Routledge
Taylor & Francis Group

Studies in Economics and Econometrics

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/rsee20

Cryptocurrencies fall from grace: Snatched safe flight to which haven during Russia-Ukraine conflict?

Suraj Velip & Mrunali Jambotkar

To cite this article: Suraj Velip & Mrunali Jambotkar (09 Jan 2025): Cryptocurrencies fall from grace: Snatched safe flight to which haven during Russia-Ukraine conflict?, Studies in Economics and Econometrics, DOI: 10.1080/03796205.2024.2441820

To link to this article: https://doi.org/10.1080/03796205.2024.2441820

Published online: 09 Jan 2025.

STUDIES IN ECONOMICS AND ECONOMETRICS
https://doi.org/10.1080/03796205.2024.2441820

Cryptocurrencies fall from grace: Snatched safe flight to which haven during Russia-Ukraine conflict?

Suraj Velip[a] and Mrunali Jambotkar[b]

[a]Goa Business School, Goa University, Goa India; [b]SSA Govt. College of Arts and Commerce, Pernem, Goa India

ABSTRACT

The unprecedented upheaval in an economic and financial system facilitates herding behaviour and flight-to-safety (FTS) episodes from a riskier asset into a safer one. The Russia-Ukraine conflict shows that the financial market assets are still prone to external shock. In line with this, the study explores the inconclusive insights on an FTS from cryptocurrencies to US treasury securities. The paper employs dynamic conditional correlation – generalized autoregressive conditional heteroskedasticity (DCC-GARCH) to test the FTS episode for a period from February 24, 2022 to February 23, 2023. The findings hold a sizeable negative and significant volatility coefficient, particularly DCCα, which directs to support the notion of short-lived FTS from cryptocurrencies to treasury securities during the invasion period. Nevertheless, some evidence of the positive volatility effect points out the risk diversification benefits. The results also show flight-to-quality from BTC, ETH, USDT, BNB, ADA and MATIC to the US dollar index (USDX), however, for other cryptocurrencies, it acts as a diversifier. We unfolded several implications that could be interesting for a market participant looking for evidence on the behaviour of cryptocurrencies and govt. backed securities during times of market uncertainty in the future.

ARTICLE HISTORY
Received 24 June 2023
Accepted 7 December 2024

KEYWORDS
Flight-to-safety; Russia-Ukraine war; cryptocurrencies; US treasury securities; DCC-GARCH

JEL CODES
C32; G01: G10

1. Introduction

The cryptocurrencies following its launch till January 2022, gained a greater milestone. Its tremendous growth can witness this - reached a market capitalization to $2.188 trillion on 01 January 2022. But since then, by the end of 26 February 2023, nearly 48.17% of its value has been erased from the cryptocurrency market [1, 2]. In particular (Table 1), Bitcoin is collapsed by 49.22%, Ethereum by 55.94%, Dogecoin by 52.89%, XRP by 52.84% and Cardano by 72.28% since the last peak observed. This impact closely corroborates the argument of Aliu *et al.* (2023), who stated that the investors fear a Russian attack on the Eurozone countries, sentiment investors to move the fund to safe places such as US. In contrast, during the unwavering shock (Russia-Ukraine conflict), US treasury securities gained value, as the 5-year bond recorded a 97.46% surge in yield, the 10-year bond

CONTACT Suraj Velip, Assistant Professor and Program Director (MBA) suraj@unigoa.ac.in Goa Business School, Goa University, Goa 403 206, India.

Table 1. Top ten cryptocurrencies as per market capitalization (as of 26 February 2023).

		02 January 2022		26 February 2023			
Name	Symbol	Price ($)	Market Cap ($)	Price ($)	Market Cap ($)	Price Fall (in %)	Market Cap Fall (in %)
Bitcoin	BTC	47345.22	895688387523.14	23561.21	454795165822.82	−50.24	−49.22
Ethereum	ETH	3829.57	455713570380.85	1640.82	200793139093.29	−57.15	−55.94
Tether	USDT	1	78373882136	1	70853056161.10	0.00	−9.60
USD Coin	USDC	0.99	42562534941	1	42627802559.27	0.02	0.15
Binance Coin	BNB	531.40	88637570485	309	48789334458.76	−41.85	−44.96
Binance USD	BUSD	0.99	14625354833	1	11133434699.84	0.05	−23.88
XRP	XRP	0.86	40838984414	0.38	19261559273.94	−56.00	−52.84
Cardano	ADA	1.38	46129061736	0.37	12788186746.65	−73.26	−72.28
Dogecoin	DOGE	0.17	23138181423	0.08	10905805148.02	−52.87	−52.87
Polygon	MATIC	2.55	18259576689	1.28	11190260041.65	−49.80	−38.72
Total			**1703967104561.51**		**883137744005.34**		**48.17 (Fall)**

