Interest Rate Parity in Decentralized Finance

Amit Chaudhary[*], Roman Kozhan [†], Ganesh Viswanath-Natraj [‡§]

This version: May 4, 2023

Abstract

This paper studies determinants of interest rates on Decentralized lending protocols. Using transaction level data, we show these protocols are being used to make long or short leveraged positions in the cryptocurrency market. We identify a significant relationship between the interest rate differential and the perpetual futures premium for the ETH/USDT market. However, the link is economically weak, indicating that the speculative beliefs in the two markets are only weakly correlated and that the markets are segmented. Arbitrage across the two markets is ineffective due to wide no-arbitrage bounds, which are governed by high trading costs, gas fees, and price impacts.

Keywords: Cryptocurrency, decentralized finance, lending protocols, perpetual futures, arbitrage.

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

[*]amitchaudhary2003@gmail.com, Warwick Gillmore Centre Research Fellow

[†]roman.kozhan@wbs.ac.uk, Warwick Business School

[‡]ganesh.viswanath-natraj@wbs.ac.uk, Warwick Business School

[§]For detailed comments, we would like to thank discussant Stefan Voigt, and Dirk Baur, Agostino Capponi, William Cong, Oliver Gloede, Lai Hoang, Edouard Mattille, Julien Prat, Siddarth Naik, Angelo Ranaldo, Thomas Rivera, David Skeie, Ruslan Sverchkov, John Thannasoulis and seminar participants at the Bank of England, the University of Southampton Cryptocurrency Research Conference, the Tokenomics 4th International Conference on Blockchain Economics Security and Protocols, the inaugural ToDeFi-Turin Decentralized Finance Conference, the UC Berkeley Crypto Economics Security Conference, the University of St Gallen and the University of Western Australia.

1 Introduction

"...They can use the borrowed assets (on DeFi lending protocol Compound) to engineer leveraged long or short positions...if an investor is bearish on the price of ETH, they can simply deposit a stablecoin, such as DAI or USDC, as collateral and then borrow ETH and sell it for more of the stablecoin. If the price of ETH falls, investors use some of the DAI to purchase (cheaply) ETH to repay the debt."[1] **Harvey, Ramachandran and Santoro (2021)**

Decentralized lending protocols, like Compound or Aave, have gained a lot of popularity in recent years and offer several different ERC-20 assets for borrowing and lending. All the tokens in a single market are pooled together so every lender earns the same variable rate and every borrower pays the same variable rate. In contrast to centralized lending markets, variable rates are determined by demand and supply and based on pre-defined algorithms. While traditional intermediation rely on credit ratings to infer borrower quality, DeFi protocols require borrowers to post excess collateral as insurance against default. In this paper, we study equilibrium pricing of interest rates, and pin down the fundamental sources determining interest rates in DeFi protocols.

Given that interest rates in DeFi are determined algorithmically, the key to understanding the determinants of interest changes are the factors driving lending/borrowing decisions by market participants. One of the main functions of DeFi lending protocols is to enable users to take long or short leveraged positions in a cryptocurrency. We define a long leveraged position when an investor deposits the risky asset, for example ETH, and borrows a stablecoin to invest in ETH in the secondary market. Short leveraged positions, in turn, are when investors deposit a stablecoin and borrow the risky asset, which they can then sell to the secondary market. Hence the net demand for borrowing currencies by these investors determines interest rates in the lending protocol. Expectations about future price of the risky asset by speculators are the key drivers of the net demand. These expectations can be manifested in different forms, for example via speculative positions in futures market. The main question of this paper is to what extent these speculative beliefs determine interest rates in the DeFi protocol and what is the degree of market integration between the markets which are theoretically linked.

We start by building a simple equilibrium model of speculative trading that features a stable and unstable asset, and two investor types: mean-variance investors with optimistic and pessimistic beliefs on the unstable asset (e.g., ETH). They determine the spot price on ETH, and lending and borrowing rates in the protocol. Each investor can either borrow the unstable or stable asset depending on their speculative beliefs. Optimistic investors borrow the stable asset to take long leveraged positions in the underlying asset.

1. Excerpt taken from Harvey, Ramachandran, and Santoro (2021)

Conversely, pessimistic investors borrow in the unstable asset to take short leveraged positions. Interest rates on borrowing and lending are determined through utilization, which is a measure of the net demand for the asset. In equilibrium, interest rates on the protocol are determined through the net demand for long or short leveraged positions by investors. We connect interest rates to the futures market by deriving pricing conditions assuming the bullish and bearish investor can use long and short futures positions as an alternative to the lending protocol.

The model features the following testable implications. First, interest rate differences reflect the relative bearish and bullish beliefs of investors. The equilibrium interest rate differential is positively correlated to average expected return by two types of traders and negatively correlated to the risk premium associated with the volatility of the unstable asset. If long positions dominate short positions, we show that the net demand for borrowing in stablecoins is higher, which predicts higher interest rates. Second, we show that if the DeFi lending and futures markets are integrated in the sense of speculators holding the same beliefs about the future value of the risky asset, then interest rate differences between stablecoins and risky cryptocurrencies reflect futures premia. A positive funding rate is consistent with bullish investor beliefs and investors taking a long futures position. When futures trade at a premium due to long positions dominating short positions, we find this is consistent with utilization and interest rates that are higher for the stable asset.

We take these predictions to the data. First, we test whether trading in DeFi lending protocols are integrated with futures markets using a rich dataset of wallet-level transactions. This blockchain-based data records how individual users use the lending protocol to track their deposits and borrowings of different currencies. Using this data, we classify wallets based on whether they take long or short positions on ETH respectively. A long trader is classified as a user that deposits ETH and borrows USDT to take a leveraged position on ETH, and a short trader is a wallet that deposits USDT and borrows ETH to short sell ETH. Our algorithm allows us to construct a measure of aggregate net long positions. Empirically, we observe an increase in futures premia is a robust predictor of an increase in long positions and a decline in short positions in the lending protocol. Therefore we show using granular data that lending protocols are being used for leveraged trading.

Second, we investigate the fundamental determinants of interest rates. Through the lens of the model, an increase in futures premia is indicative of net bullish beliefs on the risky cryptoasset. All else equal, net bullish beliefs correspond to optimists taking leveraged positions by depositing the unstable asset and borrowing the stable asset. Higher borrowing of the stable asset increases utilization and causes stable asset interest rates to increase. We find further support through the funding rate, where a positive rate indicates excess long futures positions corresponds to an increase in stablecoin interest rates relative to ETH. Other sources of interest-rate differences include measures of risk premia, such as the volatility of ETH, and the relative wealth of optimists in the protocol.

Third, while we document evidence of integration between the lending protocol and futures markets, we show that the link between the two markets are weak. The sensitivity of the interest rate differential to changes in futures premium is significantly smaller than under the benchmark case of perfect market integration. The coefficient on the futures premium is typically in the range of 0.002 to 0.01, which implies that a 1 per cent change in the futures premium leads to a 0.2 to 1 basis point change in the interest rate differential. We further explore factors that may break the link between interest rates and futures premia. A key measure of integration between these two markets is to construct Covered interest rate parity (CIP) deviations. CIP is a standard no-arbitrage conditions in currency markets, and allows us to investigate efficiency of the futures and DeFi Lending protocol markets jointly. We provide lower and upper bounds for CIP deviations based on arbitrage strategies that can be employed using both a DeFi lending protocol and futures markets. After accounting transaction costs, such as gas fees to authenticate transactions on the blockchain, we find CIP deviations are typically within the arbitrage bounds. In addition to gas fees, an increase in the volatility of ETH/USDT, and periods of extreme returns in ETH lead to larger CIP deviations. Hence, both weakly correlated expectations of speculators and limits to arbitrage lead to only a weak market integration.

Fourth, we test if speculators in both DeFi and futures markets have unbiased expectations about future price of the risky asset. To do so, we estimate a regression of future ETH returns on the interest rate differential. If aggregate beliefs of bullish and bearish investors are unbiased, we expect that the rate of appreciation of the unstable asset equals to interest rate differential. Our results indicate, however, that interest rate differential are not statistically significant. We find similar result if we use futures premium as a measure of expectations in the futures market. This speaks in favor of hypotheses that the speculators in both markets trade based on information unrelated to future price changes. On the other have, we find that the funding rate of perpetual futures, wealth ratio and ETH volatility can forecast future ETH returns. This may suggest that investors tend to trade based on some stale historical information, react to past price changes and changes in risk premium.

The remainder of the paper is structured as follows. In section 2 we summarize the contributions of our paper to related literature. In section 3 we summarize the properties of the DeFi lending protocol Compound and describe the data sources for our empirical work. In section 4 we introduce the model of equilibrium interest rates. We produce testable implications on the determinants of interest rates, and the link between interest rates on the DeFi lending protocol and derivative markets. In section 5 we conduct our empirical analysis. Section 6 concludes.

2 Related literature

Our paper contributes to an emerging literature on decentralized finance (DeFi) (Harvey, Ramachandran, and Santoro 2021; Schär 2021). The defining feature of DeFi is that it uses programmability, in the form of smart contracts, as an alternative to centralized intermediaries. While the focus of this paper is on decentralized lending protocols, other applications include the pegging dynamics and feedback with collateral of stablecoins and the role of stablecoins in taking leveraged positions (Kozhan and Viswanath-Natraj 2021; Perez et al. 2020; Gorton et al. 2022), and decentralized exchanges, such as automated market makers which rely on algorithms and do not require a limit order book to execute trades (Angeris and Chitra 2020; Capponi and Jia 2021; Capponi, Jia, and Wang 2022; Aoyagi and Ito 2021; Hasbrouck, Rivera, and Saleh 2022; Lehar and Parlour 2021; Barbon and Ranaldo 2021; Park 2022; Lehar, Parlour, and Zoican 2022). This research focusing on the design of AMMs, the role of arbitrage and liquidity provision with competing platforms of DEX and centralized exchanges.

The literature on lending protocols has focused on understanding market efficiency, such as uncovered interest rate parity, the behavior of liquidations during risk-off events and the dynamics of the COMP governance token (Gudgeon et al. 2020; Perez et al. 2020; Saengchote 2021; Chiu et al. 2022; Lehar and Parlour 2022; Castro-Iragorri, Ramirez, and Velez 2021; Qin et al. 2021; Xu and Vadgama 2022; Mueller 2022; Chaudhary and Pinna 2022; Warmuz, Chaudhary, and Pinna 2022; Rivera, Saleh, and Vandeweyer 2023). One aspect studied is systemic risk of DeFi protocols. For example, Chiu et al. (2022) focus on the adverse selection channel of DeFi lending and how it can create feedback loops between the risky collateral price and lending in the protocol, and Lehar and Parlour (2022) study systemic risk due to liquidations and how it generates feedback to cryptoasset prices. Rivera, Saleh, and Vandeweyer (2023) theoretically derive equilibria of lending protocols and compare the welfare and pricing efficiency relative to traditional financial markets which rely on off-chain information. Our contribution within this literature is to model the fundamental sources of pricing the cross-section of interest rates of both risky cryptocurrencies and stablecoins. Investors use the protocol to take long or short leveraged positions. If long positions dominate, we show that investors typically deposit the risky currency as collateral and borrow stablecoins. Higher utilization of stablecoins in turn leads to higher interest rates. We further connect our predictions for interest rates to futures premia, providing support for our hypothesis that DeFi lending protocols are primarily used for leverage trading.

A final strand of literature deals with covered interest rate parity violations, yield farming and carry returns using the futures market (Franz and Valentin 2020; Cong, He, and Tang 2022; Schmeling, Schrimpf, and Todorov 2022; Augustin, Chen-Zhang, and Shin 2022; LI et al. 2023), and price discovery in crypto derivatives markets (Baur and Dimpfl 2019; Hoang and Baur 2020; Alexander, Choi, Massie, et al. 2020) and price discovery and liquidity properties in perpetual futures (Shiller 1993; De Blasis and Webb, n.d.; Soska et al. 2021; Alexander, Choi, Park, et al. 2020; He et al. 2022). We make two contributions to this literature. First, we derive a testable relation between the funding rate on perpetual futures and the interest-rate differences between stablecoins and risky cryptocurrencies on DeFi lending protocols. In particular, when futures trading at a premium, and investor long positions dominating short positions. For example, Franz and Valentin (2020) note significant departures from CIP based on lending rates across exchanges, and He et al. (2022) show that perpetual futures also violate no-arbitrage conditions. We construct an alternative measure of CIP deviations at an intra-day frequency using perpetual futures contracts. Our choice of perpetual futures follows the "crypto carry" documented in Schmeling, Schrimpf, and Todorov (2022), which finds significant futures premia using perpetual futures. Our contribution is that in addition to crypto carry, we account for interest rate differences across currencies. We find that CIP deviations are typically within arbitrage bounds after taking into account ETH gas fees. They are also higher during periods of extreme ETH returns and periods of high volatility.

3 Definitions and Data

3.1 Collateralized Lending

Collateralized lending markets like Compound allow users to borrow and lend in multiple currencies by tapping into liquidity pools of multiple assets. Users supply a collateral asset, and can borrow a fraction as tokens in another asset that is based on the collateral factor of a given asset.

The first panel of Figure 1 illustrates the process of supplying ETH to Compound (this gets you cETH token). Every currency supplied to the protocol is converted to a Compound token. For example, ETH collateral is converted to cETH, WBTC collateral is converted to cWBTC. Exchange rates between ETH and cETH can vary over time and cETH can accrue interest (i.e. cETH appreciates over time). The user first dictates that they want to use ETH as collateral. This returns the borrowing limits/collateral factors the user can borrow any token depending on the borrowing limits. For example, the user can borrow Dai and will have some remaining cETH in account in account as Compound works on over-collateralization. The protocol is flexible in that it allows the user to invest in multiple assets. The second panel shows an investor that borrows multiple currencies, such as USDC and DAI. Each market has separate interest rate curves on borrowing and lending that is based on the relative utilization (ratio of borrowing to lending) of that asset. The supply and borrow interest rates are compounded every block (approximately 15 seconds on Ethereum producing approximately continuous compounding).

Finally, users can supply multiple assets as collateral. In the third panel of Figure 1, the user deposits both ETH and wrapped Bitcoin (WBTC). The borrower receives collateral factors for ETH and WBTC. The borrower can deposit multiple collateral assets and have a consolidated borrowing limit from the Compound Comptroller that is based on the collateral factors and health of their account.[2]

3.2 Governance

Governance token COMP used to vote on interest rate rules and other system parameters (collateral and reserve factors). To create a proposal a user requires at least 100,000 COMP tokens. A user with 100 COMP can initiate a proposal but require community to support through delegating tokens. All proposals are first discussed publicly in an official governance forum, are written in smart contracts. Users can also be incentivized to borrow and lend through COMP token rewards. [3]

One key feature of governance is to vote on interest rate rules. Parameters like the base-rate and slope of the interest rate model are chosen by voters as part of the governance protocol. The interest rate model for borrowing rates is given by the piece-wise equation (1). a_0 is the base rate, and is the rate corresponding to zero utilization. The slope parameter $b_0 > 0$ measures the sensitivity of interest rates to utilization. The utilization rate u is used as an input parameter to a formula that determines the interest rates. Interest rates are determined by the utilization percentage in the market. Utilization is calculated as total borrow/total supply. All else equal, a positive slope parameter implies higher utilization leads to higher interest rates. An additional feature of the interest rate model is the kink, in which the slope parameter changes for utilization above a threshold rate $\bar{u}$, typically 80 per cent. The kink makes interest rates more sensitive to a higher utilization rate, $b_1 > b_0$. [4]

$$i_L = \begin{cases} a_0 + b_0 u, u \leq \bar{u} \\ a_0 + b_0 \bar{u} + b_1 (u - \bar{u}), u > \bar{u} \end{cases} \tag{1}$$

2. See section 3.3 for more details.
3. For example, the *Yield farming* craze in April 2020 was due to the reward of 10 million COMP.
4. This corresponds to the literature on modeling excess reserve balances with a logistic function in Veyrune, Della Valle, and Guo (2018). The authors find that in money markets the interest rate schedule becomes steeper when excess reserves are smaller. Excess reserves are the inverse of the utilization rate, and is consistent with the behavior of the kink in the Compound interest rate model.

Deposit rates i_D is a function of utilization and borrowing rates. θ captures the fraction of interest income that is in a reserve buffer managed by the interest rate protocol:

$$i_D = ui_L(1-\theta) \tag{2}$$

Interest spread for the protocol is a function of θ which is a reserve factor.

$$i_L - i_D = i_L(1-u(1-\theta)) \tag{3}$$

Based on utilization $0 \leq u \leq 1$, we have a lower and upper bound for the interest rate spread:

$$\theta i_L \leq i_L - i_D \leq i_L \tag{4}$$

3.3 Collateral factors and liquidations

Decentralized protocols allow individual account borrowing to be tracked in real-time through smart contracts. In equation (5), the health of an account is measured based on the relative borrowing in each currency and the individual supply of each collateral type. To determine an accounts health one needs to analyze the supplied assets, collateral factor, and borrowed assets. The collateral factor indicates the percentage you can borrow against the collateral supplied and is a number between 1 and 0. We define D_j as the supply of asset j, L_j is the borrowing of asset j and Γ_j is collateral factor (eg. 0.8 for ETH).

$$\text{Account health} = \frac{\sum_{j=1}^{N} \Gamma_j D_j}{\sum_{j=1}^{N} L_j} \tag{5}$$

An account health < 1 triggers liquidation. Decentralized participants, such as Liquidators, are responsible for liquidating the collateral and repaying the borrowed funds. The incentive is to receive the collateral in another asset with a discount, typically around 5%. Liquidators can repay up to 50% of the assets borrowed, and the process will continue until the health of individual's account is > 1.

