Leverage and Stablecoin Pegs*

Gary B. Gorton†1, Elizabeth C. Klee‡2,
Chase P. Ross§2, Sharon Y. Ross¶2, and Alexandros P. Vardoulakis‖2

[1]Yale & NBER
[2]Federal Reserve Board

This draft: August 7, 2023
First draft: December 28, 2022

Abstract

Money is debt that circulates with no questions asked. Stablecoins are a new form of private money that circulate with many questions asked. We show how stablecoins can maintain a constant price even though they face run risk and pay no interest. Stablecoin holders are indirectly compensated for stablecoin run risk because they can lend the coins to levered traders. Levered traders are willing to pay a premium to borrow stablecoins when speculative demand is strong. Therefore, the stablecoin can support a $1 peg even with higher levels of run risk.

JEL Codes: E40, E51, G12, N21

Keywords: money, leverage, stablecoins, cryptocurrencies

*We thank Oliver Hyman-Metzger for excellent research assistance. For comments and suggestions, thanks to Joseph Abadi, David Arseneau, Christoph Bertsch (discussant), Eduardo Davila, John Geanakoplos, Pedro Gomis Porqueras (discussant), Daniel Graves, Todd Keister, Michael Palumbo, Greg Phelan, David Rappoport, Thomas Rivera (discussant), Raluca Roman, Alp Simsek, K. Sudhir, Dimitrios Tsomocos, Quentin Vandeweyer (discussant), Chris Waller, Sean Wilkoff (discussant), Russell Tsz-Nga Wong, and seminar participants at the Office of Financial Research, the Fed Board 2022 Summer Workshop on Money, Banking, Payments, and Finance, the Fed System Committee on Financial Institutions, Regulation, and Markets, the Philadelphia Fed, the Fed Board FS workshop, the 2023 MFA, the 2023 Yale Cowles Conference on General Equilibrium, the OCC, the 2023 Edinburgh Economics of Financial Technology conference, the 2023 NASMES, the 2023 CEBRA, the 2023 Oxford Saïd-Risk Center at ETH Zürich Macro-finance Conference, and the 2023 MoFiR Workshop on Banking. The analysis and conclusions set forth are those of the authors and do not indicate concurrency by members of the Board of Governors of the Federal Reserve System or their staffs.

†`gary.gorton@yale.edu`
‡`elizabeth.c.klee@frb.gov`
§`chase.p.ross@frb.gov`
¶`sharon.y.ross@frb.gov`
‖`alexandros.vardoulakis@frb.gov`

I'm trying to buy the dip, but this dip is so big that now my stablecoins are dipping too.

Trifusi0n, Reddit, May 10, 2022

1 Introduction

Money is debt that satisfies Holmström (2015)'s *no questions asked* principle. New forms of private money have recently emerged which do not satisfy this property, like stablecoins. This is nothing new. Historical private monies have long struggled to become no questions asked. Past incarnations of private money nearly always traded at a discount to par—stablecoins, however, trade without a discount. We resolve a simple puzzle: how can stablecoins with nontrivial run risk ostensibly succeed in keeping their price nearly constant at $1? We show stablecoin holders demand compensation from levered traders by lending their coins for a fee. When speculative motives wane, stablecoin issuers must adjust their reserves and tokens in circulation to keep a fixed $1 price.

Cryptocurrency trading has exploded in recent years. Despite aspirations to be a store of value and an alternative to fiat money, cryptocurrencies like Bitcoin have exhibited extreme price volatility measured in dollars. Stablecoins emerged to solve the volatility problem. Stablecoins promise to maintain a constant price of $1 and to be redeemable at par on demand. Unlike unbacked digital assets, like Bitcoin, stablecoins are usually backed by reserves, potentially consisting of illiquid assets, and denominated in fiat currency.[1] Stablecoins are envisaged to act as a widely used medium of exchange and bring innovations in payments globally (e.g., Libra and Diem). Thus far, they mainly facilitate crypto trading.

Unlike fiat currency, stablecoins are economically equivalent to deposits and subject to runs. The same strategic complementarities for fragile banks, mutual funds, and money market funds apply to stablecoins.[2] Stablecoin holders should demand compensation for run risk if stablecoin reserves become too illiquid to maintain a $1 peg in bad states. But

[1]We focus on so-called collateralized stablecoins that hold reserves, as opposed to algorithmic stablecoins. The reserves could be either traditional financial assets (commercial paper, reverse repurchase agreements, Treasuries) or crypto-related assets. Collateralized stablecoins constitute the majority of stablecoins by market capitalization, even before the failure of the largest algorithmic stablecoin TerraUSD in May 2022.

[2]For banks, the literature on runs is abundant. See Chen, Goldstein, and Jiang (2010) and Schmidt, Timmermann, and Wermers (2016) for runs on open-ended mutual funds and money market funds.

stablecoins pay no interest, unlike bank deposits and money market funds. At the same time, the use of stablecoin in payments has concentrated so far in some special cases at best and it is not clear whether stablecoins could command a convenience yield like other money-like liabilities. On the contrary, Gorton and Zhang (2021) and Gorton, Ross, and Ross (2022) argue that stablecoins carry an *inconvenience* yield. Thus, it is unclear how stablecoins have offered compensation for run risk enough to keep the price fixed at $1.

We argue theoretically and show empirically that stablecoin compensation comes from their role in speculative cryptocurrency trading. A main use of stablecoins has been for leveraged trading in other more volatile—and higher expected return—digital assets. Traders borrow stablecoins for levered bets on other cryptocurrencies. Stablecoin holders are indirectly compensated for run risk because they can lend the stablecoin to traders. In other words, the primary market issuer does not pay interest, but secondary lending markets compensate for the issuer's run risk. Loans to traders are collateralized, and lending rates are high—often above 20 percent per year and about 10 percent on average. We show that these lending rates are closely correlated with measures of speculative demand for cryptocurrencies. Many exchanges and decentralized lending platforms allow holders to lend stablecoins to others that want to speculate on cryptocurrencies, resulting in an unruly nexus between run risk and leverage. Although our paper focuses on this specific use-case of stablecoins—the leverage/money nexus—our model can easily be adjusted to include additional services, such as payment services, as we show in an Online Appendix. Such services may become more important as stablecoins mature and earn a convenience yield, which should be expected to be lower that the aforementioned lending rates.[3]

We model the leverage-money nexus by combining a bank-run model akin to Goldstein and Pauzner (2005) and Kashyap, Tsomocos, and Vardoulakis (2023) with a model of leveraged collateralized trading akin to Fostel and Geanakoplos (2008), Gromb and Vayanos (2002), and Brunnermeier and Pedersen (2009). Stablecoin issuers raise funds from investors and invest them in a portfolio of liquid and illiquid assets. The liquid asset always trades at par, while the illiquid asset may trade at a discount. We use global game techniques to pin down a unique probability of a run that depends on the issuer's balance sheet. With this probability,

[3]Van den Heuvel (2022) estimates the convenience yield of deposits over same maturity Treasuries, which should partially capture the convenience yield from payments, to be about 80 basis points in recent years. Our model implies that reliance on smaller convenience yields should push the issuer towards a safer and more liquid reserves portfolio, which has been the case for stablecoins that attempt to specialize in payments.

we can compute the premium that stablecoin holders require to maintain a price of $1 and connect it to the rate that speculators offer to borrow the stablecoin. Higher speculative demand for cryptocurrencies increases the lending rate on stablecoins and, hence, their price. A less liquid portfolio of reserves increases run risk, reducing their price. The two forces interact by pushing the peg in opposite directions. Given a demand for crypto, the stablecoin issuer chooses the liquidity of its reserves and the supply of tokens to maximize its profits while achieving a price of $1 for the issued tokens.

We show how the issuer can stabilize the peg in response to crypto shocks. An adverse shock to cryptocurrency demand pushes the lending rate down, and the stablecoin trades below its peg, which materializes in redemptions. As the supply of tokens shrinks, the lending rate may recover to its previous level, re-stabilizing the peg. Redemptions result in fewer tokens that can be lent out to satisfy speculative demand, despite its relative decline. We call this the *redemption channel* of peg stabilization, which works for both good and bad crypto shocks. But there are limits to how much adjusting the token supply can stabilize the peg in response to shocks. The issuer may not have enough liquidity to meet all redemptions required to reduce the supply enough to re-stabilize the peg. If the issuer can re-balance the portfolio of liquid and illiquid assets without incurring any liquidation or portfolio re-balancing costs, then the issuer may choose a higher level of liquidity to reduce the probability of a run and stabilize the peg. We call this the *liquid asset portfolio share channel*. The issuer will use both channels to stabilize the peg in response to crypto shocks in "normal" times when the illiquid assets can be liquidated at their face value. We show that this result holds independent of whether the share of liquid assets in reserves is observable, although unobservability introduces limits to stabilization for low cryprocurrency demand.

On the contrary, when the issuer incurs liquidation costs from selling the illiquid asset, the liquid asset portfolio share channel is not operational. The redemption channel still works, but there are limits. The peg can be defended only up to a level of redemptions. Beyond that, the issuer becomes insolvent. In that case, the stablecoin tokens lose their usefulness for speculative trading and cannot earn the lending rate necessary to maintain the peg.

We corroborate our theoretical analysis with three sets of empirical results. First, we connect speculative demand for cryptocurrencies to the lending rate on stablecoins. We approximate speculative demand using the funding rate from perpetual futures, liquid crypto derivatives that bet on cryptocurrencies. We show that increases in funding rates result in statistically and economically significant increases in stablecoin lending rates: A one percentage point (pp) increase in the funding rate translates to a 20 basis point rise in the lending rate. To account for unobserved endogeneity, we instrument the speculative demand using the viewership of Major League Baseball (MLB) games and exploiting the sponsorship deal between MLB and FTX, a major cryptocurrency exchange. We find similar results.

Second, we empirically establish the two stabilization mechanisms to maintain the peg: adjusting the liquidity of reserves and letting the lending rate re-adjust via token redemptions/issuance. Data for the reserve rebalancing mechanism are scarce given the opacity of stablecoin issuers and their infrequent disclosures. Still, they are suggestive of the intuitive relationship in our model that lower speculative demand and lending rates should accompany higher liquidity to mitigate run risk. Data for redemptions/issuance are available at high frequency, enabling us to establish more tightly how lower demand for cryptocurrencies leads first to more stablecoin redemptions and second to higher lending rates.

Third, we apply the model to the May 2022 crypto turmoil following the collapse of TerraUSD and the near run on Tether. We document how Tether experienced large redemptions and traded considerably below its peg but regained its peg once lending rates increased and stabilized at a higher level, consistent with our theoretical predictions. One consideration is that the higher lending rates were driven by an incentive of borrowers to bet on the collapse of Tether: their debt would be stablecoin-denominated and, thus, worth zero if Tether collapsed. In the Online Appendix, we present an extension of our model that incorporates the motive to bet on the stablecoin's collapse. We show that lending rates are higher only if the probability of collapse is high enough, which is consistent with the May 2022 episode. Nevertheless, the lender should rationally expect that the borrower would fully repay in some states of the world, implying that the demand for cryptocurrencies would have not completely faded.

In terms of policy implications, we show that stablecoins can harm financial stability by directly linking speculation in crypto markets to the real economy and vice versa. Stablecoin issuers invest their reserves to earn profits but must adjust their reserves—possibly quickly—in response to crypto shocks. Such reallocations can disrupt the money markets that stablecoins invest their reserves in, such as Treasuries and commercial paper. Stablecoins can also transmit volatility from the crypto markets to the real economy depending on the liquidity in the markets and the relative size of the stablecoin's holding. Even though we do not present a thorough welfare analysis, it should be clear that the indirect interconnectedness between crypto markets and money markets that stablecoins introduce, can generate externalities that a regulator may want to address.

The leverage-money nexus is likely broader than stablecoins and cryptocurrency trading; such a nexus has important implications for the future of private money. For example, JP Morgan is experimenting with a Tokenized Collateral Network where traders could use their tokenized assets, such as Money Market Fund (MMF) shares, to post margin in repo transactions, essentially introducing a collateral/money premium on these assets. Our mechanism could be used to study such innovations. Historically, private money has often proved fragile (Gorton, 2017). We show that even *fragile* money, like stablecoins, may maintain a constant exchange value if it generates secondary benefits for its holders. But fragile money could collapse quickly if this secondary use faces a significant shock.

Related Literature. Our paper relates to the two strands of the literature on leveraged collateralized trading and on bank-runs. We contribute by bringing these two strands together and show how their interaction can generate the leverage-money nexus described earlier.

Brunnermeier and Pedersen (2009), Fostel and Geanakoplos (2008), Geanakoplos (2010), and Gromb and Vayanos (2002) has investigated the importance of private wealth to meet haircut requirement in collateralized trading, but has mostly focused on shocks on the value of collateral that can result in an unfolding of leverage and drop in asset prices. We show that the fragility of the "assets" in which agents hold their private wealth and use to meet haircut requirements, stablecoin tokens in our case, can also be an independent source of instability, interacting with speculative motives.[4]

By contrast, the bank-run literature has studied in large depth the possibility of fragile liabilities issued by financial institutions and has used state-of-the-art global game techniques to link institutions' balance sheet and profitability to the probability of a run (Goldstein and Pauzner 2005, Kashyap et al. 2023, Infante and Vardoulakis 2020, Vives 2014; and Morris and Shin 2003, Carlsson and van Damme 1993), However, this literature has not connected the run risk in institutions' liabilities to the premium they can earn in external trading, which is what we explore in our paper. There is a good reason for this. The traditional liabilities of financial institutions are not fungible and are not bearer instruments, with the exception of

[4]To keep our model tractable, we do not incorporate a channel through which leverage affects asset prices, but such channel could be incorporated in our analysis and could be an interesting avenue for future work.

private banknotes during the Free Banking Era. Tokenization renders such liabilities fungible so investors can use them for external activities to earn additional premia.

Our paper is also related to what makes money no-questions-asked, which implies that the money is not sensitive to costly private information production about its value. This *information insensitivity* is a key attribute of money. Coins, for example, were sometimes information sensitive as they could be debased or shaved (Gorton, 2017). A shortage of safe assets compels the private sector to produce alternatives (Krishnamurthy and Vissing-Jorgensen 2012, Krishnamurthy and Vissing-Jorgensen 2015, Greenwood, Hanson, and Stein 2015, Carlson, Duygan-Bump, Natalucci, Nelson, Ochoa, Stein, and Van den Heuvel 2016). Stablecoins follow a well-trodden path.

More narrowly, our paper contributes to the emerging literature that studies the stability of stablecoins (Lyons and Viswanath-Natraj 2023, Hoang and Baur 2021, Li and Mayer 2021, Kozhan and Viswanath-Natraj 2021, d'Avernas, Maurin, and Vandeweyer 2022, Kwon, Pongmala, Qin, Klages-Mundt, Jovanovic, Parlour, Gervais, and Song 2023). Ma, Zeng, and Zhang (2023) study the market mechanism through which stablecoins traded in the secondary markets can be redeemed for fiat currency and conclude that the number of arbitragers, allowed to interact with the stablecoin issuer and request redemptions, is crucial for stablecoin stability. Bertsch (2023) study how the use of stablecoins in payments could affect run risk and their desirability over deposits, while Liao and Hadeed (2023) studies the transition of stablecoins toward means of payments. Mizrach (2022) documents the market microstructure of stablecoins and stablecoins' survival rates. Chaudhary and Viswanath-Natraj (2022) and Uhlig (2022) study the fragility of algorithmic stablecoins. Kim (2022) and Barthélémy, Gardin, and Nguyen (2023) studies the effects of stablecoin issuance on commercial paper issuance, rates, and Treasury yields. We also contribute to the literature on asset pricing and the market structure of decentralized protocols and blockchains (Makarov and Schoar 2022, Lehar and Parlour 2021). Our measurement of speculative demand for cryptocurrencies, including our instrumental identification, may be of independent interest to the literature along with the connection between speculation, stablecoin size, and stability.

More generally, our analysis of stablecoin pegs relates to the literature studying the fragility of currency pegs (Krugman 1979, Obstfeld 1986, Morris and Shin 1998, Routledge and Zetlin-Jones 2022). Similar to stablecoin issuers, central banks may choose to peg their currency to the dollar without holding all their reserves in perfectly liquid and safe dollar denominated assets. Doing so exposes them to speculative attacks and the ability of the central bank to defend the peg does not only depend on its available reserves, i.e., the strength of the regime, but also on the cost of attacking the currency. Intuitively, higher demand for local currency increases the opportunity cost of a self-fulfilling run. In our paper, the higher demand stems from the ability to lend the stablecoin to traders that want to speculate on cryptocurrency appreciation, but more generally one could substitute this benefit with other uses to generate demand.

2 Model

This section presents the model to study the leverage-money nexus summarized in Figure 1. There are three periods ($t = 0, 1, 2$), four assets, and three agents. Two of the assets are traditional, a liquid asset and an illiquid asset, and the other two are digital assets, a stablecoin and a cryptocurrency. All assets are perfectly divisible. The first type of agent is the stablecoin issuer and manager. The second type consists of a continuum of investors, which are identical ex ante, but heterogeneous ex post as described below. The third type consists of a continuum of traders that want to take a leveraged long position in the cryptocurrency.

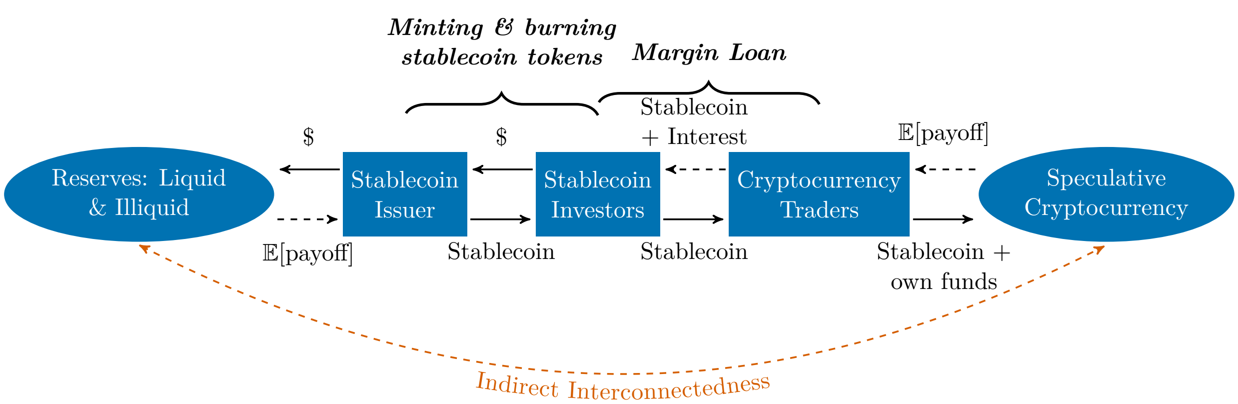

Figure 1: Model Sketch.

The stablecoin raises funds in fiat currency from investors at $t = 0$ in exchange for tokens, which are the liabilities of the stablecoin issuer and the first digital asset in the model. Denote by s the number of tokens in circulation. Given that the issuer will offer tokens at unitary price, s also captures the total funds invested in the stablecoin. In turn, the stablecoin invests the funds in a portfolio of the traditional assets.[5] Both assets are in perfectly elastic supply, their returns are denominated in fiat currency, and they can be bought for one unit of fiat currency at $t = 0$. The liquid asset yields a gross return of one at $t = 2$ and can be sold at any time before $t = 2$ for the price of one. The payoffs and the liquidation value of the illiquid asset depend on the realization of a fundamental state $\theta \sim U[0, 1]$ with its true value realized at $t = 1$, but not publicly revealed. If $\theta \geq \overline{\theta}$, which is exogenously chosen, the illiquid asset yields $X > 1$ at $t = 2$ with certainty and can be liquidated at $t = 1$ also for X. If $\theta < \overline{\theta}$, the illiquid asset yields $X > 1$ at $t = 2$ only with probability θ and zero otherwise, while its liquidation value drops to $\xi < 1$. The assumption about the liquidation value and payoffs of the illiquid asset follows Goldstein and Pauzner (2005). Without loss of generality and to simplify the notation when we derive the stablecoin price and the issuer's optimization problem later on, we will consider $\overline{\theta} \to 1$. Finally, denote by ℓ the portion of the portfolio invested in the liquid asset. We will also assume that both liquid and illiquid assets can be resold between $t = 0$ and $t = 1$—that is before the shock on the illiquid asset—for the price of one to allow the issuer to re-balance their reserves portfolio, i.e., adjust ℓ, if warranted.

