Modelling and Simulation of Cryptocurrency Lending

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Modelling and Simulation of Cryptocurrency Lending

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Abstract

Depositing and borrowing in a currency other than the local currency is a well-documented phenomenon. The associated exchange rate and monetary risks, pivotal during the Asian Financial Crisis of 1997, prompted an academic discourse. Financial dollarization literature explains why individuals and corporations domiciled in emerging markets deposit and borrow in hard currencies, mainly in U.S. dollars. This thesis proposes a model for cryptocurrency lending and assesses model predictions with a data set containing more than one million Ethereum transactions. The computational modelling and statistical analysis show that the main theoretical explanations provided by financial dollarization literature may not be directly transferable to cryptocurrencies. The results suggest that the popularity of depositing and borrowing in cryptocurrencies must be largely motivated by other factors.

Dedication

This thesis work is dedicated to my family, which has been a constant source of support and encouragement during the challenges of graduate school and life.

Acknowledgments

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Chapter I.

Introduction

This microeconomic model and simulation of cryptocurrency lending is designed to identify and to quantify factors motivating depositing and borrowing in cryptocurrencies. Depositing and borrowing in cryptocurrencies via decentralized finance (DeFi) systems has became increasingly popular (Aramonte et al., 2022), but, to the best knowledge of the author, the motivation for these transactions has not been formally assessed. The question of whether to deposit and borrow in cryptocurrencies or in fiat currencies is comparable to questions addressed by financial dollarization literature. The preference of individuals and corporations domiciled in emerging markets for deposits and loans in U.S. dollars over local currencies is called financial dollarization (Ize & Yeyati, 2003). The terms dollarization and euroization are often interchangeable, but euroization is mostly used in the context of emerging Eastern European countries aspiring to an integration into the European Monetary Union (Yeyati, 2006). Depositing and borrowing in U.S. dollars exposes residents of emerging markets to foreign currency risks and external monetary shocks, but access to foreign funds, a lack of trust in the local financial system, the need to hedge cash flows, and a desire to diversify or to optimize returns are important reasons for financial dollarization (Yeyati, 2006; McBrady & Schill, 2007; Basso et al., 2011; Fidrmuc et al., 2013). Numerous studies have shown that financial institutions influence dollarization as well (Luca & Petrova, 2008; Brown & De Haas, 2012; Ivashina et al., 2015).

Some of these factors, especially return optimization or diversification, might also explain depositing and borrowing in cryptocurrencies. The unique lending mechanism of DeFi systems enables individuals to deposit and borrow in cryptocurrencies. This lending mechanism is shaped by the fixed money supply and anonymity in the cryptocurrency space. Unlike fiat currencies, cryptocurrencies cannot be issued by central authorities, nor can financial institutions create cryptocurrencies at will. In that sense, the supply of cryptocurrencies is fixed. This means that borrowers depend on depositors to provide liquidity. The supply of liquidity and the demand for it determine the interest rates of cryptocurrency loans and deposits in DeFi systems. The credit quality of borrowers does not influence the interest rates of cryptocurrency loans because borrowers are anonymous. The anonymity of borrowers and the volatility of cryptocurrencies call for sufficient collateral to secure loans. Cryptocurrency loans are typically well-overcollateralized and backed by cryptocurrency assets. Hence, borrowers have a net long position in cryptocurrencies and benefit from a price appreciation of the long leg. This stands in contrast to financial dollarization literature where borrowers have a net short position in the foreign currency.

This thesis contributes to financial dollarization literature by expanding its scope to cryptocurrencies and by adjusting its model to the lending mechanism of cryptocurrencies in DeFi systems. The economic model covers cryptocurrency borrowing in two variations and cryptocurrency depositing. Transactional data was extracted from the Ethereum blockchain to assess the economic model. The data set containing more than one million on-chain transactions reveals realized deposit and borrow rates as well as the amounts deposited or borrowed. The computational modelling and statistical analysis evaluates major predictions of the economic model. Time series regression models were used to assess the predictability of the economic model with the data set containing more than one million Ethereum transactions. Model predictions related to cryptocurrency depositing and borrowing were rigorously tested in several specifications. The results suggest that the popularity of depositing and borrowing in cryptocurrencies must be largely motivated by factors unrelated to the theoretical explanations provided by financial dollarization literature.

The rest of the study is organized into six chapters. Chapter II provides background information describing the lending mechanism of cryptocurrencies and contrasting it with the lending mechanism of fiat currencies. The formalization of the microeconomic model can be found in Chapter III. Chapter IV contains the presentation of the data, Chapter V explains how model predictions were tested empirically, and Chapter VI gives core empirical results. Finally, Chapter VII provides a conclusion to the study.

Chapter II.

Background

This chapter provides background information describing the lending mechanism of cryptocurrencies and contrasting it with the lending mechanism of fiat currencies. The economic significance of lending and lending of fiat currencies in the traditional banking system are summarized first. The subsequent description of the lending mechanism of cryptocurrencies emphasizes some unique characteristics reflected in the theoretical framework of this study.

The Economic Significance of Lending

Lending promotes economic growth by financing investments and consumption (Koursaros et al., 2021). Entrepreneurs rely on lending to carry out innovative and productivity-enhancing activities. These activities improve the long-term growth potential of economies (King & Levine, 1993a). King and Levine (1993a, 1993b) as well as Koursaros et al. (2021) provide empirical evidence for the positive relationship between lending and economic activity. Berger and Sedunov (2017) demonstrate the same relationship between liquidity created by banks and economic activity.

The relationship between lending and economic growth is not trivial. Rousseau and Wachtel (1998), for example, observe country-specific differences in this relationship. Moreover, Koursaros et al. (2021) as well as Law and Singh (2014) show that lending only has a positive effect on economic growth as long as debt levels do not exceed a certain threshold. Excessive or rapidly increasing debt levels can even have a negative impact on economic growth by triggering a financial crisis (Rousseau & Wachtel, 2011).

Traditional Bank Lending

Traditionally, banks act as intermediaries in lending. Although their regulatory frameworks give banks some discretion over the use of their funds, banks typically lend a large part of their funds out. While deposits are an important funding source for banks, banks do have multiple other funding sources at their disposal.

Individuals placing fiat currency into deposit accounts are savers. They are not directly involved in lending. Banks are largely financed with deposits, and they can use these deposits to issue loans or to acquire other assets (Hanson et al., 2015). Liquid assets and sight deposits held by banks at central banks are necessary to meet minimum reserve requirements and liquidity needs (Jordan, 2018). As long as banks meet these requirements, they can lend deposits or newly created money to creditworthy borrowers (McLeay et al., 2014). The assessment of creditworthiness alone is a crucial function of banks because it ensures that loans are used productively (Bernanke & Blinder, 1988). Banks assess the creditworthiness of borrowers and may ask for collateral to secure loans (Bianchi & Mendoza, 2018). Banks can hold these loans to maturity or securitize them (Brunnermeier, 2009). The demand for loans depends predominately on the official rate set by the central bank, because this rate determines borrowing costs (McLeay et al., 2014). Attracting deposits, money creation, securitization, wholesale funding, and other tools usually allow banks to meet this demand.

Cryptocurrency Lending in DeFi Systems

Amongst other systems, DeFi systems facilitate cryptocurrency lending. DeFi systems, such as Aave, Compound, and MakerDao, are intermediaries operating liquidity pools in which individuals can deposit their cryptocurrency assets and from which individuals can borrow these assets. As measured by the total value locked, cryptocurrency lending temporarily hit the $50 billion mark in early 2022 (Aramonte et al., 2022). This study investigates cryptocurrency lending with a data set of more than one million on-chain transactions with a combined transaction value of more than $350 billion.

DeFi systems operate liquidity pools to match the supply and demand for cryptocurrency assets with blockchain-based lending protocols governed by a smart contract. Ethereum supports blockchain-based smart contracts efficiently (Hegedűs, 2018), and, therefore, Ethereum became the dominant blockchain for hosting lending protocols (Qin et al., 2021). Lending protocols set the rules for depositing and borrowing. Individuals can contribute to the liquidity pool by depositing cryptocurrency assets in order to earn interest on them. When individuals deposit cryptocurrency assets, they receive interest-bearing tokens in return for their cryptocurrency assets (Sriman & Kumar, 2022). Other individuals can borrow from the liquidity pool (Qin et al., 2021). DeFi systems use interest rate rules to set the price of loans and deposits. Interest rates are mostly a function of the supply and demand for liquidity within a DeFi system (Gudgeon et al., 2020a). In contrast to banks, DeFi systems have no discretion over the use of liquidity. Only liquidity provided by depositors can be borrowed. DeFi systems cannot invest in other assets when the demand for loans is low. Nor can DeFi systems provide additional liquidity by borrowing in the wholesale market or by money creation when the demand for loans is high.

Unlike banks, DeFi systems do not assess the creditworthiness of borrowers. Since creditworthiness does not play a role in cryptocurrency lending, the borrow rate is the same on all loans and no credit spread is added. Collateral requirements are designed to mitigate credit risks. Borrowers need to deposit collateral in order to borrow assets. The collateral typically becomes part of the liquidity pool and is also lent out (Qin et al., 2021). To incentivize borrowers to honor their obligations despite their anonymity, collateral requirements far exceed 100% of the loan value (Aramonte et al., 2022). These collateral requirements limit borrowing to borrowers owning sufficient assets, which affects financial inclusion. Price volatility can lead to violations of collateral requirements. If the collateral value falls below a predefined threshold and the borrower cannot provide additional collateral, the loan will be liquidated (Ojog, 2021).

Gudgeon et al. (2020a) as well as Zhang and Jin (2020) point out that insufficient liquidity is a common problem in P2P and DeFi lending systems. The design of Bitcoin and most other cryptocurrencies does not allow central authorities and financial institutions to issue currency at will to provide liquidity (Nakamoto, 2008). In that sense, the supply of cryptocurrencies is fixed. The fixed supply has often been regarded as an advantage of cryptocurrencies supposedly preserving their value (Thompson, 2018), but the fixed supply also has implications for cryptocurrency lending. In addition to shortages of liquidity, cryptocurrencies and cryptocurrency lending would potentially create deflationary pressure and debt-deflation problems in real economies (Malherbe et al., 2019). Debt-deflation describes a situation in which the real value of debt increases over time due to deflation. The burden of interest and of principle payments increases for borrowers in this situation (Fisher, 1933). Nevertheless, this study is focused on microeconomic factors explaining cryptocurrency lending, and further considerations, such as debt-deflation problems or financial inclusion, are not part of this evaluation.

Chapter III.

Modelling and Simulation

This chapter presents the economic model. It is based on models found in financial dollarization literature (Levy, 1981; Thomas, 1985; Ize & Yeyati, 2003). The proposed theoretical framework is introduced briefly in the first part of this chapter. The second part presents the model for depositing and the third part the model for borrowing. The fourth part provides some background information describing interest-rate rules of DeFi systems.

Proposed Theoretical Framework for Cryptocurrency Lending

The proposed theoretical framework for cryptocurrency lending is inspired by dollarization literature and takes the lending mechanism of cryptocurrencies in DeFi systems into account. DeFi systems facilitate cryptocurrency lending by operating liquidity pools in which individuals can deposit cryptocurrency assets and from which individuals can borrow these assets. Individuals only interact with liquidity pools and not directly with each other. Individuals placing cryptocurrency assets in liquidity pools are called depositors. Depositors are not directly involved in lending, but they provide the liquidity needed to offer loans. Individuals taking out cryptocurrency loans are called borrowers.

The economic model treats depositing and borrowing as separate transactions. The model for depositing regards depositors as price-takers choosing between fiat currency and cryptocurrency deposits. This model is based on Levy (1981) as well as on Ize and Yeyati (2003). The model for borrowing considers borrowers as individuals optimizing their balance sheet consisting of assets and loans depending on capital and collateralization constraints as well as on current market prices. Ize and Yeyati (2003), McBrady and Schill (2007), and Basso et. al. (2011) serve as examples for the borrowing model. Both models use portfolio theory concepts.

Model for Depositing and Simulation of Model Predictions

Depositors optimize their short-term liquidity needs (l) by placing some of their assets into interest-bearing accounts. In this simple one-period model, inspired by Levy (1981) as well as Ize and Yeyati (2003), depositors can hold a combination of fiat currency deposits (d_f) at traditional banks and cryptocurrency deposits (d_c) at DeFi systems. The holding period begins the day after the funds were deposited (t_0) and includes the day the funds were withdrawn (t_1). Traditional banks offer a deposit rate equivalent to the risk-free rate (r_f) set by the central bank. The rate on deposits at DeFi systems (r_{cd}) is determined by supply and demand. In addition to r_{cd}, the value of d_c in fiat currency terms depends on the exchange rate (S). Depositors decide on the composition of their deposits in t_0 and earn a return (r_d) in t_1:

$$r_d = \frac{d_{f,1} + \frac{S_1}{S_0} d_{c,1}}{d_{f,0} + S_0 d_{c,0}} - 1 \tag{1}$$

The total return on deposits is expressed in fiat currency terms. The equation can be simplified by replacing $d_{f,0}$ with d_f and $d_{f,1}$ with $d_f(1+r_f)$. Likewise, $d_{c,0}$ can be replaced with d_c and $d_{c,1}$ with $d_c(1+r_{cb})$. By further normalizing S_0 to 1, r_d can be expressed as:

$$r_d = \frac{d_f r_f + d_c(S_1 + S_1 r_{cd} - 1)}{d_f + d_c} \tag{2}$$

It is further demanded that the sum of the deposits must equal the value of liquid assets and it is assumed that all variables are non-negative. This prevents depositors from shorting and rates from becoming negative. Negative deposit rates might prompt depositors to hold liquid assets in cash rather than in deposits. This expression can then be simplified to:

$$r_d = x_f r_f + x_c(S_1 + S_1 r_{cd} - 1) \tag{3}$$

where x_f is the share of liquid assets deposited in fiat currency, and x_c is the share deposited in cryptocurrency. The first term on the right-hand side can be thought of as the portion of return coming from fiat currency deposits. The second term is the return contribution of cryptocurrency deposits.

It can be assumed that depositors are risk-averse, and their maximization problem can be represented by:

$$max\, U(r_d) = r_d - \frac{a_d}{2} Var(r_d) \tag{4}$$

s.t.: $x_f + x_c = 1$

$x_f, x_c \geq 0$

$a_d > 0$

a_d reflects the risk aversion of depositors, while Var is the variance operator. Assuming that r_f is risk-free and has a volatility of zero, x_f and x_c can be obtained by using the Lagrangian method to solve this optimization problem (see Appendix for details):

$$x_c = \frac{S_1 + S_1 r_{cd} - r_f - 1}{a_d(Var(S_1) + Var(S_1 r_{cd}) + 2Cov(S_1, S_1 r_{cd}))} \tag{5}$$

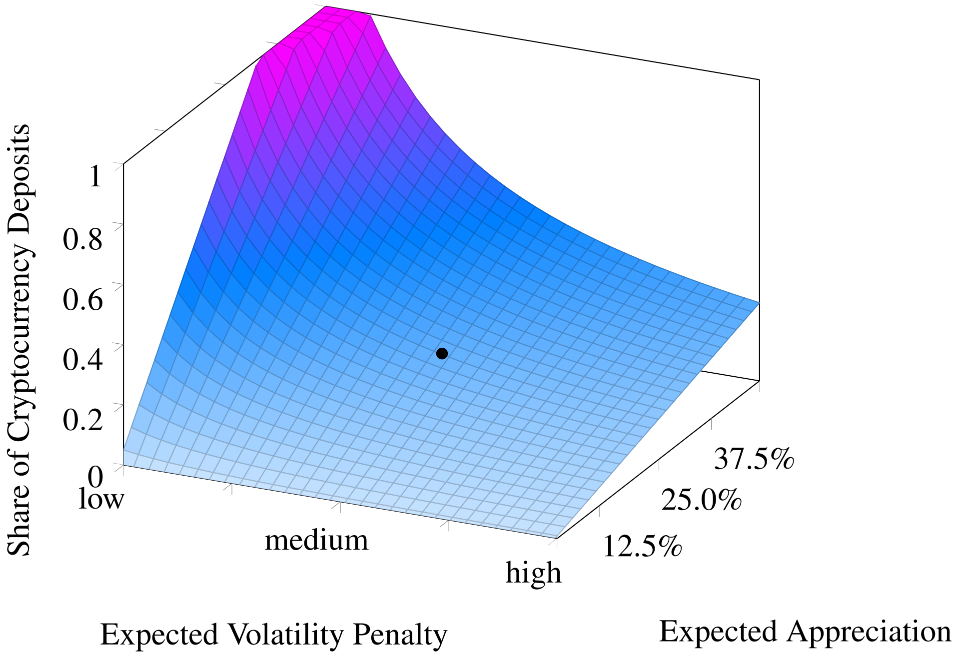
$$x_f = 1 - \frac{S_1 + S_1 r_{cd} - r_f - 1}{a_d(Var(S_1) + Var(S_1 r_{cd}) + 2Cov(S_1, S_1 r_{cd}))} \tag{6}$$

Cov denotes the covariance operator. It can be seen that x_f is simply $1 - x_c$. The share of fiat currency deposits increases with r_f and the total variance associated with cryptocurrency deposits $(Var(S_1) + Var(S_1 r_{cd}) + 2Cov(S_1, S_1 r_{cd}))$. x_f decreases with S_1 and r_{cd}. Conversely, depositors will hold more cryptocurrency deposits if they expect S_1 or r_{cd} to increase. The higher the risk aversion (a_d), the lower the share of cryptocurrency deposits.

