HONG KONG MONETARY AUTHORITY

Research Memorandum 09/2022

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AN EVENT STUDY ON THE MAY 2022 STABLECOIN MARKET CRASH

Key points

- *Crypto-asset prices collapsed in May 2022 when an algorithmic stablecoin, TerraUSD (UST), failed to maintain its $1 price target and triggered widespread sell-offs across the crypto space. Yet some stablecoins experienced notably less redemption pressure than others. This paper uses an event study approach to explore possible attributes that may explain such differences.*

- *We consider a sample of 18 existing stablecoins as of May 2022 and estimate the fair value of their reserve assets using an option pricing model. To the best of our knowledge, our study is the first to systematically compare the strength of asset backing across stablecoin projects, notwithstanding sometimes-significant data quality issues especially among non-fiat-backed stablecoins. We find that stablecoins backed by a greater amount of reserve assets suffered from a smaller decline in market capitalisation (i.e. less run pressure), on average, in May 2022.*

- *An application of the Diebold-Yilmaz spillover methodology reveals that crypto-collateralised stablecoins were the major shock receivers of the Terra crash, conceivably given their role as crypto leverage providers and were, therefore, subject to extra redemption pressure. We find that, among crypto-collateralised stablecoins, those with a stricter lending requirement (i.e. a higher collateralisation ratio) were better shielded from run pressure in May 2022, highlighting the importance of having sufficient margin of safety.*

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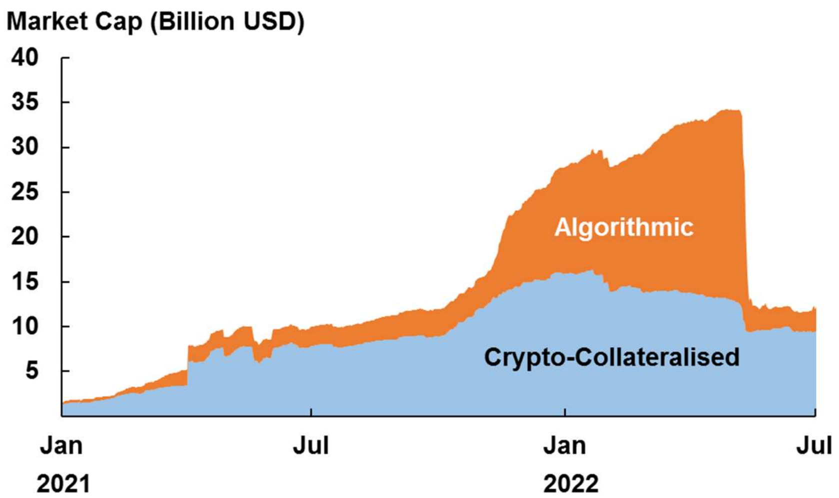
I. INTRODUCTION

The crypto-asset sector has evolved into a sizeable market over the past decade, breeding a growing number of ancillary financial services collectively known as decentralised finance (DeFi). The DeFi ecosystem — in which more non-fiat-backed stablecoins were invented and gained traction amid the post-pandemic, low-interest-rate environment — evolved to offer "yield farming" and "staking" opportunities with attractive returns to yield-seeking investors. Thus being the backbone of the DeFi ecosystem, non-fiat-backed stablecoins recorded a rapid annual growth rate of almost 1,000% in its total market capitalisation from January 2021 to April 2022 (Chart 1).

Chart 1: Market capitalisation of non-fiat-backed stablecoins



Source: The Block (https://www.theblock.co/data/decentralized-finance/stablecoins)

However, crypto-asset prices collapsed in May 2022, the proximate trigger being a crypto-specific event (panic withdrawals of TerraUSD deposits by investors leading to a downward spiral in the price of TerraUSD and its staking token, Luna). Yet other stablecoins that have no direct exposure to TerraUSD, such as Tether, also suffered from heavy redemptions and briefly broke their $1 peg target. The crash not only highlighted the fragility of certain stablecoin designs and DeFi sectors, but also exposed the risk of contagion among crypto-assets.

Interestingly, investor runs on stablecoins were far from indiscriminate, with some stablecoins (e.g. USDP, a fiat-backed stablecoin) only experiencing modest outflows. This observation motivates us to identify which characteristics of stablecoins could explain the degree of run pressure they faced. Our findings can be summarised as follows. Firstly, stablecoins having a larger amount of high-quality (i.e. low-volatility) reserve assets tend to face less severe run pressure. Secondly, crypto-collateralised stablecoins (see Section III for details) with more restrictive lending requirements may face less redemption pressure during market strains. Thirdly, we conjecture that a hit to confidence in the stablecoin sector could trigger DeFi deleveraging.

Another issue investigated in our study is the spillover of shocks among the various classes of crypto-assets during the crash episode. By applying the Diebold-Yilmaz spillover methodology, we discover that that crypto-collateralised stablecoins were the major shock receivers of the Terra crash, conceivably due to their role as crypto leverage providers.

The rest of this paper is organised as follows. Section II reviews related literature and highlights our contributions. Section III describes the classification, design and stabilisation mechanisms of the three major types of stablecoins covered in our study. Section IV provides background information on the Terra-Luna crash, and illustrates the results of our spillover analysis to the wider digital asset market using the Diebold-Yilmaz methodology. Section V presents the econometric framework and data sources of our event study analysis, with the key results presented in Section VI. Section VII concludes.

II. LITERATURE REVIEW

The literature on stablecoin stability is expanding along with the evolving sector and growing attention to its risk implications. A large body of the literature performs either an in-depth analysis of a specific sub-set of stablecoins or a broad analysis of crypto price connectedness.

A strand of literature explores the stability of specific stablecoin designs. For example, Klages-Mundt (2021) uses a market microstructure approach to understand a deleveraging spiral of the stablecoin DAI, and Uhlig (2022) uses a run model to explain Terra-Luna dynamics in May 2022. In addition, some studies (Platias and DiMaggio, 2019; Gudgeon, 2020) test the stability of TerraUSD and DAI under scenarios generated from geometric Brownian motion. Others proposed risk assessment frameworks that are based on blockchain data, such as Evans' (2019) work on the credit risk of DAI and Darlin et al.'s (2022) work on fund flows of DeFi lending protocols.

Another branch of the literature covers a wider group of stablecoins and cryptos. For instance, Clements (2021) warns about the fragility of algorithmic stablecoins. Catalini (2021) presents two dimensions of stablecoin design, namely, (1) volatility of reserve assets and (2) exposure to the risk of a "death spiral"[1], and ranks the stability of different stablecoin classes, in an order that is similar to that implied by our analysis.