Source: https://coinmarketcap.com/historical/

displayed 120.73%, the 30-year bond by 70.39%, the 10-year treasury note by 97.01% and US dollar index rise by 7.68% as on 23 February 2023. Since the invasion, the cryptocurrencies plunged and fixed-income securities yield escalated due to many factors, particularly inflation and US monetary policy uncertainty (Theiri *et al*., 2023). The onset of Russia-Ukraine on 24 February 2022 has created havoc in many economies, financial markets and economic dynamics (Wiseman and McHugh, 2022). This has given rise to the quest for flight-to-safety or quality (FTS) from cryptocurrency to treasury assets. The FTS often happens when the market is experiencing increased uncertainty (Baele *et al*., 2020) and the investors' desire for safe assets increases in relation to risky investments (Beber *et al*., 2009). Mohamad (2022) defined FTS as a fear of investors during a particular situation that the assets they are holding in their portfolio will bear a higher risk than before, so taking a prompt decision to sell it in exchange for a safe asset.

Since the inception, cryptocurrencies has experienced significant growth and this has created an iconic image of appreciation among the researchers and investment community. Through testing its performance, some research studies labelled it as a diversifier, a hedge, or a safe haven (Baur and Lucey, 2010; Naeem *et al*., 2021), including during turbulent times (Abdelmalek and Benlagha, 2023). In fact, (Klein *et al*., 2018) claimed that cryptocurrencies such as bitcoin as a new gold. However, some heated arguments opposed this in recent years and pointed out that crypto investment risk is similar to conventional assets and that this currency market is highly bubble prone and volatile during drawdowns (Cheah and Fry, 2015; Corbe *et al*, 2020; Theiri *et al.,* 2023). Considering that the cryptocurrencies value fell from a great height during the invasion, where does this investment fly? In the light of this backdrop, the question triggers: if the cryptocurrencies fall from a great height during the invasion, where does this investment fly?

2. Literature review

Most of the research on the theme 'safe haven attributes of assets' started expanding in the literature based on the theoretical argument of (Baur and Lucey, 2010). As per the author's definition, a safe haven asset usually exhibits a negative correlation with other assets in times of market stress. On this note, extensive past research focused on testing the safe haven capabilities of assets, particularly non-risky gold (Baur and Lucey, 2010; Baur and McDermott, 2010).

To verify the FTS phenomenon, Baele *et al*. (2020) put forward three desirable criteria: (i) when higher positive bond returns coincide with higher negative stock returns; (ii) a high-

frequency negative correlation between equity and bond returns; and there should be large volatility in the stock market during the extreme market disorder. In a similar line, the growing curiosity of researchers directed them to test the flight-to-safety phenomenon over the past years. The following literature demonstrates this.

In the study of FTS with implied volatility, Troster et al. (2019) noticed a negative correlation and suggested that gold-mining stocks can substitute gold. Baele *et al*. (2020) investigated flight-to-safety days for a twenty-three countries bond against stock returns. They qualify the incidence of flight-to-quality and liquidity in stressful times in international stock markets, particularly for US bonds.

Klein *et al*. (2018) address the volatility, correlation and portfolio performance concerning the properties of gold and bitcoin. The result reveals the flight-to-quality role of gold in times of market turbulence. However, the positive correlation with the downward market, bitcoin, does not reflect any superiority over gold. Corbe *et al*. (2020), under a DCC approach, identify a volatility relationship between the China stock market and Bitcoin. They conclude that although cryptocurrencies emerged as a new financial instrument but whether it is a potential diversifier or otherwise is still yet unclear. Abdelmalek and Benlagha (2023) answered that bitcoin is able to provide safe haven attributes during the Covid-19 pandemic.