Investors are identical ex ante and have deep pockets. At $t = 0$, each investor can hold one token issued by the stablecoin in exchange for fiat currency. Tokens are initially issued in exchange for fiat currency and are redeemable on demand for fiat currency at a fixed exchange rate of one. Following Diamond and Dybvig (1983), an individual investor receives with probability δ an idiosyncratic preference shock urging them to redeem their tokens to use their funds for purposes outside the digital asset ecosystem. We will call these investors *impatient*. By the law of large numbers, the total expected redemption at $t = 1$ from impatient investors is equal to δs. The remaining $(1 - \delta)s$ investors do not have a pressing need to redeem but can decide to do so based on private noisy signals $x_i = \theta + \epsilon_i$, with $\epsilon_i \overset{\text{iid}}{\sim} U[-\epsilon, \epsilon]$, about the realization of θ at $t = 1$. We will call these investors *patient*.

The benefit for patient investors from not redeeming is that they can lend the tokens to traders that want to take exposure to the cryptocurrency, expecting a gross return $y = \int \tilde{y} dF(\tilde{y})$, where $\tilde{y}$ is the cryptocurrency return realization. Traders borrow the stablecoin from patient investors, and, combining it with their funds, they buy a cryptocurrency on

[5] The issuer may also have chosen to invest in crypto assets, extend loans, or even invest in stablecoins of other issuers and lend them out for a profit. These alternatives may be important in practise but are inconsequential, and would just add complexity. For our analysis, it only matters that the issuer may invest in illiquid assets and that the stablecoin tokens issued against these reserves can be re-used by investors.

margin, as described in detail below. For simplicity and without loss of generality, we make four assumptions, which can be relaxed. First, we assume that patient investors do not want to hold the cryptocurrency directly.[6] Second, we assume the lending of tokens takes place at $t = 1$ after patient investors have decided whether to redeem (see the Online Appendix for an extension where lending takes place before $t = 1$). If the stablecoin issuer defaults, which materializes with probability $1 - \theta$, the tokens are worth zero and the trader does not need to return anything to investors because the loan is stablecoin-denominated (this is a reasonable assumption but one that can be seamlessly relaxed). Denote by θR the expected return per unit of lending the token, which will be endogenously determined. Third, we assume traders have access to an outside option with gross return ρ. Fourth, the distribution of cryptocurrency returns is independent of the distribution of θ.

The funding structure of stablecoin issuers is fragile because the liquidation value of its reserves may not be enough to fully cover potential redemptions by all token holders. As such, the stablecoin issuer is exposed to run risk from self-fulfilling beliefs giving rise to multiple equilibria described in the bank run literature. To resolve this indeterminacy, we model a global game where each individual token holder receives a private noisy signal x_i and decides to redeem or not based on their posterior about θ and their beliefs about the actions of others. We will solve for a threshold equilibrium such that token holders decide to redeem if their signal x_i is below a threshold. Using this threshold, we can compute the ex ante probability at $t = 0$ that the stablecoin may experience a run at $t = 1$ and the price at which stablecoins will trade. A higher run probability pushes the price of tokens down, while a higher lending rate pushes their price up, other things equal.

We derive the expected return from lending the stablecoin token and, given this return, we compute the probability of a run on the stablecoin issuer and the stablecoin price. Thereafter, we examine and evaluate the peg-stabilization mechanisms.

[6]One way to microfound this assumption is to have investors that are less optimistic than traders about cryptocurrency returns, so they would rather lend to traders who would like to take leverage as in Fostel and Geanakoplos (2008), Geanakoplos (2010), and Simsek (2013). Alternatively, investors could be made sufficiently risk averse at $t = 2$ or incur costs when holdings the cryptocurrency directly. We present an extension along the latter dimension in the Online Appendix.

2.1 Expected return from lending the stablecoin

In this section, we study how the expected return from lending stablecoin tokens is determined in equilibrium. We proceed backward assuming that the stablecoin has not suffered a run at $t = 1$ and that the realization of θ has become common knowledge.[7] Patient token holders can lend their tokens to traders that want to take a leveraged position in the cryptocurrency. For each dollar of cryptocurrency they buy, traders need to post m percent of margin. Assume the cryptocurrency exchange exogenously sets m. This is not critical for our results. We show how one may endogenize the derivation of m.[8]

The expected payoff from a leveraged position in one dollar of the cryptocurrency is $y-(1-m)\theta R$. Observe that the trader compensates investors with probability θ, because the margin loan is stablecoin denominated and the tokens are worth zero when the issuer default, which happens with probability $1-\theta$. Note that R is the expected return to lending—not the contractual lending rate—that incorporates the case the trader defaults.[9] Traders compete and, in equilibrium, offer an R that makes them break even with their outside option ρ, which depends on the aggregate funds invested in the alternative technology, but traders take it as given. If they break even, traders will not invest in the outside option. The equilibrium R is then given by equating levered profits per unit of investment, $(y-(1-m)\theta R)/m$, to the unlevered outside option profit per unit of investment, ρ, or

$$R = \frac{1}{\theta}\frac{y - m\rho}{1-m}. \tag{1}$$

We assume that the outside option consists of a technology, F, common to all traders,

[7]Note that it is not necessary for our analysis that the true θ is perfectly learned after $t = 1$. All our results continue to hold even if agents just infer that $\theta \geq \theta^*$ should a run not occur.

[8]An additional advantage of buying the cryptocurrency with a stablecoin token is that there are small or no haircuts on the pledgeable dollar value. Thus, the dollar value that traders must post to meet margin m is equal to m under a zero haircut, and they just need to borrow $1-m$ stablecoin tokens per dollar of exposure to the cryptocurrency. For other cryptocurrencies, the haircuts are higher, and traders must post a higher dollar value than m to meet the margin requirement (see Table 2).

[9]Denote by R_c the contractual lending rate and suppose $\tilde{y} \sim F(\tilde{y})$ with $y = \int \tilde{y} dF(\tilde{y})$. Conditional on the issuer not defaulting, the trader defaults if $\tilde{y} < y\prime \equiv (1-m)R_c$; otherwise, the tokens are worth zero and the trader never defaults. The expected return to the trader is $\theta \int_{\tilde{y} \geq y'} (\tilde{y} - (1-m)R_c)\, dF(\tilde{y}) + (1-\theta)y = y - \theta \int_{\tilde{y}<y'} \tilde{y} dF(\tilde{y}) - (1-m)\theta R_c \int_{\tilde{y} \geq y'} dF(\tilde{y}) = y-(1-m)\theta R$, because investors receive the collateral for $\tilde{y} < y'$. Given risk-neutrality, we focus on R, but control for cryptocurrency volatility in our empirical analysis where we use contractual borrowing rates to account for the difference between R and R_c.

with decreasing marginal returns depending on the aggregate amount of funds invested ($F' > 0, F'' < 0$). Denote by e the total funds of traders and by $m(1-\lambda)s/(1-m)$ the total funds invested in leveraged cryptocurrency trades, where λ is the number of tokens redeemed at $t = 1$ and not available for lending. Then, ρ in equilibrium is given by

$$\rho = F'\left(e - \frac{m}{1-m}(1-\lambda)s\right). \tag{2}$$

We assume that $F'(e) > y$, which will imply that traders have an incentive to use leverage, resulting in $R < y$.[10] Moreover, there might be a $\bar{s}$ such that $y - m\rho < 0$ for $s > \bar{s}$. The number of tokens in circulation may be so high that there is no benefit to lending them. Thus, we will also assume that $\bar{s}$ is high enough such that there is room for the number of tokens to adjust while still paying positive interest when lent out.

Combining 1 and 2, we get that the lending rate as a function of outstanding tokens $(1-\lambda)s$ at $t = 2$, where λ is the percentage of early redemptions:

$$R(\lambda, s) = \frac{1}{\theta}\frac{y - mF'\left(e - \frac{m}{1-m}(1-\lambda)s\right)}{1-m}. \tag{3}$$

Before determining how runs on the stablecoin issuer occur, we derive some important comparative statics for what will follow in Sections 2.2 and 2.4.

An increase in the cryptocurrency expected return, y is

$$\frac{dR(\lambda, s)}{dy} = \frac{1}{\theta}\frac{1}{1-m} > 0. \tag{4}$$

Because $F'(e) > y$, An increase in the margin, m is

$$\frac{dR(\lambda, s)}{dm} = \frac{1}{\theta}\left[\frac{y}{(1-m)^2} - \frac{F'\left(e - \frac{m}{1-m}(1-\lambda)s\right)}{(1-m)^2} + \frac{m(1-\lambda)sF''(e - \frac{m}{1-m}(1-\lambda)s)}{(1-m)^3}\right] < 0. \tag{5}$$

[10] Otherwise, the relevant outside option may be $\rho = y$ since traders would prefer to invest directly in the cryptocurrency. In that case, $R = y$, which is independent of the stablecoin supply s, and the redemtpion channel for peg-stability would be absent. The outside option could be any speculative investment outside cryptocurrencies. For example, it could be memestocks, binary options, or sports betting. As a simple example: in 2021, BTC had a 61 percent return, while Gamestop's equity had a 690 percent return. Ex post, an investor would need 11 $\times$ leverage on her BTC position to be indifferent with Gamestop.

An increase in the number of tokens, s is

$$\frac{dR(\lambda,s)}{ds} = \frac{1}{\theta}\frac{m^2(1-\lambda)F''(e-\frac{m}{1-m}(1-\lambda)s)}{(1-m)^2} < 0, \tag{6}$$

while an increase in redemptions λ is

$$\frac{dR(\lambda,s)}{d\lambda} = -\frac{1}{\theta}\frac{m^2 sF''(e-\frac{m}{1-m}(1-\lambda)s)}{(1-m)^2} > 0. \tag{7}$$

Changes in y and m could be interpreted as higher demand for cryptocurrencies and higher cryptocurrency volatility or risk, respectively. Both changes affect the lending rate R, destabilizing the stablecoin peg. Changing the number of tokens, s, is one way to undo the change in the lending rate and re-stabilize the peg; for example, a decrease in s following a decrease in y could bring the lending rate back to its original value. We elaborate on this stabilization mechanism in detail in section 2.4 after we show how the liquidity of the stablecoin's reserves matters for run risk and, thus, for its peg stability.

2.2 Probability of a stablecoin run

Redemptions and Issuer's Portfolio. The issuer collects funds at $t = 0$ equal to s, invests ℓ percentage of them in the liquid asset, and invests the rest in the illiquid asset. If the issuer defaults, the stablecoin holders cannot lend their tokens and earn a lending rate but are just distributed pro-rata the remaining assets of the issuer. The expected payoff to an individual investor if only impatient investors redeem is equal to $\theta R(\delta,s) + (1-\theta)\max({}^{\ell-\delta}/{}_{1-\delta}, 0)$.

Yet, the issuer may become insolvent and/or illiquid depending on the realization of θ. If $\theta \geq \overline{\theta}$, the issuer has enough liquidity to serve all possible redemptions. If $\theta < \underline{\theta} = {}^{[1-\max({}^{\ell-\delta}/{}_{1-\delta},0)]}/{}_{[R(\delta,s)-\max({}^{\ell-\delta}/{}_{1-\delta},0)]}$, every individual investor will redeem independent of what other investors choose to do. For intermediate realizations of $\theta \in [\underline{\theta}, \overline{\theta})$, the issuer does not have enough liquidity to serve all possible redemptions because the liquidation value of the illiquid asset drops to $\xi < 1$. The liquidity position of the issuer at $t = 1$ is $L(\lambda) = [\ell + (1-\ell)\xi - \lambda]s$, where λs are the total redemptions, with $\lambda \in [\delta, 1]$, depending on how many patient investors decide to redeem. Hence for $\lambda > \overline{\lambda}(\xi)$ the stablecoin issuer does not have enough liquidity to serve all redemptions, where $\overline{\lambda}$ is the solution to $L(\overline{\lambda}) = 0$, i.e.,

$$\overline{\lambda} = \ell + (1-\ell)\xi. \tag{8}$$

Conditional on having enough liquid resources ($\lambda \leq \overline{\lambda}$) and with probability θ, the profits of the stablecoin issuer at $t = 2$ as a function of λ are given by

$$\Pi(\lambda) = \left[X(1-\ell)\left(1 - \frac{\max(\lambda-\ell, 0)}{\xi(1-\ell)}\right) + \max(\ell-\lambda, 0) - (1-\lambda)\right] s. \tag{9}$$

That is, the issuer extracts all seigniorage after repaying remaining stablecoins at par. The issuer first uses the liquid asset for redemptions and then starts liquidating the illiquid asset. This is optimal since the liquid asset has a higher liquidation value, while the risky one has a higher expected payoff. For $\lambda \leq \ell$, $\Pi(\lambda) > 0$. For higher λ and because $d\Pi(\lambda)/d\lambda < 0$, the stablecoin issuer becomes insolvent at $t = 2$ for $\lambda > \hat{\lambda}(\xi)$, given by $\Pi(\hat{\lambda}(\xi)) = 0$, i.e.,

$$\hat{\lambda} = \frac{X(\ell + \xi(1-\ell)) - \xi}{X - \xi}. \tag{10}$$

Moreover, we can re-write $\hat{\lambda}(\xi) = (X\overline{\lambda}(\xi) - \xi)/(X - \xi) < \overline{\lambda}(\xi)$, i.e. the issuer becomes insolvent before running out of liquidity. This is a typical property in bank-run global games.

Finally, note that conditional on having enough liquid resources ($\lambda \leq \overline{\lambda}$) and with probability $1 - \theta$, the issuer always defaults and any unused liquid assets $\max(\ell - \lambda, 0)$ are distributed pro-rata to the remaining $1 - \lambda$ investors.

Redemptions and Investor Payoffs. A patient investor needs to decide at $t = 1$ whether to redeem their token. The payoff differential between not redeeming and redeeming depends on the beliefs about θ and λ:

$$\nu(\theta, \lambda) = \begin{cases} \theta R(\lambda, s) + (1-\theta)\max\left(\frac{\ell-\lambda}{1-\lambda}, 0\right) - 1 & \text{if} \quad \delta \leq \lambda \leq \hat{\lambda} \\ \theta \frac{X(1-\ell)\left(1-\frac{\lambda-\ell}{\xi(1-\ell)}\right)}{1-\lambda} - 1 & \text{if} \quad \hat{\lambda} < \lambda \leq \overline{\lambda} \\ -\frac{\ell+(1-\ell)\xi}{\lambda} & \text{if} \quad \overline{\lambda} < \lambda \leq 1 \end{cases}. \tag{11}$$

Given θ, if the belief about λ is below $\hat{\lambda}$, not redeeming yields the payoff from lending out the token, $R(\lambda, s)$, conditional on the issuer not defaulting, and the residual assets distributed pro-rata, $\max((\ell - \lambda)/(1 - \lambda), 0)$, conditional on the issuer defaulting. Redeeming yields one dollar, since the issuer has enough liquidity to meet redemptions. For $\lambda \in (\hat{\lambda}, \overline{\lambda}]$, investors that do not redeem receive pro rata the remaining assets in insolvency, while those that redeem receive one dollar since the issuer has enough liquidity to serve all redemptions. The issuer has depleted all liquid assets for this level of λ, so investors are only distributed the proceeds from the remaining illiquid assets at insolvency. Finally, for $\lambda > \overline{\lambda}$, the benefit from not redeeming is zero, as the stablecoin issuer will be fully liquidated; the benefit from redeeming is joining the line in the run and being able to redeem at par with probability $(\ell + (1 - \ell)\xi)/\lambda$, according to sequential servicing. Figure 2 plots for a certain parametrization and some value of θ, the payoff differential $\nu(\theta, \lambda)$ as beliefs about λ vary.

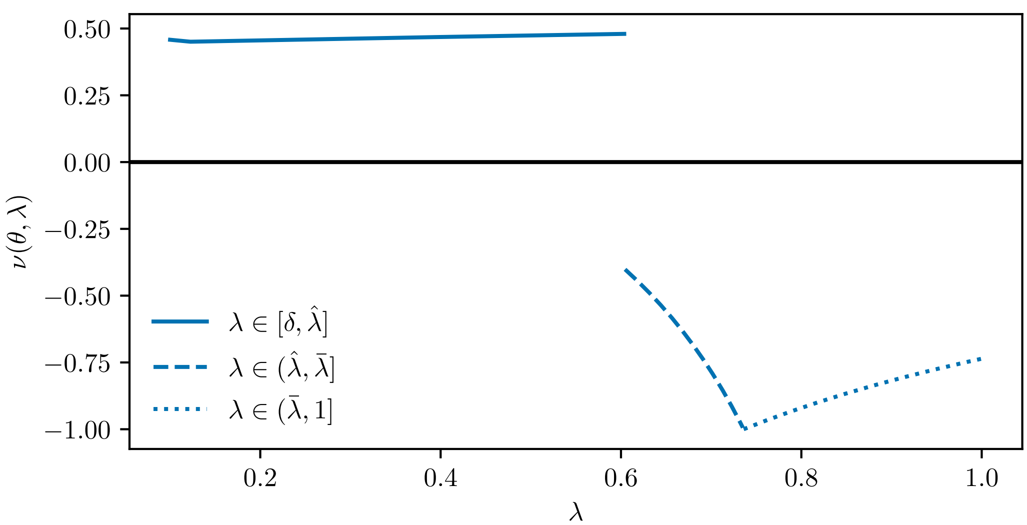

Figure 2: Payoff differential $\nu(\theta, \lambda)$ as beliefs about λ vary

Defending the Peg. Figure 2 is useful to understand the (in)ability of the issuer to defend the peg. For $\lambda \leq \hat{\lambda}$, the issuer will first liquidate the liquid and then the illiquid asset to meet redemptions, while remaining solvent. Thus, investors can earn the expected lending rate $R(\lambda, s)$, which is increasing in the number of redemptions from (7). A higher lending rate is a stabilizing force that helps the issuer defend the peg. But for $\lambda > \hat{\lambda}$, the issuer becomes first insolvent and then illiquid, and cannot defend the peg, because the liquidation value of the illiquid asset drops to $\xi < 1$. The decision to redeem, which we derive next, will depend on beliefs about total redemptions and, hence, the ability of the issuer to defend the peg.

Redemption Decision and Run Threshold. Given the private signal, an individual patient investor will update their posterior about θ, which will be uniform in $[x_i - \epsilon, x_i + \epsilon]$ and compute the expected payoff differential

$$\Delta(x_i) = \int_{x_i-\epsilon}^{x_i+\epsilon} \nu(\theta, \lambda) \frac{d\theta}{2\epsilon}. \tag{12}$$

If $x_i \geq \overline{\theta} + \epsilon$, the individual patient investor can conclude that $\theta \geq \overline{\theta}$ and will not redeem, independent of their belief about λ ($\Delta(x_i) > 0$). Similarly, if $x_i < \underline{\theta} - \epsilon$, the individual patient investor can conclude that $\theta < \underline{\theta}$ and will redeem, independent of their belief about λ ($\Delta(x_i) < 0$). These are the *upper and lower dominance* regions for θ, where the individual action is independent of the beliefs about the actions of others.

For intermediate $x_i \in [\underline{\theta} - \epsilon, \overline{\theta} + \epsilon)$, the sign of $\Delta(x_i)$ depends on the beliefs about λ. To pin down these beliefs, we focus on a threshold strategy that all patient investors follow. We show that there exists a unique signal threshold x^*, such that every investor redeems if their private signal $x_i < x^*$ and does not redeem if $x_i > x^*$. Given this threshold, an individual investor can form well-defined beliefs about the total number of redemptions by patient investors, denoted by $\lambda^b(\theta, x^*)s$, and given by the probability that other investors receive a private signal below x^*. If $\theta > x^* + \epsilon$, all patient investors get signals $x_i > x^*$, none redeem, and $\lambda^b(\theta, x^*) = \delta$. If $\theta < x^* - \epsilon$, all patient investors get signals $x_i < x^*$, all redeem, and $\lambda^b(\theta, x^*) = 1$. If $x^* - \epsilon \leq \theta \leq x^* + \epsilon$, some patient investors get signals $x_i > x^*$, while others get signals $x_i < x^*$; thus, under the threshold strategy, $\lambda^b(\theta, x^*) = (1-\delta)\Pr(x_i < x^*) = \delta + (1-\delta)(x^* - \theta + \epsilon)/(2\epsilon)$. The following equation summarizes these beliefs:

$$\lambda^b(\theta, x^*) = \begin{cases} 1 & \text{if } \theta < x^* - \epsilon \\ \delta + (1-\delta)(x^* - \theta + \epsilon)/(2\epsilon) & \text{if } x^* - \epsilon \leq \theta \leq x^* + \epsilon \\ \delta & \text{if } \theta > x^* + \epsilon \end{cases}. \tag{13}$$

Using (13), an investor can compute the expected payoff differential using their posterior about θ, given her signal x_i and an assumed value for x^*:

$$\Delta(x_i, x^*) = \int_{x_i-\epsilon}^{x_i+\epsilon} \nu(\theta, \lambda^b(\theta, x^*)) \frac{d\theta}{2\epsilon}. \tag{14}$$

Unlike in (12), beliefs in (14) are uniquely determined and pin down the payoff differential.

