Tokenomics: How "Risky" are the Stablecoins?

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Abstract

This study proposes a new risk measure for stablecoins, that is based on the probability of the stablecoin's price hitting a threshold exchange rate post which the stablecoin is subjected to the risk of "break the buck/ death spiral". We also juxtapose the risk measure computed using different models - Vasicek, CIR, ARMA+GARCH and Vasicek+GARCH and suggest the policy implication of the estimated model parameters - rate of reversion *(a)* and long term mean exchange rate *(b)* for stablecoin issuers. The study compares the volatility behaviour of the stablecoins with that of the traditional cryptocurrency, Bitcoin, equity index, NASDAQ composite and fiat currency, EURO. Stablecoins tend to be "stable" barring the events such as Terra – Luna crisis, FTX Bankruptcy and Silicon Valley Bank crisis. Traditional asset backed stablecoins – Tether, USD Coin, Binance USD and True USD are less risky than the decentralized algorithmic stablecoin, FRAX and decentralized cryptoasset backed stablecoin, DAI. The proposed risk measure could be of utility to the stablecoin issuers of algorithmic and cryptoasset backed stablecoins and the regulators for setting the capital requirement to guard against the break the buck/ death spiral risk.

Keywords: Cryptocurrency, Stablecoins, Terra – Luna crisis, FTX Bankruptcy, Silicon Valley Bank crisis, Risk Measure, VaR, Vasicek, CIR, GARCH, Bitcoin, Tether, USD Coin, Binance USD, True USD, DAI, FRAX

JEL codes: F31, G01, G11, G15, G23, G28

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[3] *The findings, interpretations, and conclusions expressed in this study are entirely those of the authors. They do not necessarily represent the views of Tata Consultancy Services (TCS), India.*

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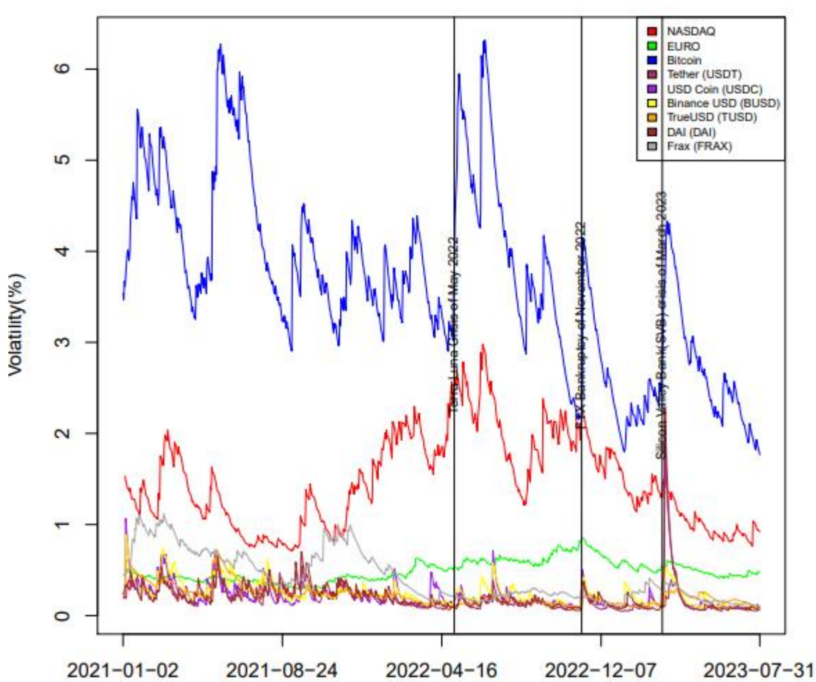
“The most important initiative you could take to improve the world economy would be to stabilize the dollar-euro rate.”

-Robert Mundell

1. Introduction

Stablecoin will make the Metaverse go round. Cryptocurrencies or the “Tokens” of a Metaverse must be “Stable”. Only a currency that is stable and retains the purchasing power in both the short and the long run – with minimal risk of pathologies such as the hyperinflation can serve as a medium of exchange in a Metaverse. A volatile cryptocurrency such as Bitcoin cannot be a medium of exchange in a Metaverse. A class of cryptocurrencies that maintains a stable exchange rate with a fiat currency such as the US Dollar, using various mechanisms, is called Stablecoins (Berentsen and Schär, 2019; Baumöhl and Vyrost, 2020; Dirk and Hoang, 2021; Anadu et. al. 2023). Thus, stablecoins are cryptocurrencies that are designed to minimize the exchange rate volatility. Stablecoins are inherently different than cryptocurrencies such as Bitcoin that do not have a mechanism to control the exchange rate volatility and are therefore not appropriate to serve as a hard currency for an economy. Figure 1 juxtaposes the daily volatility of NASDAQ composite index, price of EURO in USD, Bitcoin and the six stablecoins considered in this study. Stablecoins exhibit lower volatility than the other asset classes. Other studies have reported similar results (Harvey et.al., 2022; Shah and Bahri 2018).

Figure 1: Daily conditional volatility of NASDAQ Composite, EURO Exchange Rate, Bitcoin and six stablecoins



Relationship between the stablecoin design and its stability is crucial to the decentralized finance (DeFi), non-fungible tokens (NFTs), and Web3 protocols (Catalini, de Gortari and Shah; 2021). The table 1 below lists the market capitalization and other characteristics of the six stablecoins considered in this study, as on 28th August 2023. Tether and USD Coin with the market capitalization of 82.8 and 26 billion USD were the leading stablecoins.

Table 1 Market Capitalization and other characteristics of the stablecoins:[5]

Stablecoin	*Market Capitalization * , USD Billion*	*Type*	*Collateral*	*Launch Date*
Tether (USDT)	82.80	Centralized	Traditional asset backed - USD, EUR	2014
USD Coin (USDC)	26.00	Centralized	Traditional asset backed - USD	
DAI (DAI)	5.35	Decentralized	Crypto asset backed - ETH	2017
Binance USD (BUSD)	3.15	Centralized	Traditional asset backed - USD	2019
True USD (TUSD)	2.90	Centralized	Traditional asset backed - USD	2018
Frax (FRAX)	0.80	Decentralized	Collateral; Algorithmic Market Operations (AMO) contracts	2019

There are three major classes of stablecoins based on the underlying governance mechanism and the collateral asset type; 1. Centralized traditional asset backed (fiat currencies, treasury securities, commercial bonds, bullions etc) 2. Decentralized cryptoasset, example Ethereum backed 3. Decentralized algorithm governed.

A centralized traditional asset backed stablecoin is minted by a central issuer and issued to a limited set of investors on their public address on a blockchain, against a payment of a fiat currency. General market participants can transact stablecoins on crypto exchanges. The redemption occurs when an investor returns a stablecoin to the public address of the central issuer on the blockchain and in return the issuer credits the fiat currency in the investor's bank account. Tether, USD coin, Binance USD and True USD are examples of centralized traditional asset backed stablecoins and are pegged to the USD.

Decentralized stablecoins such as DAI are not managed by a central issuer. These stablecoins are managed by a lending protocol and a decentralized autonomous organization (DAO) whose

[5] As on 28th August 2023
https://medium.com/@92CLUB.ETH/stablecoins-demystified-a-comparison-of-dai-usdt-and-usdc-6f43c2dac0a3
https://builtin.com/blockchain/stablecoin
https://www.coingecko.com/learn/what-is-frax-crypto
https://www.coingecko.com/learn/what-are-decentralized-stablecoins
https://www.coingecko.com/en/categories/stablecoins
https://docs.frax.finance/amo/overview
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participants vote to decide collectively on the governance mechanism of the stablecoin. DAI's protocol - MakerDao, for example, uses collateralized debt positions to control the price volatility. DAI is over collateralized as MakerDao lending system requires a market participant to deposit 150% i.e. USD 150 worth of Ethereum (ETH) collateral to mint USD 100 worth of DAI. These minted DAI's are a loan to the investor. When the investor returns the "borrowed" DAI with the accrued interest, ETH collateral is released, and DAI is burnt.

The overcollateralization of DAI makes it more stable but also capital inefficient. FRAX (v1 – base stability mechanism) was conceptualized as a fractional algorithm stablecoin, using both an asset collateral and a governing algorithm to maintain the peg stability (to 1 USD). Most decentralized algorithmic stablecoins depend on an accompanying counterweight volatile cryptocurrency for maintaining the price stability. The accompanying cryptocurrency to FRAX is the FRAX share - FXS. To mint a FRAX an investor provides collateral in cryptocurrency such as the USD Coin (USDC) and FXS. The ratio of the collateral to FRAX depends on the market conditions. During the adverse market conditions – i.e. FRAX price below 1 USD, a higher collateral ratio (CR) is required. For example, this adverse market conditions dictate a CR of 75%, then to mint one FRAX, 75% of USDC and 25% of FXS supply is required. One FRAX is minted and 25% FXS is burnt. If a FRAX is redeemed in the given adverse market conditions, i.e. CR ratio of 75%, the investor receives 75% USDC and 25% FXS and FXS is minted and FRAX is burnt post redemption. In favourable market conditions – i.e. FRAX above 1 USD a lower collateral ratio is required[6]. Thus, the methodology of variation in the CR ratio is used to influence the demand of FRAX.

Stablecoins exhibit lower conditional volatility than Bitcoin, NASDAQ composite and EURO but the conditional volatility of stablecoins does increase during crises (figure 1). We consider the following three stablecoin crisis (Table 2) and test if these crises had a significant influence on the realized mean and the volatility of the stablecoins:

Table 2: Crypto crisis

	Crisis	Dummy Variable Dates
1	Terra-Luna crisis of May 2022	5th May to 13th May 2022
2	FTX Bankruptcy of November 2022	9th November to 11th November 2022
3	Silicon Valley Bank (SVB) crisis of March 2023	8th March 2023 to 16th March 2023

[6] https://www.coingecko.com/learn/what-is-frax-crypto

Terra USD (UST) – an algorithmic stablecoin with the fourth largest market cap in May 2022, suffered a run. While UST was pegged to USD, LUNA was the counterweight cryptocurrency used to reduce volatility in UST. 1 UST had a fixed peg to 1 USD worth of Luna tokens. When UST prices traded below 1 USD (say 1 UST = 0.995 USD), implying that the supply of UST was more than the market demand, investors would buy 1 UST and exchange it for 1 USD worth Luna, thus making the corresponding profit (0.005 USD). In the process, 1 UST was burned and 1 LUNA was minted. Thus, reducing the UST supply and fostering the upward movement of UST to hit fixed peg (Yip 2022; Uhlig 2022; Briola et.al. 2023; Liu et.al. 2023). In May 2022, fearing that the UST would break the dollar peg investors started redeeming UST for 1 USD worth of LUNA, thus creating pressure on the LUNA prices. This led to a death spiral (Briola et.al. 2023), wherein LUNA had turned worthless by the end of the crisis. Liu, Makarov and Schoar (2023) consider the death spiral unlikely due to the market manipulation but consider a concern of systemic failure as a more plausible reason. The death spiral was further accelerated due to the blockchain technology as the investors could monitor each other's action on the blockchain. The losses were disproportionate favouring the sophisticated investors who could and responded to the crisis faster. The crisis exhibited risk of contagion, Tether that was unrelated to the Terra USD was affected by heavy redemption and broke the 1 USD fixed peg but surprisingly, fiat backed stablecoins suffered comparatively lower redemptions (Yip 2022).

The second crisis we consider is the collapse of third largest crypto exchange FTX in November 2022[7]. A surge in investor withdrawals post reports of questionable valuations and related party transaction resulted in FTX bankruptcy. The event affected the cryptocurrencies especially Bitcoin. In March 2023, Silicon Valley Bank (SVB) collapsed. SVB was part of the traditional financial ecosystem and had no bearing on the cryptocurrencies except that the USD Coin, a stablecoin with the second largest market cap then, held collateral – treasury securities and deposits at SVB (Lai and Huong; 2023). Thus, investors lost confidence and consequently USD coin suffered a run. This crisis spilled over into DAI and FRAX as these had USD coin as the collateral. During the crisis investors diverted the funds towards Tether, which was perceived to be stable (Anadu et.al. 2023).

We contribute to the growing literature on stablecoin stability. Past works have compared stablecoins with other cryptocurrencies and traditional financial assets and analysed the volatility behaviour and stability of the stablecoins (Berentsen and Schär, 2019; Eichengreen, 2019; Bullmann, Klemm and Pinna, 2019; Baur and Hoang, 2020; Baumöhl and Vyrost, 2020, Gorton and Zhang, 2021; Clements, 2021; d'Avernas, Maurin, and Vandeweyer, 2022; Lyons and Viswanath-Natraj, 2023). Causal analysis of cryptocurrency crisis has been subject of many studies, Uhlig, 2022; Yip, 2022; Briola et.al. 2023; Lai Van and Huong, 2023; Liu, Makarov and Schoar, 2023; to name a few. Catalini and Gortari (2021) state that the volatility of the reserve

[7] https://www.investopedia.com/what-went-wrong-with-ftx-6828447

assets against the reference asset and the risk of a death spiral to the stablecoin are the two critical dimensions in the economic design of every stablecoin.