The Terra-Luna collapse provides researchers with a unique opportunity to study the price dynamics of stablecoins, and their interconnectedness, under market stress. For example, Briola at el. (2022) apply network science techniques on hourly price data during TerraUSD's failure. De Blasis at el. (2022) examine the volatility spillover from TerraUSD's collapse with the use of a multivariate GARCH model on minute-by-minute price data.

Our work contributes to, and extends, the stablecoin literature in several ways. Firstly, instead of prices, we consider circulating market capitalisation as a preferred measurement of redemption pressure confronted by stablecoins. This is because, while the run pressure would often be reflected in the price of those with restricted convertibility, it would be reflected in the quantity of those that defended the peg. Secondly, we present a metric computed from reserve asset composition data across different stablecoin designs (see sub-section 5.1), which to the best of our knowledge is the first attempt in the literature to convert a diverse range of reserve assets held by stablecoins into a single, comparable metric, which we call "expected liquidation value".

III. STABLECOIN CLASSIFICATION

Stablecoins are a subset of cryptocurrencies that attempt to maintain a stable price relative to another asset. Stablecoins can be broadly classified into three types – (fractional) algorithmic, fiat-backed and crypto-collateralised, differing mainly by their design and asset backing.[2] Chart 2 illustrates the balance sheet structure of the three types of stablecoins and the rest of this section elaborates their designs, roles in DeFi and stabilisation mechanism.

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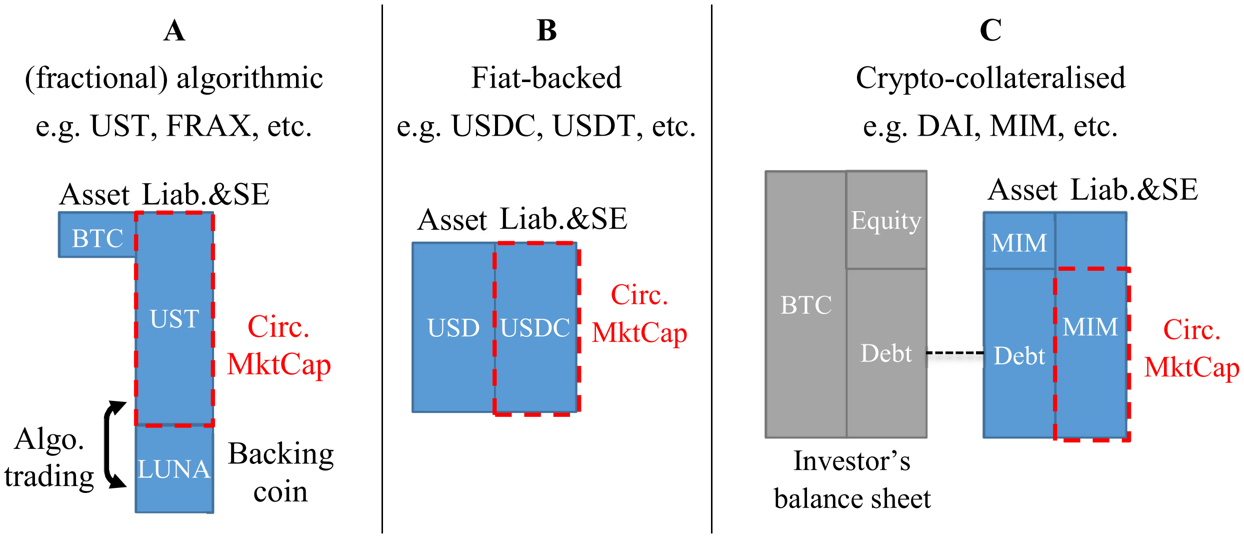
[1] A "death spiral" refers to a self-reinforcing vicious cycle in which redemptions result in falling prices, followed by loss of investor confidence and further redemption pressure. According to Catalini (2021), "…death spirals are likely to occur whenever the value of a stablecoin … is tied to the future success of the stablecoin itself".

[2] A fourth type of stablecoins, commodity-backed, is collateralised using physical assets such as precious metal, oil or real estate. They mainly serve the purpose of asset tokenisation and are not discussed here.

Chart 2: Stablecoin classification, simplified balance sheet and circulating market capitalisation



Note: "Liab.&SE" refers to liability and shareholders' equity, which is also the credit side in double-entry accounting. The balance sheets are highly simplified for illustrative purposes. In fact, stablecoins on the asset side are held through liquidity provider (LP) / decentralised exchange (DEX) tokens. Also, crypto-collateralised stablecoins typically hold numerous debts backed by a wide variety of collaterals.

3.1 Algorithmic stablecoins

An algorithmic stablecoin, also called an algo-based stablecoin or a seigniorage-style stablecoin, is minted when a user submits a backing coin, sometimes referred as "stabilising coin" or "sister token", of equivalent value.[3] Afterwards, the stablecoin peg is maintained by arbitraging between the backing coin and the stablecoin.[4] It is worth noting that the backing coin is issued by the same project as the stablecoin, and the former's total supply, rather than being as predictable as other cryptocurrencies like Bitcoin (BTC) or Ether (ETH), depends on the demand-supply balance of the stablecoin. Such a feature is commonly referred as endogenous backing, or "endogenous stabilisation" in a pioneer paper on algorithmic stablecoin by Sams (2015).

Given the endogenous feature of the backing coin and that it is issued by the same entity as the stablecoin, we argue that the backing coin should appear on the credit side of the stablecoin project's balance sheet (Chart 2A), i.e. the side of liability and shareholders' equity. As such, an algorithmic design can be seen as a "central bank" with "money" (i.e. the stablecoin) as liability and backing coin as "equity", and dynamically adjusting the ratio of "money" to

[3] There is a variant called "fractional algorithmic stablecoins" that are minted and backed against a certain ratio of a backing coin and fiat-backed stablecoins (e.g. USD Coin), e.g. an approximately 15/85 mix for FRAX.

[4] See, for example, Kereiakes et al. (2019) for an explanation of Terra's implementation of this minting and stabilisation mechanism.

"equity" to control the money supply in the secondary market such that the price of the stablecoin is on par with the pegged asset.

