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DeFi liquidations: Volatility and liquidity

By

Ana Sasi-Brodesky and Iota Kaousar Nassr

This work delves into the liquidations mechanism inherent in Decentralised Finance (DeFi) lending protocols and the connection between liquidations and price volatility in decentralised exchanges (DEXs). The analysis employs transactional data of three of the largest DeFi lending protocols and provides evidence of a positive relation between liquidations and post-liquidations price volatility across the main DEX pools. Without directly observing the behaviour of liquidators, these findings indirectly indicate that liquidators require market liquidity to carry out large liquidations and affect market conditions while doing so.

Authorised for release by Carmine Di Noia, Director, OECD Directorate for Financial and Enterprise Affairs.

Keywords: DeFi, decentralised finance, lending protocols, decentralisation, finance, tokens, liquidity pools, liquidity providers, decentralised exchanges.

JEL Codes: G12, G14, G23, O39.

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Executive summary

This working paper aims to examine DeFi lending protocol automated liquidation mechanism and the connection between liquidations and price volatility in decentralised exchanges (DEXs). This paper builds on earlier OECD work on DeFi and markets for crypto-assets and contributes to the growing empirical analysis on the characteristics of activity in DeFi lending pools and decentralised exchanges.

The empirical analysis is based on an original on-chain transaction-level dataset of three of the largest DeFi lending protocols for the period between December 2020 and December 2022. The analysis focuses on liquidations data of these DeFi lending protocols and provides evidence of a positive relation between liquidations and post-liquidations price volatility across the main DEX pools. Without directly observing the behaviour of liquidators, these findings indicate that liquidators require market liquidity to carry out swaps associated with large liquidations and affect market conditions while doing so. In particular, price volatility increases in the presence of frequent liquidations.

The paper also discusses liquidity conditions in a set of lending pools examined in the analysis and highlights the importance of sufficient liquidity for the functioning of liquidations. In particular, drawing on the analysis of the examined lending pools, it appears that at extreme events when investors pursue the same strategy at large numbers, liquidity of a particular asset may dry up in each of the pools across protocols. This implies that the liquidation mechanism might be limited in its ability to restore liquidity, as liquidators themselves rely on the liquidity available in the pools to repay underwater loans. Notably, liquidators' ability to liquidate is constrained and will depend on 'exogenous' liquidity provision, if the under-collateralised debt is denominated in a scarcely available or volatile asset, and if liquidity is absent and borrowing is expensive.

The analysis finds a positive correlation among borrowing rates in the three large lending pools examined and across different assets, which indicates that the liquidity in DeFi lending pools examined is connected. This finding implies a possible further risk of intensification of illiquidity. It suggests that based on the pools examined, investors often pursue similar strategies in DeFi lending protocols. This kind of herding behaviour may further intensify liquidity shortages in lending pools as assets are used as collateral in a simultaneous manner. Low liquidity in a lending pool will translate into the inability of depositors to withdraw their deposits. Though depositors are made aware that their ability to withdraw depends on the available liquidity, the over-collateralisation method might downplay the risk associated with liquidity provision in the eyes of investors. Because the net leverage position of investors is not taken into account, rather each deposit-borrow transaction is considered as a stand-alone for risk assessment purposes, an inherent feature in an anonymised market, participants can quickly and significantly leverage, even if their initial capital is low, which can dry up liquidity in the pools.

1 Liquidations in DeFi lending protocols

1.1. DeFi lending protocols

Lending and borrowing protocols and decentralised exchanges (DEXs) have been two of the most popular types of DeFi protocols deployed on chain, alongside staking protocols (OECD, 2022[1]). DeFi lending and borrowing protocols enable users to obtain leverage through borrowing tokens against collateral. There is also the possibility to take out a flash loan (borrowing and repayment are carried out in the same transaction) without having to provide collateral. Adjustable interest rate payments, transferred from borrowers to depositors (with a share going to the platform), are the main mechanism used to maintain demand and supply equilibrium for sufficient liquidity to remain, because quantity adjustment is very much limited, especially for smaller, scarcely available, crypto assets (see an example in Section 3). Different lending protocols are similar in the sense that they are not assuming any risk on their balance sheet, and that all credit and liquidity risks are carried out by users. Lending protocols include automated liquidation procedures, to liquidate positions that fall under the prespecified under-collateralisation limit (see Section 1.2).

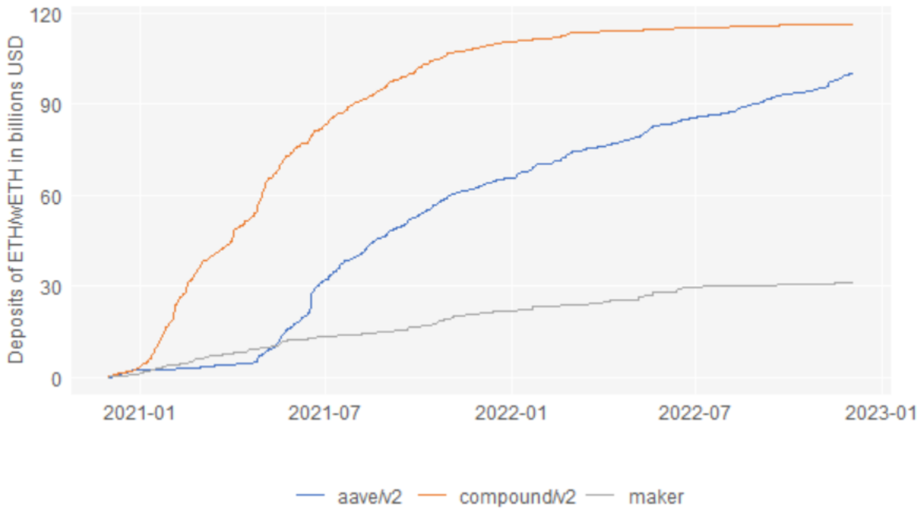
The analysis in this paper uses historical transaction-level data on several leading lending and borrowing protocols: Aave, Compound and Maker for the period between 1 December 2020 and 8 December 2022.[1] As of 22 March 2023, Maker, Aave V2 and Compound were the three top lending protocols in terms of deposited amount (DeBank, 2023[2]). The data breaks down the five types of transactions possible in the pools: deposit, withdrawal, borrowing, repayment and liquidation, with characteristics associated with the transactions such as the asset involved, the interest rate prevailing at the time, and the user address performing the action. Figure 1.1 presents the cumulative deposited amount of ETH/WETH[2] in these lending protocols since the beginning of the sample.

[1] Original datasets provided by cryptocurrency market data provider Kaiko.

[2] WETH is the ERC-20 tradable version of ETH. ERC-20 tokens can only be traded with other ERC-20 token. Crypto wallets and exchanges on Ethereum network natively support ERC-20 tokens and make WETH more useful in DeFi. To generate WETH a person must send their ETH to a smart contract that then provides WETH in return. The wrapping ratio is 1 to 1 but gas fees still need to be paid for the wrapping operation. This means that WETH created is backed up by ETH reserves. Alternatively, it is possible to swap another token for WETH using a crypto exchange.

Figure 1.1. Comparison of cumulative amount of ETH/WETH deposited in lending protocols

In USD billions, as of 5 December 2022



Note: Cumulative amount of ETH or WETH (depending on the protocol options) deposited into lending pools since 1 December 2020.
Source: Kaiko and OECD calculations.

The maximum amount that can be borrowed by a user from a lending pool depends on the asset that was supplied as collateral, the asset that the user wishes to borrow and the available liquidity in the pool. The value of collateral should remain well above the value of the loan, in a continuous manner, throughout the life of the loan. If the ratio between the value of the borrowed assets and the value of the supplied collateral declines below a pre-defined threshold, the borrowing position becomes under-collateralised and eligible for liquidation. The numeric representation of the safety of the collateral against the borrowed assets is sometimes called the 'health factor' or the 'collateral factor'.

The strategies that have been followed in the past two years by investors in lending protocols were either taking a long position when the expectation is that volatile crypto asset prices will rise, or a short position in the opposite market sentiment (Carey and Melachrinos, 2022[3]). A long position requires the deposit of a volatile asset (ETH/BTC), which becomes the collateral, and the borrowing of another (usually less volatile, uncorrelated or negatively correlated with the collateral) asset, which is the debt asset, such as a stablecoin. The less volatile asset might then be exchanged for the volatile asset in an exchange, and the user can perform another set of deposit and borrowing actions to increase their leverage. This can happen several times as there is no monitoring of leverage by the platform on a cumulative basis. If the volatile asset increases in price, a profit is made from the change in the price ratio of the volatile asset against the "stable" asset. If instead the price declines, the position should be liquidated. A short position would be the opposite – the deposit of a "stable" asset and borrowing of a volatile asset. Other types of investments are also possible through borrowing such as staking or investment in derivatives. The possibilities of unrestricted leverage allowed by such strategies was one of the key drivers of the rise of popularity of DeFi lending protocols (OECD, 2022[1]).

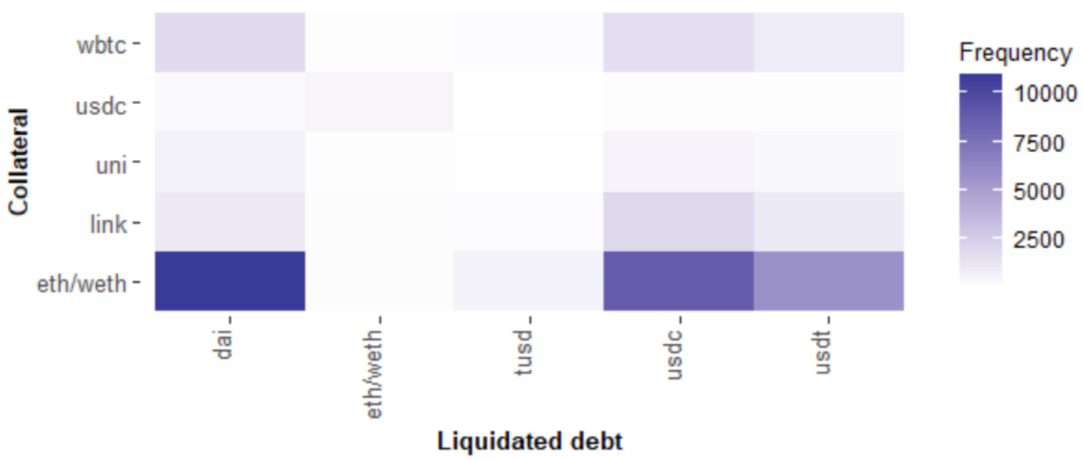
1.2. DeFi Liquidations

A liquidation is a process that occurs when a borrower's 'health factor' drops below 1 or if the value of the collateral drops below the 'liquidation ratio' defined by the protocol. This might happen when the collateral decreases in value or the borrowed debt increases in value. A rise in the borrowing interest rate is also a way that results in a deterioration in the health factor as the loan increases in nominal value. In a liquidation, a liquidator repays part of the underwater debt and receives from the protocol in return part of the collateral that was deposited at a discount price compared to the current market price. Some protocols execute auctions with a bidding process for the liquidation of the collateral (Maker) while others allow instant liquidation by liquidators for a pre-determined bonus/incentive (Aave, Compound).[3] Platforms differ in the mechanism used to determine who will be able to liquidate the debt, but in general, this function is open to any user. Previously, (Qin et al., 2021[4]) found that different liquidation designs well incentivise liquidators in terms of the profit that liquidators make, with the result of excessive amounts of discounted collateral being sold at the borrowers' expenses.