Drawing on exchange-rate and interest-rate data from popular cryptocurrencies, such as Ether and Bitcoin, this model suggests that depositors are unlikely to hold the majority of their deposits in cryptocurrency. Figure 1 provides a visualization of the influence of key variables on the optimal share of cryptocurrency deposits. The graph is based on a simulation and shows the share of cryptocurrency deposits as a function of the expected price appreciation (S_1) and the expected penalty associated with the volatility of cryptocurrency deposits $(a_d(Var(S_1) + Var(S_1 r_{cd}) + 2Cov(S_1, S_1 r_{cd})))$. The x-axis labels say *low*, *medium*, and *high* because the numeric value of the penalty associated with the volatility of cryptocurrency deposits is difficult to interpret. The *medium* value is based on daily return data for Ether. The *high* value is 70% higher than the *medium* value, while the *low* value is 70% lower. An explanation for the choice of parameters can be found in the chapter on data. Assuming an expected price appreciation of 25%, an a_d of 2.4, a r_f of 5%, and a r_{cd} of 1.97%, the share of cryptocurrency deposits of l will be about 22.9% based on daily return data for Ether.

Figure 1

Simulation of the Share of Cryptocurrency Deposits



In conclusion, stable coin deposits with minimal price volatility and deposit rates comparable to r_f would be a preferable alternative to fiat currency deposits. Highly volatile cryptocurrencies would be an unlikely choice.

Model for Borrowing and Simulation of Model Predictions

Borrowers choose an ideal combination of funding sources for their investments (I) depending on capital and collateralization constraints. Funding influences the leveraged rate of return (r_b). Maximization of returns is a common approach in dollarization models (Ize & Yeyati, 2003; McBrady & Schill, 2007; Basso et al., 2011). I generates an unlevered return of r_i. The initial capital (w) controlled by borrowers is given, and borrowers can choose to borrow additional funds in fiat currency (b_f) or cryptocurrency

(b_c) as long as they meet capital requirements. Including all costs, b_f must not exceed a specific multiple (k_f) of w. In addition to the risk-free rate (r_f), borrowers have to compensate lenders for bearing credit risk (cs). If borrowers choose to combine b_f with b_c, they need to hold cryptocurrency assets (c) to back b_c. c serving as collateral is assumed to be not-interest bearing, which is a standard practice with many DeFi systems. b_c must not exceed a specific fraction (k_c) of w. The costs of borrowing cryptocurrency is r_{cb}. Like I, w, and b_f, b_c is denominated in fiat currency terms. It is assumed that loans are either denominated in a stable coin or fiat currency. The exchange rate of c is S. In this simple model, borrowers decide on investing and funding in t_0 and earn a (leveraged) rate of return (r_b) in t_1:

$$r_b = \frac{Ir_i + c(S_1 - 1) - b_f(r_f + cs) - b_c r_{cb}}{I + c - b_f - b_c} \tag{7}$$

For the sake of simplicity, S_0 has been normalized to 1. Borrowers can choose I, b_f, b_c, and c to influence r_b, but they have to respect the capital requirements. In the style of Bianchi (2011), the capital requirements are:

$$w \geq \frac{1}{k_f} b_f(1 + r_f + cs) + \frac{1}{k_c} b_c(1 + r_{cb}) \tag{8}$$

The given level of w restricts borrowing in general. The first term on the right-hand side is the capital requirement for b_f and the second term is the capital requirement for b_c. The latter term is the minimum value of c according to the collateralization requirement:

$$c \geq \frac{1}{k_c} b_c(1 + r_{cb}) \tag{9}$$

The overcollateralization of b_c implies that k_c is strictly smaller than one and that the choices of b_c and c are interdependent. Furthermore, it is demanded that the sum of assets ($I + c$) must equal the sum of liabilities ($b_f + b_c + w$) and it is assumed that all variables are non-negative. Since the sum of assets must equal the sum of liabilities, w equals the sum of assets minus the sum of loans, while r_b can be expressed as:

$$r_b = \frac{Ir_i}{w} + \frac{c(S_1 - 1)}{w} - \frac{b_f(r_f + cs)}{w} - \frac{b_c r_{cb}}{w} \tag{10}$$

or

$$r_b = y_i r_i + y_c(S_1 - 1) - y_f(r_f + cs) - y_{cb} r_{cb} \tag{11}$$

y_i is the share of w spent on I, y_c is the share of w held in cryptocurrency, and y_f and y_{cb} are the proportions borrowed in fiat currency and cryptocurrency. The first term on the right-hand side can be thought of as the leveraged return on I. The second term is the return on cryptocurrency assets held (as collateral). The third term is the cost of borrowing in fiat currency, and the last term is the cost of the cryptocurrency loan.

Three observations can be made at first glance from market data and literature on mean-variance utility maximization. Firstly, it confirms the necessity of the capital constraints in (8). If borrowers have optimistic expectations, they will be tempted to leverage their investments excessively. The unconstrained optimization of mean–variance utility can lead to excessive leverage (Jacobs & Levy, 2012; Markowitz, 2013). Secondly, borrowers would have no incentive to back cryptocurrency loans calling for the collateral requirement in (9). As shown in Chapter IV, borrow rates on stable coins can be lower than the effective federal funds rate. Taking advantage of the interest differential without providing collateral would be appealing, particularly for borrowers being charged high credit spreads on loans in fiat currency. Furthermore, holding cryptocurrency assets would introduce additional exchange rate volatility dominating potential return and diversification benefits. Thirdly, although the collateralization requirement is a limitation, borrowers are likely to provide more collateral than required when they choose to take out a cryptocurrency loan. Additional collateral reduces the liquidation risks (Aramonte et al., 2022). It can be inferred from this observation that the constraints in (8) and (9) are inequality conditions.

The maximization of returns for borrows incorporates these observations. As in Markowitz (1956), the expected return can be further reduced to:

$$r_b = r_f + cs + y_i(r_i - r_f - cs) + y_c(S_1 - r_f - cs - 1) - y_{cb}(r_{cb} - r_f - cs) \tag{12}$$

The expected return can be explained as the sum of four components. The first component is traditional funding costs (r_f and cs), which can be regarded as the threshold for investments. The latter are the second and third components: the excess return on investments (r_{invest} = r_i - r_f - cs) and on cryptocurrency assets held as collateral ($r_{collateral}$ = S_1 - r_f - cs - 1) compensating borrowers for taking risks. The fourth component is the implicit costs of cryptocurrency borrowing (r_{cloan} = r_{cb} - r_f - cs). If r_{cb} is smaller than the sum of r_f and cs, total funding costs will decline by taking out a cryptocurrency loan. The expected return is:

$$r_b = r_f + cs + y_i r_{invest} + y_c r_{collateral} - y_{cb} r_{cloan} \tag{13}$$

Like depositors, borrowers are assumed to be risk-averse and to maximize their expected mean-variance utility as in Markowitz (1952). Hence, their maximization problem is:

$$max\, U(r_b) = r_b - \frac{a_b}{2} Var(r_b) \tag{14}$$

s.t.: $1 \geq m_f y_i + m_f y_c + (m_c - m_f) y_{cb} - m_f$ where $m_f > 0$ and $m_c > 1$

$y_c \geq m_c y_{cb}$

$0 \leq y_i, y_f, y_{cb}, y_c, a_b, cs, r_f, r_{cb}, r_i, S_1$

where:

$m_f = \frac{1+r_f+cs}{k_f}$

$m_c = \frac{1+r_{cb}}{k_c}$

The ideal weights for each component can be obtained by using the Lagrangian method to solve this optimization problem. Since the feasible region is bounded by two inequality constraints and non-negativity constraints, Karush-Kuhn-Tucker conditions have been applied to formalize this optimization problem (see Appendix for details). Optimal sets of variables satisfying the inequality and non-negativity constraints can be expressed as:

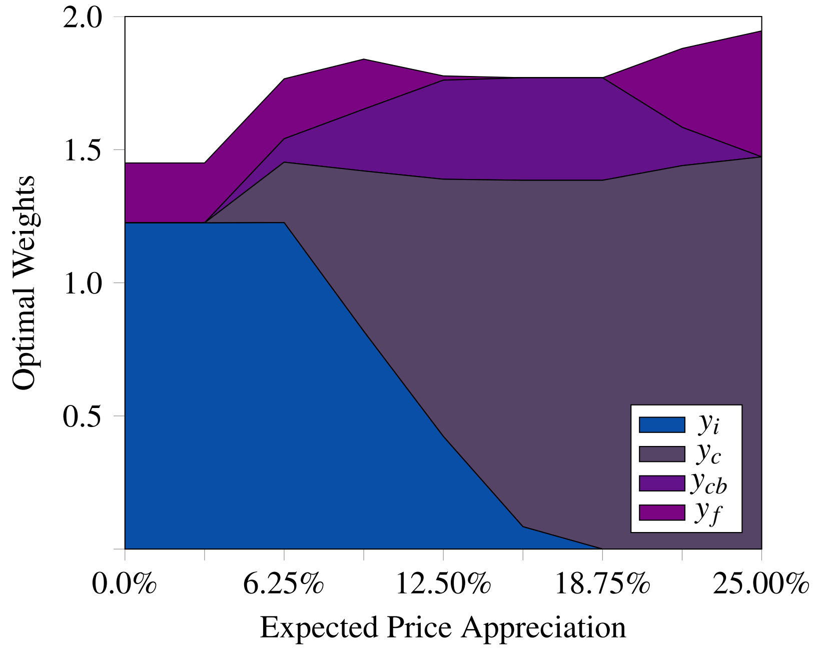
$$y = \Sigma^{-1} \left(\frac{1}{a_b} r \right) \tag{15}$$

In this matrix notation, y denotes a column vector with the weights of y_i, y_c, and y_{cb}. The column vector r represents r_{invest}, $r_{collateral}$, and r_{cloan}. The square matrix Σ is the covariance matrix of all returns. The solution above is valid for sets of variables satisfying the two inequality and the non-negativity constraints. Non-linear programming techniques have to be applied for other sets. This solution with four different components is regarded as the general case.

A second simulation illustrates the ideal weights for different return expectations. The horizontal axis describes the expected price appreciation of the cryptocurrency held as collateral. All other independent variables are held constant. The simulation can be below:

Figure 2

Simulation of Weights Depending on Price Expectations (General Case)



According to this simulation, cryptocurrency borrowing does not strictly increase with the expected price appreciation of cryptocurrencies. This simulation demonstrates that borrowers will prioritize the investment and borrow in fiat currency if they expect muted returns on cryptocurrencies. If they have more optimistic return expectations, borrowers will shift from the investment to cryptocurrencies and from fiat currency to cryptocurrency borrowing. The shift will be more pronounced if borrowers assume that the volatility of cryptocurrencies will be low. If borrowers have highly optimistic expectations, however, they will hold cryptocurrencies and borrow in fiat currency. Although the simulation assumes that the interest on cryptocurrency loans is lower than the interest on fiat currency loans, fiat currency loans become the preferred choice because they allow borrowers to increase their leverage.

Ether is assumed to be the collateral asset in this simulation. The volatility of the collateral asset is based on the current variance of daily Ether returns. $r_{collateral}$ depends on multiple components, but only S_1 has been changed in this simulation. All other components of $r_{collateral}$ were held constant. Overall, a_b is assumed to be 2.4, r_f to be 5%, cs to be 0.7%, r_i to be 8.4%, and r_{cb} to be 3.84%. The absolute value of r_{cb} and its volatility are based on observed USD Coin (USDC) rates at Aave V3. A detailed explanation of the choice of parameters appears in the next chapter.

An alternative case is presented below to account for situations in which cryptocurrencies are the sole asset. When the risk-return expectations for cryptocurrencies are much more favorable than expectations for the investment, the model would suggest shorting the latter. Moreover, some borrowers might only consider investing in cryptocurrencies. Conversely, cases in which the investment is the sole asset are less relevant for this analysis because the collateralization requirement would not allow borrowing cryptocurrencies in these cases. Without y_i, the capital requirement reduces to:

$$m_f y_c + (m_c - m_f) y_{cb} - m_f \leq 1 \tag{16}$$

The collateralization requirement does not change. In this alternative solution, optimal sets of variables satisfying the capital requirement and the collateralization requirement and non-negativity constraints can be written as follows (see Appendix for details):

$$y_c = \frac{Var(r_{cloan})r_{collateral} + Cov(r_{collateral}, r_{cloan})r_{cloan}}{a_b Var(r_{collateral})Var(r_{cloan}) - a_b\left(Cov(r_{collateral}, r_{cloan})\right)^2} \tag{17}$$

$$y_{cb} = \frac{Cov(r_{collateral}, r_{cloan})r_{collateral} + Var(r_{collateral})r_{cloan}}{a_b\left(Cov(r_{collateral}, r_{cloan})\right)^2 - a_b Var(r_{collateral})Var(r_{cloan})} \tag{18}$$

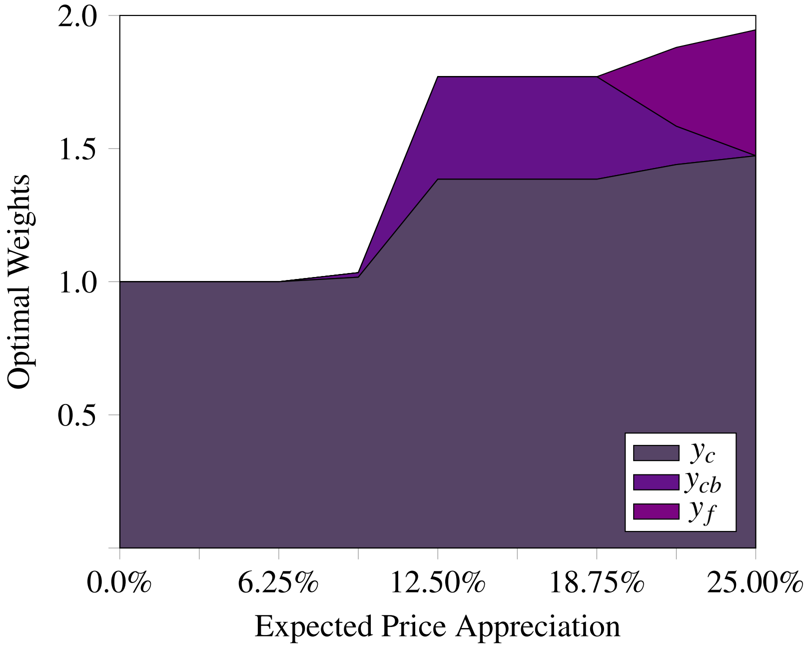
$$\begin{aligned} y_f = {} & \frac{Var(r_{cloan})r_{collateral} + Cov(r_{collateral}, r_{cloan})r_{cloan}}{a_b Var(r_{collateral})Var(r_{cloan}) - a_b\left(Cov(r_{collateral}, r_{cloan})\right)^2} \\ & - \frac{Cov(r_{collateral}, r_{cloan})r_{collateral} + Var(r_{collateral})r_{cloan}}{a_b Var(r_{collateral})Var(r_{cloan}) - a_b\left(Cov(r_{collateral}, r_{cloan})\right)^2} - 1 \end{aligned} \tag{19}$$

The latter equation could be expressed as $y_f = y_c - y_{cb} - 1$. This solution is valid only for sets of variables satisfying the two inequality and non-negativity constraints of the optimization problem. Non-linear programming techniques have to be applied for other sets.

A simulation portrays the alternative case. This simulation shows the optimal weights of y_c, y_{cb}, and y_f depending on the expected price appreciation of the cryptocurrency held as collateral (S_1). Like the previous simulation, this simulation of the alternative case demonstrates that cryptocurrency borrowing does not strictly increase with price expectations. According to this simulation, borrowers will not use loans to leverage their cryptocurrency holdings when they have moderate price expectations. They will only hold cryptocurrency assets then. When price expectations become more optimistic, borrowers will pledge their holdings to take out cryptocurrency loans. The volatility forecast influences this decision. Borrowers expecting low levels of volatility will leverage their holdings sooner than borrowers expecting high levels of volatility. In general, this leverage allows borrowers to participate in the expected market rally. Borrowers might even choose a comparably expensive fiat currency loan to increase their leverage further when price expectations are overly optimistic. The same parameters have been used for this and the previous simulation. All other independent variables were held constant when the effect of price expectations on weights have been simulated. The simulation can be found below:

Figure 3

Simulation of Weights Depending on Price Expectations (Alternative Case)



Model of DeFi Systems

DeFi systems match cryptocurrency depositors and borrowers with interest-rate rules to set the prices of loans and deposits (Aave, 2023a; Compound 2023a). The illustration below explains this price-setting mechanism because it is of economic importance, although interest-rate rules are not directly part of this model.