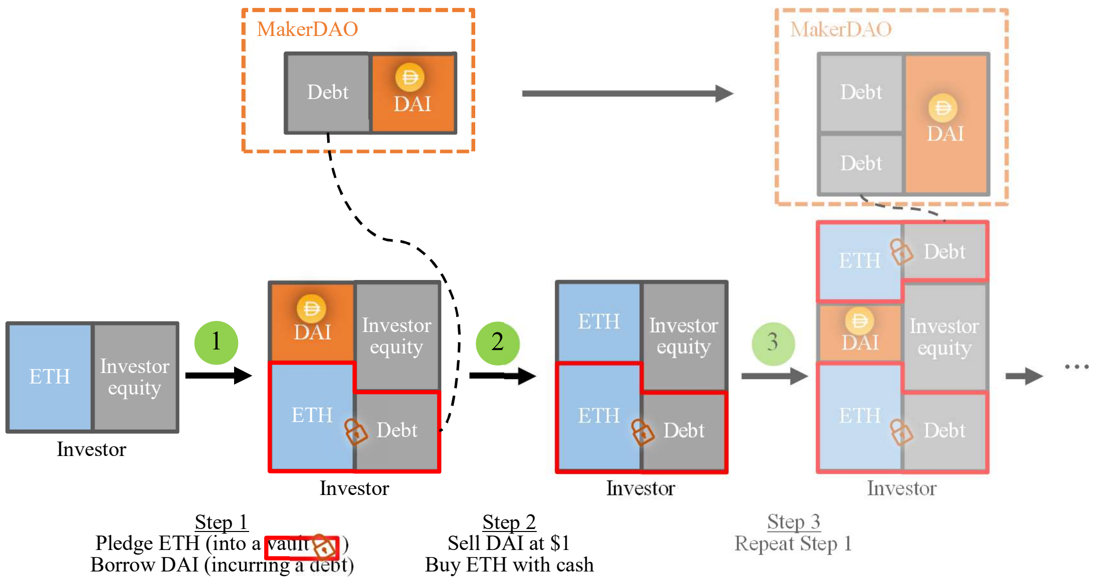
3.2 Fiat-backed stablecoins

Fiat-backed stablecoins have the simplest structure among the three, and are mostly issued by companies operating centralised crypto service platforms in which the stablecoin serves as a medium of exchange. It is minted whenever a user exchanges with the anchor currency, typically the US dollar, of an equivalent amount. The received funds are then usually held at regulated banks or custody accounts in a form of a bank balance or high-quality assets such as short-term government securities, disclosed in periodic audit reports. Most fiat-backed stablecoins run a de facto currency board system, with 100% anchor currency reserves (Chart 2B) and unlimited convertibility at a fixed exchange rate. A typical exception is Tether, which holds also commercial papers and corporate bonds, making it resemble a money market mutual fund.

3.3 Crypto-collateralised stablecoins

Crypto-collateralised stablecoins, also referred to as crypto-backed stablecoins, are backed by overcollateralised (with cryptocurrencies) debts – that is, the value of crypto collateral (denominated in anchor currency) exceeds the notional value of the debt that backs the stablecoin issuance (Chart 2C).

Chart 3: Crypto-collateralised stablecoins (e.g. DAI) as crypto lending platforms in the DeFi ecosystem



It is worth noting that this type of stablecoin serves as a lending platform in DeFi, closely resembling the margin lending business in traditional finance. Taking the most prominent crypto-collateralised stablecoin DAI as an example, when crypto investors wish to borrow money against their ETH holdings, they could pledge the ETH into a vault of MakerDAO, which can be seen as "DAI's central bank", to receive DAI stablecoins (Step 1 in Chart 3). Afterwards, they may purchase ETH with the borrowed "DAI money" (Step 2 in Chart 3).[5] While a stock investor borrows money (in his or her brokerage account balance) by making a margin loan through locking its stock position in a margin account and meeting margin requirements, a crypto investor borrows money (in DAI) by making a DAI debt from locking its crypto position (e.g. ETH as shown in Chart 3) in a vault and meeting liquidation ratio requirements.

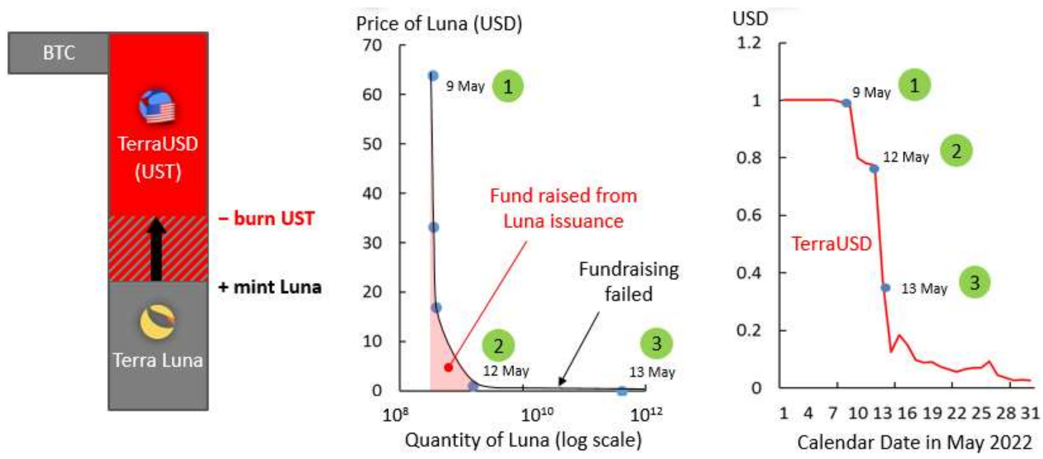
IV. Cryptocurrency and Stablecoin crash in May 2022

4.1 Algorithmic vulnerability and the Terra crash

Terra's failure in "equity issuance" and defending the stablecoin peg is summarised as follows. The crash began when investors began to question the unsustainably high deposit rates, of up to 19.5% APR, offered by the Anchor protocol, an incentive programme that underpins the demand for TerraUSD. This, coupled with tightening global liquidity amid aggressive Fed tightening to fight inflation, triggered heavy redemption of TerraUSD.

Chart 4: The crash of the Terra ecosystem

A. Terra's balance sheet B. Luna price-quantity path C. TerraUSD price



Source: CoinGecko

[5] The steps of interacting with the Maker Protocol are detailed in the DAI whitepaper by the Maker Team (2020).

The Terra system, by design, responded to the redemption by minting Luna to burn its stablecoin TerraUSD, much like equity-funded repurchase of debt (Chart 4A). As redemption pressure persisted, the supply of Luna increased exponentially, pushing its price down to zero (Chart 4B). Subsequently, the Terra system failed to raise new funds from Luna issuance, rendering TerraUSD completely unbacked and its price dropping to zero (Chart 4C).

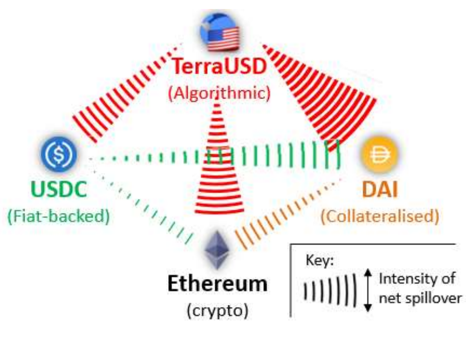
4.3 Spillover to wider digital asset sector and DeFi

As the largest decentralised stablecoin with a vision to be a global payment solution in the camp of DeFi, Terra's crash sent forceful shockwaves across the stablecoin sector and DeFi ecosystem. To analyse the spillover effect, we deployed the time-varying parameter vector autoregressive (TVP-VAR)-based Diebold-Yilmaz spillover index proposed by Antonakakis et al. (2020), which is sensitive enough to capture a one-off event, on crypto market capitalisations.

