Leverage and Stablecoin Pegs*

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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

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> 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. 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 to keep a fixed $1 price.

Cryptocurrency trading volume 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 dollar price of $1 and to be redeemable at par on demand. Unlike unbacked digital assets, like Bitcoin, stablecoins are usually backed by reserves and denominated in fiat currency.[1] Stablecoins were also envisaged to act as a widely used medium of exchange and bring innovations in payment systems globally (e.g., Libra and Diem). Thus far, they mainly facilitate crypto trading by decreasing the risk of getting in and out of trading positions. The advantage of stablecoins over fiat currencies is that stablecoins live on the blockchain and face lower transaction costs of using them as a store of value between trades and allow for faster trading.

Stablecoins are notable for two reasons. First, they do not satisfy Holmström (2015)'s *no questions asked* criteria for money despite aspiring to be used as circulating money, even narrowly in the crypto-assets world (Gorton and Zhang, 2021; Gorton et al., 2022). Second, a main use of stablecoins is for leveraged trading in other more volatile—and higher expected return—digital assets. Traders borrow stablecoins for levered bets on other cryptocurrencies.

[1] We focus on so-called collateralised 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. Collateralised stablecoins constitute the majority of stablecoins by market capitalisation, even before the failure of the largest algorithmic stablecoin TerraUSD in May 2022.

Unlike fiat currency, stablecoins are economically equivalent to deposits and subject to runs. The same strategic complementarities for fragile banks and money market funds apply to stablecoin issuers. Stablecoin holders should demand compensation for run risk if stablecoin reserves become illiquid to maintain a \$1 peg in bad states. But stablecoins pay no interest, unlike bank deposits and money market funds. Thus, it is unclear how stablecoins issuers compensate their borrowers for run risk enough to keep the price fixed at \$1.

We show that priced run risk can compel stablecoins to have a constant \$1 price. Demand for stablecoins comes from their role in speculative trading on cryptocurrencies. Stablecoin owners are indirectly compensated for the run risk because they can lend it to traders who want to take on leverage. Several exchanges and decentralized lending platforms allow agents to lend stablecoins to others who want to speculate on more volatile cryptocurrencies.

Such an equilibrium leads to an unruly nexus between run risk and leverage. The gain from lending the debt depends on the appetite for leveraged trading and the volatility of the speculative asset, affecting margin requirements. A few examples make the intuition clear:

1. Suppose that suddenly there is no demand for the speculative asset. Then, there would be no premium from lending the stablecoin, and its price would collapse below \$1—quickly precipitating a run as stablecoin holders rush to redeem to fiat currency.

2. Suppose that demand for the speculative asset is strong, but volatility increases and trades become riskier. Intermediaries may increase the margin requirement for leveraged trades, which reduces the benefit from taking leverage and, hence, the compensation from lending out the stablecoin. As a result, the stablecoin issuer would need to shift to a safer portfolio of reserves to reduce run risk and support a \$1 peg.

3. Suppose, instead, there is a higher demand for the speculative asset without an increase in the underlying volatility and margin requirements. Taking leverage is more profitable, which pushes the lending rate for stablecoins up and allows the issuer to maintain the \$1 peg with a riskier reserve portfolio composition.

We model the leverage-money nexus by combining a bank-run model akin to Goldstein and Pauzner (2005), Kashyap et al. (2020), and Infante and Vardoulakis (2020) with a model of leveraged collateralized trading akin to Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009). We use global game techniques to pin down a unique probability of a run that depends on the balance sheet of the stablecoin. Using this probability, we can compute the premium that stablecoin holders require to maintain a traded price of \$1 and connect this to the rate that speculators are willing to offer to borrow the stablecoin.

Our model reconciles two important facts: first, the current generation of 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—often above 20% per year—and are closely correlated with measures of speculative demand.

We show that stablecoins directly link 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 of the stablecoin. Such reallocations can cause disruptions in the real economy.

Suppose expected returns for cryptocurrencies fall and demand for stablecoins to take on leverage falls. Then stablecoin issuers will quickly try to increase their portfolio's safe asset share. In that case, this adjustment can cause disruptions in the markets they invest in, like the commercial paper market that provides financing to the real economy. JP Morgan estimates that Tether, the largest stablecoin, was one of the largest investors in the U.S. commercial paper market in June 2021.

Alternatively, the stablecoin issuer can allow lower leverage demand to manifest in more redemptions. Stablecoin redemptions and issuance, in turn, are directly linked to the real economy. For example, Kim (2022) shows that a one standard deviation increase in the daily issuance of major stablecoins results in a 10.7% increase in the commercial paper issuance quantity. The reverse link from traditional to crypto markets is also incorporated in the model: a bad shock for the traditional risky financial asset held in the stablecoin's reserves leads to an increase in the stablecoin's run risk.

We have three sets of empirical results. First, we connect speculative demand for cryptocurrencies to the lending rate on stablecoins. Second, we empirically establish the two stabilization mechanisms to maintain the peg, namely adjusting the liquidity of stablecoin reserves and letting the lending rate re-adjust via token redemptions and issuance. Third, we apply the model to the May 2022 turmoil in crypto markets following the collapse of TerraUSD and the following near run on Tether.

The leverage-money nexus is likely broader than just stablecoins and cryptocurrency trading; such a nexus has important implications for the future of private money, which requires a constant value *no questions asked* to be a medium of exchange. Yet, historically private money has often proved to be fragile in nature (Gorton, 2017). Our contribution is to show that even *fragile* money, like stablecoins, may also maintain a constant exchange value if it generates secondary benefits for its holders. Yet, if this secondary use receives a large enough negative shock, then fragile money can quickly collapse.

Related Literature Our paper is related to papers that study the stability of stablecoins and the effects of different proposed regulations on their stability (Lyons and Viswanath-Natraj 2021, Hoang and Baur 2021, Li and Mayer 2021, Kozhan and Viswanath-Natraj 2021, d'Avernas et al. 2022). 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) studies the effects of stablecoin issuance on commercial paper issuance, rates, and Treasury yields.

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.

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. 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 illiquid asset yields $X > 1$ at $t = 2$ only

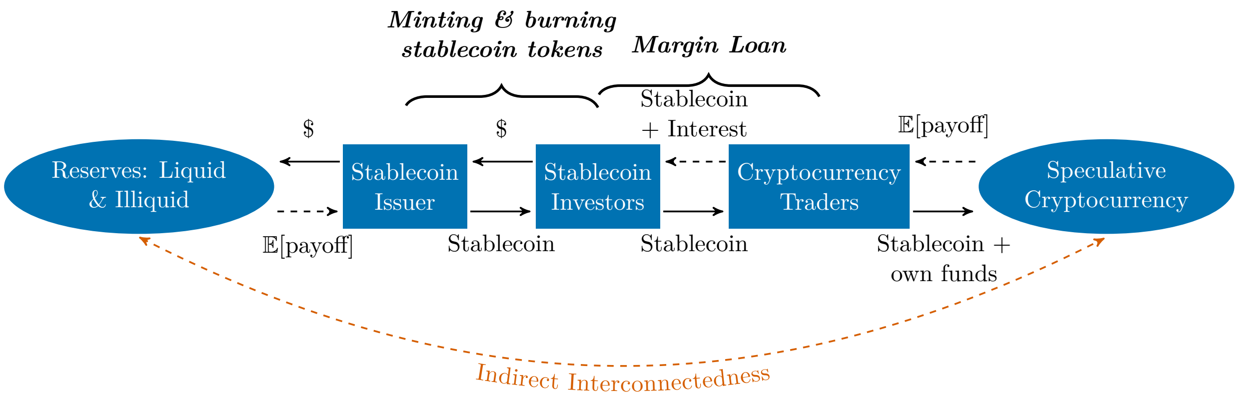

Figure 1: Model Sketch. Figure plots the relationship of the agents in the model and the flow of transactions.