The objective of this study is to compare the volatility behaviour of various stablecoins against that of the equity index (NASDAQ composite), fiat currency, EURO and "traditional" cryptocurrency - Bitcoin. The study also investigates the differences in the volatility behaviour of the stablecoins based on their characteristics (table 1) and impact of the three-crisis stated above. Furthermore, the value proposition of a stablecoin is its ability to maintain a stable peg – an exchange rate or price of 1 USD/Stablecoin. Anadu et. al. (2023) estimate that if a stablecoin price drops below USD 0.99 ("break the buck/ death spiral" threshold), the stablecoin experiences a 3.4% greater daily outflow. Thus, the redemption accelerates below this threshold (L) and investors tend to consider a stablecoin depegged and the stablecoin is subject to a "break the buck/death spiral" risk. Hence, we propose a stablecoin risk measure based on the probability of hitting a given threshold *(L)* over the next *n* days. This risk measure could then be used to set the level of regulatory traditional collateral/ capital requirement for a coin issuer to guard against the break the buck or death spiral risk. The higher the level of collateralization or regulatory capital, better is the peg stability and lower is the death spiral risk (Lynos and Vishwanath Natraj; 2022).

2. Data and stylized facts of Stablecoins

The data for various assets used in this study is summarized under table 3 below:

Table 3: Data[8]

Index/ Asset	Period	Frequency
NASDAQ	1st January 2021 - 31st July 2023	Daily
EURO	1st January 2021 - 31st July 2023	Daily
Bitcoin	1st January 2021 - 31st July 2023	Daily
Tether (USDT)	1st January 2021 - 31st July 2023	Daily
USD Coin (USDC)	1st January 2021 - 31st July 2023	Daily
DAI (DAI)	1st January 2021 - 31st July 2023	Daily
Binance USD (BUSD)	1st January 2021 - 31st July 2023	Daily
True USD (TUSD)	1st January 2021 - 31st July 2023	Daily
Frax (FRAX)	1st January 2021 - 31st July 2023	Daily

The Annexure 1 presents the daily exchange rate/ prices in level for the period stated in table 3. Stablecoins prices/ exchange rates do not exhibit any trend or seasonality, as they are pegged to 1 USD. Thus, assuming stationarity, we could perform the analysis on the stablecoin prices in level without differencing or using the log returns of the series. We used the log returns[9] of the time

[8] Bitcoin and Stablecoin exchange rates (price) data are obtained from CoinGecko website).

[9] $Log\ return\ r_t = ln\left(\frac{x_t}{x_{t-1}}\right)$, where x_t is the exchange rate/price of the asset at the time t.

series in this study for comparison across the asset classes. The plots of the daily log returns (Annexure 2) show the evidence of the volatility clustering. Table 4 below provides the descriptive statistics and the results of the Jarque-Bera (JB) test of normality for the log returns.

Table 4: Descriptive statistics and *t* test results

Descriptive Statistics of Returns

Daily Log returns

	NASDAQ Composite	EUR	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
Mean	0.00019	-0.00016	0.00001	-	-0.00000	-0.00000	-0.00000	-0.00000	0.00000
Median	0.00039	-0.00009	-0.00024	0.00002	0.00001	0.00004	-0.00011	0.00005	0.00008
Maximum	0.07093	0.02111	0.17603	0.01731	0.02867	0.01939	0.02930	0.02812	0.03083
Minimum	-0.05297	-0.01526	-0.17252	-0.01404	-0.02849	-0.01860	-0.02031	-0.02920	-0.03071
Stdev	0.01545	0.00503	0.03546	0.00247	0.00303	0.00304	0.00312	0.00285	0.00580
Skewness	-0.15107	0.14907	-0.20062	0.00485	0.13431	-0.18397	0.87880	-0.22564	-0.00481
Kurtosis	1.01869	1.03126	3.18852	6.45096	21.13586	7.45560	16.76259	23.24214	4.77518
Mean/Stdev	0.012	-0.031	0.000	-	-0.000	-0.000	-0.001	-0.001	0.001
J-B	31.1	32.9	408.3	1,641.8	17,603.4	2,197.8	11,193.8	21,290.2	900.3
P-value	0.00	0.00	-	-	-	-	-	-	-
Obs	646	671	941	941	941	941	941	941	941

t tests for mean, skewness and Kurtosis

Daily Log returns

	NASDAQ Composite	EUR	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
t-value mean	0.311	-0.806	0.008	0.002	-0.015	-0.005	-0.020	-0.034	0.013
	0.756	*0.421*	*0.994*	*0.998*	*0.988*	*0.996*	*0.984*	*0.973*	*0.989*
t-value skewness	-1.571	1.576	-2.516	0.061	1.685	-2.308	11.023	-2.830	-0.060
	0.117	*0.115*	*0.012*	*0.951*	*0.092*	*0.021*	*0.000*	*0.005*	*0.952*
t-value Excess kurtosis	5.285	5.453	19.965	40.394	132.345	46.684	104.962	145.534	29.901
	0.000	*0.000*	*0.000*	*0.000*	-	*0.000*	-	-	*0.000*

The JB test indicates that, the normality assumption is strongly rejected for all the log returns. The means of all the log returns are not significantly different from zero and all the log returns exhibit pronounced excess kurtosis. Log returns of Bitcoin, Binance USD, True USD and DAI exhibit significant skewness. Annexure 3 depicts the density plots of various log returns; Bitcoin and NASDAQ composite exhibit significantly greater standard deviation than the stablecoins.

Annexure 4 shows the autocorrelation (ACF) and partial autocorrelation (PACF) functions of daily log returns. Table 5 provides the results of the unit root (Augmented Dickey Fuller and Philips-Perron tests) and the Ljung Box tests.

Table 5: Unit Root tests and the Ljung-Box test Results

Unit Root tests									
Daily Log returns									
	NASDAQ Composite	EUR	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
ADF Stat. nc (no constant)	-6.75	-7.33	-8.25	-12.54	-13.68	-12.74	-13.21	-12.45	-13.42
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
ADF Stat. c (only contant)	-6.74	-7.38	-8.25	-12.54	-13.68	-12.74	-13.20	-12.44	-13.42
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
Ljung- Box, Q stat lag=1	0.27	0.00	0.49	235.91	159.44	175.28	231.34	175.38	233.28
	0.60	*0.98*	*0.48*	-	-	-	-	-	-
Ljung- Box, Q stat lags=5	2.45	1.70	1.96	239.14	183.62	219.61	280.96	184.41	234.60
	0.78	*0.89*	*0.85*	-	-	-	-	-	-
Ljung- Box, Q stat lags=12	12.21	14.73	12.04	249.13	191.87	238.40	301.31	185.24	245.91
	0.43	*0.26*	*0.44*	-	-	-	-	-	-
Ljung- Box, Q stat lags=20	23.39	21.62	19.01	260.77	208.80	245.71	319.36	208.34	271.18
	0.27	*0.36*	*0.52*	-	-	-	-	-	-
PP Test Stat.	-617.15	-641.95	-998.85	-1,158.28	-1,042.14	-1,056.04	-1,141.77	-1,055.86	-1,155.40
	0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*

The null hypothesis of the existence of a unit root is rejected under the Augmented Dickey Fuller (ADF, 12 lags) and Phillips–Perron (PP) tests for all the log returns time series. But all the stablecoins exhibit significant serial correlation at 1, 5, 12 and 20 lags (significant Ljung-Box statistic, Ljung and Box, 1978). In an efficient market, there should be no predictability in the log returns (Lo 2005; Shah and Bahri, 2019). The predictability in the log returns could be the result of initiatives by coin issuers to maintain the stablecoin peg. For example, if the price is more than 1 USD today, there is a likelihood of a negative return the next day to maintain the peg at 1 USD. If the log returns are small, it may not be possible to economically exploit this inefficiency in the market. This is only an untested assertion.

The annexure 5 shows the autocorrelation (ACF) and the partial autocorrelation (PACF) functions of the daily squared log returns of the various assets. Table 6 below provides the results for the Ljung Box tests. The predictability of squared log returns in all the time series suggests the presence of volatility clustering and utility of GARCH process in modelling the conditional volatility.

Table 6: Ljung-Box tests for the squared log returns

Summary of Ljung Box Tests for squared return series

	Daily Log returns								
	NASDAQ Composite	EUR	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
Ljung- Box, Q stat lag=1	4.16	10.89	8.31	159.23	253.85	149.83	161.38	224.78	223.58
	0.04	*0.00*	*0.00*	-	-	-	-	-	-
Ljung- Box, Q stat lags=5	54.99	63.33	18.83	259.99	258.28	178.76	223.32	226.39	346.38
	0.00	*0.00*	*0.00*	-	-	-	-	-	-
Ljung- Box, Q stat lags=12	136.47	109.41	39.02	321.48	259.02	201.95	280.66	226.88	451.55
	-	-	*0.00*	-	-	-	-	-	-
Ljung- Box, Q stat lags=20	221.16	167.01	54.64	341.33	260.84	220.54	281.85	228.16	605.13
	-	-	*0.00*	-	-	-	-	-	-

A simple correlation analysis (Table 7) between the log returns of various assets indicates that Bitcoin log returns show low, albeit significant correlation with other stablecoins. But the correlation between USD Coin, Binance USD, True USD, DAI and FRAX is high and significant, despite differing characteristics (table 1). This is quite surprising. DAI is correlated with Tether but this could be because DAI holds cryptocurrencies as the collateral. Diversification benefit in a portfolio of stablecoins would be low.

Table 7: Unconditional Correlation Analysis

Covariance Analysis : Pearson
Sample : Daily log returns

Correlation Probability	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
Bitcoin	1.00000						

Tether	-0.00464	1.00000					
	0.88692	-----					
USD Coin (USDC)	0.15476	0.19444	1.00000				
	0.00000	*0.00000*	-----				
Binance USD (BUSD)	*0.12998*	*0.12691*	*0.56082*	*1.00000*			
	0.00006	*0.00009*	-	-----			
TrueUSD (TUSD)	0.18313	0.19163	0.61985	0.68274	1.00000		
	0.00000	*0.00000*	-	-	-----		
DAI	0.05634	0.59970	0.52776	0.23773	0.27603	1	
	0.08413	-	-	*0.00000*	-	-----	
FRAX	0.19569	0.15770	0.51466	0.36762	0.45007	0.36551674	1.00000
	0.00000	*0.00000*	-	-	-	-	-----

3. Value at Risk and Expected Shortfall using Extreme Value Theory:

A widely used risk measure in the field of financial risk management is Value at Risk (VaR). The daily VaR of an investment in an asset at the confidence level α is given by the smallest number q such that the probability that the daily log return r_t of that asset is lower than q is no larger than $(1-\alpha)$ (McNeil, Frey and Embrechts 2005).

$$VaR_\alpha = inf\{q \in \mathbb{R} : \ P(r_t \le q) \le (1-\alpha)\} \tag{1}$$

We use $\alpha = 0.99$ in this study. Here, VaR is not reported as an absolute loss but as the negative log return that an investor could realize. VaR though is not a coherent risk measure. A risk measure that addresses the shortcomings of VaR is the expected shortfall (ES) which is the expected r_t give that r_t is less than VaR (McNeil 1999). Note, in the equation below, *E* is the expectation operator under the real world or *P* measure.

$$ES_\alpha = E^P(r_t | r_t \le VaR_\alpha) \tag{2}$$

We calculate VaR and the expected shortfall using the Extreme Value Theory (EVT), as the log returns exhibit high kurtosis (table 4). EVT is an apt tool that provides a good estimate of the tail area of the distribution. There are two kinds of models for the extreme risks in EVT (McNeil 1999).

1. Block maxima models
2. Peak over threshold models (POT)

Block over maxima model is based on the smallest log returns collected from large blocks of identically distributed observations while POT models utilize all the observations that exceed a specified threshold. Thus, POT model is used more frequently due to its efficient use of the limited extreme data. POT models either use Hill Estimator or Generalized Pareto Distribution (GPD). In this study, we used GPD model to analyse the extreme risk in the log returns of the stablecoins. A GPD is a two-parameter distribution given by:

$$G_{\xi,\beta}(x) = \begin{cases} 1-\left(1+{}^{\xi x}/_{\beta}\right)^{-1/\xi} & \xi \neq 0 \\ 1-exp\left(-{}^{x}/_{\beta}\right) & \xi = 0 \end{cases} \tag{3}$$

$where\ \beta > 0,$

$if\ \xi \ge 0\ then\ x \ge 0,$

$if\ \xi < 0\ then\ 0 \le x \le -{}^{\beta}/_{\xi}$

Here x represents negative returns which are lower than a chosen threshold negative return[10], ξ is the shape parameter and β is the scaling parameter. Based on the parameters following distributions emerge:

$\xi > 0$	Ordinary Pareto distribution
$\xi = 0$	Exponential distribution
$\xi < 0$	Short tailed Pareto II type distribution

For risk management $\xi > 0$ case is more relevant as the distribution is heavy tailed. Note, for GPD with $\xi > 0$, $E(X^k)$ is infinite for $k \geq 1/_{\xi}$. This means that for $\xi \geq 1/_2$, the loss distribution that is fitted with GPD has infinite variance. This is very crucial for the risk management (McNeil 1999). Once an appropriate extreme value GPD distribution is fitted to the excess log return data, extreme value VaR and ES could be calculated. Table 7 below provides the parameter of GPD and calculated VaR and ES for all the assets.

Table 8: GPD Parameters, VaR and Expected Shortfall

	NASDAQ Composite	EUR	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
Xi	(0.089)	(0.061)	(0.041)	0.030	0.479	0.245	0.324	0.235	(0.035)
se	*0.163*	*0.143*	*0.111*	*0.090*	*0.131*	*0.101*	*0.107*	*0.095*	*0.118*
Beta	0.010	0.003	0.031	0.002	0.001	0.002	0.002	0.002	0.005
se	*0.002*	*0.001*	*0.005*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*
Var99	4.00%	1.25%	10.49%	0.75%	0.87%	0.89%	0.84%	0.80%	1.76%
ES99	4.71%	1.48%	13.18%	0.99%	1.71%	1.33%	1.34%	1.18%	2.24%

For all the stablecoins except FRAX, $\xi > 0$, indicating an ordinary pareto distribution fit for the tail area. Though this distribution is heavy tailed, none of the stablecoins exhibit infinite variance i.e. $\xi > 0.5$. But for USD coin and True USD, $\xi > 0.25$, indicating that these stablecoins exhibit infinite fourth moment. Both the VaR and the expected shortfall of all the stablecoins is comparable to those of EURO and significantly lower than Bitcoin.