3.4 Data and Summary Statistics

3.4.1 Lending Protocol: Compound

Figures 2 and 3 plots the cross-section of borrowing and lending in the lending protocol. An interesting observation is that stablecoins (USDT, USDC, DAI) typically have high interest rates, and unstable cryptocurrencies (ETH, WBTC, ZRX) typically have low interest rates. However, since the bear market in 2022, we see a reversal with a relative decline in stablecoin rates. To explain this pattern, We hypothesize that differences between high and low interest rate currencies reflect differences in long and short positions on the underlying risky asset. In addition, the most liquid currencies in both deposits and the most utilized currencies are stablecoins, lead by USDC and DAI. In contrast, while ETH is at times the most supplied currency, it is the fourth most borrowed currency. Therefore the utilization, which is the fraction of supplied assets that are borrowed, is much lower for risky currencies. In Figure 4, we plot the interest rate model for currencies on the Compound platform. This plots borrowing rates as a function of the utilization percentage in the market. Interest rate rules for more risky assets have a higher base-rate and slope parameters.

3.4.2 Transaction-level data

We have utilized a data set, provided by cryptocurrency data firm Kaiko, that records every transaction made on Compound. The data set includes all amounts deposited and borrowed by each wallet, including a breakdown of currencies and the timestamp of each transaction. For each wallet transaction, "deposit" and "withdrawal" refer to actions of depositing and withdrawing collateral from the lending protocol. Conversely, the actions "borrow" and "repay" are for borrowing and redeeming a currency. The sample starts on January 1st, 2021, and ends on April 22, 2023. This data set allows us to test whether investors are using the protocol to take leveraged positions. We can classify wallets as taking long or short leveraged positions in the market. We illustrate our algorithm for classifying these wallets in Section 5.1.

3.4.3 Perpetual Futures

A key feature of traditional futures contracts is the expiration date. When a contract expires, a process known as settlement begins. Typically, traditional futures contracts settle on a monthly or quarterly basis. At settlement, the contract price converges with the spot price, and all open positions expire. Perpetual contracts are widely offered by crypto-derivative exchanges, and it is designed similar to a traditional futures contract. Unlike conventional futures, traders can hold positions without an expiry date and do not need to keep track of various delivery months. For instance, a trader can keep a short position to perpetuity unless she gets liquidated. To calculate the futures premium, we use an index price calculated by Binance. [5]

5. Binance uses a volume weighted average of prices at the following exchanges: uses a price Index of major Spot Market Exchanges, such Huobi, Okex, Bittrex, HitBTC, Gate.io, Bitmax, Poloniex, FTX and MXC. For more details on the construction of the price index see https://www.binance.com/en/support/faq/price-index-547ba48141474ab3bddc5d7898f97928.

Since perpetual futures contracts never settle, exchanges need a mechanism to ensure that futures prices and index price converge on a regular basis. This mechanism is also known as a funding Rate. Funding rates are periodic payments either to traders that are long or short based on the difference between perpetual contract markets and spot prices. Therefore, depending on open positions, traders will either pay or receive funding. Binance Futures does this every eight hours. Funding rates are designed to encourage traders to take positions that keep perpetual contract prices line in with spot markets. Perpetual futures contracts have unique properties: while subject to margining requirements like standard futures, they have a funding rate which investors of long positions pay short positions, and are charged at regular intervals during the trading day.

Table 1 presents summary statistics, and Figure 5 plots the ETH/USDT spot and futures price, the futures premium, funding rate and interest rate difference between USDT and ETH. Futures premia and the funding rate are typically positive, which is consistent with a net bullish market in ETH/USDT futures. Periods in which the funding rate are negative correspond to a decline in the futures premium, negative ETH returns and a compression of the interest rate spread between USDT and ETH.

As DeFi lending protocols offers the opportunity to take long and short positions on risky cryptocurrencies, we examine if there are systematic relationships between interest rates and futures premia measured using perpetual futures contracts.[6] As illustrated in Figure 6, we observe a positive correlation between the interest rate differential between USDT and ETH rates and the futures premium and funding rate. This direct outcome of speculative trading connects equilibrium interest rates to futures. Taken as a whole, our results suggest a correlation between the interest rate differential, futures premia, and the funding rate. We provide a model to link interest rates to futures premia in section 4 and analyze the determinants of interest rates in section 5.

4 Model

The model features two investor types, and two assets. Mean-variance investors have bearish and bullish beliefs (we denote them by indices "P" and "O" respectively) on the future state of the unstable asset (we denote this asset by E). Investors can trade in the spot market trading stable (we denote this asset by U) for unstable coin, use the lending protocol to take long and short positions on the unstable asset, or trade in the futures market. An investor with bullish beliefs on the unstable asset takes a long position. They can further leverage their positions by depositing the unstable asset and borrow the stable asset. Conversely, a bearish investor will short sell the risky asset by depositing the stable asset as collateral and borrow the unstable asset.

6. Lending protocols have no term structure; interest rates are compounded at an intra-day frequency.

The relative borrowing and lending determines interest rates through an algorithm set by the governance of the protocol. The algorithm requires interest rates on borrowing and lending to be based on utilization of the asset, which measures the fraction the asset is borrowed on the protocol. All else equal, higher utilization implies higher rates, and we impose a simple linear relation that is used by the DeFi lending protocol Compound. Based on the algorithm for setting rates, we derive a relation between interest rates and the bearish and bullish beliefs of investors regarding the future state of the unstable asset. Finally, we connect interest rates to the futures market by deriving pricing conditions assuming the bullish and bearish investor can use long and short futures positions as an alternative to the lending protocol. The model generates testable implications on the fundamental determinants of interest rates and parity conditions.

4.1 Spot market trading

There are two assets: stable asset U and unstable asset E. A stable asset U is a stablecoin with price 1 USD (e.g. DAI, USDC). The price of the unstable asset E in the spot market is p_0 and its future price p_1 is a random variable. The volatility of its returns is σ and everybody in the market agrees on this parameter. Optimists believe that the expected future price of the unstable asset is $p_1 = p^+$ while pessimists believe it is $p_1 = p^-$ with $p^+ >> p^-$. The corresponding exp The unstable coin is in positive supply ξ.

We denote the total initial wealth of optimists by W_O and the total initial wealth of pessimists by W_P. Both wealth are in the stable coin units. Both types of investor are mean-variance maximizers and have the same relative risk aversion coefficient γ.

In order to ensure the relevance of DeFi lending protocol, we assume that p^+ is substantially high so that optimists find it optimal to leverage their positions and p^- is low enough for pessimists to short sell the unstable coin. Let Δ_O be a leveraged fraction of optimists' wealth. That is, they invest their entire wealth into asset E, post it as collateral into DeFi protocol, borrow $\Delta_O W_O$ of U and invest this borrowed amount further in E. Optimists' next period wealth is

$$\tilde{W}_O = W_O \left[r + \Delta_O (r-1) + i_D^E - \Delta_O i_L^U \right]. \tag{6}$$

Pessimists post their stable coins into the protocol, borrow $\Delta^P W^P$ of the unstable coin and sell it in the spot market. Their wealth is

$$\tilde{W}_P = W_P \left[1 + \Delta_P (1-r) + i_D^U - \Delta_P i_L^E \right]. \tag{7}$$

Both types of investors maximize their corresponding mean-variance utility functions subject to the evolution of wealth and constraints on the share of borrowing to be bounded between 0 and $\bar{\Delta}$, which is defined by the maximum level of leverage an investor can take:

$$U(\Delta_j) = E\left[\tilde{W}_j(\Delta_j)\right] - \frac{1}{2}\gamma Var\left[\tilde{W}_j(\Delta_j)\right],\ 0 \leq \Delta_j \leq \bar{\Delta},\ j = O, P. \tag{8}$$

4.2 DeFi lending and borrowing

Define the utilization of asset E as the ratio borrowed amount of token E to total wealth deposited into the protocol:

$$u_E = \frac{\Delta_P W_P}{W_O} \tag{9}$$

Similarly, the utilization of asset U is defined as the ratio borrowed amount of token U to total wealth deposited into the protocol:

$$u_U = \frac{\Delta_O W_O}{W_P}. \tag{10}$$

Interest rates are a function of utilization. Borrowing and lending rates on assets E and B are i_L^E and i_L^U respectively. They are a function of utilization and the slope parameter b set up by the governance body of DeFi lending protocol. Deposit rates on assets E and U are i_D^E and i_D^U. They are also functions of utilization and borrowing rates, and an additional term θ which captures the fraction of interest income that is in a reserve buffer managed by the interest rate protocol.

$$i_L^E = b_E u_E = \frac{b_E \Delta_P W_P}{W_O}, \tag{11}$$

$$i_L^U = b_U u_U = \frac{b_U \Delta_O W_O}{W_P}, \tag{12}$$

$$i_D^E = u_E i_L^E (1-\theta) = \frac{b_E \Delta_P^2 W_P^2 (1-\theta)}{W_O^2}, \tag{13}$$

$$i_D^U = u_U i_L^U (1-\theta) = \frac{b_U \Delta_O^2 W_O^2 (1-\theta)}{W_P^2}. \tag{14}$$

4.2.1 Governance Block

The protocol requires some fraction of interest income to be kept as reserves. Reserves can be used to meet depositor withdrawals and as a buffer. We capture the fraction of income used as reserves through a reserve factor θ. The protocol maximizes the net interest (NI) income in each coin allocated to the reserve buffer:

$$V_g = NI_E + NI_U, \tag{15}$$

where

$$NI_E = -W_O i_D^E + W_P \Delta_P i_L^E = W_O i_L^E u_E \theta = \frac{b_E \theta \Delta_P^2 W_P^2}{W_O}, \tag{16}$$

$$NI_U = -W_P i_D^P + W_O \Delta_O i_L^U = W_P i_L^U u_U \theta = \frac{b_U \theta \Delta_O^2 W_O^2}{W_P}. \tag{17}$$

We can express the governance problem as maximizing net interest income. The parameters are the slope of the interest rate schedule b_E and b_U. For simplicity, we hold the reserve factor θ fixed. The corresponding first order conditions are:

$$\frac{\partial V_g}{\partial b_E} = \frac{\theta \Delta_P^2 W_P^2}{W_O} + \frac{2\theta \Delta_P W_P^2}{W_O} \frac{\partial \Delta_P}{\partial b_E} = 0 \tag{18}$$

and

$$\frac{\partial V_g}{\partial b_U} = \frac{\theta \Delta_O^2 W_O^2}{W_P} + \frac{2\theta \Delta_O W_O^2}{W_P} \frac{\partial \Delta_O}{\partial b_U} = 0, \tag{19}$$

which yield

$$b_E = -\frac{\Delta_P}{2\frac{\partial \Delta_P}{\partial b_E}} \tag{20}$$

and

$$b_U = -\frac{\Delta_O}{2\frac{\partial \Delta_O}{\partial b_U}}. \tag{21}$$

4.3 Spot market equilibrium

Proposition 1: Optimal demands of pessimists and optimists and optimal slope coefficients setup by the governance body are as follows:

$$\Delta_O = \frac{p^+/p_0 - 1 - \gamma\sigma^2 W_O}{2\gamma\sigma^2 W_O}, \tag{22}$$

$$\Delta_P = \frac{1 - p^-/p_0}{2\gamma\sigma^2 W_P}, \tag{23}$$

$$b_E = \frac{\gamma\sigma^2 W_O}{2}, \tag{24}$$

$$b_U = \frac{\gamma\sigma^2 W_P}{2}. \tag{25}$$

See Appendix for proof.

The spot market clearing condition

$$W_O(1+\Delta_O) - \Delta_P W_P = \xi \tag{26}$$

implies the price for asset E:

$$p_0 = \frac{\bar{p}}{1+\gamma\sigma^2\left[\xi - \frac{W_O}{2}\right]}, \tag{27}$$

where $\bar{p} = \frac{p^+ + p^-}{2}$.

Given the equilibrium utilization ratios for both types of investor, the interest rates for assets E and U are:

$$i_L^E = \frac{1-\mu^-}{4} = \frac{1-p^-/p_0}{4}, \tag{28}$$

$$i_L^U = \frac{\mu^+ - 1 - \gamma\sigma^2 W_O}{4} = \frac{p^+/p_0 - 1 - \gamma\sigma^2 W_O}{4}. \tag{29}$$

The interest rate differential between borrowing rates on assets E and U is given as follows:

$$i_L^U - i_L^E = \frac{1}{2}\left(\frac{\bar{p}-p_0}{p_0}\right) - \frac{\gamma\sigma^2 W_O}{4}. \tag{30}$$

4.4 Futures market

We assume that in addition to the spot and DeFi lending/borrowing market there is futures market. Investors of type O and P can take long and short positions in the futures market (we assume that the pool of investors is different for spot and futures market, i.e., they are segmented). In addition to optimists and pessimists, there are arbitrageurs who monitor for arbitrage deviation (similar to covered interest parity) and attempt to exploit them.

We model a perpetual futures contract with no expiry. Holders of the long position have to pay the short position a funding rate δ in each period to equate long and short positions. Let f_0 denotes the current future rate of the risky asset E. We assume that in order to trade futures one does not need to put in any collateral and the amount of leverage and shorting in futures market is bounded by the risk aversion coefficients of the traders. We denote the optimists' expected value of futures contract by $f^+ = E_0[f_t]$ and the pessimists' expected value by $f^- = E_0[f_t]$.

Suppose that optimists decide to buy n_O number of futures contracts. Their expected utility

$$U_O = n_O\left(f^+ - f_0 - \delta\right) - \frac{1}{2}\gamma n_O^2\sigma^2. \tag{31}$$

Maximizing this utility function yields

$$n_O = \frac{f^+ - f_0 - \delta}{\gamma\sigma^2}. \tag{32}$$

Expected utility of pessimists

$$U_P = n_P\left(f_0 - f^- + \delta\right) - \frac{1}{2}\gamma n_P^2\sigma^2, \tag{33}$$

which implies the optimal demand

$$n_P = \frac{f_0 - f^- + \delta}{\gamma\sigma^2}. \tag{34}$$

In the case of no arbitrage activity (e.g., no incentive to exploit a wedge between futures market and the lending protocol rates), the market clearing condition in the futures market is

$$n_O = n_P \tag{35}$$

implies

$$\bar{f} = f_0 + \delta, \tag{36}$$

where $\bar{f} = \frac{f^+ + f^-}{2}$.

There are two aspects of the perpetual futures market that is relevant to the lending protocol. First, it provides us an alternative way of measuring investors' expectation of the future value of the risky asset E. Secondly, it open up for arbitrage activity between the futures market and the lending-borrowing rates, similar to the well-known CIP arbitrage (see He et al. (2022)).

Let us denote by $\tilde{p} = \frac{\tilde{p}^+ + \tilde{p}^-}{2}$ the average of the expected values of the risky asset between optimists and pessimists trading in the futures market. If the two markets (DeFi protocol and the perpetual futures) are integrated and the beliefs of the groups of traders are identical, then $\bar{p} = \tilde{p}$. If one could measure $\tilde{p}$ using the data from the futures market, the integration hypothesis could be tested empirically. In reality, $\tilde{p}$ and $\bar{f}$ can be different as they reflect the value of asset E at different horizons. The mechanism that keeps those two variables aligned is the funding rate which increases as the wedge between f_t and p_t increases and decrease otherwise. (see He et al. (2022)).

Assumption 1: $\delta_t = (f_t - p_t)$.

Given Assumption 1 we can rewrite expectations of the optimists and pessimists in the futures market as

$$f^+ = E^O[f_t] = E^O[p_t + \delta] = \tilde{p}^+ + \delta$$

and

$$f^- = E^P[f_t] = E^P[p_t + \delta] = \tilde{p}^- + \delta.$$

As a result, the average of the expectations of optimists and pessimists is equal to the forward rate.

$$\tilde{p} = f_0.$$

Another force that can affect futures rate f_0 is arbitrage activity. If the futures rate is far away from the spot price and/or funding rates i^E and i^U are not appropriately aligned with the spot and futures prices, arbitrageurs can profitably exploit this gap. Arbitrageurs do this by adopting strategies similar to those they use to exploit the covered interest rate parity relation in the traditional fixed-maturity futures markets. Below we describe the arbitrage strategies and then discuss no-arbitrage bounds that prevents prices from convergence due to price impacts and transaction costs.

While traditional arbitrage strategies assume no initial endowment by arbitrageurs, we deviate from this assumption and consider an arbitrageur who starts with an initial wealth in asset U. This is because when participating in the lending and borrowing activities of the DeFi protocol, collateral is required, which is not the case in typical margin trading in the FX market.