Prices of loans and deposits depend on supply and demand subject to rules mitigating liquidity risks. In general, DeFi systems try to maintain excess liquidity in their pools in order to absorb deposit outflows and loan liquidations. Excess liquidity can be inferred from the utilization rate (U), which is the ratio of loans to deposits in a liquidity pool. The target utilization rate ($U_{optimal}$) is less than one so that excess liquidity remains available. r_{cb} typically increases moderately with U until U reaches $U_{optimal}$. r_{cb} increases sharply from this point on to encourage depositing and discourage borrowing. In this simple example, the price setting mechanism for r_{cb} is:

$$r_{cb} = \frac{\frac{1}{100}}{1-U} \qquad \forall\, \mathrm{U} \in \mathbb{R} \mid 0 < \mathrm{U} < 1 \tag{20}$$

In this example, r_{cb} is close to one percent when the utilization rate is low. The rate increases moderately at first, but r_{cb} increases sharply as U approaches one.

Interest payments are distributed to all depositors to compensate them for providing capital. Since borrowers borrow from a pool and not from individual depositors, interest payments are being shared among depositors contributing to the liquidity pool. Therefore, r_{cd} also depends on U and is given by:

$$r_{cd} = r_{cb}U(1-R) \tag{21}$$

R denotes the reserve factor of the DeFi system. DeFi systems keep reserves to offset loan losses.

Chapter IV.

Data

This chapter describes the data sources and provides some background information that will be useful for the empirical analysis. The Ethereum blockchain is introduced briefly. This introduction is focused on a description of transactional data and transaction logs on the Ethereum blockchain. This information is highly relevant for the empirical analysis. This part is followed by a discussion of the extraction of transactional data. The full set of cryptocurrency-related data is then presented. This presentation also brings the limitations of this data source and some surprising observations to the attention of the reader. A short summary of additional data is the final part of this chapter.

Ethereum Blockchain and Transactions

The Ethereum blockchain is the data source for cryptocurrency-related information. Ethereum became the dominant blockchain hosting lending protocols because it supports blockchain-based smart contracts efficiently (Hegedűs, 2018; Qin et al., 2021). Smart contracts and other programs stored on the Ethereum blockchain enable automated services (Buterin, 2014). DeFi systems, for example, implement liquidity pools and lending protocols with smart contracts. Individuals controlling so-called externallyowned accounts (EOAs) can interact with contract accounts (CAs) of liquidity pools of DeFi systems. The behavior of CAs solely depends on the code of the corresponding smart contract. The code of CAs is public (Buterin, 2014).

The public availability of the code of CAs and of all transactions allows for an empirical analysis of cryptocurrency lending. Ethereum transactions are actions initiated by EOAs. These transactions are stored on the blockchain and contain information such as sender, recipient, value, and other data. The latter can reveal how EOAs intend to interact with their counterparties. If an EOA intends to interact with a CA, this piece of information will indicate what part of the code, like depositing or withdrawing, the EOA called. In general, the sender and recipient of a transaction are accounts, which can be identified by their addresses (Buterin, 2014). Since the addresses of CAs controlled by DeFi systems are known, information about transactions between EOAs and CAs of DeFi systems can be collected. These transactions are interactions between potential depositors and borrowers on the one side, and a DeFi system on the other side. In conclusion, the Ethereum blockchain stores all transactions between EOAs and DeFi systems including the amount of cryptocurrency involved, the time, and the type (i.e. deposit, withdrawal, borrowing, or repayment). An example can be found below:

Table 1

Example Transaction of an EOA with the Aave Liquidity Pool V3

This table lists selected information from the example transaction with the hash 0x4315ab29b40bec0c5f41112a263f74bcb7d63bc3998f4a1fd518bc520cfe864b

Data Field	Value
functionName	supply
from	0xc5ec4153f98729f4eaf61013b54b704eb282ecf4
to	0x87870bca3f3fd6335c3f4ce8392d69350b4fa4e2
asset (input)	0x2260FAC5E5542a773Aa44fBCfeDf7C193bc2C599
amount (input)	00000000000000000000000000000000002c99558
timeStamp	1688283431

Note. This information has been collected with Etherscan.io.

In this example, an EOA deposited 0.467654 wrapped Bitcoin (WBTC) at Aave on July 2, 2023. The deposit rate was 0.31%. The function to deposit cryptocurrencies with the Aave Liquidity Pool V3 is called supply. The date can be inferred from the $timeStamp$. The EOA is anonymous but its address can be found in the $from$ data field. The recipient (to data field) is a liquidity pool operated by Aave. The EOA called the supply function of the liquidity pool and entered the address of the asset and the amount as a hexadecimal number in the *input* field of this function. The asset with this specific address is WBTC, and the equivalent decimal value of this hexadecimal number is 0.467654. The hash of this transaction identifies it uniquely (see Appendix for details). In general, transactions follow the same protocol on the Ethereum blockchain (Buterin, 2014). The structure of transactions between EOAs and other pools is the same.

It is possible to gather additional information, such as deposit and borrow rates, from transaction logs. A transaction log is a collection of events related to a specific transactions (Ethereum Foundation, 2023). The aforementioned deposit rate can be found in the transaction log (see Appendix for details). Transactions with liquidity pools can affect their reserves. Changes in their reserves will be reflected in interest rates. Most DeFi systems document these changes as events in the transaction log, but what DeFi systems document varies substantially and depends on the implementation of the CA of their liquidity pools.

Deposit and borrow rates can be retrieved directly from log data of transactions with Aave V3 and V2 liquidity pools. Only borrow rates can be inferred from log data of transactions with Compound V2 liquidity pools, whereas deposit rates have to be estimated by subtracting a fixed spread from borrow rates. The interest rate models of the Compound V2 liquidity pools changed multiple times, and trying to replicating these models may have led to inaccurate estimates. Both deposit and borrow rates have to be estimated for transactions with Compound V3. Estimates for Compound V3 involved several computations and a replication of its interest rate model. The table below discloses how interest rates were collected from transaction logs:

Table 2

Retrieval of Interest Rates from Log Data

This table discloses how interest rates were inferred from log data

Rate	Aave V3	Aave V2	Compound V3	Compound V2[a]
deposit	*liquidityRate* of the *ReserveDataUpdated* event	*liquidityRate* of the *ReserveDataUpdated* event	Estimated based on flows and interest rate models	Estimated based on borrow rate and fixed spread of 0.4%
borrow	*variableBorrowRate* of the *ReserveDataUpdated* event	*variableBorrowRate* of the *ReserveDataUpdated* event	Estimated based on flows and interest rate models	Inferred from *borrowIndices* of *AccrueInterest* events

Note. This information is based on Etherscan.io.
[a] Compound (2023b) explains the calculation of interest rates for V2.

Blockchain Data Extraction

Data was extracted from the Ethereum blockchain to analyze the economic motivation of interactions with DeFi systems. As in Aramonte et al. (2022), the DeFi systems Aave, Compound, and MakerDao have been considered as sources for cryptocurrency-related data. Processes vary between these DeFi systems, and these nuances are relevant for the empirical analysis. Despite its size and popularity, MakerDao has not been included in this analysis. The design of this DeFi system is not compatible with the economic model in two key aspects related to the mechanism of the DAI stable coin. Firstly, individuals pay interest on their deposits and not on their loans. The MakerDao system allows individuals to deposit collateral assets in return for DAI stable coins (MakerDao, 2017). The system is designed to fix the value of the DAI stable coin to \$1. Each DAI stable coin is backed by cryptocurrency assets worth more than \$1 to guaranty the fixed exchange rate. MakerDao allows individuals to borrow DAI against collateral assets and charges so-called stability fees on collateral assets. The loan in DAI is interest-free, but DAI can be deposited in MakerDao or other DeFi systems. Secondly, the governing body of MakerDao sets interest rates. Interest rates are a policy tool to maintain the parity exchange rate of the DAI stable coin to the U.S. dollar (MakerDao, 2017). Interest rates are not determined by demand and supply for liquidity. Hence, the variance of interest rates at MakerDao is negligible. According to the economic model, interest-free loans in a stable coin with a fixed exchange rate would reduce the leveraged rate of return formula of borrowers to $r_b = y_i r_i + y_{cb}((S_1 - 1)/k_c) - y_f(r_f + cs)$. The costs of the cryptocurrency loan would drop out of the equation, and only the expected return on collateral assets would remain relevant. The model could no longer be used to explain cryptocurrency borrowing. Moreover, the model assumes positive deposit rates.

Consequently, the Aave and Compound DeFi systems were used in the empirical analysis. Both DeFi systems recently upgraded their protocols from version two to version three. Including both versions of Aave and Compound allows for a time series analysis over multiple years and different interest-rate regimes. Aave V2 and Compound V2 are comparable. Compound V2 was introduced in the year 2019, and Aave V2 was launched in the year 2020. Individuals can deposit selected cryptocurrency assets at both liquidity pools in exchange for interest-bearing tokens wrapped around the same underlying asset (Aave, 2023b; Compound, 2023b). While Compound issues so-called cTokens, Aave issues aTokens. Depositors can withdraw their cryptocurrency assets anytime by returning their interest-bearing tokens. The deposited cryptocurrency assets can serve as collateral for loans. Interest rates on deposits and loans are a function of supply and demand in both cases. Rates are typically variable, but fixed-rate loans are also available. Aave V2 and Compound V2 are both still operational.

Whereas previous versions were similar, Aave and Compound moved into different directions with their upgrades. Compound V3, introduced in the year 2022, is available for the USDC and ETH base assets. Compound V3 maintains two separate liquidity pools for the two base assets. The two base assets can be borrowed from their liquidity pool, if sufficient collateral assets have been deposited. Only deposited base assets, however, earn interest. Other collateral assets can still back loans. The introduction of base assets is supposed to protect the liquidity pools from faultily cryptocurrencies, like TerraUSD (UST). Only the USDC liquidity pool was included in the analysis. As measured by transaction volumes, the launch of the ETH liquidity pool was not successful. Aave V3 followed in the year 2023. Version three also introduced some security as well as some efficiency features. These efficiency features reduce collateral requirements for individuals borrowing assets against collateral with highly correlated prices. The collateral requirements will be lower when individuals borrow one stable coin against another, and requirements will be higher when both assets are uncorrelated.

The extraction of Ethereum blockchain data is powered by Etherscan.io application program interfaces (APIs). Etherscan is a data gathering and retrieval system specifically designed for the Ethereum blockchain (Etherscan, 2023a). Etherscan.io APIs enable developers to retrieve large sets of data electronically (Etherscan, 2023b). The data sets were processed and analyzed with an application implemented in Python. This application was used to extract, organize, and aggregate transactions of EOAs with CAs of liquidity pools of DeFi systems. Erroneous transactions, flash loans, and fixed-rate loans have been excluded. The small number of fixed-rate loans typically has much higher rates than variable loans, and including these loans would have skewed average borrow rates up. Flash loans are predominantly motivated by arbitrage trading. These loans have to be repaid within one arbitrage trade. The complete set of transactional data can be found below:

Table 3

Descriptive Statistics of Transactional Data with Selected DeFi Systems (Functions)

Aggregation of transactions grouped according to functions					
Function[a]	Aave V3	Aave V2	Compound V3[b,c]	Compound V2	Total
deposit	11,898	215,622	5,320	452,035	684,875
withdraw	6,892	129,222	2,266	244,608	382,988
borrow	12,835	179,909	3,685	144,941	341,370
repay	5,208	94,573	1,474	91,042	192,297
others	5,255	52,799	7,146	56,281	121,481
Total	42,088	672,125	19,891	988,907	1,723,011

Note. This information has been collected with Etherscan.io.

[a] The names of functions have been standardized (see Appendix for details).

[b] Compound V3 refers to its USDC liquidity pool only.

[c] The functions for depositing and replaying are the same in Compound V3. The functions for withdrawing and borrowing are also the same. All transactions have been categorized into the four types for this pool in order to understand their economic motivation.

Table 3 summarizes the complete set of observed transactions, which were executed between May 2019 and July 2023. The total number of transactions was 1,723,011. Transactions have been grouped according to functions. The functions borrow, deposit, withdraw, and repay are relevant to the model of cryptocurrency lending. In total, 684,875 times EOAs deposited cryptocurrencies, and 382,988 times deposits were withdrawn again. A total of 341,370 transactions represented borrowing arrangements between EOAs and liquidity pools. A total of 192,297 repayments were observed. The category others include transactions such as liquidation calls, setting changes, approvals, or transfers. Technically, these actions are recorded as transactions on the Ethereum blockchain, but they are not necessarily economically relevant. Table 4 provides an overview of the complete set of observed transactions grouped according to cryptocurrencies. Cryptocurrencies are important because deposit and borrow rates as well as exchange rates are cryptocurrency-specific. Derivatives of the same underlying cryptocurrency were aggregated.

Table 4

Descriptive Statistics of Transactional Data with Selected DeFi Systems (Currencies)

Aggregation of transactions grouped according to cryptocurrencies					
Currency	Aave V3	Aave V2	Compound V3[a]	Compound V2	Total
USDC	13,661	198,274	9,743	430,047	651,725
DAI	3,574	58,760	0	191,773	254,107
USDT	7,047	85,806	0	95,193	188,046
WETH	1,486	6,096	1	97,248	104,831
WBTC	4,079	45,151	1,125	53,793	104,148
others	6,986	225,239	1,876	64,572	298,673
Total	36,833	619,326	12,745	932,626	1,601,530

Note. This information has been collected with Etherscan.io.

[a] Compound V3 refers to its USDC liquidity pool only.

The overview above is focused on major cryptocurrencies. Transactions were settled in more than 40 different underlying cryptocurrencies. The concentration on established stable coins, such as USDC, Tether (USDT), and DAI, was high across DeFi systems. Overall, more than two-thirds of all observed transactions were executed in these three stable coins. This share even reached almost 77% at Compound V2. The share of the five most-frequently used cryptocurrencies was about 81% across DeFi systems. More than 30 cryptocurrencies accounted for about 1% or less of all transactions each. DeFi systems discontinued their services for some of these cryptocurrencies. A small number of transactions involved failed cryptocurrencies, like TerraUSD (UST). Many transactions not related to depositing, borrowing, withdrawing, or repaying, such as setting changes, often do not involve cryptocurrencies. Consequently, the number of transactions involving cryptocurrencies is lower than the total number of transactions.

Cryptocurrency Data

This part presents economically relevant cryptocurrency-related data used in the empirical analysis. The large number of different cryptocurrencies in the data set necessitates focusing the analysis on selected cryptocurrencies. Some cryptocurrencies have not been accepted by all DeFi systems, some have only been popular for a short period of time, and some have even failed. Therefore, economically relevant data is only being presented for USDC, DAI, USDT, WBTC, and wrapped Ether (WETH). These five cryptocurrencies account for more than 80% of all observed transactions and have been used widely across DeFi systems. Moreover, transactions in these cryptocurrencies are available for the whole observation period.

Table 5 provides an aggregation of the total value of transactions in the stable coins USDC, DAI, and USDT in order to quantify the economic significance of the observed transactions executed between May 2019 and July 2023. Values in cryptocurrency terms are expressed in billions. Again, derivatives of the same underlying cryptocurrency were aggregated. Since these stable coins target a fixed exchange rate to the U.S. dollar, the value of these cryptocurrency transactions can be interpreted easily. USDC did account for the most transactions. The total value of all USDC deposits amounted to USDC 54.1 billion, and USDC 52.2 billion were withdrawn. Overall, USDC 39.0 billion were borrowed, and USDC 37.1 billion were return again. This aggregation also implies that the average value of transactions varied between DeFi systems. Compound V2 saw the greatest number of USDC transactions, but the total value of USDC transactions at Aave V2 exceeded that at Compound V2. On average, EOAs deposited USDC 695,199 at Aave V2 and USDC 80,709 at Compound V2. The value of individual transactions ranged between USDC 600 million to below one cent. The largest transactions on record occurred at Aave V2 in 2021.