A patient investor does not redeem ($\Delta(x_i, x^*) > 0$) if $x_i > x^*$ and redeems ($\Delta(x_i, x^*) < 0$) if $x_i < x^*$. By continuity, the investor that receives the threshold signal x^* is indifferent between not redeeming and redeeming, i.e.,

$$\Delta(x^*, x^*) = \int_{x^*-\epsilon}^{x^*+\epsilon} \nu(\theta, \lambda^b(\theta, x^*)) \frac{d\theta}{2\epsilon} = 0. \tag{15}$$

A threshold strategy also implies thresholds for fundamentals $\theta_{\hat{\lambda}}$ and $\theta_{\bar{\lambda}}$ such that the issuer is solvent at $t = 2$ for $\theta \geq \theta_{\hat{\lambda}}$ and has enough liquidity at $t = 1$ for $\theta \geq \theta_{\bar{\lambda}}$ given signal threshold x^* and redemptions $\lambda^b(\theta, x^*)$. These thresholds are determined by $\hat{\lambda} = \lambda^b(\theta_{\hat{\lambda}}, x^*)$ and $\overline{\lambda} = \lambda^b(\theta_{\bar{\lambda}}, x^*)$. Using these, the threshold (15) can be expanded to

$$\begin{aligned}\Delta(x^*, x^*) = &- \int_{x^*-\epsilon}^{\theta_{\bar{\lambda}}} \frac{\ell + (1-\ell)\xi}{\lambda^b(\theta, x^*)} \frac{d\theta}{2\epsilon} + \int_{\theta_{\bar{\lambda}}}^{\theta_{\hat{\lambda}}} \left[\theta \frac{X(1-\ell)\left[1 - \frac{\lambda^b(\theta, x^*) - \ell}{\xi(1-\ell)}\right]}{1 - \lambda^b(\theta, x^*)} - 1 \right] \frac{d\theta}{2\epsilon} \\ &+ \int_{\theta_{\hat{\lambda}}}^{x^*+\epsilon} \left[\theta R(\lambda^b(\theta, x^*), s) + (1-\theta) \max\left(\frac{\ell - \lambda^b(\theta, x^*)}{1 - \lambda^b(\theta, x^*)}, 0 \right) - 1 \right] \frac{d\theta}{2\epsilon} = 0.\end{aligned} \tag{16}$$

As is typical in the global game literature, we focus on the limiting case where noise $\epsilon \to 0$, which also implies that $\theta_{\hat{\lambda}}, \theta_{\bar{\lambda}} \to x^*$. We will denote by θ^* this common threshold that the fundamentals' thresholds and signal threshold converge to. Expressing (16) in terms of θ^* and changing variables from θ to λ, such that as θ decreases from $x^* + \epsilon$ to $x^* - \epsilon$, λ uniformly increases from 0 to $1 - \delta$, we get

$$\begin{aligned}\bar{\Delta}^* = &\int_{\delta}^{\hat{\lambda}} \left[\theta^* R(\lambda, s) + (1-\theta^*) \max\left(\frac{\ell - \lambda}{1 - \lambda}, 0 \right) - 1 \right] \frac{d\lambda}{1-\delta} \\ &+ \int_{\hat{\lambda}}^{\overline{\lambda}} \left[\theta^* \frac{X(1-\ell)\left[1 - \frac{\lambda - \ell}{\xi(1-\ell)}\right]}{1-\lambda} - 1 \right] \frac{d\lambda}{1-\delta} - \int_{\overline{\lambda}}^{1} \frac{\ell + (1-\ell)\xi}{\lambda} \frac{d\lambda}{1-\delta} = 0.\end{aligned} \tag{17}$$

$\bar{\Delta}^*$ is continuous in θ^*, because all integrands are continuous and the discontinuity in v occurs only at one discrete point, $\hat{\lambda}$. Then, from the existence of the upper and dominance regions, there exists a θ^* such that $\bar{\Delta}^* = 0$. Moreover, $d\bar{\Delta}^*/d\theta^* > 0$, so θ^* is unique.

The run threshold θ^* implies a run probability θ^*, which is a function of the lending rate R given in (1) and the ratio of liquid assets in total assets, ℓ. Before we proceed to show how ℓ can be chosen to maintain the peg for the stablecoin tokens, we show how θ^* changes with y, m, s, and ℓ. Total differentiating (17) yields the following derivatives:

$$\frac{d\theta^*}{dx} = -\frac{d\bar{\Delta}^*}{dx}\left[\frac{d\bar{\Delta}^*}{d\theta^*}\right]^{-1} \qquad \text{for } x \in \{y, m, s, \ell\}$$

Note $d\bar{\Delta}^*/dx = \int_{\delta}^{\hat{\lambda}} \theta^* {}^{dR(\lambda,s)}/_{dx} d\lambda > 0$ for $x \in \{y, m, s\}$, thus they affect ξ^* only through R. Using (4)–(6) and $d\bar{\Delta}^*/d\theta^* > 0$, we have

$$\frac{d\theta^*}{dy} < 0 \qquad \& \qquad \frac{d\theta^*}{dm} > 0 \qquad \& \qquad \frac{d\theta^*}{ds} > 0. \tag{18}$$

Finally,

$$\begin{aligned}\frac{d\bar{\Delta}^*}{d\ell} &= \frac{d\hat{\lambda}}{d\ell}\left[\theta^* R(\hat{\lambda}, s) - 1\right]\frac{1}{1-\delta} + \int_{\delta}^{\ell}(1-\theta^*)\frac{1}{1-\lambda}\frac{d\lambda}{1-\delta} \\ &- \frac{d\hat{\lambda}}{d\ell}\left[\theta^*\frac{X(1-\ell)\left[1-\frac{\hat{\lambda}-\ell}{\xi(1-\ell)}\right]}{1-\hat{\lambda}} - 1\right]\frac{1}{1-\delta} + \int_{\hat{\lambda}}^{\bar{\lambda}}\frac{X(1/\xi - 1)}{1-\lambda}\frac{d\lambda}{1-\delta} - \int_{\bar{\lambda}}^{1}\frac{1-\xi}{\lambda}\frac{d\lambda}{1-\delta}.\end{aligned} \tag{19}$$

Given that $d\hat{\lambda}/d\ell > 0$ from (10), all the terms in the above condition are positive apart from the last one, which means that effect of ℓ on θ^* may be ambiguous. This is a typical property in bank-run models, and it is intuitive: It suggests that in the region of beliefs about redemptions that a run materializes, higher liquidity increases the payoff from redeeming because individuals can successfully redeem their tokens with higher probability. We derive in the Online Appendix a (weak) sufficient—not necessary—condition for $d\bar{\Delta}^*/d\ell > 0$, which requires that the expected lending rate is below a threshold, supported by the data. Under the sufficient condition we unambiguously obtain

$$\frac{\partial \xi^*}{\partial \ell} < 0. \tag{20}$$

Note that (20) can still hold in alternative parameterizations violating the sufficient condition, but may also not hold. In the latter cases the issuer would set $\ell = 0$, not in line with observed stablecoin reserve portfolios (see Section 2.4 for issuer optimization problem).

2.3 Stablecoin Price

In this section, we compute the price for one stablecoin token given the lending rate R derived in Section 2.1 and the run threshold ξ^* derived in Section 2.2.

Given that stablecoins tokens are continuously traded in secondary markets, we compute the price at which investors are willing to trade their stablecoin token rather than the cost of getting a token from the issuer, which is equal to one. Moreover, we derive the stablecoin price before the realization of θ and the resolution of uncertainty about the possibility of a run.[11] Denote by P the market price of traded stablecoin tokens, which is given by

$$P = \int_{\theta^*}^{1} \left[\theta R(\delta, s) + (1-\theta) \max \left(\frac{\ell - \delta}{1-\delta}, 0 \right) \right] d\theta + \int_{0}^{\theta^*} (\ell + (1-\ell)\xi) d\theta, \tag{21}$$

as $\overline{\theta} \to 1$. The market capitalization of the stablecoin is equal to $P \cdot s$.

The first term in (21) is the expected payoff conditional on no run on the issuer, which is equal to the expected value of being able to lend out the token and the expected repayment should the issuer default. Note that the lending rate is equal to $R(\delta, s)$ because δ impatient investors have redeemed their tokens at $t = 1$. The second term in (21) is the payoff conditional on a run, which is equal to the liquidation value of the asset portfolio of the stablecoin issuers for a dollar of tokens held.

Hence, P reflects investors' valuation for one token in "normal times" and is equal to the secondary market price in the absence of trading frictions.[12] In practice, such trading frictions exists and the secondary market price would deviate from what we derive in (21). For

[11] For realization $\theta < \theta^*$ at $t = 1$ there is a run on the issuer and the token price collapses to zero. Similarly, for $\theta \geq \theta^*$ and with probability $1 - \theta$, the issuer defaults and the token price again goes to zero.

[12] Note that during a run our model predicts that the secondary market price should drop to $\ell + (1-\ell)\xi$, i.e., the expected payoff from redeeming a token.

example, Ma et al. (2023) examine the role that arbitrageurs—who intermediate redemptions between the issuer and investors—play in secondary price dislocations for stablecoins. We abstract from such consideration to derive the simple stablecoin pricing equation (21), which will be very useful to illustrate the peg-stabilization mechanisms. Introducing trading frictions would interact with these mechanisms but the general principles of stabilization should not be expected to change. We leave these interesting extensions for future work.

Before discussing the peg stabilization mechanisms, we show how the price of the stablecoin changes with changes in the demand and riskiness of cryptocurrencies and the size and liquidity of the stablecoin.

We first examine the effect stemming from the cryptocurrency demand, y, and riskiness, m, as well as the size of the stablecoins s. For $x \in \{y, m, s\}$ we have

$$\frac{dP}{dx} = \frac{dR(\delta,s)}{dx}\frac{1-(\theta^*)^2}{2} - \frac{d\theta^*}{\partial x}\left[\theta^* R(\delta,s) + (1-\theta^*)\max\left(\frac{\ell-\delta}{1-\delta},0\right) - (\ell+(1-\ell)\xi)\right]. \quad (22)$$

Using (4)–(6) and (18), and $\theta^* R(\delta,s) + (1-\theta^*)\max\left(^{(\ell-\delta)}/_{(1-\delta)},0\right) > 1 > (\ell+(1-\ell)\xi)$ since $\theta^* > \underline{\theta}$, we have that

$$\frac{dP}{dy} > 0 \qquad \& \qquad \frac{dP}{dm} < 0 \qquad \& \qquad \frac{dP}{ds} < 0. \quad (23)$$

In other words, the higher the cryptocurrency demand, the lower the risk, or the smaller the stablecoin circulation, the higher the price they are willing to trade stablecoin tokens for two reasons. First, a higher y, and lower m or s, increases the payoff from the stablecoin token conditional on a run not occurring (first term in (22)). Second, the probability that a run does not occur increases with y, and decreases with m or s, as the incentives to run are lower, all other things, such as ℓ, being equal (second term in (22)).

Finally, a change in ℓ changes P according to

$$\frac{dP}{d\ell} = \int_0^{\theta^*}(1-\xi)d\theta - \frac{d\theta^*}{\partial \ell}\left[\theta^* R(\delta,s) + (1-\theta^*)\max\left(\frac{\ell-\delta}{1-\delta},0\right) - (\ell+(1-\ell)\xi)\right] > 0. \quad (24)$$

In other words, the higher the percentage of liquid assets in stablecoin reserves, the higher the price they are willing to trade their tokens for two reasons. First, a higher ℓ increases the probability of being paid conditional on a run occurring (first term in (24)). Second, the probability that a run does not occur increases with ℓ, all else equal (second term in (24)).[13]

In sum, the stablecoin price may fluctuate not only in response to shocks in the expected return and riskiness of the cryptocurrency, but also due to adjustments in the size and liquidity of the stablecoin. In section 2.4, we discuss the mechanisms through which the size and liquidity of the stablecoin can stabilize the peg in response to crypto shocks.

2.4 Peg stability

We show how the issuer can maintain the peg in response to shocks. We make a distinction between stabilizing the peg, discussed herein, and defending the peg, discussed in section 2.2. We view stabilizing the peg as the actions the issuer can take to maintain the peg before the realization of fundamentals' uncertainty, that is between $t = 0$ and $t = 1$. By contrast, defending the peg corresponds to the (in)ability of the issuer to survive a run at $t = 1$; when uncertainty about θ and ξ is realized. This distinction is important because stablecoins are traded continuously and they may trade above or below their peg even outside run episodes, which are only characterized by peg devaluations. As it will become more clear, at the center of the distinction is whether the issuer incurs portfolio re-balancing costs when changing the share of liquid asset held in reserves, which in the model are captured by a potentially lower liquidation value for the illiquid asset after, but not before, $t = 1$.

As such, we focus here on how crypto shocks that may arrive between $t = 0$ and $t = 1$ can destabilize the peg, that is move P above or below 1. Given that the liquid and illiquid assets can be sold for one before $t = 1$ and there are no other portfolio re-balancing costs, we do not need to track the portfolio allocation of the stablecoin issuer before the shock and just need to compute the new portfolio allocation after the shock, resembling a comparative statics exercise. We could easily complicate the analysis by introducing an intermediate period between $t = 0$ and $t = 1$ when crypto-related shocks materialize and track the portfolio allocations; yet the results we derive below for peg stability would remain unaltered.

There are two mechanisms to maintain the peg. The first mechanism relates to how ℓ should vary and proxies for how close to money stablecoins are. The second mechanism relates to how s should adjust and is driven by the usefulness of stablecoins in leveraged crypto trades; captured by the lending rate R. Although the issuer can optimally choose a

[13] As mentioned in Section 2.2 if $d\theta^*/d\ell > 0$ and, hence, $dP/d\ell < 0$, then the issuer will choose $\ell = 0$. See the Online Appendix for a sufficient condition to exclude this case.

combination of the two stabilization mechanisms in response to crypto shocks between $t = 0$ and $t = 1$, the choice will depend on whether changes in ℓ and s are observable or not, studied in Sections 2.4.1 and 2.4.2. Before deriving the optimal choice, we examine how changes in y and m between $t = 0$ and $t = 1$ matter for ℓ and s. A change in y, while keeping m constant, could be interpreted as higher demand for cryptocurrencies. A change in m, while keeping y constant, could be interpreted as higher volatility or risk for cryptocurrencies. Our objective is to examine how such developments can affect real financial markets through the demand of the stablecoin issuer for safer versus riskier assets, captured by ℓ, keeping s constant, or through up-sizing or down-sizing the stablecoin, captured by s, keeping ℓ constant.

Proposition 1. *A decrease in demand for the cryptocurrency or an increase in its riskiness pushes the stablecoin price below its peg. To stabilize the peg, the stablecoin issuer can either increase ℓ keeping the s the same, can keep the same ℓ and allow lower demand for tokens to manifest in more redemptions and lower s, or can jointly increase ℓ and decrease s. The opposite is true for higher cryptocurrency demand or lower riskiness.*

The proof of Proposition 1 is straightforward. From equation (23), we know that a decrease in y or an increase in m result in a lower price of the tokens P. Therefore, ℓ needs to increase to maintain the peg for a certain s (equation 24). Alternatively, the issuer may keep the same ℓ. This results in lower demand for the stablecoin tokens, and more investors will want to redeem their tokens. A lower number of tokens, s, results in a higher P (equation 23), and the stablecoin price can return to its peg.

Proposition 1 says that the issuer can choose a level of liquidity, ℓ, and stablecoin size, s, such that the stablecoin price is pegged to the dollar. Below we derive the optimal ℓ and s when ℓ is observable and when it is not; s is always observable given that the number of tokens in circulation is reported on the blockchain in real time. We show that there are limits to stabilization depending on ℓ-observability, even without portfolio re-balancing costs.

As an aside, recall that the issuer cannot freely adjust ℓ and s to defend the peg at $t = 1$ in the cases that the liquidation value of the illiquid asset drops to ξ, introducing portfolio re-balancing costs (see Section 2.2). Actually, the stabilization mechanism via ℓ would go in the opposite direction as the issuer would first sell the liquid asset to meet redemptions, effectively increasing the share of illiquid assets in reserves. The stabilization mechanism via s would still be operational, but it's effectiveness would vanish after the level of withdrawals that pushes the issuer to insolvency; we show in Figure 2 that the payoff from not redeeming increases as s decreases, as long as the issuer remains solvent. Defending the peg at $t = 1$ should not be confused with stabilizing the peg in normal times studied below.

2.4.1 Peg stability: Token supply and Liquidity under observability

In this section we derive the optimal choice of ℓ and s when both ℓ and s are observable. Observability implies that the stablecoin issuer can write a complete contract, such that the issuer internalizes how ℓ and s affect the stablecoin price P.[14]

The issuer maximizes their profits, $\max_{\ell,s} \int_{\theta^*}^{1} \theta\Pi(\delta)d\theta$ (recall that $\overline{\theta} \to 1$), subject to investors' participation constraint $P \geq 1$; P is investors' valuation of one token, i.e., the price they are willing to pay for it, given by (21). If their valuation was lower than one, they would prefer to redeem their tokens for \$1 and invest in the liquid asset. $\Pi(\delta)$ are the profits when only impatient investors withdraw and the issuer does not default—with probability θ—given by (9) for $\lambda = \delta$. The issuer internalizes how ℓ and s affect the run threshold and the lending rate, which can be expressed as functions of ℓ and s using (17) and (3), and substituted in issuer's optimization problem. In equilibrium, $P = 1$ because the issuer can always decrease ℓ or increase s to increase their profits further if $P > 1$ without violating the participation constraint of investors. Combining the optimality conditions for ℓ and s yields

$$\frac{1-(\theta^*)^2}{2}\left(\frac{d\Pi(\delta)}{d\ell} - \Pi(\delta)\frac{dP/d\ell}{dP/ds}\right) + \theta^*\Pi(\delta)\left(\frac{d\theta^*}{ds}\frac{dP/d\ell}{dP/ds} - \frac{d\theta^*}{d\ell}\right) = 0, \tag{25}$$

which together with the *peg stability condition* $P = 1$ yields the optimal (ℓ, s).

As mentioned, P can deviate from 1 in response to shocks until the issuer resets ℓ and s to restore the peg. The optimal ℓ and s derived above require observability. In principle, it is feasible for stablecoin arrangements to be backed by on-chain assets—either other cryptocurrencies or tokenized traditional financial assets—such that ℓ is observable in real-time along with s. Yet, the biggest stablecoins are currently backed by off-chain financial assets and disclose their reserves only infrequently, at best.[15] Thus, the peg stabilization

[14] See Kashyap et al. (2023) for similar modeling of complete and incomplete deposit contracts with run risk.

[15] There might be pressure from the industry to start disclosing the composition of reserves more frequently. Following the collapse of UST and the run on USDT in May 2022, USDC has started reporting their reserves weekly, potentially putting pressure on other stablecoin issuers to follow suit in the future.

studied above would work when ℓ is observable at disclosure dates. Between these dates, peg stability after a shock could again be achieved by changing ℓ and s, but the issuer will have an incentive to deviate from the choice of ℓ studied herein, discussed in the next section.