Strategy 1: Arbitrageur goes long one futures contract at rate f_0. She covers this position by shorting one coin of E. To execute the short position the arbitrageur puts p_0 worth of coins U as collateral into the DeFi protocol and borrows 1 unit of asset E. She then sells borrowed E coins in the spot market at price p_0 and deposits p_0 units of asset U into the protocol to earn interest. At time t, she closes the futures contract at price f_t and pays funding rate δ, buys one unit of E at price p_t in the spot market and closes the borrowing transaction in the DeFi protocol. She pays interest $p_0 i_L^E$ for borrowing E and receives $p_0 i_D^U$ for depositing U. The strategy is profitable if the total cash flow at time t is positive:

$$f_t - f_0 - \delta - p_t + p_0(1 + i_D^U - i_L^E) = -f_0 + p_0(1 + i_D^U - i_L^E) > 0.$$

Strategy 2: Arbitrageur goes short one futures contract at rate f_0. She covers this by buying one unit of E asset at price p_0 and deposits it into the DeFi protocol. At time t, she closes the futures contract at price f_t and receives funding rate δ and sells one unit of E at price p_t in the spot market. She receives interest $p_0 i_D^E$ for depositing E and pays opportunity costs $p_0 i_D^U$ for not depositing his initial capital U. The strategy is profitable if the total cash flow at time t is positive:

$$-f_t + f_0 + \delta + p_t - p_0(i_D^E - 1 - i_D^U) = f_0 + p_0(i_D^E - 1 - i_D^U) > 0.$$

The following table summarizes the cash flow in period 0 and t:

time		Strategy 1	Strategy 2
0	futures	0	0
	spot	p_0	$-p_0$
	cash	$-p_0$	p_0
t	futures	$f_t - f_0 - \delta$	$-f_t + f_0 + \delta$
	spot	$-p_t$	p_t
	cash	$-p_0 i_L^E + p_0(1 + i_D^U)$	$p_0 i_D^E - p_0(1 + i_D^U)$
	total	$f_t - f_0 - \delta - p_t + p_0(1 + i_D^U - i_L^E)$	$f_0 - f_t + \delta + p_t + p_0(i_D^E - 1 - i_D^U)$

So, absence of any transaction costs, the arbitrageurs will have incentives to exploit the deviations as long as the no-arbitrage relation

$$i_D^U - i_L^E \leq \frac{f_0 - p_0}{p_0} \leq i_D^U - i_D^E \tag{37}$$

is violated.

However, even if the CIP relation (37) is violated, the arbitrageur faces transaction costs in the form of gar fee (fees required to pay in the Ethereum blockchain in order to execute lending/borrowing transaction) and price impacts in the protocol.[7]

In order to derive no-arbitrage bounds, let as consider a case when an arbitrageur observes a deviation from the CIP relation with a paper profit:

$$pr_1 = i_D^U - i_L^E - \frac{f_0 - p_0}{p_0} > 0.$$

Suppose she decides to execute Strategy 1 by going long n_A futures contracts and cover them accordingly. This in turn, will change the interest rates in the protocol since the utilization ratios will change as a result of his transaction. In particular, the new rates that are established in the market after the impact of arbitrageur's trade are:

$$\tilde{i}_L^E(n_A) = b_E \tilde{u}_E = \frac{b_E\left(\Delta_P W_P + n_A p_0\right)}{W_O} = i_L^E + \frac{b_E\left(n_A p_0\right)}{W_O} > i_L^E, \tag{38}$$

$$i_D^U(n_A) = \tilde{u}_U \tilde{i}_L^U(1-\theta) = \frac{b_U \Delta_O^2 W_O^2 (1-\theta)}{(W_P + n_A p_0)^2} = \frac{i_D^U W_P^2}{(W_P + n_A p_0)^2} < i_D^U. \tag{39}$$

So, arbitrageur's position would increase the interest rate deferential and widen the no-arbitrage bound.

7. Given we focus mainly on determination of the interest rates in the DeFi platform, we ignore trading cost as well as price impacts in the futures and spot markets assuming that they are much more liquid relative to the DeFi protocol. Moreover, gas fees are not applicable for the futures and spot market as they these transactions can be executed in she centralized exchanges.

Moreover, the arbitrager will have to pay double gas fee (for borrowing E and depositing U). So, the profit after accounting for price impact and gas fee is

$$\tilde{pr}_1(n_A) = n_A \left(\tilde{i}_D^U(n_A) - \tilde{i}_L^E(n_A) - \frac{f_0 - p_0}{p_0} \right) - 2C. \tag{40}$$

There two factors effecting the arbitrageur's profit. First, gas fee is the fixed costs, so its effect is substantial for strategies with small trading volume but diminishes if the volume of the transaction becomes large. On the order hand, if the volume of the transaction increases, it also increases the price impact. So, arbitrageur has to solve for an optimal trading size to trade-off these two effects, i.e. solve for n_A such that $\tilde{pr}_1 > 0$.

Analogous condition for profit in Strategy 1 is

$$\tilde{pr}_2(n_A) > 0,$$

where

$$\tilde{pr}_2(n_A) = n_A \left(\frac{f_0 - p_0}{p_0} - i_D^U + \tilde{i}_D^E(n_A) \right) - C, \tag{41}$$

$$\tilde{i}_D^E(n_A) = b_E \tilde{u}_E^2 (1-\theta) = \frac{b_E \left(\Delta_P W_P\right)^2 (1-\theta)}{(W_O + n_A p_0)^2} < i_L^E. \tag{42}$$

4.5 Testable implications

The main question we seek to answer in this paper is what are the determinants of the interest rates in the DeFi protocol. Our model implies that there are several forces that can shape these interest rate: arbitrage and beliefs of speculators. If arbitrage is unlimited (transaction costs, price impacts and no constraints on arbitrage capital), then the CIP relation should hold irrespective of speculators' beliefs and the relation between the interest rate differential and the futures rate should be equal to 1. Indeed, Equations (40) and (41) imply that

$$\tilde{i}_D^U(n_A) - \tilde{i}_L^E(n_A) = \frac{f_0 - p_0}{p_0} + \frac{2C}{n_A}, \tag{43}$$

$$i_D^U - \tilde{i}_D^E(n_A) = \frac{f_0 - p_0}{p_0} - \frac{C}{n_A}. \tag{44}$$

So, our first testable hypothesis is:

$\mathbf{H1_0}$: *The interest rate differential in the DeFi protocol is entirely determined by the arbitrage forces. Hence, in the regression of the futures basis on the interest rate differential, the slope coefficient in front of the futures rate is equal to 1.*

If arbitrage is limited, then the interest rates are determined by actions (demand and supply) of the DeFi traders. If the DeFi protocol is populated by risky asset speculators (as described in the model), then the interest rate differential is driven purely by beliefs of the speculators $\bar{p}$.

In the case of perfect market integration (the pool of investors trading in the futures market and in the DeFi protocol are the same or, at least, their beliefs are identical), measuring the futures rate f_0 allows us to proxy unobserved expected future price of the risky asset $\bar{p}$:

$$\bar{p} = \tilde{p} = f_0.$$

Substituting relation (36) into the expression for interest differential gives us the first measurable relation in equation (45):

$$i_L^U - i_L^E = \frac{1}{2}\left(\frac{f_0 - p_0}{p_0}\right) - \frac{\gamma\sigma^2 W_O}{4}. \tag{45}$$

In this case, the equilibrium interest rate differential is positively correlated to the futures premium. A positive futures premium and funding rate is consistent with bullish investor beliefs and investors taking a long futures position. In the DeFi lending protocol, more investors take a long position in the risky asset E by posting it as collateral and borrowing stable asset U, and there is less short selling of asset E. Therefore there is higher utilization of borrowing asset U, and lower utilization of borrowing asset E. Interest-rate setting on the protocol synchronize rates with utilization, leading to higher interest rates (on average) on stable currencies. This leads to the following hypothesis:

$\mathbf{H2_0}$: *If arbitrage is limited and the beliefs of speculators in the lending protocol is equal to the beliefs of speculators in the futures market. The interest rate differential is related to the futures premium and the coefficient in front of the futures premium is one half.*

Alternatively, the demand and supply in the lending protocol can be driven entirely or partially by pure noise and/or passive yield harvesting without any relation to the expected future risky asset return. In this case, we expect $\bar{p}$ to be at most non-perfectly correlated with f_0:

$$\bar{p} = \tilde{p} + \eta = \alpha f_0 + \eta, \qquad cov[f_0, \eta] = 0, \quad 0 < \alpha < 1.$$

In this case, the slope coefficient in front of the futures premium will decrease as α decreases and in the extreme scenario where $\alpha = 0$, the interest rate differential is unrelated to the futures premium. This leads to an alternative hypothesis $H3_0$:

$\mathbf{H3_0}$: *The interest rate differential is determined by pure noise and is unrelated to the beliefs of speculators in the futures market (market segmentation). The interest rate differential is unrelated to the futures premium and the coefficient in front of the futures* *premium is zero.*

Our final hypothesis is related to ability DeFi traders to predict future returns on the risky asset. If the interest rates are determined by the speculators expectations who hold on average unbiased beliefs about future value of the risky asset, then the interest rate differential should have a forecasting power for future risky return. In particular, let us consider a return of the risky asset r over the future $(0, t)$ interval. If the speculators have on average unbiased expectations ($E[p_1] = \bar{p}$, where p_1 denotes future price of the unstable asset and the expectation is taken with respect to an objective measure (from the point of view of a rational econometrician who could forecast the prices in an unbiased fashion), then Equation (30) implies that

$$E[r] = \frac{\bar{p} - p_0}{p_0} = 2(i_L^U - i_L^E) + \gamma\sigma^2 W_O/2. \tag{46}$$

Similarly, if f_0 is an unbiased expectation of future price p_1, then

$$E[r] = \frac{f_0 - p_0}{p_0}. \tag{47}$$

$\mathbf{H4_0}$: *Speculators hold on average unbiased beliefs about future returns of the risky asset. Hence, in the regression of the future spot returns on interest rates, the slope coefficient is equal to 2.*

While we focus on the relationship between futures premium and interest rates, we note other factors that can potentially affect the interest rate differential are: ratio of total wealth locked in U and E assets (measures the fluctuation of the risk premium associated with the risky asset), volatility of the interest rates (associated with the interest roll-over risk; it is not modelled in the theory section; it can affect both arbitrageurs activity as well as propensity to speculate by the speculators), ratio of wealth in the DeFi from passive investors (related to the noise trading or yield harvesting), volatility of the risky asset returns (associated with the risk premium of risky asset as well as possible liquidation risk and margin calls; not modelled explicitly in the theory section). We will use some of these variables as controls in our empirical specification.

5 Empirical Evidence

5.1 Integration between lending protocols and futures markets: transaction level data

In this section we test whether trading in DeFi lending protocols are integrated with futures markets using a rich dataset of wallet-level transactions. We classify wallets based on whether they take long or short positions on ETH respectively. A long trader is classified as a user that deposits ETH and borrows USDT to take a leveraged position on ETH, and a short trader is a wallet that deposits USDT and borrows ETH to short sell ETH. Our algorithm allows us to construct a measure of aggregate net long positions.

Figure 7 plots the aggregate long and short positions using transaction data at the wallet level. For most of the sample, long positions dominate short positions, suggesting that traders are primarily using the protocol to conduct long leveraged positions. This is generally consistent with futures typically trading at a premium during 2021. However, starting in 2022, we observe more short positions, and this is in line with a bearish market for ETH in the latter half of 2022. We empirically test the fundamentals of long and short positions in the lending protocol in Equation (48):

$$LS_t = \beta_0 + \beta_1 f_t - s_t + \beta_2 \delta_t + \beta_3 \sigma_{spot_t} + u_t. \tag{48}$$

Here, the outcome variable is the difference between long and short positions in the ending protocol. The explanatory variable are the futures premium $f_t - s_t$, the funding rate δ_t, the volatility of both USDT and ETH interest rates and volatility of the spot exchange rate.

The results are summarized in Table 2. All explanatory variables are measured in per cent, and the outcome variable is defined in USD Billion. Consistent with our model prediction, the forward premium is a robust predictor of net long positions in the lending protocol. In column (3), a specification which controls for the funding rate and ETH/USDT spot volatility, we find a 1% increase in the forward premium leads to a 2.9 USD Billion increase in net long positions in the protocol. For reference, the standard deviation of the futures premium in our sample is approximately 10 basis points. We test whether long and short positions react symmetrically to a change in the futures premium in columns (4) to (9). We find that the integration between lending protocols and futures markets is asymmetric: long positions are more sensitive to futures premia. A 1% increase in the futures premia leads to 2.8 USD billion increase in long positions, however leads to only a decrease in 0.07 USD Billion in short positions. In addition to our analysis of ETH-USDT long and short positions, we show that leveraged trading can be done for other currency pairs on the lending protocol. In addition to ETH-USDT, futures markets are integrated with ETH-USDC and ETH-DAI long and short positions on Compound. For regression results using these pairs we refer readers to Appendix B. Empirically, we observe an increase in futures premia is a robust predictor of an increase in long positions and a decline in short positions in the lending protocol for these currencies as well.

5.1.1 Dynamic effects

One empirical concern with the long-short position results is that feedback effects from these variables to the long-short position should be considered. We investigate dynamic effects using a vector autoregression (VAR) framework. The autoregressive equations for the long-short position, the funding rate, and the difference in returns between the two assets are illustrated in equations (49), (50), and (51). We allow for feedback effects between the three variables, with a baseline specification of $L = 1$ lags. [8]

$$f_t - s_t = \alpha_1 + \sum_{k=1}^{L} \gamma_{1,k} \left(f_{t-k} - s_{t-k}\right) + \sum_{k=1}^{L} \beta_{1,k} \delta_{t-k} + \sum_{k=1}^{L} \theta_{1,k} LS_t + \epsilon_{1,t} \tag{49}$$

$$\delta_t = \alpha_2 + \sum_{k=1}^{L} \gamma_{2,k} \left(f_{t-k} - s_{t-k}\right) + \sum_{k=1}^{L} \beta_{2,k} \delta_{t-k} + \sum_{k=1}^{L} \theta_{2,k} LS_t + \epsilon_{2,t} \tag{50}$$

$$LS_t = \alpha_3 + \sum_{k=1}^{L} \gamma_{3,k} \left(f_{t-k} - s_{t-k}\right) + \sum_{k=1}^{L} \beta_{3,k} \delta_{t-k} + \sum_{k=1}^{L} \theta_{3,k} LS_t + \epsilon_{3,t} \tag{51}$$

Figure 8 presents the effects of a unit shock to the forward premium, the funding rate, and the difference in returns between the two assets. We find that a 1% shock to the forward premium leads to a peak response of 3 USD Billion in long-short positions in the protocol after approximately 2 days. In contrast, we find no significant effects of the funding rate on long-short positions. Similar responses are observed for ETH-USDC and ETH-DAI positions in Appendix B. In sum, we find robust evidence that lending protocols and futures markets are integrated. We now quantify the extent of integration through testing the pricing of interest rates and futures premia.

5.2 Determinants of interest rate differential

The model tests the channels through which futures premia and exchange rate risk translate to differences in interest rates. Through our model's first prediction in (45), an increase in futures premia is indicative of net bullish beliefs on the risky cryptoasset. We empirically test the fundamental of interest-rate differences in Equation (52):

$$i_L^{USDT} - i_L^{ETH} = \beta_0 + \beta_1 f_t - s_t + \beta_2 \delta_t + \beta_3 \sigma_{iETH,t} + \beta_4 \sigma_{iUSDT,t} + \beta_5 \frac{W_{ETH}}{W_{USDT}} + \beta_6 \sigma_{spot_t} + u_t. \tag{52}$$

8. As the forward premia and funding rates are jointly determined, we do not impose a specific ordering of the structural VAR. In our specification, shocks to each variable can only affect other variables with a delay.

Here, the outcome variable is the interest-rate difference between USDT and ETH. The explanatory variable are the futures premium $f_t - s_t$, the funding rate δ_t, the volatility of both USDT and ETH interest rates and volatility of the spot exchange rate.

The results are summarized in Table 3. All explanatory variables are measured in per cent, and the outcome variable is defined in basis points for readability of the results. Consistent with our model prediction, the forward premium and funding rate is positively related to the interest rate differential. In particular, positive futures premia and funding rates are indicative of net optimistic beliefs in ETH. This results in an increase in investor positions that borrow stablecoins to take long leveraged positions in the unstable asset, and in turn higher interest rates on the stablecoin.

An additional implication of the model prediction in equation (45) is that the interest rate differential has a risk premium that is based on the wealth of optimists and the volatility of the risky asset. To capture this risk premium, we measure the wealth of Ethereum deposited relative to the wealth of USDT on the Compound platform. The relative wealth of optimistic speculators and spot rate volatility in turn measures a risk premium. Both variables lower borrowing by optimists and therefore we predict a decline in stablecoin interest rates. Consistent with our model, our regression results show that the wealth ratio and spot rate volatility are negatively related to the interest rate differential.