The dataset used in this analysis allows to identify the asset pairs that were involved in liquidations on the collateral and on the debt sides (Figure 1.2). Most frequently during the sample period, debt that was liquidated had been borrowed in "stablecoins" such as USDC, USDT or DAI, with collateral pledged in volatile assets, such as WETH and WBTC. It is important to note that borrowing in Maker is only possible in the token DAI, while collateral can be provided in a variety of assets. The liquidation pairs frequency implies that the investment strategies that were most often liquidated were of users expecting to profit from an increase in the price of volatile crypto assets. Such strategies were negatively affected during the sharp price declines in 2022 H1, eventually leading to the default of service providers in the crypto assets that had their business model rely on participation in such lending protocols (OECD, 2022[5]). Indeed, many liquidations across the lending pools occurred in 2022 H1 (Figure 1.3).

Figure 1.2. Most frequent pairs of liquidated debt and collateral

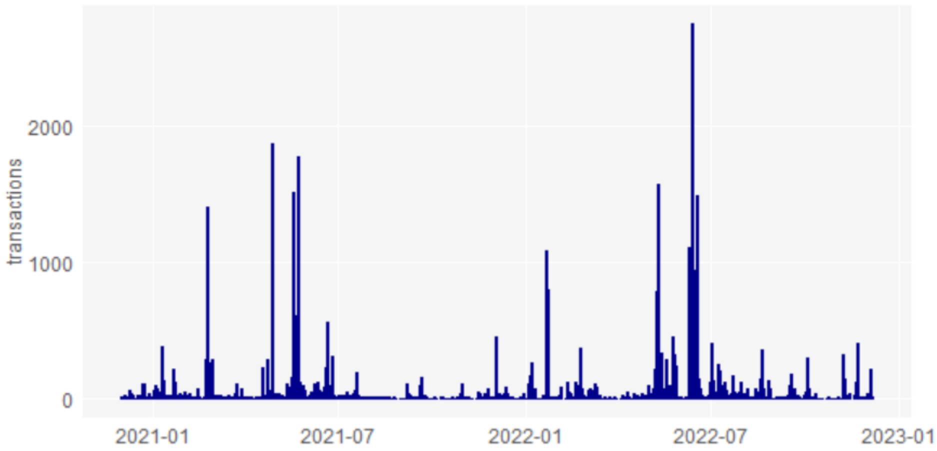
Frequency of liquidation pairs as of 8 December 2022, for Aave V1, Aave V2, Compound V2 and Maker pools



Note: Frequency of liquidated collateral-debt pairs for top five liquidated debt assets and top five liquidated collateral assets. These liquidation pairs account for 78% of all liquidated transactions in the data sample. Pools included in the analysis are Aave V1, Aave V2, Compound V2 and Maker. Though Maker is used less often than Aave V2 and Compound, it only allows to borrow DAI, so liquidations from this pool will always have DAI as the liquidated debt.
Source: Kaiko and OECD calculations.

[3] Liquidation fees and penalties also apply and differ depending on the protocol.

Figure 1.3. Liquidations from leading lending pools over time



Note: Daily number of liquidation transactions carried out in Aave V1, Aave V2, Compound and Maker.
Source: Kaiko and OECD calculations.

During the sample period and for the protocols in the dataset, close to 50 000 liquidations took place only of USDC and USDT denominated debt. Though liquidations are open, in theory, to the participation of any user, and borrowing positions eligible for liquidation are publicly displayed, industry reports claim that most liquidations are performed by bots (Qin et al., 2021[4]). The data in the sample points to concentration of liquidators; it indicates that 530 distinct user addresses have executed the 50 000 liquidations, with top 10 liquidators responsible for 60% of the liquidation transactions.

2 DeFi liquidations and volatility impact

2.1. The connection between lending pools and DEXs

This chapter outlines the methodology and results of the analysis of the effect of liquidations in DeFi on price volatility in DEXs. Specifically, we assess the impact of liquidations involving a particular pair of debt and collateral assets on the price volatility of these two assets when exchanged one against the other on DEXs in the period between 1 December 2020 until 8 December 2022. If the data portrays evidence that liquidations are associated with wider fluctuations in the price of underlying crypto assets on DEXs, it will point to a major risk posed by the liquidations mechanism of adding systemic risk to the system. Because liquidations tend to occur during adverse market conditions, the liquidation mechanism, designed to maintain the stability of lending pools, contributes to the negative dynamic of a distress episode through more volatility in the spot market.

We expect that if liquidators have a preference to avoid holding large capital, to not expose themselves to the risk of exchange rate fluctuation, there will be increased swapping activity associated with an increase in liquidations. If liquidators require loans to repay the under-collateralised debt, then that increases the likelihood that they will swap the received collateral back to the debt asset to repay their loans. This conjecture regarding the preference of liquidators to avoid holding large capital pre and post liquidations is supported by the claim that most liquidations are apparently performed by bots and by an overall small number of active users that carry out liquidations in the lending pools examined (see Section 1.2). If liquidators use their own capital to repay the under-collateralised debt, then they do not have to trade post liquidation, but might still prefer to do so to lock in their profit. Thus, the analysis provided in the paper also sheds light on the magnitude of swaps taking place after liquidations.

A study by Lehar and A. Parlour (2022[6]) documented a price impact of trades performed by liquidators on different DEXs. They focused on the price impact of liquidations on DEXs, where the liquidator swapped the collateral for the debt asset in the same transaction where the liquidation was recorded, including flash loans and liquidations in which another asset was swapped for the debt asset in order to recover the collateral. In contrast, the available dataset does not allow us to witness the transactions carried out by liquidators around the liquidation event and be able to directly assess their use of pre-available capital compared with flash loans and swaps. In this analysis, the variable of interest is all liquidations involving a pair of two tokens, and its relation to fluctuations in the price of the following trades taking place on DEXs.

Box 2.1. Decentralised exchanges (DEX)

A DEX is a peer-to-peer marketplace where users can trade cryptocurrencies in a non-custodial manner. There are several DEX designs, with automated market makers (AMMs) being the most widely used. Instead of an order book, an AMM utilises a liquidity pool that traders can swap their tokens against, with the price determined by an algorithm based on the proportion of tokens in the pool, usually a pair of such tokens. Liquidity is supplied to the DEX pools by liquidity providers, and liquidity events relate to the addition or removal of (often pairs of) tokens to/from a liquidity pool.

Order book DEXs have been less common in DeFi and suffered from low liquidity, as they require every interaction within the order book to be posted on the blockchain. To overcome this complexity and associated cost, some exchanges employ a hybrid order book design, where the order book management and matching processes take place off-chain while the settlement of trades occurs on-chain. Importantly, reserves and prices in AMM exchanges are updated automatically *every time* a trade takes place. Users can get instant access to liquidity, while liquidity providers (depositors into the AMM's liquidity pool) can earn passive income via trading fees that are paid for the swaps. Liquidity is essential for AMMs to function properly; If an AMM doesn't have a sufficient liquidity in the pool, it can give rise to a large price impact when traders buy and sell assets.

Source: OECD (2022[1]) Why Decentralised Finance (DeFi) Matters and the Policy Implications, https://www.oecd.org/finance/why-decentralised-finance-defi-matters-and-the-policy-implications.htm, Chainlink (2023[7]) Automated Market Makers (AMMs) Explained, https://chain.link/education-hub/what-is-an-automated-market-maker-amm, Coindesk (2023[8]) What Is an Automated Market Maker? - AMMs Explained, https://www.coindesk.com/learn/what-is-an-automated-market-maker/.

2.2. Data and methodology

The main hypothesis of this analysis postulates that liquidations increase the volatility of the price of the pair of assets involved in a liquidation, as discussed, because on the one hand, liquidators want to lock in their profit and remain unexposed to fluctuations in the price of volatile assets and because, on the other hand, of insufficient liquidity in the crypto market. We choose to focus in the test on liquidations of USDC debt with collateral denominated in ETH or WETH. According to Figure 1.2, this has been one of the most frequent liquidated debt-collateral pairs. In addition, both ETH and USDC are among the most liquid and highly capitalised assets in the crypto space, so testing the effect for this pair will provide large number of observations and an effect measured for overall liquid assets where volatility impact should be minimal. Data on lending protocols covers three of the leading decentralised venues: AAVE (V1[4] and V2), Compound and Maker. The five transactions available on these three protocols, known as events, constitute: borrowings, deposits, repayments, withdrawals, and liquidations. For the purpose of this analysis, we focus on liquidations. Data from Maker is irrelevant for the pair of USDC and ETH, as only debt in DAI is lent and may be liquidated on Maker, we thus remain with liquidation data coming from AAVE V1 and V2 and Compound.

Table 2.1 presents the distribution of USDC debt collateralised by ETH liquidations among the lending pools in the sample. A liquidation on average occurs every two hours; the median is however every 48 seconds, pointing to the clustering of liquidations, or their tendency to occur in "waves". Most liquidations in terms of value have taken place on AAVE V2 in this sample. Figure 2.1 displays daily value

[4] The Aave community has gradually moved away from the V1 version after V2 was launched. The calculations in this paper still include the liquidations transactions in the tests, though these represent a small share of the overall observations.

of liquidations by lending protocol. It demonstrates that liquidations follow a volatile pattern, with some periods without liquidations and others with high liquidation spikes. The spikes do not necessarily seem to be correlated across the protocols, due to differences in individual borrowing positions value.

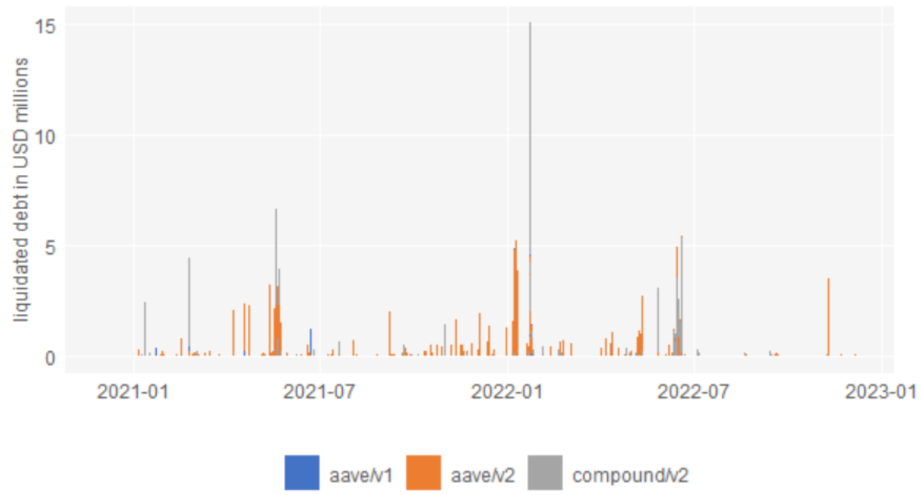
Table 2.1. Summary statistics on liquidations of USDC debt with collateral in ETH/WETH

From 1 December 2020 until 8 December 2022

Protocol	Amount of debt liquidated in million USD	Number of liquidation transactions
Compound	211.33	2 841
Aave V2	263.51	5 765
Aave V1	9.17	235

Source: Kaiko and OECD calculations.