Among various digital assets, crypto-collateralised stablecoins such as DAI, being a decentralised neighbour in the stablecoin sector as well as crypto-based, were found to be the major shock receivers of the algorithmic crash (Chart 5). ETH came second in terms of impact for being akin to a DeFi concept stock, enjoying shares of transaction fees charged on the most prominent DeFi blockchain ERC-20, and the centralised fiat-backed USDC was found to be the least affected.

Chart 5: Pairwise net spillover of market capitalisation shock among TerraUSD, USDC, ETH and DAI at end-May 2022

		From			
		UST	USDC	ETH	DAI
To	UST	-			
	USDC	7.1%	-		
	ETH	11.3%	1.6%	-	
	DAI	24.6%	3.4%	–2.9%	-

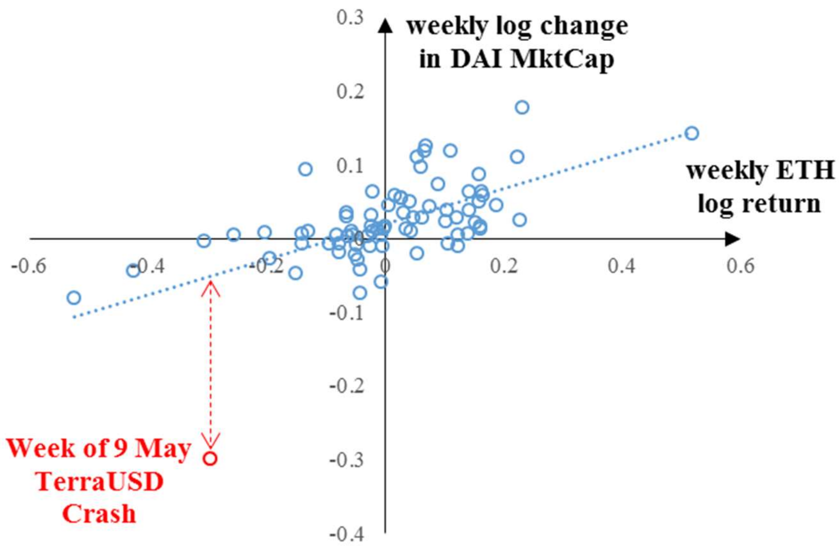


Sources: CoinGecko and HKMA staff estimates.

Notes: The net spillover is the net (pairwise offsetting) portion of the 10-step-ahead forecast error variance on daily log change of market cap explained by the others, estimated by the Diebold-Yilmaz Connectedness Index with TVP-VAR(10) model.

The changes in DAI market capitalisation warrant further investigation, for the reason that they could reveal DeFi deleveraging as a result of general redemptions by vault owners. Since a crypto price crash also happened simultaneously, one may attribute the DAI market cap contraction to a downswing of collateral values such as ETH, instead of stablecoin runs. However, this alternative explanation was not consistent with the usually tight historical relationship between the weekly logarithmic change in the DAI market cap against weekly ETH returns, which failed to predict the unprecedented shrinkage in the DAI market cap over the week of 9 May (red dot, Chart 6), suggesting that factors other than ETH prices, such as shifts in investor sentiment, may have contributed to DAI's outflow pressure. Furthermore, the net pairwise spillover was generally directed from ETH to DAI before May (5.7% at end-April 2022) but reversed after that (–2.9% at end-May 2022), implying that crypto-collateralised stablecoins may have indeed amplified the effect of the algorithmic crash on unbacked crypto prices.

Chart 6: Crypto price crash is unlikely the cause of stablecoin-issuing DeFi deleveraging



Sources: CoinGecko and HKMA staff estimates.

Note: Slope = 0.209 *** (significant at 1%). R^2 = 0.36. Sample: Jan 2021 – Jun 2022. Predicted = –0.038 vs. Actual = –0.299

V. Identifying Factors determining Stablecoin Resilience: Methodology And Data

Having explained the inherent vulnerabilities leading to the crash of the TerraUSD and documenting the direction of spillovers to other crypto-assets, this section elaborates upon our event study methodology for investigating factors that may have explained the differences in run pressures faced by stablecoins.

5.1 Methodology

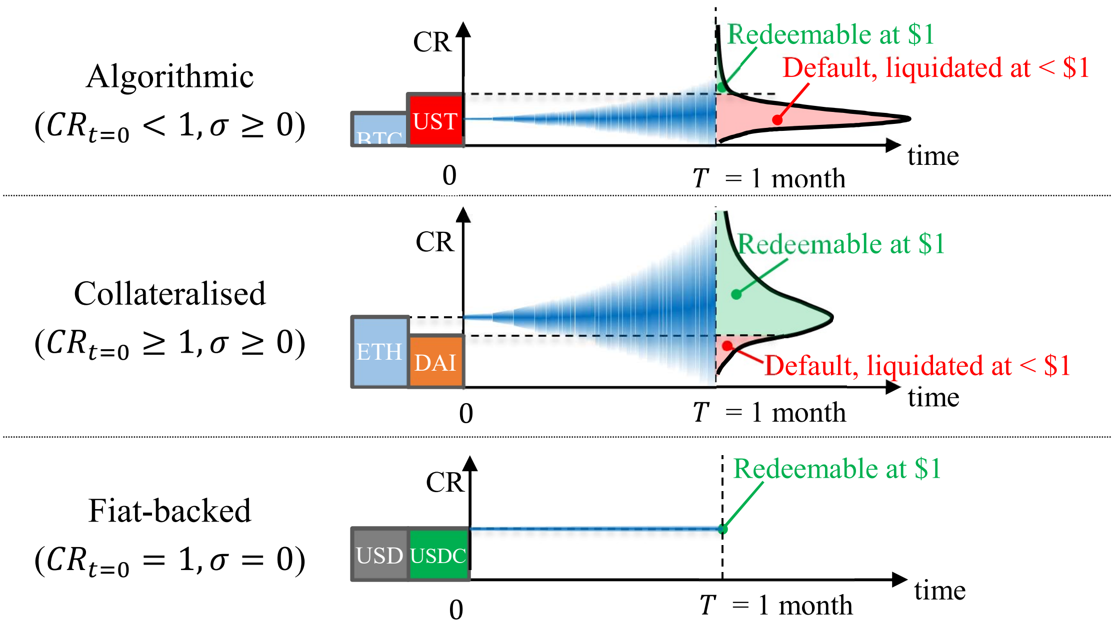
$$\%\Delta\text{CircMktCap}_{\text{2022May}} = \beta_0 + X\beta + \varepsilon \qquad (1)$$