5.2.1 Dynamic effects

One empirical concern with the results in Table 3 is that interest rates and futures premia are jointly determined, and we are not taking into account feedback effects from interest rates to forward premia. In addition to the contemporaneous effects of the funding rate and the futures premia on the interest rates, we test for dynamic effects using a vector autoregression (VAR) framework. The autoregressive equations for the futures premium, the funding rate and interest rate differential are illustrated in equations (53), (54) and (55). We allow for feedback effects between the three variables. Our baseline specification contains $L = 8$ lags. [9]

$$f_t - s_t = \alpha_1 + \sum_{k=1}^{L} \gamma_{1,k} \left(f_{t-k} - s_{t-k}\right) + \sum_{k=1}^{L} \beta_{1,k} \delta_{t-k} + \sum_{k=1}^{L} \theta_{1,k} \left(i_L^{USDT} - i_L^{ETH}\right) + \epsilon_{1,t} \quad (53)$$

9. As futures premia and interest rates are jointly determined, we are agnostic about the ordering of our structural VAR. In our specification, shocks to each variable can only affect other variables with a delay.

$$\delta_t = \alpha_2 + \sum_{k=1}^{L} \gamma_{2,k} \left(f_{t-k} - s_{t-k}\right) + \sum_{k=1}^{L} \beta_{2,k}\delta_{t-k} + \sum_{k=1}^{L} \theta_{2,k} \left(i_L^{USDT} - i_L^{ETH}\right) + \epsilon_{2,t} \tag{54}$$

$$i_L^{USDT} - i_L^{ETH} = \alpha_3 + \sum_{k=1}^{L} \gamma_{3,k} \left(f_{t-k} - s_{t-k}\right) + \sum_{k=1}^{L} \beta_{3,k}\delta_{t-k} + \sum_{k=1}^{L} \theta_{3,k} \left(i_L^{USDT} - i_L^{ETH}\right) + \epsilon_{3,t} \tag{55}$$

We test the effects of a unit shock to the forward premium, the funding rate and the interest rate difference between USDT and ETH in Figure 9. In line with the results presented in Table 3, we find a 1 per cent shock to the forward premium leads to peak response of the interest rate difference of 0.008 percentage points. A 1 per cent increase in the funding rate leads to short-term increase in the interest rate difference by 0.01 percentage points. In contrast, a 1 percentage point shock to the interest rates lead to a 2 per cent change in the futures premium, and a 0.5 percentage point increase in the funding rate that is weakly significant at the 5 per cent level of significance.

5.3 Covered Interest Rate Parity Deviations

Using the nomenclature of the model, We empirically test whether CIP holds. We define it using benchmark borrowing rates in equation (56). [10] The first component is expressed (in logs) is the forward premium. The second term is the interest-rate difference between USDT and ETH.

$$cip_t = \frac{f_t - p_0}{p_0} - (i_L^U - i_L^E) \tag{56}$$

We plot CIP deviations, including each component, in Figure 10. The average size of absolute CIP deviations are approximately 7 basis points per funding period of 8 hours. This translates to approximately a 76 per cent per annum measure. In addition, we show the funding rate and futures premium correlate with each other. When futures trade at a premium, this is consistent with net long positions in the futures market, leading long position holders to pay the short position δ. The large CIP deviations we compute are in line with the large futures premium calculated in the literature (Franz and Valentin 2020; Cong, He, and Tang 2022; Schmeling, Schrimpf, and Todorov 2022). For example, Schmeling, Schrimpf, and Todorov (2022) document a futures premium that is in excess of 60 per cent per annum.

10. If the CIP deviation is defined using deposit rates, $cip_t = \frac{f_t - p_0}{p_0} - (i_D^U - i_D^E)$. Our analysis on CIP violations are quantitatively similar when using deposit rates to construct the CIP deviation.

5.3.1 Determinants of CIP deviations

As a starting point in understanding limits to arbitrage, we can construct arbitrage bounds based on strategies outlined in section 4. These strategies capture bounds on the forward premium: if the futures and funding rate are too high, it is profitable to borrow stablecoins in the protocol, buying ETH in the spot market and entering a short futures position to make a profit. Conversely, if the futures and funding rate are too low, it is profitable to deposit a stablecoin on the lending protocol, borrow ETH and enter a long futures position to make a profit. From equation (37), we can establish the following bounds for the sum of the forward premium and the funding rate.

$$i_D^U - i_L^E \leq \frac{f_t - p_0}{p_0} \leq i_D^U - i_D^E \tag{57}$$

The lower and upper bounds for the CIP deviation expressed using borrowing rates are then given by:

$$i_D^U - i_L^U < cip_t < i_D^U - i_D^E \tag{58}$$

Table 4 reports summary statistics of the CIP lower and upper bound, and percentage of violations of the arbitrage bounds. Over the sample, we find a total of 97 per cent violations of the arbitrage bound when we neglect transaction costs and other limits to arbitrage. In practice, we can control for transaction costs such as gas fees on the Ethereum blockchain. Gas is a measure of the amount of ether (ETH) a user pays to perform a given activity, or batch of activities, on the Ethereum network. These transaction costs are analogous to commissions on exchanges, however these costs are paid to the miners who authenticate the transactions on the Ethereum blockchain. Therefore arbitrageurs that deposit or borrow stablecoins and ETH on the protocol are required to pay these gas fees. [11] We can express the CIP bounds with transaction costs as $cip_{LB} - gasfee < cip_t < cip_{UB} + gasfee$, where $cip_{LB} = i_D^U - i_L^U$, and $cip_{UB} = i_D^U - i_D^E$. Figure 11 plots CIP deviations and the lower and upper bounds (inclusive of ETH gas fees). Visually, the majority of CIP deviations lie within the arbitrage bounds with gas fees. The lower panel of Table 4 reports summary statistics of CIP arbitrage bound violations in excess of transaction costs. We now find only 5.7 per cent of violations are outside the bounds after taking into account gas fees. These exploitable opportunities are asymmetric, with 4.8 per cent of violations of the lower bound, and 1.0 per cent of violations of the upper bound.

11. As we do not have transaction level gas fees, we use a daily index of ETH gas prices from coinmetrics network statistics as a proxy.

Therefore gas fees are a key factor to explain persistent deviations of CIP in the data. We note additional factors that can limit arbitrage capital. There is no term structure in DeFi lending, so investors have to conduct an arbitrage trade based on expectations of interest rate movements. Futures premia and funding rates determined on the futures exchange have a high degree of leverage, leading to increased risk of liquidations. Governance risk of DeFi protocols and counterparty risk on a centralized exchange can also lead to unexploited arbitrage opportunities. We empirically test the fundamental of CIP deviations in Equation (59):

$$|cip_t| = \beta_0 + \beta_1 gasfee_t + \beta_2 1.[R_{ETH/USDT} > 2std] + \\ \beta_3 1.[R_{ETH/USDT} < 2std] + \beta_4 \sigma_{ETH/USDT} + u_t. \quad (59)$$

The outcome variable is the absolute CIP violation. The gas fee is the median transaction fee paid to miners on Ethereum blockchain and calculated by coinmetrics. $1.[R_{ETH/USDT} > 2std]$ and $1.[R_{ETH/USDT} < 2std]$ are indicator variables for ETH/USDT returns that are greater or less than 2 standard deviations. By capturing periods of extreme returns, we indirectly control for periods of liquidations and when positions become over-leveraged and less investors can participate in arbitrage trades. $\sigma_{ETH/USDT}$ is a rolling standard deviation of ETH/USDT. Periods of high volatility, all else equal, act as a limit to arbitrage. Finally, we control for interest rate volatility of USDT and ETH. As there is no term structure, expectations about future interest rates matter for the profitability of arbitrage trades. All variables are measured in per cent. The results are summarized in Table 5. In line with our results, gas fees are correlated positively with the magnitude of CIP deviations, and deviations are higher in both periods of extreme positive and negative returns. Turning to measures of volatility, we find an increase in the volatility of ETH/USDT increases deviations from parity, suggesting risky collateral is a limit to arbitrage.

5.4 Return predictability

In accordance with the testable implication of our model in equation (46), we can empirically test return predictability through the following two specifications in Equation (60) and (61):

$$r_{t+h} = \beta_0 + \beta_1 f_t - s_t + u_t. \quad (60)$$

$$r_{t+h} = \beta_0 + \beta_1 i_L^{USDT} - i_L^{ETH} + \beta_2 \sigma_{spot,t} + \beta_3 \frac{W_{ETH}}{W_{USDT}} + u_t. \tag{61}$$

The outcome variable r_{t+h} is the change in the future spot rate using hourly data, where we use a horizon of 8 hours corresponding to the interval over which funding rates are calculated. The results are summarized in Table 6. In accordance with model hypothesis $H4_0$, coefficient β_1 should approximate 1 and corresponds to the case when futures premia are a significant predictor of future spot rates. The funding rate is significant in predicting future spot rate changes, however with a coefficient less than 1 it suggests that the investor beliefs are not fully rational. This supports the failure of market efficiency in line with results in Gudgeon et al. (2020). We find the interest rate differential is statistically insignificant in column (2). In a specification in column (4) that includes controls for the other factors that affect risk premia such as the relative wealth of optimists and spot rate volatility, we find interest rates and futures premia have no significant correlation with future returns. In summary, our results show that futures markets and DeFi lending protocols do not have unbiased beliefs regarding the future spot rate, and these markets are segmented as investors typically have different beliefs.

6 Conclusion

In this paper, we examine the fundamental determinants of interest rates on DeFi protocols. Through a model framework and empirical evidence, we show that interest rates reflect investor beliefs on speculative assets. Our novel contribution is connecting interest rate determination to the futures market.

The model features a stable and unstable asset. Lending protocols allow investors to take long and short positions on the unstable asset. Long positions are by depositing the unstable asset and borrowing a fraction as stable assets. Short positions are the reverse: investors deposit stable collateral and borrow the unstable asset. Investors can alternatively take long and short futures positions: this leads to a link between futures premia and relative interest rates across currencies.

The model features three testable implications. First, interest rate differences reflect the relative bearish and bullish beliefs of investors. If long positions dominate short positions, utilization of the stable asset (measured as the fraction of stable asset that is borrowed) is higher than utilization of the unstable asset. Algorithmically, this results in a higher interest rate on the stable asset. Second, we show that interest rates reflect futures premia. When futures trade at a premium due to long positions dominating short positions, we find this is consistent with utilization and interest rates that are higher for the stable asset.

We take these predictions to the data. First, we analyze a rich dataset of wallet-level transactions, and show that DeFi lending protocols are integrated with futures markets, allowing for leveraged trading. Our algorithm's ability to classify wallets as long or short traders and construct an aggregate net long position measure has enabled us to observe a correlation between an increase in futures premia and an increase in long positions and a decline in short positions in the lending protocol.

Second, we investigate the fundamental determinants of interest rates. Through the lens of the model, an increase in futures premia is indicative of net bullish beliefs on the risky cryptoasset. Third, we conduct market efficiency tests of uncovered interest rate parity. Our results indicate that futures premia and the funding rate on perpetual futures contracts are significant in predicting future spot rate changes.

Third, we construct lower and upper bounds for CIP deviations based on arbitrage strategies that can be employed using both a DeFi lending protocol and futures markets. After accounting for transaction costs, such as gas fees to authenticate transactions on the blockchain, we find CIP deviations are typically within the arbitrage bounds. In addition to gas fees, an increase in the volatility of ETH/USDT, and periods of extreme returns in ETH lead to larger CIP deviations.

Fourth, we investigate the potential market segmentation between traders on futures protocols and lending protocols by conducting market efficiency tests. The findings suggest that there is indeed a difference in beliefs between these two groups of traders, which leads to a breakdown of the link between interest rates and futures premia. Futures premia are shown to be more predictive of spot returns than interest rates, indicating that traders on futures protocols have different beliefs about the future spot rate compared to traders on lending protocols.

Taken together, our findings suggest that there is a significant level of market inefficiency between DeFi protocols and perpetual futures, which could lead to misallocation of capital. If the interest rates offered by DeFi protocols are much lower than those achievable through perpetual futures, this implies that a large amount of capital is locked in the protocol and could be utilized more efficiently. This inefficiency could be attributed to irrational behavior among DeFi market participants, or it may be evidence of additional benefits associated with using DeFi markets over centralized futures trading.

To address this inefficiency, DeFi protocols could be redesigned to reduce transaction costs, and the level of segmentation could be decreased as the market matures, thereby increasing liquidity and reducing the price impact of arbitrage trading. Exploring the optimal design of lending protocols and their potential use in mainstream finance is an important area for future research.

References

Alexander, Carol, Jaehyuk Choi, Hamish RA Massie, and Sungbin Sohn. 2020. "Price discovery and microstructure in ether spot and derivative markets." *International Review of Financial Analysis* 71:101506.

Alexander, Carol, Jaehyuk Choi, Heungju Park, and Sungbin Sohn. 2020. "BitMEX bitcoin derivatives: Price discovery, informational efficiency, and hedging effectiveness." *Journal of Futures Markets* 40 (1): 23–43.

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

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

Augustin, Patrick, Roy Chen-Zhang, and Donghwa Shin. 2022. "Yield Farming." *Available at SSRN 4063228.*

Barbon, Andrea, and Angelo Ranaldo. 2021. "On The Quality Of Cryptocurrency Markets: Centralized Versus Decentralized Exchanges." *arXiv preprint arXiv:2112.07386.*

Baur, Dirk G, and Thomas Dimpfl. 2019. "Price discovery in bitcoin spot or futures?" *Journal of Futures Markets* 39 (7): 803–817.

Capponi, Agostino, and Ruizhe Jia. 2021. "The Adoption of Blockchain-based Decentralized Exchanges: A Market Microstructure Analysis of the Automated Market Maker." *Available at SSRN 3805095.*

Capponi, Agostino, Ruizhe Jia, and Ye Wang. 2022. "The evolution of blockchain: from lit to dark." *arXiv preprint arXiv:2202.05779.*

Castro-Iragorri, Carlos, Julian Ramirez, and Sebastian Velez. 2021. "Financial intermediation and risk in decentralized lending protocols." *Available at SSRN 3893278.*

Chaudhary, Amit, and Daniele Pinna. 2022. "Market risk assessment: A multi-asset, agent-based approach applied to the 0VIX lending protocol." *arXiv preprint arXiv:2211.08870.*

Chiu, Jonathan, Emre Ozdenoren, Kathy Yuan, and Shengxing Zhang. 2022. "The Fragility of DeFi Lending."

Cong, Lin William, Zhiheng He, and Ke Tang. 2022. "Staking, Token Pricing, and Crypto Carry." *Available at SSRN.*

De Blasis, Riccardo, and Alexander Webb. n.d. "Arbitrage, contract design, and market structure in Bitcoin futures markets." *Journal of Futures Markets.*

Franz, Friedrich-Carl, and Alexander Valentin. 2020. "Crypto Covered Interest Parity Deviations." *Available at SSRN 3702212.*

Gorton, Gary B, Elizabeth C Klee, Chase P Ross, Sharon Y Ross, and Alexandros P Vardoulakis. 2022. *Leverage and Stablecoin Pegs.* Technical report. National Bureau of Economic Research.

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

Harvey, Campbell R, Ashwin Ramachandran, and Joey Santoro. 2021. *DeFi and the Future of Finance.* John Wiley & Sons.

Hasbrouck, Joel, Thomas J Rivera, and Fahad Saleh. 2022. "The need for fees at a dex: How increases in fees can increase dex trading volume." *Available at SSRN.*

He, Songrun, Asaf Manela, Omri Ross, and Victor von Wachter. 2022. "Fundamentals of Perpetual Futures." *Available at SSRN 4301150.*

Hoang, Lai T, and Dirk G Baur. 2020. "Forecasting bitcoin volatility: Evidence from the options market." *Journal of Futures Markets* 40 (10): 1584–1602.

Kozhan, Roman, and Ganesh Viswanath-Natraj. 2021. "Decentralized stablecoins and collateral risk." *WBS Finance Group Research Paper Forthcoming.*

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

Lehar, Alfred, and Christine A Parlour. 2022. "Systemic Fragility in Decentralized Markets."

Lehar, Alfred, Christine A Parlour, and Marius Zoican. 2022. "Liquidity Fragmentation on Decentralized Exchanges." *Available at SSRN 4267429.*

LI, Thomas, Siddharth Naik, Andrew Papanicolaou, and Lorenzo Schoenleber. 2023. "Maneuvering and Investing in Yield Farms." *Available at SSRN 4422213.*

Mueller, Peter. 2022. "DeFi Leveraged Trading: Inequitable Costs of Decentralization." *Available at SSRN 4241356.*

Park, Andreas. 2022. "Conceptual Flaws of Decentralized Automated Market Making."

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

Qin, Kaihua, Liyi Zhou, Pablo Gamito, Philipp Jovanovic, and Arthur Gervais. 2021. "An empirical study of defi liquidations: Incentives, risks, and instabilities." In *Proceedings of the 21st ACM Internet Measurement Conference,* 336–350.

Rivera, Thomas J, Fahad Saleh, and Quentin Vandeweyer. 2023. "Equilibrium in a DeFi Lending Market." *Available at SSRN 4389890.*

Saengchote, Kanis. 2021. "Decentralized lending and its users: Insights from Compound." *Available at SSRN 3925344.*

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

Schmeling, Maik, Andreas Schrimpf, and Karamfil Todorov. 2022. "Crypto Carry." *Available at SSRN.*

Shiller, Robert J. 1993. "Measuring asset values for cash settlement in derivative markets: hedonic repeated measures indices and perpetual futures." *The Journal of Finance* 48 (3): 911–931.

Soska, Kyle, Jin-Dong Dong, Alex Khodaverdian, Ariel Zetlin-Jones, Bryan Routledge, and Nicolas Christin. 2021. "Towards understanding cryptocurrency derivatives: a case study of bitmex." In *Proceedings of the Web Conference 2021,* 45–57.