Figure 2.1. Liquidations of USDC debt collateralised by ETH/WETH



Source: Kaiko and OECD calculations.

Linear regression estimated with Ordinary Least Squares (OLS) is fitted to test for the effect that the value of liquidations may have on the price volatility on DEXs. The explanatory variable of interest is the amount of liquidated USDC debt collateralised by ETH, across AVVE V1 and V2, and Compound. The dependent variable is the volatility of USDC/WETH price, which corresponds to the price prevailing in DEX liquidity pools where WETH trades against USDC, reported each time a liquidity event in those pools takes place.

Data are sourced from Kaiko. On an AMM type of DEX, there can be two types of transactions – either a swap or a liquidity event. Swaps always occur between just two tokens, both should be available in the pools. Liquidity pools generally contain two or more tokens and most DEXs require liquidity providers to deposit pairs of tokens reflecting the current composition of the pool, which corresponds to the current price of the deposited assets (Kaiko, 2023[9]).[5] Liquidity events are made by liquidity providers, who earn profits from trading fees paid by traders. Thus, the more liquid a pool is and the more it is able to attract

[5] UnisSwap V3 allows for liquidity providers to pre-select their position on the supply curve of a traded pair of assets. By choosing several parameters of their deposit, such as their fee tier and price range, their ratio of assets to be allocated to the pool will change. Thus, a continuum of ratios is possible.

volume, the more profits liquidity providers will receive. At the same time, because the withdrawn proportion of assets by a liquidity provider will depend on the prevailing price of tokens at the time of withdrawal, liquidity providers are subject to “impermanent loss”[6]. Every time a token is added or removed from a pool as a consequence of a swap, the price of the tokens adjusts. The larger the divergence of price that has occurred since depositing the liquidity, the larger will be the impermanent loss for the liquidity provider (CoinMarketCap, 2022[10]).

In terms of DEXs, Kaiko covers the most liquid Ethereum-based DEXs. Combined, these DEXs account for the majority of decentralised trading activity across all blockchain networks (Kaiko, 2023[9]). Both trades and liquidity events are registered by Kaiko at transaction level data. USDC-WETH price for the purpose of the analysis is derived from swaps taking places on DEXs that offer an option to trade USDC versus WETH. Such DEXs are Uniswap V2 and V3; SushiSwap; Balancer, Balancer V2 and 1inch (Kaiko, 2023[11]). We use the Asset Price endpoint made available by Kaiko and retrieve an aggregated price that is based on all trades at all the covered exchanges which support spot markets for the pair USDC-WETH, as mentioned above, in 1-minute intervals (Kaiko, 2023[12]).

The price of USDC versus WETH derived from the swaps is depicted in Figure 2.2. Sharp devaluations of WETH, such as those that occurred in 2021 H1 and 2022 H2 correspond to the significant increases in liquidated debt amounts shown earlier in Figure 2.1.

Figure 2.2. USDC-WETH price aggregated from swaps on DEXs

Source: Kaiko and OECD calculations.

Standard methodology for high frequency trading data consists of estimating price volatility at constant time intervals, rather than taking account of all observations available (Zhang, Mykland and Aït-Sahalia, 2005[13]). This explains the decision to sample the aggregated swaps price data in constant one-minute intervals. In the baseline test, volatility is calculated over the following two-hours window, equivalent to 120 such one-minute price observations. Within each one-minute interval, there are usually seven to eight trades, meaning that a shorter sampling interval will result in many observations carrying no new pricing

[6] Impermanent loss in DeFi occurs when the price of the assets deposited in DeFi liquidity pools changes compared to the price at the time the deposit was made. It indicates the loss incurred to the user by choosing to provide liquidity to the pool instead of just holding the asset. It is called “impermanent” because it is possible to recover such loss if the asset price returns to the initial exchange rate.

information. The two-hours interval for volatility estimation is chosen to take the frequency of liquidations under consideration. A liquidation wave, previously defined as a cluster of at least five liquidations in DeFi, was measured to last on average 1.63 hours (Lehar and Christine A. Parlour, 2022[6]). Choosing to measure the effect of liquidations on volatility over a two-hour horizon, i.e. considering a wave of liquidations as a single event, means to take the view of a systemic vulnerability analysis. In contrast, a shorter time horizon measure of volatility and liquidations dynamic would be more appropriate for assessing market efficiency. A two-hour horizon is chosen as the baseline. Nonetheless, robustness check is performed in Section 2.5 to compare the results of the analysis with a shorter time horizon.

The econometrical model follows most closely (Shum et al., 2016[14]) who test the relation between potential rebalancing needs of leveraged ETFs and intraday equity volatility using an OLS estimator. In terms of setting and rationale, their test is similar to the test here because the authors do not directly observe the trades performed by ETFs, and consider instead the potential need for rebalancing as the main explanatory variable of price volatility, in the same way that we do not observe the trading activity of liquidators, and conjecture that liquidators potentially need to trade after performing liquidations to adjust their portfolio composition or repay loans. In another work assessing the effect of ETF ownership on stock volatility, Ben-David, Franzoni and Moussawi (2018[15]) also use an OLS framework. In contrast, it is common to use time series modelling for equity volatility forecasting. The limitations from using such setting for the current analysis are, first, it is not aimed at forecasting volatility but at assessing a potential causal effect; and, second, the dynamics of liquidations do not seem to be appropriate for time series modelling as they tend to be of zero value for considerable time periods. Their persistency seems to be very short lived. Alternatively, we use lagged estimates of realised volatility within the OLS specification to account for persistence in volatility.

From the aggregated price of USDC-WETH sampled in one-minute intervals we produce continuously compound returns by taking the difference of the natural logarithm of the price series. Realised volatility is then measured as the square root of the average variance of returns, assuming the return has a zero-mean. Specifically, volatility is measured as follows:

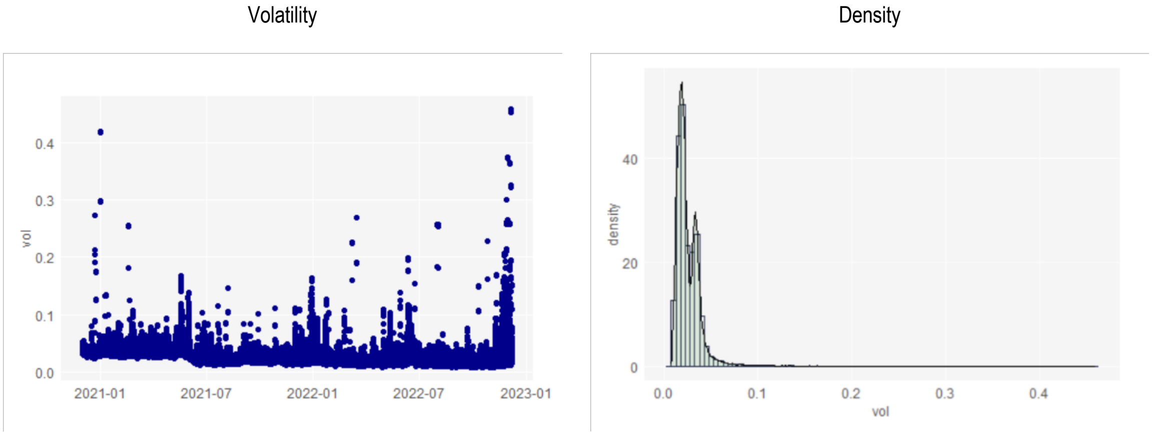
$$(1)\ Vol_{t+1} = \sqrt{\sum_{k=0}^{t+1} r_{t+k}^2}$$

Where r_{t+k} is the logarithmic (continuously compounded) return of the price of USDC versus WETH measured each k interval (one-minute), from time t and until two hours later (in the baseline case) denoted by $t+1$. Each volatility estimation is thus based on 120 return observations.

Volatility data was constrained to match the sample of liquidations from 1 December 2020 until 8 December 2022. Figure 2.3 left hand side portrays the result of the realised volatility. There are some high results in the volatility estimation, measured during turbulent market periods such as 2021 H1 and 2022 H2. On the right-hand side, the density distribution of the realised volatility is depicted. Most values lie below 0.05, with a long tail.

Due to the non-negative nature of both volatility and liquidated debt, their spread-out and right skewed distribution, we employ a logarithmic transformation on the dependent and independent variables. In effect this means that we are testing the effect of change in liquidation amounts on the change in volatility. This implies that we discard observations of zero liquidations. There is additional merit in using a logarithmic transformation because liquidations tend to be very volatile, and of different magnitude (see Section 1.2).

Figure 2.3. Realised volatility properties



Source: Kaiko and OECD calculations.

The OLS regression model is specified as follows:

$$(2)\ \log(\mathrm{Vol}_{t+1}) = \beta_0 + \beta_1 \log(\mathrm{LIQ}_t) + \beta_2 \log(\mathrm{Vol}_t) + \beta_3 R_t + \beta_4 I_t + \beta_5 R_t \times I_t + \varepsilon_{t+1}$$

Where, Vol_{t+1} – Realised volatility measured per equation 1

LIQ_t- the amount of USDC debt, evaluated in USD millions, that was liquidated between time $t-1$ and t (two hours), summed across all protocols in the sample.

Vol_t – Realised volatility measured per equation 1 from time $t-1$ up to t

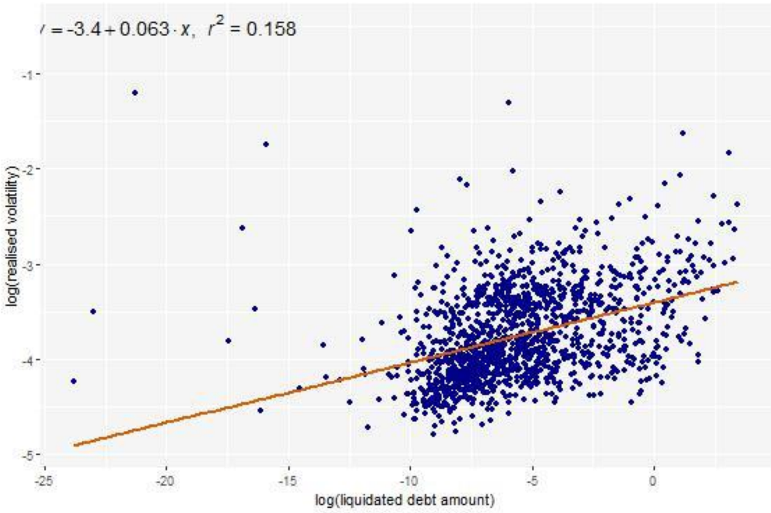
R_t – return over the previous two hours, from P_{t-1} to P_t.