Finally, using (25) we can show that the issuer will optimally choose $\ell < 1$ and thus expose the stablecoin to runs, as long as speculative demand to crypto is high enough and, thus, the return from lending the stablecoin is higher than 1. For that reason, consider that $y > 1 + m[F'(e) - 1]$ such that $R(\delta, s) > 1$ for some $s > 0$; we consider the opposite below. Now, suppose that $\ell = 1$ such that $\theta^* \to 0$. Then, (25) is negative, because $d\Pi(\delta)/d\ell < 0|_{\ell=1}$. Intuitively, the issuer makes zero profits for $\ell = 1$ such that accepting some run risk by decreasing ℓ is optimal, while investors' participation constraint is not violated because $R(\delta, s) > 1$ can support some level of run risk. Next, consider $y \leq 1 + m[F'(e) - 1]$, which means that $R(\delta, s) \leq 1$ for any s. Thus, investors would never hold the stablecoin for the purpose of lending it out and will only keep on it if the run probability is zero and the token is always worth 1. The issuer can guarantee that by setting $\ell = 1$, otherwise investors would immediately redeem their tokens if there is a shock pushing y below the aforementioned threshold.[16] Proposition 2 summarizes these results.

Proposition 2. *Consider that both ℓ and s are observable. For $y > 1 + m[F'(e) - 1]$, $\ell < 1$ is optimal. Otherwise, the issuer set $\ell = 1$.*

2.4.2 Peg stability: Token supply and Liquidity without observability

As mentioned, the choice of ℓ may not be observable in real time contrary to s. The issuer may still use a combination of ℓ and s to maintain the peg in response to crypto-related shocks between $t = 0$ and $t = 1$ but cannot credibly commit to a certain choice of ℓ given that it is not observable. This information resembles an incomplete contract whereby the issuer may deviate from the choice of ℓ after the peg is stabilized (see Online Appendix in Kashyap et al. 2020). The issuer will maximize the profits accruing to them when choosing ℓ and s but will only internalize the effect of s and not ℓ on the peg stability condition $P = 1$. Yet, the issuer will still internalize the effect of both ℓ and s on the run threshold θ^*, since

[16] Although not explicitly modeled in order to keep the analysis simple, one could think of reasons why the issuer may prefer setting $\ell = 1$ rather than having all investors redeem, presumably because the negative shock on y is transitory and scaling up the stablecoin from scratch may entail considerable fixed costs.

the run may happen later at $t = 1$. Then, the optimality condition with respect to ℓ is

$$\frac{1 - (\theta^*)^2}{2} \frac{d\Pi(\delta)}{d\ell} s - \theta^* \Pi(\delta) s \frac{d\theta^*}{d\ell} = 0, \tag{26}$$

which together with $P = 1$ yields the optimal (ℓ, s). Comparing (26) to (25) we see that former misses a wedge W equal to

$$W = -\frac{dP/d\ell}{dP/ds} \Pi(\delta) \left(\frac{1 - (\theta^*)^2}{2} - \theta^* \frac{d\theta^*}{ds} s \right). \tag{27}$$

For a given s, the issuer will choose a lower (higher) ℓ if $W > 0$ ($W < 0$) when ℓ is unobservable compared to the case that it is.[17] In turn, this means that the change in s should be higher (lower) to stabilize the peg for the same level of crypto-related shocks. Importantly, the issuer will use both stabilization mechanisms to maintain the peg even when ℓ is unobservable. The following Proposition shows that the sign of W depends on the level of run risk.

Proposition 3. *There exist a unique* $\hat{\theta} \in (0, 1)$ *such that* W *in* (27) *is positive for* $\theta^* < \hat{\theta}$ *and negative for* $\theta^* > \hat{\theta}$.

The proof is straightforward. Since $dP/ds < 0$ and $dP/d\ell > 0$ from (23) and (24), the sign of W depends on the sum of the terms in the parenthesis, which is continuous in θ^*, negative for $\theta^* \to 1$ and positive for $\theta^* \to 0$, while $d\theta^*/ds$ is positive and increasing in θ^*. Hence, $\hat{\theta}$ exists and is unique. This result is intuitive. When ℓ is not observable, the issuer has an incentive to deviate but at the same time still internalizes how the choice of ℓ matters for run risk and, thus, their expected profits. If run risk is low, i.e., $\theta^* < \hat{\theta}$ and $W > 0$, the issuer deviates toward a lower ℓ, and vice versa if run risk is high. Investors anticipate this deviation and respond by redeeming more or fewer tokens compared to the case of observable ℓ.

Proposition 3 has also implications for the viability of the stablecoin when the speculative demand for cryptocurrencies wanes. In particular, suppose that there is a shock pushing y below $1 + m[F'(e) - 1]$. If ℓ is observable, the issuer would set $\ell = 1$ and keep the stablecoin running with $\theta^* = 0$, i.e., no run risk (Proposition 2). However, with unobservable ℓ, the issuer will have an incentive to deviate towards $\ell < 1$. Investors would anticipate this and

[17] To see this, note that the solution under observable ℓ can be implemented in an environment where ℓ is not observable under a Pigouvian tax/subsidy on liquid holdings ℓ: A negative (positive) W calls for tax (subsidy), implying lower (higher) ℓ than in the unconstrained equilibrium with unobservable ℓ.

redeem all their tokens immediately; otherwise they would be exposed to run risk without the proper compensation. By continuity, the same would hold for y close to, but higher than, $1 + m[F'(e) - 1]$, even though expected lending rates would be (somewhat) higher than 1 for this level of y. Overall, stablecoins are not viable for low enough y under non-observability of ℓ, which also provides an additional rationale why issuers may want to disclose their reserves more frequently during crypto turmoils, similar to what USDC did in May 2022.

3 Institutional Details and Data

3.1 Leverage

Leverage is a critical feature of crypto markets. Crypto traders often speculate with leverage, and exchanges provide leverage as a key service. Crypto traders can get leverage in several ways. We focus on two products offered by centralized exchanges: margin trading and futures derivatives. There are several other mechanisms to get leverage at centralized exchanges and on the blockchain: levered tokens and options, to name a few. We focus on futures and margin trading as they are two long-standing and large sources of leverage. While data on the levered trading volumes are scarce, open interest across all crypto derivatives was $250 billion in June 2022, the vast majority of which likely comes from perpetual futures derivatives.[18] Data on margin lending are even more incomplete but likely exceed tens of billions of dollars.

Margin in crypto is like margin trading in traditional finance: levered traders borrow the coin for a specified time at a given interest rate and use it along with their own funds to take a position on a cryptocurrency. Margin trading can be used to take long or short positions. The main difference with traditional margin is that offshore crypto exchanges generally do not comply with Regulation T or other similar requirements

Traders can also get leverage using futures—not unlike traditional finance futures—many of which are *perpetual* futures, which do not have an explicit expiration date, as indicated by their name. Perpetual futures are likely the largest and most liquid type of offshore cryptocurrency derivatives and, at times, can offer more than 100 times leverage.

For a traditional vanilla future, the future and spot prices converge as the expiration date approaches. Such phenomena do not happen with perpetual futures. Instead, perpetual futures use a *funding premium* to keep the spot and future price linked. If the future trades

[18] https://coinmarketcap.com/rankings/exchanges/derivatives/

at a premium to the spot price, the investors that are long on the future must pay a funding premium to investors that are short. On the rare occasion the future price trades at a discount to the spot price, the investors that are short on the future must pay a funding premium to investors that are long. For simplicity, we will say the funding premium is positive when investors that are long on the future pay a fee to investors that are short. The details vary across exchanges, but the funding payments are paid daily or more frequently. Perpetual futures are typically stablecoin-settled, meaning that the perpetual future is quoted and settled in a stablecoin, and funding payments are paid in the stablecoin. A BTC/USDT perpetual future, for example, is settled in USDT.

Investors may prefer getting leverage from either futures or margin trading. Margin trading has two advantages. First, the borrowed coins are fungible and can be used to settle spot transactions. Second, margin trading allows investors to take levered trading positions at spot market prices. Alternatively, futures allow investors to take a levered position in a coin, but they do not obtain the underlying coin until the future's expiration unless it is a perpetual future. Limits to arbitrage cause persistent dislocations, often preventing the future price from being equal to the spot price. Futures, however, are generally larger markets and allow levered exposure for extended periods.

3.2 Data

We collect prices, volume, and market capitalizations of cryptocurrencies from CoinGecko.[19] We collect margin lending rates from FTX. We focus on two stablecoins, Tether (USDT) and Dai (DAI), because they are large collateralized stablecoins and have long time series of lending data available from FTX.[20] We collect perpetual future funding premia from Binance, which is likely the largest market for them. We collapse higher-frequency data on lending rates, funding premia, and prices to a daily frequency using daily averages after converting

[19] For details on how Coingecko aggregates information across several exchanges to calculate prices, see `https://www.coingecko.com/en/methodology`.

[20] In the online appendix, we show that FTX's lending rates are highly correlated with other lending rates in the digital asset ecosystem, and so are not idiosyncratic to FTX. Table A.1 regresses FTX's Tether lending rates on decentralized finance (defi) platforms' lending rates. We collect defi lending rates from DefiLlama, and our sample includes all protocols in the lending category that also includes Tether. In general, FTX's lending rates are more correlated with the largest lending platforms, as measured by total value lock.

them to U.S. eastern time.[21] We use implied volatility for BTC and ETH calculated by T3 using option prices. Our sample runs from December 1, 2020, to November 5, 2022. The sample does not include the period of FTX's collapse, which began on November 6, 2022.[22]

Table 1 presents the summary statistics for the main variables, including the stablecoin prices and lending rates and the funding premium for BTC/USDT and ETH/USDT. The average price of both stablecoins is close to $1, as expected. The average lending rate is 8 percent for USDT and 7 percent for DAI. Relative to prices, the lending rates are more volatile. The average funding premium is 19 percent for BTC/USDT and 21 percent for ETH/USDT, indicating that the future price typically exceeds the spot price for both contracts.

4 Empirical Results

We have three sets of results. First, we show that stablecoin lending rates are tightly linked to speculative demand for cryptocurrencies. Second, we test proposition 1, which shows how stablecoins maintain their peg by linking cryptocurrency demand and risk to the stablecoin issuer's safe asset share and token issuance or redemptions. Third, we apply the model to the May 2022 turmoil in crypto markets following the collapse of TerraUSD.

4.1 Lending Rates and Expected Speculative Returns

We show that when the expected return for the speculative asset—y in the model—increases, the stablecoin lending rate grows, as depicted in equation (4).[23] Speculators' expected returns are challenging to measure. Because cryptocurrency expected returns are not directly observable, we use perpetual futures funding rates to infer the speculative demand. Futures funding rates reflect the cost investors face to take leverage. We argue that the magnitude of the annualized funding rates is directly related to speculative cryptocurrency demand because no other liquid products provide similar levels of leverage as the perpetual futures.

[21] We remove one hour of outlier data from USDT's lending rate on August 10, 2021, at 6 am because it is implausibly high and likely a data entry error. Lending rates are available in hourly snapshots until September 2022, when it becomes daily.

[22] The run began after a tweet by the CEO of Binance that Binance would sell its FTT tokens: `https://twitter.com/cz_binance/status/1589283421704290306`.

[23] In the online appendix, we also confirm the model's prediction about the relationship between the outside option ρ and stablecoin volumes. We find that net stablecoin issuance coincides with higher ρ, described in Table A.2, consistent with the prediction that ρ is increasing in s as shown in equation 2.

We proxy for expected returns using the BTC/USDT perpetual future on Binance, likely the largest perpetual future contract in the world. Figure 3 shows the time series of the annualized funding rate of Binance's BTC and ETH USDT-settled perpetual futures. The funding rate is typically small but positive, indicating that investors who want to take levered long positions must pay a fee. In the online appendix, we check that Binance's BTC/USDT perpetual futures funding rate is a robust proxy for expected returns.[24] One concern is that using the BTC/USDT perpetual futures as a proxy of y overweighs idiosyncrasies specific to Bitcoin. But the BTC/USDT and ETH/USDT perpetual futures funding rates are tightly linked with a correlation coefficient of 0.86. Binance also has perpetual futures that settle in Binance USD, another stablecoin. We show that funding rates across perpetual futures are highly correlated regardless of which stablecoin is used for settlement.

Yet another concern is that Bitcoin and Ether are special because they are relatively liquid and mature markets compared to other digital assets. We include a column showing the measures are highly correlated with the perpetual futures funding rate for Dogecoin. Dogecoin is the largest memecoin, a digital asset that ostensibly started as a joke, and exhibits comparatively higher volatility than Bitcoin and Ether.

Finally, we rule out the possibility that Binance's futures funding rates mainly reflect idiosyncrasies specific to Binance, rather than aggregate expected returns for cryptocurrency beyond just Binance. We compare Binance's perpetual future funding rates with analogous rates from FTX and find that funding rates are similar and highly correlated across the exchanges, confirming that the funding rates are not principally capturing exchange-specific factors. Finally, we show that perpetual futures funding rates are closely linked to expected returns embedded in crypto futures traded on the CME.

Figure 4 shows a binscatter of the perpetual future funding rate and the USDT stablecoin lending rate: the two are strongly positively related. More formally, we test the model's prediction that lending rates are increasing in y—equation (4)—by regressing Tether's lending rate on FTX on the perpetual futures funding rates using

$$\text{USDT Lending Rate} = \alpha + \beta \text{ Futures Funding Rate}_t + \gamma X_t + \varepsilon_t,$$

where X_t is a vector of controls. Table 3 shows the regression results. The first row shows that

[24]See Table A.3 which presents the correlation of our main measure of y with several other potential measures.

a 1pp increase in the futures funding rate is associated with an increase in stablecoin lending rates between 0.12 and 0.26pp, depending on the control variables. A one-standard-deviation increase in the future funding rate (30pp) corresponds to lending rates increasing roughly 3.6pp, using the estimates in column 3. Across all specifications, there is a positive and significant relationship between lending rates and our proxy for expected returns. We include a measure of risk, bitcoin's implied volatility, as a control since the lending rates are not risk-free and may be higher when risk of counterparty default is higher.[25]

4.2 Peg Stability

Proposition 1 predicts that stablecoin issuers can maintain their peg following shocks to speculative demand with two tools: either increasing their safe asset share ℓ or redeeming tokens s. We empirically verify both mechanisms.

Safe Asset Portfolio Share Channel The model shows that stablecoin issuers can offset negative shocks to cryptocurrency demand by increasing their portfolio share of safe assets, all else equal. The model assumes that the stablecoin issuer's safe asset holdings, ℓ, are public knowledge. In practice, it is rarely the case that a stablecoin issuer gives disclosures with enough granularity to calculate its safe asset share. Disclosures are infrequently published, and there are some doubts about their accuracy.

Despite these limitations, we confirm the model's prediction of a negative relationship between y (and R) and ℓ using public disclosure data from the largest stablecoin, Tether, which has given seven quarterly disclosures with enough granularity to estimate Tether's ℓ. Figure 5 is a scatterplot comparing the safe asset share against the perpetual futures funding rate (y) and the USDT lending rates (R). We define Tether's safe asset portfolio share ℓ as its share of reserves held in cash, bank deposits (including fiduciary deposits), reverse repurchase agreements, and Treasury bills. While the data are limited to seven quarterly data points, there is a clear negative relationship that ℓ is higher when expected returns and Tether's lending rate are lower. When crypto demand or the stablecoin lending rates are low, stablecoin issuers hold more safe assets to maintain the stablecoin's peg.[26]

[25]In the online appendix, Table A.4 includes robustness tests by regressing stablecoin lending rates on measures of expected returns inferred from CME cryptocurrency futures instead of futures funding rates.

[26]One concern is that during our sample period, 2020 to 2022, the Federal Reserve raised interest rates, and Tether may have simply substituted its portfolio toward Treasuries as their yields increased. The spread

Redemption Channel Stablecoin issuers do not provide continuous information on their safe asset holdings, and quick adjustments in their safe asset share would be difficult over short periods. Proposition 1 shows that stablecoin issuers can maintain their peg by adjusting the supply of the tokens while still holding ℓ fixed. Information on the token's supply is public, and the supply often fluctuates in the short term. We calculate a stablecoin i's net issuance on date t as

$$\Delta s_{i,t} = \left(\frac{\text{Market Cap}_{i,t}}{P_{i,t}} - \frac{\text{Market Cap}_{i,t-1}}{P_{i,t-1}} \right).$$

Net redemptions equal $-1 \times \Delta s_{i,t}$. We divide the market capitalization by the stablecoin's price because we are interested in the face value of the stablecoin's liabilities, which the issuer can directly affect. If we did not divide by prices, it would appear that the stablecoin had issued more coins when its price increased, even if the stablecoin issuer took no action.

Table 4 shows summary statistics for redemptions for the largest stablecoins and orders the stablecoins in descending order based on their average 2021 market capitalization. The largest three stablecoins have net redemptions between 25 percent and 39 percent of days, even though stablecoins have grown rapidly over the period. The average redemption for the three ranges between 0.3 percent (USDT) and 1.4 percent (BUSD). TerraUSD (USTC) had the largest one-day net redemption of $4.7 billion, about 27 percent of its market cap, during its collapse in May 2022. In the post-2019 period, each stablecoin has faced large single-day redemptions: 4.1 percent for Tether, 8.2 percent for USDC, and 11.9 percent for BUSD, amounting to $3.4, $3.8, and $460 million.

The magnitudes of stablecoins' redemptions are economically large compared to the traditional banking system. Gorton and Zhang (2021) and Gorton et al. (2022) argue that Free Banking era-banks and stablecoin issuers are similar because they both created private money—private bank notes and stablecoins—and both did so without a lender of last resort or deposit insurance. The average safe asset share of New York banks during the period from 1818 to 1861 was 5.7 percent, using data from Weber (2018), defined as specie, checks, cash items, and U.S government bonds. Single-day redemptions on the scale of those faced by stablecoins would have plausibly exhausted the Free Banking system's safe and liquid assets.

between 3-month AA financial commercial paper and 3-month T-bills, however, increased from 8bps in December 2020 to 31bps in November 2022.

We test the redemption channel in two stages. In the first stage, we regress the changes of the token's change in log face value supply on variables linked by the proposition: speculative cryptocurrency expected returns and speculative cryptocurrency risk:

$$\Delta \ln(s_{i,t}) = \alpha + \beta_1 y_{t-1} + \beta_2 \sigma_{t-1} + \gamma' X + a_i + b_t + \varepsilon_{i,t},$$

where y is the perpetual futures funding premium, σ is the risk of Bitcoin measured by Bitcoin futures' implied volatility, $s_{i,t}$ is the face value of stablecoin i, X is a vector of controls including lags of the stablecoin's face value and issuance, a_i is a stablecoin fixed effect, and b_t is a time fixed effect.

In the first stage, the proposition predicts the stablecoin's supply will increase in y, $\beta_1 > 0$, and decrease in σ, $\beta_2 < 0$. We lag the independent variables by a day to ensure they are in the stablecoin issuer's information set. We include monthly fixed effects to capture possibly slower moving changes in ℓ, as the proposition's redemption channel holds ℓ fixed.

Table 5 shows the results from the first stage regression. The first three columns focus on USDT, and the last three include USDT and DAI. Implied volatility has a negative coefficient, and the funding rate coefficient is consistently positive, so stablecoin redemptions are larger when implied volatility is higher and when funding premia, our proxy for demand of cryptocurrency speculation, is lower. The results are similar across all specifications including month and coin fixed effects and including lags of redemptions and the token's face value. $\Delta \ln(s_{i,t})$ is in basis points, so a 10pp increase in the funding premium, all else equal, corresponds to subsequent stablecoin issuance between 6 and 13 basis points.

The model predicts that lending rates increase after the token's supply falls. Thus, the second stage regresses stablecoin lending rates on predicted changes in the token's supply $\widehat{\Delta \ln(s_{i,t})}$ estimated from the first stage:

$$\Delta R_{i,t} = \alpha + \gamma \left(\widehat{\Delta \ln(s_{i,t})} \right) + a_i + b_t + \varepsilon_{i,t},$$

The model predicts that $\gamma < 0$. We run this regression as 2SLS so the standard errors reflect that fact that the independent variable in the second stage regression is estimated.

Table 6 shows the second stage regression of the change in lending rates on the expected change in supply. Like the previous table, the first three columns limit the sample USDT, and the last three include both USDT and DAI. The table shows the results after estimating

$\Delta \widehat{\ln(s_{i,t})}$ using the first stage regression described above, and the third and sixth columns also include controls for contemporaneous changes in y_t and σ_t. The table shows that an expected one basis point increase in token supply decreases the lending rate by 1.5 to 11.9 basis points.