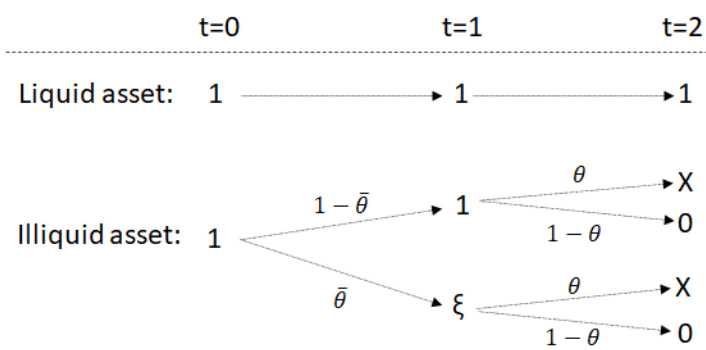

Figure 2: Liquidation values & payoffs of traditional assets

with probability θ and zero otherwise; θ is a uniformly distributed variable taking values in $[0, 1]$ with its true value realized at $t = 1$, but not publicly revealed. The liquidation value of the illiquid asset also depends on the realization of θ. If $\theta \geq \overline{\theta}$, which is exogenously chosen, the illiquid asset can be liquidated at $t = 1$ for one, otherwise its liquidation value drops to $\xi < 1$. The assumption about the liquidation value and payoff of the illiquid asset follow Goldstein and Pauzner (2005). Figure 2 shows the payoffs and market prices of the two assets at $t = 0, 1, 2$. Finally, denote by ℓ the portion of the portfolio invested in the liquid asset.

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 assets 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 the tokens is that they can lend the tokens to traders that want to take exposure to the cryptocurrency, expecting a gross return y. For simplicity and without loss of generality, we make three assumptions, which can be relaxed. First, we assume that patient investors do not want to hold the cryptocurrency directly.[2] Second, we assume the lending of stablecoin tokens takes place at $t = 1$ after patient investors have decided whether to redeem their stablecoin tokens. Denote by R the expected return per unit from lending the token, which will be endogenously determined. Third, we assume traders have access to an outside option with gross return ρ. Traders borrow the stablecoin from patient investors, and, combining it with their funds, they buy a cryptocurrency on margin, as described in detail below.

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. In particular, 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. To stabilize the price and maintain the peg, the stablecoin issuer will adjust their portion of liquid assets ℓ,

[2] This assumption could be justified by having 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).

while allowing supply and demand to determine the number of tokens in circulation s.

Two features of the model are important to map it to cryptocurrency trading in practice. First, the model assumes that agents receive a private noisy signal x_i about the illiquid traditional asset, which acts as a coordination device in an incomplete information game with strategic complementarities (global game). Such a feature is realistic, and several papers empirically study strategic complementarities in money market mutual funds during the Global Financial Crisis and Covid-19 crisis. Chen et al. (2010) and Schmidt et al. (2016) show that outflow behavior and strategic complementarities in open-ended mutual funds and money market funds are consistent with incomplete information games where agents receive private noise signals. Cipriani and La Spada (2020) show how investors produce private information about the money funds' run risks stemming from the illiquidity of the reserve assets, and they bifurcate investors into sophisticated and unsophisticated types.

The second feature is that investors observe ℓ and that it can be adjusted to maintain the stablecoin price peg, as discussed in section 2.4. In practice, ℓ may be observable only infrequently. For stablecoins collateralized by off-chain assets, investors learn ℓ only from issuers' disclosures which may be weekly or quarterly—if at all. There are two issues related to this assumption when we empirically study the model's related predictions.

The first practical issue is whether investors trust the issuer to truthfully disclose its reserves and not change them dramatically toward riskier holdings between disclosure dates. These are important considerations, which we abstract from to keep the model simple. Yet, investors could use the logic in Gorton (1996) that investors monitor ℓ using redemptions: when an investor redeems their stablecoins to fiat currency, they learn a lower bound of ℓ.

Another practical issue is that ℓ is not observed in real-time, so it cannot be used as a continuous instrument to stabilize the peg between disclosure dates. This issue can be address by assuming that ℓ adjusts only at disclosure dates and that peg stabilization relies on supply and demand between disclosures. In particular, in our model the equilibrium lending rate on the stablecoin will be a decreasing function of its aggregate supply. For small deviations from the peg, investors can redeem their tokens or request new ones, moving the lending rate in a direction that stabilizes the peg given a fixed ℓ. We theoretically derive the limitations of this stabilization mechanisms and empirically test its effects on lending rates.[3]

[3]Of note, this feature is realistic and can be automatically embedded in smart contracts such as the Dai Savings Rate (DSR) in the MakerDao protocol. The purpose of DSR is to affect the demand for stablecoin

The stabilization mechanism relying on the lending rate is an additional tool on top of liquid reserves required for peg stability. For example, an unbacked stablecoin may be able to maintain its peg for small deviations through supply and demand, but it would collapse if investors run in mass to redeem their token, as was the case for TerraUSD.

The stabilization mechanism through continuous and observable changes in ℓ could be possible—absent adverse shocks on θ—for stablecoins backed by on-chain assets, which can be cryptocurrencies or tokenized traditional financial assets minted and traded on the same blockchain as the stablecoin. The MakerDao protocol is one example. The collateral backing Dai stablecoins tokens is locked in smart contracts (vaults) on the same blockchain that Dai circulates on and is verifiable in real-time.

We first derive the expected return from lending the stablecoin token. Second, given this return, we compute the probability of a run on the stablecoin issuer. Finally, we show how the stablecoin can maintain its peg to the dollar despite its exposure to run risk.

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 and assume that the stablecoin has not suffered a run at $t = 1$. Thus, 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.[4]

The gross expected payoff from taking a leveraged position in one dollar of the cryptocurrency is equal to $y - (1 - m)R$. We assume that traders compete with each other and, in equilibrium, are willing to offer an expected return on borrowing stablecoins that makes them break even with their exogenous outside option ρ. As we derive below, ρ depends on the aggregate funds invested in the alternative technology, but traders take ρ as given. As long as 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, $(y - (1 - m)R)/m$, to the unlevered

Dai and stabilize its peg given a level of collateralization or ℓ in our model.

[4]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).

outside option profit per unit of investment, ρ, or

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

We assume that the outside option consists of a technology, F, common to all traders, 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 will assume that $\rho > y$, so traders have an incentive to use leverage, implying $R < y$.[5] Moreover, given that ρ is increasing in s, there might be a $\bar{s}$ such that $y - m\rho < 0$ for $s > \bar{s}$. In other words, 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:

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

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

An increase in the cryptocurrency expected return, y, while keeping the required margin, m, and the number of tokens, s, constant is

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

[5]Otherwise, the relevant outside option is $\rho = y$ since traders would prefer to invest directly in the cryptocurrency. In this case, $R = y$, which is independent of the stablecoin supply s, and thus, the stabilization mechanism using the lending rate, described above, would be absent.

An increase in the margin, m, while keeping y and s constant is

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

since $\rho > y$.

An increase in the number of tokens, s, while keeping y and m constant is

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

A change in y could be interpreted as higher demand for cryptocurrencies, while a change in m could be interpreted as higher cryptocurrency volatility or risk. Both changes would 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 the number of tokens following a decrease in the demand for the cryptocurrency 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

The stablecoin issuer collects total funds at $t=0$ equal to s, invests ℓ percentage of them in the liquid asset, and invests the rest in the illiquid asset. We assume that if the issuer defaults, then 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 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 drop 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.,

$$\overline{\lambda} = \ell + (1-\ell)\xi. \tag{7}$$

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

$$\Pi(\lambda) = \left[X(1-\ell)\left(1 - \frac{\max(\lambda-\ell, 0)}{\xi(1-\ell)}\right) + \max(\ell-\lambda, 0) - (1-\lambda)\right] s. \tag{8}$$

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.,

$$\hat{\lambda} = \frac{X(\ell + \xi(1-\ell)) - \xi}{X - \xi}. \tag{9}$$

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.