I_t – dummy equal to 1 if R_t has a positive value.

Figure 2.4 allows to get preliminary findings about the relationship between volatility and liquidations by simply plotting the values of the volatility and the liquidated amount. The plot seems to support the conjecture of a positive relation between volatility and liquidated amount, and also to justify our decision to use a logarithmic transformation on both volatility and liquidated debt to better account for a linear dependence. According to the scatter plot, the link between volatility and liquidated debt amount seems to be weakened in the presence of low levels of liquidated debt.

The main econometric challenge herein is to isolate the impact of liquidations among the array of factors that may impact DEX volatility. Due to well-documented persistence in volatility in traditional equity markets (see for example (Patton and Sheppard, 2015[16])), we control for the expected level of volatility by introducing the lagged value of the dependent variable as an explanatory variable. The purpose is to ensure that the results are not driven by incidents of a higher overall level of volatility in the market. As a robustness check, we introduce an additional lag of realised volatility in a separate regression to allow for even stronger persistence. We also control for the magnitude and direction of price change by introducing the value of the return of USDC/WETH, as well as an interaction term between the return and a dummy that takes the value one for positive return incidences. This has two main objectives: i) ensure that the results are not driven by a decline in the price of WETH, as liquidations tend to increase under adverse market conditions, and ii) control for asymmetric pattern of volatility under bullish and hawkish market conditions.

Figure 2.4. Volatility and liquidations scatter plot



Source: Kaiko and OECD calculations.

We suspect that at least a certain part of liquidations is performed using flash loans, where both the liquidation and swap transactions are carried out in the same block. Alternatively, we claim that liquidators that do not use flash loans are nevertheless incentivised to quickly swap the asset they receive from the lending pool in exchange for repaying the under-collateralised debt (i.e. the collateral asset) to lock in their profit. Both these scenarios imply that the swaps associated with liquidations happen at the same time or adjacent to the liquidation. Ideally, we would like to measure the effect of liquidations on the volatility measured on DEXs simultaneously to liquidations. However, a potential caveat with such specification of the model would be the presence of endogeneity. For instance, DEX price volatility might affect the price reported through Oracles to the lending pools protocols contracts, inducing more liquidations.[7] We thus look at volatility measured after liquidations have taken place, to avoid such econometrical challenge. However, in doing so, we might be accounting for the effect of consecutive liquidations on volatility as well. Indeed, liquidation waves (i.e. when many liquidations take place during a short period of time) are a common phenomenon, and maybe caused by a range of factors. Investors often take similar investment strategies in crypto leveraged lending (see Section 1.2), and massive liquidations have a negative price impact, that may reinforce liquidation volumes through Oracles (Lehar and Christine A. Parlour, 2022[6]).

Table 2.2 presents the summary statistics for the variables used for the regression. The model is estimated for the entire set of observations, where all liquidations of USDC debt with collateral in ETH/WETH are accounted for. In addition, data is also subsampled, removing the lower 10 and 20% of debt liquidations observations in Panel B and C, respectively. The subsampling is performed given the indication in Figure 2.4 that small amounts of liquidations are irrelevant for volatility. This is also supported by (Lehar and Christine A. Parlour, 2022[6]) who observe swaps and flash loans carried out by liquidators more often to execute large liquidations. The three panels differ in the distribution of liquidated amount and return – both medians are higher the more the sample is reduced, moving from Panel A to B and then C. This makes sense as the observations with the lowest amount of debt are removed. Larger liquidations coincide with higher return, which is equivalent to a greater depreciation of WETH. Average and median measures of volatility seem similar across the three panels.

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[7] A caveat to this is the fact that Oracles aggregate many markets where a given pair of crypto-assets is traded, including not only DEXs but also CEXs, and such oracles are oblivious to small price changes.

Table 2.2. Descriptive statistics for regression variables

<Descriptive Statistics Panel A>

Statistic	N	Min	Mean	Median	Max	St. Dev.
USDC/ETH Price	1,323	0.000	0.001	0.001	0.002	0.000
Realised Volatility	1,323	0.01	0.03	0.02	0.3	0.02
Return	1,323	-0.2	0.01	0.003	0.1	0.02
Liquidated Debt in USD Millions	1,323	0.0	0.4	0.002	30.3	2.0

<Descriptive Statistics Panel B>

Statistic	N	Min	Mean	Median	Max	St. Dev.
USDC/ETH Price	1,190	0.000	0.001	0.001	0.002	0.000
Realised Volatility	1,190	0.01	0.03	0.02	0.3	0.02
Return	1,190	-0.2	0.01	0.004	0.1	0.02
Liquidated Debt in USD Millions	1,190	0.000	0.4	0.004	30.3	2.1

<Descriptive Statistics Panel C>

Statistic	N	Min	Mean	Median	Max	St. Dev.
USDC/ETH Price	1,059	0.000	0.001	0.000	0.002	0.000
Realised Volatility	1,059	0.01	0.03	0.02	0.3	0.02
Return	1,059	-0.2	0.01	0.01	0.1	0.03
Liquidated Debt in USD Millions	1,059	0.000	0.5	0.01	30.3	2.3

Note: In Panel A, all observations with non-zero liquidated debt are used. In Panel B, liquidations with debt value in the bottom 10% compared with Panel A were removed. In Panel C, liquidations with debt value in the bottom 20% compared with Panel A were removed.
Source: OECD calculations based on Kaiko data.

2.3. Empirical findings and interpretation

The regression results are reported in Table 2.3. Column (1) presents the results from estimating equation (2) using OLS for the entire sample. In column (2) we use Panel B subsample and in column (3) Panel C subsample is used. In column (4) we take under consideration a longer persistence in volatility by adding two additional lags of realised volatility as explanatory variables, estimated for Panel B. We calculate robust standard errors to avoid a miss interpretation of coefficients significance due to heteroscedasticity in all estimates.

The results of the estimations support the hypothesis that liquidations have a positive and significant effect on the price volatility of USDC – WETH in DEX pools. Because both the dependent variable and the independent variable of interest have been logarithmically transformed, the coefficient of the liquidated amount is interpreted as the percent increase in the dependent variable for every 1% increase in the independent variable. This implies that the impact of a 1% increase in USD millions liquidated debt is associated with 0.017% – 0.024% increase in volatility. Since liquidations are volatile and occasionally take extremely high values, their impact in such instances on volatility might be very large. The highest coefficient for liquidated amount is obtained in column (2) where the bottom 10% of liquidations have been removed. This might indicate that the effect of the change in liquidations on volatility is irrelevant for small liquidations and that liquidators do not require swaps for such small liquidations, being able to use their own available capital, in contrast to large liquidation clusters.

Table 2.3. OLS regression results

	Dependent Variable			
	log (Realised Volatility (t+1))			
	(1)	(2)	(3)	(4)
Log (liquidated debt in USD millions)	0.017** (0.007)	0.024*** (0.005)	0.017*** (0.005)	0.021*** (0.005)
Log (Volatility (t))	0.522*** (0.035)	0.502*** (0.034)	0.536*** (0.031)	0.274*** (0.037)
Log (Volatility (t+1))				0.204*** (0.033)
Log (Volatility (t+2))				0.183*** (0.032)
Return	-5.968*** (2.133)	-5.675** (2.231)	-5.594** (2.363)	-4.682* (2.516)
Dummy (Return>0)	0.038 (0/035)	0.020 (0.036)	0.034 (0.038)	0.019 (0.037)
Return (+)	11.849*** (2.413)	11.242*** (2.502)	11.101*** (2.641)	10.166*** (2.771)
Constant	-1.822*** (0.127)	-1.839*** (0.133)	-1.745*** (0.129)	-1.257*** (0.131)
Robust standard errors	Yes	Yes	Yes	Yes
Observations	1,323	1,190	1,059	1,188
R^2	0.470	0.479	0.478	0.545
Adjusted R^2	0.468	0.477	0.476	0.542
Residual Std. Error	0.361 (df=1317)	0.345 (df=1184)	0.342 (df=1053)	0.323 (df=1180)
F Statistic	233.373*** (df=5; 1317)	217.782*** (df=5; 1184)	193.003*** (df=5; 1053)	201.737*** (df=7; 1180)

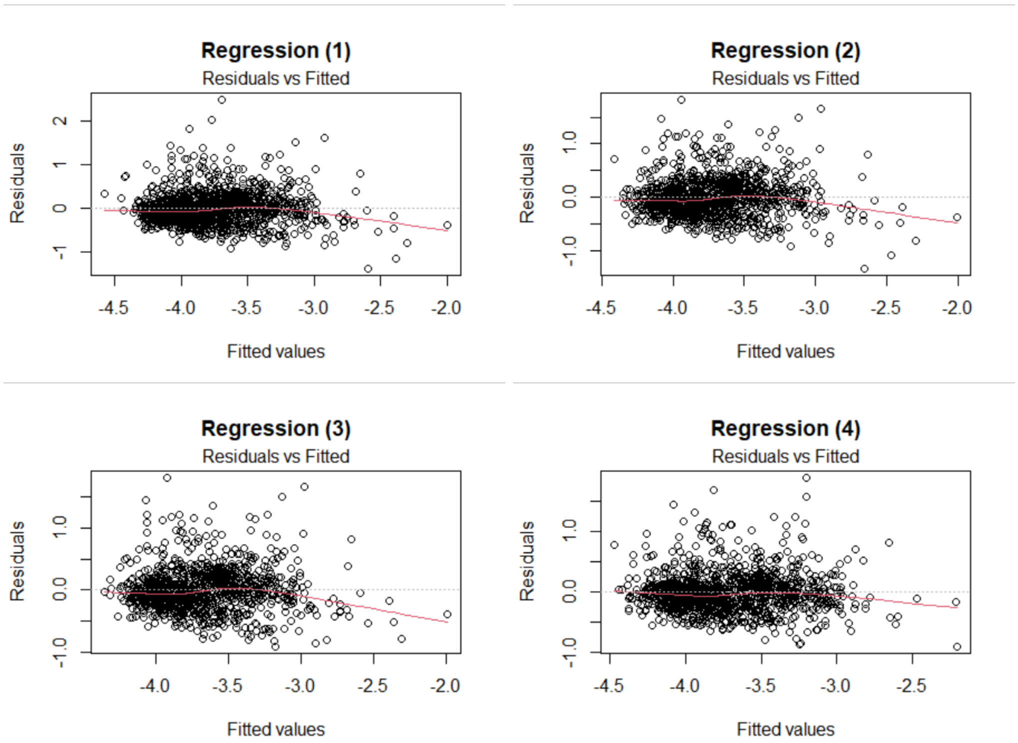
Note: *p<0.1; **p<0.05; ***p<0.01

The table reports estimate from ordinary least squares (OLS) regressions of intra-day volatility of USDC-WETH DEX price on USDC debt collateralised by WETH liquidations. Dependent variable: Realised volatility over 2 hours computed using 5-mimutes realised return. Subsamples formed by filtering on the condition of non-zero value of liquidations. *Liquidated debt* in USD millions is the liquidated amount in the 2-hours up to *t* of USDC debt collateralised by WETH, evaluated at USD millions. *Log(Liquidated debt* in USD millions) is the logarithmic transformation of the liquidated amount in the 2-hours up to *t* of USDC debt collateralised by WETH, evaluated at USD millions. *Log(Volatility(t))* is the realised volatility measured 2 hours earlier. *Return* is the return over the previous 2 hours, from $P_{(t-1)}$ to $P_{(t)}$. *Dummy (Return>0)* is a dummy variable indication if Return has a positive sign. *Return(+)* is equal to *Return* under positive values and zero otherwise. In Panel A (column 1), all observations are used. In Panel B (columns 2) only observations with value of liquidations higher than the bottom 10% are considered. In Panel C (columns 3) only observations with value of liquidations higher than the bottom 20% are considered. Column 4 uses Panel B observations with two additional lagged Log(Volatility) variables. T-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period 1 December 2020 to 8 December 2022.
Source: OECD calculations based on Kaiko data.