Table 5

Descriptive Statistics of transactions in Stable Coins in Selected DeFi Systems

Aggregation of the total value of cryptocurrency transactions in billions					
Function[a]	Aave V3	Aave V2	Compound V3[b,c]	Compound V2	Total
Cryptocurrency: USDC					
deposit	1.1	28.8	1.0	23.2	54.1
withdraw	0.9	27.7	0.8	22.8	52.2
borrow	0.4	19.0	0.3	19.3	39.0
repay	0.3	17.9	0.1	18.9	37.1
Cryptocurrency: DAI					
deposit	0.2	3.8		14.9	18.9
withdraw	0.2	3.7		14.6	18.5
borrow	0.1	3.6		15.6	19.4
repay	0.1	3.3		14.8	18.2
Cryptocurrency: USDT					
deposit	0.5	12.3		8.8	21.6
withdraw	0.4	11.7		8.6	20.8
borrow	0.4	15.7		8.8	24.9
repay	0.3	14.8		8.0	23.2

Note. This information has been collected with Etherscan.io. The number of observations varied between DeFi systems and cryptocurrencies: Aave V3 (USDC 13,661, DAI 3,574, USDT 7,047, WETH 1,486, and WBTC 4,079), Aave V2 (USDC 198,274, DAI 58,760, USDT 85,806, WETH 6,096, and WBTC 45,151), Compound V3 (USDC 9,743), and Compound V2 (USDC 430,047, DAI 191,773, USDT 95,193, WETH 97,248, and WBTC 53,793).

[a] The names of functions have been standardized (see Appendix for details).

[b] Compound V3 refers to its USDC liquidity pool only.

[c] The functions for depositing and replaying are the same in Compound V3. The functions for withdrawing and borrowing are also the same. All transactions have been categorized into the four types for this pool in order to understand their economic motivation.

Table 6 reveals the aggregated value of WETH and WBTC transactions in thousands. The value of transactions is expressed in cryptocurrency terms. The number of transactions and the value of transactions recorded between May 2019 and July 2023 are material:

Table 6

Descriptive Statistics of Transactions in WETH and WBTC at Selected DeFi Systems

Aggregation of the total value of cryptocurrency transactions in thousands					
Function[a]	Aave V3	Aave V2	Compound V3[b]	Compound V2	Total
Cryptocurrency: WETH					
deposit	60.6	566.9			627.5
withdraw	48.7	456.3			505.0
borrow	21.9	177.3			199.2
repay	10.5	142.1			152.6
Cryptocurrency: WBTC					
deposit	14.4	374.6		342.3	731.3
withdraw	8.9	338.8		336.3	684.0
borrow	5.3	59.6		59.8	124.6
repay	4.4	54.6		50.6	109.5

Note. This information has been collected with Etherscan.io. The number of observations varied between DeFi systems and cryptocurrencies: Aave V3 (USDC 13,661, DAI 3,574, USDT 7,047, WETH 1,486, and WBTC 4,079), Aave V2 (USDC 198,274, DAI 58,760, USDT 85,806, WETH 6,096, and WBTC 45,151), Compound V3 (USDC 9,743), and Compound V2 (USDC 430,047, DAI 191,773, USDT 95,193, WETH 97,248, and WBTC 53,793).

[a] The names of functions have been standardized (see Appendix for details).

[b] Compound V3 refers to its USDC liquidity pool only.

Across DeFi systems, more than WBTC 731 thousand and more than WETH 627 thousand were deposited. Based on daily closing prices, the total value of WBTC deposits was approximately $22.9 billion, while the value of WETH deposits was about $1.1 billion. More than 80% were pulled out again. In total, about WBTC 125 thousand and WETH 199 thousand were borrowed. The total value of WBTC loans was approximately $3.2 billion. The equivalent value of WETH loans was about $0.1 billion. While the economic model covers depositing in volatile cryptocurrencies such as WBTC or WETH, it does assume borrowing in stable coins. Transactions for borrowing and repayments in WBTC and WETH were included for the sake of completeness.

Similar to the stable coin case, transaction values were higher at Aave V2, although the number of transactions was higher at Compound V2. As measured by transaction values, EOAs seem to be more likely to borrow in stable coins. The value of deposits in WBTC and WETH far exceeds the value of loans in these volatile cryptocurrencies. This observation is consistent with a key assumptions of the model.

Like transaction values, interest rates are economically relevant and used in the model. Interest rates typically change constantly as most transactions influence the liquidity (or utilization rate) of pools which is part of their interest rate models. Depositing and repaying improve the liquidity position of pools and push rates down. Withdrawing and borrowing weakens the liquidity position of pools and lifts rates up. Average borrow and deposit rates were computed for each cryptocurrency and pool per day.

Table 7

Descriptive Statistics of Interest Rates at Aave V3

Borrow and deposit rates in percentage.

	minimum	5% percentile	average	95% percentile	maximum
Cryptocurrency: USDC					
Deposit	0.4	1.3	2.5	3.1	27.5
Borrow	1.5	2.5	3.5	3.9	24.0
Cryptocurrency: DAI					
Deposit	0.3	0.7	2.3	6.4	14.8
Borrow	1.3	1.9	3.4	6.6	16.2
Cryptocurrency: USDT					
Deposit	0.7	1.5	3.7	9.6	50.5
Borrow	1.6	2.9	5.1	14.9	57.6
Cryptocurrency: WETH					
Deposit	0.2	1.4	1.9	2.5	3.1
Borrow	2.3	3.1	3.7	4.3	4.6
Cryptocurrency: WBTC					
Deposit	0.0	0.0	0.2	0.7	0.9
Borrow	0.6	0.7	1.6	2.8	7.3

Note. This information has been collected with Etherscan.io. The number of observations varied between cryptocurrencies: USDC 13,661, DAI 3,574, USDT 7,047, WETH 1,486, and WBTC 4,079.

The statistics shown in Table 7 are based on interest rates retrieved directly from log data of transactions with Aave V3. The data set contains transactions recorded between January 2023 and July 2023. The table is broken down into cryptocurrencies. Interest rates can be differentiated in terms of deposit and borrow rates. Average rates on stable coins tended to be higher than rates on WETH and WBTC. Moreover, rates on WETH and WBTC fluctuated less widely, while rates on stable coins climbed into the double digits on some days. Table 8 provides the same statistics for Aave V2.

Table 8

Descriptive Statistics of Interest Rates at Aave V2

Borrow and deposit rates in percentage.

	minimum	5% percentile	average	95% percentile	maximum
Cryptocurrency: USDC					
Deposit	0.2	0.5	3.5	10.4	28.0
Borrow	0.9	1.5	4.9	15.3	49.1
Cryptocurrency: DAI					
Deposit	1.1	2.1	4.8	7.9	12.5
Borrow	1.8	3.3	6.3	10.9	32.7
Cryptocurrency: USDT					
Deposit	0.8	1.3	4.6	13.4	53.1
Borrow	1.9	2.3	6.3	21.0	62.7
Cryptocurrency: WETH					
Deposit	0.2	0.4	1.5	2.3	37.1
Borrow	0.3	1.4	3.2	4.1	40.2
Cryptocurrency: WBTC					
Deposit	0.0	0.0	0.1	0.2	0.5
Borrow	0.2	0.3	0.8	1.7	2.9

Note. This information has been collected with Etherscan.io. The number of observations varied between cryptocurrencies: USDC 198,274, DAI 58,760, USDT 85,806, WETH 6,096, and WBTC 45,151.

These statistics of interest rates at Aave V2 were calculated with data collected from the inception of these liquidity pools until July 2023. While interest rate data for USDC, DAI, USDT, and WBTC was available since December 2020, data for WETH was not available before March 2022. The interest rates used in the computation of these statistics were retrieved directly from log data of transactions with Aave V2. On average, interest rates on stable coins were higher and more volatile than interest rates on WETH and WBTC. The daily average reached the double-digit percentage range in the case of WETH, but the 95% percentile shows that daily averages mostly remained in the low-single digits.

Table 9 summarizes descriptive statistics of interest rates at Compound V3. Only the USDC liquidity pool of Compound V3 was considered.

Table 9

Descriptive Statistics of Interest Rates at Compound V3[a]

Borrow and deposit rates in percentage.

	minimum	5% percentile	average	95% percentile	maximum
Cryptocurrency: USDC					
Deposit	0.8	1.1	1.7	2.7	5.3
Borrow	1.7	1.8	2.3	3.3	5.4

Note. This information has been collected with Etherscan.io. The number of observations: 9,743.

[a] Compound V3 refers to its USDC liquidity pool only.

These statistics are based on transactions executed between September 2022 and July 2023. The realized interest rates had to be estimated for each transaction by tracking the liquidity position and replicating the interest rate model of Compound V3. The estimated interest rates ranged between 0.8% and 5.4%. The difference between 5% and 95% percentiles of about 1.5% was comparatively narrow.

Table 10 shows descriptive statistics of interest rates at Compound V2. Data was available for USDC from May 2019 onwards. WETH followed in June 2019, WBTC in July 2019, DAI in November 2019, and USDT in May 2020. The liquidity of some pools dried up before July 2023. DAI and WETH data was available up until July 2022 and WBTC data up until May 2021. The different observation periods complicate a comparison of interest rates between cryptocurrencies. The interest rates used in the computation of these statistics were inferred from borrow indices collected from transaction logs (Compound , 2023b).

Table 10

Descriptive Statistics of Interest Rates at Compound V2

Borrow and deposit rates in percentage.

	minimum	5% percentile	average	95% percentile	maximum
Cryptocurrency: USDC					
Deposit	0.0	5.2	7.4	9.6	18.2
Borrow	0.3	5.6	7.8	10.0	18.6
Cryptocurrency: DAI					
Deposit	0.1	1.3	5.1	11.2	19.9
Borrow	0.5	1.7	5.5	11.6	20.3
Cryptocurrency: USDT					
Deposit	0.4	2.7	5.7	14.7	30.9
Borrow	0.8	3.1	6.1	15.1	31.3
Cryptocurrency: WETH					
Deposit	0.8	0.9	1.3	1.8	2.4
Borrow	1.3	2.5	3.0	3.6	4.2
Cryptocurrency: WBTC					
Deposit	1.9	2.3	5.2	9.0	26.5
Borrow	2.3	2.7	5.6	9.4	26.9

Note. This information has been collected with Etherscan.io. The number of observations varied between cryptocurrencies: USDC 430,047, DAI 191,773, USDT 95,193, WETH 97,248, and WBTC 53,793.

Tables 7 to 10 also bring extreme maxima to light. The highest daily average was 62.7%. The maximum deposit rate on USDC offered by Aave V3 has higher than the maximum borrow rate. The absolute level of the maximum deposit and borrow rate exceeded 20% in this case. More information on this time series is provided below.

Analysis of Trends in USDC Rates and Flows at Aave V3

In this part, Aave V3 serves as an example to elaborate on USDC rates and flows over time in order to explain some surprising observations. Table 11 summarizes USDC transactions between EOAs and Aave V3 as well as USDC rates at Aave V3. It displays 13,661 USDC transactions between EOAs and Aave V3. In total, close to USDC 1,070 million were deposited with an average rate of 2.51%. The average amount was about USDC 0.3 million, and 3,515 deposits were observed. About USDC 919 million were withdrawn again. Withdrawals were recorded on 2,317 occasions. Almost USDC 428 million were borrowed from the liquidity pool. The average loan amount was about USDC 76,371, and 5,600 loans were taken out. The average rate was 3.49% on these loans. Over 2,229 different transactions, approximately USDC 258 million, were returned to the liquidity pool. On average, the repayment and borrowing amounts were much lower than the amounts of deposits and withdrawals.

Table 11

Descriptive Statistics of USDC Transactions with the Aave Liquidity Pool V3

This aggregation of transactions (n = 13,661) is split between functions and rates

Function	Total Value (in USDC)	Average (in USDC)	Count
deposit	1,069,712,807	304,328	3,515
borrow	427,674,892	76,371	5,600
withdraw	918,583,673	396,454	2,317
repay	257,812,226	115,662	2,229

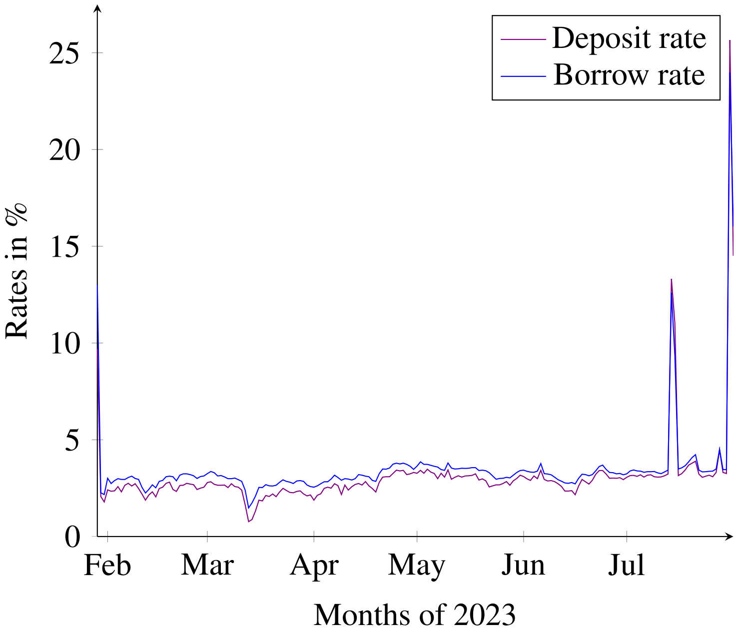
Rate	Minimum	Average	Maximum
deposit	0.44%	2.51%	27.51%
borrow	1.49%	3.49%	23.98%

Note. This information has been collected with Etherscan.io.

The range between minimum and maximum rates was wide in both cases. Average deposit and borrow rates were computed for each day. Daily rates are based on realized rates on each day. Minimum and maximum rates refer to these daily averages. Intraday rates fluctuated even more extremely, but the time series shows that rates mostly hovered around their averages. The spread between deposit and borrow rates averaged 0.98%. Figure 4 depicts daily deposit and borrow rates at Aave V3 since inception up until July 31, 2023. The first observation dates back to January 27, 2023.

Figure 4

USDC Rates at Aave V3

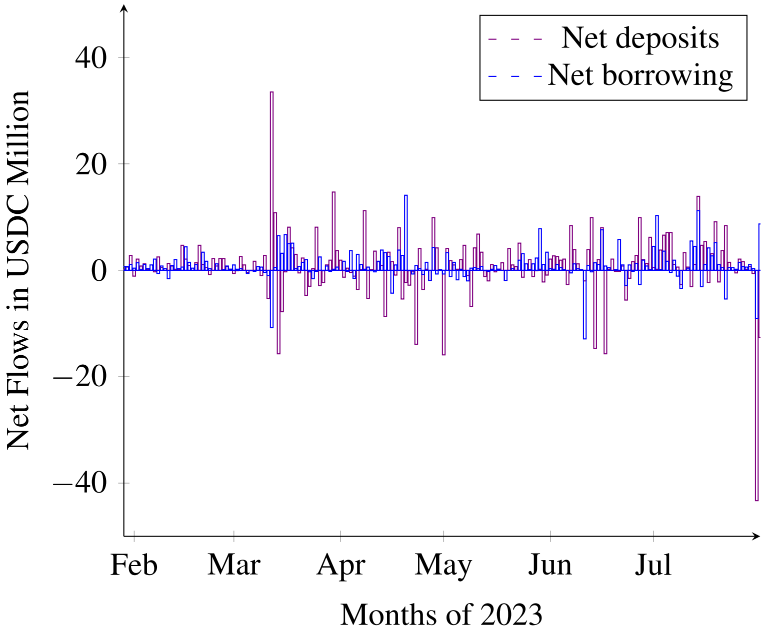


The figure above shows that maxima and minima were only reached during temporary market dislocations. The highest realized deposit rate was observed on July 30, 2023. The deposit rate surged from 2.7% to 56.5% and fell back to 35.7% on that day. The average was 25.7% on July 30. The maximum borrow rate was 63.0% on the same day. Rates spiked because the Aave Liquidity Pool V3 saw large deposite outflows of USDC 43.3 million. Withdrawals totaled USDC 46.9 million, whereas only USDC 3.7 million were deposited. Higher rates prompted borrowers to repay USDC 15.3 million. Including new loans over USDC 6.2 million in total, the liquidity pool lost USDC 34.2 million in reserves. According to its price setting mechanism, a decline in reserves leads to an increase in deposit and borrow rates in order to encourage depositing and to discourage borrowing. Another market dislocations occurred on July 13, when the intraday deposit rate hit 30.8%. The intraday borrow rate reached 37.9% on high borrowing activity. About USDC 23.4 million were borrowed from the Aave Liquidity Pool V3 from July 11 to July 13, 2023. This increase in borrowing caused a decline in reserves. Rates normalized when large amounts were deposited and repaid on July 14, 2023. Conversely, rates fell below 1% in mid-March. The Aave Liquidity Pool V3 recorded deposits of more than USDC 100 million between March 11 and March 13, 2023. This large inflow coincided with the collapse of Silicon Valley Bank. The price of USDC fell to a record low on March 11 because some of its reserves were being held at Silicon Valley Bank, which concerned market participants (Howcroft & Jaiswal, 2023). This large inflow led to excess liquidity in the pool pushing rates down. The price setting mechanism is designed to discourage further depositing and to promote borrowing when liquidity levels are high.