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:

$$\nu(\theta, \lambda) = \begin{cases} \theta R(\lambda, s) + (1-\theta)\max\left(\frac{\ell-\lambda}{1-\lambda}, 0\right) - 1 & \text{if} \quad \delta \leq \lambda \leq \hat{\lambda} \\ \theta \frac{X(1-\ell)\left(1-\frac{\lambda-\ell}{\xi(1-\ell)}\right)}{1-\lambda} - 1 & \text{if} \quad \hat{\lambda} < \lambda \leq \overline{\lambda} \\ -\frac{\ell+(1-\ell)\xi}{\lambda} & \text{if} \quad \overline{\lambda} < \lambda \leq 1 \end{cases}. \tag{10}$$

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 3 plots for a certain parametrization and some value of θ, the payoff differential $\nu(\theta, \lambda)$ as beliefs about λ vary.

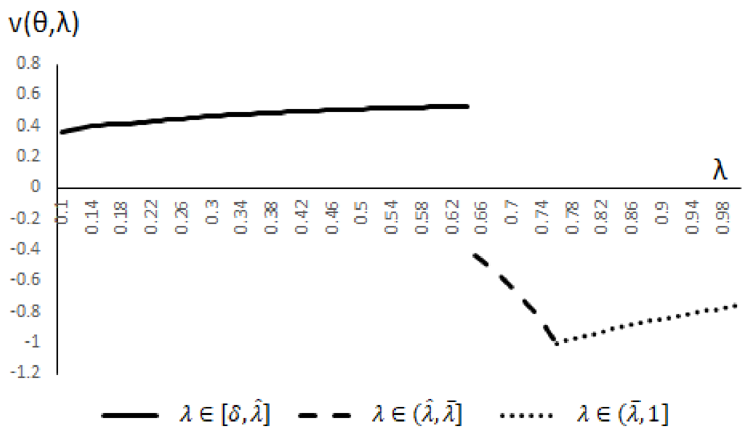

Figure 3: Payoff differential $\nu(\theta, \lambda)$ as beliefs about λ vary

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

$$\Delta(x_i) = \int_{x_i-\epsilon}^{x_i+\epsilon} \nu(\theta, \lambda) \frac{d\theta}{2\epsilon}. \tag{11}$$

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:

$$\lambda^b(\theta, x^*) = \begin{cases} 1 & \text{if } \theta < x^* - \epsilon \\ \delta + (1-\delta)(x^* - \theta + \epsilon)/(2\epsilon) & \text{if } x^* - \epsilon \leq \theta \leq x^* + \epsilon \\ \delta & \text{if } \theta > x^* + \epsilon \end{cases} . \tag{12}$$

Using (12), an investor can compute the expected payoff differential using their posterior about θ, given her signal x_i and an assumed value for x^*:

$$\Delta(x_i, x^*) = \int_{x_i - \epsilon}^{x_i + \epsilon} \nu(\theta, \lambda^b(\theta, x^*)) \frac{d\theta}{2\epsilon}. \tag{13}$$

Unlike in (11), beliefs in (13) 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.,

$$\Delta(x^*, x^*) = \int_{x^* - \epsilon}^{x^* + \epsilon} \nu(\theta, \lambda^b(\theta, x^*)) \frac{d\theta}{2\epsilon} = 0. \tag{14}$$

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 threshold (14) can be expanded to

$$\Delta(x^*, x^*) = -\int_{x^*-\epsilon}^{\theta_{\bar{\lambda}}} \frac{\ell + (1-\ell)\xi}{\lambda^b(\theta, x^*)} \frac{d\theta}{2\epsilon} + \int_{\theta_{\bar{\lambda}}}^{\theta_{\hat{\lambda}}} \left[\theta \frac{X(1-\ell)\left[1 - \frac{\lambda^b(\theta,x^*)-\ell}{\xi(1-\ell)}\right]}{1-\lambda^b(\theta, x^*)} - 1 \right] \frac{d\theta}{2\epsilon}$$
$$+ \int_{\theta_{\hat{\lambda}}}^{x^*+\epsilon} \left[\theta R(\lambda^b(\theta, x^*), s) + (1-\theta) \max\left(\frac{\ell - \lambda^b(\theta, x^*)}{1-\lambda^b(\theta, x^*)}, 0 \right) - 1 \right] \frac{d\theta}{2\epsilon} = 0. \tag{15}$$

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 this common threshold that the fundamentals' thresholds and signal threshold converge to θ^*. Expressing (15) 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

$$\bar{\Delta}^* = \int_{\delta}^{\hat{\lambda}} \left[\theta^* R(\lambda, s) + (1-\theta^*) \max\left(\frac{\ell - \lambda}{1-\lambda}, 0 \right) - 1 \right] \frac{d\lambda}{1-\delta}$$
$$+ \int_{\hat{\lambda}}^{\overline{\lambda}} \left[\theta^* \frac{X(1-\ell)\left[1 - \frac{\lambda-\ell}{\xi(1-\ell)}\right]}{1-\lambda} - 1 \right] \frac{d\lambda}{1-\delta} - \int_{\overline{\lambda}}^{1} \frac{\ell + (1-\ell)\xi}{\lambda} \frac{d\lambda}{1-\delta} = 0. \tag{16}$$

$\bar{\Delta}^*$ 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 (16) yields the following derivatives:

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

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

$$\frac{d\theta^*}{dy} < 0 \qquad \& \qquad \frac{d\theta^*}{dm} > 0 \qquad \& \qquad \frac{d\theta^*}{ds} > 0. \tag{17}$$

Finally,

$$\begin{aligned} \frac{d\bar{\Delta}^*}{d\ell} &= \frac{d\hat{\lambda}}{d\ell}\left[\theta^* R(\hat{\lambda}, s) - 1\right]\frac{1}{1-\delta} + \int_\delta^\ell (1-\theta^*)\frac{1}{1-\lambda}\frac{d\lambda}{1-\delta} \\ &- \frac{d\hat{\lambda}}{d\ell}\left[\theta^* \frac{X(1-\ell)\left[1-\frac{\hat{\lambda}-\ell}{\xi(1-\ell)}\right]}{1-\hat{\lambda}} - 1\right]\frac{1}{1-\delta} + \int_{\hat{\lambda}}^{\bar{\lambda}} \frac{X(1/\xi-1)}{1-\lambda}\frac{d\lambda}{1-\delta} - \int_{\bar{\lambda}}^1 \frac{1-\xi}{\lambda}\frac{d\lambda}{1-\delta}. \end{aligned} \tag{18}$$

Given that $d\hat{\lambda}/d\ell > 0$ from (9), 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 show in the Online Appendix that for $d\bar{\Delta}^*/d\ell > 0$ it is sufficient to set

$$\xi < \frac{\delta X}{X - 1 + \delta}. \tag{19}$$

Under this not very restrictive sufficient condition we unambiguously obtain

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

For the rest of the paper we consider parametrizations that satisfy (19). Note that (20) can still hold in alternative parameterizations violating (19).

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.[6] Denote by P the market price of traded stablecoin tokens, which is given by

$$P = \int_{\theta^*}^{1} \left[\theta R(\delta, s) + (1-\theta) \max\left(\frac{\ell - \delta}{1-\delta}, 0\right)\right] d\theta + \int_0^{\theta^*} (\ell + (1-\ell)\xi) d\theta. \tag{21}$$

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. 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

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

Using (4)–(6) and (17), 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

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

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

[6] 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.

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, under parametrization (19), 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)).[7]

In sum, the stablecoin price in secondary markets fluctuates 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 the next section, we discuss the mechanisms through which the size and liquidity of the stablecoin can stabilize the peg in response to shocks in the expected return and riskiness of the cryptocurrency.