All other estimated coefficients in Table 2.3, except for the dummy of return, are highly significant and with the expected signs. Previous period volatility is an important factor explaining the current level of volatility, as evident from the significance of the coefficient of realised volatility at time t and the high coefficient. Additional lagged values of volatility as in column (4) add additional explanatory power to the model, but do not alter the results overall. The accumulated effect of return (combining the coefficients on Return and on Return(+)) is negative for negative return values and positive, and twice larger in magnitude, for positive return values, consistent with the asymmetric nature of volatility under bullish and adverse market conditions. As explained earlier, the return is positive when the value of WETH is depreciating, showing a positive and economically larger relationship between WETH depreciation and increasing volatility. Large negative return is also associated with increased volatility but not as much as positive return of the same absolute magnitude. The adjusted R^2 statistic is close to half in columns (1) to (3) and increases slightly in column (4). Accounting for additional lags of volatility only incrementally ameliorates the explanatory power of the specification. One potentially important factor affecting price volatility in AMM type of DEXs is the deposited amount in the liquidity pools, or in other words – the depth of the pool. Current data limitations are preventing from taking this under account. However, importantly, there is no obvious rationale to believe that deposited amount in liquidity pools is connected to liquidations in lending pools. This is because the economic incentive of depositors in lending pools and in liquidity pools are different. In the first case, profits depend on the demand for borrowing, while in the second case, profits depend on the demand for trade.

Figure 2.5. Residual analysis

Residuals versus fitted log(volatility) plots



Note: Fitted values of the OLS regressions from Table 2.3 are plotted on the x-axis, and y-y hat, the residuals, are plotted on the y-axis.
Source: OECD calculations based on Kaiko data.

Figure 2.5 presents a visual analysis of the fitted linear model of volatility for the four specifications in Table 2.4.

The results of the two-stage least square estimation support a positive relationship between liquidations and price volatility. The coefficient on the variable of interest is about half the size of the coefficient received in the OLS estimation. The results support the conjecture that an effect of liquidations on the price volatility is present. All other estimated coefficients in Table 2.4, except for the return dummy, are highly significant and with the expected signs, and similar in magnitude to the OLS coefficients in Table 2.3.

Table 2.4. For the vast majority of observations and for the four models, the residuals seem randomly spread around the zero line, suggesting that the assumption that the relationship between the change in liquidations and the change in volatility is linear is reasonable. The residuals also roughly spread at equal distance around the zero line, suggesting that there is no issue with heteroskedasticity. Nevertheless, we employed robust standard errors for coefficient significance. In all four specifications, the linear model over-estimates log-volatility for large values, with negatively biased residuals for high fitted values. However, this result concerns a small number of observations.[8]

These empirical findings suggest that a link exists between DeFi debt liquidations and DEX prices in the studied DeFi lending protocol pools. The existence of such effect implies that liquidations contribute to boost price volatility during periods of stress in the market with a stronger effect in the presence of massive liquidations. This supports the suggestion that DeFi may amplify the vulnerabilities of the system in which it operates such as operational fragilities, liquidity and maturity mismatches, leverage, and interconnectedness (OECD, 2022[1]; FSB, 2023[17]). The direction of the trades by liquidators and their timing are predictable and might attract other traders to trade against them. The increased volatility might also disincentivise liquidators or require a greater discount from the pool on the price of the collateral to execute liquidations. This relation between liquidations and volatility might have a deterring effect on liquidators to carry out liquidations in the presence of large price changes, and when many loans become eligible for liquidation simultaneously, as the spot volatility might hinder their profits from carrying out the liquidations. Alternatively, they might demand or bid for the repayment of the debt with a price reflecting high discount from market price to compensate for the risk.

A more general problem currently in the DeFi markets is that there are no last-resort measures in place. DeFi markets are subject to extreme events, perhaps more often than traditional finance, because leverage is not monitored and investors are able to leverage up quickly, pursuing the same strategy. In contrast, in the traditional finance, limits are placed on leverage, lending utilisation rates (reserves for banks); and diversification is encouraged. Ultimately, last resort measures exist in traditional financial markets, circuit breakers being one example.

2.4. A 2SLS approach to estimating liquidations effect on volatility

To test for an effect of liquidations on price volatility without raising concerns over endogeneity, the model postulated in equation (2) includes liquidations that occurred in the two-hours prior to the estimation of realised volatility, which is done over the following two-hours, so that the time difference will ensure there is no reverse causality between volatility and liquidations that would have otherwise resulted in a biased estimation of the regression coefficients.

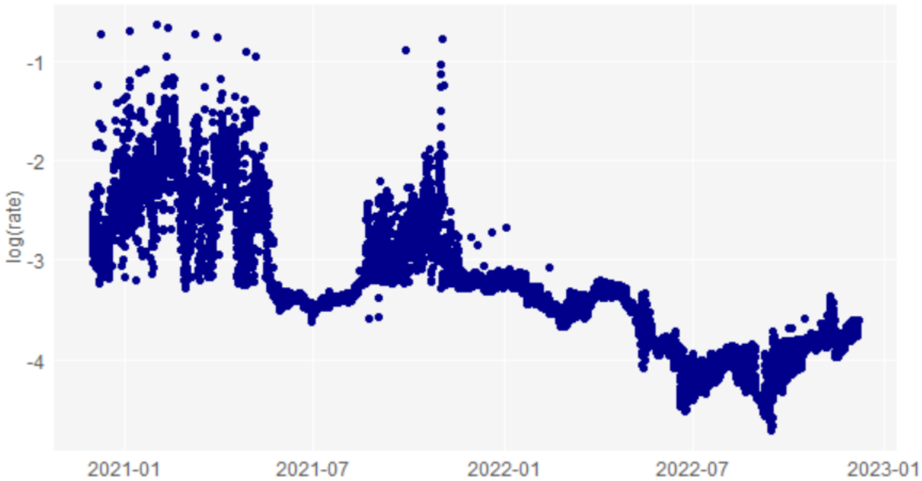
This section presents an alternative approach to tackle the possible simultaneity existing between price volatility and liquidations using a two-stage least-square (2SLS) approach with an instrumental variable. A valid instrumental variable, $\mathrm{Z_t}$, must specify two conditions: (1) It must show relatively high level of correlation with the explanatory variable of interest, $\mathrm{LIQ_t}$, and (2) $\mathrm{Z_t}$ should not affect Vol_t directly, except through $\mathrm{LIQ_t}$. While the first condition can be tested for, and such test is performed further below, the second conditions cannot be directly tested and relies on theoretical justification.

An appropriate candidate for such an instrumental variable for liquidations could be the adjustable interest rate charged by lending protocols for USDC loans. Borrowing (and deposit) interest rate is expected to rise

[8] Q-Q plots indicate that residuals distribution for the four models deviates from the normal distribution at extreme low and high values. Normality tests also point to rejection of the null that the residuals are normally distributed. At the same time, since the sample is quite large, the rejection by the tests is expected, yet is not a severe concern for parameter significance as t and F statistics have approximately t and F distributions for large sample sizes (Jeffrey M. Wooldridge, 2012[26]).

amid scarce liquidity on the lending pool (see Sections 1.1, 1.2 and 3.2 below). A substantial increase in the adjustable interest rates is expected to increase deposit inflows and trigger also repayments or liquidations, due to the increase in the value of existing loans. Because of such features of lending protocols, the adjustable interest rate should be a good predictor of liquidations. In contrast, there should not be a direct relation between spot price volatility and the adjustable interest rate. The borrowing interest rate at focus is set in each protocol and for each asset separately, depending on the available liquidity of this asset in that pool. Figure 2.6 displays the weighted (by value of the borrowing amount) average of USDC adjustable borrowing rate, in logarithmic transformation, derived from transactions that took place on the lending protocols covered by the data. Importantly, there is considerable amount of variation in the borrowing rate so that it might offer valuable information associated with the liquidations amount.

Figure 2.6. USDC adjustable borrowing rate in lending protocols



Note: lending protocols include AAVE V1 and V2 and Compound. Rate is the weighted mean borrowing interest rate measured across protocols offering USDC lending, within every 2-hour interval.
Source: OECD calculations based on Kaiko data.

Unlike the interest rate of currencies in traditional finance, the DeFi adjustable borrowing or deposit rates are not associated with macroeconomic conditions. The focus of the analysis is on high frequency changes to interest rate and price so the argument of a long-term relation between interest rates and exchange rates, as exists in traditional financial markets (interest rates parity), is less likely to apply in this case. To reject concerns of a possible connection between the USDC-WETH price in DEXs and the adjustable borrowing rate, a correlation analysis between the borrowing interest rate in lending pools and the USDC-WETH exchange rate was performed and was found to be zero.

The two-stage estimation model includes two equations. The first equation is used to estimate the relationship between the instrumental variable, i.e. the borrowing rate in USDC pools, and the liquidations amount. Control variables are also included.

$$(3)\ \log(\mathrm{LIQ_t}) = \pi_0 + \pi_1 \log(B_\mathrm{t}) + \pi_2 \log(\mathrm{Vol_{t-1}}) + \pi_3 R_{t-1} + \pi_4 I_{t-1} + \pi_5 R_{t-1} \times I_{t-1} + \mathrm{v_t}$$

Where LIQ_t – is the endogenous variable, and is, as before, the liquidated amount during the 2-hours from $t-1$ up to t of USDC debt collateralised by WETH, evaluated at USD millions.