[10] We substitute $x = -r_t$ as GPD is fitted to a positive random variable. We fit GPD to only those r_t that are lower than a threshold. We consider a threshold value of 0.1 percentile of the empirical log return distribution for each asset.

4. GARCH Modelling

One of the objectives of the study was to estimate the conditional volatility of various stablecoins and compare the volatility behaviour with that of the Bitcoin, EURO and NASDAQ Composite index especially during the three crises. Exploratory analysis in the section 2 showed that the daily log returns of the stablecoins exhibited the stylized facts of non-normal empirical distribution, fat tail and the volatility clustering. GARCH models are known to explain these of these stylized facts. A GARCH model consists of a separate conditional mean and a conditional volatility model (Alexander 2008). The conditional mean could be a constant or a low order Autoregressive Moving Average (ARMA) model. A typical conditional volatility model consists of lagged squared residuals (i.e. Autoregressive Conditional Heteroskedasticity - ARCH terms) and lagged conditional variance (GARCH terms) terms. Usually, a GARCH (1,1) model wherein the conditional volatility model has only one lagged squared residual term and one lagged conditional variance term is adequate to obtain a good fit for most financial time series (Zivot 2009). Hansen and Lunde (2004) provide the evidence that the GARCH (1,1) model usually outperforms the complex GARCH model with more lags.

Furthermore, the volatility exhibits asymmetric impact of negative shocks, i.e. volatility could increase more after a negative shock than a positive shock of the same magnitude – Leverage Effect (Glosten, Jagannathan and Runkle, 1993; Bekaert and Wu, 2000; Cappiello, Engle and Sheppard, 2006). The common asymmetric GARCH models that incorporate the leverage effect are TGARCH (Zakoin 1994), GJR-GARCH, EGARCH and APARCH. In this study we used GJR-GARCH model proposed by Glosten, Jagannathan and Runkle (1993) to test for leverage effect. The univariate Generalized Autoregressive Conditional Heteroskedasticity - GARCH model – sGARCH (Bollerslev, 1986) or GJR-GARCH (Glosten, Jagannathan and Runkle, 1993) was selected based on the BIC information criterion. The effects of all three crises were investigated by introducing the corresponding dummy variables in both the mean and the variance models.

The general univariate conditional mean and the conditional volatility model that used in this study are given below:

The mean model:

$$r_t = \mu_t + a_t \tag{4}$$

$$\mu_t = \mu_0 + \sum_{j=1}^{3} \varphi_j d_{jt} + \sum_{j=1}^{p} \phi_j r_{t-p} + \sum_{j=1}^{q} \varsigma_j a_{t-q} \tag{5}$$

$$a_t = \sigma_t \epsilon_t \qquad \epsilon_t \sim N(0,1)\ or \sim t_{\vartheta}^{*}\ or \sim t_{\vartheta}^{*}(\kappa)$$

Here the error term, ϵ_t is either standard Normal $\sim N(0,1)$ or standardized student $t \sim t_\vartheta^*$ or standardized skew student *t* distributed ~ $t_\vartheta^*(\kappa)$ with ϑ degree of freedom and κ - skew parameter, distributed. The selection is based on the significance of skewness and kurtosis of the log returns. In the conditional mean model, r_{t-p} and a_{t-q} are the AR and MA terms with p and q lags. These lags for each sectoral log return time series are determined based on the BIC criterion (Tsay 2010). The conditional mean model (equation 4 and 5) is same for both sGRACH and GJR-GARCH models. We introduced dummy variables d_{1t}, d_{2t} and d_{3t}, in both the conditional mean and the variance models, to investigate the impact of three crises – Terra Lune crisis of May 2022, FTX Bankruptcy of November 2022 and Silicon Valley Bank crisis of March 2023 respectively. The dummy variable, d_{jt} = 1 during the crisis period and 0 otherwise. The conditional volatility models are given below:

The volatility model (sGARCH):

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{3} \psi_j d_{jt}\right) + \alpha a_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{6}$$

The volatility model (GJR-GARCH):

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{3} \psi_j d_{jt}\right) + (\alpha a_{t-1}^2 + \gamma I_{t-1} a_{t-1}^2) + \beta \sigma_{t-1}^2 \tag{7}$$

We considered only one ARCH and one GARCH terms for a parsimonious representation (equations 6 and 7). In the GJR-GARCH volatility model, as per the convention, the parameter γ captures the leverage effect. *I* is an indicator function that has value 1 for $a_t \leq 0$ and 0 otherwise. Thus a_{t-1}^2 now has a different impact on the conditional variance σ_t^2. When $a_{t-1} > 0$, the total effect is αa_{t-1}^2 ,and when $a_{t-1} \leq 0$, the total effect is $(\alpha a_{t-1}^2 + \gamma a_{t-1}^2)$. Hence, we should find, $\gamma > 0$ if bad news were to a have larger impact on the conditional volatility as proposed under the leverage effect (Zivot 2009; Alexios Ghalanos 2022a).

5. Risk Measure for the Stablecoins

VaR and Expected Shortfall are standard risk measures used in the field of financial risk management. VaR is a measure of the worst expected loss over a given time horizon and confidence level; Expected Shortfall is the average of all the losses exceeding the VaR. But both these risk measures do not capture the critical risk of "break the buck/ death spiral" of the stablecoin. Post a threshold *L*, the market participants consider the stablecoin depegged and the risk of flight to safety and corresponding stablecoin redemption increases drastically. Anadu et.al (2023) consider *L*= 0.99 USD as the threshold, post which the stablecoin redemption risk increases drastically and a possible investor flight to safety and the consequent death spiral for the stablecoin. Thus, we define a new risk measure - the probability under P measure that the closing price of the exchange rate/ price of the stablecoin hits the threshold L (the barrier) over a period of next n days.

$$E^P\left(1_{\left\{\min\limits_{0\le t\le n}(X_t)\le L\right\}}\right) = P\left(\min_{0\le t\le n}(X_t) \le L\right) \quad t \in \{1,2,\dots n\} \tag{8}$$

Only end of the day exchange rate is included in the risk measure because of the possibility of liquidity issues during the day. We compute this risk measure using the following methodologies:

- **Vasicek Model:**

We assume that the stablecoin exchange rate follows Vasicek process (Vasicek; 1977) as given below:

$$dX_t = a_v(b_v - X_t)dt + \sigma_v dW_{1t} \tag{9}$$

where,

X_t: Stablecoin exchange rate (USD/Stablecoin)

a_v: Rate of Reversion of X_t in the Vasicek model

b_v: Long term value of X_t in the Vasicek model

σ_v: Volatility or standard deviation of X_t (constant in Vasicek model)

W_{1t}: Brownian motion of X_t

Note: The volatility, σ_v is constant in this model. The parameters, Rate of Reversion a_v and the Long-term value of the exchange rate, b_v have policy implications for the stablecoin issuer. b_v captures the target price of the stablecoin pegged by the issuer of the stablecoin. The issuer would set this price, b_v marginally above 1 USD to guard against the risk of the price falling below 1 USD. Rate of Reversion a_v captures the efficiency with which the stablecoin issuer makes policy decisions i.e. for example undertakes the open market operations such as buying and selling of the stablecoin or passively let arbitrage work to revert the price back to b_v. A higher value of a_v indicates higher efficiency i.e., faster reversion to the b_v level.

We first perform the Euler discretisation of the Vasicek model and the use Maximum Likelihood Estimation (MLE) to estimate the parameters of the model (Dunn et.al.; 2014). The Euler discretisation for dt = 1 is given below (equation 10):

$$X_{t+1} - X_t = a_v(b_v - X_t) + \sigma_v Z_1 \tag{10}$$

Where Z_1 is the standard normal random variable. Thus $(X_{t+1} - X_t)$ is normally distributed (equation 11).

$$X_{t+1} - X_t \sim N(a_v(b_v - X_t), \sigma_v^2) \quad (11)$$

Probability density function of $(X_{t+1} - X_t)$ is given by (equation 12):

$$f(X_{t+1} - X_t) = \frac{1}{\sqrt{2\pi}\sigma_v} exp\left(-\frac{1}{2}\left(\frac{X_{t+1} - X_t - a_v(b_v - X_t)}{\sigma_v}\right)^2\right) \quad (12)$$

a_v, b_v and σ_v are the values of the parameters that maximize the log likelihood.

- **Cox – Ingersoll – Ross (CIR) Model:**

Under this methodology, we assume that the stablecoin exchange rate follows CIR process (Cox, Ingersoll and Ross; 1985). The advantage of the CIR process is that it does not allow for a negative exchange rate, as the conditional volatility tends to zero as the exchange rate approaches zero.

$$dX_t = a_c(b_c - X_t)dt + \sigma_c\sqrt{X_t}dW_{1t} \quad (13)$$

a_c: Rate of reversion of X_t in the CIR model

b_c: Long term value of X_t in the CIR model

σ_c: Volatility or standard deviation of X_t (constant in CIR model)

W_{1t}: Brownian motion of X_t

Euler discretisation of the model for *dt* = 1 gives (equation 14),

$$X_{t+1} - X_t = a_c(b_c - X_t) + \sigma_c\sqrt{X_t}Z_1 \quad (14)$$

Where Z_1 is the standard normal random variable.

$$X_{t+1} - X_t \sim N(a_c(b_c - X_t),\ X_t\sigma_c^2) \quad (15)$$

Thus, pdf of $(X_{t+1} - X_t)$ for Maximum Likelihood Estimation is given by (equation 16):

$$f(X_{t+1} - X_t) = \frac{1}{\sqrt{2\pi X_t}\sigma_c} exp\left(-\frac{1}{2}\left(\frac{X_{t+1} - X_t - a_c(b_c - X_t)}{\sigma_c\sqrt{X_t}}\right)^2\right) \quad (16)$$

a_c and b_c have similar interpretation as that in the Vasicek model.

- **Vasicek + GARCH model:**

Under this approach, the volatility of the stablecoin exchange rate is not constant as assumed under Vasicek and CIR model. We assume that the exchange rate follows a Vasicek process and the conditional volatility is not constant but variable and is modelled by the corresponding GARCH volatility model presented in the earlier section (equation 6 and 7). In this study the estimation of GARCH and Vasicek model parameters is not performed jointly, instead the ARMA + GARCH model parameters are estimated first, and the estimated conditional volatility is then used to estimate Vasicek model parameters using Maximum Likelihood estimation[11]. The exchange rate process given is by equation 17.

$$dX_t = a_v(b_v - X_t)dt + \sigma_t dW_{1t} \qquad (17)$$

We use Vasicek model instead of CIR model because given the used stablecoin data, the probability of hitting a negative exchange rate value i.e. a threshold of $L = 0$ is near zero[12]. A stochastic volatility model such as the Heston[13] model could also be used with the Vasicek model

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[11] ARMA+GARCH model estimates the conditional volatility for the log returns of the exchange rate i.e. $r_{t+1} = ln\left(\frac{X_{t+1}}{X_t}\right) = ln(X_{t+1}) - ln(X_t) \approx X_{t+1} - X_t$. Note this approximation is a result of Taylor expansion $ln(X) = X - 1 \; at \; X \approx 1$. Stablecoins are pegged at USD 1. Thus, the estimated volatility of the log returns of the exchange rate using ARMA+GARCH model provides approximation for the varying volatility used in the Vasicek model.

[12] Given the assumption that X_{t+n} is normally distributed as, $X_{t+n} \sim N((X_t + a_v(b_v - X_t))n, \; n\sigma_v^2)$. As the stablecoins are pegged to the USD, the exchange rate should not deviate significantly from zero. Under the assumption of $(X_{t+n} - X_t) \sim N(0, \; n\sigma_v^2)$, and the continuity assumptions and a simple application of the reflection principle yields:

$P\left(\min_{0 \le t \le n}(X_t) \le L\right) = 2\,P(X_{t+n} \le L) = 2\,P\left(\frac{(X_{t+n} - X_t)}{\sigma_v\sqrt{n}} < \frac{(L - X_t)}{\sigma_v\sqrt{n}}\right) = 2\Phi\left(\frac{(L - X_t)}{\sigma_v\sqrt{n}}\right)$; for threshold of L=0 i.e. no negative exchange rate, $P\left(\min_{0 \le t \le n}(X_t) \le L\right) = 2\Phi\left(\frac{(-X_t)}{\sigma_v\sqrt{n}}\right) \approx 0; \; (X_t = 1, \sigma_v = 0.5\% \; and \; n = 10)$.

[13]

$$dX_t = a(b - X_t)dt + \sigma_t dW_{1t}$$

$$d\sigma_t^2 = \kappa(\theta - \sigma_t^2)dt + \varphi\sigma_t dW_{2t}$$

$$dW_{1t}dW_{2t} = \rho dt$$

X_t: Stablecoin exchange rate (USD/Stablecoin)

a: Rate of reversion of X_t

b: Long term value of X_t

σ_t: Volatility or standard deviation of X_t

φ: Volatility of the variance σ_t^2

θ: Long term variance of X_t

κ: Rate of reversion to θ

W_{1t}: Brownian motion of X_t

W_{2t}: Brownian motion of V_t

ρ: Correlation coefficient for W_{1t} and W_{2t}

For $dt = 1$ the SDEs can be discretized per Euler's scheme as (Dunn et.al.; 2014):

$$X_{t+1} - X_t = a(b - X_t) + \sigma_t\left(\rho Z_1 + \sqrt{1 - \rho^2}Z_2\right)$$

to compute the stated risk measure, but we did not adopt that approach as the joint estimation of both the Vasicek and Heston models is difficult and we needed a *P* measure instead of a *Q* measure for our risk measure (Heston, 1993; Heston and Nandi, 2000). Next, we present results of GARCH modelling and the risk measures computed using different methodologies.