2.4 Peg stability

We show how the stablecoin tokens can maintain their peg in response to shocks. Note that the stablecoin issuer issues new tokens in exchange for one dollar and returns one dollar for each redeemed token, at least until the available funds run out. Yet, investors value these tokens before the realization of fundamentals' uncertainty, that is between $t = 0$ and $t = 1$, at P given by (21). As such we focus on how *unexpected* crypto-related shocks that arrive between $t = 0$ and $t = 1$ can destabilize the peg, that is move P above or below 1.

There are two mechanisms to maintain the peg. The first mechanism relates to how ℓ should vary to maintain the peg in response to changes in y and m given s and proxies for how close to money stablecoin tokens are.[8] The second mechanism relates to how s should adjust to maintain the peg in response to changes in y and m keeping ℓ constant. It is driven by the usefulness of stablecoins in leveraged crypto trades, captured by the lending rate

[7] As mentioned, above (24) can hold even if (19) is not true, which is our baseline parametrization assumption. Nevertheless, we cannot outright exclude equilibria that (24) if violated. We will discuss the implications of such equilibria along with our baseline analysis.

[8] As elaborated earlier, this mechanism applies when a change in ℓ is observable and, thus, can change the price at which investors value the stablecoin tokens. We now focus on the details of the mechanism.

R that traders are willing to pay to borrow a token from investors. We will discuss these mechanisms in turn. Although we examine these mechanisms in isolation we also show how they can be optimally used in combination to achieve peg stability.

We now turn to our main results: how can the liquidity of stablecoin reserves, ℓ, or the number of tokens, s, be adjusted to maintain the peg when the cryptocurrency conditions change? We examine how changes in the expected return y and the margin requirement m 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 in the crypto world 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, or the issuer can keep the same ℓ and allow lower demand for tokens to manifest in more redemptions and lower 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)).[9]. Alternatively, the issuer may keep the same ℓ. This results in lower demand for the stablecoin tokens, and more investors will want to remove their funds from the stablecoin, which redeems more tokens. A lower number of tokens, s, results in a higher P (equation (23)), and the stablecoin price can return to its peg. Note that the issuer can maintain the same ℓ while allowing s to adjust because they can sell/buy any portfolio of the liquid and illiquid assets for a unitary price, since both assets can be traded at 1 between $t = 0$ and $t = 1$. The reason is that the adverse shock affecting the liquidation value of the illiquid asset has not materialized yet.

Proposition 1 tells us that the stablecoin issuer can choose a level of liquidity, ℓ, and stablecoin size, s, such that the price of the stablecoin tokens is pegged to the dollar. In

[9]As we show below, for potential parametrizations that (24) does not hold, the issuer would choose $\ell = 0$, so this stabilization mechanism would not be operational

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 verifiable in real-time along with s. In practice, the current biggest stablecoins are backed by off-chain traditional financial assets and disclose their reserves only infrequently, at best.[10] As a result, the stabilization mechanism through ℓ would work when it becomes observable at disclosure dates. Between these dates, peg stability after a shock could be achieved by the stabilization mechanism through s. While theoretically sound, this situation raises challenges when we try to take the model's prediction to the data. We discuss in detail how we tackle those issues in section 4, but before that, we show how a stablecoin issuer could optimally choose ℓ and s.

Below we show how the issuer will optimally choose ℓ and s to maintain the peg when both stabilization mechanisms are operational. Moreover, we derive the limitations of the second stabilization mechanism when adjustments to ℓ are not possible.

2.4.1 Optimal stablecoin liquidity and token supply for peg stability

In this section we derive the optimal choice of ℓ and s. The stablecoin issuer maximizes the profits accruing to them, $\max_{\ell,s} \int_{\theta^*}^{1} \theta\Pi(\delta)d\theta$, subject to the peg stability condition $P = 1$, with P is given by (21). $\Pi(\delta)$ are the profits when only impatient investors withdraw and the issuer does not default—with probability θ—given by (8) 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 (16) and (3), and substituted in the issuers' optimization problem. Combining the optimality conditions for ℓ and s yields

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

which together with $P = 1$ yields the optimal (ℓ, s). We plot these for different values of y and m in Figure 4. Choosing among these pairs of ℓ and s the issuer can maintain the peg in response to shock to y or m: For lower y (higher m) the issuer does not only choose higher ℓ, but also lower s both of which help stabilize the peg back to one (and vice versa).

Finally, using (25) we can show that the issuer will optimally choose $\ell < 1$ and thus

[10]There might be pressure from the industry to start disclosing the composition of reserves more frequently. In the aftermath of the collapse of UST and the mini-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.

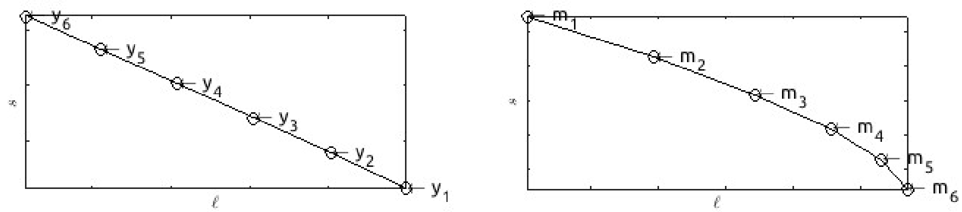

Figure 4: Optimal (ℓ, s) for different values of y (left) and m (right); y and m are monotonically increasing from y_1 to y_6 and m_1 to m_6

expose the stablecoin to runs. To see this, consider $\ell = 1$ 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. Proposition 2 summarizes this result.

Proposition 2. *For $X > 1$, $\ell < 1$ is optimal, exposing the stablecoin issuer to runs.*

2.4.2 Limits to stabilization

When the issuer can freely adjust both ℓ and s in response to crypto shocks, there are adequate degrees of freedom to maintain the peg. Notice that shocks to y or m matter through their effect on the lending rate. Issuers can always allow redemptions to decrease s and push the lending rate up. Yet, there is a limit to this stabilization mechanism. For example, assume that y drops massively to a level below $\bar{y} \equiv mF'(e)$. Then, the lending rate in (3) cannot be positive even if also tokens are redeemed ($s = 0$). This does not constitute a problem if the issuer can freely choose ℓ because it can be set to one implying zero risk for stablecoin investors and, hence, peg stability. Similarly, for smaller decreases in y. However, if the issuer cannot seamlessly adjust ℓ in response to shocks in y, then the peg collapses for smaller drops than those that drive y down to $\bar{y}$. From (3), the ability to maintain the peg in this case depends on how responsive F' is in changes to s.

3 Institutional Details and Data

3.1 Leverage

Leverage is a critical feature of cryptocurrency markets. Cryptocurrency 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.[11] 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 off-shore 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. One key difference is that many of the largest crypto futures are *perpetual* futures. The derivatives do not have an explicit expiration date, as indicated by their name. Perpetual futures are likely the largest and most liquid type of off-shore 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 at a premium to the spot price, the investors long the future must pay a funding premium to investors short the future. On the rare occasion the future price trades at a discount to the spot price, the investors short the future must pay a funding premium to investors long the future. For simplicity, we will say the funding premium is positive when investors long the future pay a fee to short investors. 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

[11] `https://coinmarketcap.com/rankings/exchanges/derivatives/`

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 aggregate prices, volume, and market capitalizations of cryptocurrencies from CoinGecko.[12] 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. We collect perpetual future funding premia from Binance, which is likely the largest market for perpetual futures. We collapse higher-frequency data on lending rates, funding premia, and prices to a daily frequency using daily averages.[13] 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. Importantly, the sample does not include the period of FTX's collapse, which began on November 6, 2022.[14]

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% for USDT and 7% for DAI. Relative to prices, the lending rates are more volatile. The average funding premium is 19% for BTC/USDT and 21% for ETH/USDT, indicating that the future price typically exceeds the spot price for both contracts.

