic price, as well as at a 3%

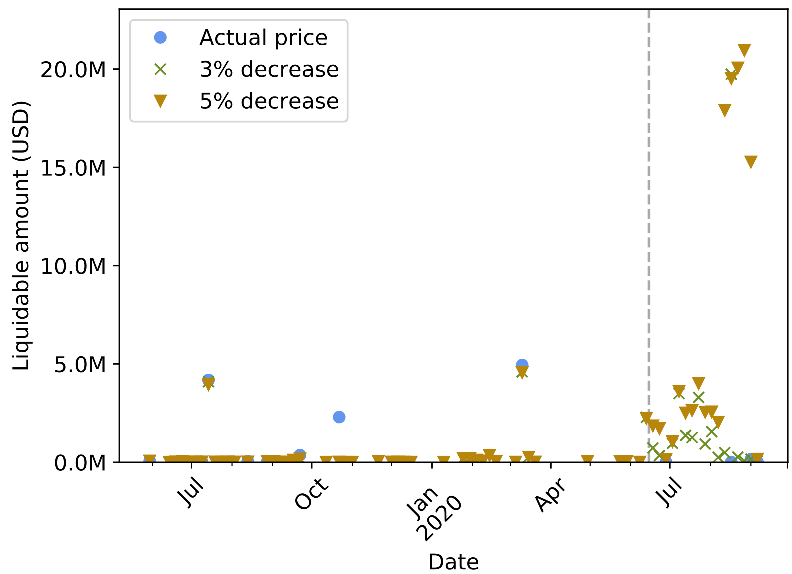


Fig. 5: Sensitivity analysis of the liquidable collateral amount given `DAI` price movement. `COMP` launch date is marked by the dashed vertical line.

and 5% decrease relative to the historic price for `DAI`. We mark the date on which the `COMP` governance token launched with a dashed line. It can be seen that since the launch of `COMP`, 3% and 5% price decreases would have resulted in a substantially higher amount of liquidable collateral. In particular, a 3% decrease would have turned collateral worth in excess of 10 million USD liquidable.

4.4 Liquidations and Liquidators

In order to better understand the implications of the increased liquidation risk since the launch of `COMP`, we examine historical liquidations on Compound and subsequently measure the efficiency of liquidators.

Historical Liquidations The increased risk-seeking behavior suggested by the low collateral to borrow ratios presented in the previous section are in accordance with the trend of rising amount of liquidated collateral since the introduction of `COMP`. The total value of collateral liquidated on Compound over time is shown in Figure 6. It can be seen that the majority of this collateral was liquidated on a few occasions, perhaps most notably on Black Thursday (March 12, 2020), July 29, 2020 (`DAI` deviating from its peg), and in early September 2020 (`ETH` price drop).

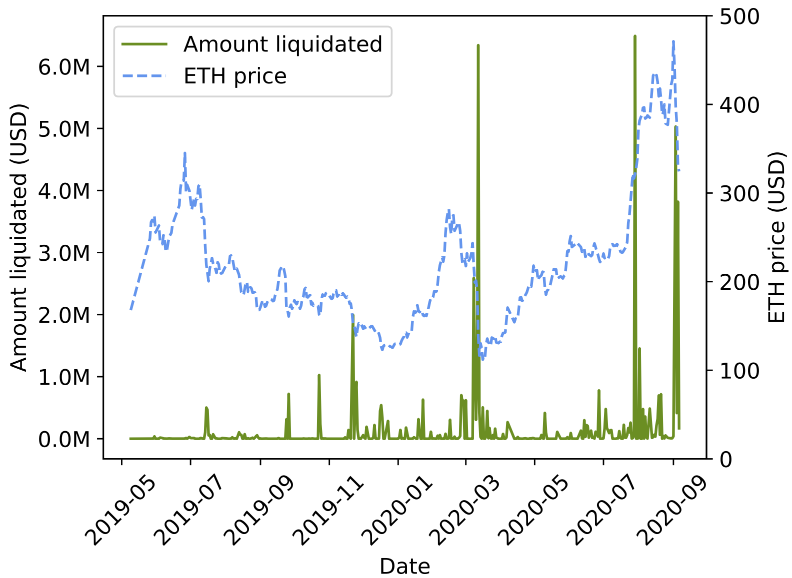


Fig. 6: Amount (in USD) of liquidated collateral from May 2019 to August 2020.

