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Intelligent design: Stablecoins (in)stability and collateral during market turbulence

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Abstract

How does stablecoin design affect market behavior in turbulent periods? Stablecoins attempt to maintain a "stable" peg to the US dollar, but do so with wildly varying structural designs. The spectacular collapse of the TerraUSD (UST) stablecoin and linked Terra (LUNA) token in May 2022 precipitated a series of reactions across major stablecoins, with some experiencing falls in value and others gaining value. Using a BEKK model, we examine the reaction to this exogenous shock and find significant contagion effects from the UST collapse, likely partially due to herding behavior among traders. We test the varying reactions among stablecoins and find that stablecoin design differences affect the direction, magnitude, and duration of the response to shocks. Implications for stablecoin developers, exchanges, traders, and regulators are discussed.

Keywords: Stablecoins, herding, information cascade, volatility spillovers, market crashes, financial contagion.

JEL Codes: D47, F31, F61, G14, G41

*Full list of declaration *statements*[7], along with a full list of authors' *information*[7], are available at the end of the article.

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1 Introduction

Cryptocurrencies are an increasingly important part of the financial system that offers new opportunities for investors, although their volatility remains a significant barrier to their wider adoption. Among cryptocurrencies, a subset known as stablecoins – designed to maintain a 'stable' peg to another financial asset, usually the US dollar – is crucial to the market. In theory, stablecoins allow traders to store value in a US dollar equivalent. Stablecoins, particularly Tether which is the third largest cryptocurrency by market value and by far the largest in terms of volume,[1] may be used as a safe haven for Bitcoin investors (Baur and Hoang, 2021). However, Stablecoins sometimes trade at a premium to the underlying asset they mimic because of the high fees to trade cryptocurrencies in US dollars, the difficulty of using US dollars on cryptocurrency exchanges, as well as the speed and ease of transferring stablecoins between exchanges (Lyons and Viswanath-Natraj, 2020).[2] The recent collapse of the TerraUSD (UST) stablecoin and linked Terra (LUNA)[3] token in May 2022 brought down a $60 billion ecosystem, making this exogenous shock an important natural opportunity for study.

At approximately midnight (UTC time) on May 9, 2022, UST began what would soon become a spectacular collapse. By the early hours of May 10, 2022, UST had unambiguously lost its peg with the dollar, trading at 98 cents at 2 a.m. (UTC), 90 cents at 8 a.m. (UTC), but only 79 cents by 9 a.m. (UTC). The impact of the decline in UST was felt with a delay in other cryptocurrency stablecoins. Around the time of the crash, UST had a market capitalization of $18 billion,[4] valuing it similarly to corporates such as Best Buy or Clorox.

[1]Tether's July 27, 2022, volume at 8:40 a.m. UTC was $45 billion, compared to Bitcoin and Ethereum's volume of 26 billion and 17 billion respectively. For another data point showing the same phenomenon consult the chart later in the paper.

[2]There is also evidence that an unknown user or entity may have used Tether to inflate the price of Bitcoin (Griffin and Shams, 2020).

[3]TerraUSD was a stablecoin traded under the symbol UST. It has commonly been referred to as Terra. A related coin traded under the symbol LUNA was technically named Terra. To ease confusion, and to match popular parlance, we refer to the stablecoin as UST or TerraUSD while we refer to the related coin using only its ticker, LUNA.

[4]`https://www.coindesk.com/markets/2022/05/15/the-collapse-of-terra-was-devastating-but-there-is-still-hope-for-crypto/`. Accessed July 26, 2022.

During the days surrounding this period of market turmoil, other stablecoins experienced significant price deviations from their \$1 peg. Tether, for example, dropped to 97 cents,[5] on May 12, 2022, around 4 p.m. (UTC). While BUSD rose to 1.0149 and USDC rose to 1.01 around 4 p.m. (UTC).[6] In contrast, DAI experienced small fluctuations around \$1.[7] Although all the stablecoins mentioned above aim to maintain a stable \$1 peg, they experienced vastly different price behavior, with some trading at a premium and others at a discount during the crash. The aim of this paper is to examine the time period before and after the collapse of stablecoin UST, on May 9, 2022, to test the extent to which this market crash impacted other major digital assets and investigate the causes of the hypothesized contagion. In particular, we examine the question of whether differences across stablecoins in the mechanism used to maintain the peg help explain differences in the magnitude, direction, and duration of their response to the UST stablecoin crash.

Answering this question is important as the May 2022 collapse of UST, alongside the resultant volatility in multiple important stablecoins, demonstrated the fragility of algorithmic stablecoins and the importance of credible collateral for stablecoins linked to fiat currencies. We use intraday data and a multivariate BEKK model over a sample period of 40 days surrounding the UST crash on the 9^{th} of May 2022 in order to test how differences in stablecoin designs affect trader behaviors and market reactions, and investigate the causes of spillover effects in the cryptocurrency markets. This method has also been used by previous literature to test whether contagion effects are due to herding behavior (e.g. Corsetti et al, 2005; Boyer et al, 2006; Chiang et al, 2007; Syllignakis and Kouretas, 2011). Indeed, we find evidence of contagion effects across all the cryptocurrency and stablecoins analyzed, with signs of herding behavior by traders after an information cascade that is apparent in the subsequent event study analysis. Deviations from the \$1 peg show how traders "vote with their feet" by

[5] `https://www.cnbc.com/2022/05/12/tether-usdt-stablecoin-drops-below-1-peg.html`. Accessed July 26, 2022

[6] `https://beincrypto.com/usdc-market-cap-soared-more-than-4-billion-in-may/`. Accessed July 26, 2022.

[7] `https://cointelegraph.com/news/makerdao-price-rebounds-as-dai-holds-its-peg-and-investors-search-for-stablecoin-security`. Accessed July 26, 2022.

moving in or out of various stablecoins. We finally demonstrate how smaller market players can cause financial contagion which infects larger players, finally feeding back to the market as a whole.

We contribute to the literature by investigating financial contagion in cryptocurrency markets during turbulent periods, such as the UST stablecoin crash. Additionally, this paper is the first to provide implications for stablecoin design, trader behavior, and contagion effects in stablecoin markets crisis, which is useful for academics, practitioners, and policymakers alike interested in potential destabilizing risk arising from the cryptocurrency ecosystem. We also extend prior research on the effects of volatility spillovers in cryptocurrency markets to stablecoin markets. Although prior research has tried to examine volatility spillover effects between Bitcoin and stablecoins (Hoang and Baur, 2021; Grobys et al, 2021), and between stablecoins only (Thanh et al, 2022), to the best of our knowledge, a comprehensive investigation of the magnitude, direction, and duration of response to stablecoin price movements is yet to be done. This study fills this gap and extends previous works on volatility spillover across stablecoins by testing whether differences in their underlying design affect market behavior. Moreover, this study investigates herding behaviors in cryptocurrency crashes, as the bubbles in Haykir and Yagli (2022), and tests the information cascade effects, as Tse and Hackard (2006) do in different US markets, provoked by the UST collapse on other stablecoins market activities, which enable us to make an additional contribution to the literature.

The paper proceeds as follows. Section 2 provides a review of the literature. Section 3 details the institutional background. Section 4 presents the methodology used in the empirical analysis. In section 5 we describe the intraday data used in the study and in section 6 we discuss the empirical findings, while section 7 provides some policy recommendations and concluding remarks.

2 Literature review

Cryptocurrencies may be thought of as privately produced money. However, the idea that money should be decentralized and privately produced is not new. Hayek (1976) argues for the denationalization of money, claiming that money, like other aspects of a capitalist economy, would be most efficiently provided through open competition. He also argues that, by definition, a monopoly cannot efficiently balance supply, and that the removal of the government's monopoly over money would prevent politician-led inflation and other destabilizing state-led interference with currencies. Interestingly, the first Bitcoin block mined, contains a message seen as criticizing government bailouts of the financial system and some see cryptocurrencies as an alternative to government-issued currencies.