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

[13]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.

[14]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`.

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/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). 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.

We proxy for expected returns using the BTC/USDT perpetual future on Binance, which is likely the largest perpetual future contract in the world. Figure 5 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 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 overweights idiosyncrasies specific to Bitcoin. However, the BTC/USDT and ETH/USDT perpetual futures funding rates are tightly linked with a correlation coefficient of 0.84. Binance also has perpetual futures that settle into Binance USD, another stablecoin. We show that funding rates across perpetual futures are highly correlated regardless of which stablecoin is used for settlement. Another concern is that Binance's futures funding rates 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 6 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 a one percentage point increase in the futures funding rate is associated with an increase in stablecoin lending rates between 0.24 and 0.11 percentage points, depending on the control variables. A one-standard-deviation increase in the future funding rate (33pp) corresponds to lending rates increasing roughly 4pp, 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.

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 7 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. In other words, when crypto demand or the stablecoin lending rates are low, stablecoin issuers hold more safe assets to maintain the stablecoin's peg.

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% and 39% of days, even though stablecoins have grown rapidly over the period. The average redemption for the three ranges between 0.3% (USDT) and 1.4% (BUSD). TerraUSD (USTC) had the largest one-day net redemption of $4.7 billion, about 27% 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% for Tether, 8.2% for USDC, and 11.9% 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%, 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.

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 5.5 and 11 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 $\widehat{\Delta \ln(s_{i,t})}$ using the first stage regression described above. The table shows that an expected one basis point increase in token supply decreases the lending rate by 1.8 to 5.3 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 extremely bearish after the depeg. Several prominent crypto firms failed shortly after that: 3 Arrows Capital, Voyager Digital, and Celsius. 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 8 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 8. The bottom-right panel shows that Tether's lending rates spiked and remained elevated, helping stabilize the peg. We should note that the rise in the lending rate may not have sufficed to halt the run on Tether, which could have experience a full run under more severe shocks we elaborate when discussing the limits 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% 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% 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% losses. In response, Tether explicitly said that would increase ℓ in the long run:[15]

> "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.[16] 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.

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

[16] 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.[17] 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. 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 et al. (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.

Second, the timing of the baseball schedule is set well in advance of the season[18], and it is

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

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

highly improbable cryptocurrency events affect the timing or viewership of MLB games.

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 one percentage point larger in the futures funding premium estimated using the household rating instrument, Tether's margin lending rate is about 13bp higher on an annualized basis (column 2). Using DAI's lending rate or different controls gives similar estimates ranging from 11bps to 22bps.

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

Panel D shows a placebo test. We use the week-ahead household rating as the instrument. Baseball viewership one week in the future should not affect today's lending rate through the funding premium, because it is unknown at date t. Using the week-ahead household rating as the instrument leads to an insignificant relationship between the funding premium and the lending rate. The F-statistic indicates the instrument is weak.

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 reconciles 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.

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6 Figures

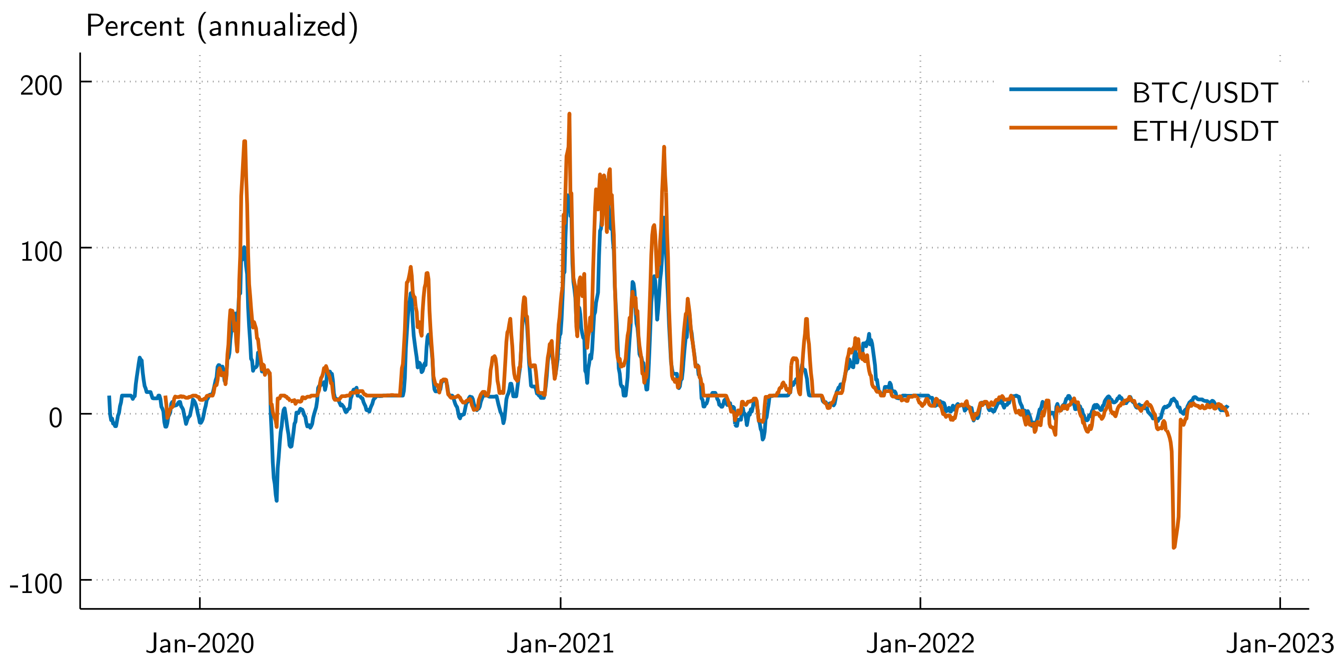

Figure 5: Perpetual Futures Funding Rate. Figure plots the annualized funding rate of USDT-settled Bitcoin perpetual futures for Bitcoin and Ether on Binance. A positive funding rate indicates that long-future investors make payments to short-future investors. Series are seven-day trailing averages.