Veyrune, Mr Romain M, Guido Della Valle, and Shaoyu Guo. 2018. *Relationship Between Short-Term Interest Rates and Excess Reserves: A Logistic Approach.* International Monetary Fund.

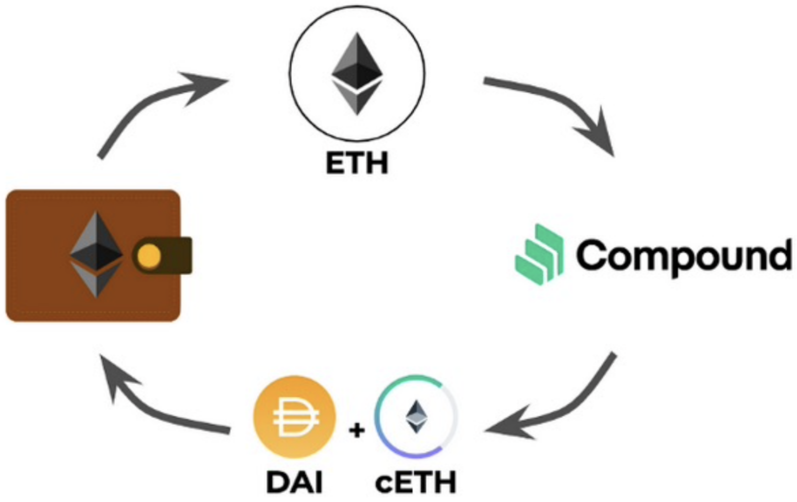
Warmuz, Jakub, Amit Chaudhary, and Daniele Pinna. 2022. "Toxic Liquidation Spirals: Evidence from the bad debt incurred by AAVE." *arXiv preprint arXiv:2212.07306.*

Xu, Jiahua, and Nikhil Vadgama. 2022. "From banks to DeFi: the evolution of the lending market." In *Enabling the Internet of Value,* 53–66. Springer.

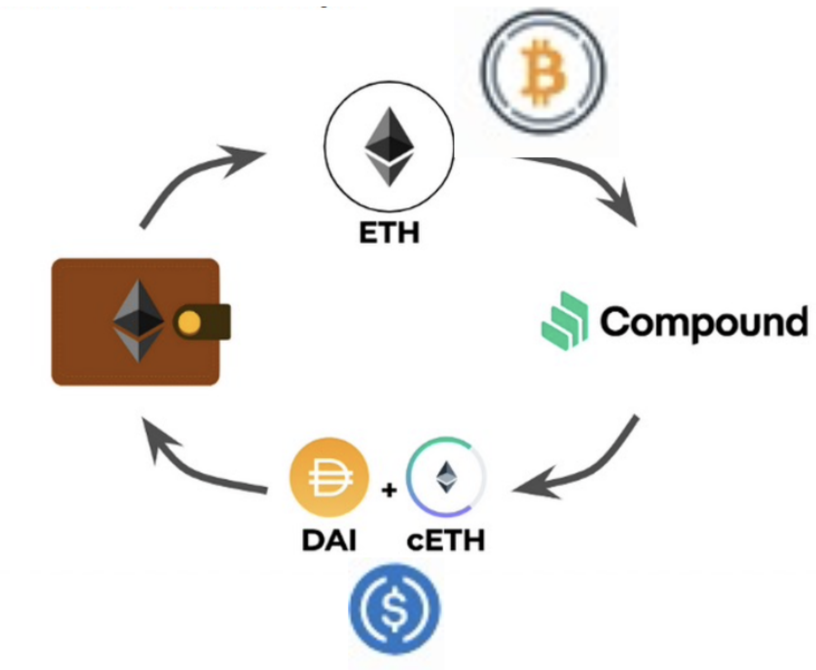
Figures

Figure 1: Compound: Multiple Borrowing and Lending Assets

Panel A: Single Collateral and Borrowing Currency

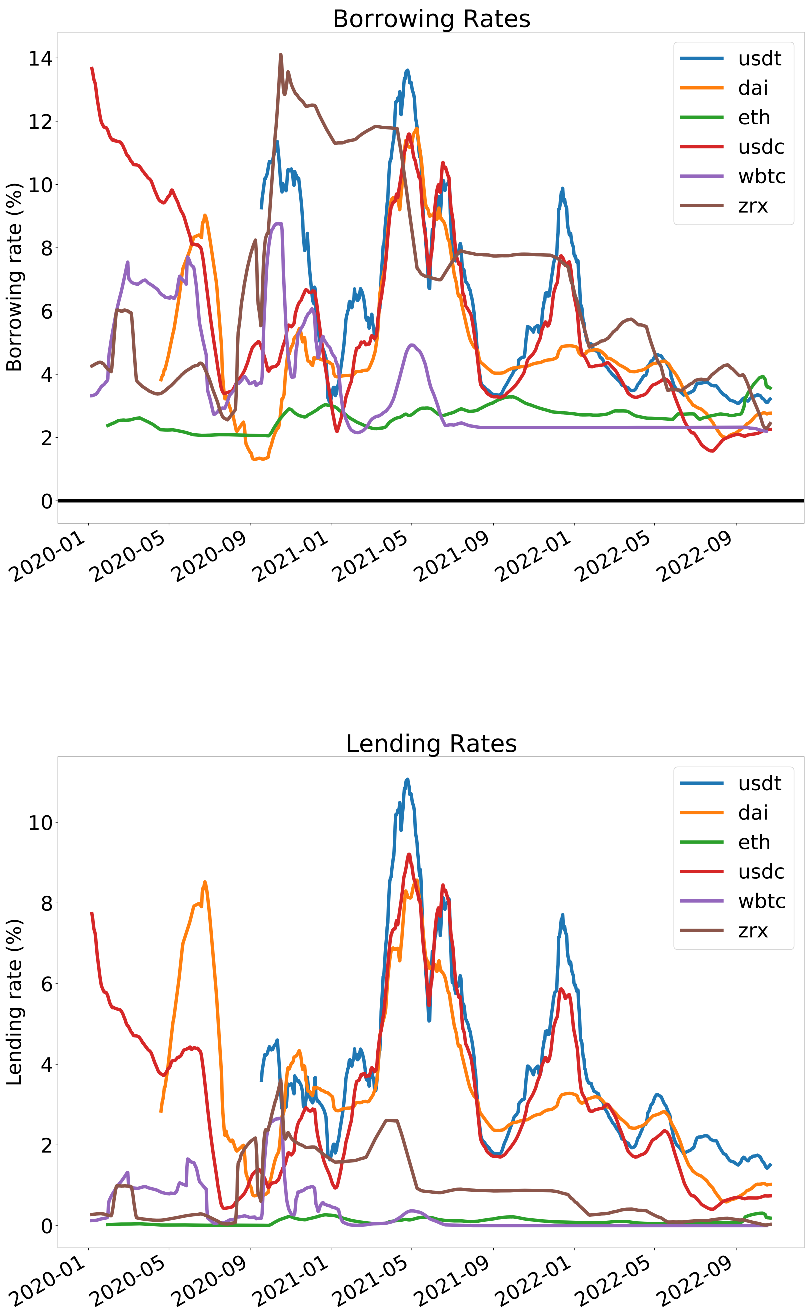


Panel B: Multiple Collateral and Borrowing Currencies



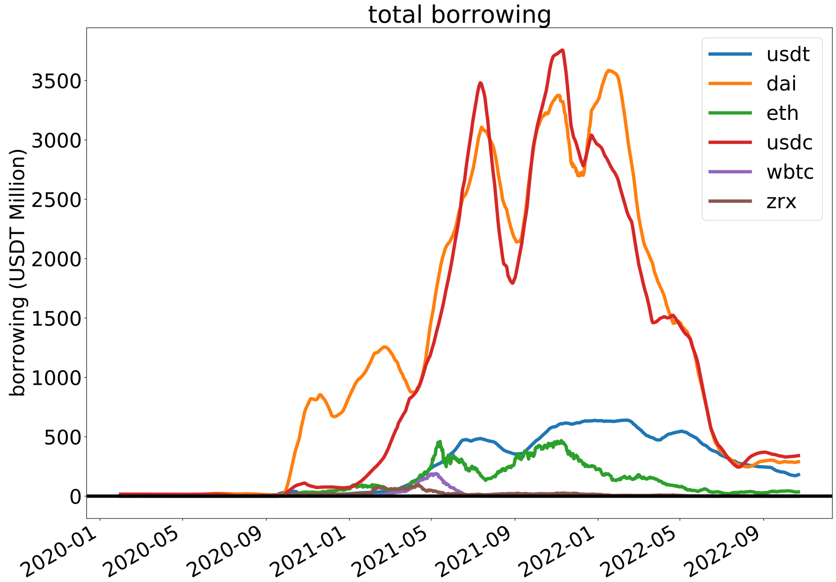
Note: Figure Panel A illustrates the process of supplying ETH to Compound (this gets you cETH token). Every currency supplied to the protocol is converted to a Compound token. For example, ETH collateral is converted to cETH, WBTC collateral is converted to cWBTC. Exchange rates between ETH and cETH can vary over time, and cETH can accrue interest. Panel B shows an investor that borrows multiple currencies, such as USDC and DAI, and supply multiple collateral types like ETH and wrapped Bitcoin (WBTC).

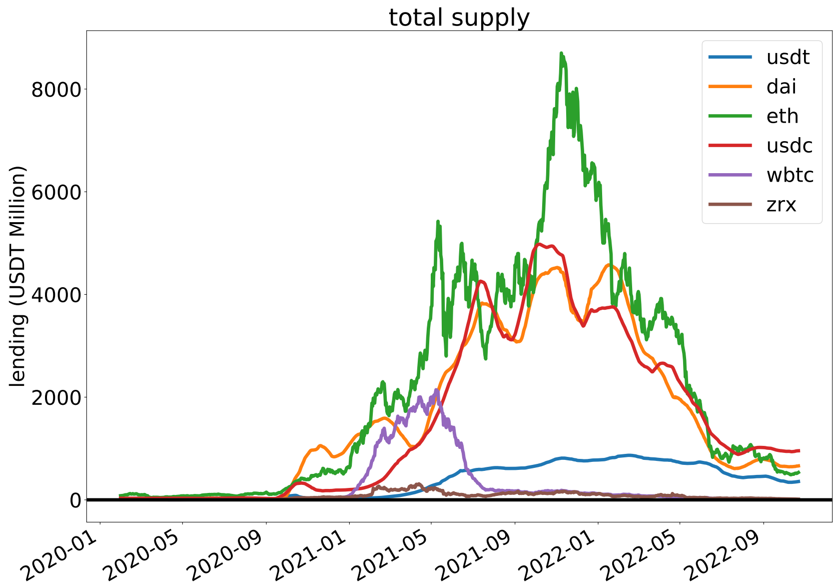
Figure 2: Borrowing and Lending Rates



Note: Figure presents borrowing and lending rates on multiple assets (annualized), calculated as a historical rolling average over the last 30 days. Source: Compound API.

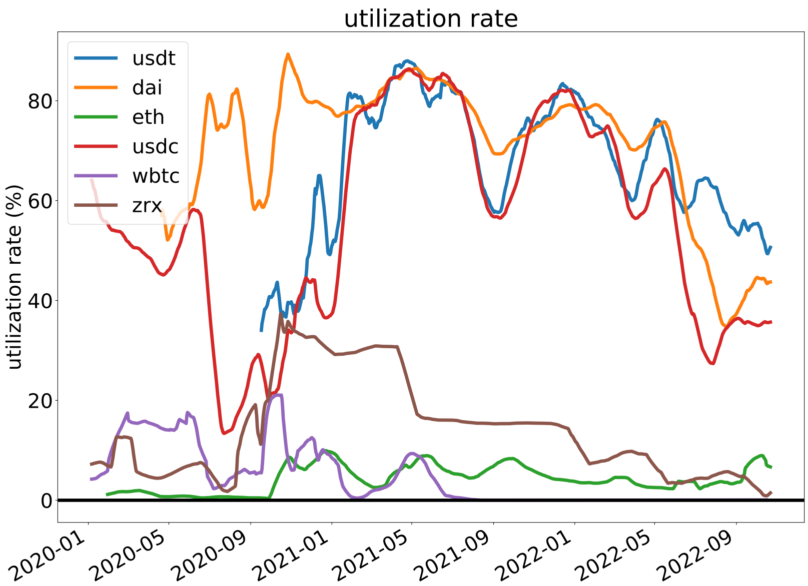
Figure 3: Borrowing and Lending

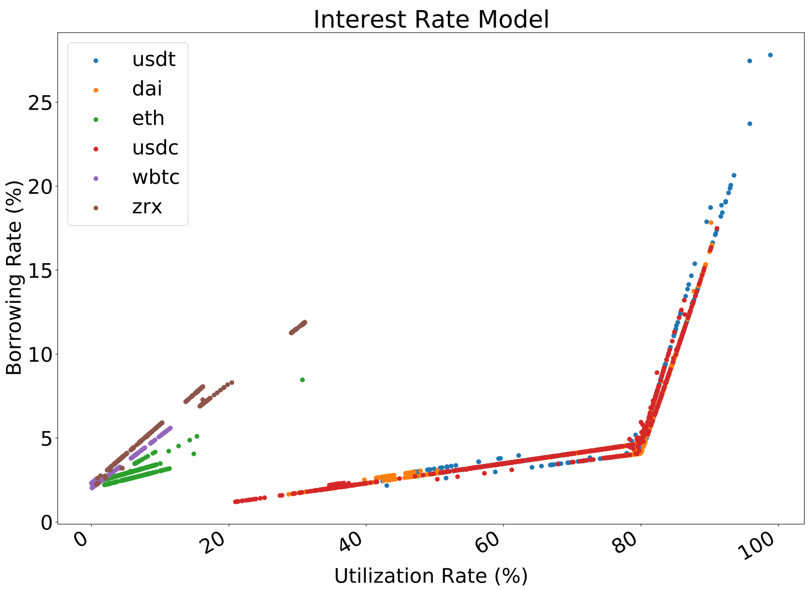




Note: Figure presents aggregate borrowing and supply (deposits) in multiple currencies, calculated as a historical rolling average over the last 30 days. Source: Compound API.

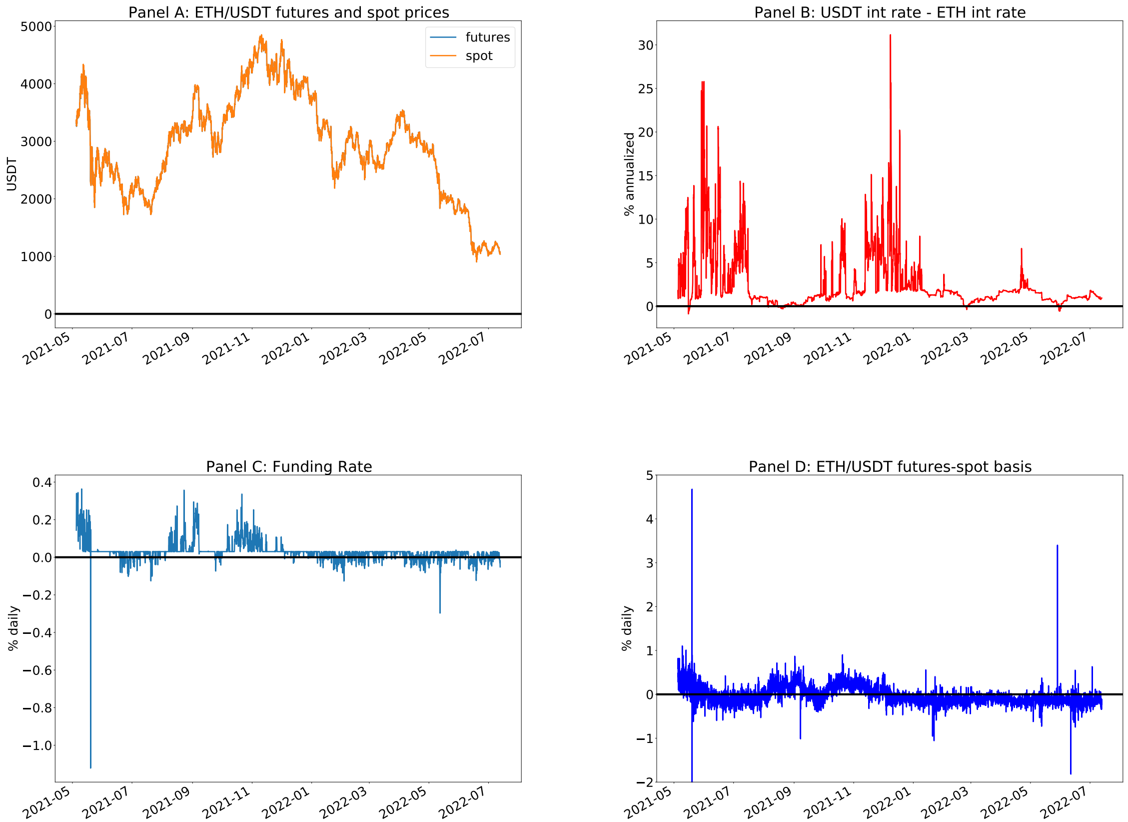
Figure 4: Utilization Rate and Interest Rate Rules





Note: Figure top panel presents utilization rates (in percentage points) on multiple assets, calculated as a historical rolling average over the last 30 days. Bottom panel plots interest rate models on multiple assets, in which borrowing rates are determined as a function of the utilization rate, Source: Compound API.