6. Results

Volatility Models

GARCH models are selected using the following methodology:

1. Estimate the conditional mean $\widehat{\mu_t}$ of log return series $\{r_t\}$ of each index using an autoregressive moving average (ARMA) model with lags *p* and *q*. Determine the appropriate AR and MA lags using BIC criterion.
2. Fit *ARMA(p,q) + sGARCH* and *ARMA(p,q) + GJR-GARCH* models with mean and variance dummy variables representing each of the three crisis to the log return series $\{r_t\}$ of each stablecoin and select the model with the lower BIC value. The selected model provides the estimate of the conditional volatility $\widehat{\sigma_{u,t}}$.

Table 9 and Figure 2 present the results of ARMA + sGARCH /GJR-GARCH models for all the time series. The ARMA coefficients of all the stablecoins are statistically significant indicating the existence of return predictability. Returns of Bitcoin were significantly affected by Terra Luna and FTX Bankruptcy crisis. FRAX returns were significantly affected in all the three crises, but the conditional volatility shows a regime change probably induced by a policy change[14] implemented by the FRAX coin issuer (figure 2). Statistically significant impact of the crises on the conditional volatility is difficult to measure but figure 2 shows a sharp increase in the conditional volatility of

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Where $Z_1 = Z_2 \sim N(0,1)$

$X_{t+1} - X_t \sim N(a(b - X_t), \sigma_t^2)$

$\sigma_{t+1}^2 - \sigma_t^2 = \kappa(\theta - \sigma_t^2) + \varphi\sigma_t Z_1$

$\sigma_{t+1}^2 - \sigma_t^2 \sim N(\kappa(\theta - \sigma_t^2),\ \varphi^2\sigma_t^2\ )$

The log likelihood function to be maximized is calculated from the joint probability density function given as:

$$f(X_{t+1} - X_t, \sigma_{t+1}^2 - \sigma_t^2) = \frac{1}{2\pi\varphi\sigma_t\sqrt{1-\rho^2}} \times$$

$$exp\left\{\frac{-\left(\frac{X_{t+1} - X_t - a(b - X_t)}{\sigma_t}\right)^2 + 2\rho\left(\frac{X_{t+1} - X_t - a(b - X_t)}{\sigma_t}\right)\left(\frac{\sigma_{t+1}^2 - \sigma_t^2 - \kappa(\theta - \sigma_t^2)}{\varphi\sigma_t}\right) - \left(\frac{\sigma_{t+1}^2 - \sigma_t^2 - \kappa(\theta - \sigma_t^2)}{\varphi\sigma_t}\right)^2}{2(1-\rho^2)}\right\}$$

[14] https://docs.frax.finance/amo/overview

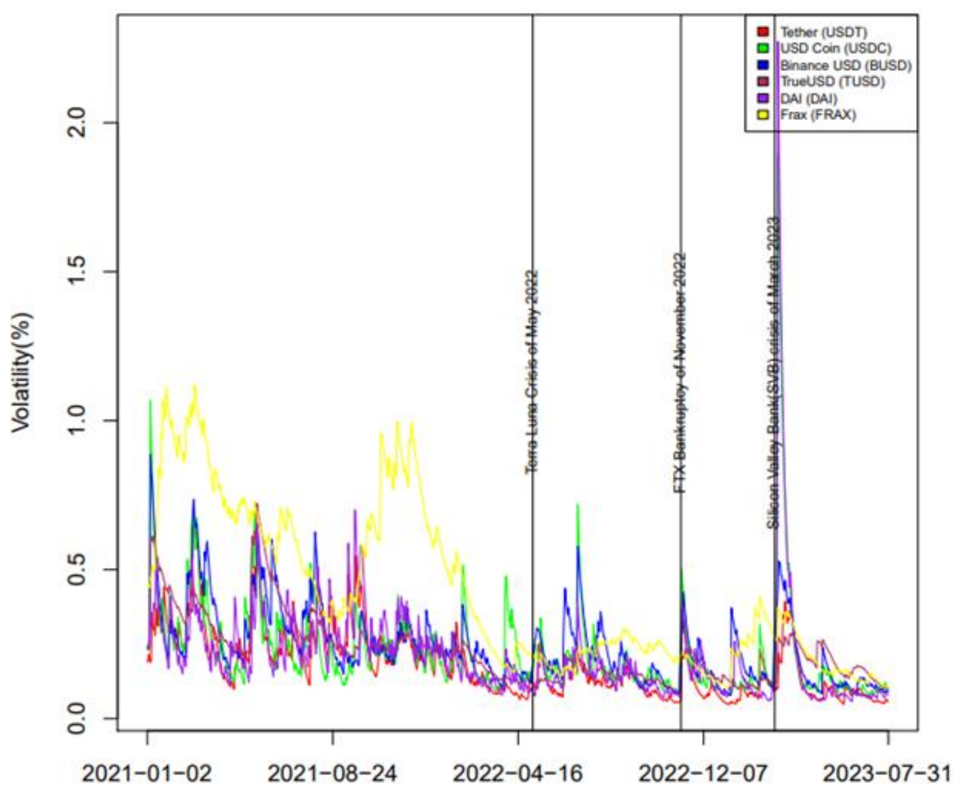
USD Coin and DAI during the Silicon Valley Bank crisis. Note FRAX is an algorithmic coin and DAI is backed by cryptoassets.

Table 9: Results of Univariate ARMA + s/GJR-GARCH models

	NASDAQ Composite	EUR	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
Mean model	ARMA(0,0)	ARMA(0,0)	ARMA(0,0)	ARMA(0,1)	ARMA(1,1)	ARMA(1,2)	ARMA(0,1)	ARMA(0,2)	ARMA(3,2)
Variance Model	gjrGARCH(1,1)	sGARCH(1,1)	gjrGARCH(1,1)	sGARCH(1,1)	sGARCH(1,1)	sGARCH(1,1)	sGARCH(1,1)	sGARCH(1,1)	gjrGARCH(1,1)
Distribution	norm	norm	sstd	std	std	sstd	sstd	norm	std
Parameters									
mu	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-
ar1	-	-	-	-	0.117303	0.899621	-	-	1.057964
	-	-	-	-	*0.02*	*0.00*	-	-	*0.00*
ar2	-	-	-	-	-	-	-	-	-0.08027
	-	-	-	-	-	-	-	-	*0.00*
ar3	-	-	-	-	-	-	-	-	-0.05738
	-	-	-	-	-	-	-	-	*0.00*
ar4	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-
ar5	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-
ma1	-	-	-	-0.80263	-0.90395	-1.72032	-0.80994	-0.83781	-1.87027
	-	-	-	-	-	*0.00*	-	*0.00*	*0.00*
ma2	-	-	-	-	-	0.72491	-	0.00580	0.87648
	-	-	-	-	-	*0.00*	-	*0.90*	*0.00*
ma3	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-
ma4	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-
ma5	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-
Terra LUNA Crisis	-1.21%	-0.32%	-2.67%	0.00%	0.03%	0.02%	0.02%	0.01%	0.01%
	0.21	*0.00*	*0.00*	*0.63*	*0.01*	*0.10*	*0.00*	*0.13*	*0.04*
FTX Bankruptcy	1.50%	0.86%	-10.62%	0.03%	0.04%	-0.01%	0.05%	0.06%	0.08%
	0.01	*0.00*	*-*	*0.16*	*0.24*	*0.75*	*0.08*	*0.51*	*0.00*
Silicon Valley Bank default	0.03%	0.01%	-0.32%	0.05%	0.01%	-0.01%	0.06%	0.20%	0.05%
	0.94	*0.94*	*0.73*	*0.00*	*0.83*	*0.28*	*0.00*	*0.05*	*0.00*
Omega	0.000002	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000	0.00000	0.00000
	0.09	*0.64*	*0.86*	*0.13*	*0.11*	*0.33*	*0.68*	*0.15*	*0.86*
alpha1	0.00007	0.041765	0.022973	0.211343	0.271886	0.177608	0.06067	0.29664	0.12006
	1.00	*0.19*	*0.16*	*0.00*	*0.00*	*0.01*	*0.18*	*0.01*	*0.00*
beta1	0.93019	0.95232	0.95915	0.82269	0.76927	0.85524	0.94325	0.76208	0.95335
	-	-	-	-	-	-	-	*0.00*	*0.00*
gamma1	*0.12*	-	*0.04*	-	-	-	-	-	-0.11472
	0.01	-	*0.11*	-	-	-	-	-	-
Terra LUNA Crisis	0.000%	0.000%	0.025%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
	1.00	*0.99*	*0.05*	*0.91*	*0.12*	*0.14*	*0.91*	*0.87*	*0.98*
FTX Bankruptcy	0.000%	0.000%	0.000%	0.000%	0.001%	0.000%	0.000%	0.000%	0.000%
	1.00	*1.00*	*1.00*	*0.92*	*0.18*	*0.17*	*0.98*	*0.98*	*0.99*
Silicon Valley Bank default	0.000%	0.000%	0.012%	0.000%	0.001%	0.000%	0.000%	0.000%	0.000%
	1.00	*1.00*	*0.31*	*0.91*	*0.57*	*0.01*	*0.98*	*0.95*	*0.99*
skew	-	-	1.01566	-	-	1.07204	1.02183	0.00000	-
	-	-	-	-	-	-	-	-	-
shape	-	-	3.31092	3.57429	3.10581	3.02507	3.46584	-	3.26969
	-	-	-	-	-	*0.00*	*0.00*	-	-
AIC	-5.69543	-7.84004	-4.07889	-10.31018	-9.99340	-9.79808	-9.76008	-9.86188	-8.76436
BIC	-5.62623	-7.77956	-4.01708	-10.25352	-9.93159	-9.72597	-9.69827	-9.80522	-8.68195

	NASDAQ Composite	EUR	Bitcoin	Tether	USD Coin (USDC)	Binance USD (BUSD)	TrueUSD (TUSD)	DAI	FRAX
Weighted Ljung-Box Test on Standardized Residuals									
Lag	1	1	1	1	1	1	1	1	1
Statistic	0.00007571	0.7309	0.8318	0.000707	0.343	0.1211	0.001513	1.216	0.005616
	0.99	*0.39*	*0.36*	*0.98*	*0.56*	*0.73*	*0.97*	*0.27*	*0.94*
Lag	2	2	2	2	5	8	2	5	14
Statistic	0.6549	0.9389	0.8875	0.68738	1.898	5.5433	0.029141	1.387	5.704899
	0.63	*0.52*	*0.54*	*0.90*	*0.97*	*0.05*	*1.00*	*1.00*	*1.00*
Lag	5	5	5	5	9	14	5	9	24
Statistic	1.729	1.2915	1.2172	2.421759	3.556	9.5221	3.609172	1.788	11.61027
	0.68	*0.79*	*0.81*	*0.59*	*0.79*	*0.16*	*0.29*	*0.99*	*0.61*
Weighted Ljung-Box Test on Standardized Squared Residuals									
Lag	1	1	1	1	1	1	1	1	1
Statistic	4.199	0.06298	3.287	0.1503	0.01923	0.06059	5.973	2.078	0.7368
	0.04	*0.80*	*0.07*	*0.70*	*0.89*	*0.81*	*0.01*	*0.15*	*0.39*
Lag	5	5	5	5	5	5	5	5	5
Statistic	5.293	2.34384	4.075	0.3422	1.019	0.459	6.439	4.773	1.6854
	0.13	*0.54*	*0.24*	*0.98*	*0.86*	*0.96*	*0.07*	*0.17*	*0.69*
Lag	9	9	9	9	9	9	9	9	9
Statistic	7.107	3.70695	4.796	0.6209	1.6454	0.76837	6.982	6.756	4.3906
	0.19	*0.64*	*0.46*	*1.00*	*0.94*	*0.99*	*0.20*	*0.22*	*0.52*

Figure 2: Volatility Behaviour of the Stablecoins



Simulation of the Risk Measure:

Annexure 6 provides, for each stablecoin, a table of the parameters of each model (Vasicek, CIR and Vasicek with GARCH volatilities and ARMA+GARCH) estimated using the full data set (1st January 2021 to 31st July 2023) and the corresponding forecasted returns, conditional volatilities and Risk measure over next 10 days as on 31st July 2023. Note the estimated parameters a, b and the constant volatility, σ for Vasicek and CIR models are approximately equal and so are the forecasted exchange rates and the conditional volatilities. The forecasted exchange rates for Vasicek, CIR and Vasicek + GARCH revert back to the long term mean exchange rate, b and the rate of reversion depends on the parameter a. The forecasted conditional volatilities of the Vasicek and CIR models are constant and are reflected as such in the figures of Annexure 6. The forecasted conditional volatilities of Vasicek + GARCH and ARMA + GARCH models are comparable as we have used ARMA+GARCH conditional volatilities in the estimation of Vasicek model parameters. The risk measure is computed for *n* = 10 days, two thresholds (Limits) are marked $L_1 = 0.99\ (Red\ boundary)$ and $L_2 = 0.995\ (Yellow\ boundary)$ per the thresholds tested by Anadu et.al. (2023). The risk measure figure depicts the probability of the day end closing price of a stablecoin hitting the different thresholds over the next 10 days, computed using each of the four methodologies. The risk measure computed using Vasicek and CIR models is greater than that computed using the other two methodologies because the constant σ used in the computation of Vasicek and CIR risk measures is much greater than the estimated conditional volatility as on 31st July 2023, using a GARCH model. This may not always be the case. Use of ARMA+GARCH in computing the risk measure is a good alternative but it does not directly capture the policy parameters such as the long term mean exchange rate (*b*) that the stablecoin issuer could set and the rate of reversion (*a)* that the stablecoin issuer could control using the simple open market operations i.e. buying or selling of the stablecoins (example Shah 2022).