Liquidation Efficiency We measure the efficiency of liquidators as the number of blocks elapsed since a borrow position has become liquidable and the position actually being liquidated. The overall historical efficiency of liquidators is shown as a cumulative distribution function in Figure 7, from which it can be seen that approximately 60% of the total liquidated collateral (35 million USD) was liquidated within the same block as it became liquidable, suggesting that the majority of liquidations occur via bots and are very efficient. After 2 blocks have elapsed (on average half a minute), 85% of liquidable collateral has been liquidated, while after 16 blocks this value amounts to 95%.

It is worth noting that liquidation efficiency has been skewed by the more recent liquidation activities which were of a much larger scale than when the protocol was first launched. Specifically, in 2019, only about 26% of the liquidations occurred in the block during which the position became liquidable, compared to 70% in 2020. This resulted in some lost opportunities for liquidators as shown in Figure 5. The account `0xd062eeb318295a09d4262135ef0092979552afe6`, for instance, had more than 3,000,000 USD worth of `ETH` as collateral exposed at block 8,796,900 for the duration of a single block: the account was roughly 20 USD shy of the collaterization threshold but eventually escaped liquidation. If a liquidator had captured this opportunity, he could have bought half of this collateral (given the close factor of 0.5), at a 10% discount, resulting in a profit of 150,000 USD for a single transaction. It is clear that with such stakes, par-

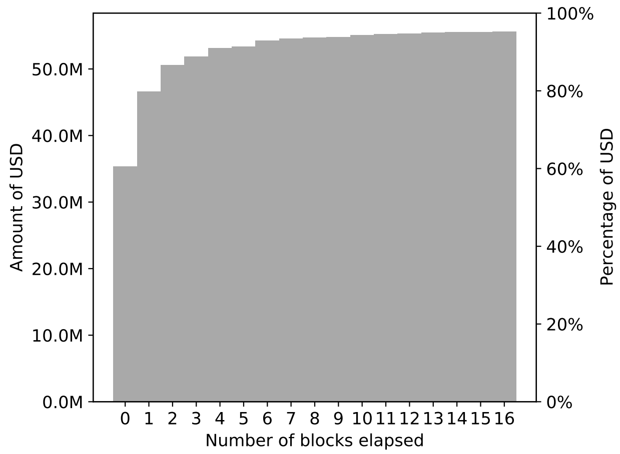


Fig. 7: Number of blocks elapsed from the time a position can be liquidated to actual liquidation, shown as a CDF.

ticipants were incentivized to improve liquidation techniques, resulting in a high level of liquidation speed and scale.

4.5 Summary

In this section, we have analyzed the Compound protocol with a focus on liquidations. We have found that despite the number of suppliers and borrowers having increased with time, the total amount of funds supplied and borrowed remain extremely concentrated among a small set of participants.

We have also seen that the introduction of the `COMP` governance token has changed how users interact with the protocol and the amount of risk that they are willing to take. Users now borrow vastly more than before, with the total amount borrowed surpassing the total amount locked. Due to excessive borrowing without a sufficiently safe amount of supplied funds, borrow positions now face a higher liquidation risk, such that a crash of 3% in the price of `DAI` could result in an aggregate liquidation value of over 10 million USD.

Finally, we have shown that the liquidators have become more efficient with time, and are currently able to capture a majority of the liquidable funds instantly.

5 Discussion

In this section, we enumerate several points that we deem important for the future development of PLFs and DeFi protocols. We first discuss ho governance tokens can, intentionally or not, change how users behave within a protocol.

Subsequently, we discuss the contagion effect that user behavior in a protocol can have on another protocol.

As analyzed in Section 4, the distribution of the `COMP` token has vastly changed the Compound landscape and user behavior. Until the introduction of the token, borrowing was costly due to the payable interest, which implies a negative cash flow for the borrower. Therefore, a borrower would only borrow if he could justify this negative cash flow with some application external to Compound. With the introduction of this token, borrowing started to yield a positive cash flow because of the monetary value of the governance token. This creates a situation where both suppliers and borrowers end up with a positive cash flow, inducing users to maximize both their supply and borrow. This model is, however, only sustainable when the price of the `COMP` token remains sufficiently high to keep this cash flow positive for borrowers. This directly results in users taking increasingly higher risk in an attempt to gain larger monetary rewards, with liquidators making more risk-free profit from their operations.