Decentralized exchanges (DEXs) play an increasingly important role in major market events. Not surprisingly, given that stablecoins are a relatively recent innovation, there is limited literature on the stability of stablecoins during turbulent periods. The collapse of UST resembles other situations where there is panic. Indeed, if the research question is viewed more broadly as instances where pegs in financial markets are broken during turbulent markets there is a related literature on foreign exchange, money market mutual funds, and bank runs. For instance, the collapse of TerraUSD bears some similarity to a run on the Primary Reserve money mutual fund in the wake of the Lehman Brothers' bankruptcy filing on September 15, 2008. Like the collapse of the Primary Reserve money market mutual fund on 16 September 2008, amid fears that the fund held a substantial amount of potentially worthless Lehman Brothers short-term debt, the collapse of TerraUSD started with "breaking the buck". Unlike the Primary Reserve money market mutual fund case, the causes that triggered TerraUSD's collapse remain obscure to the public. Also, unlike the Primary Reserve money market mutual fund collapse, the Federal Reserve and US Treasury did not rush in to guarantee the stability of stablecoins in seeming trouble.[8] Similar problems can arise in the foreign exchange market. For instance, the Argentine Peso was convertible to the US Dollar

[8] See Kacperczyk and Schnabl (2010) as well as pages 24-25 of Pozsar et al (2013).

on a 1:1 basis under a "hard peg" for the period from April 1991 until January 6, 2002, when the peg broke and the Peso was allowed to float. De La Torre et al (2003) examine the causes of the sudden failure of Argentina's hard peg of its Peso to the US Dollar. Hanke and Schuler (2002) argue that the essential reason for the failure was that Argentina did not employ a true currency board system. The commonality in both examples is that fear that the peg will not hold sparks the type of behavior typically observed during a bank run.

A large body of literature has indeed examined the effects of financial markets contagion in periods of crises. Many analyzed the Global Financial Crisis (e.g. Baur, 2012; Fry-McKibbin et al, 2014; Kenourgios and Dimitriou, 2015), with some focusing on emerging markets (Celık, 2012; Boubaker et al, 2016), Asian markets (Yiu et al, 2010), European markets (Syllignakis and Kouretas, 2011), or foreign exchange markets (Ding and Vo, 2012) with bond, equity, and commodity markets (Diebold and Yilmaz, 2012). Others have instead investigated crises such as the Covid-19 Pandemic (Akhtaruzzaman et al, 2021; Uddin et al, 2022), or both the Global Financial Crisis and the Covid-19 Pandemic (Nguyen et al, 2022). Overall, all the studies mentioned above find that during market turmoil or periods of economic shocks, financial markets react by spreading volatility effects across different markets and countries.

A more recent stream of research, instead, examines volatility spillover effects in cryptocurrency markets and finds that overall, Bitcoin drives the interconnections between those digital assets. This includes studies analyzing solely cryptocurrencies (Moratis, 2021; Ampountolas, 2022); cryptocurrency and foreign exchange markets (Hsu, 2022), Non-Fungible Tokens (NFTs) markets (Wang, 2022), Bitcoin and Alternative Coins (altcoin) (Nguyen et al, 2019), Bitcoin, gold and the US Dollar (Dyhrberg, 2016), and stablecoin-linked perpetual futures (De Blasis and Webb, 2022).

Although the efficient market hypothesis suggests new information should be incorporated into market prices almost immediately, evidence of "information cascades" or herd behavior is also present in the literature. For example, Tse and Hackard (2006) report that the 2003 finding of Mad Cow Disease in a single cow in Canada led to a series of lagged price reactions or shocks to the news across various commodities and common stocks. Avery and Zemsky (1998) advance, instead, a model where rational herd behavior can substantially impact market prices for short periods of time when there is uncertainty about the value of an asset, whether an event has caused the value of an asset to change, and the quality of the information sparking a potential change in asset prices. These streams of research are all related to our study.

3 Institutional details

A stablecoin is understood as a cryptocurrency or token designed to maintain a "stable" peg to another currency, usually the US Dollar, on a one for one basis. Although they share a common objective of maintaining a stable peg to the US dollar they often differ sharply in the mechanism used to ensure stability by maintaining the peg. There are, indeed, a wide variety of stablecoins with differing designs.A US Government report on Stablecoins[9] speaks to their complexity, noting a stablecoin, depending on its design, might be classified as a "security, commodity, and/or derivative." We engage in further discussion of the designs of various stablecoins in the appendix.

In the United States, most stablecoins are treated as "value that substitutes for currency"[10] although this status may differ, with differing treatment even at the State level. There remain substantial legal, design, and market performance differences between major stablecoins, despite the fact they are all attempting to mirror the US dollar on a one-for-one basis. Stablecoins support their pegs to the US dollar via various mechanisms including cash, treasuries, corporate paper, algorithms, or other cryptocurrencies. On June 10, 2022, New York issued guidance noting stablecoins legal in the State must be fully backed by reserves,

[9]`https://home.treasury.gov/system/files/136/StableCoinReport_Nov1_508.pdf`. Accessed July 6, 2022.

[10]`https://www.fincen.gov/sites/default/files/2019-10/CVC%20Joint%20Policy%20Statement_508%20FINAL_0.pdf`. Accessed July 6, 2022.

with a redemption plan approved in advance by the New York State Department of Financial Services, amongst other requirements.[11] Not all major stablecoins are in compliance with this regulation. The design and reserve structure of major stablecoins is summarized in Table 1.

[Table 1 about here]

The question naturally arises as to why stablecoins are used. As mentioned earlier, Lyons and Viswanath-Natraj (2020) argue that Stablecoins sometimes trade at a premium to the underlying asset they mimic because of high fees to trade US dollars, the difficulty of using US dollars on cryptocurrency exchanges, and the speed and ease of transferring stablecoins between exchanges. The extreme volatility of some cryptocurrencies may be another reason. By comparison, the US dollar, and the stablecoins that mimic it, are generally less volatile.

An article published in Bloomberg[12] claims "the real reason people use stablecoins is regulations make it difficult to convert crypto assets to traditional assets. Stablecoins are a creature of regulation in the same sense that money market funds were created in the 1970s to get around government limits on interest banks could pay retail depositors while the economy was running at double-digit inflation". The most popular, and therefore liquid, stablecoins include Tether, DAI, TerraUSD, and USDC. Each is considered in the *Appendix*[7], with particular emphasis on their design characteristics, differences, and limitations. We then test how these differences in stablecoin designs affect trader behavior, market reactions, and contagion effects during turbulent periods.

4 Methodology

In order to test the financial contagion effect between stablecoins, we follow the approach proposed in Celık (2012), who found evidence of contagion during the U.S. subprime cri-

[11] https://www.dfs.ny.gov/industry_guidance/industry_letters/il20220608_issuance_stablecoins. Accessed July 6, 2022.

[12] https://www.bloomberg.com/opinion/articles/2021-12-20/crypto-regulators-are-taking-the-wrong-approach-to-stablecoins?srnd=opinion&sref=htOHjx5Y. Accessed July 6, 2022.

sis employing the DCC-GARCH model developed by Engle (2002). The DCC-GARCH model is a class of the multivariate GARCH models to measure the conditional covariances and correlations, thus, to measure the interaction between time series. Departing from the methodology in Celık (2012) and considering that the BEKK model developed by Engle and Kroner (1995) is preferred over the DCC-GARCH model (Caporin and McAleer, 2012), we assess the existence of contagion effects during the UST collapse by employing the BEKK model.

Assuming that the log-returns follow a normal distribution with zero means and variance-covariance matrix H_t, we can model the conditional covariances as

$$H_t = CC' + A\left(e_{t-1}e_{t-1}'\right)A' + BH_{t-1}B' \tag{1}$$

where C, A and B are parameters matrices with C being lower triangular.

The BEKK representation in (1) poses some difficulties during the estimation process as the number of parameters is very high when considering many time series. To reduce the parameters, we can employ a scalar version of (1) and apply the concept of variance targeting to eliminate the term CC'. Thus, the model becomes

$$H_t = (1-a-b)\bar{H} + a\left(e_{t-1}e_{t-1}'\right) + bH_{t-1},$$

where $\bar{H} = \sum_{t=1}^{T} e_{t-1}e_{t-1}'$ is the unconditional covariance matrix estimated from the full sample. In this scalar version the parameters are only a and b, subject to a, $b > 0$ and $a + b < 1$. These constraints are imposed to keep the process stationary and to guarantee the positive definiteness of the covariance matrices.