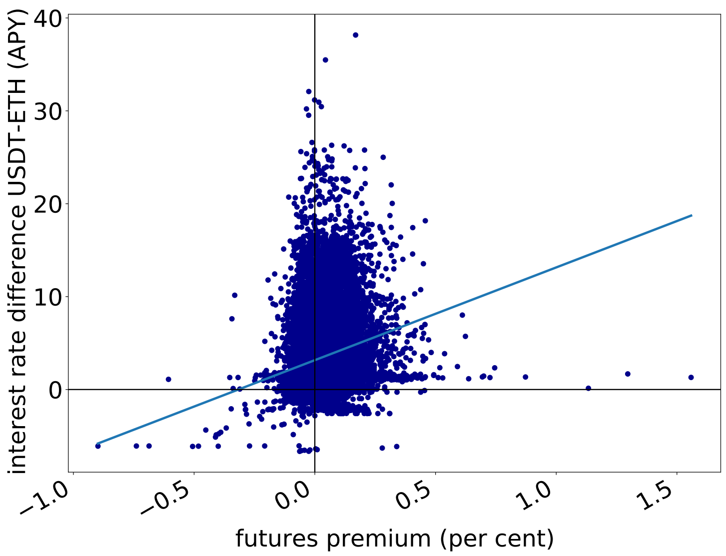
Figure 5: Spot price, interest rate differential and funding rates



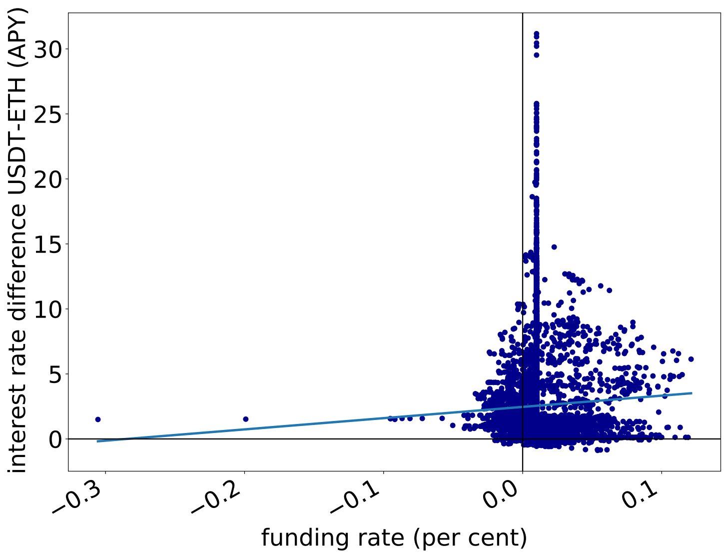
Note: Figure presents time series on the ETH/USDT price (Panel A), the interest rate differential between USDT and ETH (panel B), the ETH/USDT perpetual futures funding rate (Panel C) and the futures premium (Panel D). All variables are measured in per cent (hourly).

Figure 6: Interest rate difference between USDT and ETH plotted against futures premium (Panel A) and funding rate (Panel B)

Panel A: Interest rate difference and futures premium

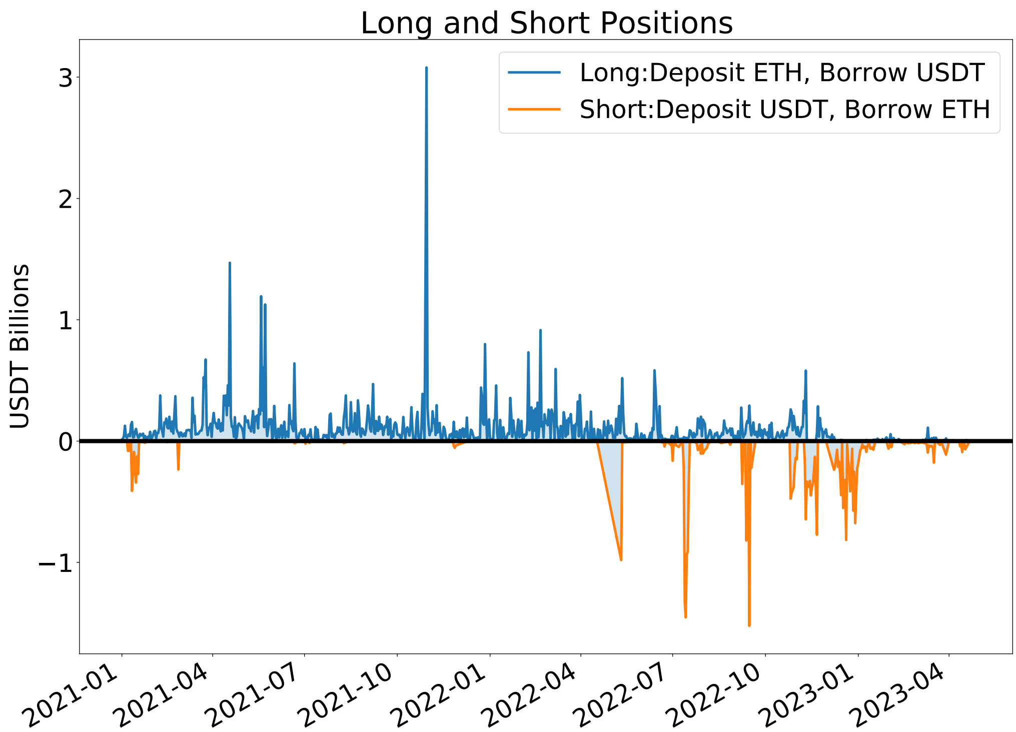


Panel B:Interest rate difference and funding rate



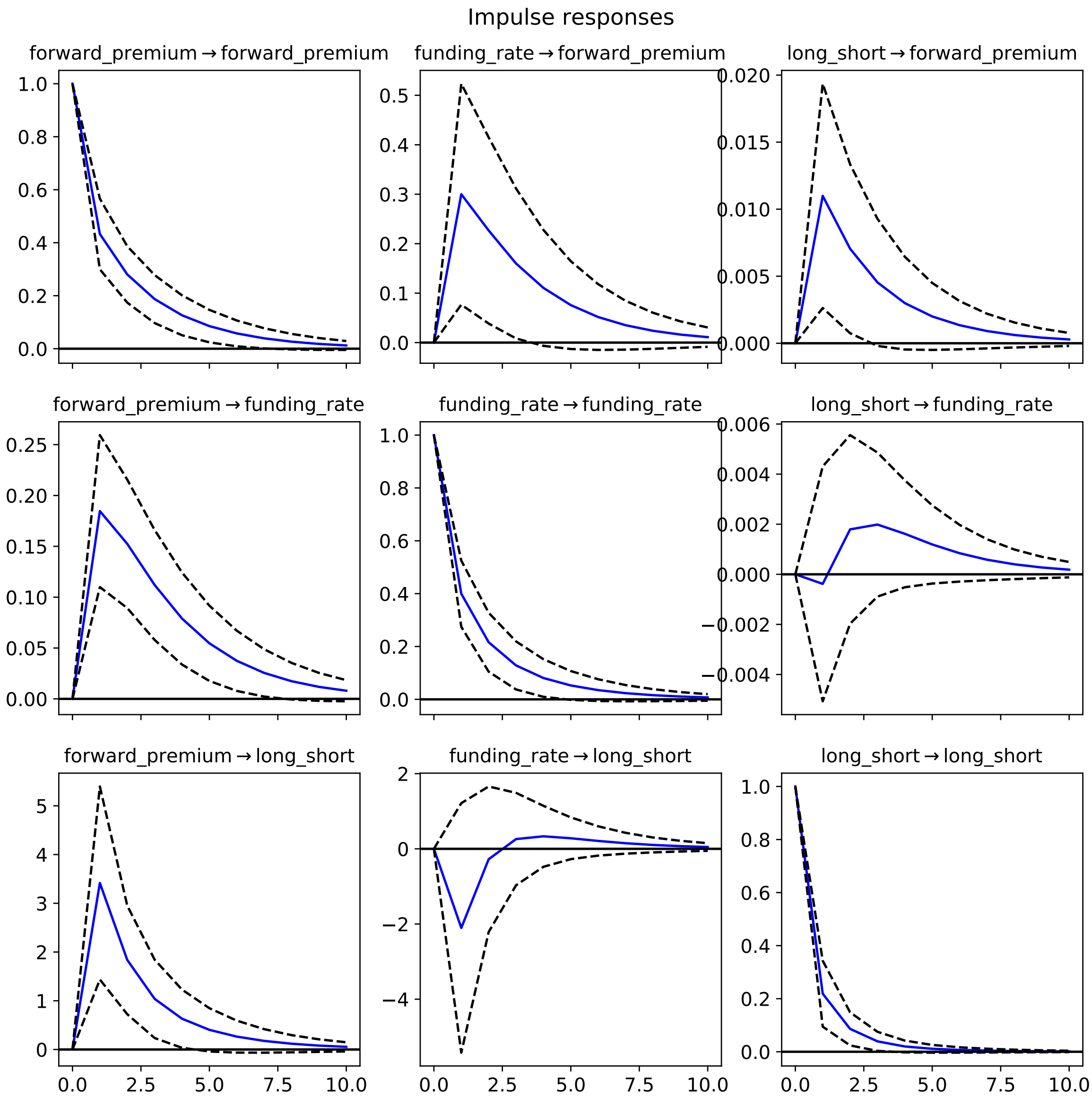
Note: This figure plots a scatter plot of interest rate differences between USDT and ETH, and the futures premium (panel A) and funding rate (panel B) on ETH-USDT perpetual futures contracts. Price data for futures and funding rate obtained from Tardis api, and DeFi lending protocol interest rates from Compound.

Figure 7: Aggregate long and short positions for ETH-USDT



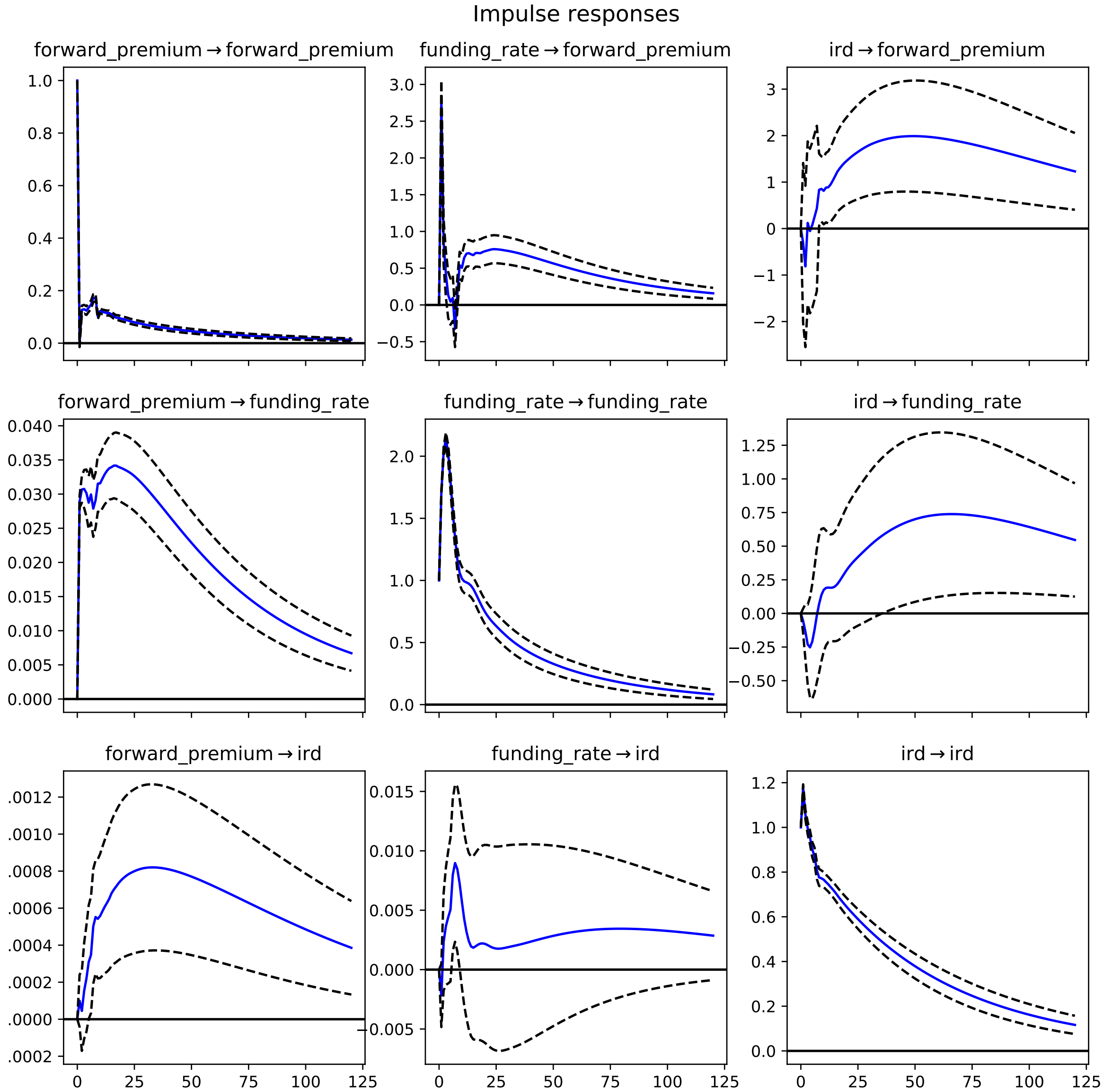
Note: Figure plots the aggregate long and short positions using transaction data at the wallet level. Long positions (measured along the positive y-axis) aggregate USDT borrowed by investors that deposit ETH as collateral on the Compound protocol. Short positions (measured along the negative y-axis) aggregate ETH borrowed by wallets that deposit USDT as collateral on the protocol. Sample is daily from 1st January 2021 to 22nd April 2023.

Figure 8: VAR impulse responses: feedback effects of forward premia, long-short positions and the funding rate



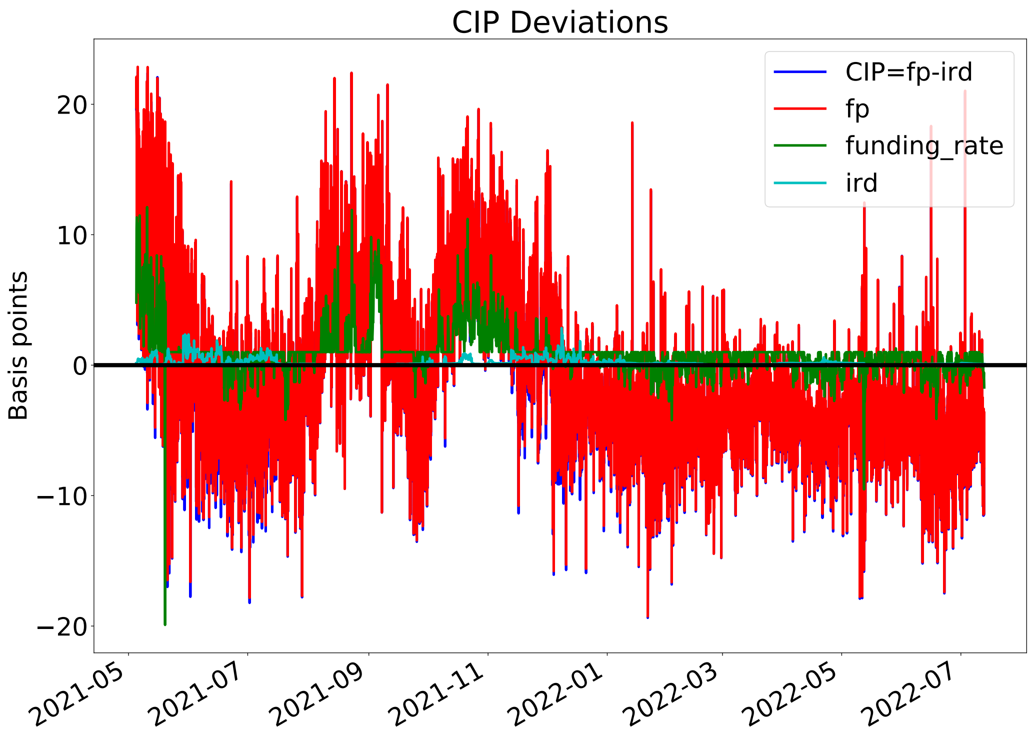
Note: Figure plots the impulse responses of a VAR with three variables: the forward premium, the funding rate and the aggregate long-short positions. *longshort* is measured as the difference between long (deposit ETH and borrow USDT) and short (deposit USDT and borrow ETH) position using wallet-level data, in billions USD. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. 1 lag is included in the baseline specification and daily data is used for the analysis. Dotted lines denote a standard error band equivalent for statistical significance at the 5% level. Sample is daily from 1st January 2021 to 22nd April 2023.