B_t – is the instrumental variable, calculated as the weighted mean borrowing interest rate measured between time $t-1$ and t across all borrow transactions of USDC in the pools in the sample data.

$\mathrm{Vol_{t-1}}$ – is an exogenous variable in the second stage and is the realised volatility measured per equation (1) from time $t-2$ up to $t-1$, and.

R_{t-1} – is another exogenous variable in the second stage and is the USDC to WETH price return over 2 hours, from P_{t-2} to P_{t-1}

I_{t-1} – dummy equal to 1 if R_{t-1} has a positive value.

The liquidations and borrowing rate variables are taken from the same two-hour time interval in the 2SLS estimation, unlike in equation (2), where volatility from the next time interval after liquidations is used in the OLS estimation.

In the second stage, the price volatility is regressed on the predicted values of the endogenous regressor, $\widehat{\log(LIQ_t)}$ and all other exogenous variables using OLS, with a similar specification as in equitation 2. The main difference from equation (2) it that in this specification, the volatility and liquidations are both estimated for the same time interval, from $t-1$ to t.

$$(4)\ \log(\mathrm{Vol_t}) = \gamma_0 + \gamma_1 \widehat{\log(LIQ_t)} + \gamma_2 \log(\mathrm{Vol_{t-1}}) + \gamma_3 R_{t-1} + \gamma_4 I_{t-1} + \gamma_5 R_{t-1} \times I_{t-1} + u_\mathrm{t}$$

The measured correlation between the logarithm of liquidated debt amount and logarithm of USDC borrowing rate is 0.37, significant at a 5% level. To assess whether the chosen instrument is a valid instrument, its ability to explain variability in the endogenous variable should be examined. To verify this, the F-statistic is computed from the first stage of the 2SLS regression (equation (3)) corresponding to the hypothesis that the coefficient of the instrumental variable, $\log(B_\mathrm{t})$, is zero. The resulting F-statistic is 62.04, which is sufficiently high to reinforce the choice of the borrowing rate as the instrumental variable. Results of the second stage estimation, which display the estimator of the coefficient of interest, i.e. γ_1 from equation (4), are presented Table 2.4.[9]

The results of the two-stage least square estimation support a positive relationship between liquidations and price volatility. The coefficient on the variable of interest is about half the size of the coefficient received in the OLS estimation. The results support the conjecture that an effect of liquidations on the price volatility is present. All other estimated coefficients in Table 2.4, except for the return dummy, are highly significant and with the expected signs, and similar in magnitude to the OLS coefficients in Table 2.3.

[9] The estimation of the 2SLS model was performed using the function ivreg() from the package “ivreg” in R.

Table 2.4. 2SLS regression results

	Dependent Variable
	log (Realised Volatility (t+1))
Log (liquidated debt in USD millions)	0.112***
	(0.018)
Log (Volatility (t-1))	0.365***
	(0.048)
Return	-5.706**
	(2.476)
Dummy (Return>0)	-0.003
	(0.042)
Return (+)	8.835***
	(2.792)
Constant	-1.823***
	(0.139)
Robust standard errors	Yes
Observations	1,317
R^2	0.231
Adjusted R^2	0.228
Residual Std. Error	0.434 (df=1311)

Note: *p<0.1; **p<0.05; ***p<0.01

Note: The table reports estimate from the second stage of a two-stage least squares (2SLS) model of intra-day volatility of USDC-WETH DEX price on USDC debt collateralised by WETH liquidations. Dependent variable: Log-realised volatility over 2 hours computed from $t-1$ up to t using 5-mimutes realised return. *Log(liquidated debt in USD millions)* is the lod-liquidated amount in the 2-hours from $t-1$ up to t of USDC debt collateralised by WETH, evaluated at USD millions. This is the endogenous explanatory variable. It was estimating in the first stage regression with one instrumental variable, log-borrowing adjustable interest rate. *Lagged volatility* is the realised volatility measured 2 hours earlier between $t-2$ up to $t-1$ *Return* is the return over the previous 2 hours, from $P_{(t-2)}$ to $P_{(t-1)}$. *Dummy(Return>0)* equal to 1 if *Return* has a positive value. *Return(+)* is equal to *Return* for positive values, and is zero otherwise. T-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period 1 December 2020 to 8 December 2022, filtered for non-zero liquidations.

Source: Kaiko and OECD calculations.

2.5. Alternative measure of realised volatility

In the OLS and 2SLS specifications, realised volatility was measured over a two-hour horizon using one-minute returns. In accordance, liquidations were aggregated by their value over matching two-hour time intervals. The frequency of price sampling should not be shorter than one minute because this frequency well reflects the frequency of trades on DEXs in the data where USDC-WETH pair is available, and no more than a few trades occur in a minute on average. One-minute price sampling allows for volatility computation over shorter as well as longer than two-hour time horizons. Because the flow of information in the DeFi space is probably fast and there is much use of automation, choosing a longer time horizon for estimation, such as a 24-hours window, will likely include many additional influences on top of the liquidations in DeFi lending protocols. It would be hard to justify any econometric result as pointing to a direct link between liquidations and volatility. Alternatively, a shorter time horizon can be assessed, and that is the test performed in this section. The time horizon chosen for the additional robustness check is that of 30 minutes. The intervals between price samplings are as before one minute.

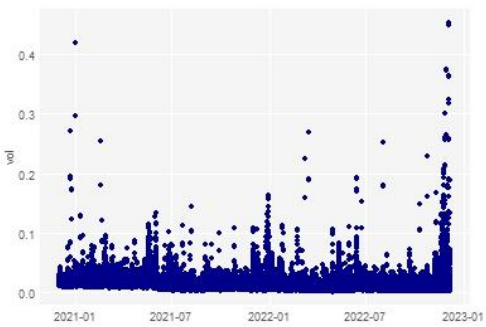
From the aggregated price of USDC-WETH sampled in one-minute intervals we produce continuously compound returns by taking the difference of the natural logarithm of the price series. Realised volatility is then measured as the square root of the average variance of returns, assuming the return has a zero-mean. Specifically, volatility is measured as follows:

$$(4)\ Vol_{t+1} = \sqrt{\sum_{k=0}^{t+1} r_{t+k}^2}$$

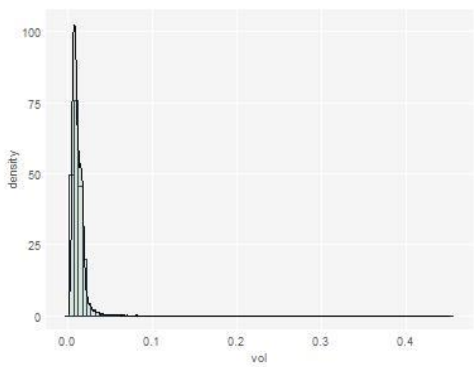
Where r_{t+k} is the logarithmic (continuously compounded) return of the price of USDC versus WETH measured each k interval (one-minute), from time t and until 30 minutes later denoted by $t+1$. Each volatility estimation is thus based on 30 return observations. Figure 2.7 portrays the characteristics of the USDC-WETH price volatility measured over 30 minutes horizons. Compared with the longer horizon volatility in Figure 2.3, the majority of values are lower, as can be expected, making the extreme values in certain periods to appear even more extreme.

Figure 2.7. Realised alternative volatility properties

Volatility



Density



Source: Kaiko and OECD calculations.

Table 2.5 displays the summary statistics for the variables relevant to the OLS modelling. As can be expected, the average values of volatility and of liquidations are lower compared with the base line specification in Table 2.2, as we are aggregating over shorter time intervals.

Table 2.5. Descriptive statistics for variables for regression with alternative measure of volatility

<Descriptive Statistics Panel A>

Statistic	N	Min	Mean	Median	Max	St. Dev.
USDC/ETH Price	2,213	0.000	0.001	0.001	0.002	0.000
Realised Volatility	2,213	0.003	0.01	0.01	0.3	0.01
Return	2,213	-0.2	0.003	0.001	0.2	0.02
Liquidated Debt in USD Millions	2,213	0.0	0.2	0.002	26.4	1.3

<Descriptive Statistics Panel B>

Statistic	N	Min	Mean	Median	Max	St. Dev.
USDC/ETH Price	1,991	0.000	0.001	0.001	0.002	0.000
Realised Volatility	1,991	0.003	0.01	0.01	0.3	0.01
Return	1,991	-0.2	0.004	0.002	0.2	0.02
Liquidated Debt in USD Millions	1,991	0.000	0.2	0.002	26.4	1.4

<Descriptive Statistics Panel C>

Statistic	N	Min	Mean	Median	Max	St. Dev.
USDC/ETH Price	1,770	0.000	0.001	0.001	0.002	0.000
Realised Volatility	1,770	0.003	0.02	0.01	0.3	0.01
Return	1,770	-0.2	0.004	0.002	0.2	0.02
Liquidated Debt in USD Millions	1,770	0.000	0.3	0.003	26.4	1.5

Note: In panel A, all observations with non-zero liquidated debt are used. In Panel B, liquidations with debt value in the bottom 10% compared with Panel A were removed. In Panel C, liquidations with debt value in the bottom 20% compared with Panel A were removed.
Source: OECD calculations based on Kaiko data.

Below, results from the OLS estimation are presented in Table 2.6. As before, column (1) presents the results from estimating equation (2) with volatility and liquidations measured over a 30 minutes time horizon, using OLS, for the entire sample. In column (2) we use Panel B sub-sample and in column (3) Panel C sub-sample is used. In column (4) we allow for a longer persistence in volatility by adding two additional lags of realised volatility as explanatory variables, estimated for Panel B. We calculate robust standard errors to avoid a miss interpretation of coefficients significance due to heteroscedasticity in all estimates. Results are generally similar to the findings of the base line estimation in Section 2.3 and support the hypothesis that liquidations have a positive and significant effect on the price volatility of USDC – WETH in DEX pools, for shorter horizon volatility. The coefficients of the liquidated amount, interpreted as the percent increase in the dependent variable for every 1% increase in the independent variable, are about twice the magnitude compared with the base line specification in Table 2.4. This might be interpreted as indicating that trade associated with liquidations takes place mostly right after liquidations and has in particular a short time effect on volatility that afterwards gradually decreases. All other estimated coefficients, except for the dummy on return, are highly significant. The coefficient on previous period volatility has similar magnitude as in the base line regression; the coefficient of the return, and the positive return, have larger coefficients than in the baseline regression and the same signs, demonstrating once more the asymmetric reaction of volatility to negative and positive returns.