Next, we present simulation of risk measures and trends in the policy parameters over 365 days. We first select a sub-sample window from 1st January 2021 up till 31st July 2022 $\{r_t\}_{t=1}^{576}$ and estimate the ARMA+GARCH and Vasicek + GARCH parameters, then simulate the exchange rate paths ($number\ of\ simulations = 10^6$) over the next 10 days and compute the risk measure for a threshold of $L_2 = 0.995\ (Yellow\ Boundary)$. For the next simulation we add the following day to the sub-sample (1st January 2021 up till 1st August 2022 $\{r_t\}_{t=1}^{577}$ and re-estimate the parameters, simulate the exchange rate paths and compute the risk measure. We reiterate this procedure up till 31st July 2023 i.e. $\{r_t\}_{t=1}^{941}$ and compute the parameters and risk measures. Figures 3 and 4 depict the estimates of the policy parameters (*a* and *b)* over the 365 subsamples. FRAX and True USD exhibit high rates of reversion *(a)* indicating a higher efficiency in the maintaining the peg. Thus, the coin issuer of FRAX and True USD could set a lower long term exchange rate *(b)*. FRAX has the lowest long term exchange rate. DAI and USD Coin have lower rates of reversion, thus these coin issuers have to set a long term exchange rate *(b)* higher than the *(b)* set by the other stablecoin issuers.

Figure 3: Trend in the Rate of Reversion *(a)* of various Stablecoins

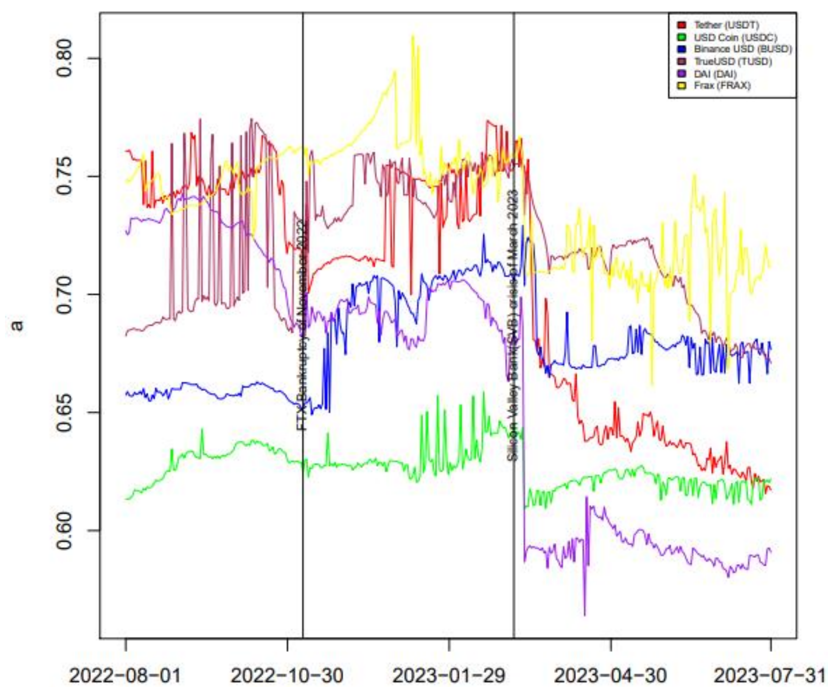
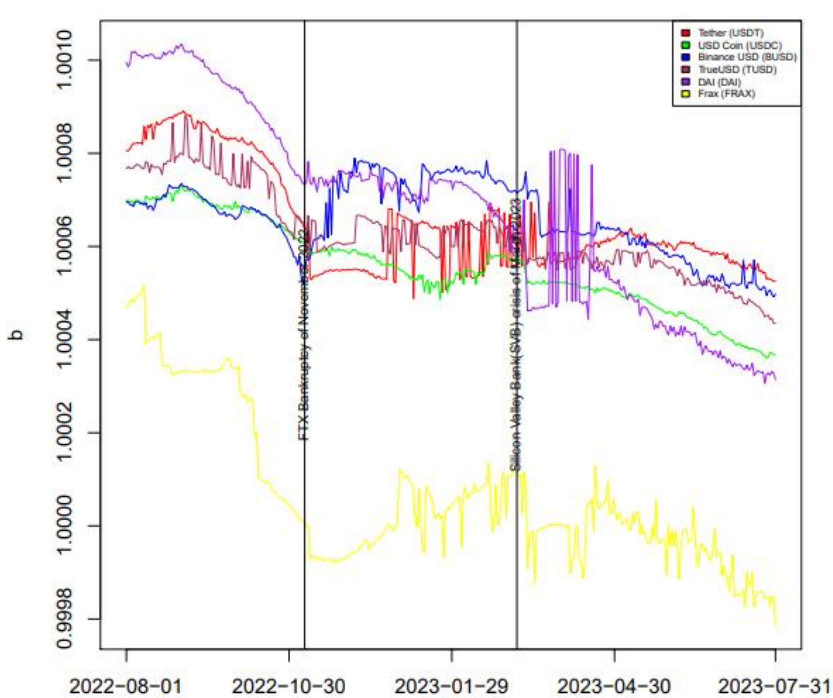


Figure 4: Trend in the mean exchange rate *(b)* of various Stablecoins



Next, we present the risk measures computed using Vasicek + GARCH (figure 5) and ARMA + GARCH (figure 6). Both the risk measures capture the two adverse events, FTX bankruptcy and SVB crisis. These events were not introduced as dummy variables in the ARMA + GARCH model for this simulation exercise. FRAX, DAI and Binance USD exhibited higher risk over the simulation period as indicated by both the risk measures. Risk measure computed using Vasicek + GARCH seem to indicate higher risk overall during the crises than the risk measure computed using ARMA + GARCH.

Figure 5: Risk Measure (Vasicek + GARCH)

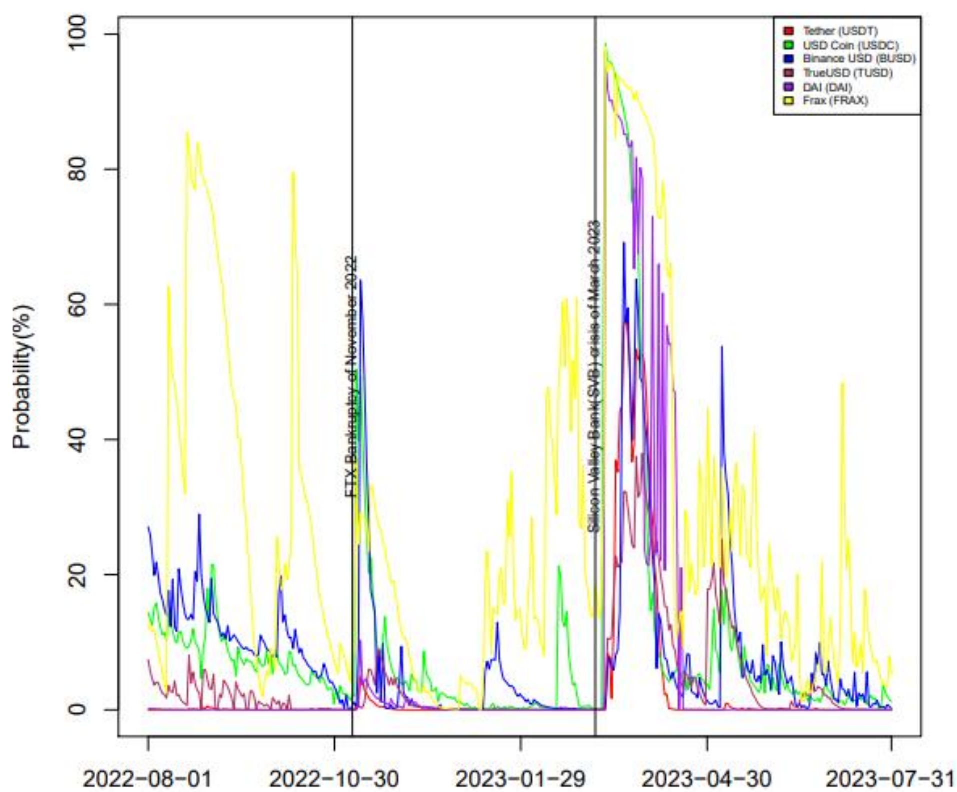
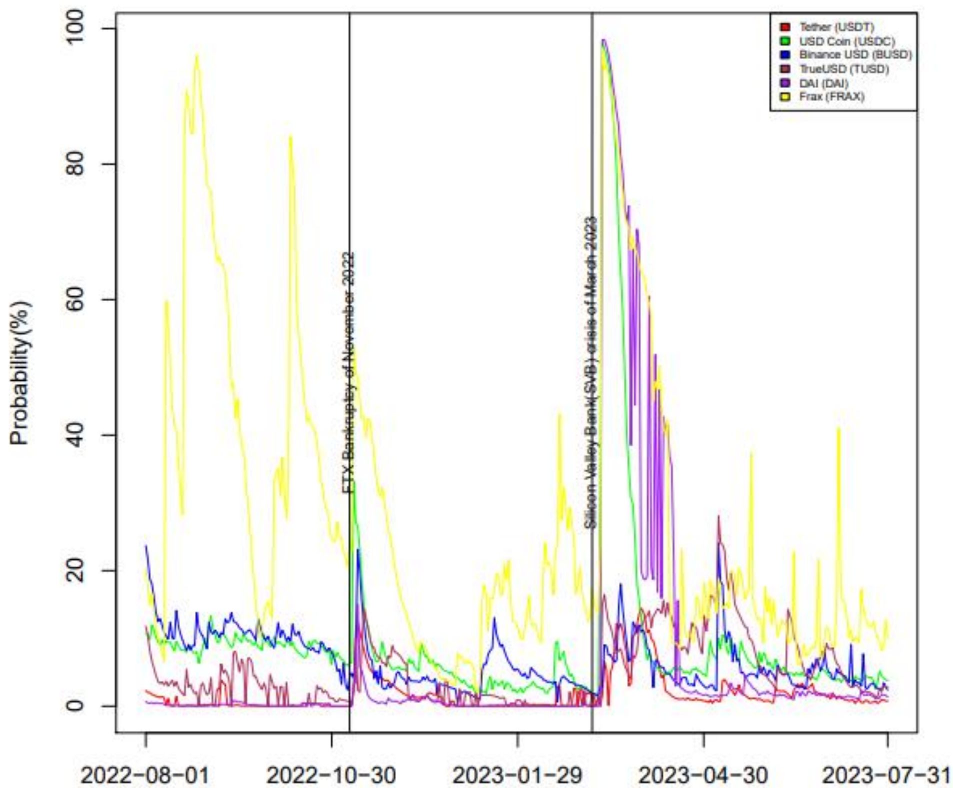


Figure 6: Risk Measure (ARMA+ GARCH)



6. Conclusion

This study proposes a new risk measure for stablecoins, that is based on the probability of the stablecoin's price hitting a threshold exchange rate post which the stablecoin is subjected to the risk of "break the buck/ death spiral". We also juxtapose the risk measure computed using different models - Vasicek, CIR, ARMA+GARCH and Vasicek+GARCH and suggest the policy implication of the estimated model parameters - rate of reversion *(a)* and long term mean exchange rate *(b)* for stablecoin issuers. The study compares the volatility behaviour of the stablecoins with that of the traditional cryptocurrency, Bitcoin, equity index, NASDAQ composite and fiat currency, EURO. Stablecoins tend to be "stable" barring the events such as Terra – Luna crisis, FTX Bankruptcy and Silicon Valley Bank crisis. Traditional asset backed stablecoins – Tether, USD Coin, Binance USD and True USD are less risky than the decentralized algorithmic stablecoin, FRAX and decentralized cryptoasset backed stablecoin, DAI. The proposed risk measure could be of utility to the stablecoin issuers of algorithmic and cryptoasset backed stablecoins and the regulators for setting the capital requirement to guard against the break the buck/ death spiral risk.