Once we obtain the conditional covariances, thus the conditional correlations, we can perform the contagion test as proposed in Celık (2012). The hypothesis is

$$H_0 : \mu_{\text{pre}} = \mu_{\text{post}},$$

where μ_{pre} and μ_{post} are the matrices of the means of conditional correlations from the population during the UST pre-collapse and collapse periods respectively with variances σ_{pre} and σ_{post}. Considering two samples with sizes n_{pre} and n_{post} and the matrices of the means of the conditional correlations computed from the BEKK model, $\bar{\rho}_{\text{pre}}$ and $\bar{\rho}_{\text{pre}}$ with variances $s_{\text{pre}}^2 = \frac{1}{n_{\text{pre}}-1}\sum_{t=1}^{n_{\text{pre}}}\left(\rho_{\text{pre}} - \bar{\rho}_{\text{pre}}\right)^2$ and $s_{\text{post}}^2 = \frac{1}{n_{\text{post}}-1}\sum_{t=1}^{n_{\text{post}}}\left(\rho_{\text{post}} - \bar{\rho}_{\text{post}}\right)^2$, we can compute the t-statistics as

$$t = \frac{\left(\bar{\rho}_{\text{post}} - \bar{\rho}_{\text{pre}}\right) - \left(\mu_{\text{post}} - \mu_{\text{pre}}\right)}{\sqrt{\frac{s_{\text{post}}^2}{n_{\text{post}}} + \frac{s_{\text{pre}}^2}{n_{\text{pre}}}}},$$

with degrees of freedom

$$v = \frac{\left(\frac{s_{\text{post}}^2}{n_{\text{post}}} + \frac{s_{\text{pre}}^2}{n_{\text{pre}}}\right)^2}{\frac{\left(\frac{s^2{\text{post}}}{n_{\text{post}}}\right)^2}{n_{\text{post}}-1} + \frac{\left(\frac{s^2{\text{pre}}}{n_{\text{pre}}}\right)^2}{n_{\text{pre}}-1}}.$$

When the t-statistics is significantly greater than the critical value, the null hypothesis is rejected supporting the existence of contagion effect.

5 Data

This study uses proprietary minute-by-minute price transactions data for the most liquid cryptocurrency, Bitcoin (BTC), and the six most liquid stablecoins, namely: Tether (USDT); Binance Coin (BUSD); US Dollar Coin (USDC); Dao Coin (DAI); TerraUSD (UST); and Terra (LUNA), the companion cryptocurrency linked to UST. The sample spans a 40-day period extending from April 20, 2022, to May 29, 2022, and covering a symmetrical pre- and post-period of 20 days around the TerrUSD crash between the 9th and the 10th of May 2022. We collect the data from different exchanges and providers, such as Kaiko (for BTC, USDT, USDC, DAI, and UST), and CryptoCompare (for BUSD and LUNA), all supplied by Refinitiv (formerly Thomson Reuters), a London Stock Exchange Group (LSEG) business, and sourced from the Thomson Reuters Tick History (TRTH) database. The final dataset consists of 57,600 price observations of the 7 digital assets.

Given that the cryptocurrency market is fragmented with many alternative trading venues the question naturally arises as to which price series to choose to analyze. We use price data from Refinitiv because it is a weighted average of the prices reported on various exchanges. This decision reduces the observed volatility and magnitude of the price moves in response to news because the price data are essentially smoothed by averaging. However, we believe that this drawback is outweighed by the fact that the smoothed data avoids giving too much weight to transactions on smaller trading venues and thereby presents a more accurate snapshot of where price was at any moment in time.

We compute cryptocurrency and stablecoin returns as $ln(P_t/P_{t-1})$ where P_t is the price of the digital asset at time t. According to the literature, determining the cut-off date of a crisis period might not be straightforward (Kaminsky and Schmukler, 1999). Consequently, we consider the very beginning of a significant decline in the UST price, which also coincides with the day of the first news-based announcement of the stablecoin potential crash. Therefore, we use midnight of the 10th of May 2022 as the starting point of the collapse period. Finally, we also calculate cumulative abnormal returns (CARs), for the purpose of the second analysis, by assuming that the expected return on a stablecoin is $E[RS] = 0$ and subtracting the returns of BTC from its mean return during the first two days of the sample period taken as a benchmark.

6 Results

Table 2 illustrates the descriptive statistics of the stablecoins returns during both periods (i.e. pre-collapse in Panel A and collapse of UST in Panel B) and for the entire sample (panel C). In order to run the analysis, we test whether the returns (and squared returns) are normally distributed with the Jarque-Bera test, whether the null hypothesis that a unit root is present in the returns time series sample through the augmented Dickey-Fuller test if there is heteroskedasticity in sample distribution with the ARCH model, and finally we use Ljung-Box test for autocorrelations within our data. All the statistical tests are consistently significant at the 1% level in the three periods. Panel C also clearly shows that the assumption made in the methodology section holds as all the returns have approximately zero mean. Another noteworthy statistic is the median being 0 in all the return distributions during every period. As in Celık (2012), all the distributions of returns are leptokurtic, a common characteristic of financial markets data.

[Table 2 about here]

Figure 1 shows the stationary returns of all the cryptocurrencies studied over the sample period. An anomaly is evident on the right-hand side of each chart. Namely, the charts show that abnormal returns occurred after UST started to collapse. Interestingly, the day on which the highest return occurred for UST and LUNA differs from the spike in USDT, USDC and DAI. This might signal an information cascade effect. Table 3, instead, presents the dynamic conditional covariances matrix between all the cryptocurrencies during both the pre-collapse (Panel A) and collapse (Panel B) periods.

[Figure 1 and Table 3 about here]

Of course, a stablecoin should ideally have zero cumulative returns, as it should maintain a precise peg with the US dollar. The results of the study confirm that traders are responsive to the underlying design of the cryptocurrency, and the underlying design itself affects trader activity. For example, BUSD – which is backed dollar for dollar with cash in US banks and regulated in New York – was the beneficiary of a flight to safety during the collapse period. Figure 2 illustrates the cumulative abnormal returns (CARs) of the digital assets analyzed over the entire sample period, while Figures 3 and 4 (hourly basis) show the CARs during the period of greater price reactions between 9 and 13 May 2022. The zoomed-in version of the CARs also outlines the information cascade that started from the UST and, simultaneously, LUNA, whose underlying is based on UST, and then spread to USDT a couple of days later, which spilled over to USDC and DAI almost instantaneously before bouncing back to UST and LUNA and slightly affecting also BUSD. There was a clear market reaction at the event of the USDT decline that precipitated a sharp increase of around 6% in USDC within a couple of hours. One hour later, USDT reached its all-time low with an abnormal return of -5%, causing a simultaneous spike in DAI (a positive abnormal return of 3%). Only a day later, UST collapsed entirely to a handful of cents, triggering a slight de-peg of a negative near -0.1% even in BUSD. Bitcoin dropped to -50%, while overall UST and LUNA crashed with a magnitude of almost -300% and -1500% abnormal returns. A non-technical analysis showed how there was a two-day delay in market events happening on centralized exchanges that could have been predicted by looking at market activities in decentralized liquidity pools.[13] However, we leave this topic as a future research project.

[Figure 2 - 3 - 4 about here]

Table 4 presents the dynamic conditional covariance estimates of the BEKK-GARCH model and the relative t-test statistics on the existence of contagion. Evidence shows that the TerraUSD collapse provoked a spillover effect across all the major stablecoins analyzed, plus the bitcoin. All the tests are statistically significant at the 1% per cent level, supporting the existence of contagion effects. Figure 5 shows those dynamic conditional covariances plotted throughout the sample period. It is clear as the right-hand side of all charts presents an evident movement in the stationary covariances, meaning that after the UST collapse all the other digital assets experienced a significant price movement caused by a spillover effect in the period after the 9^{th} of May 2022.

[Table 4 and Figure 5 about here]

These results show a statistically significant level of contagion between UST and other stablecoins. This suggests that the UST collapse was responsible for broader dislocation and

[13] `https://blog.kaiko.com/predicting-the-ust-collapse-with-dex-liquidity-pool-data-6e8d6e62660`. Accessed August 2, 2022.

contagion in the stablecoin market in May 2022. The differential behaviour of stablecoins and cryptocurrency assets, instead, suggests herding among traders as a likely cause of these market results. Although UST caused the initial crash in the stablecoin market, it was not until a collapse in USDT on May 12, 2022, led to an even further, and final blow to UST. Moreover, the duration of the impact was uneven across cryptocurrencies. The impact did not persist for BUSD, but Tether continued to deviate from its dollar peg until the 19^{th} of July, 2022, albeit far smaller than the initial reaction to the news. This demonstrates how smaller market players can cause financial contagion which infects larger players, finally feeding back to the market as a whole.

7 Conclusion

This paper examines how stablecoin design affects the reaction of stablecoins to price shocks. We examine differences in the magnitude, direction, and duration of their response using a multivariate BEKK model over a sample period of 40 days surrounding the crash on the 9^{th} of May 2022. We find evidence of a contagion effect across all cryptocurrencies analysed, with signs of herding behavior by traders after an information cascade. Traders voted with their feet, buying stablecoins with safer designs, such as BUSD, which is backed \$1 for 1 with cash in a US Bank. USDC also rose above \$1, while DAI fluctuated around \$1. That demand was so high that USDC and BUSD reached 1.01 on at least some exchanges showing traders were willing to pay extra for a flight to safety.