To visualize follows and to perform the empirical analysis, aggregates were defined and calculated for every day. Net deposits are defined as the sum of deposits minus the sum of withdrawals. Net borrowing is the difference between total borrowing and repayments. A visualization of daily USDC flows at Aave Liquidity Pool V3 can be found on the following page. Figure 5 shows daily USDC net flows at Aave V3 since inception up until July 31, 2023. The aforementioned large decline in net deposits on July 30, which caused a sharp increase in rates, stands out. Depositors withdrew USDC 46.9 million in total over 49 transactions throughout the day. 30 deposits totaling USDC 3.7 million could not offset this large outflow on July 30. The above-mentioned increase in borrowing, which also led to an increase in rates, is less evident because transactions spanned over multiple days. Also, changes in daily borrowing are less obvious because their average amounts are smaller than the size of average deposits. In contrast to this event, significant net deposits in mid-March are striking. The liquidity pool recorded 633 deposits between March 11 and March 13, 2023. More than USD 100 million were deposited on these days. With total deposits of USDC 68.2 million and net deposits of USDC 33.5 million, March 11 was the day with the greatest inflow.

Figure 5

Daily USDC Net Flows at Aave V3



This data set has some important limitations. As mentioned above, the computation of deposit and borrow rates required estimates in some cases. Furthermore, anonymity is a limitation. While the CAs of DeFi systems are known, personal information about the holders of EOAs are not available. Account holders are anonymous and might control one or multiple EOAs alone or together with other individuals. In the context of lending, information about the creditworthiness or wealth of account holders would have been particularly useful. Moreover, it is close to impossible to infer the reasons for and the context of transactions from the data, especially because

EOAs sometimes combine multiple transactions involving several DeFi systems and cryptocurrencies (Gudgeon et al., 2020b).

Additional Data

Some additional data sources with economic relevance were used in the empirical analysis. Additional data sources related to the traditional economic system are the U.S. Treasury bill rate, cs, r_i, and r_f. The effective federal funds rate is a proxy for the latter (Federal Reserve, 2023a). The cs data for the analysis come from Global Financial Data (GFD) and are based on the Bank of America Merrill Lynch U.S. Corporate 1-3 Year Option-Adjusted Spread Index. Since cryptocurrency borrowing is typically short-term, only the spreads on short-term corporate bonds were included in the analysis. The model defines borrowing costs as r_f plus cs for traditional loans. r_i is based on the aggregated Credit Suisse (CS) HOLT Cash Flow Return on Investments (CFROI) for U.S. companies. The aggregated CFROI is the internal rate of return of all U.S. companies in the HOLT database. The CFROI is an unlevered gauge of economic performance (Credit Suisse HOLT, 2023).

Information about capital requirements (k_f and k_c) can be inferred from public sources as well. Since Aramonte et al. (2022) noted that actual collateralization ratios at DeFi systems ranged between $> 300\%$ and $> 200\%$, k_c was set at 0.4. This value is equivalent to a collateralization ratio of 250%. Mandated collateralization ratios are lower, but borrowers typically post more collateral to avoid liquidations (Aramonte et al., 2022). The Financial Stability Report published in May 2023 implies that k_f was about 0.5 for large non-financial corporations. The gross leverage ratio - the ratio of debt to assets - of large non-financial corporations of less than 35% is equivalent to a k_f

of about 0.5 (Federal Reserve, 2023b).

Finally, the two risk-aversion coefficients (a_d and a_b) were borrowed from Black and Litterman (1991). An overview of all additional data sources can be found below:

Table 12

Descriptive Statistics of Additional Data Sources

Parameter	Last Value	Description
r_f	5.3%	Effective Federal Funds Rate (Federal Reserve, 2023a)
r_i	8.4%	U.S. Aggregate CFROI (CS HOLT, 2023)
cs	0.8%	U.S. Corporate Credit Spread (GFD - BofA ML)
k_f	0.5	Leverage Ratio of Large Corp. (Federal Reserve, 2023b)
k_c	0.4	Actual Collateralization Ratios (Aramonte et al., 2022)
a	2.4	Risk-aversion Coefficient (Black and Litterman, 1991)
–	5.4%	U.S. Treasury Bill Rate (GFD - S&P)

Note. The two risk-aversion coefficients are the same for depositors and borrowers.

The U.S. Treasury bill rate is not a parameter of the economic model. It is used to model price expectations according to Moskowitz et al. (2012). The U.S. Treasury bill rate is the yield on non-inflation-indexed Treasury securities with a maturity of one year.

Chapter V.

Model Assessment

This chapter describes the empirical tests of major predictions of the economic model. Empirical tests assess the predicted levels of cryptocurrency depositing and borrowing using the data set presented in Chapter IV. The introductory part of this chapter outlines how the data set is used in the empirical analysis. The second part presents the test design. The part following this derives three testable predictions from the model which guide the empirical analysis.

Utilization of the Data Set in the Empirical Analysis

The data set described in Chapter IV is used to carry out empirical tests. To summarize data for descriptive statistics and to perform empirical tests, daily aggregates had to be computed for cryptocurrency deposit and borrow rates as well as for net depositing and borrowing. Deposit and borrow rates are expressed as daily averages. As explained in Chapter IV, this information is based on transactional data. The Ethereum blockchain records these transactions as they occur, and their character and frequency fully depends on EOAs. Therefore, the frequency of transactions varies over time and across DeFi systems and cryptocurrencies. The daily aggregation ensures even spacing of cryptocurrency-related time series. It also aligns cryptocurrency-related time series with other time series, such as the effective federal funds rate or credit spreads, which are only available on a daily basis.

The data set contains realized rates and prices, but decision making is based on expectations. These expectations have to be derived from the data set. A key assumption is that recently realized rates and prices inform the decision-making processes of depositors and borrowers. Assuming a short-term investment horizon of market participants in the cryptocurrency space, current interest rates and credit spreads can be treated as expected interest rates and credit spreads. Expected variances equal observed variances in the empirical analysis.

Exchange rate expectations, however, require additional modelling. It is assumed that depositors and borrowers expect the USDC, DAI, and USDT stable coins to maintain their parity exchange rate to the U.S. dollar. The exchange rate parity implies that the returns on these stable coins are zero and that their variances are negligible. The observed average daily returns on USDC and DAI were 0.00% and 0.01% on USDT. The implicit assumption is that returns are calculated in U.S. dollar terms. In the case of WBTC and WETH, depositors and borrowers are assumed to form return expectations based on momentum factors (Liu et al., 2019; Caporale & Plastun, 2020; Borgards, 2021). A simple gauge of momentum is the moving average of returns over short horizons. Cutler et al. (1991), for example, find a positive serial correlation of excess returns on exchange rates. An exponentially weighted moving average (EWMA) over thirty days with an α of 0.3 was used in the empirical analysis. Liu et al. (2019) as well as Caporale and Plastun (2020) documented momentum effects in cryptocurrencies over short horizons. The EWMA with an α of 0.3 gives more recent observations greater weights. According to Moskowitz et al. (2012), a more sophisticated gauge is time series-momentum (TSMOM). Moskowitz et al. (2012) document a significant positive predictability of the performance of currencies from their past returns. The TSMOM effect is stronger for short lags up to one year and then partially reverses. Borgards (2021) presented evidence supporting TSMOM in cryptocurrencies. Unlike Moskowitz et al. (2012), TSMOM was computed with spot prices and not with future prices because the time series of cryptocurrency futures were too short. The thirty-day EWMA and TSMOM with a lag of one month were solely used to model return expectations. One should not infer from this modelling that EWMA or TSMOM exhibit positive predictability of cryptocurrency returns.

Design of Empirical Tests

Time series regression models were used to assess the predictability of the economic model. The time series regressions are focused on model predictions related to cryptocurrency depositing and borrowing. Although the economic model does cover fiat currency deposits and loans, the research question is centered on cryptocurrency depositing and borrowing.

Time series regressions were carried out to test model predictions for cryptocurrency depositing and borrowing separately. Borrowing regressions were differentiated between the general and the alternative case. The dependent variable was net borrowing at DeFi systems in both cases. The sole independent variable was the optimal share of cryptocurrency borrowing computed either according to the general or the alternative case. Likewise, time series regressions were performed to test whether the optimal share of cryptocurrency depositing has a positive and statistically significant influence on net deposits at DeFi systems. The sole independent variable was the optimal share of cryptocurrency deposits in each regression. The dependent variable was the level of net deposits.

The t-statistics presented in Chapter VI indicate whether or not the independent variables have a positive and statistically significant influence on dependent variables. A t-statistic is positive when the corresponding coefficient is positive as well. Coefficients and t-statistics have the same sign because the null hypothesis is the claim that this influence does not exist ($\beta_0 = 0$). Whether or not the influence is statistically significant cannot be directly inferred from the t-statistics. Therefore, t-statistics are highlighted when the corresponding coefficient is statistically significant. The corresponding coefficients, however, are difficult to interpret and to compare across DeFi systems and cryptocurrencies. Hence, result tables do not contain coefficients.

Testable Predictions

This formalization of testable predictions guides the empirical analysis. One prediction is derived for each part of the model.

1. The optimal share of liquid assets deposited in cryptocurrency is expected to positively influence the level of net deposits at DeFi systems. Regressing net deposits (nd_t^{sc}) at DeFi system s for each cryptocurrency c in month t on $x_{c,t-1}^{sc}$ helps to examine the predictability of the economic model:

$$nd_t^{sc} = \alpha + \beta x_{c,t-1}^{sc} + \varepsilon_t^{sc} \tag{22}$$

   sc is the unique combination of DeFi system s and cryptocurrency c. According to the economic model, the coefficient (β) should be positive and statistically significant. The higher $x_{c,t-1}^{sc}$, the higher the level of predicted cryptocurrency depositing in t.

2. The optimal share of cryptocurrency loans is anticipated to have a positive effect on the level of net borrowing at DeFi systems. In a regression setting, this prediction can be captured using the following specification:

   $$nb_t^{sc} = \alpha + \beta y_{cb,t-1}^{sc} + \varepsilon_t^{sc} \tag{23}$$

   The term nb_t^{sc} denotes net borrowing at DeFi system s in a specific cryptocurrency c in month t. The values of $y_{cb,t-1}^{sc}$ were calculated for each s and c as specified by the economic model in the general case. Again, a positive and statistically significant coefficient would confirm the model.

3. The testable prediction in the alternative case is equivalent to the testable prediction in the general case. The only difference is the computation of $y_{cb,t-1}^{sc}$.

In all three cases, the null hypothesis is that the coefficient possesses no statistical significance. The t-statistics of the regressions presented in Chapter VI indicate whether the null hypothesis can be rejected.

Chapter VI.

Results

This chapter summarizes the results of the empirical analysis introduced in Chapter V. Empirical results are presented for depositing, for borrowing in the general, and for borrowing in the alternative case.

Cryptocurrency Depositing

This part investigates the predictability of the optimal share of cryptocurrency depositing on observed net deposits in DeFi systems. For each DeFi system, cryptocurrency, and month, the optimal share of cryptocurrency depositing at the end of the previous month was calculated. The optimal share was derived from the exchange rate (S_1) over the past thirty days, the realized deposit rate (r_{cb}) over the past thirty days, and the last effective federal funds rate (r_f). For the sake of simplicity, S_1 was set to 1 for stable coins, which reduced their optimal share of cryptocurrency depositing to $\left.(r_{cd}-r_f)\middle/a_d Var(r_{cd})\right.$. The value of net deposits was converted into U.S. dollars for WETH and WBTC everyday. This conversion adjusts for exchange rate effects on net deposits. Overall, the predicted level of net deposits in month t was based on information available in month $t-1$. Table 13 shows the results of the time series regressions.

Table 13

Results of Time Series Regressions of Monthly Net Deposits

The t-statistics of the betas (coefficients) from time series regressions of monthly net deposits in selected DeFi systems are reported according to the economic model. Panel A shows results for three stable coins and Panel B for WETH and WBTC.

Currency	Aave V3	Aave V2	Compound V3[a]	Compound V2
Panel A: Stable coins				
USDC	-	-.185	-	.786
DAI	-	.479		-.521
USDT	-	.259		.582
Panel B: WETH and WBTC				
WETH (EWMA)	-	.191		
WETH (TSMOM)	-	.162		
WBTC (EWMA)	-	-.742		.127
WBTC (TSMOM)	-	-.682		.606

Note. The time series were too short to give results for Aave V3 and were fraught with problems for Compound V3. The number of observations varied between DeFi systems and cryptocurrencies: Aave V2 (USDC 31, DAI 31, USDT 31, WETH 15, and WBTC 31), and Compound V2 (USDC 49, DAI 31, USDT 38, and WBTC 20).

[a] Compound V3 refers to its USDC liquidity pool only.

The table above provides the t-statistics of the coefficients from time series regressions of monthly net deposits. A generalized least squares (GLS) regression model was used to estimate coefficients because Breusch–Pagan tests suggested the presence of heteroscedasticity. Autocorrelation was also documented with Durbin-Watson tests. Most of the coefficients are positive, implying the predicted relationship between the optimal share of cryptocurrency deposits and observed net deposits. Nevertheless, one third of all estimated coefficients are negative. Different patterns between cryptocurrencies and DeFi systems are not obvious. The value of R^2 was at or below 0.02 in all cases. No estimate has statistical significance, and the model prediction cannot be confirmed.

The regressions were performed in multiple ways to challenge this test result. Different values of the risk-aversion coefficient a_d were tested, but the assumed risk tolerance did not seem to have a material effect on test results. Test results were reported for an optimal share of cryptocurrency deposits with an a_d of 2.4. Furthermore, the non-negativity constraint was relaxed. The lower bounds of x_c and x_f are 0, while the implied upper bounds are 1. Regressing net deposits on unconstrained values of x_c did not change the test results greatly. Relaxing the non-negativity constraint confirmed the necessity of this constraint in the optimization of mean–variance utility because unconstrained values of x_c fluctuated widely and took on unrealistic values. Moreover, the specification of the regressions was modified to $nd_t^{sc*} = \alpha + \beta x_{c,t-1}^{sc} + \varepsilon_t^{sc}$ where $nd_t^{sc*} \in \{0,1\}$. The binary dependent variable allowed this specification to focus on the direction of the prediction. nd_t^{sc*} was defined as a month-over-month change in net deposits. The value of 1 indicated a month-over-month increase in net deposits. The regression results of this specification were qualitatively similar to the results reported above. The vast majority of coefficients holds no statistical significance.

The test result was also challenged by adjusting time horizons. A focus on the low-interest rate environment was meant to reduce multicollinearity problems, but did not improve the test results. Different investment horizons were tested as well. In addition to monthly net deposits, quarterly, weekly, and daily net deposits were considered. The number of observations is clearly too short for quarterly data, but daily data has some advantages. One might argue that daily data is more suitable for the cryptocurrency space notorious for its fast pace. The example provided in Chapter IV shows that flows respond quickly to changes in the deposit and borrow rates. Monthly data might not be granular enough to capture these effects. Daily data has the additional advantage of increasing the number of observations. It might be objected that daily data is noisier. Large individual flows, for instance, have a greater effect on daily than on monthly data.

The values of x_c^{sc} were calculated for every cryptocurrency and DeFi system for every day to estimate the net deposits on the following day in this specification. The results of the time series regressions of daily net deposits can found below:

Table 14

Results of Time Series Regressions of Daily Net Deposits

The t-statistics of the betas (coefficients) from time series regressions of daily net deposits in selected DeFi systems are reported according to the economic model. Panel A shows results for three stable coins and Panel B for WETH and WBTC.

Currency	Aave V3	Aave V2	Compound V3[a]	Compound V2
Panel A: Stable coins				
USDC	-0.532	-0.079	-	2.282**
DAI	1.117	0.381		-0.290
USDT	0.284	1.475		0.512
Panel B: WETH and WBTC				
WETH (EWMA)	-3.844***	-1.105		
WETH (TSMOM)	-1.328	0.273		
WBTC (EWMA)	-1.918*	1.105		-0.326
WBTC (TSMOM)	3.518***	-0.110		1.183

Note. Number of observations varied between DeFi systems and cryptocurrencies: Aave V3 (USDC 155, DAI 139, USDT 138, WETH 127, and WBTC 109), Aave V2 (USDC 909, DAI 908, USDT 909, WETH 444, and WBTC 907), Compound V3 (USDC 265), and Compound V2 (USDC 1456, DAI 918, USDT 1128, and WBTC 600).

*, **, and *** represent statistical significance of the corresponding coefficient at the 10%, 5%, and 1% confidence levels, respectively.

[a] Compound V3 refers to its USDC liquidity pool only.