We deploy linear regression models to assess how stablecoin designs could have affected run pressure during May 2022. The dependent variable, the change in circulating[6] market capitalisation during the month, is intended to capture run pressure experienced by the stablecoin. On the other side, we include variables that can capture various aspects of stablecoin designs, as denoted by vector X. However, the difficulty lies in the fact that stablecoins could be fundamentally very different in their designs. For example, stablecoins could have different levels of collateral ratio (CR, also a reciprocal of loan-to-value ratio), and accept different asset classes as reserves or collaterals ranging from US dollars to highly volatile crypto-currencies. Even more, many crypto-collateralised stablecoins run a multi-collateral structure akin to a multi-asset portfolio, while other stablecoins do not involve any collateralisation at all. A regression model that includes all these numerical and dummy variables would face almost insolvable statistical challenges.[7]

[6] Circulating market capitalisation = price of the stablecoin in USD * quantity of currency in circulation. Those stablecoins held by the same project or protocol for any purposes are non-circulating, thus are not counted towards circulating market capitalisation.

[7] Examples include multi-collinearity (asset portfolio weights add up to 1 for many stablecoins), difficulties in interpreting the coefficients (the sum of asset portfolio weights for an algorithmic stablecoin is smaller than 1, meaning that a lower weight for low-quality assets does not necessarily imply the presence of more high-quality assets), limited data points (sample size = 18) and model misspecification (stablecoin features like collateral ratio and asset volatility likely have non-linear relationships with run pressure).

Chart 7: Expected liquidation value (ELV) framework



Notes: CR refers to collateral ratio (Formula 4) and σ refers to asset return volatility (Formula 3).

$$ELV_i = \Pr(Default) \times E\left(CR_{i,t=1\text{ month}}\right) + \Pr(No\ \ Default) \times \$1 \qquad (2)$$

Therefore, we propose a metric called expected liquidation value (ELV), defined as "how much a stablecoin holder can expect to get when all reserve assets are liquidated[8] 1 month[9] from now", to measure the presence and quality of reserve assets. This way, we can incorporate those stablecoin features, including different asset classes at different collateral ratios and whether or not it is collateralised, into a single metric. Conceptually, stablecoins with more volatile assets or a lower amount of assets will be expected to liquidate at a lower value (Chart 7). To be more specific, such a relationship can be described numerically by (see "Annex 1" for more detail):

$$ELV_i = 1 + \Phi\left[\frac{\ln\dfrac{1}{CR_{i,t=0}} - \dfrac{\sigma_i^2}{24}}{\sigma_i\sqrt{\dfrac{1}{12}}}\right] CR_{i,t=0} - \Phi\left(\frac{\ln\dfrac{1}{CR_{i,t=0}} + \dfrac{\sigma_i^2}{24}}{\sigma_i\sqrt{\dfrac{1}{12}}}\right) \qquad (3)$$

where Φ is the cumulative density function of standard normal distribution, σ_i is the annualised collateral asset return volatility and collateral ratio CR_i for an

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[8] If a stablecoin holds another stablecoin as its asset or collateral, a recursive liquidation is assumed, i.e. the latter is to be liquidated first at ELV and then paid back to holders of the former.

[9] While many papers in the hedge fund return literature run a cross-sectional regression of monthly returns on 1-month value-at-risk (VaR), we believe that it is appropriate to run a regression of monthly change in market cap on 1-month ELV, as both VaR and ELV are metrics based on a 1-month ahead distribution.

asset class i is defined as total collateral value V_i divided by corresponding money issuance M_i:

$$CR_i = \frac{V_i}{M_i} \tag{4}$$

The ELVs for each asset class (ELV_i) will then be aggregated to obtain a stablecoin-wide ELV, weighted by respective share in total money issuance, i.e. "asset portfolio weight" w_i:

$$ELV = \sum w_i \times ELV_i \tag{5}$$

Several assumptions are made to obtain the formula of ELV (Formula 3). We model reserve asset prices with geometric Brownian motion (GBM), which is commonly used in the finance literature. To examine a stress scenario, the GBM is assumed to be twice as volatile as in normal times[10]. Also, we assume a 1-month horizon ("1/12" year in Formula 3) for the GBM, and reserve assets to have an expected return of 0%. This set of assumptions, together with the ELV framework, is referred as the "baseline", while alternative assumptions are tested in Annex 2 ("Robustness tests").

5.2 Data

This study covers 18 stablecoins (Table 1) and collected data from a wide variety of data sources (such as audit reports, application programming interfaces (APIs), official dashboards, whitepapers, Twitter, Discord, Medium blogs, CoinGecko, the Internet Archive and other third-party sites) to infer the classification, adjust reserve asset compositions and market capitalisations for complex tokens[11]. We consider only US dollar stablecoin projects with market capitalisations over \$100 million before the crash, due to the dominance of US dollar in the stablecoin space and data scarcity for lower-cap stablecoins[12].

[10] The annualised volatility in normal time is estimated by multiplying $\sqrt{365.25}$ with the standard deviation of daily logarithmic returns during January 2021 – April 2022. For crypto positions with unknown names, the historical return volatility is not available and therefore the normal time volatility is assumed to be 120% annualised, higher than that of BTC or ETH.

[11] Any token derived from one or more underlying cryptocurrencies and taking risks, including wrapped, synthetic, LP, yearned, staked, etc. Under the ELV framework, they are redeemed for underlying cryptos and then liquidated. Furthermore, holding of some LP tokens could require adjustment for non-circulating market capitalisation when they point back to the stablecoin itself (e.g. FRAX holds shares in UNIV3 FRAX/USDC LP).

[12] We also exclude a few qualified stablecoins including MIMATIC, GUSD and FELXUSD from our dataset mostly because the data on their asset compositions or market capitalisations are not reliable.