Paying \$1.01 for a \$1 asset is uneconomic, suggesting major worries about the stability and, potentially even the survival, of other cryptocurrencies or stablecoins. This fear was shown most prominently in the price action of UST, which faced a near-total collapse, and also in Tether, which traded as low as 95 cents on some exchanges.

Herd behavior helps explain how traders seek perceived safety, overpaying for "safe" stablecoins while selling stablecoins deemed unsafe during turbulent periods. Stablecoin developers, exchanges, and regulators should consider the results of this study to design more robust systems in order to prevent other scenarios in which a stablecoin de-pegging process spills over negative effects across other digital assets and deteriorates the market by allowing flash crashes. That Tether, the most popular stablecoin by market capitalization and volume, which generally trades for $1 was able to be purchased for 95 cents speaks to the depth of the market uncertainty.

Future research may further compare the institutional and algorithmic designs of various stablecoins to further investigate the market reaction to various design structures. Should the data become available, a comparison of the reserve structure and quality amongst major stablecoins would create interesting research opportunities. Our research suggests that market participants can accurately discriminate among stablecoins in terms of their safety during a crash but may continue to trade coins with larger market capitalization – even if they may be riskier – during less volatile times. A subsequent research avenue for future studies is the potential prediction of cryptocurrency market crises using Decentralized Exchanges (DEXs) liquidity pool data, which could potentially shed more light on the interconnections between decentralized and centralized markets and the reasons behind herding behavior by traders during turbulent periods.

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Abbreviations

UST	TerraUSD stablecoin
LUNA	Terra token
BEKK	Baba, Engle, Kraft and Kroner's model
US	United States of America
UTC	Coordinated Universal Time
BUSD	Binance USD stablecoin
USDC	USD Dollar Coin
DAI	MakerDAO Coin
DEXs	Decentralized Exchanges
NFTs	Non Fungible Tokens
Altcoin	Alternatives coins
DCC	Dynamic Conditional Correlations
ARCH	Autoregressive Conditional Heteroskedasticity
GARCH	Generalized ARCH
USDT	Tether stablecoin
LSEG	London Stock Exchange Group
TRTH	Thomson Reuters Tick History database
CARs	Cumulative Abnormal Returns
TRFM	Target Rate Feedback Mechanism
SEC	Securities and Exchange Commission
DeFi	Decentralized Finance

Availability of data and materials

The data that support the findings of this study are available from Refinitiv but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Refinitiv and Rozetta.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

RDB contributed to the design of the empirical analysis, analyzed the data, and wrote the method section. LG collected the data, contributed to the design of the analysis, analyzed the data, wrote part of the introduction and literature review sections, the data section, the results section and part of the conclusion section, and revised and formatted the manuscript. AW contributed to the development of the idea, wrote part of the introduction, literature review, and conclusion sections, wrote the institutional details and the appendix sections, and revised the manuscript. RIW contributed to the idea development, wrote part of the introduction, literature review, data, and conclusion sections, and revised the manuscript. All authors read and approved the final version of the manuscript.

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Tables

Table 1: Comparison of Bitcoin and popular Stablecoins by backing, market capitalization, and trading volume as of 7:50 a.m. UTC, June 28, 2022

Coin	**Asset class**	**Financial backing structure**	**Market cap ($)**	**Volume ($-24h)**
USDT	Stablecoin	Diversified reserves	66,759,936,925	41,133,272,015
USDC	Stablecoin	Cash and US bonds	55,826,655,034	4,330,623,305
BUSD	Stablecoin	$1 for 1	17,439,109,190	5,255,903,027
DAI	Stablecoin	Collateralized debt	6,780,302,604	250,145,391
UST	Stablecoin	Algorithmic design, some cryptocurrency reserves	476,000,027	97,740,154
BTC	Cryptocurrency	N/A	398,452,637,815	21,643,828,415

Table 2: Descriptive statistics of Stablecoins returns. The table shows the descriptive statistics for pre-collapse, collapse and the entire period. $Jarque-Bera$ represents the test statistics from the normality test. ADF represents the augmented Dickey-Fuller test. $ARCH(6)$ and $ARCH(12)$ correspond to the test statistics from the ARCH test with 6 and 12 lags respectively. $Q(6)$, $Q(12)$ and $Q^2(6)$, $Q^2(12)$ represent the test statistics from the Ljung-Box test for serial correlation in returns and squared returns with 6 and 12 lags respectively. *** indicates the rejection of the null hypothesis at the 1% significance level.

	BTC	**BUSD**	**DAI**	**LUNA**	**UST**	**USDT**	**USDC**
	Panel A: pre-collapse period (20 April 2022 - 9 May 2022)						
Mean	-0.0011	0	0	-0.004	-0.0009	0	0
Median	0	0	0	0	0	0	0
Max	1.3604	0.01	0.6764	7.5653	5.9968	0.626	1.0925
Min	-1.2013	-0.01	-0.6765	-4.6747	-2.8252	-0.6271	-0.8492
Std. Dev.	0.0846	0.0045	0.0263	0.1932	0.0591	0.0183	0.0255
Skewness	0.1752	-0.0002	0.0545	0.7353	25.7039	0.1591	1.9935
Excess Kurtosis	19.1692	2.0482	60.5877	157.2306	4198.0988	231.8142	466.2319
Jarque-Bera	441098.0***	5034.0***	4405060.0***	29668355.0***	21152011210.0***	64485485.0***	260865729.0***
ADF	-23.1***	-40.1***	-38.4***	-14.1***	-3.3**	-36.5***	-39.4***
ARCH(1)	1492.1***	211.5***	6866.4***	719.0***	29.2***	7084.0***	8035.1***
ARCH(6)	2656.9***	444.5***	9637.9***	2732.5***	1038.9***	11674.6***	8705.1***
ARCH(12)	2926.4***	602.3***	9748.4***	5020.3***	1880.5***	12069.9***	8736.9***
Q(6)	30.7***	2509.1***	7037.5***	324.5***	1235.3***	6469.0***	8112.6***
Q(12)	64.1***	2522.6***	7049.2***	432.0***	1834.3***	6480.5***	8113.4***
$Q^2(6)$	4823.9***	567.3***	7051.2***	4236.6***	1122.0***	7122.2***	11766.0***
$Q^2(12)$	7139.7***	928.3***	7303.3***	10180.7***	2125.8***	7130.7***	11766.1***
	Panel B: collapse period (10 May 2022 - 29 May 2022)						
Mean	-0.0001	0	0	-0.0437	-0.0118	0	0
Median	0	0	0	0	0	0	0
Max	2.5506	0.1	1.8215	608.336	43.8416	1.7807	6.3763
Min	-1.8623	-0.1	-2.6808	-607.3849	-46.106	-1.7589	-6.4213
Std. Dev.	0.1302	0.0137	0.0612	52.9634	1.7118	0.0584	0.097
Skewness	0.8269	0.0016	-1.7094	-0.0164	0.2579	-0.1884	0.5163
Excess Kurtosis	23.612	41.9405	210.6163	108.6154	89.4661	160.844	1418.0227
Jarque-Bera	672311.0***	2110805.0***	53245085.0***	14156761.0***	9605345.0***	31045112.0***	2412947437.0***
ADF	-24.1***	-34.2***	-38.1***	-32.0***	-22.1***	-29.8***	-38.5***
ARCH(1)	1678.3***	4751.9***	686.7***	7409.7***	2721.6***	5390.1***	7088.5***
ARCH(6)	3383.1***	8253.2***	4212.7***	11858.9***	3749.0***	6446.3***	11601.0***
ARCH(12)	3762.7***	9288.2***	5717.0***	12365.3***	4719.2***	7627.5***	12291.3***
Q(6)	21.1***	4910.3***	5034.8***	7721.5***	292.8***	4152.2***	6675.5***
Q(12)	50.0***	4967.9***	5164.5***	7887.4***	336.0***	4457.9***	7158.2***
$Q^2(6)$	6528.1***	23465.1***	4038.3***	40460.8***	5904.1***	10990.2***	7094.9***
$Q^2(12)$	10228.6***	45786.2***	7064.8***	74407.5***	9964.4***	19652.8***	8124.4***
	Panel C: entire period (20 April 2022 - 29 May 2022)						
Mean	-0.0006	0	0	-0.0239	-0.0064	0	0
Median	0	0	0	0	0	0	0
Max	2.5506	0.1	1.8215	608.336	43.8416	1.7807	6.3763
Min	-1.8623	-0.1	-2.6808	-607.3849	-46.106	-1.7589	-6.4213
Std. dev.	0.1098	0.0102	0.0471	37.451	1.2111	0.0433	0.0709
Skewness	0.7357	0.0021	-1.8707	-0.0248	0.3521	-0.2256	0.7069
Excess Kurtosis	27.246	70.5863	304.6165	220.2247	181.4897	272.5424	2488.7769
Jarque-Bera	1786828.0***	11957823.0***	222732570.0***	116397447.0***	79053611.0***	178270929.0***	14865629446.0***
ADF	-33.0***	-44.1***	-49.4***	-41.1***	-29.1***	-39.9***	-49.2***
ARCH(1)	3424.5***	9740.3***	1456.8***	14949.5***	5578.0***	10893.0***	14188.9***
ARCH(6)	6763.1***	16830.6***	8361.1***	23865.9***	7701.9***	12990.2***	23185.7***
ARCH(12)	7490.7***	18902.5***	11344.4***	24880.7***	9667.5***	15311.5***	24562.2***
Q(6)	26.1***	9233.3***	10516.0***	15441.7***	581.3***	8589.3***	13293.0***
Q(12)	70.6***	9327.7***	10710.5***	15773.4***	667.0***	9097.4***	14135.8***
$Q^2(6)$	13175.9***	48299.2***	8106.1***	81691.3***	12327.5***	22026.3***	14202.6***
$Q^2(12)$	20655.8***	94295.5***	14136.6***	150341.0***	20902.1***	39178.6***	16264.7***