4.3 May 2022 Stablecoin Turmoil

In May 2022, the algorithmic stablecoin TerraUSD depegged. Sentiment in crypto markets had been slagging but turned bearish after the depeg. Several prominent crypto firms failed shortly after that: 3 Arrows Capital, Voyager Digital, and Celsius. In the words of Gorton and Zhang (2023), crypto space entered crypto winter. Pressure on TerraUSD spilled to other stablecoins, and Tether's market capitalization fell from \$83 to \$73 billion in May following a stream of redemptions. Several other algorithmic stablecoins failed or teetered on the brink of viability. USDC, viewed as the highest quality stablecoin, traded at a premium to its peg and saw net inflows. Such turmoil is a natural experiment to study the model's predictions.

Figure 6 shows the market dynamics for Tether during TerraUSD's price collapse. The vertical line on May 10 denotes the date that TerraUSD lost its peg. The model posits that a stablecoin will lose its peg when speculative cryptocurrency risk increases or when demand for the speculative cryptocurrency falls. The top half of the figure shows that Tether lost its peg for at least two days, coinciding with spikes in BTC implied volatility and a collapse in perpetual futures funding premia, a proxy for speculative demand.

The model predicts that Tether could potentially maintain its peg by decreasing s, equivalent to redeeming and burning tokens to reduce its market capitalization, while holding ℓ fixed. Tether redeemed roughly \$10 billion of tokens over three weeks, consistent with the prediction, as shown in the bottom-left panel of Figure 6. The bottom-right panel shows that Tether's lending rates spiked and remained elevated, helping stabilize the peg. We should note that the increase in the lending rate alone may not have been enough to stop the run on Tether, which could have resulted in a complete depletion of reserves following more severe shocks. We will further elaborate on these limitations to stabilization in section 2.4.

Proposition 1 also shows that the stablecoin issuer could maintain its peg by increasing ℓ. It is unlikely this was the primary tool used to stabilize the peg in the immediate aftermath of the TerraUSD failure. Tether's most recent disclosure for the quarter ending March 2022 showed safe asset holdings of \$43 billion (52 percent of its total assets), defined as the sum of its cash, reverse repos, and Treasury bills. Its safe asset holdings would have fallen to $33 billion (46 percent of total assets), assuming it paid for redemptions entirely out of safe asset sales. To increase ℓ, Tether would have needed to sell $4.4 billion of its non-safe assets to safe assets. Such a large shift out of risky assets over a short period seems unlikely without material losses, so arguably the main channel of adjustment was through s during this episode.

The ℓ adjustment mechanism to maintain the peg is likely more useful over longer periods. In June 2022, rumors circulated that Tether's commercial paper portfolio had suffered 30 percent losses. In response, Tether explicitly said that would increase ℓ in the long run:[27]

> "Tether can report that its current portfolio of commercial paper has since been further reduced to 11 billion (from 20 billion at the end of Q1 2022), and will be 8.4 billion by end June 2022. This will gradually decrease to zero without any incurrences of losses. All commercial papers are expiring and will be rolled into US Treasuries with a short maturity."

Such dynamics are not limited to Tether. Dai, a decentralized and collateralized stablecoin, uses the USDC stablecoin as collateral for more than half its outstanding coins. In the summer of 2022, USDC's issuer—Circle—began blocking wallets holding USDC that were associated with Tornado Cash.[28] Market participants grew concerned that DAI would be compelled to comply with the sanctions given their large USDC holdings. Rune Christianson, DAI's co-founder, suggested that DAI should move its USDC holdings to ETH, functionally increasing the risk of its reserves (decreasing ℓ). In response, users redeemed roughly four percent of DAI's outstanding tokens the next day, amounting to $320 million.

4.4 Robustness

The model shows a causal relationship between expected returns (y) and stablecoin lending rates, and we show the two are highly correlated in Table 3. A concern is that some other unobserved variable is driving the behavior in both variables, driving their high correlation.

[27] `https://web.archive.org/web/20220721170350/https://tether.to/en/tether-condemns-false-rumours-about-its-commercial-paper-holdings/`

[28] Tornado Cash is a virtual currency mixer designed to obfuscate transaction details on the Ethereum blockchain. The U.S. Treasury sanctioned it in August 2022 for its role in money laundering.

We approach this concern using an instrumental variables approach using Major League Baseball (MLB) data.

In June 2021, MLB and FTX announced a sponsorship deal naming FTX the "Official Cryptocurrency Exchange" of the MLB. In particular, the deal placed a prominent FTX logo on all umpire uniforms beginning July 13, 2021—previously, umpires had never worn advertising patches. Umpires wore the patch for all regular season, postseason, and spring training games. The sponsorship agreement also included promotions on nationally televised MLB games, MLB.com, MLB Network (a television channel), and social media.[29] While the monetary value of the sponsorship deal is unknown, it is likely substantial: FTX signed sponsorship deals with other sports leagues worth at least $345 million. The deals included a 19-year, $135 million agreement for naming rights to the NBA's Miami Heat stadium and a 10-year, $210 million agreement for naming rights to the esports team TSM.

We collect television viewership data on nationally televised MLB games from showbuzzdaily.com.[30] The data include a household rating, which measures the percentage of households watching the game. The television viewership data run from July 13, 2021, to November 5, 2022, corresponding to the period when umpires started wearing the logo (beginning during the 2021 All-Star game) through the end of the 2022 World Series. On many days there is only one game with a household rating. We use daily averages of the household rating as our instrument for the funding premium. Notably, the sample does not include the period of FTX's collapse, which began on November 6, 2022.

Our identification relies on two assumptions: first, we assume that the advertising is effective, and some MLB audience members began trading cryptocurrency after viewing the advertising. FTX's agreement to the costly sponsorship deals indicates that they believed it would lead to more customers and more trading on their platform. There is considerable evidence that advertising is effective (Guadagni and Little (1983), Ippolito and Mathios (1991), Ackerberg (2003), Sethuraman, Tellis, and Briesch (2011)). Bagwell (2007)'s survey of the literature on advertising's effect on consumer behavior indicates that advertising is most effective for those without previous experience with the brand. Moreover, survey evidence shows that new retail crypto traders entered the market during rapid crypto price increases.[31]

[29] `https://www.mlb.com/press-release/press-release-mlb-ftx-cryptocurrency-partnership`

[30] The data also includes about half a dozen nationally televised baseball events, like the home run derby, all star game, trade deadline, and draft.

[31] See `https://www.jpmorganchase.com/institute/research/financial-markets/dynamics-`

Second, the timing of the baseball schedule is set well in advance of the season[32], and it is highly improbable cryptocurrency events affect the timing or viewership of MLB games.

One concern is that the advertising might bring new customers to open accounts and begin lending stablecoins rather than speculating in other digital assets, thereby increasing the demand for stablecoin. First, we include the change in the market capitalization of the stablecoin on that day to control for potential changes in the demand for the stablecoin. Second, were new customers to open account to lend stablecoins, we would expect lending rates to fall as the supply of lendable coin grew, leading to a negative relationship between the TV rating and lending rates. However, we find a positive relationship between the two. Third, the types of new customers drawn to FTX by television advertising are likely less sophisticated investors, and margin lending is more involved than simply buying a digital asset. Therefore, we think it's unlikely that the advertising materially affected stablecoin demand and drove new customers to open accounts to lend.

Table 7 shows the regression results using the instrumental variable. In the first stage, we regress the daily funding premium on the average household rating; in the second stage, we regress the lending rate on the predicted funding premium. Panel A shows the second stage result. For every 1pp increase in the futures funding premium estimated using the household rating instrument, Tether's margin lending rate is about 18bp higher on an annualized basis (column 2). Using DAI's lending rate or different controls gives similar estimates ranging from 16bps to 22bps.

Panel B reports the first stage regression. The instrument satisfies the relevance condition, and the F-statistic indicates the instrument is largely statistically strong. Panel C shows that the instrumented regression gives similar coefficients to the OLS regression.

We provide additional robustness tests in the online appendix. Table A.5 shows several placebo tests. We use future household rating as the instrument, with the columns varying by using ratings from one day, one week, or four weeks in the future. Baseball viewership in the future should not affect today's lending rate through the funding premium, because it is unknown at date t. Using the future household rating as the instrument leads to an insignificant relationship between the funding premium and the lending rate for all

demographics-us-household-crypto-asset-cryptocurrency-use.

[32] The 2022 season schedule was modified shortly before the season began due to protracted negotiations with the players' union.

specifications except the one week DAI regression. The F-statistic indicates the instruments are weak.

In the online appendix, we show that speculators have good reason to speculate in response to MLB advertising. Table A.6 shows that returns for BTC, ETH, and DOGE are indeed positively related to household ratings of MLB games, consistent with our intuition that speculators may grow bullish as FTX advertises to new customers. The table regresses the daily return of BTC, ETH, or DOGE on the household rating of nationally televised MLB games on the same day. The table also adds a column for each digital asset including day-of-week fixed effects. While the standard errors are large, the average return is increasing in household rating. DOGE coin has a positive and statistically significant relationship, perhaps because it is more even subject to animal spirits than Bitcoin and Ether.

5 Conclusion

Privately-produced money can maintain a $1 peg even if it is not no questions asked, but agents will not hold private money unless they are compensated for their risks. Speculative investors will provide that compensation if their expectations are bullish enough. We reconcile two important facts: first, stablecoins are not useful as money despite their relative success in maintaining their peg, at least for the most salient coins. Second, stablecoin lending rates are high and tightly correlated with measures of speculative demand.

Stablecoins can provide a direct link between speculation and the real economy. Stablecoin issuers invest their reserves to earn profits but must adjust their reserves—possibly quickly—to keep their debt trading at par. When speculative demand falls, they can keep their debt trading at par only by moving to a safer portfolio or allowing redemptions. Such reallocation or change in stablecoin supply can cause disruptions in the real economy. Stablecoin issuers will need to adjust quickly if expected returns for cryptocurrencies fall; otherwise, they face the risk of collapse. These adjustments can cause disruptions in the markets they invest in, like the commercial paper market that provides financing to the real economy.

References

Daniel A Ackerberg. Advertising, learning, and consumer choice in experience good markets: an empirical examination. *International Economic Review*, 44(3):1007–1040, 2003.

Kyle Bagwell. The economic analysis of advertising. *Handbook of industrial organization*, 3: 1701–1844, 2007.

Jean Barthélémy, Paul Gardin, and Benoit Nguyen. Stablecoins and the financing of the real economy. 2023.

Christoph Bertsch. Stablecoins: Adoption and fragility. *Sveriges Riksbank Working Paper Series*, 2023.

Markus K Brunnermeier and Lasse Heje Pedersen. Market liquidity and funding liquidity. *The review of financial studies*, 22(6):2201–2238, 2009.

Mark Carlson, Burcu Duygan-Bump, Fabio Natalucci, Bill Nelson, Marcelo Ochoa, Jeremy Stein, and Skander Van den Heuvel. The demand for short-term, safe assets and financial stability: Some evidence and implications for central bank policies. *International Journal of Central Banking*, 2016.

Hans Carlsson and Eric van Damme. Global games and equilibrium selection. *Econometrica*, 61(5):989–1018, 1993.

Amit Chaudhary and Ganesh Viswanath-Natraj. Algorithmic stablecoins and devaluation risk. *VoxEU*, 2022.

Qi Chen, Itay Goldstein, and Wei Jiang. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2):239–262, 2010.

Douglas W. Diamond and Philip H. Dybvig. Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3):401–419, 1983.

Adrien d'Avernas, Vincent Maurin, and Quentin Vandeweyer. Can stablecoins be stable? *Working Paper*, 2022.

Ana Fostel and John Geanakoplos. Leverage cycles and the anxious economy. *American Economic Review*, 98(4):1211–44, 2008.

John Geanakoplos. The leverage cycle. *NBER Macroeconomics Annual*, 24:1–66, 2010.

Itay Goldstein and Ady Pauzner. Demand-deposit contracts and the probability of bank runs. *Journal of Finance*, 60(3):1293–1327, 2005.

Gary B. Gorton. The history and economics of safe assets. *Annual Review of Economics*, 9: 547–586, 2017.

Gary B. Gorton and Jeffery Zhang. Taming wildcat stablecoins. *Available at SSRN 3888752*, 2021.

Gary B Gorton and Jeffery Zhang. Bank runs during crypto winter. *Available at SSRN 4447703*, 2023.

Gary B. Gorton, Chase P. Ross, and Sharon Y. Ross. Making money. *NBER Working Paper #29710*, 2022.

Robin Greenwood, Samuel G Hanson, and Jeremy C Stein. A comparative-advantage approach to government debt maturity. *The Journal of Finance*, 70(4):1683–1722, 2015.

Denis Gromb and Dimitri Vayanos. Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of financial Economics*, 66(2-3):361–407, 2002.

Peter M Guadagni and John DC Little. A logit model of brand choice calibrated on scanner data. *Marketing science*, 2(3):203–238, 1983.

Lai T Hoang and Dirk G Baur. How stable are stablecoins? *European Journal of Finance*, pages 1–17, 2021.

Bengt Holmström. Understanding the role of debt in the financial system. 2015.

Sebastian Infante and Alexandros P. Vardoulakis. Collateral Runs. *The Review of Financial Studies*, 34(6):2949–2992, 12 2020.

Pauline M Ippolito and Alan D Mathios. Information, advertising, and health choices: a study of the cereal market. In *Economics of food safety*, pages 211–246. Springer, 1991.

Anil K Kashyap, Dimitrios P Tsomocos, and Alexandros P Vardoulakis. Optimal bank regulation in the presence of credit and run risk. *Journal of Political Economy, forthcoming*, 2023.

Sang Rae Kim. How the cryptocurrency market is connected to the financial market. *Available at SSRN 4106815*, 2022.

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

Arvind Krishnamurthy and Annette Vissing-Jorgensen. The aggregate demand for treasury debt. *Journal of Political Economy*, 120(2):233–267, 2012.

Arvind Krishnamurthy and Annette Vissing-Jorgensen. The impact of treasury supply on financial sector lending and stability. *Journal of Financial Economics*, 118(3):571–600, 2015.

Paul Krugman. A model of balance-of-payments crises. *Journal of Money, Credit and Banking*, 11(3):311–25, 1979.

Yujin Kwon, Kornrapat Pongmala, Kaihua Qin, Ariah Klages-Mundt, Philipp Jovanovic, Christine Parlour, Arthur Gervais, and Dawn Song. What drives the (in) stability of a stablecoin? *arXiv preprint arXiv:2307.11754*, 2023.

Alfred Lehar and Christine A Parlour. Decentralized exchanges. *Available at SSRN 3905316*, 2021.

Ye Li and Simon Mayer. Money creation in decentralized finance: A dynamic model of stablecoin and crypto shadow banking. *Fisher College of Business Working Paper*, (2020-03):030, 2021.

Gordon Liao and Thomas Hadeed. Beyond speculation: Payment stablecoins for real-time gross settlements. *Available at SSRN*, 2023.

Richard K. Lyons and Ganesh Viswanath-Natraj. What keeps stablecoins stable? *Journal of International Money and Finance*, 131:102777, 2023.

Yiming Ma, Yao Zeng, and Anthony Lee Zhang. Stablecoin runs and the centralization of arbitrage. *working paper*, 2023.

Igor Makarov and Antoinette Schoar. Cryptocurrencies and decentralized finance (defi). *Brookings Papers on Economic Activity*, 2022(1):141–215, 2022.

Bruce Mizrach. Stablecoins: Survivorship, transactions costs and exchange microstructure. *arXiv preprint arXiv:2201.01392*, 2022.

Stephen Morris and Hyun Song Shin. Unique equilibrium in a model of self-fulfilling currency attacks. *The American Economic Review*, 88(3):587–597, 1998.

Stephen Morris and Hyun Song Shin. Global Games: Theory and Applications. *In Advances in Economics and Econometrics: Theory and Applications, Eight World Congress, Vol. 1, ed. Mathias Dewatripont, Lars P. Hanse, and Stephen J. Turnovsky. Cambridge: Cambridge University Press*, 2003.

Maurice Obstfeld. Rational and self-fulfilling balance-of-payments crises. *The American Economic Review*, 76(1):72–81, 1986.

Bryan Routledge and Ariel Zetlin-Jones. Currency stability using blockchain technology. *Journal of Economic Dynamics and Control*, 142:104155, 2022.

Lawrence Schmidt, Allan Timmermann, and Russ Wermers. Runs on money market mutual funds. *American Economic Review*, 106(9):2625–57, 2016.

Raj Sethuraman, Gerard J Tellis, and Richard A Briesch. How well does advertising work? generalizations from meta-analysis of brand advertising elasticities. *Journal of Marketing Research*, 48(3):457–471, 2011.

Alp Simsek. Belief disagreements and collateral constraints. *Econometrica*, 81(1):1–53, 2013.

Harald Uhlig. A luna-tic stablecoin crash. Working Paper 30256, National Bureau of Economic Research, 2022.

Skander Van den Heuvel. The welfare effects of bank liquidity and capital requirements. *FEDS 2022-072*, 2022.

Xavier Vives. Strategic complementarity, fragility and regulation. *Review of Financial Studies*, 27(12):3547–3592, 2014.

Warren E. Weber. Antebellum u.s. state bank balance sheets, 2018. URL `https://researchdatabase.minneapolisfed.org/collections/wd375w37w?locale=en`.

6 Figures

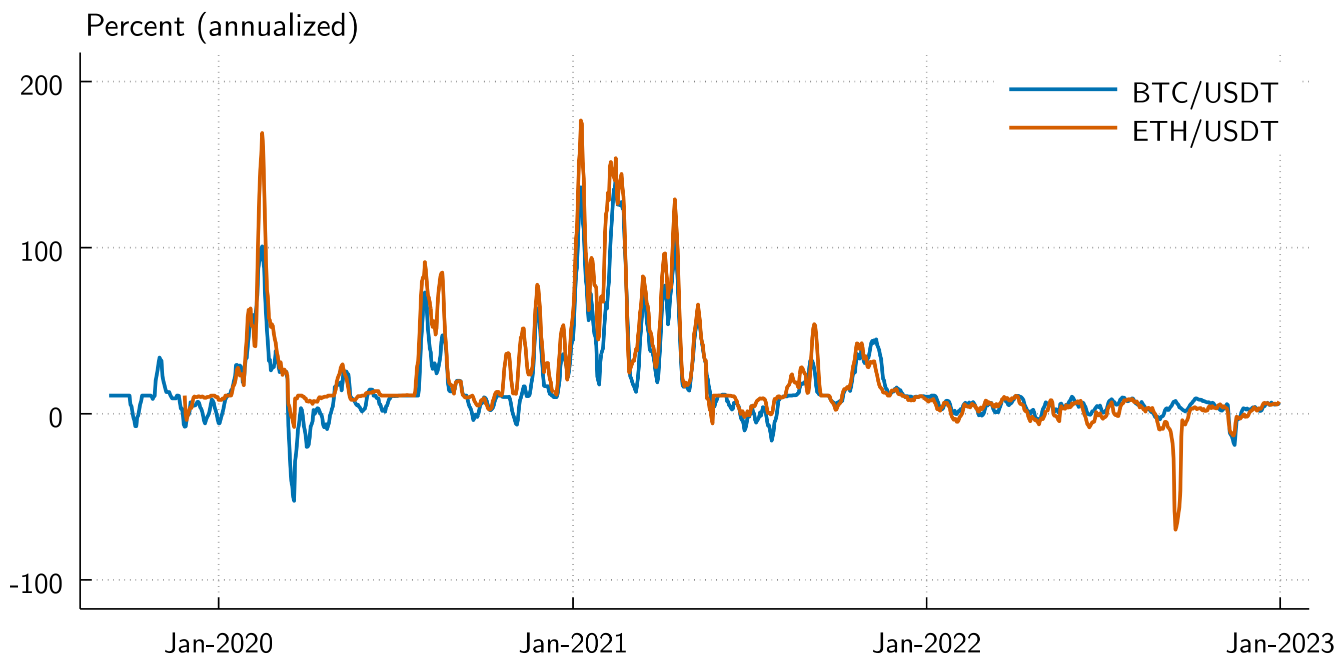

Figure 3: Perpetual Futures Funding Rate. Figure plots the annualized funding rate of USDT-settled Bitcoin perpetual futures for Bitcoin and Ether on Binance. A positive funding rate indicates that long-future investors make payments to short-future investors. Series are seven-day trailing averages.