This table contains the t-statistics of the coefficients from time series regressions of daily net deposits. Due to the persistence of heteroscedasticity across regressions, a GLS model was used to estimate coefficients. Autocorrelation was less severe in regressions of daily net deposits. Ten out of nineteen coefficients are positive, suggesting that the impact of the optimal share of cryptocurrency deposits on observed daily net deposits is not clear. Four coefficients are statistically significant, but only two of these coefficients are positive. Two coefficients are highly significant, and in these cases the value of R^2 reached 0.1, although R^2 was minimal in all other cases. Unlike monthly data, daily data is sufficient to perform regressions for the Aave V3 liquidity pools. The additional regressions do not provide additional clarity. The model prediction cannot be confirmed because of contradicting results and the low number of statistically significant coefficients. This statistical result was validated by performing alternative tests. The specification of the regressions was changed to a binary dependent variable, for example, to evaluate whether or not the direction of daily net deposits can be predicted. None of the alternative regression results were qualitatively different to the results shown above.

Regressions of daily net deposits amplified some problems. Despite its relatively long sample period, the regression for Compound V3 failed. The effective federal funds rate exceeded the deposit rate on USDC offered by Compound V3 on every single day. Hence, the value of x_c was consistently 0. From September 2022 to July 2023, Compound V3 offered an average deposit rate of 1.7% on USDC, while the effective federal funds rate averaged 4.2%. The economic model cannot explain cryptocurrency depositing in this case. This problem was not unique to Compound V3. It was common across DeFi systems since the Federal Reserve began raising rates in March 2022. Daily data amplified this problem because such data enables newer liquidity pools to be included, which have been established following the low-interest rate years. This problem motivated the aforementioned focus on the low-interest rate environment for additional tests. Interestingly, the correlation between the effective federal funds rate and net deposits was close to zero across cryptocurrencies and DeFi Systems.

The length of each time series of net deposits depends on the available data as described in Chapter IV. Aave V3 was launched in late January 2023, and, therefore only a few months of data were available up until July 2023. Data was available over the sample period December 2020 to July 2023 for Aave V2. Only the sample period of WETH was shorter because observations were not available before March 2022. The sample period of Compound V3 was September 2022 to July 2023. Data was available for Compound V2 USDC from May 2019 until July 2023. DAI followed in December 2019, while USDT came in May 2020. Data for WBTC was considered for the period July 2019 to May 2021, with the liquidity pool drying up in 2021. In general, periods with limited breadth and liquidity, such as ramp-up or phase-out periods, were excluded.

Cryptocurrency Borrowing in the General Case

This part evaluates the theoretical predictions of cryptocurrency borrowing in the general case. In the general case, borrowers can hold a combination of investments and cryptocurrency assets funded by loans in fiat currency or cryptocurrency. Cryptocurrency loans are assumed to be denominated in stable coins. Loans denominated in the stable coins USDC, DAI, and USDT were considered in this empirical analysis because of the availability of interest-rate and borrowing data for these stable coins across DeFi systems. WBTC and WETH served as cryptocurrency assets held as collateral in the empirical analysis. Twelve regressions were ran for each DeFi system: for the three stable coins both collateral assets with both momentum factors were tested.

The optimal share of cryptocurrency borrowing y_{cb}^{sc} was determined for all combinations. Non-linear optimization techniques were applied to compute the values of y_{cb}^{sc} for every month. A simple Python application utilizing the NumPy and SciPy libraries was used to perform this optimization. The optimization was based on the borrow rate r_{cb} specific to the stable coin and the DeFi system. The expected price of the collateral asset S_1 was derived from the thrity-day EWMA and TSMOM with a lag of one month. The risk-free rate r_f, the credit spread cs, and the return on investments r_i were the same for all combinations and the values of these parameters were derived as specified in Chapter IV. The optimal share of cryptocurrency borrowing at the end of month $t-1$ was calculated with information known in that month and used to predict net borrowing activity in month t.

Table 15 summarizes the results of time series regressions of monthly net borrowing. Net borrowing is defined as the sum of loans minus the sum of repayments. When the sum of loans exceeds the sum of repayments, the value of net borrowing is positive. A positive coefficient indicates that a higher value of y_{cb}^{sc} is associated with higher levels of net borrowing. A negative coefficient suggests that a higher value of y_{cb}^{sc} is negatively related to net borrowing. Table 15 presents the t-statistics of the coefficients from time series regressions of monthly net borrowing. The coefficients were estimated using a GLS regression model because heteroscedasticity has been detected with Breusch-Pagan tests in almost every regression. Durbin-Watson tests were carried out and showed the presence of autocorrelation in multiple cases. The three rows on every panel refer to the borrowed stable coin. The panels state which collateral asset and which momentum factor was used in the regression. The high share of negative coefficients contradicts the economic model of cryptocurrency lending. Half of all coefficients are positive and the other half are negative. The high share of negative coefficients at Aave V2 is striking. Nonetheless, only one coefficient has statistical significance. The value of R^2 mostly ranged between 0.00 and 0.15, but did reach higher values in some Compound V3 regressions. Overall, the predictability and the significance of the economic model is not robust.

Table 15

Results of Time Series Regressions of Monthly Net Borrowing (General Case)

The t-statistics of the betas (coefficients) from time series regressions of monthly net borrowing in the USDC, DAI, and USDT stable coins in selected DeFi systems are reported according to the economic model. Panels A and B report results for WETH as collateral asset and Panel C and D for WBTC as collateral asset. Return expectations were derived from the momentum factors EWMA (Panels A and C) and TSMOM (Panels B and D).

Currency	Aave V3	Aave V2	Compound V3[a]	Compound V2
Panel A: WETH (EWMA)				
USDC	-	-1.281	0.325	-0.247
DAI	-	-1.619		0.073
USDT	-	-0.359		0.603
Panel B: WETH (TSMOM)				
USDC	-	-0.473	1.567	0.544
DAI	-	-0.645		0.058
USDT	-	-0.083		1.228
Panel C: WBTC (EWMA)				
USDC	-	-1.556	-2.214*	-1.573
DAI	-	-0.475		-0.009
USDT	-	0.256		1.299
Panel D: WBTC (TSMOM)				
USDC	-	-0.237	0.198	0.603
DAI	-	0.912		0.611
USDT	-	-0.615		0.992

Note. The time series were too short to produce results for Aave V3. The number of observations varied between DeFi systems and cryptocurrencies: Aave V2 (USDC 31, DAI 31, USDT 31), Compound V3 (USDC 8), and Compound V2 (USDC 46, DAI 25, and USDT 32).

* represents statistical significance of the corresponding coefficient at the 10% confidence level.

[a] Compound V3 refers to its USDC liquidity pool only.

This result was validated in several ways. The value of the risk-aversion coefficient a_b was changed to evaluate different levels of risk tolerance. The level of risk tolerance appears to be insignificant to results. The value of a_b was set to 2.4 in the computation of all reported results. To validate the economic modelling the non-negativity, capital, and collateralization constraints of the optimization problem were relaxed. Unconstrained values of y_{cb}^{sc} were calculated for alternative time series regressions. The results of the unconstrained optimization showed that the constraints are necessary, especially in situations where the volatility of borrow rates is moderate and their absolute level is below the effective federal funds rate. The optimization would then suggest to borrow stable coins to an extreme extent to take advantage of the interest-rate differential. Borrowers would have little to no motivation to hold cryptocurrency assets as collateral in these situations. The unconstrained optimization did not only prove to be impractical, it also did not produce qualitatively different results. In the same manner that the specification of the depositing regressions were changed to a binary dependent variable, the specification of the borrowing regressions were modified to $nb_t^{sc*} = \alpha + \beta y_{cb,t-1}^{sc} + \varepsilon_t^{sc}$ where $nb_t^{sc*} \in \{0,1\}$. The value 1 of nb_t^{sc*} indicated a month-over-month increase in net borrowing. This specification was designed to test whether the model could predict the direction of net borrowing, but the test results were equally inconclusive.

The validation of results also included testing different time horizons. Net borrowing over one quarter, one week, and one day was considered as dependent variable. Borrowing over one day might be regarded as unusual in a traditional lending environment, but the example in Chapter IV demonstrates that flows react quickly to changes in the cryptocurrency space. Daily net borrowing data is more likely to capture quick responses to changes, although daily data might be more vulnerable to noise. The optimal share of cryptocurrency borrowing y_{cb}^{sc} was determined for every day to estimate net borrowing on the following day.

Table 16

Results of Time Series Regressions of Daily Net Borrowing (General Case)

The t-statistics of the betas (coefficients) from time series regressions of daily net borrowing in the USDC, DAI, and USDT stable coins in selected DeFi systems are reported according to the economic model. Panels A and B report results for WETH as collateral asset and Panel C and D for WBTC as collateral asset. Return expectations were derived from the momentum factors EWMA (Panels A and C) and TSMOM (Panels B and D).

Currency	Aave V3	Aave V2	Compound V3[a]	Compound V2
Panel A: WETH (EWMA)				
USDC	0.687	0.795	1.538	0.370
DAI	-1.389	0.038		0.107
USDT	-0.887	2.042**		1.271
Panel B: WETH (TSMOM)				
USDC	-0.995	0.797	-0.011	-0.896
DAI	0.231	-0.305		-0.567
USDT	-0.074	-0.376		0.832
Panel C: WBTC (EWMA)				
USDC	0.385	0.468	0.572	-2.633***
DAI	-0.942	1.127		-2.595***
USDT	-0.536	2.373**		0.549
Panel D: WBTC (TSMOM)				
USDC	-2.135**	-0.718	0.063	-0.825
DAI	0.034	-0.358		0.051
USDT	0.453	0.390		0.633

Note. Number of observations varied between DeFi systems and cryptocurrencies: Aave V3 (USDC 127, DAI 110, and USDT 94), Aave V2 (USDC 919, DAI 918, and USDT 919), Compound V3 (USDC 237), and Compound V2 (USDC 1372, DAI 735, and USDT 945).

*, **, and *** represent statistical significance of the corresponding coefficient at the 10%, 5%, and 1% confidence levels, respectively.

[a] Compound V3 refers to its USDC liquidity pool only.

Table 16 shows the t-statistics of the coefficients from time series regressions of daily net borrowing. Using daily data allows Aave V3 to be included. Shifting to daily net borrowing data almost completely diminished autocorrelation, although heteroscedasticity was persistent. Hence, coefficients were estimated with a GLS regression model. The shift from monthly to daily data changed the majority of coefficients to positive. Twenty-three out of forty coefficients are positive. Two of the positive coefficients are statistically significant, although three negative coefficients have statistical significance as well. The R^2 of the time series regressions ranged between 0.00 and 0.04. Overall, the reported results are unclear and inconclusive. Again, even though the specification was altered in several ways to validate the test results, none of the alternative regression results were qualitatively different to the reported results.

It might be pointed out that the length of the time series of net borrowing differ from the length of the time series of net depositing. Aave V3 was launched in January 2023 and data was available until July 2023, but borrowing activity did not pick up immediately for some currencies. Borrowing data was considered from January 2021 until July 2023 for Aave V2. The sample period of Compound V3 was September 2022 until July 2023. Frequent borrowing data was available from September 2019 until July 2023 for Compound V2 USDC. The sample period of USDT was May 2020 until December 2022. Borrowing data for DAI was used from December 2019 until December 2021. Some time series of net borrowing were shorter than time series of net depositing because borrowing activity followed depositing activity. Presumably liquidity pools had to reach a certain size and maturity before they could support borrowing. Borrowing might be more sensitive to phase-out periods of liquidity pools. Only periods with sufficient breadth and liquidity were included in the empirical analysis.

Cryptocurrency Borrowing in the Alternative Case

This final part tests predicted cryptocurrency borrowing in the alternative case. Cryptocurrency is the sole asset in the alternative case, and borrowers can choose a combination of loans in fiat currency and cryptocurrency. Cryptocurrency loans are assumed to be denominated in stable coins. The alternative case is centered on the borrowing decision. The design of the empirical analysis of the alternative and the general case are identical. The data source and sample periods are the same as well, but the optimal share of cryptocurrency borrowing y_{cb}^{sc} was computed without the investment in the alternative case. Constraints were adjusted accordingly. The optimization was performed for all combinations of stable coins, collateral assets, and DeFi systems for every month.

Table 17

Results of Time Series Regressions of Monthly Net Borrowing (Alternative Case)

The t-statistics of the betas (coefficients) from time series regressions of monthly net borrowing in the USDC, DAI, and USDT stable coins in selected DeFi systems are reported according to the economic model. Panels A and B report results for WETH as collateral asset and Panel C and D for WBTC as collateral asset. Return expectations were derived from the momentum factors EWMA (Panels A and C) and TSMOM (Panels B and D).

Currency	Aave V3	Aave V2	Compound V3[a]	Compound V2
Panel A: WETH (EWMA)				
USDC	-	0.128	0.087	-0.557
DAI	-	-0.192		0.055
USDT	-	0.824		-0.228
Panel B: WETH (TSMOM)				
USDC	-	-0.002	1.702	0.768
DAI	-	0.093		-0.156
USDT	-	-0.162		-0.176
Panel C: WBTC (EWMA)				
USDC	-	-1.558	-1.695	-1.410
DAI	-	-0.474		0.163
USDT	-	0.417		0.519
Panel D: WBTC (TSMOM)				
USDC	-	-0.532	0.444	0.616
DAI	-	0.258		0.606
USDT	-	-0.569		0.692

Note. The time series were too short to produce results for Aave V3. The number of observations varied between DeFi systems and cryptocurrencies: Aave V2 (USDC 31, DAI 31, USDT 31), Compound V3 (USDC 8), and Compound V2 (USDC 46, DAI 25, and USDT 32).

[a] Compound V3 refers to its USDC liquidity pool only.

Table 17 reports the t-statistics of the coefficients from time series regressions of monthly net borrowing in the alternative case. A GLS model was chosen to estimate coefficients. A narrow majority of coefficients were positive, but no coefficient had statistical significance at acceptable levels. The value of R^2 was below 0.1 in every regression, with the exception of Compound V3 regressions. This inconclusive result was validated by modifying the specification of the regressions and changing the time horizon, but all alternative results were qualitatively similar to the reported results.

Table 18

Results of Time Series Regressions of Daily Net Borrowing (Alternative Case)

The t-statistics of the betas (coefficients) from time series regressions of daily net borrowing in the USDC, DAI, and USDT stable coins in selected DeFi systems are reported according to the economic model. Panels A and B report results for WETH as collateral asset and Panel C and D for WBTC as collateral asset. Return expectations were derived from the momentum factors EWMA (Panels A and C) and TSMOM (Panels B and D).

Currency	Aave V3	Aave V2	Compound V3[a]	Compound V2
Panel A: WETH (EWMA)				
USDC	1.333	0.951	1.760*	-0.411
DAI	-1.084	0.415		-0.096
USDT	-0.866	2.281**		1.239
Panel B: WETH (TSMOM)				
USDC	-0.853	0.317	1.066	-0.262
DAI	0.490	-0.094		-0.515
USDT	1.343	0.112		1.248
Panel C: WBTC (EWMA)				
USDC	0.609	0.664	0.158	-2.094**
DAI	-0.604	1.360		-1.697**
USDT	-0.920	2.765***		0.822
Panel D: WBTC (TSMOM)				
USDC	-0.695	0.025	-1.036	-0.072
DAI	1.689*	-0.027		0.767
USDT	0.686	0.008		1.185

Note. Number of observations varied between DeFi systems and cryptocurrencies: Aave V3 (USDC 127, DAI 110, and USDT 94), Aave V2 (USDC 919, DAI 918, and USDT 919), Compound V3 (USDC 237), and Compound V2 (USDC 1372, DAI 735, and USDT 945).

*, **, and *** represent statistical significance of the corresponding coefficient at the 10%, 5%, and 1% confidence levels, respectively.

[a] Compound V3 refers to its USDC liquidity pool only.

Table 18 summarizes the t-statistics of the coefficients from time series regressions of daily net borrowing in the alternative case. A GLS regression model was used to estimate coefficients. The share of positive coefficients amounted to 60%, the highest share among borrowing regressions. Four out of twenty-four positive coefficients are statistically significant. Nevertheless, two negative coefficients also have statistical significance. The value of R^2 was minimal across time series regressions. In total, sixteen coefficients were negative questioning the robustness and conclusiveness of these results.

Chapter VII.

Conclusion

This analysis has shown that the theory of financial dollarization literature may not be directly transferable to cryptocurrencies. The lending mechanism of cryptocurrencies was reflected in the formalization of the economic model, but the predictions of the model could not be empirically substantiated. Empirical evidence has neither supported cryptocurrency depositing nor borrowing as predicted by the economic model, although several variations of the model have been tested in multiple ways. This extensive testing indicates that results do not depend on a single assumption or on the model of price expectations.