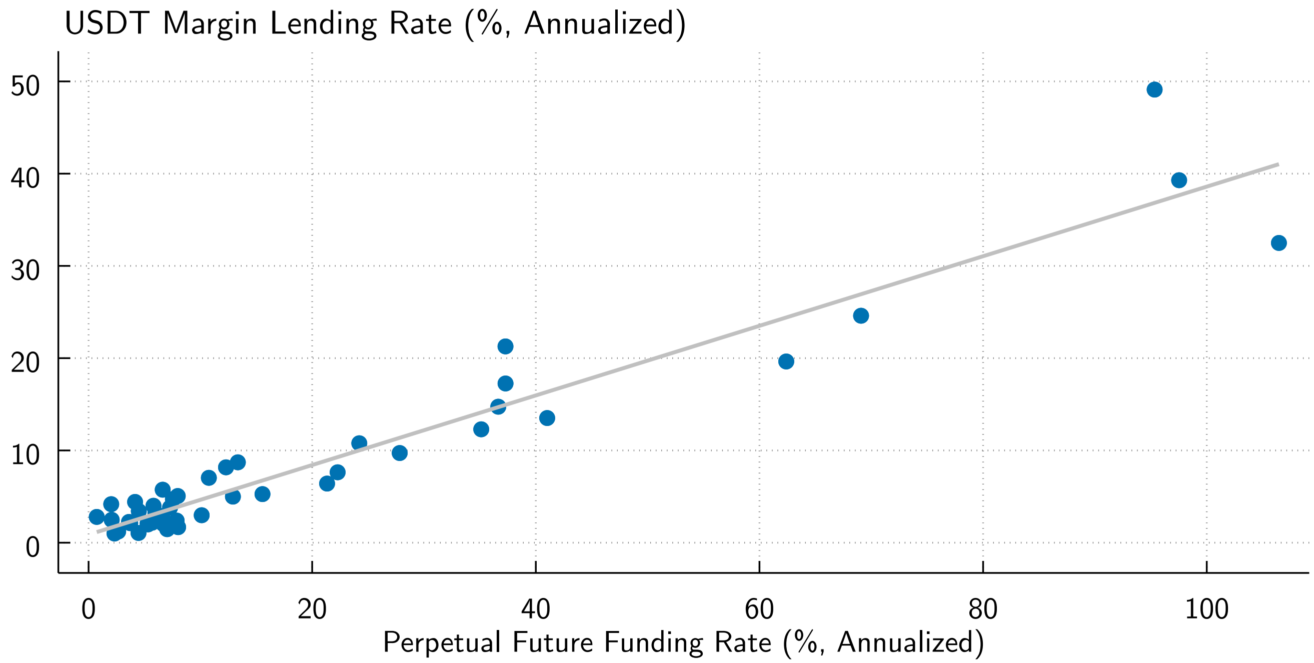

Figure 6: Stablecoin Lending Rates and Cost of Leverage. Figure plots a binscatter of daily observations of the annualized funding rate of BTC/USDT perpetual futures on Binance relative to the annualized USDT lending rate on FTX.

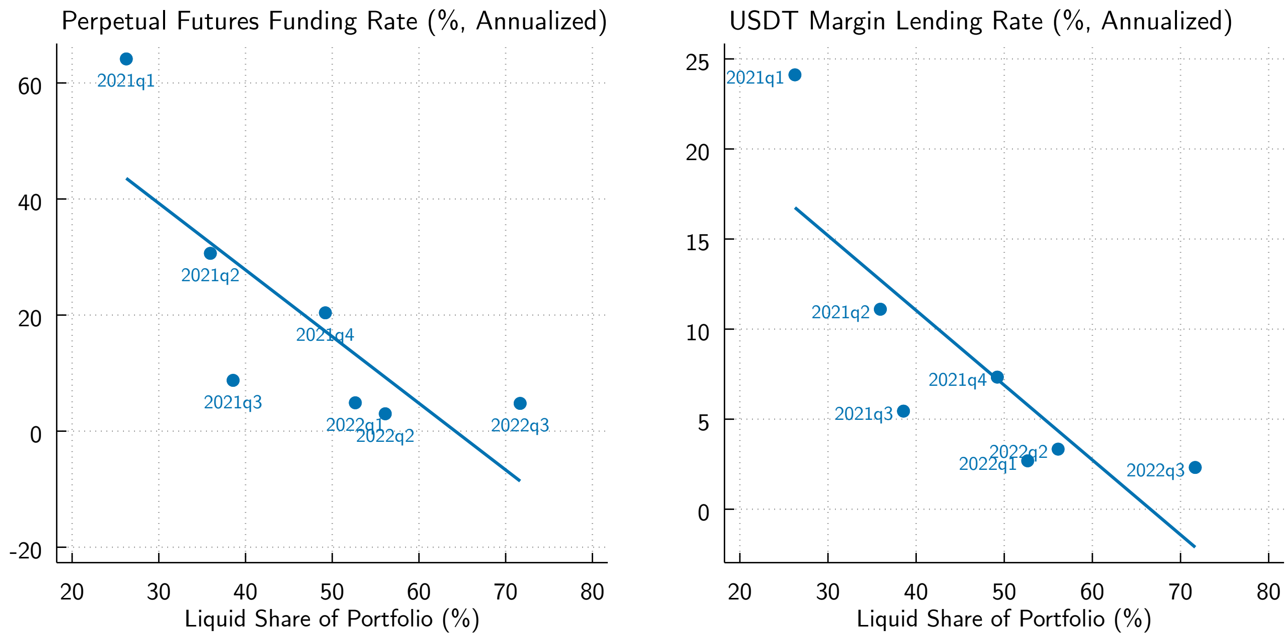

Figure 7: Tether Liquid Share vs. Perpetual Futures Funding Rate and USDT Lending Rate. Left panel plots the perpetual futures funding rate against USDT's liquid portfolio share in the same quarter. Right panel plots the average annualized lending rate for Tether on FTX by quarter against USDT's liquid 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.

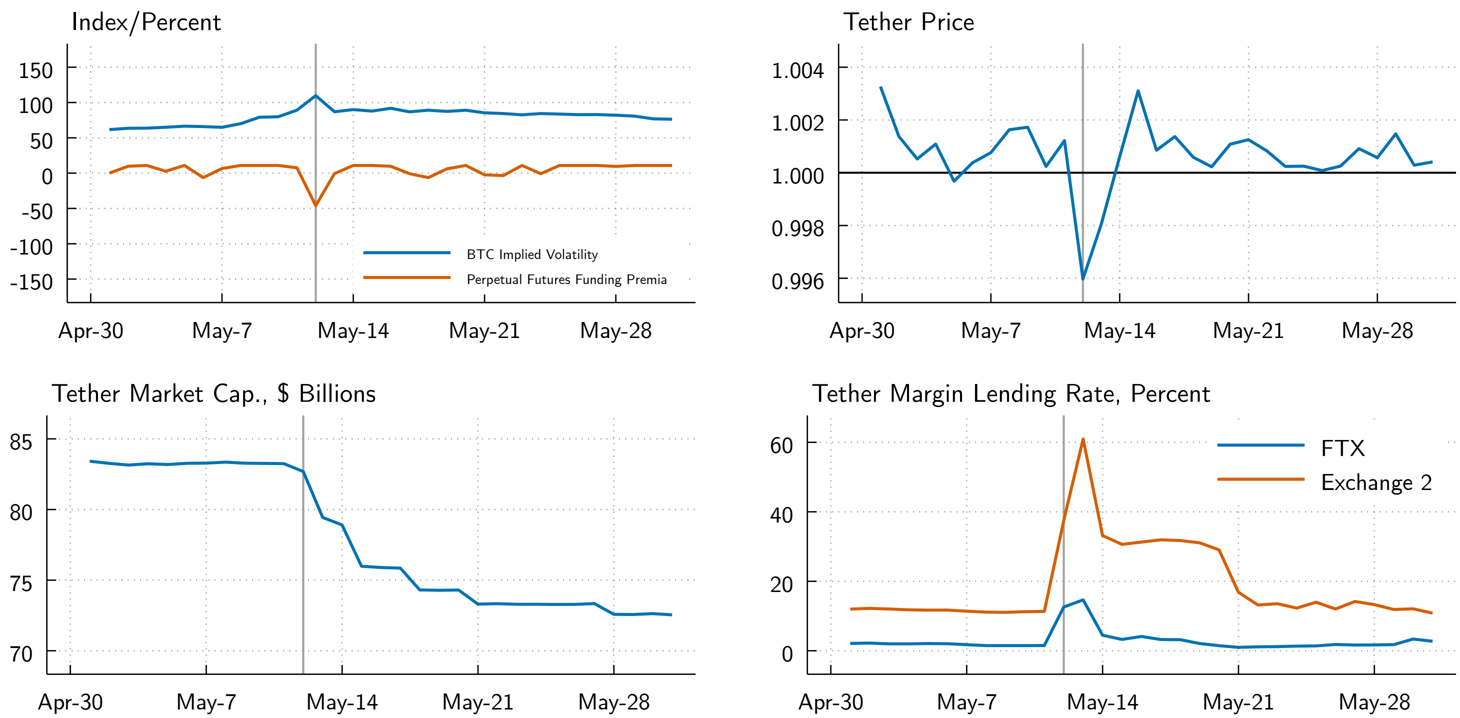

Figure 8: Tether during May 2022. Top-left figure plots BTC implied volatility and perpetual futures funding rate. Top right plots the price of Tether. Bottom left panel plots Tether's market capitalization in billions. Bottom right panel plots Tether's margin lending rates on two exchanges.