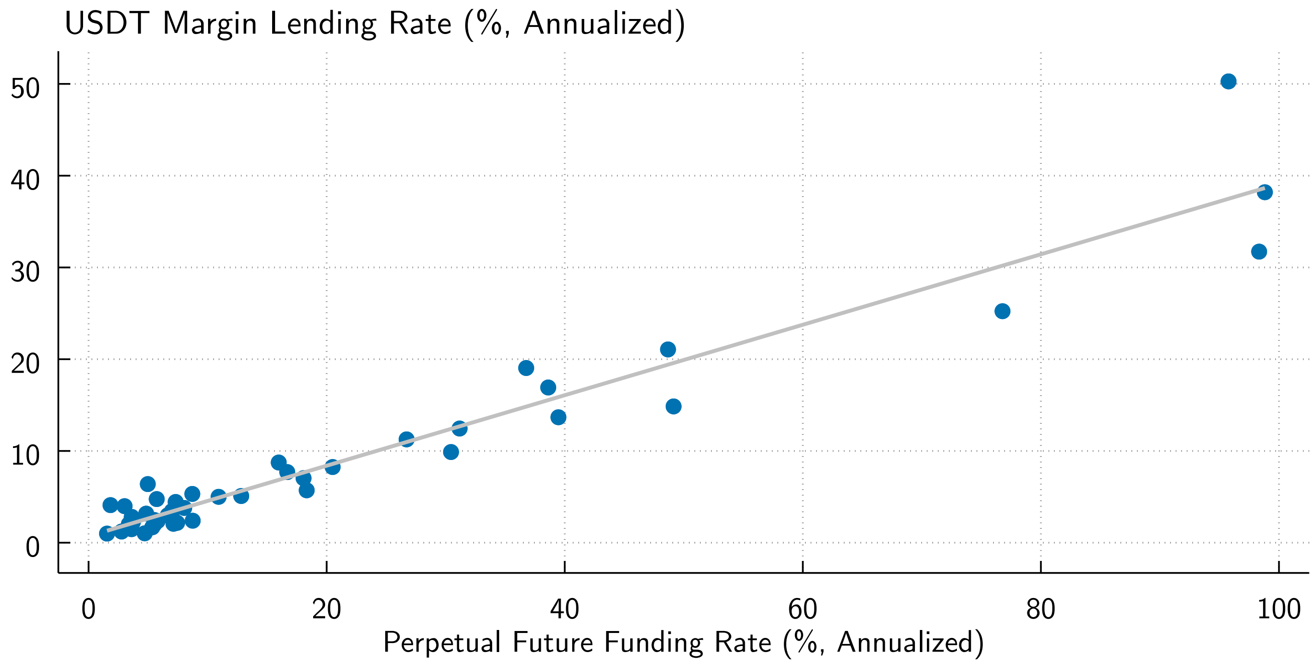

Figure 4: Stablecoin Lending Rates and Cost of Leverage. Figure plots a binscatter of daily observations of the annualized funding rate of BTC/USDT perpetual futures on Binance relative to the annualized USDT lending rate on FTX.

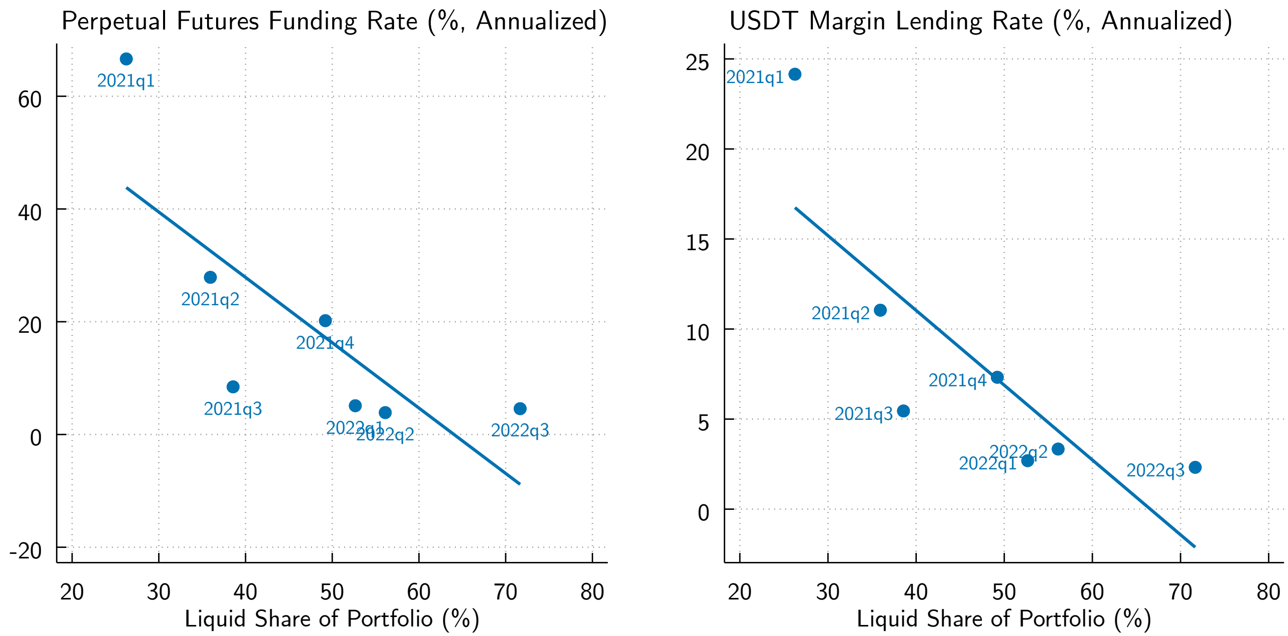

Figure 5: Tether Liquid Share vs. Perpetual Futures Funding Rate and USDT Lending Rate. Left panel plots the perpetual futures funding rate against USDT's liquid portfolio share in the same quarter. Right panel plots the average annualized lending rate for Tether on FTX by quarter against USDT's liquid portfolio share in the same quarter. Liquid portfolio share is calculated using public disclosures and is the share of reserves held in cash, bank deposits (including fiduciary deposits), reverse repurchase agreements, and Treasury bills.

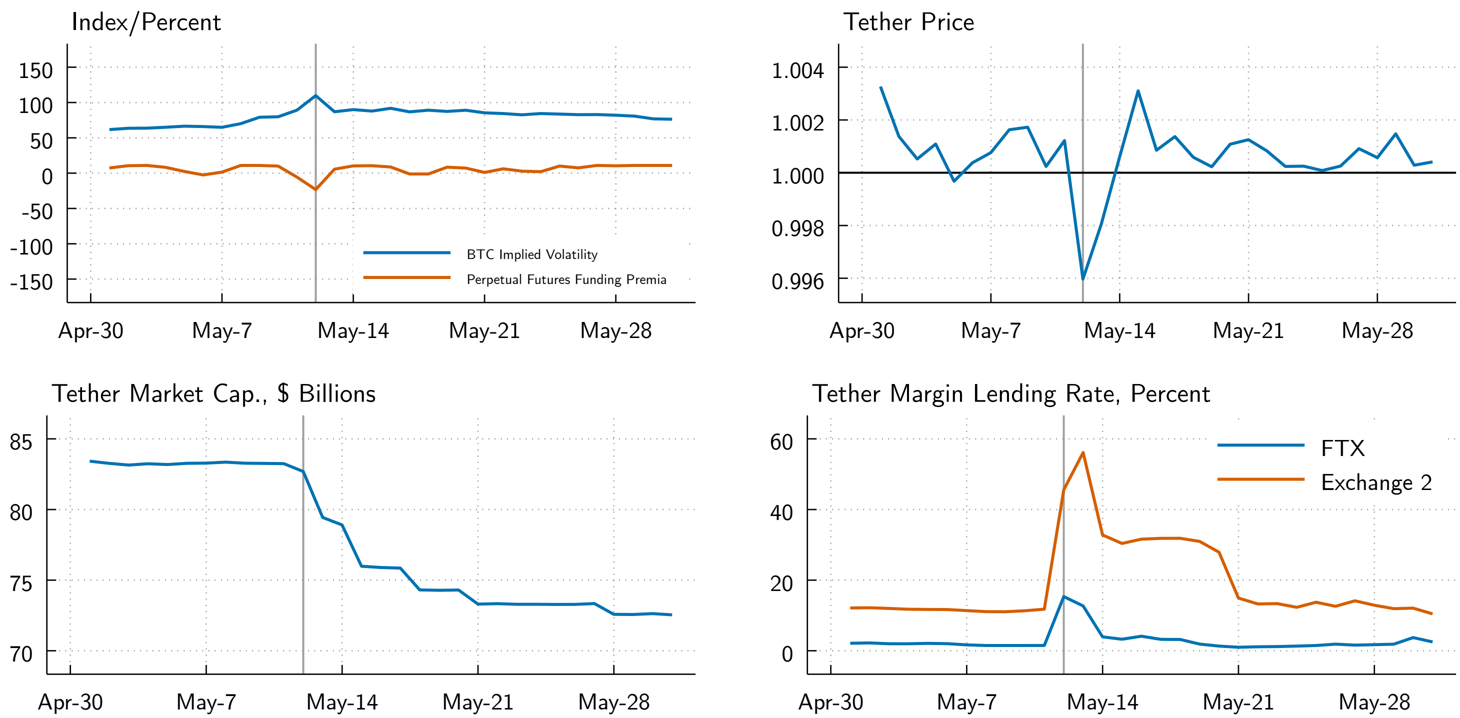

Figure 6: Tether during May 2022. Top-left figure plots BTC implied volatility and perpetual futures funding rate. Top right plots the price of Tether. Bottom left panel plots Tether's market capitalization in billions. Bottom right panel plots Tether's margin lending rates on two exchanges.

7 Tables

	Days (N)	Mean	Std. Dev.	Min	Max
Stablecoin Prices (\$)					
USDT (Tether)	705	1.0010	0.0022	0.9919	1.0114
DAI (Dai)	705	1.0013	0.0024	0.9912	1.0109
Margin Lending Rates (annualized percent)					
USDT	705	7.95	9.99	1.00	66.03
DAI	650	7.22	10.28	0.88	73.99
Perpetual Futures Funding Rate (annualized percent)					
BTC/USDT	705	18.98	30.48	−32.02	172.30
ETH/USDT	705	21.23	40.32	−239.65	215.45

Table 1: Summary Statistics. Table gives summary statistics for stablecoin prices from Coingecko, stablecoin margin lending rates from FTX, and perpetual futures funding rates from Binance. Sample runs from December 1, 2020 to November 5, 2022.

Haircut (%)	**Coin**	**Ticker**	**FTX**	**Binance**	**Bitfinex**	**Kraken**
Major Coins	Bitcoin	BTC	5	5	0	0
	Ether	ETH	10	5	0	0
	Cardano	ADA	*n.a.*	10	70	10
	Ripple	XRP	10	15	50	*n.a.*
	Solana	SOL	15	10	30	10
	Dogecoin	DOGE	10	5	80	*n.a.*
	Litecoin	LTC	10	10	0	30
	Avalanche	AVAX	15	20	80	50
	Tron	TRX	15	50	70	50
Stablecoins	Tether	USDT	5	0	0	10
	USD Coin	USDC	0	0	0	10
	Binance USD	BUSD	0	0	*n.a.*	*n.a.*
	Dai	DAI	15	*n.a.*	25	10
Average	Major Coins		11	14	42	21
	Stablecoins		5	0	8	10

Table 2: Haircuts. The Table gives haircuts across FTX, Binance, Bitfinex, and Kraken. FTX haircut is 1 minus the initial weight; Binance haircut is 1 minus the collateral rate. Average is an unweighted average of the haircuts in the corresponding rows above. Collateral haircuts updated as of November 2022, except Binance numbers are October 2022. A lower haircut implies that a larger share of the asset's nominal price can be used to back a levered position. While there is heterogeneity across exchanges, stablecoins have lower haircuts. Note that exchange deposits are economically equivalent to a non-tradeable stablecoin issued by the exchange and have similarly low haircuts. Suppose a trader wants to use ten times leverage to buy \$100 of BTC. The margin requirement depends on the trader's collateral. Using Binance haircuts, if the trader posts AVAX as collateral, they must provide $\$10/(1-20\%) = \$12.5$ of AVAX. If, however, the trader posts USDT as collateral, they need to post only $\$10/(1-0\%) = \$10$ of USDT. Posting a stablecoin as collateral requires 20% less equity capital from the trader.

	USDT			USDT and DAI		
	(1)	(2)	(3)	(4)	(5)	(6)
Futures Funding Rate$_t$	0.26***	0.19***	0.12***	0.23***	0.17***	0.12***
	(14.41)	(8.10)	(5.17)	(12.96)	(8.92)	(7.15)
Stablecoin Lending Rate$_{t-1}$			0.43***			0.30***
			(6.01)			(7.50)
BTC Implied Volatility$_t$			0.01			0.03
			(0.20)			(1.18)
R_t^{BTC}			0.05			0.09
			(0.86)			(1.49)
N	705	705	704	1,355	1,355	1,353
R^2	0.61	0.71	0.77	0.45	0.59	0.64
Month FE	No	Yes	Yes	No	Yes	Yes
Coin FE	No	No	No	No	Yes	Yes

Table 3: Stablecoin Interest Rates and Expected Returns. Table presents regression $R_{i,t} = \alpha + \beta_1 y_t + \gamma' X + a_i + b_t + \varepsilon_{i,t}$ where $R_{i,t}$ is stablecoin i's margin lending rate from the FTX exchange, y_t is Binance's BTC/USDT perpetual future funding rate, and X is a vector of controls including the lag of the stablecoin i's lending rate, the risk of Bitcoin measured by Bitcoin futures' implied volatility, and Bitcoin's contemporaneous price return, a_i is a stablecoin fixed effect, and b_t is a time fixed effect. Observations are daily. t-statistics are reported in parentheses using robust standard errors and clustered by week, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Days		Average Redemption		95%ile Redemption		Largest After 2019	
Coin	Total	% with Redemptions	$ mln	% of Face	$ mln	% of Face	$ mln	% of Face
USDT	2,788	26	62.0	0.3	230.4	1.0	3,432.4	4.1
USDC	1,493	39	79.9	0.8	360.9	2.3	3,809.4	8.2
BUSD	1,142	34	65.5	1.4	229.4	5.4	460.4	11.9
DAI	1,083	37	34.4	1.1	145.5	4.0	718.2	13.6
USTC	765	27	99.8	0.9	323.5	3.1	4,748.3	27.1
MIM	493	38	28.8	1.5	53.0	3.0	1,473.6	78.8
TUSD	1,689	43	7.1	1.3	38.0	5.1	235.1	19.0
PAX	1,502	45	7.6	1.5	34.8	5.6	178.7	15.3
LUSD	580	42	11.9	1.9	44.4	6.3	585.0	40.4
HUSD	1,143	38	9.0	2.5	42.2	8.9	171.8	35.7
USDN	1,009	40	4.2	0.8	9.8	2.0	547.2	80.5
FRAX	685	40	10.3	1.1	43.7	4.6	594.8	22.9
ALUSD	586	50	2.2	0.8	7.1	2.8	93.7	27.3
GUSD	1,508	42	4.9	3.4	23.3	17.8	169.3	41.4
USDP	589	48	1.8	3.0	9.5	18.9	64.9	52.4
MUSD	851	54	1.2	2.4	4.8	10.2	16.0	27.7
USDK	1,227	49	0.1	0.3	0.3	0.9	1.6	6.8
RSV	941	51	0.0	0.5	0.2	1.8	3.5	16.6

Table 4: Redemption Summary Statistics. Table presents summary statistics about daily net redemptions for several stablecoins. Rows ordered by average market capitalization in 2021, beginning with the largest (USDT). Sample runs from the date Coingecko has data for the coin until November 5, 2022.

	USDT			USDT and DAI		
	(1)	(2)	(3)	(4)	(5)	(6)
Funding Premium$_{t-1}$	1.02***	0.70***	0.63***	1.27***	1.05***	0.93***
	(9.10)	(4.47)	(4.03)	(10.13)	(5.07)	(4.74)
Bitcoin Implied Volatility$_{t-1}$			-0.84^{*}			-1.36^{***}
			(-1.82)			(-3.02)
$\Delta \ln(s_{i,t-1})$			-0.02			0.06
			(-0.46)			(0.77)
$\ln(s_{i,t-1})$			-113.66			-84.55^{***}
			(-1.49)			(-3.75)
N	704	704	704	1,408	1,408	1,408
R^2	0.26	0.34	0.35	0.13	0.17	0.19
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	n/a	n/a	n/a	No	Yes	Yes

Table 5: Peg Stability, First Stage. Table presents regression $\Delta \ln(s_{i,t}) = \alpha + \beta_1 y_{t-1} + \beta_2 \sigma_{t-1} + \gamma' X + a_i + b_t + \varepsilon_{i,t}$ where y is the perpetual futures funding premium, σ is the risk of Bitcoin measured by Bitcoin futures' implied volatility, $s_{i,t}$ is the face value of stablecoin i, X is a vector of controls including lags of the stablecoin's face value and issuance, a_i is a stablecoin fixed effect, and b_t is a time fixed effect. $\Delta \ln(s_{i,t})$ is in basis points. Observation at the daily level by coin. Sample in first three columns is only USDT and in last three columns is both USDT and DAI. Standard errors clustered by week. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	USDT			USDT and DAI		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \widehat{\ln(s_{i,t})}$	-2.13^{***}	-3.32^{**}	-11.89^{***}	-1.45^{**}	-1.78^{**}	-4.56^{**}
	(-2.66)	(-2.55)	(-3.24)	(-2.44)	(-2.09)	(-2.25)
Funding Premium$_t$			8.44^{***}			6.36^{**}
			(3.16)			(2.25)
Bitcoin Implied Volatility$_t$			-7.10			-3.97
			(-1.38)			(-1.11)
N	704	704	704	1,353	1,353	1,353
Month FE	No	Yes	Yes	No	Yes	Yes
Coin FE	n/a	n/a	n/a	No	Yes	Yes
First-Stage Controls	No	Yes	Yes	No	Yes	No

Table 6: Peg Stability, Second Stage. Table presents regression $\Delta R_{i,t} = \alpha + \gamma(\Delta \widehat{\ln(s_{i,t})}) + a_i + b_t + \varepsilon_{i,t}$ where $R_{i,t}$ is the lending rate of stablecoin i on date t at FTX in basis points and $\Delta \widehat{\ln(s_{i,t})}$ is the expected change in the face value of the stablecoin in basis points. $\Delta \widehat{\ln(s_{i,t})}$ is estimated using the first stage regression $\Delta \ln(s_{i,t}) = \alpha + \beta_1 y_{t-1} + \beta_2 \sigma_{t-1} + \gamma' X + a_i + b_t + \varepsilon_{i,t}$, where y is the perpetual futures funding premium, σ is Bitcoin futures' implied volatility, $s_{i,t}$ is the face value of stablecoin i, a_i is a stablecoin fixed effect, b_t is a time fixed effect, and X is a vector of controls including $s_{i,t-1}$ and $\Delta \ln(s_{i,t-1})$. Observation at the daily level by coin. Sample in first three columns is only USDT and in last three columns is both USDT and DAI. t-statistics are reported in parentheses using robust standard errors and clustered by week, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Second Stage	Lending Rate $R_{i,t}$			
	USDT		DAI	
	(1)	(2)	(3)	(4)
Futures $\widehat{\text{Funding}}$ Rate$_t$	0.279***	0.175***	0.223***	0.155***
	(4.310)	(3.069)	(2.890)	(3.159)
Bitcoin Implied Volatility$_t$	0.055	0.035	−0.020	−0.026
	(0.721)	(0.540)	(−0.463)	(−0.879)
$\Delta \ln(s_{i,t})$	−0.006	−0.004	−0.008**	−0.006**
	(−1.167)	(−0.955)	(−2.347)	(−2.264)
R_{t-1}		0.481***		0.492***
		(2.969)		(6.576)
N	258	258	258	258
Time FE	Yes	Yes	Yes	Yes

Panel B: First Stage	Funding Premium			
	USDT		DAI	
	(1)	(2)	(3)	(4)
Rating$_t$	2.587***	1.941***	2.407***	2.307***
	(3.437)	(2.830)	(3.191)	(3.359)
Bitcoin Implied Volatility$_t$	0.344*	0.210	0.331**	0.314**
	(1.730)	(1.058)	(2.303)	(2.219)
$\Delta \ln(s_{i,t})$	0.024*	0.024*	0.028***	0.028***
	(1.748)	(1.750)	(5.159)	(5.154)
R_{t-1}		1.145**		0.299
		(2.570)		(0.935)
N	258	258	258	258
Time FE	Yes	Yes	Yes	Yes
F-stat	11.82	8.01	10.18	11.28

Panel C: OLS	Lending Rate $R_{i,t}$			
	USDT		DAI	
	(1)	(2)	(3)	(4)
Futures Funding Rate$_t$	0.211***	0.119***	0.153***	0.109***
	(14.232)	(5.647)	(7.492)	(4.938)
Bitcoin Implied Volatility$_t$	0.013	0.007	0.067	0.024
	(0.281)	(0.227)	(1.180)	(0.528)
$\Delta \ln(s_{i,t})$	0.003	−0.001	0.004	0.002
	(0.264)	(−0.061)	(0.928)	(0.599)
R_{t-1}		0.489***		0.297***
		(6.906)		(5.027)
N	705	704	650	649
Time FE	Yes	Yes	Yes	Yes

Table 7: Instrument Variables Regression of Futures Funding Premia and Lending Rates. Instrumental variables regression using the mean household rating of MLB games on a given day as an instrument to predict the perpetual futures funding premium. Panel A shows the second stage regression of the instrumented variable on margin lending rates separately for USDT and DAI. Panel B shows the first stage regression of the instrument on the perpetual futures funding premium. Panel C shows the OLS regression of the lending rate on the funding premium. Time FE indicates day of week, month of year, and year fixed effects. Kleibergen-Paap rk Wald F statistics reported. t-statistics are reported in parentheses using robust standard errors and clustered by week where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Online Appendix

A.1 Sufficient condition for $d\Delta^*/d\ell > 0$.