Some factors might have had an adverse effect on reported results. The analysis was performed in U.S. dollar terms, but the U.S. dollar is not the legal tender in every jurisdiction home to depositors and borrowers. From the perspective of depositors and borrowers domiciled in the European Monetary Union, for instance, the value of the USDC, DAI, and USDT stable coins also depends on the euro to U.S. dollar exchange rate. This complexity was not modelled into the analysis, and anonymity in the cryptocurrency space makes it impossible to identify the domicile of market participants correctly. Another complexity arises from the lack of context for transactions. Depositing or borrowing might be part of elaborate trading strategies. Gudgeon et al. (2020b) describe how market participants use tokens received from one DeFi system for depositing assets as collateral in another DeFi system. Gudgeon et al. (2020b) warn about linking DeFi systems because this could create contagion effects, since a default in one system could affect other systems. The economic model treats depositing or borrowing as separate transactions and does not consider elaborate trading strategies. These trading strategies would be difficult to reconstruct. A closely related problem to this is the assumption that Ether and Bitcoin were used as collateral assets. Their large market capitalization and the availability of on-chain transactions in these cryptocurrencies speak for this assumption. Borrowers, however, may have chosen other cryptocurrencies or a combination of numerous cryptocurrencies as collateral. Determining the exact strategy followed by borrowers would be difficult. Another complexity affecting the empirical analysis might be the dynamics of DeFi systems. Flows will be muted during ramp-up or phase-out periods of liquidity pools, even when they offer attractive terms. Gudgeon et al. (2020a) as well as Zhang and Jin (2020) elaborate on periods of illiquidity in P2P and DeFi lending systems. As illiduidity will affect depositing and borrowing, this analysis, in order to mitigate this problem, only focused on selected cryptocurrencies and liquid periods. Arguably, this reduced sample periods further. One might argue that sample periods were already short for monthly data.

Omitting some factors in the economic model might have had an adverse effect on results as well. Insufficient monetary credibility is a common explanation for financial dollarization (Yeyati, 2006; Fidrmuc et al., 2013). The preference for hard currencies over local ones could be comparable to the preference for cryptocurrencies over fiat currencies. Bitcoin was established in response to the great financial crisis and was supposed to address the shortcomings of the prevailing system (Nakamoto, 2008). This financial crisis sparked a heated debate about the traditional banking system and fiat currencies. The lax monetary policy stance adopted by the Federal Reserve prior to the crisis is widely viewed as a contributing factor to the financial market turmoil (Brunnermeier, 2009). Monetary credibility is not part of the data set. Trust or credibility were not factored into the economic model, but might have explanatory power. Access is another factor that might have some explanatory power. For example, Allayannis et al. (2003) argue that access to hard-currency capital markets was imported to borrowers from regions with less deep and efficient capital markets. Individuals with no access to capital markets may still access DeFi systems. Interest rates in traditional capital markets are hardly relevant for these individuals. Nevertheless, this argument only applies to individuals from highly underdeveloped regions, to people with poor credit rating, and to individuals prohibited from accessing traditional capital markets (Kolachala et al., 2021). The access argument will not apply for most individuals and was not modelled into this analysis.

The description of the data set and the empirical analysis still shed light on some interesting aspects. As well as generating more data points, short-term data seems to have the advantage of capturing more information in the cryptocurrency space. Market participants appear to be highly responsive to changes, and short-term data is more likely to capture these responses. Using daily data will be unusual in a traditional lending environment. The short-term focus suggests that DeFi systems are used for margin trading or leverage, as pointed out by Qin et al. (2021), rather than for actual lending. Another interesting point is that traditional interest rates seem to be playing a secondary role in cryptocurrency lending. Depositing stable coins in DeFi systems allowed individuals to benefit from the interest differential in the low interest rate environment. Conversely, individuals depositing stable coins in DeFi systems when the effective federal funds rate was higher than the deposit rate offered on stable coins cannot be explained with the economic model. A stable coin with a fixed exchange rate to the U.S. dollar provides no diversification benefit, while a savings deposit or a money market mutual fund would generate a higher return. There must have been other reasons for depositing stable coins, such as using these coins in an elaborate trading strategy.

This analysis might inspire some future research. The decoupling of interest-rate rules from the effective federal funds rate is a tricky design choice in the case of stable coins. In theory, currencies pegged to the U.S. dollar should follow U.S. dollar interest rates. Material differences in interest rates present an arbitrage opportunity and could even compromise the U.S. dollar peg. It is hardly possible to borrow stable coins efficiently at this point in time, thereby preventing individuals from exploiting this opportunity. More interestingly, the question of how lenders can provide liquidity to borrowers will be critical for the adaption of cryptocurrencies in the real economy. Although cryptocurrencies are widely perceived as money (Mattke et al., 2020), and cryptocurrency lending has become more popular, lending seems to be used for margin trading and not for productivity-enhancing activities. To fund these activities, DeFi systems will not be able to rely solely on liquidity provided by depositors. Instead, they will have to develop sophisticated tools, such as money creation or wholesale funding.

Appendix A.

Model for Depositing

The maximization problem of risk-averse depositors is the following:

$$\begin{aligned} U(r_d) = x_f r_f + x_c(S_1 + S_1 r_{cd} - 1) - \frac{a_d}{2}(x_f^2 Var(r_f) + x_c^2 Var(S_1 + S_1 r_{cd} - 1)) \\ - \frac{a_d}{2}(2 x_f x_c Cov(r_f, S_1 + S_1 r_{cd} - 1)) \end{aligned} \tag{24}$$

s.t.: $x_f + x_c = 1$

$x_f, x_c \geq 0$

$a > 0$

Solving this optimization problem using the Lagrangian method leads to:

$$\begin{aligned} \mathscr{L}(U, \lambda_1) = x_f r_f + x_c S_1 + S_1 r_{cd} - 1) - \frac{a_d}{2}(x_f^2 Var(r_f) + x_c^2 Var(S_1 + S_1 r_{cd} - 1)) \\ - \frac{a_d}{2}(2 x_f x_c Cov(r_f, S_1 + S_1 r_{cd} - 1)) - \lambda_1(x_f + x_c - 1) \end{aligned} \tag{25}$$

with the partial derivatives:

$$\frac{\partial \mathscr{L}}{\partial x_f} = r_f - a_d(x_f Var(r_f) + x_c Cov(r_f, S_1 + S_1 r_{cd} - 1)) - \lambda_1 \overset{!}{=} 0 \tag{26}$$

$$\begin{aligned} \frac{\partial \mathscr{L}}{\partial x_c} = S_1 + S_1 r_{cd} - 1 - a_d(x_c Var(S_1 + S_1 r_{cd} - 1) \\ + x_f Cov(r_f, S_1 + S_1 r_{cd} - 1)) - \lambda_1 \overset{!}{=} 0 \end{aligned} \tag{27}$$

$$\frac{\partial \mathscr{L}}{\partial \lambda_1} = -x_f - x_c + 1 \overset{!}{=} 0 \tag{28}$$

By adding λ_1 to (26) and (27), (26) and (27) can be solved for x_f and x_c:

$$x_c = \frac{r_f + 1 - S_1 - S_1 r_{cd} - a_d x_f (Var(r_f) - Cov(r_f, S_1 + S_1 r_{cd} - 1))}{a_d (Cov(r_f, S_1 + S_1 r_{cd} - 1) - Var(S_1 + S_1 r_{cd} - 1))} \tag{29}$$

$$\begin{aligned} x_f = {} & \frac{r_f + 1 - S_1 - S_1 r_{cd}}{a_d (Var(r_f) - Cov(r_f, S_1 + S_1 r_{cd} - 1))} \\ & - \frac{x_c (Cov(r_f, S_1 + S_1 r_{cd} - 1) - Var(S_1 + S_1 r_{cd} - 1))}{(Var(r_f) - Cov(r_f, S_1 + S_1 r_{cd} - 1))} \end{aligned} \tag{30}$$

The optimal deposit shares can be obtained by inserting (29) and (30) into (28):

$$\begin{aligned} x_f = {} & \frac{Var(S_1 + S_1 r_{cd} - 1) - Cov(r_f, S_1 + S_1 r_{cd} - 1)}{Var(r_f) + Var(S_1 + S_1 r_{cd} - 1) - 2Cov(r_f, S_1 + S_1 r_{cd} - 1)} \\ & - \frac{S_1 + S_1 r_{cd} - r_f - 1}{a_d (Var(r_f) + Var(S_1 + S_1 r_{cd} - 1) - 2Cov(r_f, S_1 + S_1 r_{cd} - 1))} \end{aligned} \tag{31}$$

$$x_c = \frac{S_1 + S_1 r_{cd} - r_f - 1 + a_d (Var(r_f) - Cov(r_f, S_1 + S_1 r_{cd} - 1))}{a_d (Var(r_f) + Var(S_1 + S_1 r_{cd} - 1) - 2Cov(r_f, S_1 + S_1 r_{cd} - 1))} \tag{32}$$

Assuming that r_f is risk free and has a volatility of zero, the optimal deposit shares are:

$$x_c = \frac{S_1 + S_1 r_{cd} - r_f - 1}{a_d (Var(S_1) + Var(S_1 r_{cd}) + 2Cov(S_1, S_1 r_{cd}))} \tag{33}$$

$$x_f = 1 - \frac{S_1 + S_1 r_{cd} - r_f - 1}{a_d (Var(S_1) + Var(S_1 r_{cd}) + 2Cov(S_1, S_1 r_{cd}))} \tag{34}$$

Appendix B.

Model for Borrowing

The maximization problem of borrowers is given by:

$$\begin{aligned} max\,U(r_b) &= r_f + cs + y_i r_{invest} + y_c r_{collateral} - y_{cb} r_{cloan} \\ &\quad - \frac{a_b}{2} Var(r_f + cs + y_i r_{invest} + y_c r_{collateral} - y_{cb} r_{cloan}) \end{aligned} \tag{35}$$

s.t.: $1 \geq m_f y_i$ + $m_f y_c$ + $(m_c - m_f) y_{cb}$ - m_f where $m_f > 0$ and $m_c > 1$

$y_c \geq m_c y_{cb}$

$0 \leq y_i, y_f, y_{cb}, y_c, a_b, cs, r_f, r_{cb}, r_i$

A Lagrangian with Karush-Kuhn-Tucker conditions can be used to formalize this maximization problem with two inequality constraints. The Lagrangian can be written as:

$$\begin{aligned}\mathscr{L}(U,\lambda_1,\lambda_2,\lambda_3,\lambda_4,\lambda_5) = r_f + cs + y_i r_{invest} + y_c r_{collateral} - y_{cb} r_{cloan} \\ - \frac{a_b}{2}\left(y_i^2 Var(r_{invest})\right) \\ - \frac{a_b}{2}\left(y_c^2 Var(r_{collateral})\right) \\ - \frac{a_b}{2}\left(y_{cb}^2 Var(r_{cloan})\right) \\ - \frac{a_b}{2}\left(2 y_c y_{cb} Cov(r_{collateral}, r_{cloan})\right) \\ - \frac{a_b}{2}\left(2 y_i y_c Cov(r_{invest}, r_{collateral})\right) \\ - \frac{a_b}{2}\left(2 y_i y_{cb} Cov(r_{invest}, r_{cloan})\right) \\ - \lambda_1(m_f y_i + m_f y_c + (m_c - m_f) y_{cb} - m_f - 1) \\ - \lambda_2(y_c - m_c y_{cb}) + \lambda_3 y_i + \lambda_4 y_c + \lambda_5 y_{cb}\end{aligned} \tag{36}$$

Thus, the partial derivatives are:

$$\begin{aligned}\frac{\partial \mathscr{L}}{\partial y_i} = r_{invest} - a_b y_i Var(r_{invest}) - a_b y_c Cov(r_{invest}, r_{collateral}) \\ - a_b y_{cb} Cov(r_{invest}, r_{cloan}) - \lambda_1 m_f + \lambda_3 \overset{!}{=} 0\end{aligned} \tag{37}$$

$$\begin{aligned}\frac{\partial \mathscr{L}}{\partial y_c} = r_{collateral} - a_b y_c Var(r_{collateral}) - a_b y_i Cov(r_{invest}, r_{collateral}) \\ - a_b y_{cb} Cov(r_{collateral}, r_{cloan}) - \lambda_1 m_f - \lambda_2 + \lambda_4 \overset{!}{=} 0\end{aligned} \tag{38}$$

$$\begin{aligned}\frac{\partial \mathscr{L}}{\partial y_{cb}} = -r_{cloan} - a_b y_{cb} Var(r_{cloan}) - a_b y_c Cov(r_{collateral}, r_{cloan}) \\ - a_b y_i Cov(r_{invest}, r_{cloan}) - \lambda_1(m_c - m_f) + \lambda_2 m_c + \lambda_5 \overset{!}{=} 0\end{aligned} \tag{39}$$

The Karush-Kuhn-Tucker conditions are:

$$\lambda_1(m_f y_i + m_f y_c + (m_c - m_f)y_{cb} - m_f - 1) = 0 \tag{40}$$

$$\lambda_2(y_c - m_c y_{cb}) = 0 \tag{41}$$

$$\lambda_3 y_i = 0 \tag{42}$$

$$\lambda_4 y_c = 0 \tag{43}$$

$$\lambda_5 y_{cb} = 0 \tag{44}$$

$$m_f y_i + m_f y_c + (m_c - m_f)y_{cb} - m_f \leq 1 \tag{45}$$

$$y_c - m_c y_{cb} \geq 0 \tag{46}$$

$$y_i, y_c, y_{cb}, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5 \geq 0 \tag{47}$$

Three cases are relevant for cryptocurrency lending:

1. Borrowers choose a valid combination of y_i, y_c, y_{cb}, and y_f in the general case. Thus, λ_3, λ_4, and λ_5 are all zero in this case.
2. Borrowers combine loans and only invest in the collateral asset. In this case y_i, λ_4, and λ_5 are all zero. This cases occurs, when expectations for r_{invest} are muted relative to $r_{collateral}$.
3. Borrowers do not choose a cryptocurrency loan. Conditions making borrowing cryptocurrencies undesirable are important to understand.

When borrowers combine both assets and funding sources, λ_3, λ_4, and λ_5 are zero. The variables y_i, y_c, and y_{cb} are assumed to be positive. The upper bound of y_{cb} is $^1/_{m_c}$, and the upper bounds of y_i and y_c are 1 + y_{cb} + y_f. This implies that λ_1 and λ_2 must be zero. Although the term y_c - $m_c y_{cb}$ can be zero, y_c is likely to exceed $m_c y_{cb}$. The upper bound of y_{cb} multiplied by m_c is 1 and is smaller than the upper bound of y_c. Solutions of the capital requirement are not on the boundary of the interior in multiple situations, for example when the value of loans only marginally exceeds zero. Since λ_1, λ_2, λ_3, λ_4, and λ_5 are zero, the maximization problem can be rewritten in matrix notation:

$$U(r_d) = r_f + cs + y^T r - \frac{a_b}{2} y^T \Sigma y \tag{48}$$

In this matrix notation, y denotes a column vector with the weights of y_i, y_c, and y_{cb}. The column vector r represents the returns r_{invest}, $r_{collateral}$, and r_{cloan}. The square matrix Σ is the covariance matrix. The derivative with respect to y is:

$$\frac{\partial U(r_d)}{\partial y} = r - a_b \Sigma y \overset{!}{=} 0 \tag{49}$$

The optimal weights of y are:

$$y = \Sigma^{-1} \left(\frac{1}{a_b} r \right) \tag{50}$$

These optimal weights are only valid as long as the collateralization and capital requirements as well as the non-negativity constraints can be satisfied. Non-linear programming has to be applied in all other cases.