Table 1: List of stablecoin observations and data

Name	Type	Market cap data	Reserve asset data	Assumptions / Adjustments
USDT	Fiat	Audit report	Audit report	The overall reserve volatility is proxied by USDT price volatility
USDC	Fiat	Audit report	Audit report	
BUSD	Fiat	Audit report	Audit report	
TUSD	Fiat	Audit report	Audit report	
USDP	Fiat	Audit report	Audit report	
HUSD	Fiat	CoinGecko	Newspaper	Seemingly demand-driven market cap#, unclear exact composition
ALUSD	Fiat*	CoinGecko	Blog	Seemingly demand-driven market cap#, fiat as collateral
DAI	Collat.	CoinGecko	Internet Archive on a third party site	Only ERC-20 reserve data, assumed to be sufficiently representative
MIM	Collat.	Discord, dashboard	Discord screenshot on dashboard	Constant CR assumed to infer market cap from TVL@
FEI	Collat.	Dune	Dune	
LUSD	Collat.	CoinGecko	Whitepaper, blog, Dune, dashboard	Seemingly demand-driven market cap#
USDX	Collat.	CoinGecko, Twitter	Whitepaper, Discord	CR = 1.6 assumed& where minimum loan-to-value requirement is 66.67%
SUSD	Collat.	CoinGecko	Blog, dashboard	Seemingly demand-driven market cap#
YUSD	Collat.	CoinGecko	Twitter, Discord	Seemingly demand-driven market cap#
UST	Algo.	CoinGecko	News or Wikipedia	
FRAX	Algo.	Dashboard, DEXs	Whitepaper, dashboard, DEXs	Complex adjustment for LP token and non-circulating market cap
USDN	Algo.*	CoinGecko, whitepaper	Internet Archive on API	CR = 6 assumed& given ~600% C-ratio and pre-crash requirement
DEI	Algo.	CoinGecko, blog	Blog	A constant ratio of protocol-holdings to circ. market cap assumed@

#When more reliable data sources for market cap are not available, we resort to using CoinGecko checking visually if it looks demand-driven (this is needed because some stablecoins mint on-chain coins more than their issuance for buffer purposes, e.g. MIM) when more reliable data sources for market cap is not available.

* Classifications of these stablecoins are marginal cases as they carry some features of crypto-collateralised stablecoins

@Instead of adjusting for non-circulating market cap (not possible due to data unavailability), circulating market cap is estimated by proxy variables, e.g. total market cap, total value locked (TVL), which are assumed to have had a constant ratio to circulating market cap during May 2022.

& Detailed collateral data is not available, so a reasonable figure is assumed by taking reference to other information. The regression result is fairly insensitive to these assumptions.

VI. RESULTS AND FINDINGS

6.1 Regression results from event study

Table 2: Regression Model Results

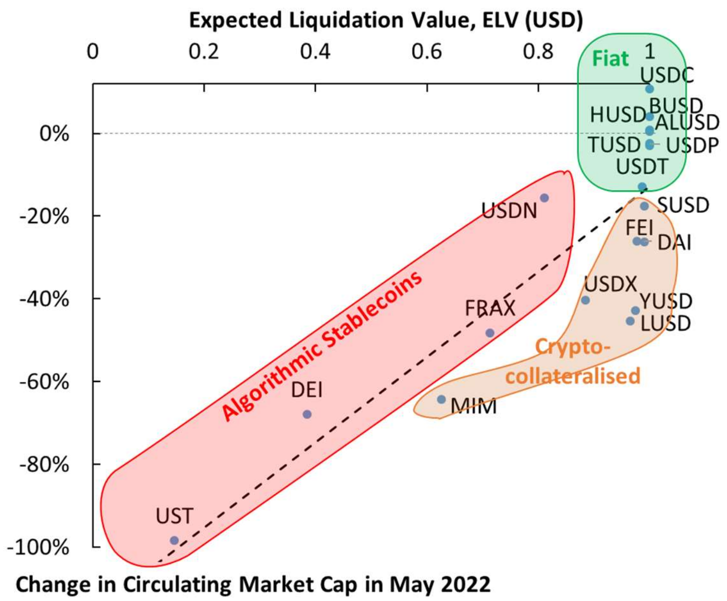
Dependent variable: $\%\Delta\mathrm{CircMktCap}_{2022\mathrm{May}}$

	A One-factor	**B** Multi-factor	**C** Control-only	**D** Alternative one-factor
Intercept	–1.16*** (–7.53)	–1.10*** (–13.55)	–0.32*** (–3.72)	–1.16*** (–6.54)
$\mathrm{ELV}_{\text{1-month, 2x vol}}$	1.04*** (5.98)	1.04*** (9.65)		
If-crypto-collateral		–0.33*** (–4.05)	–0.24 (–1.27)	
If-crypto-collateral * Non-stable CR		0.039* (1.66)	0.07 (1.27)	
If-cash-only		0.080 (1.25)	0.34*** (2.67)	
$\mathrm{ELV}_{t=0}$ (i.e. backing ratio)				1.00*** (5.18)
Adjusted R^2	0.720	0.939	0.473	0.688

* $P \leq 0.1$, ** $P \leq 0.05$, *** $P \leq 0.01$, robust standard errors shown in parentheses.
Note: Non-stable CR is calculated as the collateral value (excluding stablecoin collaterals) divided by the amount of debt outstanding. We exclude stablecoins from collateral calculations as they typically do not require overcollateralisation, and their inclusion would artificially depress the overall collateral ratio.

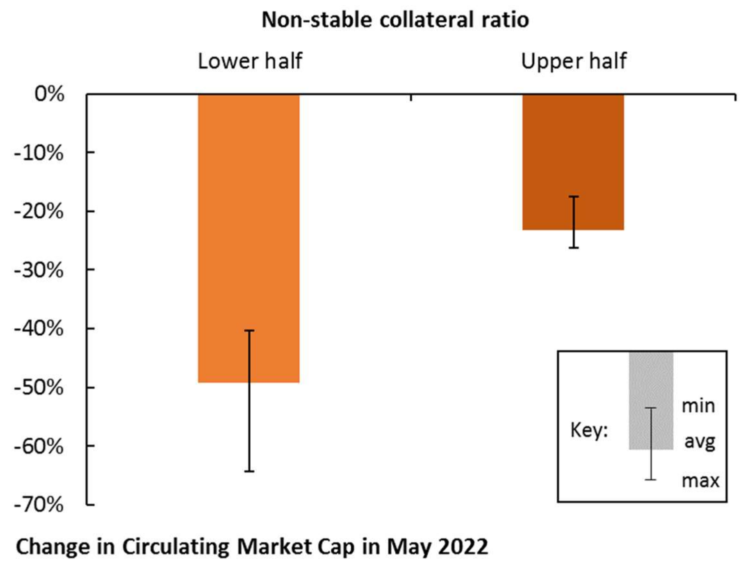
Table 2 presents the regression coefficients of several functional forms of Equation (1). Across all stablecoins, the quality and quantity of reserve assets, measured by ELV, comprise the most important determinant of the severity of a run pressure on a stablecoin. Stablecoins with sufficient assets to back their issuances faced less selling and redemption pressure from the market, as reflected by a smaller drop in their market capitalisation (Chart 8), with a 1% increase in ELV approximately narrowing the decline in the circulating market cap by 1 percentage point (Column A in Table 2). Meanwhile, other control variables and alternative measures like backing ratio (i.e. immediate liquidation value) are tested in regression (Columns C and D), and ELV (Column A) outcompetes these variables in explaining the run pressure with a higher R-squared.

Chart 8: Plot of %ΔCircMktCap$_{2022May}$—ELV



Source: HKMA staff estimates.