Table 2.6. OLS regression results with 30 minutes time horizon

	Dependent Variable			
	log (Realised Volatility (t+1))			
	(1)	(2)	(3)	(4)
Log (liquidated debt in USD millions)	0.042*** (0.005)	0.045*** (0.005)	0.040*** (0.005)	0.040*** (0.004)
Log (Volatility (t))	0.436*** (0.022)	0.426*** (0.023)	0.422*** (0.023)	0.270*** (0.025)
Log (Volatility (t-1))				0.176*** (0.024)
Log (Volatility (t-2))				0.123*** (0.024)
Return	-11.909*** (2.858)	-11.593*** (2.950)	-11.485*** (2.999)	-10.285*** (3.380)
Dummy (Return>0)	0.011 (0.029)	0.006 (0.031)	0.007 (0.033)	0.012 (0.032)
Return (+)	23.513*** (3.191)	22.795*** (3.265)	22.718*** (3.306)	20.765*** (3.719)
Constant	-2.378*** (0.104)	-2.395*** (0.107)	-2.428*** (0.111)	-1.786*** (0.124)
Robust standard errors	Yes	Yes	Yes	Yes
Observations	2,213	1,991	1,770	1,989
R^2	0.486	0.472	0.450	0.515
Adjusted R^2	0.485	0.471	0.448	0.513
Residual Std. Error	0.424 (df=2207)	0.418 (df=1985)	0.419 (df=1764)	0.401 (df=1981)
F Statistic	418.090*** (df=5; 2207)	355.498*** (df=5; 1985)	288.593*** (df=5; 1764)	299.914*** (df=7; 1981)

Note: *p<0.1; **p<0.05; ***p<0.01
The table reports estimate from ordinary least squares (OLS) regressions of intra-day volatility of USDC-WETH DEX price on USDC debt collateralised by WETH liquidations. Dependent variable: Realised volatility over 30 minutes computed using 1-mimute realised return. *Liquidated debt* in USD millions is the liquidated amount in the 30-minutes up to *t* of USDC debt collateralised by WETH, evaluated at USD millions. *Log(Liquidated debt* in USD millions) is the logarithmic transformation of the liquidated amount in the 30-minutes up to *t* of USDC debt collateralised by WETH, evaluated at USD millions. *Log(Volatility(t))* is the realised volatility measured 30 minutes earlier. *Return* is the return over the previous 30 minutes, from $P_{(t-1)}$ to $P_{(t)}$. *Dummy (Return>0)* is a dummy variable indication if Return has a positive sign. *Return(+)* is equal to *Return* under positive values and zero otherwise. In Panel A (column 1), all observations are used. In Panel B (columns 2) only observations with value of liquidations higher than the bottom 10% are considered. In Panel C (columns 3) only observations with value of liquidations higher than the bottom 20% are considered. Column 4 uses Panel B observations with two additional lagged Log(Volatility) variables. T-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period 1 December 2020 to 8 December 2022.
Source: OECD calculations based on Kaiko data.

3 Liquidity risk in DeFi lending

3.1. Liquidation mechanisms in DeFi

Liquidity supplied to DeFi lending pools is available to be borrowed by participants. DeFi Borrowing is mostly used to create a leveraged position in volatile crypto assets. To reduce the credit risk of borrowers, all loans are performed with over-collateralisation, i.e. the borrower must supply a collateral with an initial value greater than the loan. When the loan becomes under-collateralised, liquidators can repay the debt and gain the collateral at a discounted price. Platforms use the deposit and borrowing interest rates to maintain an equilibrium in the pool, so that there will remain enough liquidity. A high interest rate reduces the appeal of borrowing, and at the same time, increases the value of existing loans, invoking more liquidations and increasing liquidity in the pool.

In theory, if many depositors decide to withdraw at the same time, the protocol will be unable to provide such demand if much of the deposited amount has been borrowed. In different calibrations, lending pools use a mechanism of adjustable interest rate and liquidations to avoid this situation. If liquidity in a certain pool becomes low, the borrowing rate will rise, and this will encourage borrowers to repay, or push their position to become under-collateralised, which will induce liquidators to restore liquidity through the repayment of under-collateralised loans. In parallel, interest rate on deposits will rise, motivating more deposits.

A good example for how interest rate can be set effectively presented by Aave; the interest rate charged to borrowers follows a two-step function; the function is split according to an optimal *utilisation rate* set by Aave, individually to each token. Optimal utilisation rates (borrowed relative to deposited amount) vary around 80% for liquid “stablecoins” and, 65% for ETH and BTC, and 45% for other low liquidity crypto assets. If the utilisation rate surpasses the optimal utilisation rate specified by the protocol, the interest rate increases sharply. Surpassing the optimal utilisation rate does not necessarily imply that borrowing is halted; rather the variable interest rate mechanism is expected to incentivise users to act so that the pool remains below full utilisation (AAVE, 2023[18]).

The uncertainty related to this expectation is whether sufficient external liquidity exists to help restore the liquidity in the pool. What if borrowers locked the borrowed asset at a staking pool and are unable to repay? In parallel, there might not be enough free float of the asset that can be deposited despite the attractive interest rate. The liquidations mechanism is the back stop to restore liquidity in the absence of external flows of assets coming from outside the pools (e.g. from centralised exchanges, from cold wallets). Liquidators are thus required to possess the asset that will be used to repay the under-collateralised debt. This section shows that liquidators depend on external liquidity as well, including lending pools’ liquidity which they are expected to restore, to repay the debt.

The case of the Curve Dao Tokens (CRV) exploit attempt in November 2022 illustrates the effect that low market depth may have on the ability to liquidate under-collateralised debt. The exploit attempt began with a user that borrowed tens of millions of CRV tokens from the Aave platform, allegedly with the attempt to later drive the price of CRV down by quickly selling it on exchanges, targeting another user that at that time was supplying the CRV liquidity to Aave. However, the price of CRV in fact spiked due to a short squeeze, and the position of the borrower became under-collateralised. Presumably, because of the relative low liquidity of CRV, Aave was left with 2.64mn CRV tokens, worth more than USD 1.5 million at that time, in bad debt, that was neither liquidated nor ever repaid (Carey and Melachrinos, 2022[3]). In January 2023 the Aave governing community decided to eliminate the bad debt of 2.7 million of CRV (CoinDesk, 2023[19]).

To carry out liquidations, the liquidators need to repay the loan. They can perform this from their available capital, with borrowed funds/assets, or in the form of a flash loan. Flash loans are uncollateralised loans where the borrowing and the repayment of the loan are registered within the same block on the chain (OECD, 2022[1]). Importantly, a flash loan cannot be performed without liquidity in the pool from which it is taken, even though it is repaid at the same block and there is no default risk involved. Flash loans have also been used to attack DeFi protocols and not all lending or exchange liquidity pools offer this type of debt. (Lehar and Christine A. Parlour, 2022[6]) decompose the use of capital, swaps and flash loans by liquidators. They find that flash loans are used rarely, while capital is most often used, though the use of swaps is significant when liquidations are large. (Lehar and Christine A. Parlour, 2022[6]) do mention that they might be underestimating the use of swaps. The empirical results in Section 2 support the conjecture that liquidators indeed swap post liquidations. (Qin et al., 2021[4]) show that at least 5% of liquidations in their sample made in Aave and Compound during 2019-21 were made with flash loans taken from Aave and dXdY pools.

Poor liquidity management has been associated with many of the 2022 contagion crises in the crypto ecosystem (Conor Ryder, 2022[20]). For many crypto assets, a significant discrepancy exists between the asset's market capitalisation value and liquidity parameters such as trading volumes, market depth and bid-ask spreads (Conor Ryder, 2022[20]).

The low levels of ETH/WETH liquidity in lending pools reached around the date of the Merge,[10] a one-off exceptional conjuncture may provide some insights into crises situations that may affect liquidity conditions in DeFi lending pools. The two most liquid crypto assets are BTC and ETH. Their liquidity ranking is at the top on all parameters including market cap and trading parameters, with some gap in their favour compared to the third place (Conor Ryder, 2022[20]). High utilisation rates of ETH/WETH were reached across lending pools around the event of the Merge. Intensive borrowing of ETH/WETH, followed by withdraws of deposits led to borrowed amounts surpassing deposited amounts (disregarding accrued interest) around the 14th of September in Aave V2 pool (Figure 3.1). Daily balance data from Chainalysis, which is of lower frequency than the event data from Kaiko, confirms the drop in available liquidity of WETH in Aave V2 and a low level of available liquidity of ETH in Compound reached in mid-September (Figure 3.2). Though borrowing was halted by the Aave protocol,[11] withdrawals worsened the liquidity situation in the pool. At this point interest rate for borrowers and depositors spiked to attract liquidity. The borrowed amount then started to decline as users repaid their loans.

[10] The Merge is the name commonly given to the event when the original execution layer of Ethereum, Mainnet, was joined with its new proof-of-stake consensus layer. Since then, validation on the Ethereum network is only done through proof-of-stake consensus and by proof-of-work mining.

[11] As a pre-emptive step, Aave community voted between 30 August, 2022, and 2 September, 2022, to pause ETH lending to protect the protocol from risks associated with excessive borrowing. "High utilisation interferes with liquidation transactions, thus increasing the chances of insolvency for the protocol," Block Analitica said in the proposal. But not only the ability to carry out liquidations is at risk, but also the repayment to depositors

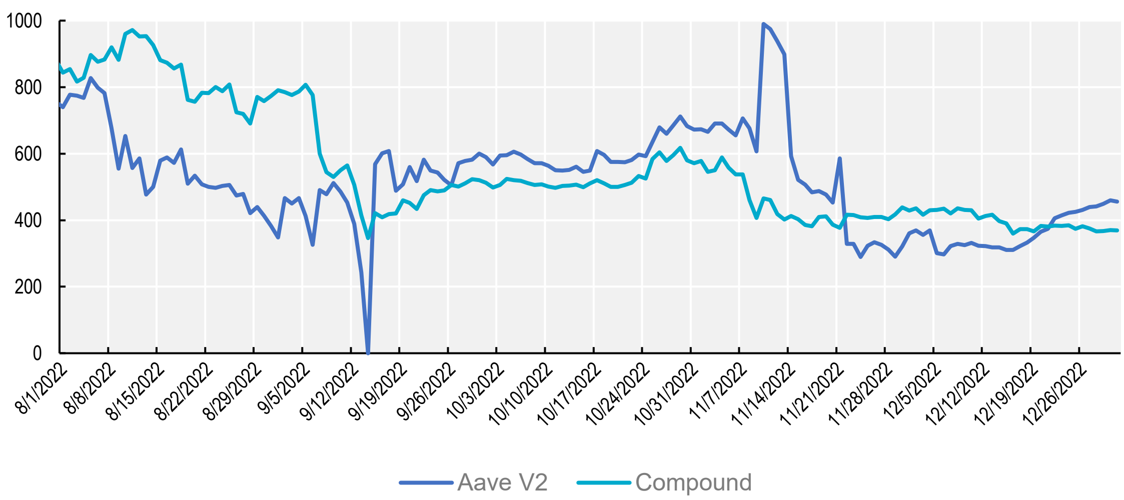
Figure 3.1. Assets and obligations on ETH liquidity pool on Aave V2

Continuous representation of assets and obligations on the pool

Note: Balance sheet is presented as is custom for banks: assets represent loans and obligations represent deposits. Balance data is approximated by accounting for net flows since the launch of Aave V2 in December 2020. Assets are calculated as loans outflow net of repayments and liquidations; obligations include inflow of deposits net of withdraws and liquidated collateral.
Source: Kaiko and OECD calculations.