Table 3: BEKK dynamic conditional covariances matrix. Pre-collapse period is from 20.04.2022 to 09.05.2022. Collapse period is from 10.05.2022 to 29.05.2022. Entire period is from 20.04.2022 to 29.05.2022.

	BTC	**BUSD**	**DAI**	**LUNA**	**UST**	**USDT**	**USDC**
	Panel A: pre-collapse period (20 April 2022 - 9 May 2022)						
BTC	1	0.088074	-0.002386	0.544775	-0.014619	-0.005339	0.002376
BUSD	0.088074	1	0.00261	0.040627	-0.007438	0.004073	0.004018
DAI	-0.002386	0.00261	1	-0.002406	0.003764	0.011446	-0.001576
LUNA	0.544775	0.040627	-0.002406	1	0.099675	0.001158	-0.004781
UST	-0.014619	-0.007438	0.003764	0.099675	1	-0.003947	-0.003941
USDT	-0.005339	0.004073	0.011446	0.001158	-0.003947	1	0.017164
USDC	0.002376	0.004018	-0.001576	-0.004781	-0.003941	0.017164	1
	Panel B: collapse period (10 May 2022 - 29 May 2022)						
BTC	1	0.014782	-0.007793	0.005863	-0.004084	0.002406	0.005606
BUSD	0.014782	1	0.000828	-0.002651	0.0013	-0.00345	-0.011825
DAI	-0.007793	0.000828	1	0.00592	0.02705	0.023904	0.002707
LUNA	0.005863	-0.002651	0.00592	1	-0.005463	0.011936	-0.005486
UST	-0.004084	0.0013	0.02705	-0.005463	1	-0.004068	0.001743
USDT	0.002406	-0.00345	0.023904	0.011936	-0.004068	1	-0.01399
USDC	0.005606	-0.011825	0.002707	-0.005486	0.001743	-0.01399	1

Table 4: BEKK dynamic conditional covariance coefficients and contagion effect tests. Pre-collapse period is from 20.04.2022 to 09.05.2022. Collapse period is from 10.05.2022 to 29.05.2022. Entire period is from 20.04.2022 to 29.05.2022. *** indicates the significance level at 1%.

	Mean	**Variance**	**T-statistic**
Pre-collapse BEKK-DCC UST_BTC	0.001314	0.00029	24.64***
Collapse BEKK-DCC UST_BTC	-0.00844	0.004223	
Pre-collapse BEKK-DCC UST_BUSD	-0.000904	0.000366	-24.71***
Collapse BEKK-DCC UST_BUSD	0.008663	0.00395	
Pre-collapse BEKK-DCC UST_DAI	0.005214	0.000277	-23.96***
Collapse BEKK-DCC UST_DAI	0.014126	0.003708	
Pre-collapse BEKK-DCC UST_LUNA	-0.003753	0.000105	-44.15***
Collapse BEKK-DCC UST_LUNA	0.009095	0.002334	
Pre-collapse BEKK-DCC UST_USDT	0.000914	0.000374	-14.78***
Collapse BEKK-DCC UST_USDT	0.007154	0.004755	
Pre-collapse BKK-DCC UST_USDC	-0.000442	0.000389	-3.84***
Collapse BEKK-DCC UST_USDC	0.001075	0.004094	