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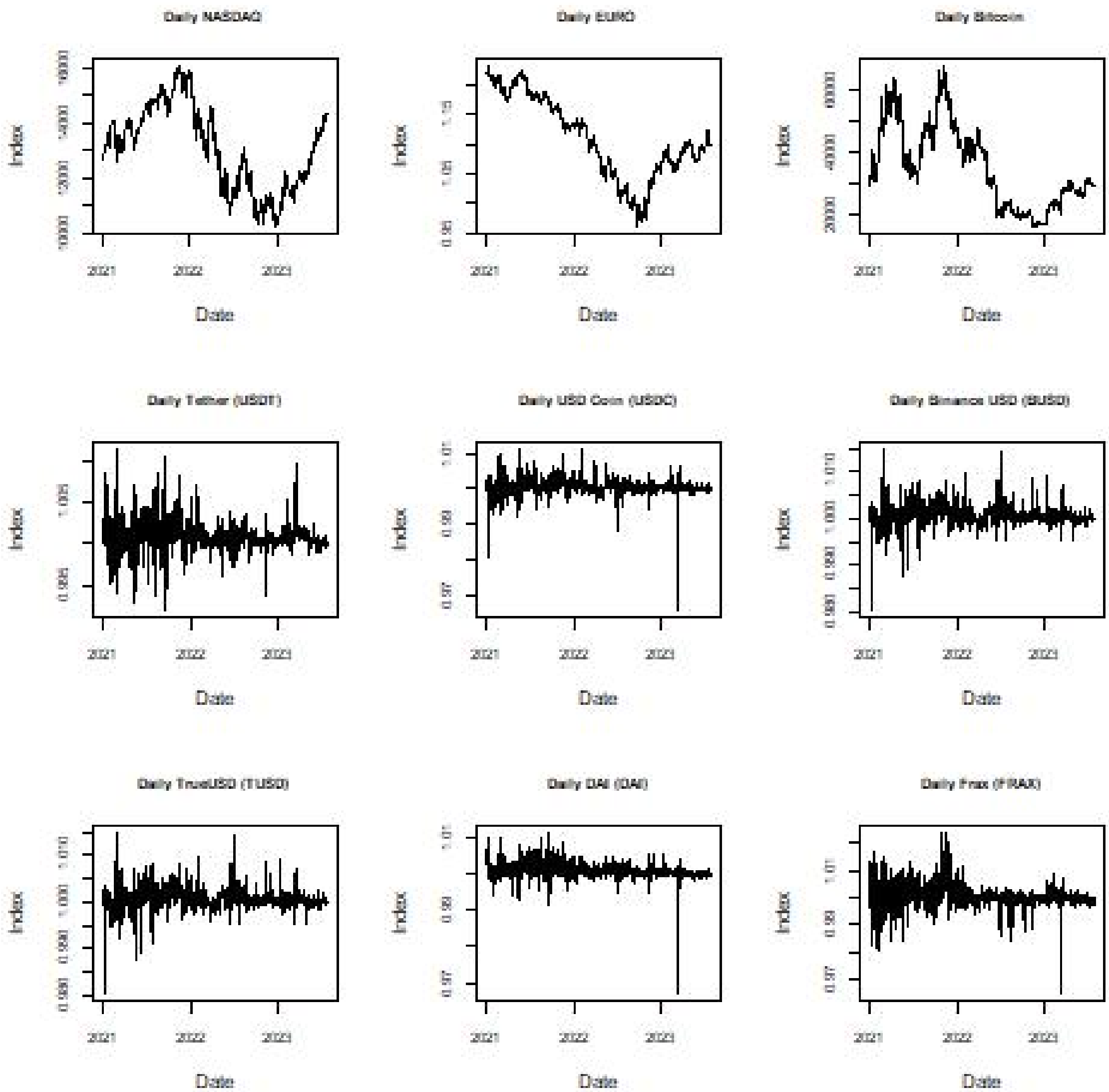
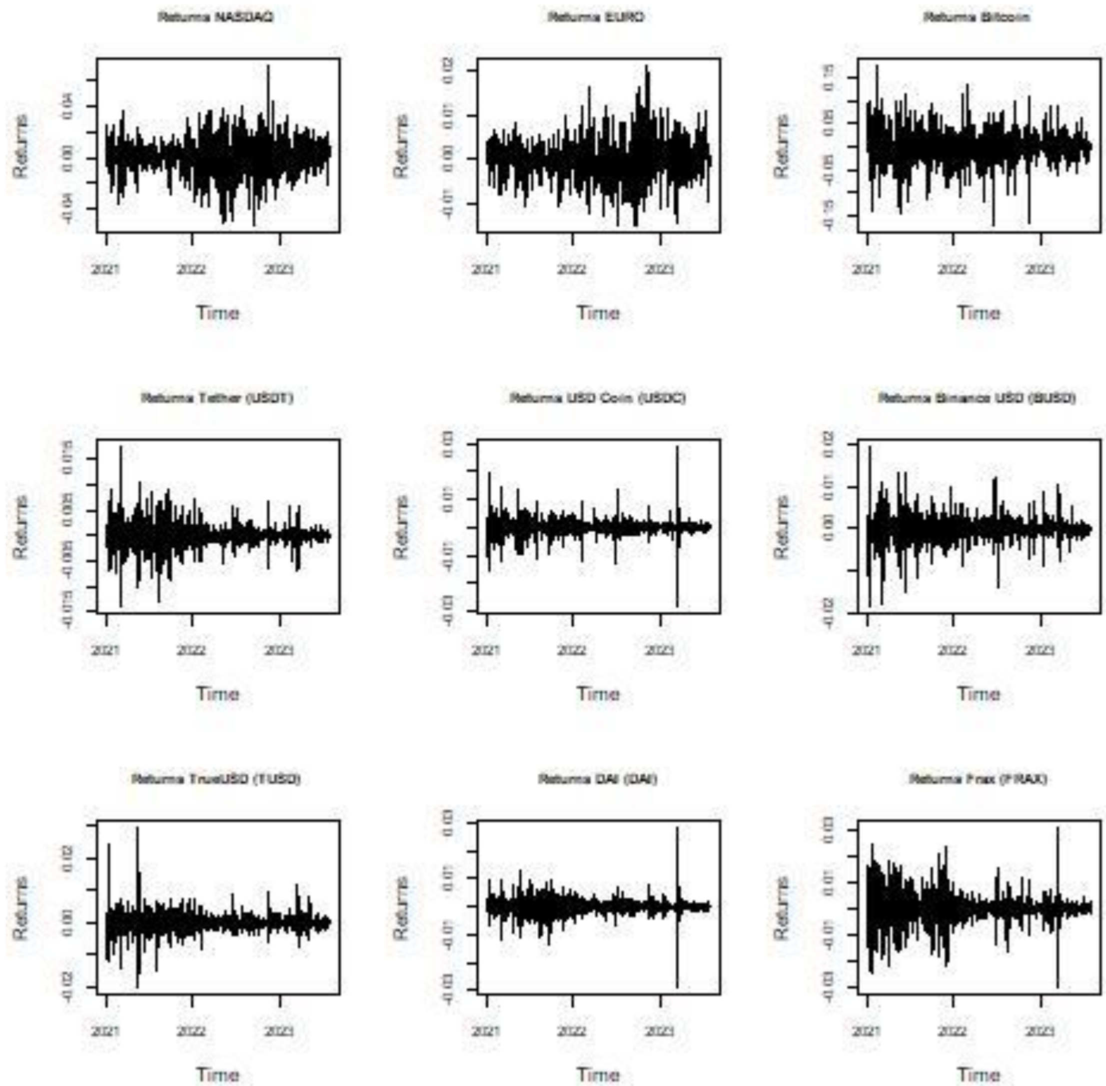
Annexures:

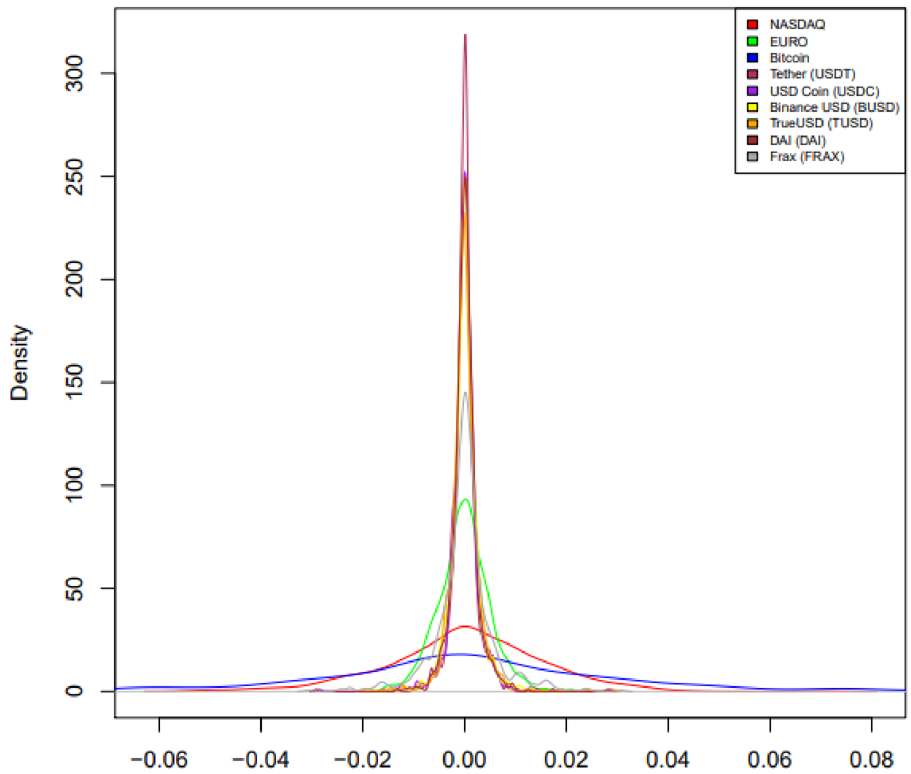
Annexure 1: Daily time series in level



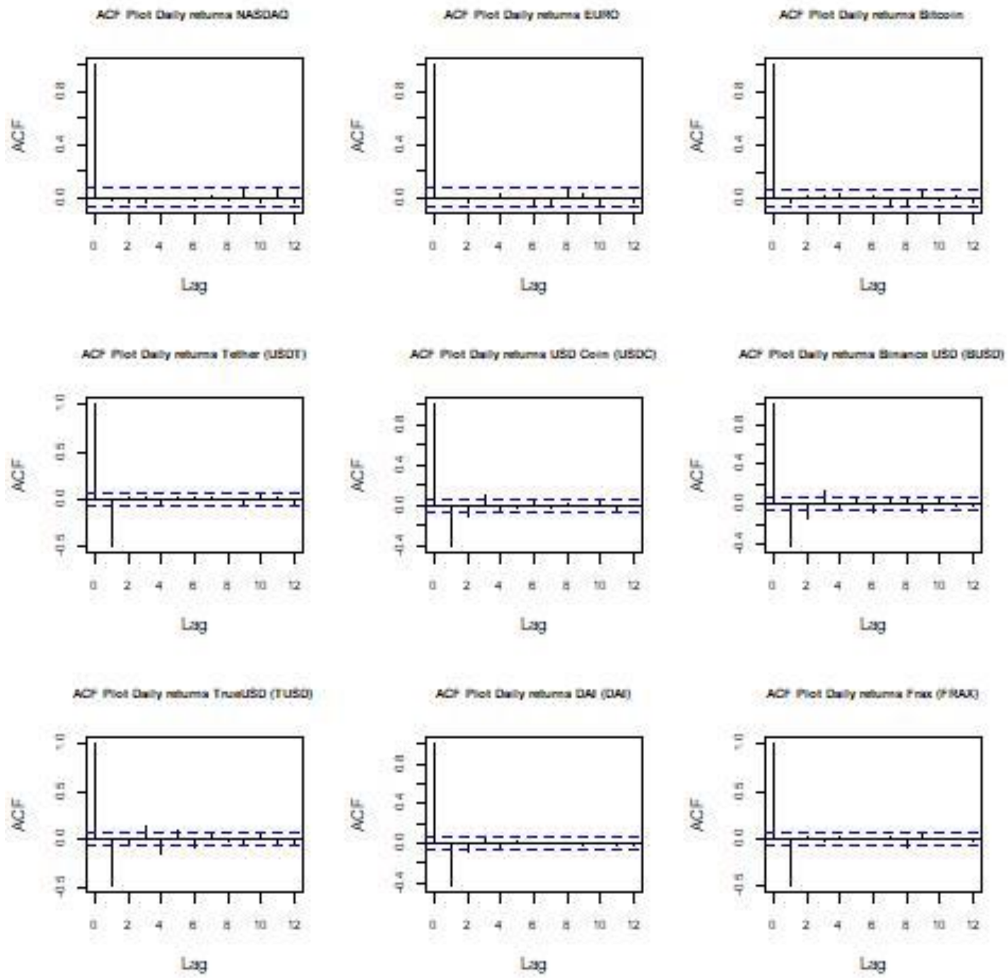
Annexure 2: Log returns of the daily time series