Lowen *et al*. (2021) check for the flight to safety effect between the equity (VIX), gold (GVZ) and oil (OVX) markets during the Covid-19 crisis. The causality observed of the equity in oil market during the crisis period, but in the case of gold, it is significant only during the normal period. During the Covid-19 pandemic, Jalan *et al*. (2021) reported that gold-backed cryptocurrencies are not a potential safe haven compared to precious metals and gold. Boucher and Tokpavi (2019) point out the FTS event in various crises such as the 1997 Asian crisis, the Russia crisis in 1998, the Dot-com crash, the global financial crisis, and the 2011-2012 European debt crisis corresponding to the stocks-bonds relationship. They proved interesting stylized facts that when the strength of FTS from stock to bond decreases, on that side, FTS from stock to gold and currencies increases.

The research work on the relationship between govt. backed securities (bond and treasury) and other financial assets are relatively sparse. For instance, Connolly *et al*. (2005) find that bond returns tend to rise (fall) relative to equity returns when there is an increase (decrease) in uncertainty. Bansal *et al*. (2010) outline the stock-bond holdings diversification benefits during high stress in the stock market. Empirical evidence of Beber *et al*. (2009) suggest that fixed-income investors in the euro area demand credit quality and flight to liquidity but at different time horizons. Ruzzi (2016) identifies US treasury and gold as a safe haven against the stock market but with different properties. Flavin *et al*. (2014), from the perspective of equity fund managers, tested a safe haven asset to their portfolio during market downturns. The results document the suitability of gold, 10-year and 1-year US treasury bonds as safe candidates, particularly longer-dated bonds when the equity market plunges. Sarwar (2017) finds US VIX causes volatility in T-note, gold and silver. Through a negative correlation between assets, the study demonstrates the FTS phenomenon and impetus for risk-averse investors to adjust their portfolio with safe assets when there is a climb in VIX.

In recent work, when Russia's invasion of Ukraine hit the market, the pursuit of a flight-to-safety phenomenon was tested by (Mohamad, 2022) using a time-varying DCC-GARCH model. Through the appearance of negative dynamics conditional correlation, the study reports the evidence of safety flight from the rubble to the assets such as USD, Yen, Silver, Brent, WTI and natural gas.

It is noticed that a number of studies focused on testing FTS from stock and implied volatility to bond and treasury market. Indeed, so far, no research has investigated the behaviour of cryptocurrencies with treasury securities. Having known a big crash in the crypto market and a large spike in securities yield, to this end, we put forth a research hypothesis of whether there is an occurrence of FTS from top cryptocurrencies to the US treasury market conforming to the Russia-Ukraine war. Deeper understanding of this phenomenon is helpful in articulating an appropriate policy decision and managing the risk in any future crisis.

The remainder of the paper is structured as follows. Section 3 presents a data and econometric framework. Results and discussion detailed in Section 4 and Section 5 conclude the paper.

3. Data and methodology

3.1. Data description

To conduct an empirical investigation, we use recent daily closing prices for the top ten cryptocurrencies (Bitcoin, Ethereum, Tether, USD Coin, Binance Coin, Binance USD, XRP, Cardano, Dogecoin and Polygon) and four US treasury securities (US 5-year, 10-year, 30-year bond and 10-year treasury note yield) along with the US dollar index [1]. The data are obtained for a period from 24/02/2022 to 23/02/2023 (the period corresponding to the Russia-Ukraine war), retrieved from https://coinmarketcap.com/ and https://investing.com. The selection of the top ten cryptocurrencies is on the basis of their highest contribution in terms of market capitalization. The choice of US govt. fixed income securities are as it reported a significant surge in yield during the invasion when cryptocurrencies plummeted.

There are significant trading differences between cryptocurrencies and govt. gilt-edged securities. The data available for cryptocurrencies is for all days and for treasuries for five days of the week. To pair the data observations, the five days of trading are considered. For the data analysis, uses the logarithmically converted daily return series, i.e., $dr_t = ln(dp_t/dp_{t-1})$. The dr_t and dp_t is the daily returns and daily prices.

The generalized autoregressive conditional heteroskedasticity (GARCH) framework mainly uses for volatility modeling of time series. The ARCH term was introduced by R. Engle (1982) and based on that (Bollerslev, 1986), constructed the generalized ARCH model. Notably, this method is widely recognized due to its applications in estimating time-varying variances in a single variable. The representation of conditional variance of the GARCH (1,1) process is as follows;

$$h_{t-1}^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{1}$$

However, the parameters in Equation 1 are subject to the following restrictions; $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$.