Substituting (17) in (19) we get that

$$\begin{aligned}\frac{d\bar{\Delta}^*}{d\ell} &= \frac{d\hat{\lambda}}{d\ell}\left[\theta^* R(\hat{\lambda},s)-1\right]\frac{1}{1-\delta}+\int_\delta^\ell (1-\theta^*)\frac{1}{1-\lambda}\frac{d\lambda}{1-\delta}\\ &-\frac{1}{\ell}\int_\delta^{\hat{\lambda}}\left[\theta^* R(\lambda,s)+(1-\theta^*)\max\left(\frac{\ell-\lambda}{1-\lambda},0\right)-1\right]\frac{d\lambda}{1-\delta}\\ &-\frac{d\hat{\lambda}}{d\ell}\left[\theta^*\frac{X(1-\ell)\left[1-\frac{\hat{\lambda}-\ell}{\xi(1-\ell)}\right]}{1-\hat{\lambda}}-1\right]\frac{1}{1-\delta}-\frac{1}{\ell}\int_{\hat{\lambda}}^{\bar{\lambda}}\left[\theta^*\frac{X(1-\ell)\left[1-\frac{\lambda-\ell}{\xi(1-\ell)}\right]}{1-\lambda}-1\right]\frac{d\lambda}{1-\delta}\\ &+\int_{\hat{\lambda}}^{\bar{\lambda}}\frac{X(1/\xi-1)}{1-\lambda}\frac{d\lambda}{1-\delta}+\frac{1}{\ell}\int_{\bar{\lambda}}^1\frac{\xi}{\lambda}\frac{d\lambda}{1-\delta}. \qquad (28)\end{aligned}$$

Given that $d\hat{\lambda}/d\ell > 0$ from (10), the terms in the last two lines in (28) are all positive and, thus, we only need to sign the terms in the first two lines. Add and subtract $d\hat{\lambda}/d\ell \cdot (1-\theta^*)\cdot {(\ell-\delta)}/{(1-\delta)^2}$. Then, because (i) $dR(\lambda,s)/d\lambda > 0$ from (3), (ii) $d{(\ell-\lambda)}/{(1-\lambda)}/d\ell = -{(1-\ell)}/{(1-\lambda)^2} < 0$, and (iii) $d(1-\lambda)^{-1}/d\lambda > 0$, the sum of the terms in the first two line is strictly higher than

$$\begin{aligned}&\left[\frac{d\hat{\lambda}}{d\ell}-\frac{\hat{\lambda}-\delta}{\ell}\right]\left[\theta^* R(\hat{\lambda},s)+(1-\theta^*)\max\left(\frac{\ell-\delta}{1-\delta},0\right)-1\right]\frac{1}{1-\delta}\\ &+(1-\theta^*)\frac{\ell-\delta}{(1-\delta)^2}\left(1-\frac{d\hat{\lambda}}{d\ell}\right). \qquad (29)\end{aligned}$$

The last term is strictly positive because $d\hat{\lambda}/d\ell = {X(1-\xi)}/{(X-\xi)} < 1$. Moreover,

$$\theta^* R(\hat{\lambda},s)+(1-\theta^*)\max\left(\frac{\ell-\delta}{1-\delta},0\right)-1 > \underline{\theta}R(\delta,s)+(1-\underline{\theta})\max\left(\frac{\ell-\delta}{1-\delta},0\right)-1=0,$$

because $\theta^* > \underline{\theta}$ and $R(\hat{\lambda},s) > R(\delta,s)$. If $d\hat{\lambda}/d\ell - {\hat{\lambda}-\delta}/{\ell} > 0 \Rightarrow \delta < {\xi(X-1)}/{X-\xi}$, then $d\bar{\Delta}^*/d\ell > 0$ always. For δ lower than that threshold, we can derive a sufficient condition for the lending rate such that the absolute value of the terms in the first line in (29) is lower than $1/\ell \int_{\bar{\lambda}}^1 \frac{\xi}{\lambda} d\lambda$ and, thus, (28) is positive. The latter terms is strictly higher than $1/\ell \xi \log \xi$, while the absolute value of the former is strictly lower than $1/\ell \cdot {\xi(X-1)}/{(X-\xi)} \cdot (\max R - 1)$, where we considered the higher possible lending rate and set $\delta = 0$. Thus, it is sufficient that $\max R \leq -\log \xi \cdot {(X-\xi)}/{(X-1)}$ for $d\bar{\Delta}^*/d\ell > 0$.This condition is easily satisfied. For example, an expected yield of 5% for the illiquid asset, i.e., $X = 2.1$, and a liquidity discount of 25%, i.e., $\xi = 0.75$, it is sufficient that the expected lending rate is lower that 35%, which is the case in our data. As mentioned, the sufficient condition on the lending rate is rather weak and we could be relaxed further if we consider the effect of the other positive terms in (28).

A.2 Model Extension: Endogenous Margin Requirements

In the baseline model we assume that the exchange sets margin m without taking into consideration how it should be chosen optimally between traders and investors. Given that levered lending takes place after run uncertainty is resolved, m should not depend on θ^*, but can depend on R. To derive an optimal m we consider a structure—akin to Fostel and Geanakoplos (2008)—under which traders offer investors a menu of contracts $k \in K$ described by a pair (R_k, m_k), where R_k is given, in equilibrium, by (3) for certain m_k. That is, traders offer investors a menu of contracts under all of which they break even. Given that these contracts are offered after redemptions λs have been observed, they are only parameterized by different m_k. Investors will then choose the contract that maximizes their utility.

To introduce a trade-off, we suppose for this extension that investors face a cost c for directly holding the cryptocurrency when the trader defaults. Recall from Section 2.1 that R is the expected lending rate, incorporating the payoff when traders defaults, and that traders will default for cryptocurrency payoff realizations $\tilde{y} < y'_k$, i.e., y'_k is the threshold below which investors receive the collateral for margin m_k and is given by

$$y'_k = (1-m)R_{k,c} \quad \Rightarrow \quad y'_k = \frac{\bar{y}(1-m)R_k - {y'_k}^2/2}{\bar{y} - y'_k}, \tag{30}$$

where we replaced the contractual lending rate, $R_{k,c}$, with the expected lending rate, R_k.

The probability that investors incur the cost c is equal to $\int_{\tilde{y}<y'_k} dF(\tilde{y})$. We assume $\tilde{y} \sim U[0, \bar{y}]$ for simplicity and, thus, $y = \bar{y}/2$. Investor's payoff from no redeeming is equal to $\theta\left(R_k - c\int_{\tilde{y}<y'_k} dF(\tilde{y})\right) + (1-\theta)\max\left(\frac{\ell-\lambda}{1-\lambda}, 0\right)$. Ihn other words, the expected return from lending the stablecoin, R, is curtailed by the expected cost of having to hold it when the trader defaults. Among all available contracts $(R_k(m_k), m_k)$ $\forall k \in K$, the investor will choose the one that delivers the higher payoff. Given that R_k is a function of m_k, we just need to find the m_k that maximizes investor's payoff, which is the solution to

$$\theta\frac{\partial R_k}{\partial m_k} - \theta c \frac{\partial y'_k}{\partial m_k}\frac{1}{\bar{y}} + \underline{\psi}_k - \overline{\psi}_k = 0 \tag{31}$$

where $\underline{\psi_k}$ and $\overline{\psi}_k$ are the Lagrange multipliers on $m_k \geq 0$ and $m_k \leq \bar{m}$, where $\bar{m}$ is the maximum margin traders would be willing to post given by $y - \bar{m}F'(e - {}^{m}/{}_{1-m}(1-\lambda)s) = 0$. Recall that ${}^{dR_k(\lambda,s)}/{}_{dm_k}$ is given by (5) and is negative. ${}^{dy'_k}/{}_{dm_k}$ is obtained by totally differentiating (30)

$$\frac{dy_k'}{dm_k} = \frac{\bar{y}}{\bar{y} - y_k'}\left((1-m)\frac{dR_k}{dm_k} - R_k\right) < 0. \tag{32}$$

For $m \to 0$, the first two terms in (31) converge to $y - (1 - c/(\bar{y} - y_k'))F'(e)$ and is positive only if $c \geq \bar{c} \equiv (\bar{y} - y_k')(1 - y/F'(e)) > 0$ given the assumption $F'(e) > y$. For $m \to \bar{m}$, the sum of the first two terms converges to $dR_k/dm_k|_{m_k=\bar{m}}(1 - c/(\bar{y} - y_k')(1-\bar{m})) < 0$. Moreover, the sum of the first two terms is strictly decreasing for $F'''' > 0$, which typical for widely used concave technologies such as Cobb-Douglas production function, and we will assume herein. Hence, the contract that investors choose is unique and depends on the level of c.

Case I. If $c \leq \bar{c}$, then $\underline{\psi}_k > 0$, $\overline{\psi}_k = 0$, and $m_k = 0$, such that our baseline analysis carries through in its entirety.

Case II. If $c \geq \bar{c}$, m_k is interior, i.e., $\underline{\psi}_k = \overline{\psi}_k = 0$. In this case, m_k will be a function of y, λ and s, and we need to show that our baseline results do not change. Essentially, we need to show that the derivatives of R_k with respect to $x \in \{y, \lambda, s\}$ do not change sign. We show that this is the case for sufficiently high c. Note that

$$\frac{dR_k}{dx} = \frac{\partial R_k}{\partial x} + \frac{\partial R_k}{\partial m_k}\frac{dm_k}{dx}. \tag{33}$$

Given that $\partial R_k/\partial x$ and $\partial R_k/\partial m_k$ are given by (4)-(7), we just need to sign dm_k/dx, which we can compute by totally differentiating (31):

$$\frac{dm_k}{dy} = -\frac{\frac{\partial^2 R_k}{\partial m_k \partial y}(\bar{y} - y_k' - c(1-m_k)) + \left(2 - \frac{\partial y_k'}{\partial y}\right)\frac{\partial R_k}{\partial m_k} + c\frac{\partial R_k}{\partial y}}{\frac{\partial^2 R_k}{\partial m_k^2}(\bar{y} - y_k' - c(1-m_k)) + \left(2c - \frac{\partial y_k'}{\partial m_k}\right)\frac{\partial R_k}{\partial m_k}}$$

$$\frac{dm_k}{dx} = -\frac{\frac{\partial^2 R_k}{\partial m_k \partial x}(\bar{y} - y_k' - c(1-m_k)) - \frac{\partial y_k'}{\partial x}\frac{\partial R_k}{\partial m_k} + c\frac{\partial R_k}{\partial x}}{\frac{\partial^2 R_k}{\partial m_k^2}(\bar{y} - y_k' - c(1-m_k)) + \left(2c - \frac{\partial y_k'}{\partial m_k}\right)\frac{\partial R_k}{\partial m_k}},\ \mathrm{x} \in \{\lambda, \mathrm{s}\}. \tag{34}$$

Since $F''' > 0$, $\partial^2 R_k/\partial m_k^2 < 0$, and $\partial^2 R_k/\partial m_k \partial y > 0$, $\partial^2 R_k/\partial m_k \partial \lambda > 0$, $\partial^2 R_k/\partial m_k \partial s < 0$. Moreover, by totally differentiating (30), we get

$$\frac{dy_k'}{dy} = \frac{1}{\bar{y} - y_k'}\left(\bar{y}(1-m)\frac{\partial R_k}{\partial dy} + 2(1-m)R_k - 2y_k'\right)$$

$$\frac{dy_k'}{dx} = \frac{\bar{y}}{\bar{y} - y_k'}(1-m)\frac{\partial R_k}{\partial x},\ \mathrm{x} \in \{\lambda, \mathrm{s}\}. \tag{35}$$

Consider $c \to {}^{\bar{y}}/_{1-m_k}{}^{+}$. Then, using (32) and (35), we get

$$\frac{dm_k}{dy} = -\frac{\frac{(2\bar{y}-2(1-m_k)R_k)}{(\bar{y}-y'_k)}}{2c - \frac{dy'_k}{dm_k}} - \frac{c - \frac{\bar{y}}{(\bar{y}-y'_k)}(1-m_k)\frac{\partial R_k}{\partial m_k}}{2c - \frac{\bar{y}}{(\bar{y}-y'_k)}(1-m_k)\frac{\partial R_k}{\partial m_k} + \frac{\bar{y}}{(\bar{y}-y'_k)}R_k} \frac{\partial R_k/\partial y}{\partial R_k/\partial m_k} < -\frac{\partial R_k/\partial y}{\partial R_k/\partial m_k}, \quad (36)$$

$$\frac{dm_k}{d\lambda} = -\frac{c - \frac{\bar{y}}{(\bar{y}-y'_k)}(1-m_k)\frac{\partial R_k}{\partial m_k}}{2c - \frac{\bar{y}}{(\bar{y}-y'_k)}(1-m_k)\frac{\partial R_k}{\partial m_k} + \frac{\bar{y}}{(\bar{y}-y'_k)}R_k} \frac{\partial R_k/\partial \lambda}{\partial R_k/\partial m_k} < -\frac{\partial R_k/\partial \lambda}{\partial R_k/\partial m_k}, \quad (37)$$

$$\frac{dm_k}{ds} = -\frac{c - \frac{\bar{y}}{(\bar{y}-y'_k)}(1-m_k)\frac{\partial R_k}{\partial m_k}}{2c - \frac{\bar{y}}{(\bar{y}-y'_k)}(1-m_k)\frac{\partial R_k}{\partial m_k} + \frac{\bar{y}}{(\bar{y}-y'_k)}R_k} \frac{\partial R_k/\partial s}{\partial R_k/\partial m_k} > -\frac{\partial R_k/\partial s}{\partial R_k/\partial m_k}. \quad (38)$$

Using the above, we get from (33) that ${}^{dR_k}/_{dy} > 0$, ${}^{dR_k}/_{d\lambda} > 0$, and ${}^{dR_k}/_{ds} < 0$, which means that qualitatively the derivatives of the lending rate with respect to x are the same as in the baseline analysis in Section 2.1 where the margin was constant.

It follows that away from the limit, but for $c \geq \bar{c}$, it also suffices to establish the bounds in (36)-(38). These latter expressions for the bounds hold if

$$2\frac{\partial^2 R_k}{\partial m_k \partial x}\frac{\partial R_k}{\partial m_k} > \frac{\partial^2 R_k}{\partial m_k^2}\frac{\partial R_k}{\partial x},$$

which holds for all $x\{y, \lambda, s\}$ using (4)-(7) and the cross-derivatives above. Hence, endogenous margins may weaken quantitatively the effect of $\{y, \lambda, s\}$ on R_k—because ${}^{\partial R_k}/_{\partial m_k}$—but qualitatively do not matter.

A.3 Model Extension: Payment services from stablecoins

In this section, we introduce an additional source of demand for stablecoins arising from use-cases other than speculation. Such services may accrue from facilitating cross-country payments, services offered exclusively by the digital-asset ecosystem, or tax evasion and illicit activities. The value of these services could be aggregated in a convenience yield V, which can be constant or depend on the number of stablecoins in circulation, that is $V(\lambda, s) \equiv V((1-\lambda)s)$ with ${}^{dV}/_{ds} < 0$ and ${}^{dV}/_{d\lambda} > 0$ following Krishnamurthy and Vissing-Jorgensen (2012). Then, the stablecoin payoff from not redeeming when the issuer does not default is given by $\theta\left(R(\lambda, s) + V(\lambda, s)\right) + (1-\theta)\max\left({}^{\ell-\lambda}/_{1-\lambda}, 0\right)$. A positive convenience yield increases the payoff and decreases the probability of a run *ceteris paribus*. Moreover, if the convenience yield is decreasing in the number of stablecoins, then the stabilization mechanism operating via the redemptions channel is strengthened. The stabilization mechanism via the liquid portfolio share continues to operate as in the absence of a convenience yield.

A.4 Model Extension: Speculating on Stablecoin Collapse

In the baseline model, we considered that investors lent their stablecoins to traders, who want to take leverage on cryptocurrencies, after run uncertainty has been resolved. Yet, traders may want to borrow the stablecoins before run uncertainty is resolved so that they can also speculate on the collapse of the stablecoin. The idea is that promised repayment is denominated in stablecoins and, thus, if stablecoin price collapses to zero after a run, traders would need to repay zero without losing their pledged collateral.

We consider a very simple extension of the model to introduce this motive. There are two types of traders and investors: type A and type B. Both types are identical with the difference that type A traders borrow stablecoins from type A investors before $t = 1$, while type B traders borrow stablecoins from type B investors after $t = 1$. Denote by $\zeta \in [0, 1]$ the portion of tokens lent early. We assume that the tokens are circulated back to other stablecoin investors, who want to lend them after run uncertainty is resolved at $t = 1$.

Traders of both types have the same endowment and each type has its own, distinct, outside technology. A-traders still need to pledge collateral, thus they buy the cryptocurrency on margin as in the baseline model. Thus, the return on the outside options are given by $\rho_A = F'[e - {}^{m}/_{(1-m)}\gamma s]$ for A-traders and $\rho_B = F'[e - {}^{m}/_{(1-m)}(1-\lambda)s]$ for B-traders.

The run decision for the B-investors is the same as in Section 2.2 and the stablecoin price they are willing to offer is given by (21) with the difference that the lending rate will be different. Next we derive the lending rate and the participation decision for the A-investors.

Denote by $\hat{R}$ the expected lending rate for borrowing before $t = 1$. As before, A-traders will break even with their outside option but in this case they additionally do not need to repay anything when the stablecoin collapses in a run because the price of tokens goes to zero:

$$\int_{\theta^*}^{1} [\theta(y - (1-m)\hat{R}) + (1-\theta)y]d\theta + \int_{0}^{\theta^*} y d\theta = m\rho_A \Rightarrow \quad \hat{R} = \frac{y - m\rho_A}{1-m}\frac{2}{1-\theta^{*2}}. \quad (39)$$

Using (1) and (39), we can compare the lending rates for lending before and after $t = 1$, R and $\hat{R}$; recall that R is contingent on the realization of θ and lending only happens for $\theta \geq \theta^*$. Comparing the two boils down to comparing ${}^{1}/_{\theta}$ and ${}^{2}/_{1-\theta^{*2}}$. The former takes its highest value for realization $\theta = \theta^*$. Then, $\hat{R} > R$ for all $\theta \geq \theta^*$ if $\theta^{*2} + 2\theta^* - 1 > 0$ if the run probability is higher than a value equal to $\sqrt{2} - 1 \approx 0.41$. Otherwise, $\hat{R}$ is lower than R for low realization of θ and higher for high realizations of θ (as can be seen by setting $\theta = 1$).

This result is intuitive. Traders face a trade-off when borrowing early: If the run occurs, they gain a lot and are willing to offer high lending rates. But, if the run does not occur, they will end up paying higher lending rates even for high realization of θ, which they would have avoided if they waited to borrow after $t = 1$. The first effect dominates for high enough run probability, i.e., when the incentive to speculate on the collapse of the stablecoin is higher. This result rationalizes the high lending rate observed during the run on Tether in May 2022.