Figure 9: VAR impulse responses: feedback effects of forward premia, interest rates and the funding rate



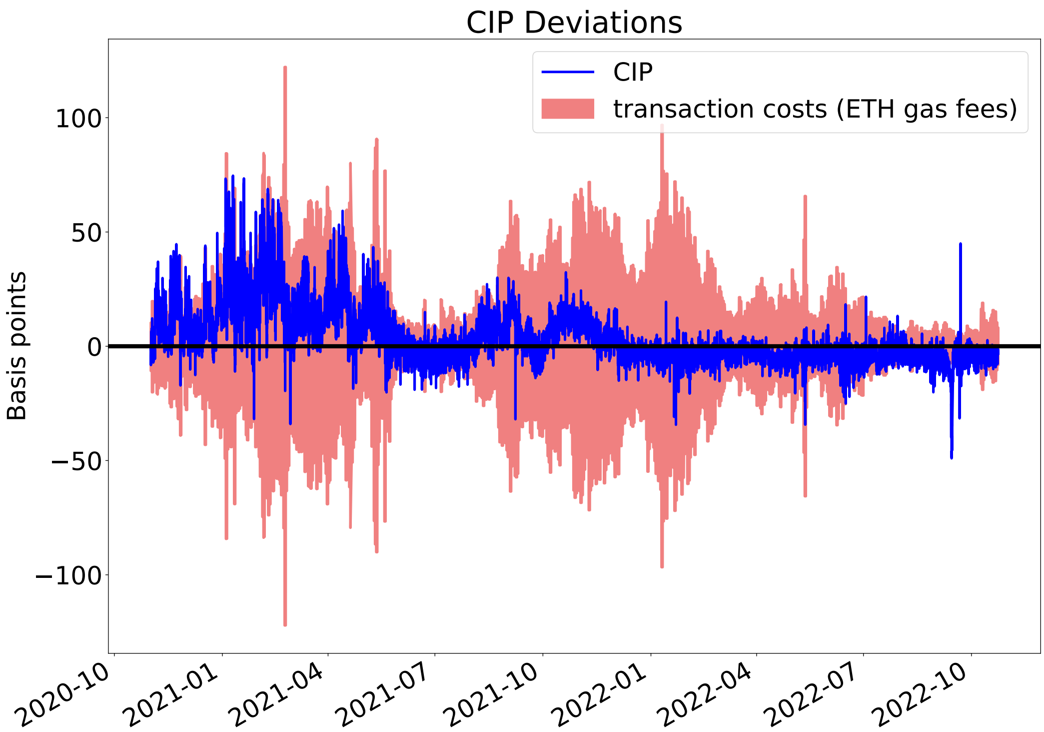
Note: Figure plots the impulse responses of a VAR with three variables: the forward premium, the funding rate and the interest rate difference. The *ird* measures the difference between the USDT interest rate and ETH interest rate (annualized). The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. 8 lags are included in the baseline specification and hourly data is used for the analysis. Dotted lines denote a standard error band equivalent for statistical significance at the 5% level

Figure 10: CIP deviations using perpetual futures



Note: Figure decomposes CIP deviations for the ETH/USDT pair into 3 components: (i) interest rate differential between USDT and ETH, (ii) the funding rate on perpetual futures ETH/USDT and (iii) the futures premium on perpetual futures ETH/USDT. Calculations are based on hourly data, and all variables are measured in per cent (hourly).

Figure 11: CIP deviations using perpetual futures, arbitrage bounds with ETH gas fee transaction costs included



Note: Figure plots CIP deviations for the ETH/USDT pair calculated using perpetual futures. Transaction costs are computed using ETH gas fees, and are used to construct lower and upper bounds for CIP arbitrage. Calculations are based on hourly data, and all variables are measured in basis points (hourly).

Tables

Table 1: Summary statistics: interest rates and futures data

	count	mean	std	min	25%	50%	75%	max
i_D^{USDT}	15996.0	5.757	3.968	0.459	3.499	4.123	6.670	40.725
i_D^{ETH}	15996.0	3.944	3.486	0.034	1.914	2.669	4.546	30.983
i_L^{USDT}	15996.0	2.832	0.397	2.206	2.615	2.762	2.972	8.957
i_L^{ETH}	15996.0	0.129	0.103	0.027	0.072	0.105	0.171	2.284
$i_L^{USDT} - i_L^{ETH}$	15996.0	2.925	4.061	-6.655	0.645	1.326	3.939	38.161
$i_D^{USDT} - i_D^{ETH}$	15996.0	3.816	3.493	-1.440	1.772	2.561	4.430	30.897
s_t	15912.0	2331.589	1086.287	374.063	1530.305	2185.513	3150.925	4847.063
f_t	15996.0	2333.849	1086.697	373.770	1533.492	2190.435	3153.455	4852.080
$f_t - s_t$	15912.0	0.020	0.117	-8.664	-0.047	-0.006	0.076	1.559
δ_t	15912.0	0.023	0.045	-0.487	0.006	0.010	0.024	0.375

Note: This table presents summary statistics of key variables in empirical analysis. i_D^{USDT} and i_D^{ETH} measure the interest rates on depositing USDT and ETH. i_L^{USDT} and i_L^{ETH} measure the interest rates on borrowing USDT and ETH. s_t and f_t are spot and perpetual futures ETH/USDT prices. δ_t is the funding rate on perpetual futures contracts. Interest rates are annualized in percentage points. The funding rate is in percentage points per 8 hour interval. Sample is hourly data from November 1st, 2020 to October 23rd, 2022.

Table 2: Determinants of ETH-USDT long and short positions using wallet-transaction level data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	long-short	long-short	long-short	long	long	long	short	short	short
forward premium	1.3348***	1.8288**	2.8881***	1.2856***	1.7693**	2.8163**	-0.0492**	-0.0595**	-0.0718**
	(0.4901)	(0.7787)	(1.1167)	(0.4864)	(0.7738)	(1.1140)	(0.0233)	(0.0295)	(0.0335)
funding rate		-1.3265	-1.2674		-1.2987	-1.2348		0.0278	0.0326
		(0.9877)	(1.3082)		(0.9850)	(1.3062)		(0.0248)	(0.0293)
$\sigma_{ETH/USDT}$			-3.5548*			-3.2152			0.3396**
			(1.9906)			(1.9834)			(0.1338)
Intercept	0.5449***	0.5689***	0.8966***	0.5563***	0.5798***	0.8786***	0.0114***	0.0109***	-0.0180**
	(0.0572)	(0.0632)	(0.1890)	(0.0570)	(0.0630)	(0.1888)	(0.0029)	(0.0028)	(0.0087)
R-squared	0.0195	0.0228	0.0566	0.0182	0.0214	0.0527	0.0148	0.0156	0.0653
No. observations	265	265	235	265	265	235	265	265	235

Note: Table presents regressions of the fundamentals of aggregate long and short positions using wallet transaction-level data. Long positions aggregate USDT borrowed by investors that deposit ETH as collateral on the Compound protocol. Short positions aggregate ETH borrowed by wallets that deposit USDT as collateral on the protocol. $long - short$ measures the difference between long and short positions. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. $\sigma_{ETH/USDT}$ is a 30 day rolling standard deviation of ETH/USDT exchange rate. The sample is daily from 1st January 2021 to 22nd April 2023. All explanatory variables are measured in per cent. White heteroscedasticity robust standard errors are used in estimation. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 3: Determinants of Interest Rate Differential: $i_L^{USDT} - i_L^{ETH}$

	(1)	(2)	(3)	(4)	(5)	(6)
	$i_L^{USDT} - i_L^{ETH}$	$i_L^{USDT} - i_L^{ETH}$	$i_L^{USDT} - i_L^{ETH}$	$i_L^{USDT} - i_L^{ETH}$	$i_L^{USDT} - i_L^{ETH}$	$i_L^{USDT} - i_L^{ETH}$
forward premium	0.0100***	0.0054***	0.0056***	0.0005	0.0020**	0.0020**
	(0.0011)	(0.0013)	(0.0013)	(0.0010)	(0.0010)	(0.0010)
funding rate		0.0145***	0.0136***	0.0053**	0.0079***	0.0081***
		(0.0028)	(0.0027)	(0.0023)	(0.0024)	(0.0023)
$\sigma_{i_{ETH}}$			-0.0022***	-0.0027***	-0.0025***	-0.0025***
			(0.0006)	(0.0006)	(0.0006)	(0.0006)
$\sigma_{i_{USDT}}$				0.0017***	0.0017***	0.0017***
				(0.0001)	(0.0001)	(0.0001)
wealth ratio					-0.0005***	-0.0005***
					(0.0001)	(0.0001)
$\sigma_{ETH/USDT}$						0.0001
						(0.0001)
Intercept	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R-squared	0.0569	0.0754	0.0780	0.4396	0.4536	0.4552
No. observations	2162	2162	2160	2160	2160	2159

Note: Table presents regressions of the fundamentals of the interest rate difference. ird measures the difference between the USDT interest rate and ETH interest rate (annualized) in basis points. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. $\sigma_{ETH/USDT}$,$\sigma_{i_{ETH}}$ and $\sigma_{i_{USDT}}$ is a 24 hour rolling standard deviation of ETH/USDT exchange rate, ETH and USDT interest rates. The sample period is from 12th November 2021 to 23rd October 2022. All explanatory variables are measured in per cent. Sample is from November 1st, 2020 to October 23rd, 2022, and is based on 8 hour intervals at UTC 0:00, 8:00 and 16:00 which correspond to when the funding rate is paid by long futures holders to short futures holders on perpetual futures contracts. White heteroscedasticity robust standard errors are used in estimation. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 4: CIP summary statistics

	count	mean	std	min	25%	50%	75%	max
$\|cip\|$	15912.0	7.049	9.390	0.001	3.102	5.532	8.731	866.496
cip	15912.0	1.688	11.620	-866.496	-4.821	-0.843	7.247	155.742
No gas fees								
cip (Lower Bound)	15996.0	-0.166	0.074	-0.944	-0.168	-0.143	-0.132	-0.039
cip (Upper Bound)	15996.0	0.348	0.319	-0.131	0.162	0.234	0.405	2.822
cip Violation (Lower Bound)	15996.0	0.523	0.500	0.000	0.000	1.000	1.000	1.000
cip Violation (Upper Bound)	15996.0	0.453	0.498	0.000	0.000	0.000	1.000	1.000
cip Violation	15996.0	0.976	0.153	0.000	1.000	1.000	1.000	1.000
Gas fees								
cip (Lower Bound)	15996.0	-28.808	19.049	-122.146	-42.240	-24.144	-12.775	-2.944
cip (Upper Bound)	15996.0	28.991	19.125	2.872	12.900	24.268	42.397	122.197
cip Violation (Lower Bound)	15996.0	0.048	0.213	0.000	0.000	0.000	0.000	1.000
cip Violation (Upper Bound)	15996.0	0.010	0.098	0.000	0.000	0.000	0.000	1.000
cip Violation	15996.0	0.057	0.233	0.000	0.000	0.000	0.000	1.000

Note: This table presents summary statistics of CIP deviations. The upper panel presents summary statistics when no gas fees are accounted for. Lower and upper bounds for CIP deviations without gas fees are based on equation (37), and violations measure the fraction of CIP deviations that exceed the lower and upper bounds. The lower panel presents summary statistics after accounting for gas fee, which is the median transaction fee paid to miners on Ethereum blockchain and calculated by coinmetrics. Sample is hourly data from November 1st, 2020 to October 23rd, 2022.

Table 5: Determinants of ETH/USDT CIP Deviations

	(1)	(2)	(3)	(4)
	$\|CIP\|$	$\|CIP\|$	$\|CIP\|$	$\|CIP\|$
gas fee	0.0568***	0.0569***	0.0569***	0.0588***
	(0.0061)	(0.0061)	(0.0061)	(0.0062)
$1.[R_{ETH/USDT} > 2std]$		0.0002**	0.0003**	0.0002***
		(0.0001)	(0.0002)	(0.0001)
$1.[R_{ETH/USDT} < 2std]$			0.0002	0.0001**
			(0.0001)	(0.0000)
$\sigma_{ETH/USDT}$				0.0056***
				(0.0013)
Intercept	0.0005***	0.0005***	0.0003**	0.0002***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
R-squared	0.0470	0.0506	0.0508	0.0659
No. observations	2156	2156	2156	2095

Note: Table presents regressions of the fundamentals of absolute CIP violations. $|CIP|$ is the absolute CIP violation and is the sum of three components: the futures premium, the funding rate, and the (negative of) interest rate difference between USDT and ETH. Explanatory variables include the gas fee, which is the median transaction fee paid to miners on Ethereum blockchain and calculated by coinmetrics. $1.[R_{ETH/USDT} > 2std]$ and $1.[R_{ETH/USDT} < 2std]$ are indicator variables for ETH/USDT returns that are greater or less than 2 standard deviations. $\sigma_{ETH/USDT}$ is a rolling standard deviation of ETH/USDT. The sample period is from 12th November 2021 to 23rd October 2022. All variables are measured in per cent. Sample is from November 1st, 2020 to October 23rd, 2022, and is based on 8 hour intervals at UTC 0:00, 8:00 and 16:00 which correspond to when the funding rate is paid by long futures holders to short futures holders on perpetual futures contracts. White heteroscedasticity robust standard errors are used in estimation. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 6: Determinants of future spot changes in ETH-USDT

	(1)	(2)	(3)	(4)
	r_{t+h}	r_{t+h}	r_{t+h}	r_{t+h}
forward premium	0.4320			-1.8995
	(0.7668)			(1.4347)
funding rate		3.8359*		4.6495
		(1.9803)		(3.0709)
$i_L^{USDT} - i_L^{ETH}$			17.2471	6.7997
			(19.6166)	(20.9461)
$\sigma_{ETH/USDT}$				0.1903
				(0.2041)
wealth ratio				0.1243*
				(0.0677)
Intercept	0.0005	-0.0003	0.0001	-0.0031*
	(0.0007)	(0.0008)	(0.0008)	(0.0019)
R-squared	0.0001	0.0029	0.0004	0.0065
No. observations	2160	2160	2160	2157

Note: Table presents regressions of the fundamentals of UIP violations. r_{t+h} is the per cent change in the 8 hour ahead spot rate. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. $\sigma_{ETH/USDT}$ is a rolling standard deviation of ETH/USDT. Sample is from November 1st, 2020 to October 23rd, 2022, and is based on 8 hour intervals at UTC 0:00, 8:00 and 16:00 which correspond to when the funding rate is paid by long futures holders to short futures holders on perpetual futures contracts. All variables are measured in per cent. White heteroscedasticity robust standard errors are used in estimation. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Online Appendix to

"DeFi Lending Protocols and the Carry Trade"

(Not for publication)

A Model Derivations

Proof of Proposition 1.

Both types of investor solve the following constrained optimization problem:

Optimists' Lagrangian function is given as follows:

$$L(\Delta_O) = E\left[\tilde{W}_O\right] - \frac{1}{2}\gamma Var\left[\tilde{W}_O\right] + \lambda_1 \Delta_O + \lambda_2(\bar{\Delta} - \Delta_O) \tag{62}$$

Expected wealth of optimists is

$$E\left[\tilde{W}_O\right] = W_O(\mu^+ + \Delta_O(\mu^+ - 1) + i_D^E - \Delta_O i_L^U) \tag{63}$$

$$= W_O\left(\mu^+ + \Delta_O(\mu^+ - 1) + \frac{b_E(1-\theta)\Delta_P^2 W_P^2}{W_O^2} - \frac{b_U \Delta_O^2 W_O}{W_P}\right) \tag{64}$$

Variance of future wealth of optimists:

$$Var\left[\tilde{W}_O\right] = W_O^2(1+\Delta_O)^2\sigma^2. \tag{65}$$

The first-order condition of the optimization problem (62) is

$$\frac{\partial L}{\partial \Delta_O} = W_O\left[(\mu^+ - 1) - \frac{2b_U W_O \Delta_O}{W_P}\right] - \gamma W_O^2 \sigma^2(1+\Delta_O) + \lambda_1 - \lambda_2. \tag{66}$$

In region $0 < \Delta_O < \bar{\Delta}$ and $\lambda_1 = \lambda_2 = 0$ we can derive an expression for the optimal leverage ratio of investor O:

$$0 = W_O\left[(\mu^+ - 1) - \frac{2b_U W_O \Delta_O}{W_P}\right] - \gamma W_O^2 \sigma^2(1+\Delta_O), \tag{67}$$

$$\Delta_O = \frac{W_P}{W_O}\left(\frac{\mu^+ - 1 - \gamma\sigma^2 W_O}{\gamma\sigma^2 W_P + 2b_U}\right). \tag{68}$$

Pessimists' Lagrangian function is given as follows:

$$L(\Delta_P) = E\left[\tilde{W}_P\right] - \frac{1}{2}\gamma Var\left[\tilde{W}_P\right] + \lambda_1 \Delta_P + \lambda_2(\bar{\Delta} - \Delta_P) \tag{69}$$

Expected wealth of pessimists is:

$$E\left[\tilde{W}_P\right] = W_P(1 + \Delta_P(1 - \mu^-) + i_D^U - \Delta_P i_L^E) \tag{70}$$

$$= W_P\left(1 + \Delta_P(1-\mu^-) + \frac{b_U(1-\theta)\Delta_O^2 W_O^2}{W_P^2} - \frac{b_E \Delta_P^2 W_P}{W_O}\right). \tag{71}$$

Variance of future wealth of pessimists:

$$Var\left[\tilde{W}_P\right] = W_P^2 \Delta_P^2 \sigma^2. \tag{72}$$

The first-order condition of the optimization problem (62) is

$$\frac{\partial L}{\partial \Delta_P} = W_P\left[(1-\mu^-) - \frac{2b_E W_P \Delta_P}{W_O}\right] - \gamma W_P^2 \sigma^2 \Delta_P + \lambda_1 - \lambda_2. \tag{73}$$