Chart 9: Collateral ratio and change in market cap in May 2022



Source: HKMA staff estimates.

Within the group of crypto-collateralised stablecoins, a higher collateral ratio, i.e. lower loan-to-value ratio, is associated with a smaller run (Chart 9), suggesting that imposing a more stringent lending restriction on crypto-collateralised stablecoins may shield them from a severe run. This shielding effect of collateral ratio could originate from both improved ELV (Formula 3) and factors unrelated to asset quality (Column B in Table 2), potentially including lower investor confidence and stronger deleveraging for highly leveraged stablecoins.

6.2 Data quality issues

Chart 10: Statistics on data source

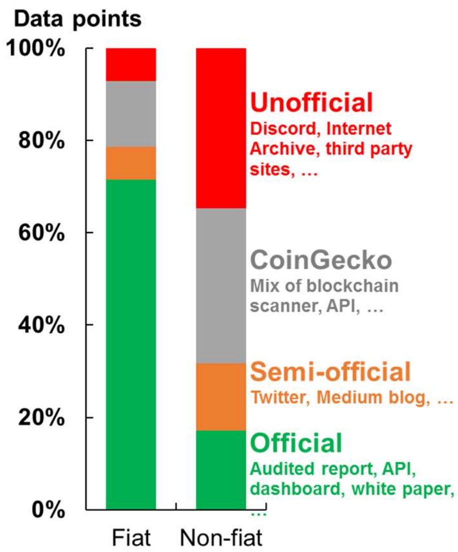


Table 3: Statistics on data quality issues

Data point	Adjustments / Assumptions / Limitations	Fiat	Non fiat
	(Number of stablecoins / total)		
Market Cap.	**Non-circulating issuance** Those held by the same project, adjustments needed	0/7	3/11
Reserve Asset	**Opaque asset composition** Incomplete disclosure on its reserve	3/7	8/11
	Exposure to complex tokens E.g. LP, wrapped, yearned, staked, synthetic	1/7	6/11
	Untimely data Data for 31 April 2022 not available	2/7	7/11

Source: HKMA staff estimates.

While the crash in May 2022 attracted broad regulatory attention from central banks, surveillance is nonetheless challenging given the pervasive transparency issue of non-fiat-backed stablecoin (Table 3). Although cryptocurrency advocates often argue that cryptos are decentralised and transparent (as all transactions are documented on blockchains), a confluence of factors — such as the lack of a one-size-fits-all toolkit to analyse stablecoin data on blockchains, chain protocol variations and custom chains, multi-chain data aggregation and evolving and upgrading protocol modules from time to time, make extraction of relevant information from blockchains highly inaccessible to general investors.

Hence, investors may rely more on data published directly by an official through dashboards, blogs, Twitter, etc., but the data quality has been found to be mixed. To name but a few, conflicting data (e.g. FEI, USDX), lack of asset history (almost all non-fiat-backed stablecoins), unclear asset composition (e.g. USDX, MIM), and dashboards that stop updating (e.g. MIM) are common data challenges. Statistics on the data source and quality are shown in Chart 10 and Table 3, showing severe disclosure issues in non-fiat-backed stablecoins. Their disclosure quality and traceability are far below what can be expected from traditional investment vehicles such as exchange-traded funds and mutual funds.

VII. CONCLUSION

Based on balance sheet analysis and the expected liquidation value framework, our study identifies the key stablecoin characteristics that can explain their run pressures in May 2022. Our analysis finds strong evidence that the presence of quality reserve assets is the most important determinant of the run pressures on a stablecoin. Furthermore, the lack of reserve assets and the presence of endogenous backing design contribute to the fragility of algorithmic stablecoins and, together with external causes, led to the crash of Terra. The crash evidently spilled over to its neighbours in the stablecoin space, the wider DeFi ecosystem, digital assets and crypto-oriented firms.

This study also finds that crypto-collateralised stablecoins were the major shock receivers of the algorithmic crash in May, with the leveraging in DeFi found to amplify the effect of a crash on underlying crypto prices, parallel to the role of excessive leverage in a financial crisis. As a precautionary measure, we find that a more stringent lending requirement can effectively shield crypto-collateralised stablecoins from a severe run.

However, there are a few caveats to our findings. Pervasive data gap issues and complex token holdings require a large number of assumptions and adjustments to compute the necessary data points for the regression. This also reflects substantial surveillance challenges for policymakers. Moreover, even though our ELV framework incorporates key features of stablecoins, many others are not included but remain relevant in the study of currency stability. They include, for instance, interest rates, stabilisation arrangements and reserve diversification and transparency. Ways of incorporating these factors into the investigation framework are left to future research.

Annex 1: Technical note on derivation of single-asset ELV formula

Recalling the expression for collateral ratio, we expand collateral value V_t to be a product of collateral quantity Q_t and collateral price P_t which is assumed to follow a geometric Brownian motion.

$$CR_t = \frac{V_t}{M_t} = \frac{P_t Q_t}{M_t}$$

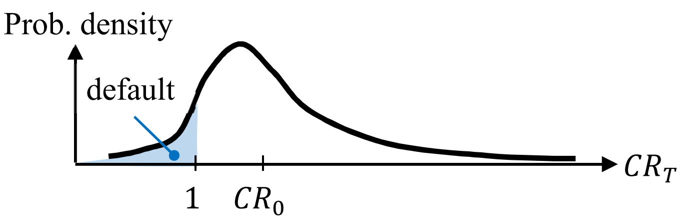
$$dP_t = \mu P_t dt + \sigma P_t dW_t$$

where W_t is a Wiener process, and μ (drift, or an instantaneous return rate) and σ (volatility) are constants. If we further assume a constant ratio of Q_t to M_t over time, Itô calculus gives

$$\frac{CR_T}{CR_0} \sim \text{lognormal}\left(\mu T - \frac{\sigma^2 T}{2}, \sigma^2 T\right)$$

At time T from now, the value of a stablecoin that is liquidated and paid back to its shareholders is called liquidation value (LV_T):

$$LV_T = min[1, CR_T]$$



Taking expectation on LV_T and computing the conditional mean with corresponding probabilities, an analytical formula for ELV_T can be derived:

$$ELV_T = 1 + e^{\mu T}\Phi\left(\frac{\ln\frac{1}{CR_0} - \mu T - \frac{\sigma^2 T}{2}}{\sigma\sqrt{T}}\right)CR_0 - \Phi\left(\frac{\ln\frac{1}{CR_0} - \mu T + \frac{\sigma^2 T}{2}}{\sigma\sqrt{T}}\right)$$

It gives Formula 3 when we assume $T = \frac{1}{12}$ and instantaneous mean return μ to be 0%. This formula is, indeed, very similar to the Black-Scholes model (See Annex 2.1 for their differences).