Figures

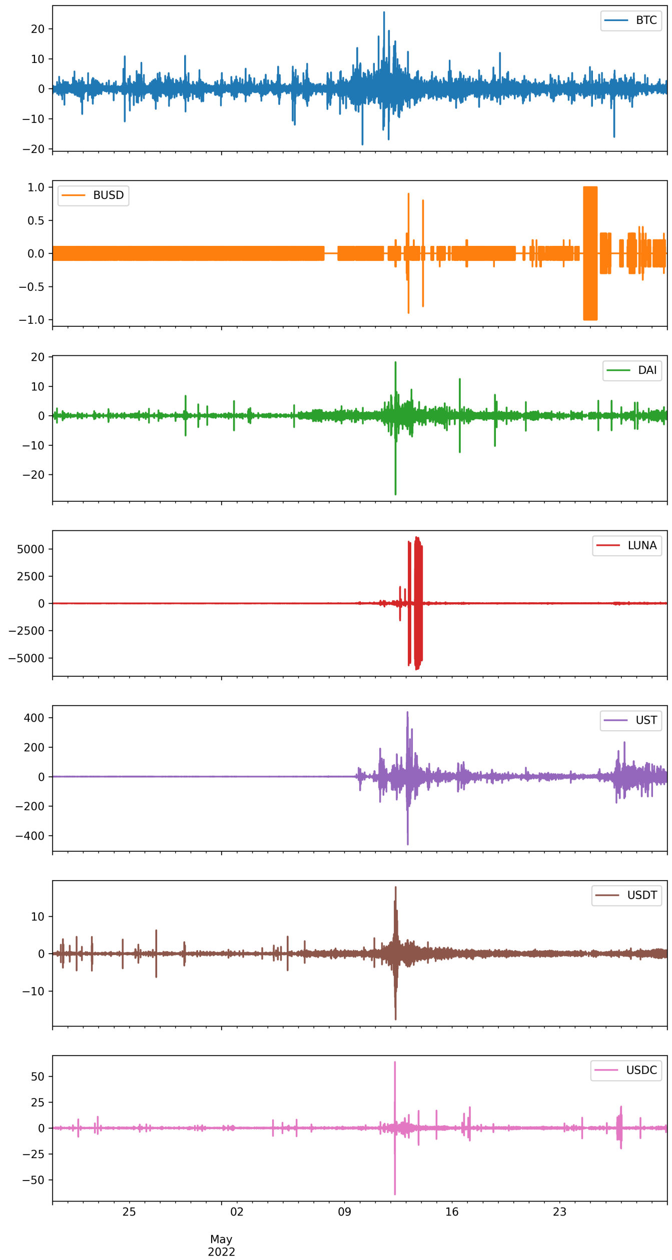

Figure 1: Stationary returns

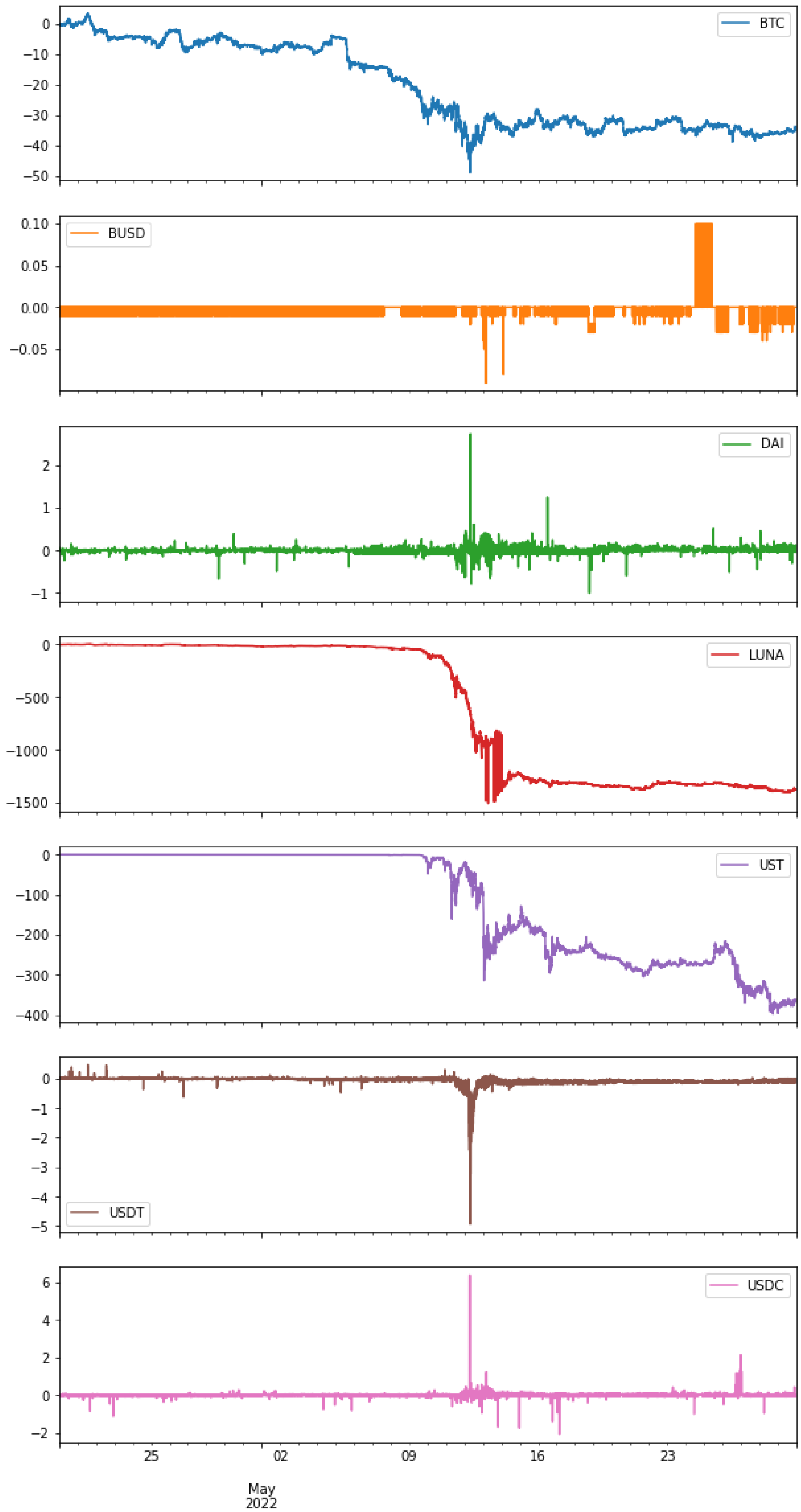

Figure 2: Cumulative abnormal returns

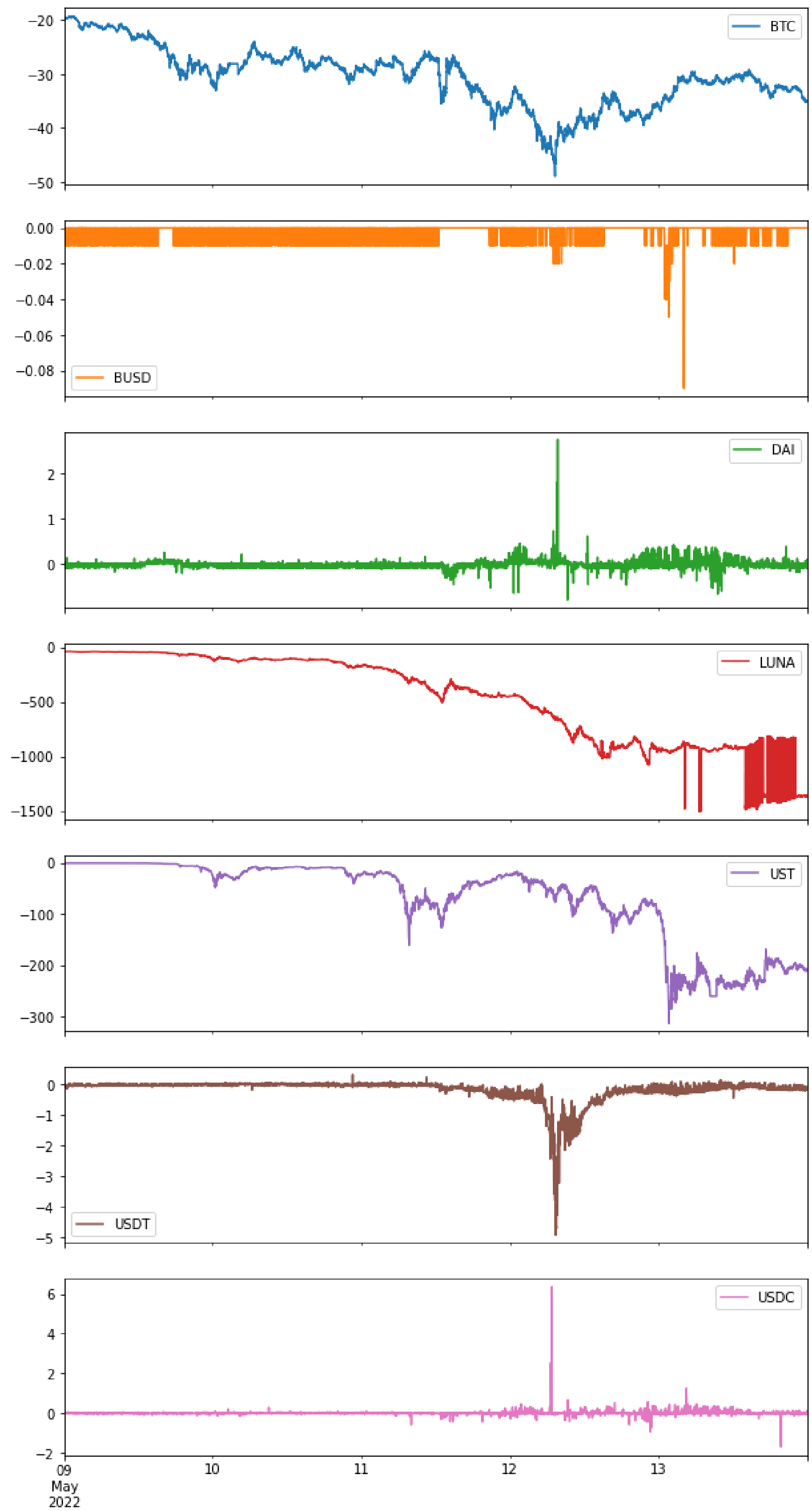

Figure 3: Cumulative abnormal returns zoomed-in

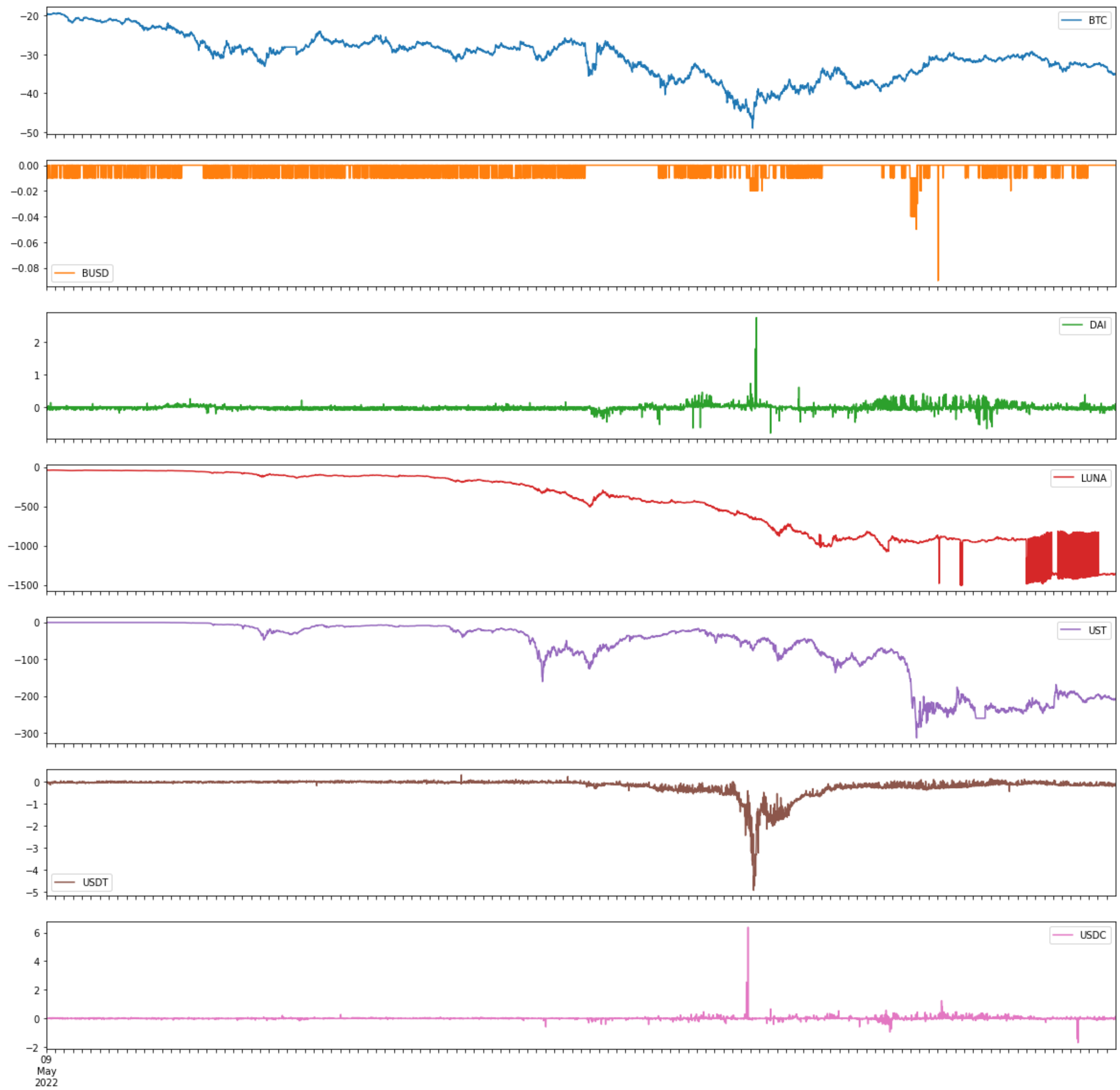

Figure 4: Cumulative abnormal returns zoomed-in (hourly basis)

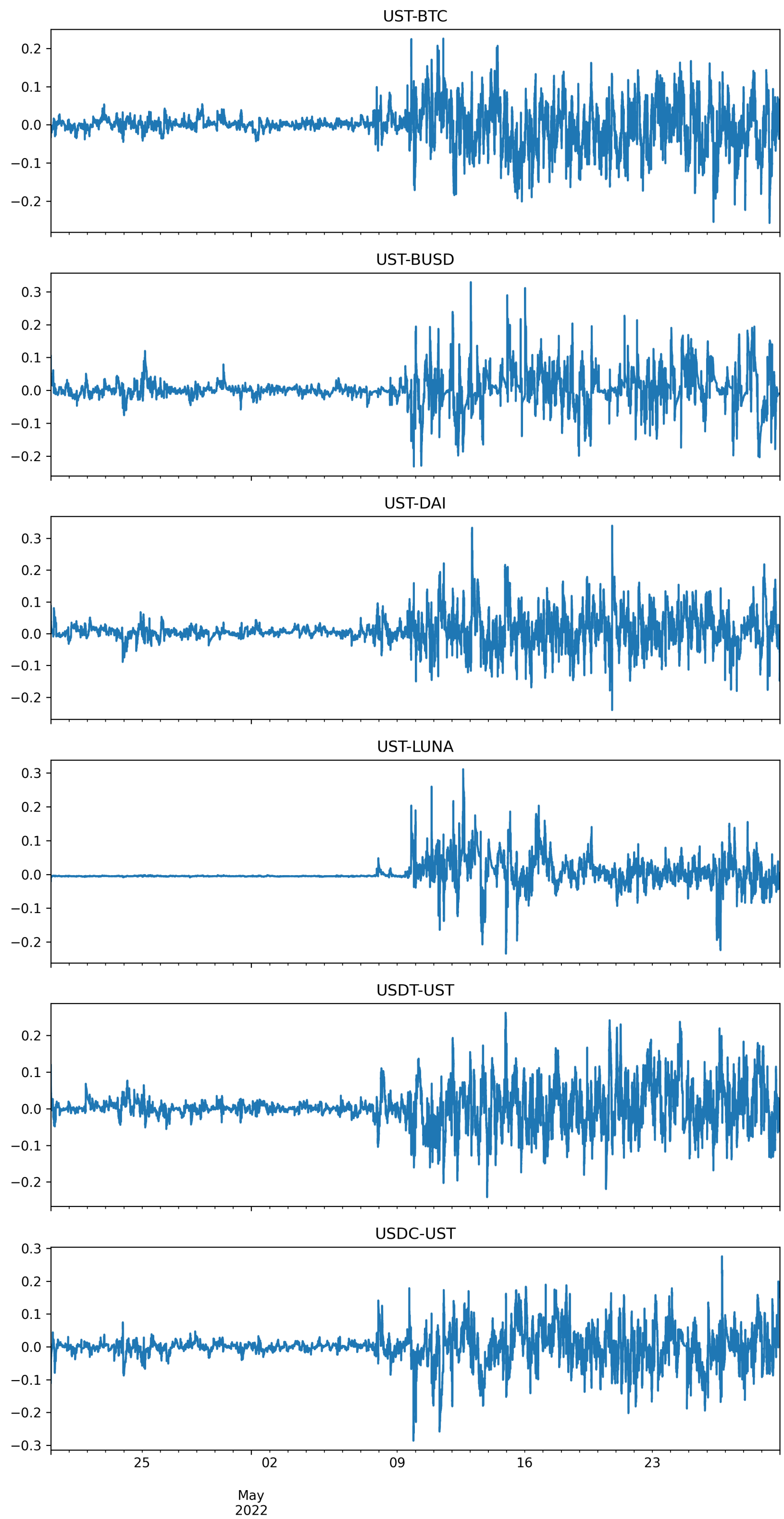

Figure 5: Stationary covariances

Figure 6: UST price series

Appendix. Stablecoins description

Tether

Tether is the largest stablecoin by market capitalization and most popular by trade volume.[14] Tether's website[15] claims its reserves are 85.64% "Cash & cash equivalents & other short-term deposits & commercial paper". With another 6.02% in "Other Investments" which includes digital tokens. The Financial Times[16] and Bloomberg[17] have both published articles questioning the makeup of Tether's commercial paper holdings, with the articles discussing speculation that some of the assets may be marked down "Chinese or Asian"[18] commercial paper, a charge Tether has denied, amidst worries over the creditworthiness of some mainland Chinese firms.[19]

Restrictions on the redemption of Tether exist. A 150 USDT verification fee is required to set up an account, while withdrawal fees of .01% or $1000 (whichever is greater) apply to any withdrawal. $100,000 is the current minimum withdrawal size.[20] Most U.S. persons or entities cannot withdraw fiat currency with the service. As a result, the redemption ability of Tether only approaches a $1 for 1 ratio at very high withdrawal sizes.[21]