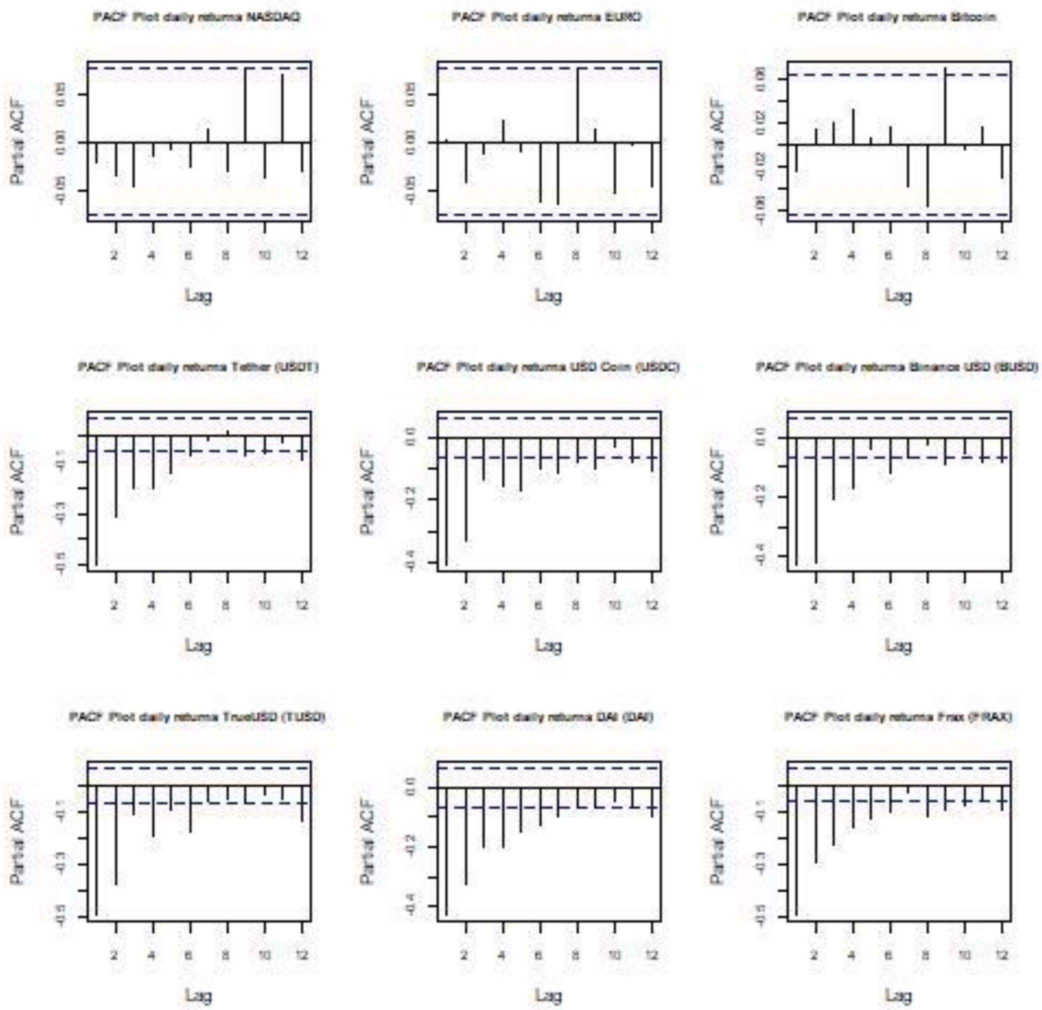


Annexure 3: Density Plots

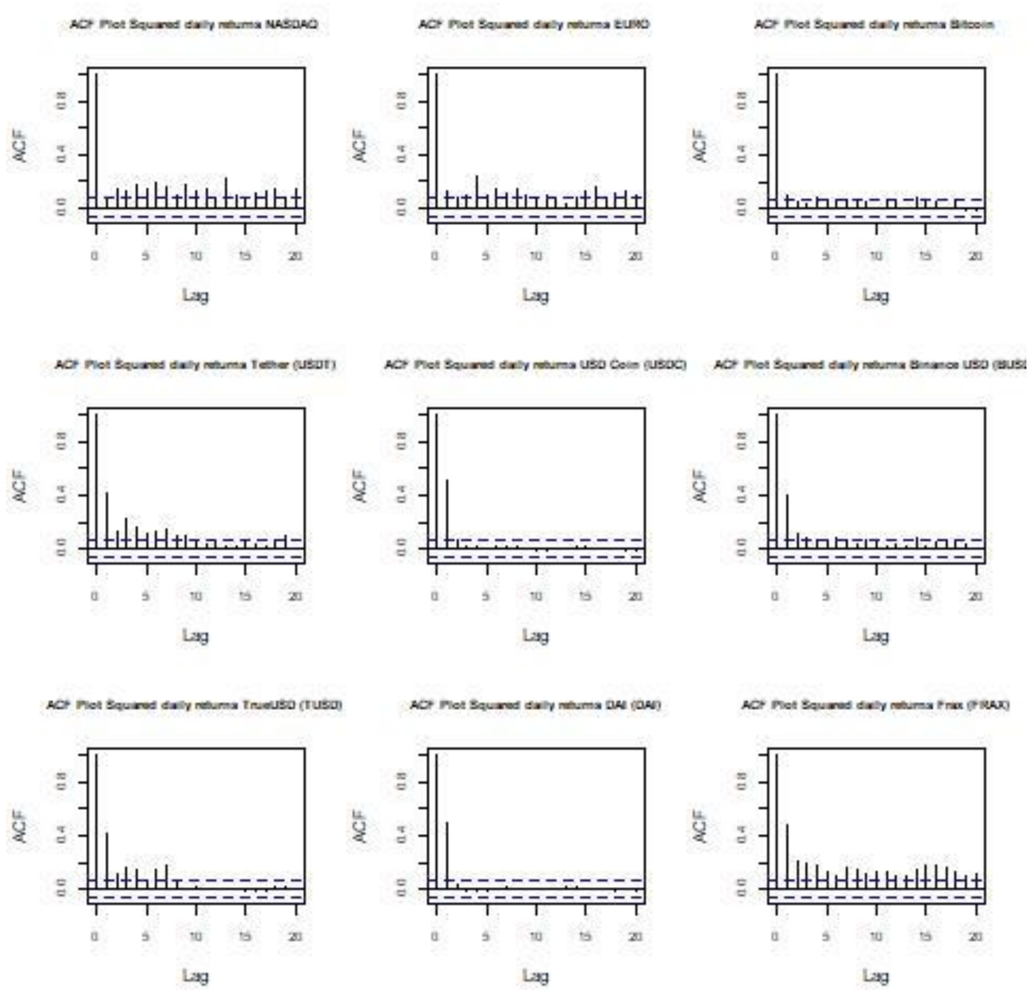


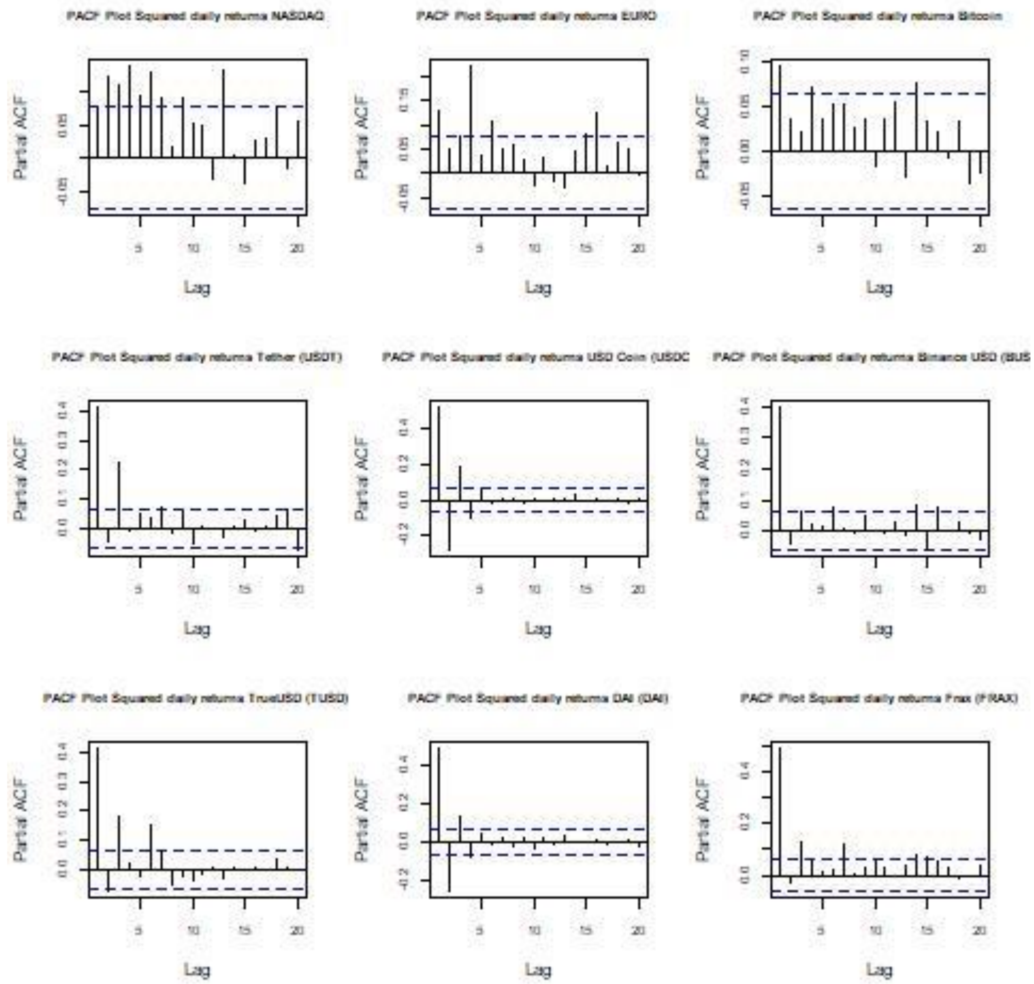
Annexure 4: ACF and PACF plots of log return series




PACF Plot daily returns NASDAQ
PACF Plot daily returns EURO
PACF Plot daily returns Bitcoin
PACF Plot daily returns Tether (USDT)
PACF Plot daily returns USD Coin (USDC)
PACF Plot daily returns Binance USD (BUSD)
PACF Plot daily returns TrueUSD (TUSD)
PACF Plot daily returns DAI (DAI)
PACF Plot daily returns Frax (FRAX)
Partial ACF
Lag

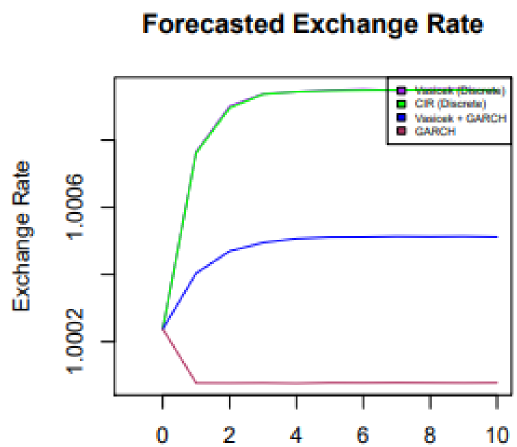
Annexure 5: ACF and PACF plots of squared log return series

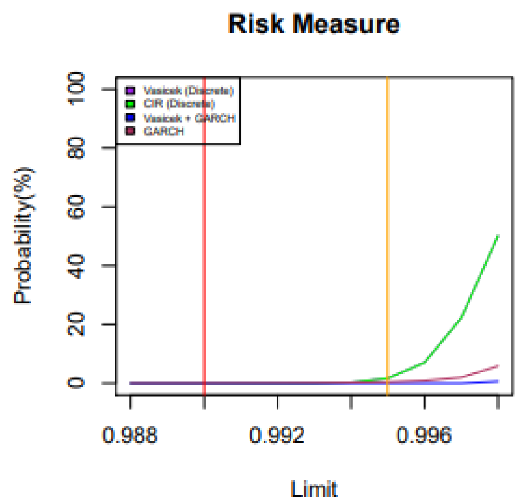


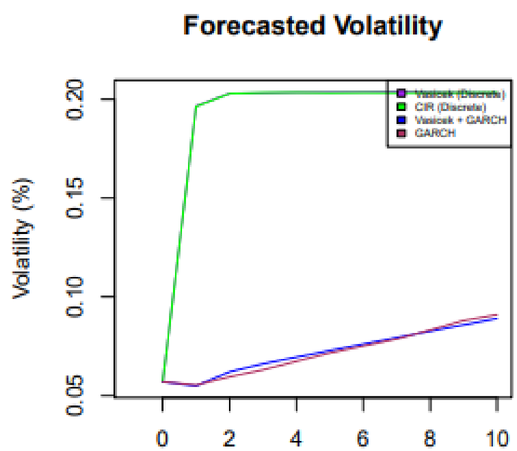

PACF Plot Squared daily returns NASDAQ
PACF Plot Squared daily returns EURO
PACF Plot Squared daily returns Bitcoin
PACF Plot Squared daily returns Tether (USDT)
PACF Plot Squared daily returns USD Coin (USDC
PACF Plot Squared daily returns Binance USD (BUS
PACF Plot Squared daily returns TrueUSD (TUSD)
PACF Plot Squared daily returns DAI (DAI)
PACF Plot Squared daily returns Frax (FRAX)
Partial ACF
Lag

Annexure 6: Forecasted Exchange Rates, Conditional Volatilities, Risk Measure and Model Parameters of various Stablecoins

TETHER (USDT)

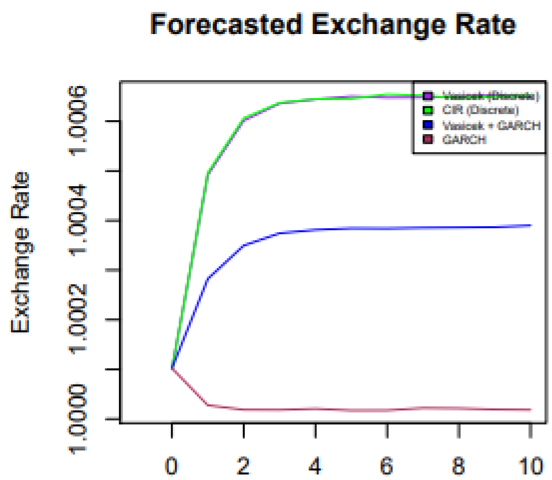


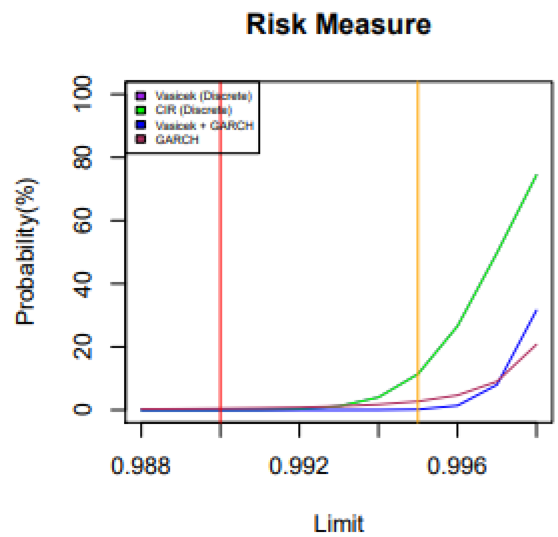


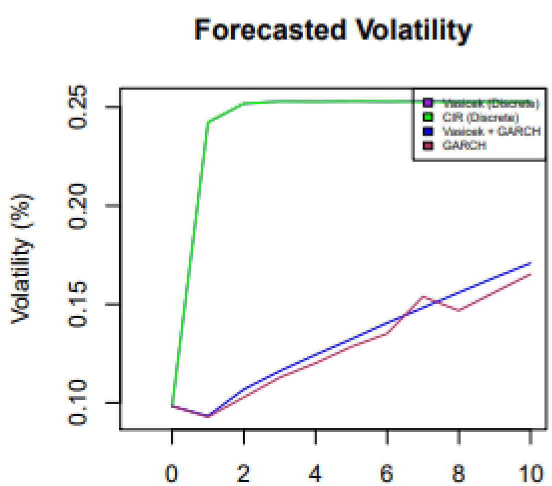


	Vasicek(Discrete)	CIR(Discrete)	Vasicek+GARCH
a	0.74	0.74	0.61
b	1.00095	1.00095	1.00051
Sigma	0.196%	0.196%	
Log Likelihood	4534.61	4534.91	4678.98