When borrowers combine loans and only invest in the collateral assets in the second case, y_i, λ_4, and λ_5 are all zero. Hence, λ_3, y_c, and y_{cb} are greater than zero. Even without y_i, assets must equal liabilities ($y_c = 1 + y_{cb} + y_f$). The lower bound of y_c is 1, and its upper bound is $1 + y_{cb} + y_f$. According to the capital requirement, the upper bound of y_{cb} is still $^1/_{m_c}$. Its lower bound is zero. For any positive y_{cb}, y_c is at least 1

+ y_{cb}. Therefore, the term y_c - $m_c y_{cb}$ is likely to be greater than 0 and λ_2 must be zero. λ_1 must be zero as well. The lower bound of y_c is 1 and can be reached when y_{cb} and y_f are zero. If y_c is 1, the capital requirement $(m_f y_i + m_f y_c + (m_c - m_f)y_{cb} - m_f - 1)$ cannot be zero. The partial derivatives become:

$$\frac{\partial \mathscr{L}}{\partial y_c} = r_{collateral} - a_b y_c Var(r_{collateral}) - a_b y_{cb} Cov(r_{collateral}, r_{cloan}) \overset{!}{=} 0 \tag{51}$$

$$\frac{\partial \mathscr{L}}{\partial y_{cb}} = -r_{cloan} - a_b y_{cb} Var(r_{cloan}) - a_b y_c Cov(r_{collateral}, r_{cloan}) \overset{!}{=} 0 \tag{52}$$

The variable y_i is no longer part of the capital requirement:

$$m_f y_c + (m_c - m_f)y_{cb} - m_f \leq 1 \tag{53}$$

By arranging the capital requirement, y_c can be expressed as a function of y_{cd} and y_{cd} as a function of y_c:

$$y_c \leq \frac{1 + m_f}{m_f} - \frac{m_c - m_f}{m_f} y_{cb} \tag{54}$$

$$y_{cb} \leq \frac{1 + m_f}{m_c - m_f} - \frac{m_f}{m_c - m_f} y_c \tag{55}$$

The optimal y_c and y_{cb} can be obtained from the two partial derivatives:

$$y_c = \frac{Var(r_{cloan}) r_{collateral} + Cov(r_{collateral}, r_{cloan}) r_{cloan}}{a_b Var(r_{collateral}) Var(r_{cloan}) - a_b \left(Cov(r_{collateral}, r_{cloan})\right)^2} \tag{56}$$

$$y_{cb} = \frac{Cov(r_{collateral}, r_{cloan}) r_{collateral} + Var(r_{collateral}) r_{cloan}}{a_b \left(Cov(r_{collateral}, r_{cloan})\right)^2 - a_b Var(r_{collateral}) Var(r_{cloan})} \tag{57}$$

Since assets must equal liabilities, y_f is:

$$\begin{aligned} y_f = & \frac{Var(r_{cloan})r_{collateral} + Cov(r_{collateral}, r_{cloan})r_{cloan}}{a_b Var(r_{collateral})Var(r_{cloan}) - a_b \left(Cov(r_{collateral}, r_{cloan})\right)^2} \\ & + \frac{Cov(r_{collateral}, r_{cloan})r_{collateral} + Var(r_{collateral})r_{cloan}}{a_b Var(r_{collateral})Var(r_{cloan}) - a_b \left(Cov(r_{collateral}, r_{cloan})\right)^2} - 1 \end{aligned} \tag{58}$$

These optimal weights are only valid as long as the collateralization and capital requirements as well as the non-negativity constraints can be satisfies. Non-linear programming has to be applied in all other cases.

Appendix C.

Example Transaction on Ethereum Block Chain

0x4315ab29b40bec0c5f41112a263f74bcb7d63bc3998f4a1fd518bc520cfe864b is a hash representing the supply transaction below:

```
{
        ”blockNumber”:”17604888”,
        ”timeStamp”:”1688283431”,
        ”hash”:”0x4315ab29b40bec0c5f41112a263f74bcb7d63bc3998f4a1fd518bc520cfe864b”,
        ”nonce”:”1131”,
        ”blockHash”:”0x92981ae7c97be3b4cc103aa2efa4b7f67c03f5d67fbe9069be6634c5c07eeb91”,
        ”transactionIndex”:”92”,
        ”from”:”0xc5ec4153f98729f4eaf61013b54b704eb282ecf4”,
        ”to”:”0x87870bca3f3fd6335c3f4ce8392d69350b4fa4e2”,
        ”value”:”0”,
        ”gas”:”300000”,
        ”gasPrice”:”13488142839”,
        ”isError”:”0”,
        ”status”:”1”,
        ”input”:”0x617ba037
            0000000000000000000000002260fac5e5542a773aa44fbcfedf7c193bc2c599
            00000000000000000000000000000000000000000000000000000000002c99558
            000000000000000000000000c5ec4153f98729f4eaf61013b54b704eb282ecf4
            0000000000000000000000000000000000000000000000000000000000000000”,
        ”contractAddress”:””,
        ”cumulativeGasUsed”:”25312695”,
        ”gasUsed”:”168795”,
        ”confirmations”:”310809”,
        ”methodId”:”0x617ba037”,
        ”functionName”:”supply(address asset, uint256 amount, address onBehalfOf, uint16 referralCode)”
}
```

In this example, an EOA (*from* data field) called the supply function of Aave (*to* data field). The parameters of this function can be found in the *input* data field.

The address of the asset follows the *methodId* in the *input* data field. The address of this asset is WBTC. The prefix 0*x* is omitted in the *input* data field. The *amount* is the third part of the *input* data field. The hexadecimal number 2c99558 is equivalent to the decimal number 46765400, and the value in WBTC is expressed in satoshi (1/100000000). The last part of the data field is the address of the EOA or the recipient if the sender deposits for somebody else.

Appendix D.

Example Event of Transaction Log

0x4315ab29b40bec0c5f41112a263f74bcb7d63bc3998f4a1fd518bc520cfe864b is a hash representing a supply transaction. All supply transactions involve updates of rates and ratios of the Aave liquidity pool. This update is represented by the event below:

```
{
        ”address”:”0x87870bca3f3fd6335c3f4ce8392d69350b4fa4e2”,
        ”topics”: [
            ”0x804c9b842b2748a22bb64b345453a3de7ca54a6ca45ce00d415894979e22897a”,
            ”0x0000000000000000000000002260fac5e5542a773aa44fbcfedf7c193bc2c599”
        ],
        ”data”:”0x000000000000000000000000000000000000000000029e4e11f533ad8eb9cfc2
            0000000000000000000000000000000000000000004cc74ed789df3be190ed65
            0000000000000000000000000000000000000000000f8352789c7b2a5e9bf55e
            0000000000000000000000000000000000000000033c1e977cfd523a2a441baf
            0000000000000000000000000000000000000000340e5691e2f6096c05ead59”,
        ”blockNumber”:”0x10ca118”,
        ”blockHash”:”0x92981ae7c97be3b4cc103aa2efa4b7f67c03f5d67fbe9069be6634c5c07eeb91”,
        ”timeStamp”:”0x64a12927”,
        ”gasPrice”:”0x323f4b9f7”,
        ”gasUsed”:”0x2935b”,
        ”logIndex”:”0x13f”,
        ”transactionHash”:”0x4315ab29b40bec0c5f41112a263f74bcb7d63bc3998f4a1fd518bc520cfe864b”,
        ”transactionIndex”:”0x5c”
}
```

This update can be identified by its *topic*. The first part of the *topic* data field indicates that this event represents an update of reserves. The address of the asset (WBTC) is the second part of the *topic* data field. The variable deposit rate of this asset is the first part of the $data$ field. The second part of the $data$ field is the fix borrow rate. The third part is the variable borrow rate. Rates are expressed as hexadecimal numbers. The fourth and fifth parts are indices.

Appendix E.

Standardized Function Names

Since naming differs across DeFi systems and versions, names of functions have been standardized. The overview below summarizes the original names for each standardized name:

Table 19

Standardized Function Names

This table summarizes the original names for each standardized function name.

Standardized	Aave V3	Aave V2	Compound V3	Compound V2
borrow	borrow	borrow	withdraw	borrow
deposit	supply	deposit	supply	mint
withdraw	withdraw	withdraw	withdraw	redeem
repay	repay	repay	supply	repay

Appendix F.

Source Code

The source code for this thesis is available at the *GitHub repository*.

References

Aave. (2023a, April 19). *Borrow Interest Rate*. https://docs.aave.com/risk/liquidity-risk/borrow-interest-rate

Aave. (2023b, September 10). *Aave Document Hub*. https://docs.aave.com/hub/

Allayannis, G., Brown, G. W., & Klapper, L. F. (2003). Capital Structure and Financial Risk: Evidence from Foreign Debt Use in East Asia. *Journal of Finance*, 58(6), 2667-2709.

Aramonte, S., Doerr, S., Huang, W., & Schrimpf, A. (2022). DeFi lending: intermediation without information? *BIS Bulletin*, 57, 1–7.

Basso, S. B., Calvo-Gonzalez, O., & Jurgilas, M. (2011). Financial dollarization: The role of foreign-owned banks and interest rates. *Journal of Banking & Finance*, 35(4), 794–806.

Bernanke, B. S., & Blinder, A. S. (1988). Credit, Money, and Aggregate Demand. *American Economic Review*, 78(2), 435-439.

Berger, A. N., & Sedunov, J. (2017). Bank liquidity creation and real economic output. *Journal of Banking & Finance*, 81, 1–19.

Bianchi, J. (2011). Overborrowing and Systemic Externalities in the Business Cycle. *American Economic Review*, 101, 3400-26.

Bianchi, J., & Mendoza, E. (2018). Optimal time-consistent macro prudential policy. *Journal of Political Economics*, 126 (2), 588-634.

Black, F., & Litterman, R. (1991). Asset Allocation: Combining Investor Views with Market Equilibrium. *The Journal of Fixed Income*, 1 (2), 7-18.

Borgards, O. (2021). Dynamic time series momentum of cryptocurrencies. *North American Journal of Economics and Finance*, 57, 1-16.

Brown, M., & De Haas, R. (2012). Foreign Banks and Foreign Currency Lending in Emerging Europe. *Economic Policy*, 27(69), 57-98.

Brunnermeier, M. K. (2009). Deciphering the Liquidity and Credit Crunch 2007-2008. *Journal of Economic Perspectives*, 23(1), 77-100.

Buterin, V. (2014). Ethereum: A Next-Generation Smart Contract and Decentralized Application Platform. https://ethereum.org/

Caporale, G. M., & Plastun, A. (2020). Momentum effects in the cryptocurrency market after one-day abnormal returns. *Financial Markets and Portfolio Management*, 34(3), 251-266.

Compound. (2023a, June 3). *Interest Rates*. https://docs.compound.finance/interest-rates/

Compound. (2023b, September 9). *Documentation*. https://docs.compound.finance

Credit Suisse HOLT. (2023, June 26). *HOLT*. https://www.credit-suisse.com/microsites/holt/en.html

Cutler, D. M., Poterba, J. M., & Summers, L. H. (1991). Speculative Dynamics. *Review of Economic Studies*, 58, 529-546.

Ethereum Foundation. (2023, August 10). *Logging data from smart contracts with events*. https://ethereum.org/en/developers/tutorials/logging-events-smart-contracts/

Etherscan. (2023a, June 19). *About Etherscan*. https://etherscan.io/aboutus

Etherscan. (2023b, June 19). *Etherscan APIs Documentation*. https://docs.etherscan.io

Federal Reserve. (2023a, June 20). *Selected Interest Rates*. www.federalreserve.gov/releases/h15/

Federal Reserve. (2023b, June 20). *Financial Stability Report - May 2023*. www.federalreserve.gov/publications/files/financial-stability-report-20230508.pdf

Fidrmuc, J., Hake, M., & Stix, H. (2013). Households' foreign currency borrowing in Central and Eastern Europe. *Journal of Banking & Finance*, 37, 1880-1897.

Fisher, I. (1933). The Debt-Deflation Theory of Great Depressions. *Econometrica*, 1(4), 337–357.

Gudgeon, L., Werner, S., Perez, D., & Knottenbelt, W. J. (2020a). DeFi Protocols for Loanable Funds: Interest Rates, Liquidity and Market Efficiency. *In Proceedings of the 2nd ACM Conference on Advances in Financial Technologies (AFT '20)*. Association for Computing Machinery, New York, NY, USA, 92–112.

Gudgeon, L., Perez, D., Harz, D., Livshits, B., & Gervais, A. (2020b). The Decentralized Financial Crisis. *In Proceedings of Crypto Valley Conference on Blockchain Technology (CVCBT)*. 2020, 1-15.

Hanson, S. G., Shleifer, A., Stein, J. C., & Vishny, R. W. (2015). Banks as patient fixed-income investors. *Journal of Financial Economics*, 117(3), 449–469.

Hegedűs, P. (2018). Towards analyzing the complexity landscape of solidity based ethereum smart contracts. *In Proceedings of the 1st International Workshop on*

Emerging Trends in Software Engineering for Blockchain (WETSEB '18). Association for Computing Machinery, New York, NY, USA, 35–39.

Howcroft, E., & Jaiswal, R. (2023, March 12). Circle assures market after stablecoin USDC breaks dollar peg. *Reuters*. www.reuters.com/business/crypto-firm-circle-reveals-33-bln-exposure-silicon-valley-bank-2023-03-11/

Ivashina, V., Scharfstein, D. S., & Stein, J. C. (2015). Dollar Funding and the Lending Behavior Of Global Banks. *The Quarterly Journal of Economics*, 130(3), 1241–1282.

Ize, A., & Yeyati, E. L. (2003). Financial dollarization. *Journal of International Economics*, 59(2), 323–347.

Jacobs, B. I., & Levy, K. N. (2012). Leverage Aversion and Portfolio Optimality. *Financial Analysts Journal*, 68(5), 89-94.

Jordan, T. J. (2018). *How money is created by the central bank and the banking system*. Zürcher Volkswirtschaftliche Gesellschaft, Zurich, Switzerland.

King, R. G., & Levine, R. (1993a). Finance, Entrepreneurship, and growth - theory and evidence. *Journal of Monetary Economics*, 32(3), 513–542.

King, R. G., & Levine, R. (1993b). Finance and Growth: Schumpeter Might Be Right. *The Quarterly Journal of Economics*, 108(3), 717–737.

Kolachala, K., Simsek, E., Ababneh, M., & Vishwanathan, R. (2021). SoK: Money Laundering in Cryptocurrencies. *In Proceedings of the 16th International Conference on Availability, Reliability and Security (ARES '21)*. Association for Computing Machinery, New York, NY, USA, 1–10.

Koursaros, D., Michail, N., & Savva, C. (2021). Tell me where to stop: thresholds in the bank lending and output growth relationship. *Empirical Economics*, 60, 1845-1873.

Law, S. H., & Singh, N. (2014). Does too much finance harm economic growth? *Journal of Banking & Finance*, 41, 36–44.

Levy, H. (1981). Optimal Portfolio of Foreign Currencies with Borrowing and Lending. *Journal of Money, Credit and Banking*, 13(3), 325–341.

Liu, W., Liang, X., & Cui, G. (2020). Common risk factors in the returns on cryptocurrencies. *Economic Modelling*, 86, 299–305.

Luca, A., & Petrova, I. (2008). What drives credit dollarization in transition economies? *Journal of Banking & Finance*, 32, 858–869.

MakerDao. (2017). The Dai Stablecoin System. https://makerdao.com/en/whitepaper/

Malherbe, L., Montalban, M., Bédu, N., & Granier, C. (2019). Cryptocurrencies and Blockchain: Opportunities and Limits of a New Monetary Regime. *International Journal of Political Economy*, 48(2), 127–152.

Markowitz, H. M. (1952). Portfolio Selection. *Journal of Finance*, 7(1), 77–91.

Markowitz, H. M. (1956). The Optimization of a Quadratic Function Subject to Linear Constraints. *Naval Research Logistics Quarterly*, 3(1-2), 111–133.

Markowitz, H. M. (2013). How to Represent Mark-to-Market Possibilities with the General Portfolio Selection Model. *Journal of Portfolio Management*, 7(1), 77–91.

Mattke, J., Maier, C., & Reis, L. (2020). Is Cryptocurrency Money? Three Empirical Studies Analyzing Medium of Exchange, Store of Value and Unit of Account.

Proceedings of the 2020 on Computers and People Research Conference (SIGMIS-CPR'20). Association for Computing Machinery, New York, NY, USA, 26–35.

McBrady, M. R., & Schill, M. J. (2007). Foreign currency-denominated borrowing in the absence of operating incentives. *Journal of Financial Economics*, 86(1), 145–177.

McLeay, M., Radia, A., & Thomas, R. (2014). Money Creation in the Modern Economy. Bank of England. *Quarterly Bulletin*, 54(1), 14-27.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104, 228-250.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. https://bitcoin.org

Ojog, S. (2021). The Emerging World of Decentralized Finance. *Informatica Economica*, 25(4), 43–52.

Qin, K., Zhou, L., Gamito, P., Jovanovic, P., & Gervais, A. (2021). An empirical study of DeFi liquidations: incentives, risks, and instabilities. *Proceedings of the 21st ACM Internet Measurement Conference (IMC '21).* Association for Computing Machinery, New York, NY, USA, 336–350.

Rousseau, P. L., & Wachtel, P. (1998). Financial Intermediation and Economic Performance: Historical Evidence from Five Industrialized Countries. *Journal of Money, Credit and Banking*, 30(4), 657–678.

Rousseau, P. L., & Wachtel, P. (2011). What is happening to the impact of financial deepening on economic growth? *Economic Inquiry*, 49(1), 276–288.

Sriman, B., & Kumar, S. G. (2022). Decentralized finance (DeFi): The Future of Finance and Defi Application for Ethereum blockchain based Finance Market. *Proceedings of the 2022 International Conference on Advances in Computing*. Communication and Applied Informatics (ACCAI), 1-9.

Thomas, L. R. (1985). Portfolio Theory and Currency Substitution. *Journal of Money, Credit and Banking*, 17(3), 347–357.

Thompson, C. (2018). In Bitcoin We Trust. *Smithsonian Magazine*, 49(1), 13-90.

Yeyati, E. L. (2006). Financial dollarization: evaluating the consequences. *Economic Policy*, 21(45), 61-118.

Zhang, Z., & Jin, S. (2020). Risk Assessment and Measurement of P2P Industry. *Proceedings of the Chinese Control And Decision Conference (CCDC)*, 4163-4166.