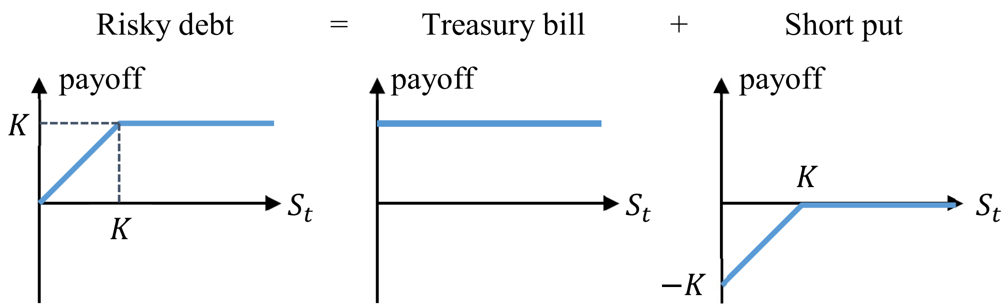
Annex 2: Robustness tests

In sub-section 5.1, we explained the advantages of using a single metric to summarise the risk characteristics of different stablecoins' reserve backing. This baseline ELV metric is straightforward and understandable but relies on simplistic assumptions. To ensure the robustness of our findings, Annex 2 tests with alternative frameworks and assumptions.

A2.1 Framework

We use the Merton risky debt model and the internal ratings-based (IRB) approach as alternatives. While the three frameworks – Merton, IRB and ELV – base their calculations on probability distributions, their core ideas and economic meanings are different, as summarised in Table A2.1.

Chart A2.1: The core idea of the Merton model



The Merton model assumes a stablecoin to be a risky debt, synthetically a portfolio of a treasury bill and a short put on collateral (Chart A2.1). Therefore, stablecoin value equals T-bill value subtracted by put option value, inferred from the well-known Black-Scholes model. Indeed, Huo at el. (2021) proposed the use of this option pricing method on evaluating stablecoins.

On the other hand, the IRB approach focusses on expected loss (EL):

$$EL = LGD \times PD \times ED$$

, where LGD is the loss given default, PD is default probability and ED is the exposure to default. The derivation of each term is similar to that of ELV in Annex 1, but based on a more realistic return rate and considering a non-zero discount rate (Table A2.1).[13]

[13] A strict application of IRB methodology also requires us to consider aspects such as interest payment and macroeconomic conditions, but these factors are omitted due to lack of relevant data and / or robust theoretical foundations for crypto assets.

Table A2.1: Baseline vs alternative frameworks for fair value estimation

Dependent variable: $\%\Delta \mathrm{CircMktCap}_{2022\mathrm{May}}$

		Baseline	**Alternative**	
		ELV	Merton	IRB
	Core idea	$E_T(LV)$	1 - put value	1 - EL
	Distribution	Real world	Risk-neutral	Real world
	Time of value	Future value	Present value	Present value
	Return rate	0%	FFF-implied 0.785%	2021 – 2022 Apr avg.
	Discount rate	0%	FFF-implied 0.785%	Lending rate 4.05%
Result	Intercept	–1.10*** (–13.55)	–1.10*** (–13.54)	–1.10*** (–13.50)
	Metric under framework	1.04*** (9.65)	1.04*** (9.64)	1.04*** (9.61)
	If-crypto-collateral	–0.33*** (–4.05)	–0.33*** (–4.05)	–0.33*** (–4.04)
	If-crypto-collateral * non-stable CR	0.039* (1.66)	0.039* (1.66)	0.039* (1.66)
	If-cash-only	0.080 (1.25)	0.080 (1.25)	0.081 (1.25)
	Adjusted R^2	0.939	0.939	0.939

* $P \leq 0.1$, ** $P \leq 0.05$, *** $P \leq 0.01$, robust standard errors shown in parentheses.
Notes: "Metric under framework" refers to ELV under the ELV framework, $1-P$ for Merton framework and $1-EL$ under the IRB framework. "FFF" refers to Fed funds futures.

The regressions based on the three frameworks yield almost the same result, likely because there is some form of equivalency between them. Under an assumption that all interest rates and discount rates = 0%, they could give the same formula (i.e. Formula 3 in sub-section 5.1). As we are not aware of any other applicable framework that could incorporate the same important set of risk characteristics, ELV is therefore proposed to be our baseline model among the three due to its mathematical and conceptual simplicity.

A2.2 Distribution

In our baseline model, collateral prices are assumed to have a classic geometric Brownian motion (GBM) and therefore follow a lognormal distribution (see Annex 1). The advantages of this price process include but are not limited to a closed-form solution for ELV (Formula 3 in sub-section 5.1), an easy calibration of parameter (i.e. σ) and a reasonable distribution even for unknown cryptos (a DeFi crypto typically fluctuates at 1.5 times ETH volatility).

However, asset prices typically behave in a manner with much richer features, such as exhibiting varying volatility and price jumps. Therefore in this section, we compare the baseline GBM against an empirical distribution[14], as well as a stochastic volatility jump-diffusion (SVJD) price process. For the latter, we applied Cape et al.'s (2015) method of Markov Chain Monte Carlo simulation to calibrate Bates models (Bates, 1995).[15]

Table A2.2: Baseline vs alternative distribution for fair value estimation

Dependent variable: $\%\Delta \mathrm{CircMktCap}_{2022\mathrm{May}}$

		Baseline	Alternative	
		GBM	SVJD	Empirical
Result	Intercept	–1.10***	–1.12***	–1.11***
		(–13.55)	(–15.61)	(–14.65)
	$\mathrm{ELV}_{\text{1-month, 2x vol}}$	1.04***	1.09***	1.02***
		(9.65)	(11.17)	(10.46)
	If-crypto-collateral	–0.33***	–0.24***	–0.33***
		(–4.05)	(–3.43)	(–4.35)
	If-crypto-collateral	0.039*	0.02	0.043**
	* non-stable CR	(1.66)	(1.03)	(1.99)
	If-cash-only	0.08	0.05	0.11**
		(1.25)	(0.84)	(1.96)
	Adjusted R^2	0.939	0.958	0.951

* $P \leq 0.1$, ** $P \leq 0.05$, *** $P \leq 0.01$, robust standard errors shown in parentheses.

The alternative models reach the same conclusion that the fair value is the single most important determinant of stablecoin runs, despite their disagreements on some control variables. Meanwhile, they both explain the run pressure at a higher adjusted R-squared than the baseline. This may corroborate with "Quality In, Quality Out" when more realistic distributions are applied, and also the ELV as a consistent framework.

[14] Two times volatility is assumed. For unknown crypto, empirical ETH distribution at three times volatility is used.

[15] We calibrate price processes against the entire crypto price history from CoinGecko and construct distributions with 5000 runs of simulation for each crypto.

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