Tether's price has diverged from $1 on multiple occasions. For example, on March 12, 2020, it traded at $1.05. On March 17, 2021, it traded below 98 cents. Those examples are indicative and not exhaustive. On February 17, 2021, Tether settled a lawsuit from New York Attorney General, Letitia James, who said "Tether's claims that its virtual currency was fully backed by US dollars at all times was a lie". Tether agreed to pay $18.5 million and end trading with New York residents and entities.

The incentive structure of coins like Tether has also come into question. Economist Tyler Cowen has suggested that Stablecoin issuers have incentives to print stablecoins in excess of the amount that reserves would directly support. In a thought experiment, he argues; "If the price of your coin stays at $1, fine, you come out ahead. If the price declines in proportion

[14] As of July 27, 2022.

[15] `https://tether.to/en/transparency/#reports`. Accessed 27 June, 2022.

[16] `https://www.ft.com/content/59849743-850a-4f67-8e78-fdc68651d2d4`. Accessed July 6, 2022.

[17] `https://www.bloomberg.com/news/features/2021-10-07/crypto-mystery-where-s-the-69-billion-backing-the-stablecoin-tether`. Accessed July 6, 2022.

[18] `https://tether.to/en/tether-condemns-false-rumours-about-its-commercial-paper-holdings/`. Accessed July 6, 2022.

[19] `https://www.bloomberg.com/news/articles/2022-04-24/china-s-restructuring-firms-staff-up-for-record-wave-of-defaults`. Accessed July 6, 2022.

[20] As of July 26, 2022. `https://tether.to/en/fees/`.