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	7.96	10.00	1.00	66.65
DAI	650	7.26	10.40	0.88	93.41
Perpetual Futures Funding Rate (annualized percent)					
BTC/USDT	705	19.07	31.86	−57.93	229.96
ETH/USDT	705	20.84	44.24	−237.60	410.63

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$_t$	0.24***	0.16***	0.12***	0.22***	0.14***	0.11***
	(19.59)	(7.64)	(6.19)	(13.65)	(7.81)	(5.27)
Margin Lending Rate$_{t-1}$			0.32***			0.26***
			(7.28)			(4.00)
BTC Implied Volatility$_t$			−0.00			0.04
			(−0.02)			(0.91)
R_t^{BTC}			0.11			0.09
			(1.47)			(1.23)
N	705	705	480	1,355	1,355	922
R^2	0.56	0.70	0.74	0.41	0.58	0.63
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 the regression of the USDT stablecoin's margin lending rate from the FTX exchange on Binance's BTC/USDT perpetual future funding rate. Observations are daily. t-statistics are reported in parentheses using robust standard errors and clustered by month, 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	25	65.0	0.3	237.7	1.2	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$_{t-1}$	0.99^{***}	0.68^{***}	0.62^{***}	1.07^{***}	0.65^{***}	0.55^{***}
	(11.17)	(5.26)	(4.37)	(10.72)	(4.73)	(4.42)
Bitcoin Implied Volatility$_{t-1}$			-0.87^{*}			-1.42^{***}
			(-1.82)			(-3.37)
$\Delta(s_{i,t-1})$			-0.02			0.07
			(-0.55)			(0.87)
$s_{i,t-1}$			-123.65^{**}			-90.51^{***}
			(-2.16)			(-2.88)
N	704	704	704	1,408	1,408	1,408
R^2	0.26	0.34	0.36	0.10	0.15	0.18
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 month. 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)
$\Delta \widehat{\ln(s_{i,t})}$	-3.23^{**}	-2.54^{*}	-5.26^{**}	-2.75^{**}	-1.78^{*}	-2.67^{*}
	(-2.10)	(-1.75)	(-2.29)	(-2.47)	(-1.73)	(-1.93)
N	704	704	704	1,353	1,353	1,353
Month FE	No	No	Yes	No	No	Yes
Coin FE	n/a	n/a	n/a	No	Yes	Yes
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 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)
$\widehat{\text{Funding Premium}}_t$	0.224***	0.132***	0.157***	0.118***
	(4.355)	(3.341)	(3.682)	(2.931)
$R_{i,t-1}$		0.575***		0.486***
		(4.881)		(4.351)
N	258	258	258	258
Time FE	Yes	Yes	Yes	Yes

Panel B: First Stage	Funding Premium			
	USDT		DAI	
	(1)	(2)	(3)	(4)
Rating	3.347***	2.714***	3.347***	3.216***
	(3.191)	(2.898)	(3.191)	(3.249)
$R_{i,t-1}$		1.182***		0.487*
		(3.951)		(1.802)
N	258	258	258	258
Time FE	Yes	Yes	Yes	Yes
F-stat	10.18	8.398	10.18	10.55

Panel C: OLS	Lending Rate $R_{i,t}$			
	USDT		DAI	
	(1)	(2)	(3)	(4)
Funding Premium$_t$	0.187***	0.103***	0.143***	0.095***
	(12.544)	(5.362)	(8.379)	(4.401)
$R_{i,t-1}$		0.518***		0.342***
		(6.845)		(3.537)
N	705	704	650	649
Time FE	Yes	Yes	Yes	Yes

Panel D: Placebo	Lending Rate $R_{i,t}$			
	USDT		DAI	
	(1)	(2)	(3)	(4)
$\widehat{\text{Funding Premium}}_t$	0.350	0.206	0.228	0.166
	(1.521)	(1.093)	(1.623)	(1.241)
$R_{i,t-1}$		0.545***		0.579***
		(2.899)		(5.839)
N	258	258	258	258
Time FE	Yes	Yes	Yes	Yes
F-stat	1.41	1.00	1.41	1.44

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. Panel D is placebo test using viewership data 7 days in the future as the instrumental variable. 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 where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Online Appendix

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

Substituting (16) in (18) we get that

$$\begin{aligned}
\frac{d\bar{\Delta}^*}{d\ell} &= \frac{d\hat{\lambda}}{d\ell}\left[\theta^* R(\hat{\lambda}, s) - 1\right]\frac{1}{1-\delta} + \int_\delta^\ell (1-\theta^*)\frac{1}{1-\lambda}\frac{d\lambda}{1-\delta} \\
&- \frac{1}{\ell}\int_\delta^{\hat{\lambda}}\left[\theta^* R(\lambda, s) + (1-\theta^*)\max\left(\frac{\ell-\lambda}{1-\lambda}, 0\right) - 1\right]\frac{d\lambda}{1-\delta} \\
&- \frac{d\hat{\lambda}}{d\ell}\left[\theta^* \frac{X(1-\ell)\left[1-\frac{\hat{\lambda}-\ell}{\xi(1-\ell)}\right]}{1-\hat{\lambda}} - 1\right]\frac{1}{1-\delta} - \frac{1}{\ell}\int_{\hat{\lambda}}^{\bar{\lambda}}\left[\theta^* \frac{X(1-\ell)\left[1-\frac{\lambda-\ell}{\xi(1-\ell)}\right]}{1-\lambda} - 1\right]\frac{d\lambda}{1-\delta} \\
&+ \int_{\hat{\lambda}}^{\bar{\lambda}} \frac{X(1/\xi - 1)}{1-\lambda}\frac{d\lambda}{1-\delta} + \frac{1}{\ell}\int_{\bar{\lambda}}^1 \frac{\xi}{\lambda}\frac{d\lambda}{1-\delta}.
\end{aligned} \tag{26}$$

Given that $d\hat{\lambda}/d\ell > 0$ from (9), the terms in the last two lines in (26) 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

$$\begin{aligned}
&\left[\frac{d\hat{\lambda}}{d\ell} - \frac{\hat{\lambda}-\delta}{\ell}\right]\left[\theta^* R(\hat{\lambda}, s) + (1-\theta^*)\max\left(\frac{\ell-\delta}{1-\delta}, 0\right) - 1\right]\frac{1}{1-\delta} \\
&+(1-\theta^*)\frac{\ell-\delta}{(1-\delta)^2}\left(1 - \frac{d\hat{\lambda}}{d\ell}\right).
\end{aligned} \tag{27}$$

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 $R(\hat{\lambda}, s) > R(\delta, s)$ as mentioned above. Then, a sufficient condition for $d\bar{\Delta}^*/d\ell > 0$ is that

$$\frac{d\hat{\lambda}}{d\ell} - \frac{\hat{\lambda}-\delta}{\ell} > 0 \qquad \Rightarrow \qquad \xi < \frac{\delta X}{X-1+\delta}. \tag{28}$$

A.2 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 overweights idiosyncrasies specific to Bitcoin. In Table A.1, 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 very 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 similar to 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.[19]

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

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

return is

$$\mathbb{E}_{t,t+n\to t+n+1}[y] \equiv \left(\frac{z_{t,t+n+1}}{z_{t,t+n}}\right)\frac{F_{t,t+n+1}}{F_{t,t+n}} \tag{29}$$

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.