In region $0 < \Delta_P < \bar{\Delta}$ and $\lambda_1 = \lambda_2 = 0$ we can derive an expression for the optimal leverage ratio of investor P:

$$0 = W_P\left[(1-\mu^-) - \frac{2b_E W_P \Delta_P}{W_O}\right] - \gamma W_P^2 \sigma^2 \Delta_P, \tag{74}$$

$$\Delta_P = \frac{W_O}{W_P}\left(\frac{1-\mu^-}{\gamma\sigma^2 W_O + 2b_E}\right). \tag{75}$$

Partial derivatives of the optimal demand functions with respect to slope parameters b_E and b_U are:

$$\frac{\partial \Delta_O}{\partial b_U} = \frac{-2\Delta_O}{\gamma\sigma^2 W_P + 2b_U} \tag{76}$$

and

$$\frac{\partial \Delta_P}{\partial b_E} = \frac{-2\Delta_P}{\gamma\sigma^2 W_O + 2b_E}. \tag{77}$$

Substituting in the formula for the slope parameter (20) and (21), optimal b_E and b_U is given as:

$$b_E = \frac{\gamma\sigma^2 W_O}{2}, \tag{78}$$

$$b_U = \frac{\gamma\sigma^2 W_P}{2}. \tag{79}$$

This, in turn, determines the optimal demands functions as:

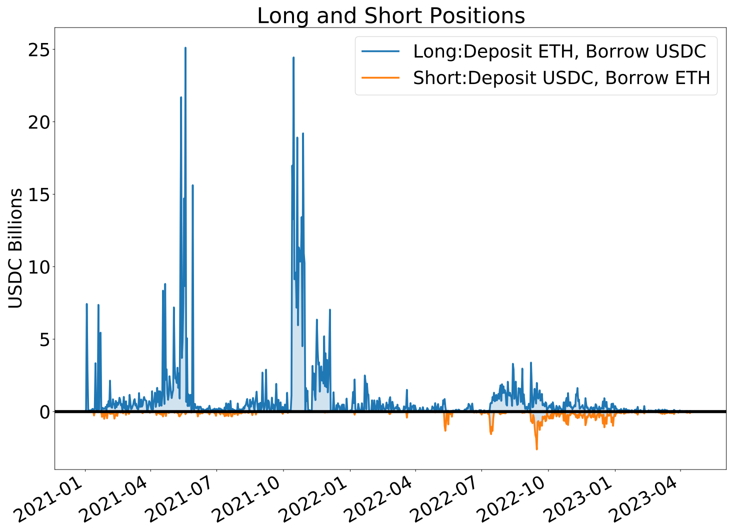
$$\Delta_O = \frac{p^+/p_0 - 1 - \gamma\sigma^2 W_O}{2\gamma\sigma^2 W_O}, \tag{80}$$

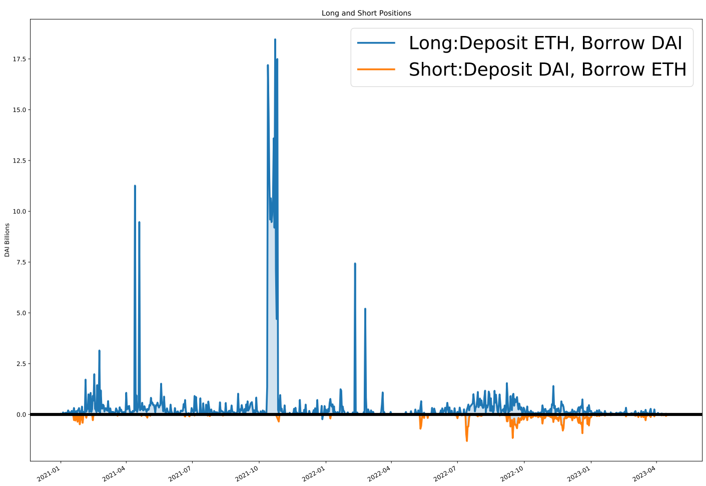
$$\Delta_P = \frac{1 - p^-/p_0}{2\gamma\sigma^2 W_P}. \tag{81}$$

Q.E.D.

B Long-short positions: Robustness using ETH-USDC and ETH-DAI

Figure A1: Aggregate long and short positions for ETH-USDC and ETH-DAI





Note: Figure plots the aggregate long and short positions using transaction data at the wallet level. Long positions (measured along the positive y-axis) aggregate USDT borrowed by investors that deposit ETH as collateral on the Compound protocol. Short positions (measured along the negative y-axis) aggregate ETH borrowed by wallets that deposit USDT as collateral on the protocol. Sample is daily from 1st January 2021 to 22nd April 2023.

Table A1: Determinants of ETH-USDC long and short positions using wallet-transaction level data

	(1) long-short	(2) long-short	(3) long-short	(4) long	(5) long	(6) long	(7) short	(8) short	(9) short
forward premium	4.8968***	5.0852***	6.6052***	3.2282***	3.8439***	5.1451***	-1.6686***	-1.2412***	-1.4601***
	(0.7597)	(1.1031)	(1.2451)	(0.6612)	(1.0010)	(1.1651)	(0.2752)	(0.3228)	(0.3796)
funding rate		-0.5446	0.1337		-1.7804	-1.4272		-1.2357**	-1.5608**
		(1.6833)	(1.9351)		(1.4303)	(1.6987)		(0.6072)	(0.7417)
$\sigma_{ETH/USDT}$			8.3211**			7.8379*			-0.4833
			(4.1622)			(4.0544)			(0.8123)
Intercept	0.6152***	0.6246***	0.2352	0.8575***	0.8880***	0.5262***	0.2423***	0.2634***	0.2910***
	(0.0558)	(0.0656)	(0.2100)	(0.0483)	(0.0568)	(0.2026)	(0.0252)	(0.0279)	(0.0497)
R-squared	0.0740	0.0741	0.1154	0.0429	0.0447	0.0823	0.0495	0.0534	0.0564
No. observations	643	643	613	643	643	613	643	643	613

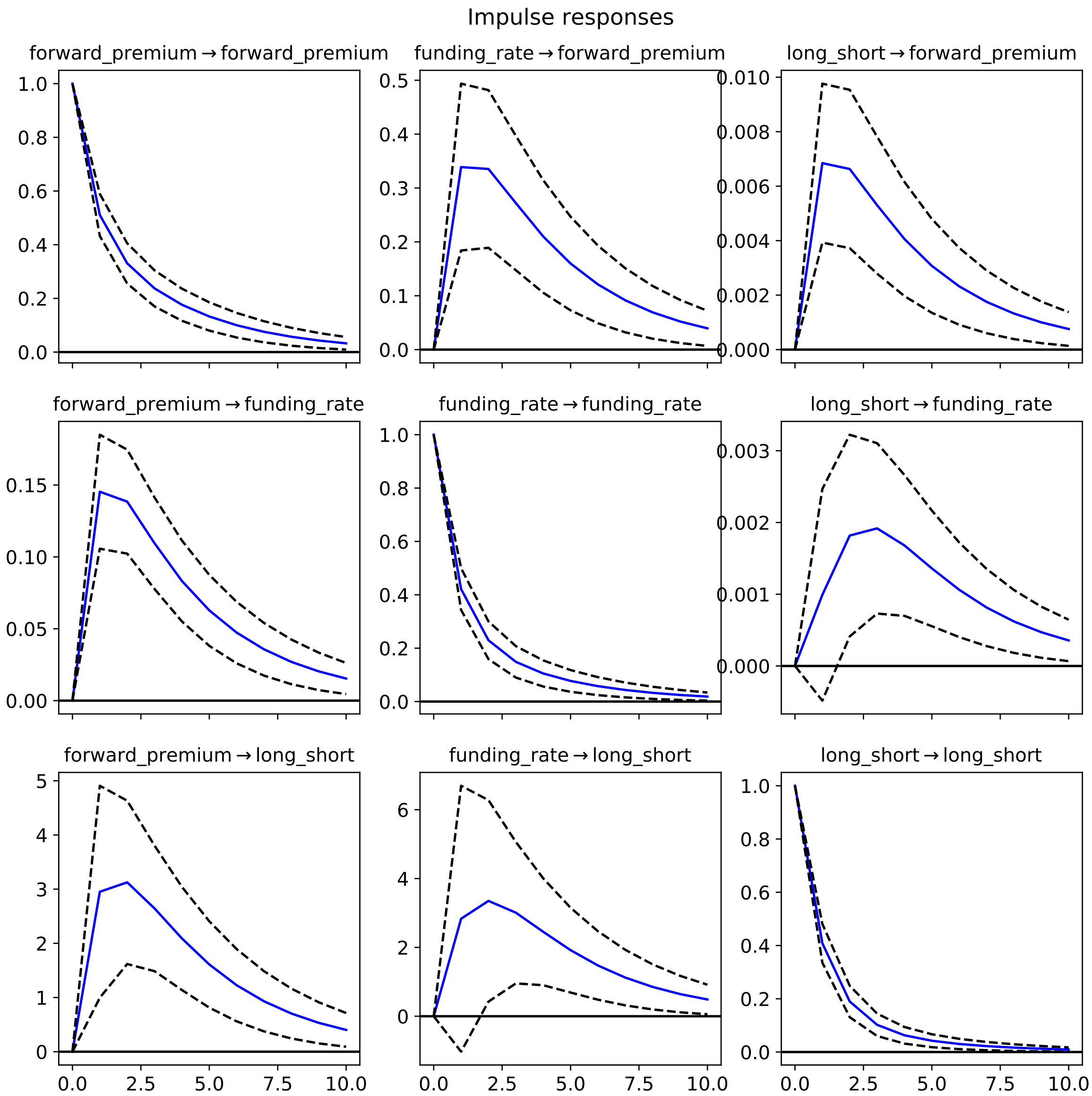
Note: Table presents regressions of the fundamentals of aggregate long and short positions using wallet transaction-level data. Long positions aggregate USDC borrowed by investors that deposit ETH as collateral on the Compound protocol. Short positions aggregate ETH borrowed by wallets that deposit USDC as collateral on the protocol. $long - short$ measures the difference between long and short positions. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. $\sigma_{ETH/USDT}$ is a 30 day rolling standard deviation of ETH/USDT exchange rate. The sample is daily from 1st January 2021 to 22nd April 2023. All explanatory variables are measured in per cent. White heteroscedasticity robust standard errors are used in estimation. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A2: Determinants of ETH-DAI long and short positions using wallet-transaction level data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	long-short	long-short	long-short	long	long	long	short	short	short
forward premium	1.6782***	1.5949***	1.8601***	1.0450***	1.0500**	1.2612**	-0.6332***	-0.5449***	-0.5989***
	(0.3679)	(0.5456)	(0.6230)	(0.3313)	(0.5100)	(0.5926)	(0.1038)	(0.1165)	(0.1282)
funding rate		0.2374	1.0707		-0.0142	0.7330		-0.2517	-0.3378*
		(0.9727)	(1.1434)		(0.9132)	(1.0999)		(0.1586)	(0.1812)
$\sigma_{ETH/USDT}$			5.1843***			4.1295**			-1.0547***
			(1.9897)			(1.9405)			(0.3416)
Intercept	0.3750***	0.3709***	0.0987	0.4575***	0.4577***	0.2416**	0.0825***	0.0868***	0.1429***
	(0.0322)	(0.0357)	(0.1132)	(0.0292)	(0.0326)	(0.1090)	(0.0111)	(0.0118)	(0.0255)
R-squared	0.0329	0.0330	0.0625	0.0155	0.0155	0.0378	0.0435	0.0445	0.0515
No. observations	580	580	556	580	580	556	580	580	556

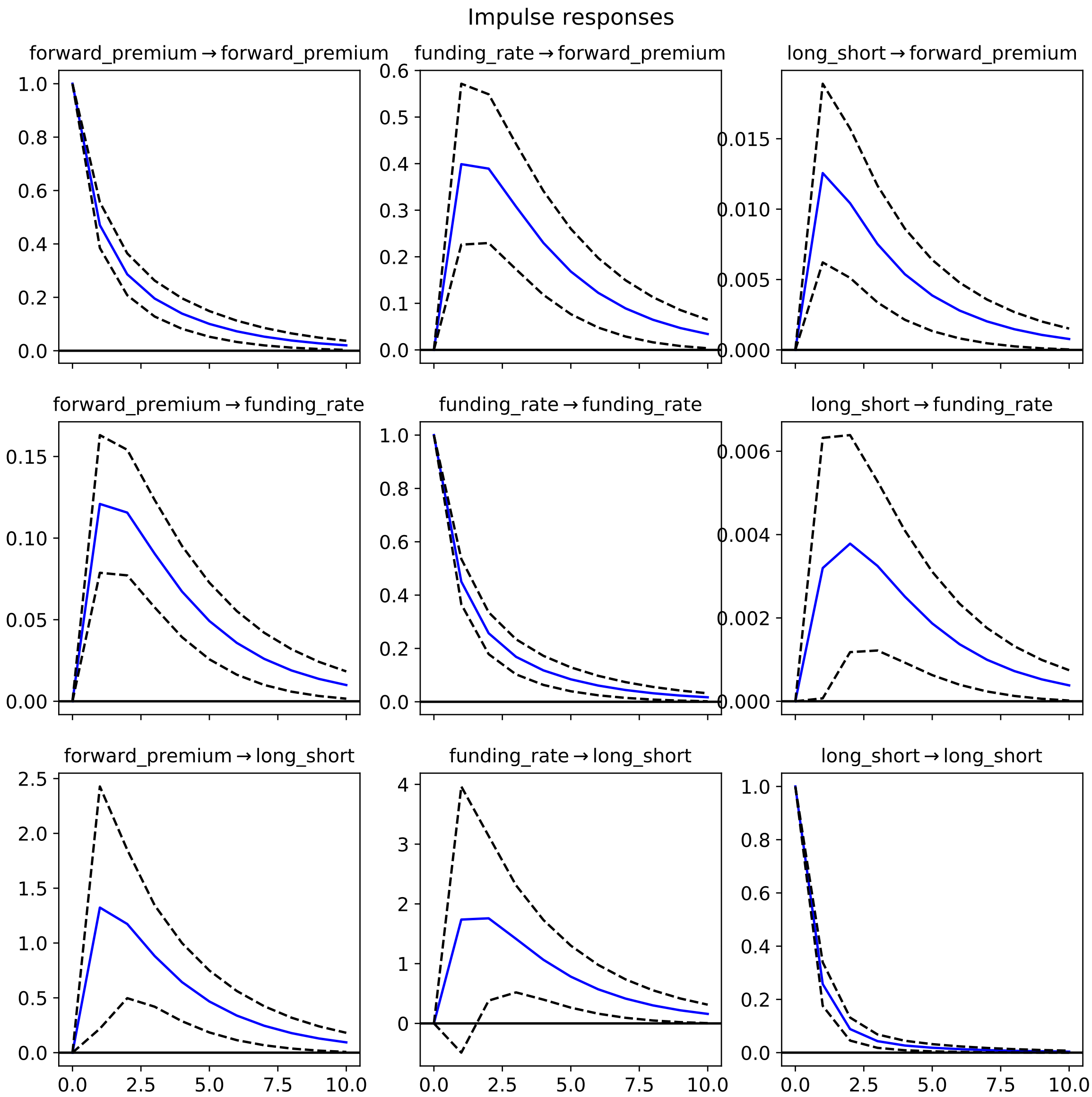
Note: Table presents regressions of the fundamentals of aggregate long and short positions using wallet transaction-level data. Long positions aggregate DAI borrowed by investors that deposit ETH as collateral on the Compound protocol. Short positions aggregate ETH borrowed by wallets that deposit DAI as collateral on the protocol. $long - short$ measures the difference between long and short positions. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. $\sigma_{ETH/USDT}$ is a 30 day rolling standard deviation of ETH/USDT exchange rate. The sample is daily from 1st January 2021 to 22nd April 2023. All explanatory variables are measured in per cent. White heteroscedasticity robust standard errors are used in estimation. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Figure A2: VAR impulse responses: feedback effects of forward premia, ETH-USDC long-short positions and the funding rate



Note: Figure plots the impulse responses of a VAR with three variables: the forward premium, the funding rate and the aggregate long-short positions. *longshort* is measured as the difference between long (deposit ETH and borrow USDC) and short (deposit USDC and borrow ETH) position using wallet-level data, in billions USD. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. 1 lag is included in the baseline specification and daily data is used for the analysis. Dotted lines denote a standard error band equivalent for statistical significance at the 5% level

Figure A3: VAR impulse responses: feedback effects of forward premia, ETH-DAI long-short positions and the funding rate



Note: Figure plots the impulse responses of a VAR with three variables: the forward premium, the funding rate and the aggregate long-short positions. *longshort* is measured as the difference between long (deposit ETH and borrow DAI) and short (deposit DAI and borrow ETH) position using wallet-level data, in billions USD. The forward premium is the difference between futures and spot prices of ETH/USDT, and funding rate is a rate paid by long position holders to the short position every 8 hours on a perpetual futures contract. 1 lag is included in the baseline specification and daily data is used for the analysis. Dotted lines denote a standard error band equivalent for statistical significance at the 5% level