[21] Tether reportedly charges a .01% redemption rate on sums up to 1 million dollars, but does not charge after 1 million dollars. `https://cryptoslate.com/you-can-redeem-tether-usdt-11-on-tether-to-but-theres-a-catch/`. Accessed July 26, 2022.

to the new and higher risk, you as an issuer still have broken even".[22]

DAI

DAI is a stablecoin on the Ethereum blockchain which maintains its peg to the dollar using a series of smart contracts and the Target Rate Feedback Mechanism (TRFM). If Dai falls below $1, the TRFM will increase, incentivising the market to push the price up. Dai tokens are created through borrowing. Users lock collateral on the blockchain, and they receive DAI in the amount of their locked collateral. The DAI is burned when this collateral is repaid.[23]

DAI was created by MakerDAO, a decentralized organization. DAI itself is also decentralized, thus, anyone can create DAI using accepted forms of collateral. Dai can be shut down in a semi-democratic process known as Global Settlement.

Collateral is not necessarily exchanged for DAI at a one-to-one basis. On April 1, 2022, the MakerDAO twitter account noted a user with $30,000 of collateral could create at most, 20,689 DAI. IDAI has historically been collateralized only with cryptocurrency assets, but in June 2022 participants voted to begin investing $500 million in US Treasury bills.[24]

On March 13, 2020, amidst financial uncertainty during the early stages of the COVID-19 pandemic, DAI traded at $1.09.[25]

TerraUSD

TerraUSD was an algorithmically balanced stablecoin, whose design was supposed to use market incentives to maintain parity with the dollar. TerraUSD was linked to Luna, with the names of these currencies analogizing their relationship to that of the earth and the moon. Beginning on May 9, 2022, a fall in UST led to a collapse of the peg between UST and the dollar. The cryptocurrency has never fully recovered, and as of July 5, 2022, UST trades at around 6 cents, after falling to under 1 cent in June 2022.

TerraUSD was theoretically pegged to $1 and supposedly balanced by the expanding or contracting supply of LUNA. When TerraUSD traded below the peg, the protocol incentivized users to "burn" (destroy) TerraUSD and "mint" (create) Luna, balancing the

[22] "Let's say your issue is currently one-to-one with the U.S. dollar and you are holding 100% reserves of very safe assets. Might you then be tempted to go down to 98% reserves? 95%? If the price of your coin stays at $1, fine, you come out ahead. If the price declines in proportion to the new and higher risk, you as an issuer still have broken even". `https://marginalrevolution.com/marginalrevolution/2021/10/will-stablecoins-have-fluctuating-prices.html`. Accessed July 6, 2022.

[23] `https://learn.bybit.com/altcoins/a-beginners-guide-what-is-dai-and-how-does-it-work/#4`. Accessed July 7, 2022.

[24] `https://www.theblock.co/post/154515/maker-governance-is-voting-to-invest-500-million-in-us-treasury-bills`. Accessed July 7, 2022.

[25] `https://coinmarketcap.com/currencies/multi-collateral-dai/`. Accessed July 7, 2022.

prices.[26] Every time a new UST was created, $1 of LUNA was "burned" on the "Terra" Blockchain.

Investopedia noted[27] "The Terra protocol maintains the price of the Terra stablecoin by ensuring that the supply and demand for it are always balanced. This is achieved by using LUNA as the variable counterweight to the TerraUSD stablecoin".

Consumers lending UST were offered a nearly 20% interest rate.[28] Binance marketed this as a "safe and happy" investment opportunity.[29] Terra founder Do Kwan told Bloomberg that "it's actually not unnatural for currencies of growing economies to offer higher interest rates than those of mature, stable economies".[30] By contrast, USDC deposits offered interest rates of 3.5-5.5%, while US dollar deposits at major American banks earned less than 1%. The interest payments came from TerraUSD's reserves, causing some trepidation amongst investors. It appears likely that the high-interest rate was necessary to keep up demand for UST tokens. Without this demand, the peg could not survive.

An entity known as Luna Foundation Guard–which was once the world's second-largest known holder of Bitcoin–backed Terra with reserves denominated in cryptocurrency. These reserves primarily included around 80,000 Bitcoin (worth around $2.4 billion on May 7, 2022) as well as approximately $65 million in Avalanche, as well as $12 million in "Binance tokens".[31] Nearly all of the Bitcoin reserves were depleted in an apparent effort to maintain the peg.

Several market observers were sceptical about the stability of TerraUSD. Galois Capital called LUNA "doomed to fail" and a "confidence game" around two months before TerraUSD's and LUNA's collapse.[32]

On May 25, 2022, Vitalik Buterin, co-creator of Ethereum, argued that stablecoins with the general algorithmic design of UST can become "extremely fragile" if the activity of the asset their price depends on (in this case, LUNA) drops significantly. Because TerraUSD required active trading and value in Luna to balance its own prices, weakness in one currency could lead to problems in the other.

On May 15, 2022, LUNA had a price of $.004173 but an incredible 24-hour volume of $15.92 Billion, showing a dramatic surge of trading activity as the coin collapsed. A month

[26] `https://www.investopedia.com/terra-5209502`. Accessed July 5, 2022.

[27] `https://www.investopedia.com/terra-5209502`. Accessed July 5, 2022.

[28] The Financial Times article notes Binance advertised this as a 19.63% rate, although Bloomberg reports lenders using the Anchor protocol made 19.45%.

[29] `https://www.ft.com/content/d459f435-edff-412c-85a5-0961d50aba69`. Accessed July 5, 2022.

[30] `https://www.bloomberg.com/news/articles/2022-03-23/terra-s-promise-of-20-defi-return-raises-sustainability-concern`. Accessed July 4, 2022.

[31] `https://fortune.com/2022/05/16/luna-foundation-guard-dumps-bitcoin-reserves-terra-usd-peg/`. Accesssed July 5, 2022

[32] `https://www.nasdaq.com/articles/is-luna-doomed-to-fail`. Accessed July 5, 2022

earlier LUNA traded at $84.5 with a 24-hour volume of 2.4 billion.[33]

Months prior to the collapse of TerraUSD, the Securities and Exchange Commission (SEC) filed a subpoena enforcement action against TerraUSD form Labs and Do Kwon relating to the Mirror Protocol, a Decentralized Finance (DeFi) protocol that allowed the creation and trading of digital assets that "mirrored" the prices of securities.[34]

UST had broken the buck before, but never in such a dramatic, sustained fashion. On 12/30/2020 UST reached 85 cents on the dollar before recovering to .9973 the next day. On 1/31/2021 it reached 1.04. On 5/23/2021 it traded at 94 cents on the dollar.[35] Despite these sharp fluctuations, UST generally traded at just over $1, suggesting some degree of market faith in the project.

[Figure 6 about here]

What motivated the creation of TerraUSD? Basically, the creators of UST wanted to establish privately issued money. What were the problems that TerraUSD was trying to solve? Essentially, the founders of TerraUSD were trying to facilitate the use of cryptocurrencies as a medium of exchange and store of value or money by eliminating their volatility. They were also trying to facilitate the adoption of UST as a medium of exchange and enlarge the network of users by incentivizing its use. TerraUSD is essentially a pegged currency. If the price falls below its pegged value, then the money supply is reduced and if its price is above its pegged value then the money supply is increased. The plan was to have a companion cryptocurrency, Luna, that acts as collateral and supports the stablecoin. The plan was to encourage arbitrageurs to act to exploit any price discrepancies from the pegged value.

USDC

USDC was developed by the Center consortium, a partnership between US-based cryptocurrency exchange Coinbase, and US-based peer-to-peer payments company, Circle. In an article published on 13, June 2022, the CFO of Circle wrote that around 80% of USDC reserves are short-dated US Treasuries and around 20% cash.[36]

Circle, the entity which co-founded USDC, "is regulated as a licensed money transmitter under US state law".[37] Short monthly "Reserve Account Reports" are available online, with

[33] Data from CoinMarketCap, accessed July 30, 2022. `https://coinmarketcap.com/currencies/terra-luna/`

[34] `https://www.sec.gov/litigation/litreleases/2021/lr25262.htm`. Accessed July 5, 2022

[35] Price information from CoinMarketCap, accessed July 26, 2022.

[36] `https://www.circle.com/blog/usdc-trust-and-transparency-liquidity-matters`. Accessed July 6, 2022

[37] `https://www.circle.com/en/usdc`. Accessed July 6, 2022

attestations that the "total fair value of US Dollar denominated assets held on behalf of USDC holders is at least" equal to the value of all USDC in circulation. Audits take place yearly as part of Circle's financial statements.[38]

Underscoring the differing acceptance of stablecoins in the traditional financial industry, on 29 March 2021, Visa announced a pilot program allowing payment settlements with USDC.[39]

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[38] `https://www.circle.com/blog/how-to-build-trust-usdc-audits-and-attestations`. Accessed July 6, 2022

[39] `https://www.reuters.com/article/crypto-currency-visa/exclusive-visa-moves-to-allow-payment-settlements-using-cryptocurrency-idINKBN2BL0XI`. Accessed July 6, 2022.