Figure 3.2. Balances of Aave V2 and Compound

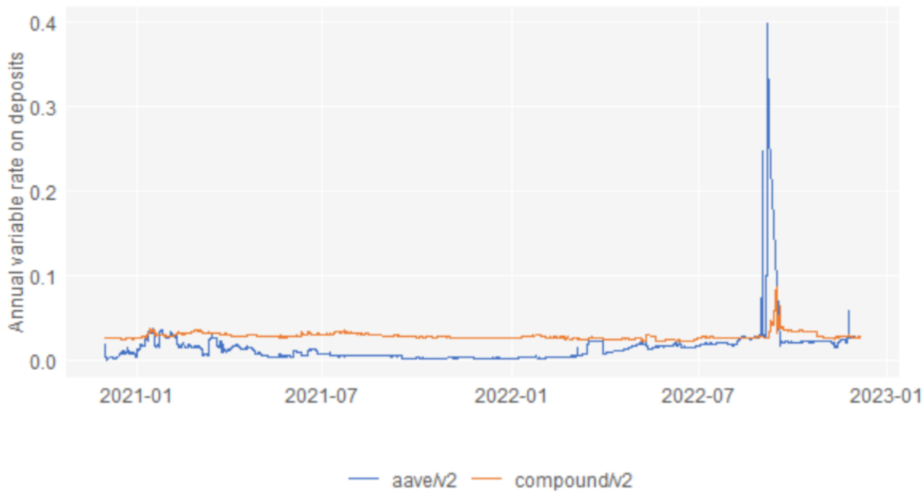
Daily balance of ETH/WETH in leading lending pools



Note: Daily balances of Aave V2 interest bearing wETH and of Compound Ether (cETH) for ETH.
Source: Chainalysis Market Intel.

As the interest rate in Compound directly accrues to the balance, it is difficult to calculate the balance on Compound through netting of the flows. The level of the interest rate charged to borrowers or paid to depositors can indirectly reveal the liquidity condition of the ETH pool in Compound and Aave V1. Indeed, interest rates for ETH on Compound spiked around the merge, indicating liquidity was scarce in Compound as well. Compound took some measures to limit ETH borrowing in the days before the Merge, including a cap on borrowing amount and higher interest rate for large borrowings (CoinDesk, 2022[21]). Data shows that interest rate on ETH lending in Aave V1 also spiked around that time.

Figure 3.3. Rate on borrowing ETH/WETH from leading lending protocols

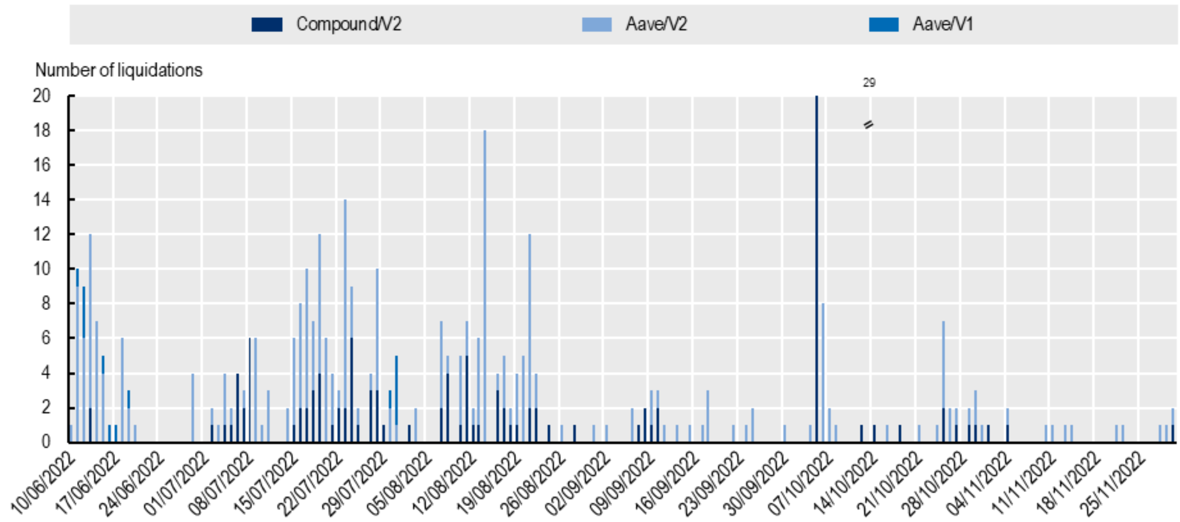


Source: Kaiko and OECD calculations.

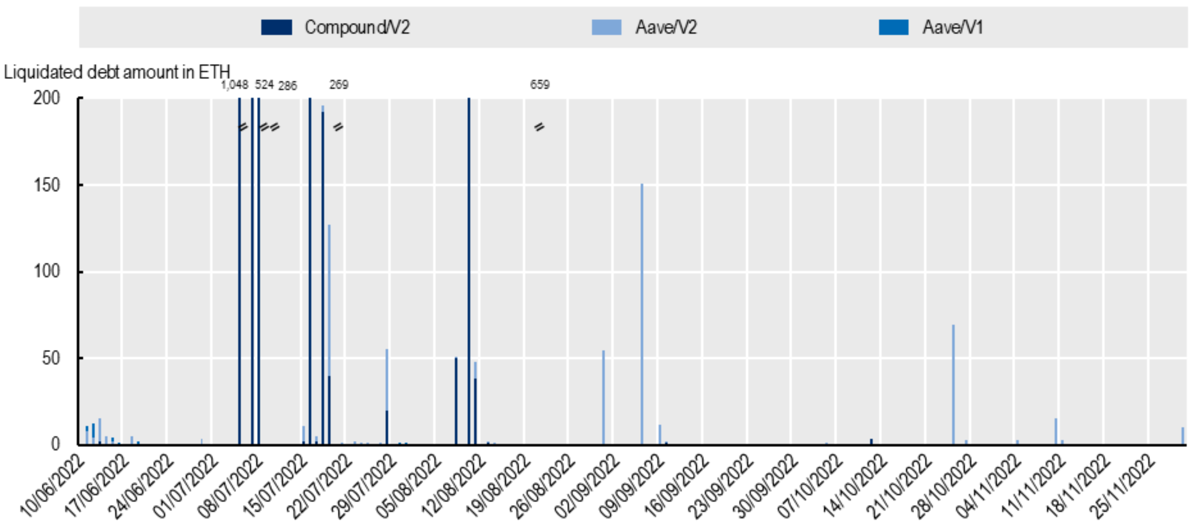
What is more, a very small number of liquidations of debt denominated in ETH were performed around the Merge, although that event was an exceptional circumstance that does not reflect normal conditions. The data does not allow a direct observation of the health factors or collateral factor of loans, but it is reasonable to assume that the high borrowing rates reached at that point across pools would have affected many borrowing positions to become under-collateralised. Despite this conjecture, the amount and value of liquidations of ETH denominated debt in Compound V2, Aave V1 and V2 pools were very low around this event in mid-September 2022. The low level of liquidations related to the case of the Merge might be partly driven by liquidity constrains faced by liquidators.

Figure 3.4. Liquidations of debt denominated in ETH

Total liquidations (in number of liquidations)



Total liquidations (in amount of debt liquidated)



Source: Kaiko and OECD calculations.

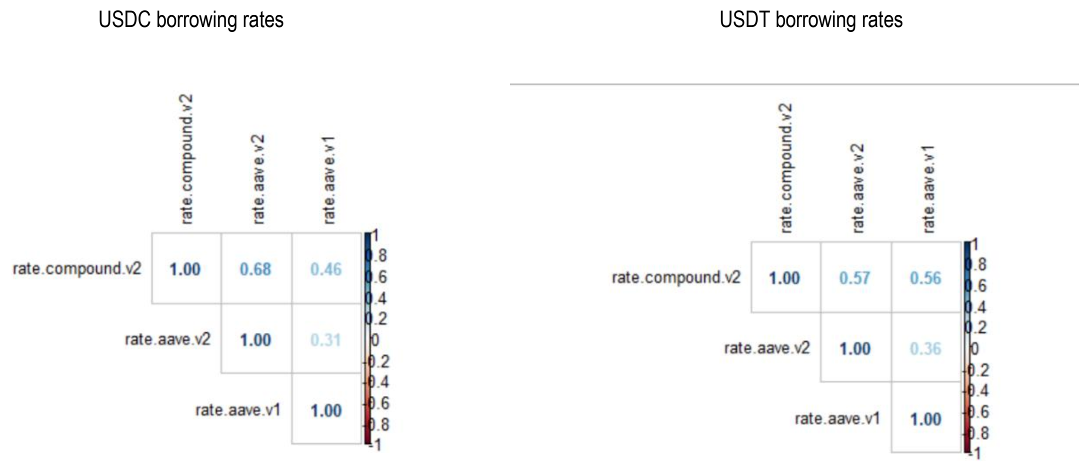
Although the event of the Merge and the behaviour of users trying to profit from it is an extreme event, as this is the only event in the sample that have resulted in such high interest rates for borrowing and depositing ETH, it demonstrates the “herd” behaviour that is typical of the crypto asset ecosystem in its current stage of development. This leads to the problem of unbalanced markets where all investors are pursuing either a long or a short position at the same time, with no balancing interest on the other side, except for arbitrageurs.

3.2. Positive correlation among borrowing rates in examined DeFi lending protocols

The phenomenon of positive correlation among borrowing rates across the examined DeFi lending pools is not unique to ETH, and it is even more prominent for stablecoins such as USDT and USDC. A correlation analysis on the adjustable lending rates received by borrowers in actual transactions in the sample used shows that correlation for the borrowing of such stablecoins is positive and significant for the three largest pools in the sample. Data frequency is hourly with rates being averaged over the transactions performed during an hour.

Figure 3.5. Correlation analysis of interest rates charged to USDC and USDT borrows in different pools

Interest rates are based on actual transactions data, measured as the average of an hour of transactions in different pools



Note: Right figure represents borrowing rates of USDC. Left figure is for USDT. The colour of the numeric value corresponds to the legend. All reported values are significant at 1%.
Source: Kaiko and OECD calculations.

The interest rate analysis and the case study around the event of the Merge point to the fact that liquidity tends to move in the same direction across lending pools. Lending pools can and have before reached maximal utilisation rates, especially for less common assets (AAVE, 2023[22]; intotheblock, 2023[23]) and even the most liquid assets, such as ETH, can reach 100% utilisation rate, as was shown, in extreme events. This analysis and anecdotal evidence suggest liquidators can face liquidity constrains in certain extreme events or when liquidations are required for less commonly traded assets.

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