USD COIN (USDC)

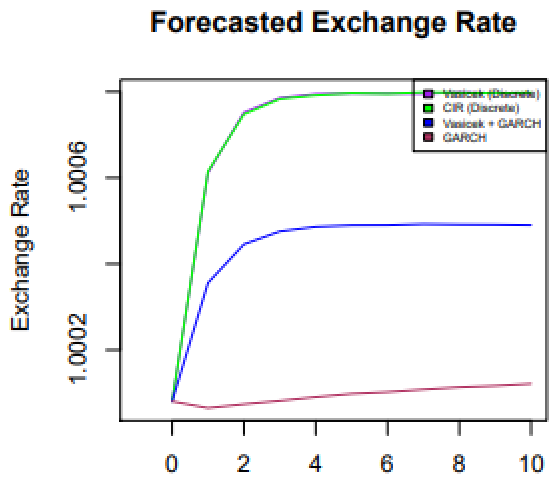


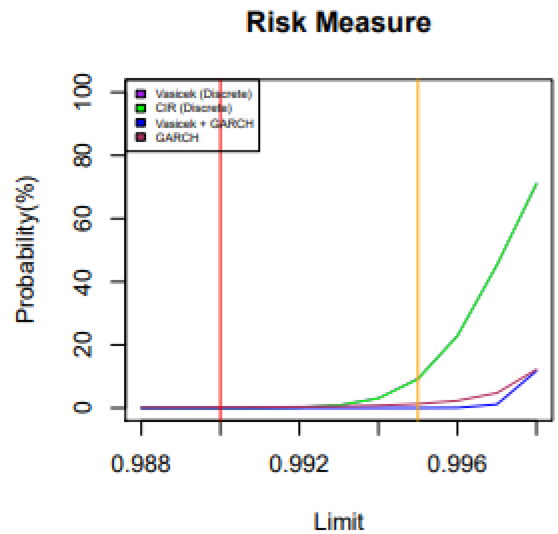


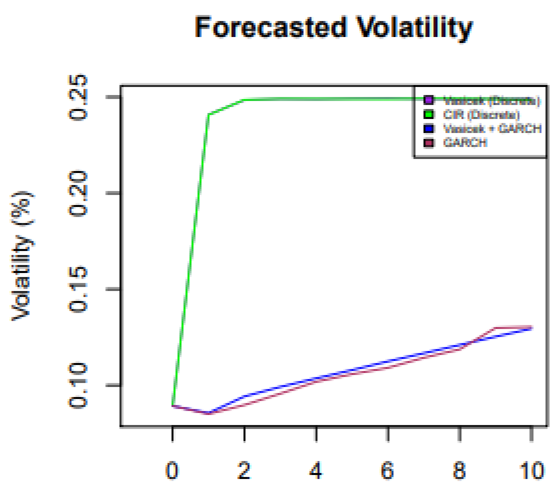


	Vasicek(Discrete)	CIR(Discrete)	Vasicek+GARCH
a	0.71	0.71	0.64
b	1.00065	1.00065	1.00039
Sigma	0.242%	0.242%	
Log Likelihood	4336.97	4336.58	4514.46

BINANCE USD (BUSD)

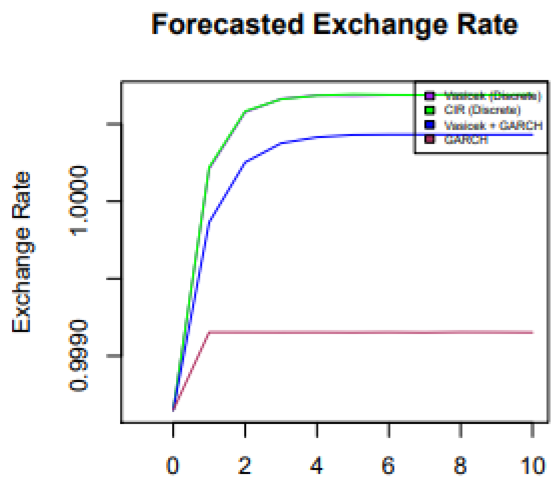


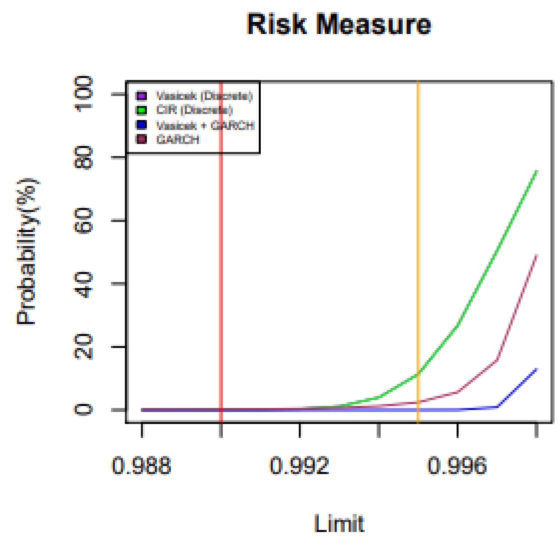


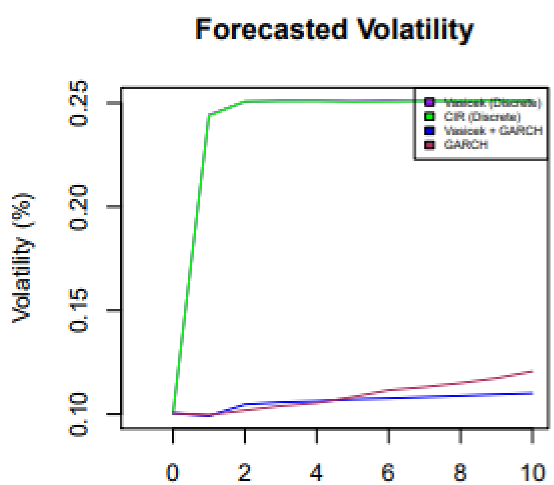


	Vasicek(Discrete)	CIR(Discrete)	Vasicek+GARCH
a	0.75	0.75	0.67
b	1.0008	1.0008	1.00049
Sigma	0.241%	0.241%	
Log Likelihood	4342.36	4342.6	4409.89

TRUEUSD (TUSD)

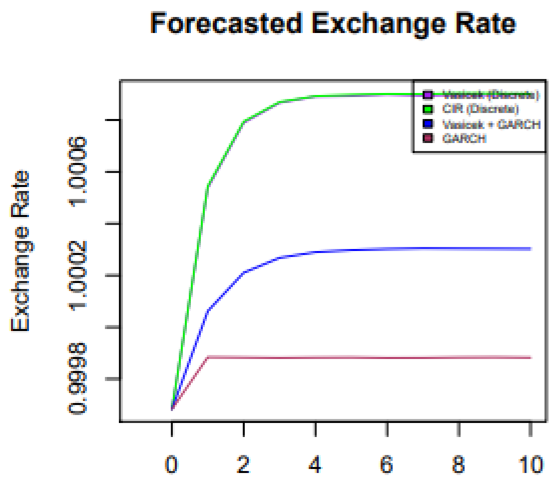


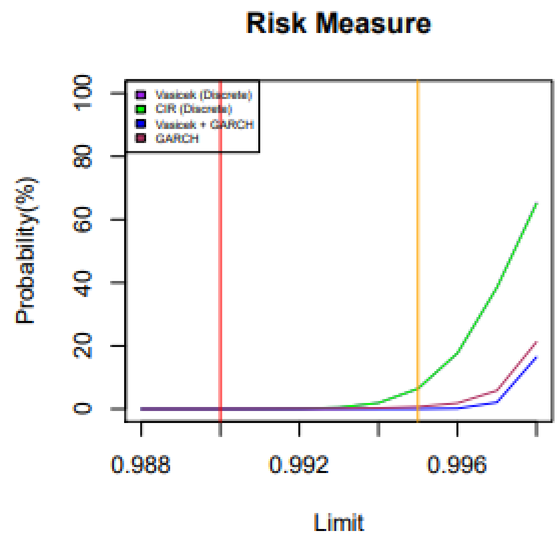


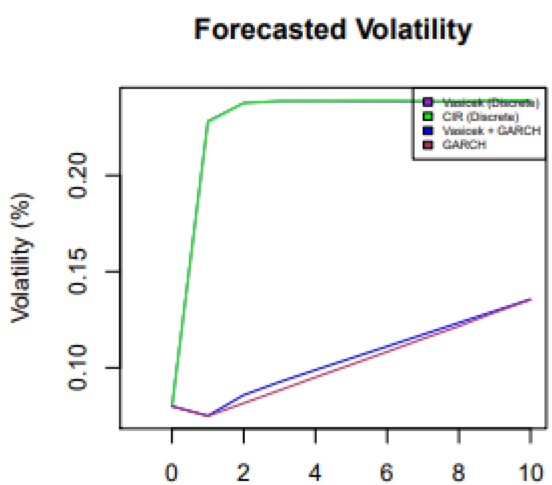


	Vasicek(Discrete)	CIR(Discrete)	Vasicek+GARCH
a	0.77	0.77	0.68
b	1.00069	1.00069	1.00043
Sigma	0.244%	0.244%	
Log Likelihood	4328.88	4328.99	4446.07

DAI (DAI)

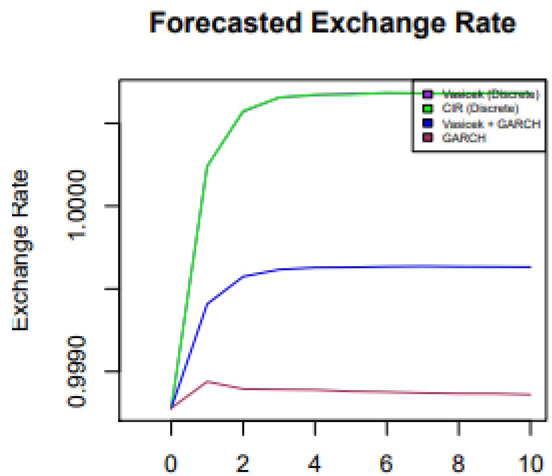


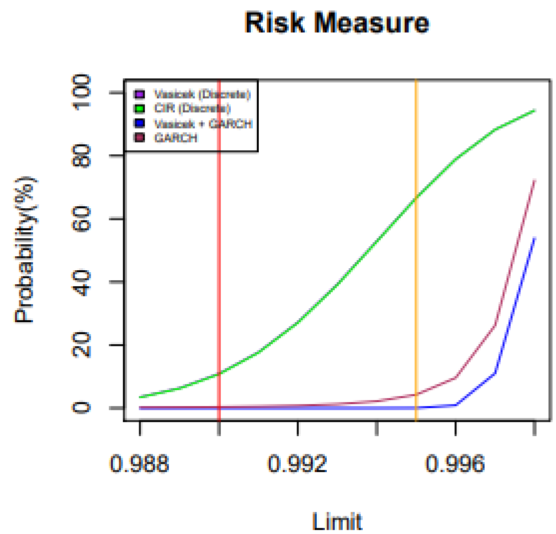


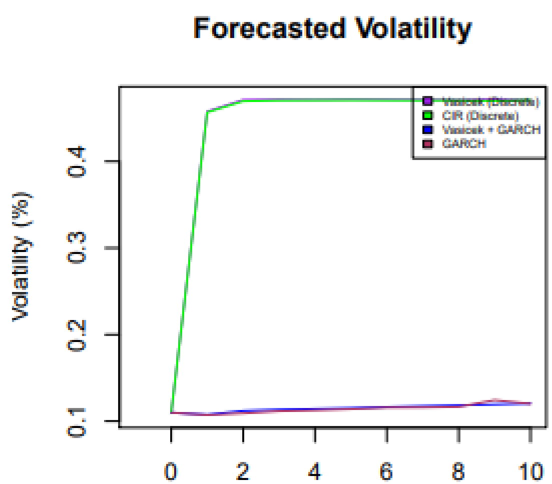


	Vasicek(Discrete)	CIR(Discrete)	Vasicek+GARCH
a	0.71	0.71	0.61
b	1.0009	1.0009	1.0003
Sigma	0.228%	0.228%	
Log Likelihood	4394.13	4393.12	4567.46

FRAX (FRAX)







	Vasicek(Discrete)	CIR(Discrete)	Vasicek+GARCH
a	0.76	0.77	0.74
b	1.00068	1.00068	0.99963
Sigma	0.458%	0.457%	
Log Likelihood	3736.54	3738.01	3899.34