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

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

where X_t is a vector of controls. Table A.2 shows the regression results. Scanning across the first row, a 1 percentage point increase in $\mathbb{E}[R^{BTC}]$ increases the stablecoin lending rates by between 0.8 and 1.4 percentage points, 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.3 Appendix Figures

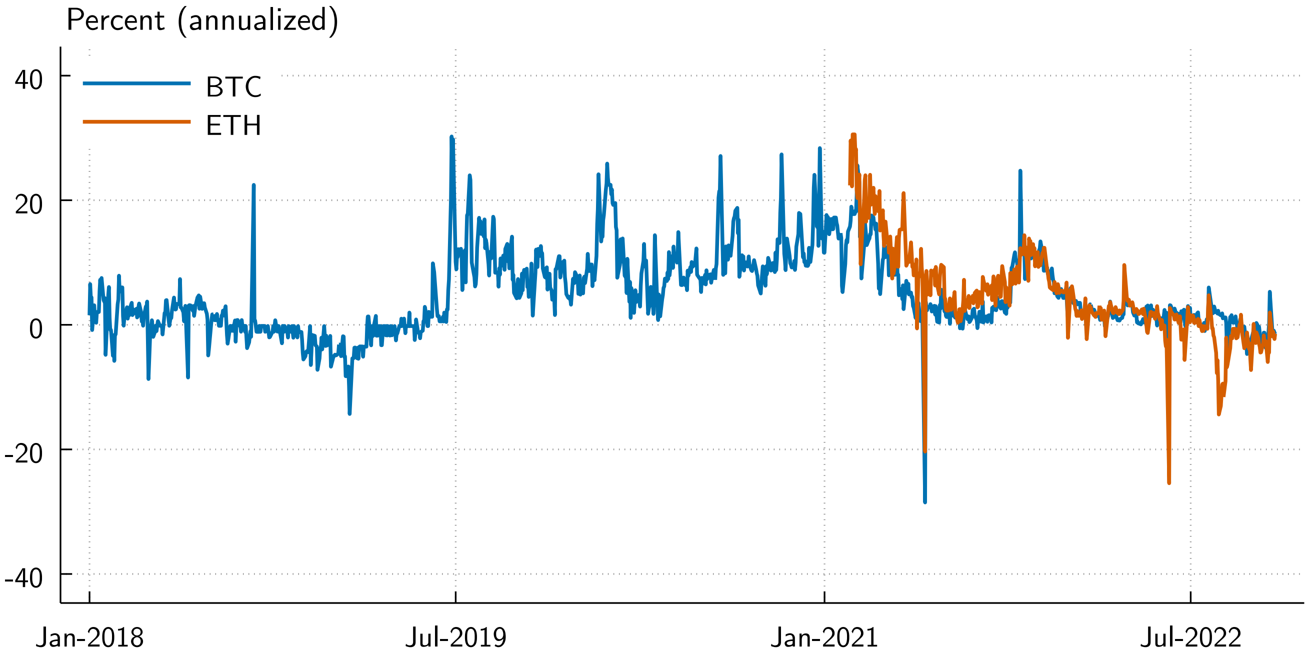

Figure A.1: Futures-Implied Expected Returns Figure plots the one-month/one-month expected return on Bitcoin and Ether estimated using the difference in present values for one-month futures prices relative to two-month futures prices. Present values are calculated using OIS interest rates, and futures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

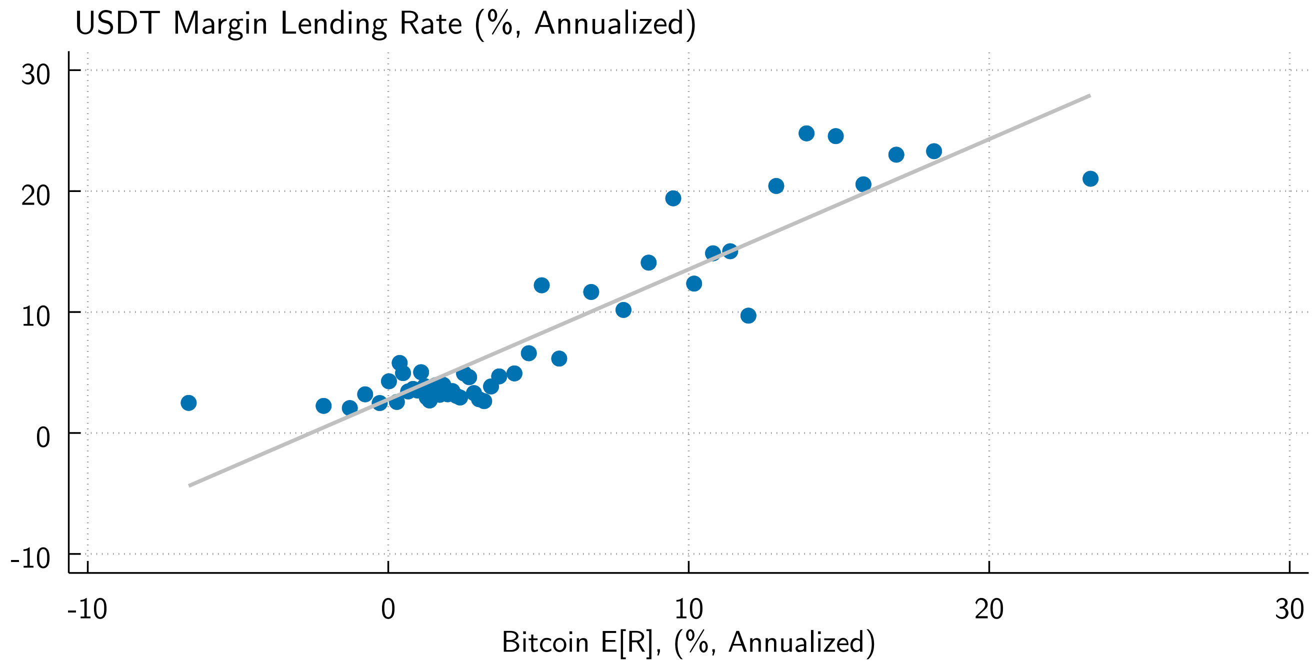

Figure A.2: Stablecoin Lending Rates and Futures-Implied Expected Returns Figure plots a binscatter of the one-month/one-month expected return on Bitcoin against USDT's margin lending rate on the FTX exchange.

A.4 Appendix Tables

	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	0.84***	1.00						
BTC/BUSD, Binance	0.80***	0.68***	1.00					
DOGE/BUSD, Binance	0.59***	0.59***	0.61***	1.00				
BTC/USD, FTX	0.79***	0.72***	0.75***	0.50***	1.00			
ETH/USD, FTX	0.73***	0.82***	0.64***	0.47***	0.81***	1.00		
$\mathbb{E}[R^{BTC}]$	0.61***	0.55***	0.53***	0.48***	0.66***	0.62***	1.00	
$\mathbb{E}[R^{ETH}]$	0.61***	0.52***	0.55***	0.54***	0.64***	0.57***	0.83***	1.00

Table A.1: 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)
$\mathbb{E}[R^{BTC}]$	1.07***	0.52**			0.54*	0.60*
	(5.51)	(2.74)			(1.99)	(2.00)
R^{BTC}		0.12				0.14
		(1.21)				(0.95)
$\mathbb{E}[R^{ETH}]$			0.79***	0.17	0.46***	−0.10
			(5.90)	(0.89)	(3.34)	(−0.37)
R^{ETH}				0.02		−0.08
				(0.38)		(−0.89)
$\mathbb{E}[R^{S\&P}]$						0.08
						(1.08)
N	924	924	868	868	868	868
R^2	0.35	0.51	0.36	0.51	0.39	0.53
Month FE	No	Yes	No	Yes	No	Yes
Coin FE	No	Yes	No	Yes	No	Yes

Table A.2: Stablecoin Interest Rates and Expected Returns. Table presents the regression of the USDT stablecoin's margin lending rate from the FTX exchange on one-month/one-month expected returns for Bitcoin and Ether and contemporaneous returns on Bitcoin and Ether. 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 month, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.