This behavior also indirectly affected other protocols, in particular `DAI`. The price of `DAI` is aimed to be pegged to 1 USD resting on an arbitrage mechanism, whereby token holders are incentivized to buy/sell `DAI` as soon as the price moves below/above 1 USD, respectively. However, a rational user seeking to maximize profit will not sell his `DAI` if holding it somewhere else would yield higher profits. This was precisely what was happening with Compound, whose users locking their `DAI` received higher yields in the form of `COMP`, than from selling `DAI` at a premium, thereby resulting in upward price pressure [9]. Interestingly, `DAI` deviating from its peg also has a negative effect for Compound users. Indeed, as we saw in Section 4, many Compound users might have been overconfident about the price stability of `DAI` and thus only collateralize marginally above the threshold. This has resulted in large amounts being liquidated due to the actual, higher extent of the volatility in the `DAI` price.

6 Related Work

In this section we briefly discuss existing work related to this paper.

A thorough analysis of the Compound protocol with respect to market risks faced by participants was done by [13]. The authors employ agent-based modeling and simulation to perform stress tests in order to show that Compound remains safe under high volatility scenarios and high levels of outstanding debt. Furthermore, the authors demonstrate the potential of Compound to scale to accommodate a larger borrow market while maintaining a low default probability. This differs to our work as we conduct a detailed empirical analysis on Compound, focusing on how agent behavior under different incentive structures on Compound has affected the protocol's state with regards to liquidation risk.

A first in-depth analysis on PLFs is given by [12]. The authors provide a taxonomy on interest rate models employed by PLFs, while also discussing market liquidity, efficiency and interconnectedness across PLFs. As part of their analysis, the authors examine the cumulative percentage of locked funds solely for the Compound markets DAI, ETH, and USDC.

In [15], the authors show how markets for stablecoins are exposed to deleveraging feedback effects, which can cause periods of illiquidity during crisis.

The authors of [11] demonstrate how various DeFi lending protocols are subject to different attack vectors such as governance attacks and undercollateralization. In the context of the proposed governance attack, the lending protocol the authors focus on is Maker [17].

7 Conclusion

In this paper, we presented the first in-depth empirical analysis of liquidations on Compound, one of the largest PLFs in terms of total locked funds, from May 7, 2019 to September 6, 2020. We analyzed agents' behavior and in particular how much risk they are willing to take within the protocol. Furthermore, we assessed how this has changed with the launch of the Compound governance token COMP, where we found that agents take notably higher risks in anticipation of higher earnings. This resulted in variations as little as 3% in an asset's price being able to cause over 10 million USD worth of collateral becoming liquidable. In order to better understand the potential consequences, we then measured the efficiency of liquidators, namely how quickly new liquidation opportunities are captured. Liquidators' efficiency was found to have improved significantly over time, reaching 70% of instant liquidations. Lastly, we demonstrated how overconfidence in the price stability of DAI, increased the overall liquidation risk faced by Compound participants. Rather ironically, many Compound participants wishing to make the most of the new incentive scheme ended up causing higher volatility in DAI—a dominant asset of the platform, resulting in liquidation of their own assets. This is not Compound's misdoing, but rather highlights the to date unknown dynamics of incentive structures across different DeFi protocols.

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A Monitored contracts

In Figure 8, we provide a list of contracts we monitored in our analysis.

Name	Address
cBAT	0x6c8c6b02e7b2be14d4fa6022dfd6d75921d90e4e
cDAI	0x5d3a536e4d6dbd6114cc1ead35777bab948e3643
cETH	0x4ddc2d193948926d02f9b1fe9e1daa0718270ed5
cREP	0x158079ee67fce2f58472a96584a73c7ab9ac95c1
cSAI	0xf5dce57282a584d2746faf1593d3121fcac444dc
cUSDC	0x39aa39c021dfbae8fac545936693ac917d5e7563
cUSDT	0xf650c3d88d12db855b8bf7d11be6c55a4e07dcc9
cWBTC	0xc11b1268c1a384e55c48c2391d8d480264a3a7f4
cZRX	0xb3319f5d18bc0d84dd1b4825dcde5d5f7266d407
Comptroller	0x3d9819210a31b4961b30ef54be2aed79b9c9cd3b
Open Oracle Price Data	0x02557a5e05defeffd4cae6d83ea3d173b272c904
Uniswap Anchored View	0x9b8eb8b3d6e2e0db36f41455185fef7049a35cae

Fig. 8: Monitored contracts