However, A-investors should rationally expect to be repaid in full in some states of the world, which puts an upper limit on $\hat{R}$. In particular, the expected payoff they receive should be higher than 1 (their outside option), i.e., using (39),

$$\int_{\theta^*}^{1} \theta \hat{R} d\theta \geq 1 \quad \Rightarrow \quad \rho_A \leq \frac{y - 1 + m}{m}. \tag{40}$$

Condition (40) places an upper bound on ζ. In equilibrium this constraint will bind, and together with the binding participation constraint of the B-investors, $P = 1$ with P given by (21), they determine s and γ given ℓ. The issuer will choose ℓ to maximize their profits while internalizing these two constraints. Importantly, constraint (40) implies that higher lending before $t = 1$ also requires that the speculative demand for the cryptocurrency, as measured by y, is high as well, because ρ_A is increasing in ζs. Otherwise, investors would not be willing to lend their tokens early.

A.5 Robustness for Measuring Expected Returns

We check that using Binance's BTC/USDT perpetual futures funding rate is a robust proxy for expected returns. One concern is that using the BTC/USDT perpetual futures as a proxy of y overweighs idiosyncrasies specific to Bitcoin. In Table A.3, we show pairwise correlations of the BTC/USDT time series with several other series. Binance also has perpetual futures that settle into Binance USD, another stablecoin, and we show that funding rates across perpetual futures are highly correlated regardless of which stablecoin they settle in. Another concern is that all futures funding rates on Binance reflect idiosyncrasies specific to Binance, rather than aggregate expected returns for cryptocurrency beyond just Binance. We compare Binance's number with another large exchange, FTX, and find that funding rates are similar across the exchanges, confirming that the funding rates are not principally capturing exchange-specific factors. Finally, we show that perpetual futures funding rates are closely linked to expected returns embedded in crypto futures traded on the CME.

To address concerns about idiosyncrasies specific to Bitcoin, USDT, or Binance, we show correlations across several different contracts (BTC, ETH, and DOGE), settled in different types of stablecoins (USDT, BUSD, and FTX's USD), and across both Binance and FTX. We include DOGE as it is known as a highly speculative currency and was arguably started as a joke. The last two columns are the expected return measures we infer from CME futures, which we describe below. Combined, all the series are highly correlated, indicating that variation in our main measure of y, BTC/USDT on Binance, is not principally reflecting something specific to BTC, USDT, or Binance instead of speculative expected returns. measures

We can also proxy for y using the expected return embedded in crypto futures traded on the CME. Unlike the highly levered offshore perpetual futures, these futures are vanilla futures and like equity index futures. The CME sets the rules for the derivatives, and they have standard monthly expirations. These crypto futures are widely used by U.S.-based institutional investors who want to speculate on the price of Bitcoin or Ether but are unwilling or unable to hold cryptocurrencies directly. While the futures have embedded leverage, they are considerably less levered than the offshore perpetual futures.[33]

We calculate expected returns y for Bitcoin and Ether using the futures prices. Let $F_{t,t+n}$ denote the price of a future at time t with delivery at $t+n$, and let $z_{t,t+n}$ denote the n-period discount factor implied by the risk-free rate. We can infer expected returns using a no-arbitrage argument comparing the present value of $F_{t,t+n}$ and $F_{t,t+n+1}$. The expected return is

$$\mathbb{E}_{t,t+n\to t+n+1}[y] \equiv \left(\frac{z_{t,t+n+1}}{z_{t,t+n}}\right)\frac{F_{t,t+n+1}}{F_{t,t+n}} \tag{41}$$

We use the overnight-indexed swap curve to estimate the n-period discount factors: $z_{t,t+n} = 1/(1+y^{\text{OIS}}_{t,t+n}/12)^{(1/12)}$ where $y^{\text{OIS}}_{t,t+n}$ is the n-month OIS yield. We prefer to use consecutive futures rather than the front-month future versus the spot because the futures include leverage which may introduce a bias relative to the spot price.

In principle, we can use the ratio of contracts with any expiration to calculate expected returns between the two contracts' expirations. We focus on the first and second front-month contracts for two reasons. First, using the shortest maturity contracts helps control for any distortions introduced by an upward-sloping term structure of risk premia. Second, the liquidity of derivative contracts falls considerably at longer terms.

Figure A.1 plots our measure of expected returns for Bitcoin and Ether. Given the tremendous bull market in cryptocurrencies over the past several years, expected returns are almost always positive, although they dipped negative in late 2018 and briefly during the 2020 pandemic. The average expected return for Bitcoin using the measure is 5.0% from December 2017 to November 2022, ranging from −10.8% in December 2018 to 23.5% in February 2021. The ETH expected return has a shorter history because the future was introduced later, but from February 2021 to November 2022 it averaged 4.8% with a standard deviation of 7.3% compared to BTC's 3.9% average and 5.3% standard deviation over the same period.

[33] As of June 2022, the CME requires 50 percent (60 percent) margin for BTC (ETH) futures, allowing roughly 1× (0.67×) leverage. See `https://www.cmegroup.com/markets/cryptocurrencies.html`.

We test the model's prediction that lending rates are increasing in y by regressing Tether's lending rate on FTX on our measure of expected returns using

$$\text{USDT Lending Rate}_t = \alpha + \beta \mathbb{E}[Ret^{BTC}] + \gamma X_t + \varepsilon_t$$

where X_t is a vector of controls. Table A.4 shows the regression results. Scanning across the first row, a 1pp increase in $\mathbb{E}[Ret^{BTC}]$ increases the stablecoin lending rates by between 0.8 and 1.4pp, depending on the control variables. Across all specifications, there is a positive and significant relationship between lending rates and expected returns. Figure A.2 is a scatter plot between expected returns on Bitcoin and Tether lending rates showing an obvious positive relationship.

One concern is that we confound expected speculative returns with the term structure of risk premium. We control for this problem by including an expected return for the SPX equity index using the same logic: we compare the present value of the first and second front-month for the SPX. Including this control in column (6) does not change the statistically strong relationship between expected returns and lending rates.

A.6 Appendix Figures

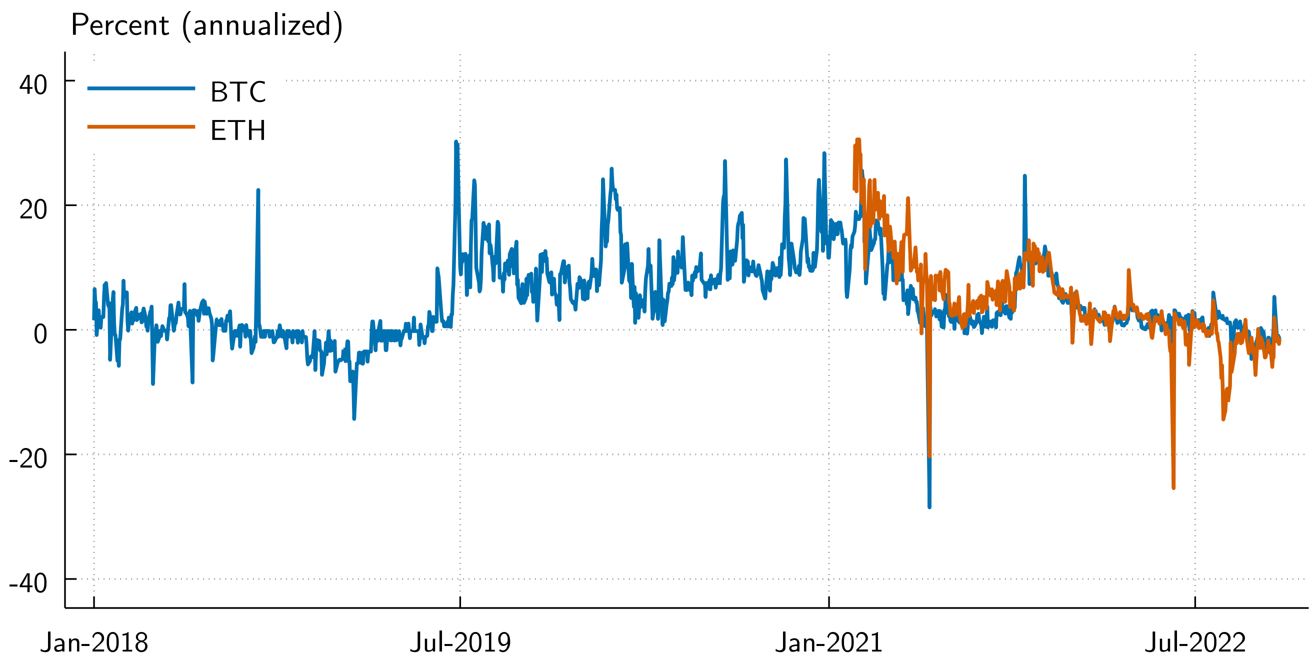

Figure A.1: Futures-Implied Expected Returns Figure plots the one-month/one-month expected return on Bitcoin and Ether estimated using the difference in present values for one-month futures prices relative to two-month futures prices. Present values are calculated using OIS interest rates, and futures prices are CME future prices.

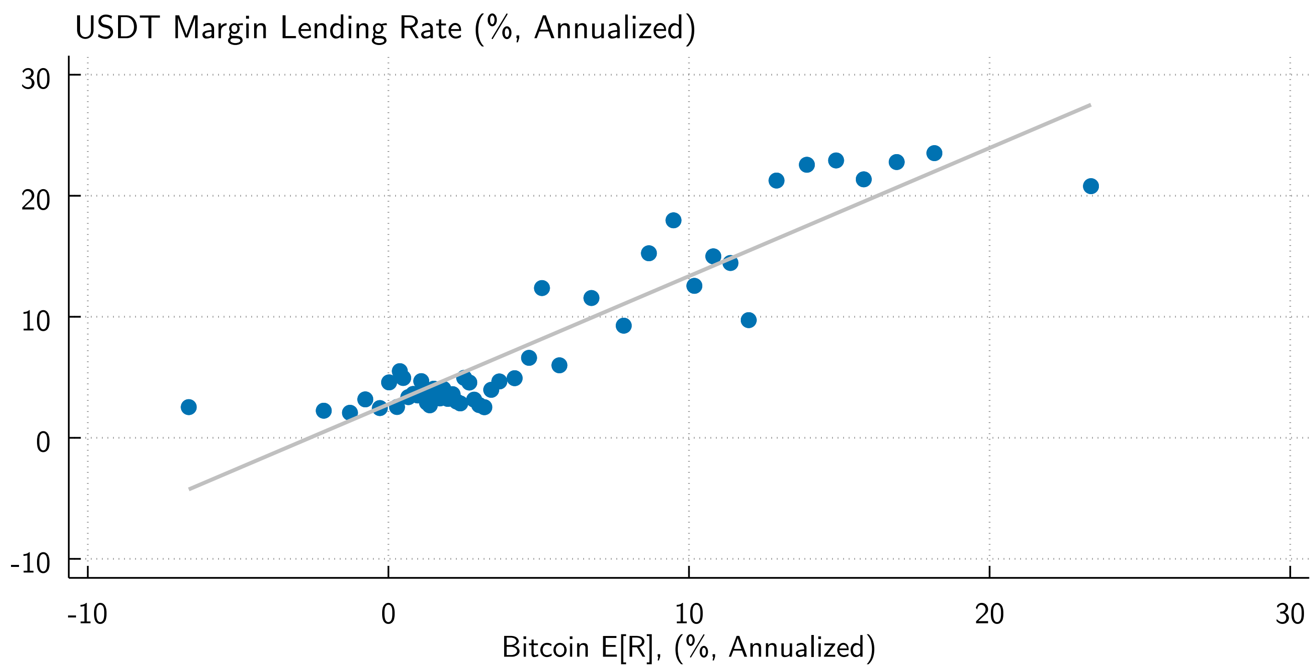

Figure A.2: Stablecoin Lending Rates and Futures-Implied Expected Returns Figure plots a binscatter of the one-month/one-month expected return on Bitcoin against USDT's margin lending rate on the FTX exchange.

A.7 Appendix Tables

	1 Largest	3 Largest	5 Largest	10 Largest	All
	(1)	(2)	(3)	(4)	(5)
FTX Tether Lending Rate$_t$	0.05***	0.03***	0.02*	0.02*	0.03***
	(23.77)	(2.70)	(1.88)	(1.66)	(3.41)
N	273	673	948	1,718	5,378
R^2	0.31	0.14	0.05	0.02	0.02
TVL Weighted	No	No	No	No	Yes
Avg. TVL ($ millions)	379	253	191	116	30

Table A.1: FTX Lending Rates and Defi Lending Rates. Table presents regression $R^{Defi}_{j,t} = \alpha + \beta_1 R^{USDT}_t + \varepsilon_{i,t}$ where R^{USDT}_t is Tether's margin lending rate from the FTX exchange and $R^{Defi}_{j,t}$ is the lending rate at the Defi lending platform j. Defi lending rates from DefiLlama, spanning all protocols in the lending category that include Tether. Observations are daily. protocols are calculated using their average 2022 total value lock (TVL) in US dollars. Column 5 includes all protocols in the sample and weights the regression by the protocol's average 2022 TVL. "Avg. TVL" row provides the average total value lock of the protocols in the given sample. Constant omitted. t-statistics are reported in parentheses using robust standard errors, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	USDT			USDT and DAI		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(s_{i,t})$	-2.65^{**}	-3.65^{**}	-4.42^{***}	-1.03^{*}	-1.23^{**}	-1.33^{**}
	(-2.57)	(-2.55)	(-3.00)	(-1.89)	(-2.07)	(-2.18)
Bitcoin Implied Volatility$_t$			-10.66			-9.25
			(-1.42)			(-1.25)
$\Delta \ln(s_{i,t-1})$			1.01			-0.55
			(0.69)			(-1.22)
$\ln(s_{i,t-1})$			-4761.73^{***}			-806.44^{**}
			(-2.69)			(-2.28)
N	704	704	704	1,353	1,353	1,353
R^2	0.01	0.02	0.04	0.00	0.01	0.01
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	n/a	n/a	n/a	No	Yes	Yes

Table A.2: Outside Option Return and Stablecoin Volume. Table presents regression $\Delta\rho_t = \alpha + \beta_1 \Delta \ln(s_{i,t}) + \gamma' X + a_i + b_t + \varepsilon_{i,t}$ where $\Delta\rho_t$ is the change in the outside option ρ_t, $\Delta \ln(s_{i,t})$ is the change in the log change in the face value of stablecoin i (either USDT or USDT and DAI), X is a set of controls, a_i is a stablecoin fixed effect, and b_t is a time fixed effect. We define the outside option $\rho_t = y_t - (1-m)R_t$ where y_t is proxied by the future funding rate, R_t is the FTX lending rate for the given stablecoin, and we assume $m = 0.2$. t-statistics are reported in parentheses using robust standard errors and clustered by week, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	BTC/USDT Binance	ETH/USDT Binance	BTC/BUSD Binance	DOGE/BUSD Binance	BTC/USD FTX	ETH/USD FTX	$\mathbb{E}[R^{BTC}]$ CME	$\mathbb{E}[R^{ETH}]$ CME
BTC/USDT, Binance	1.00							
ETH/USDT, Binance	0.89***	1.00						
BTC/BUSD, Binance	0.81***	0.70***	1.00					
DOGE/BUSD, Binance	0.64***	0.59***	0.65***	1.00				
BTC/USD, FTX	0.83***	0.79***	0.76***	0.59***	1.00			
ETH/USD, FTX	0.75***	0.87***	0.65***	0.51***	0.80***	1.00		
$\mathbb{E}[R^{BTC}]$	0.65***	0.62***	0.55***	0.50***	0.66***	0.61***	1.00	
$\mathbb{E}[R^{ETH}]$	0.65***	0.62***	0.57***	0.55***	0.64***	0.56***	0.83***	1.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Correlation of Expected Return Proxies. Table presents the pairwise correlations of several perpetual futures funding rates and the expected return inferred using CME crypto futures. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Bitcoin		Ether		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}[Ret^{BTC}]$	1.05^{***}	0.51^{***}			0.55^{***}	0.64^{***}
	(7.64)	(3.16)			(2.76)	(2.87)
Ret^{BTC}		0.23^{***}				0.37^{***}
		(2.86)				(3.01)
$\mathbb{E}[Ret^{ETH}]$			0.78^{***}	0.15	0.45^{***}	-0.14
			(8.10)	(0.94)	(4.06)	(-0.73)
Ret^{ETH}				0.09		-0.15
				(1.35)		(-1.52)
$\mathbb{E}[Ret^{S\&P}]$						0.05
						(0.60)
N	924	924	868	868	868	868
R^2	0.35	0.51	0.35	0.50	0.38	0.52
Month FE	No	Yes	No	Yes	No	Yes
Coin FE	No	Yes	No	Yes	No	Yes

Table A.4: Stablecoin Interest Rates and Expected Returns. Table presents regression $R_{t,i} = \alpha + \beta_1 \mathbb{E}_t[Ret^i] + \beta_2 Ret^i + a_i + b_t + \varepsilon_{i,t}$ where $R_{t,i}$ is the lending rate for stablecoin i, either USDT or DAI, $\mathbb{E}_t[Ret^j]$ is the one-month/one-month expected returns for coin j—either Bitcoin and Ether—Ret^j is the contemporaneous price returns on Bitcoin and Ether, a_i is a stablecoin fixed effect, and b_t is a time fixed effect. Observations are daily; the Bitcoin-only sample in columns (1) and (2) runs from December 2020 to November 5, 2022, and the remaining columns with Ether run from February 2021 to November 5, 2022. t-statistics are reported in parentheses using robust standard errors and clustered by week, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Lending Rate R_t					
	USDT			DAI		
	1 Day	1 Week	4 Weeks	1 Day	1 Week	4 Weeks
	(1)	(2)	(3)	(4)	(5)	(6)
Futures $\widehat{\text{Funding}}$ Rate$_t$	0.182	0.207	0.315	0.178	0.131**	−0.153
	(1.540)	(1.339)	(0.654)	(1.479)	(2.019)	(−0.710)
R_{t-1}	0.606***	0.519***	0.437	0.500***	0.556***	0.674***
	(4.761)	(2.992)	(1.005)	(6.712)	(7.221)	(4.719)
Bitcoin Implied Volatility$_t$	−0.033	−0.039	0.009	−0.060	−0.044	0.011
	(−0.733)	(−0.725)	(0.181)	(−1.193)	(−1.506)	(0.468)
$\Delta \ln(s_{i,t})$	−0.007*	−0.004	−0.005	−0.003	0.000	0.006
	(−1.773)	(−1.332)	(−0.569)	(−0.922)	(0.031)	(1.256)
N	258	258	258	258	258	258
F-stat	1.88	1.25	0.33	2.45	1.47	0.96
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5: Instrument Variables Placebo Regression of Futures Funding Premia and Lending Rates. Instrumental variables regression using the mean household rating of MLB games on a given day in the future as an instrument to predict the perpetual futures funding premium. Table presents several placebo tests using viewership data from the future as the instrumental variable: either 1 day, 1 week, or 4 weeks in the future. Time FE indicates day of week, month of year, and year fixed effects. Kleibergen-Paap rk Wald F statistics reported. t-statistics are reported in parentheses using robust standard errors and clustered by week where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	BTC		ETH		DOGE	
	(1)	(2)	(3)	(4)	(5)	(6)
Rating	0.14	0.14	0.23	0.23	0.35*	0.40**
	(1.18)	(1.27)	(1.31)	(1.30)	(1.94)	(2.26)
Constant	−0.14	−0.14	−0.11	−0.02	−0.27	0.25
	(−0.56)	(−0.44)	(−0.34)	(−0.03)	(−0.81)	(0.32)
N	258	258	258	258	258	258
R^2	0.00	0.04	0.01	0.04	0.01	0.04
Day-of-Week FE	No	Yes	No	Yes	No	Yes

Table A.6: Speculative Returns and Household Rating. Table presents regression $Ret_{i,t} = \alpha + \beta \text{Household Rating}_t + b_t + \varepsilon_{i,t}$ where $Ret_{i,t}$ is the price return of coin i—where i is Bitcoin, Ether, or Dogecoin—Household Rating$_t$ is the household rating of nationally televised MLB games on date t, and b_t are day of week fixed effects. Observations are daily. t-statistics are reported in parentheses using robust standard errors and clustered by week, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.