3.2. Empirical methodology

To test the existence of flight-to-safe haven in assets during the invasion, we implement the DCC-GARCH model (Engle, 2002). The merit of selecting this model is that it unveils the possible dynamic conditional correlation over time. This enables capturing investors' behavior in response to the news, shocks and innovation. Furthermore, the correlation coefficients captured from this model are of the standardized residuals and thus,

estimation directly accounts for heteroskedasticity (Chiang *et al*., 2007). In other words, since the volatility is adjusted for the standard model procedure, the estimate derived (i.e., time-varying correlation) is free from volatility bias. The dynamic conditional correlation - generalized autoregressive conditional heteroskedasticity of (Engle, 2002), its standard methodology takes the following form;

$$y_t = \mu_t(\theta) + \mathcal{E}_t \tag{2}$$

where, $\mathcal{E}_t = H_t^{1/2}(\theta) z_t$

$$H_t = D_t R_t D_t \tag{3}$$

The correlation matrix is then transformed as follows;

$$Rt = diag(\sqrt{q}_{11,t}, \ldots, \sqrt{q}_{\eta\eta,t}) Q_t diag(\sqrt{q}_{11,t}, \ldots, \sqrt{q}_{\eta\eta,t}), \tag{4}$$

where $Q_t = (q_{ij,t})$ is

$$\mathrm{Q_t} = \omega + \alpha\mu_t \ \dot{\mu}_t + \beta Q_{t-1}$$

Where $\omega = (1 - \alpha - \beta)\ \overline{Q}$, α and β are non-negative parameters i.e., $\alpha + \beta < 1$, Q_t is an unconditional variance matrix.

The estimate of the dynamic conditional correlation between asset '*i*' (cryptocurrencies) to '*j*' (treasuries) will be obtained using the standard procedure proposed by (Engle, 2002).

3.3. Testable hypothesis

With the backdrop of the literature review and the methodology explained above, the following alternative hypotheses are formulated.

H_1: A short-term investment horizon flight-to-safety episode took place from cryptocurrencies to US treasury securities during the invasion period.

H_2: Long-term investment horizon flight-to-safety happened from cryptocurrencies to US gilt-edged securities.

H_3: Flight-to-safety occurred from cryptocurrencies to the US dollar index (USDX).

When the estimated parameter (DCCα) is significantly negative, there is flight-to-safety for the considered safe asset in the short-term. This will hold hypothesis 1 true. If (DCCβ) is negatively significant, then the securities' long-term safe property is supported during extreme market conditions and this will hold hypothesis 2 true. Accordingly, to analyse the effect of cryptocurrencies on USDX and verify the safe asset role, we test hypothesis 3.

4. Empirical results and discussion

Table 2 presents a comprehensive descriptive statistic of cryptocurrencies and the US govt. securities. The results show that all cryptocurrencies' daily returns are negative and range between -0.025% to -0.309% for a higher level of risk starting from 0.074% and going up to 7.105%. It suggests a higher level of fear to the cryptocurrency investors during the Russia-Ukraine war. Discretely, ADA followed by XRP, exhibits high negative returns though MATIC followed by DOGE, is highly volatile among the cryptocurrencies. Conversely, the entirety of the treasuries returns are discovered to be positive at the cost of lower risk. Indeed, on a daily basis, the higher mean returns of US5YB are equal to 0.306% with the

Table 2. Summary statistics for daily returns series.

	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	ADF
Panel A: Cryptocurrencies							
BTC	−0.182	3.973	10.278	−25.723	−1.472	11.252	−15.43**
ETH	−0.175	5.333	24.706	−32.372	−0.825	10.455	−15.40**
USDT	0.000	0.074	0.336	−0.391	−0.120	11.413	−15.54**
USDC	0.000	0.083	0.355	−0.379	−0.070	9.698	−15.82**
BNB	−0.061	4.429	13.060	−25.120	−1.683	11.390	−18.28**
BUSD	0.000	0.108	0.688	−0.431	1.032	14.096	−15.94**
XRP	−0.225	4.823	20.005	−21.703	−0.640	8.212	−17.49**
ADA	−0.309	5.539	22.442	−25.002	−0.416	6.560	−16.59**
DOGE	−0.149	6.523	41.009	−33.471	−0.014	12.389	−15.18**
MATIC	−0.025	7.105	32.011	−32.994	−0.153	8.602	−16.19**
Panel B: US Treasury securities							
US5YB	0.306	2.842	11.261	−8.780	−0.053	4.189	−13.37**
US10YB	0.263	2.615	9.021	−7.810	−0.085	3.480	−15.66**
US30YB	0.206	2.059	6.649	−5.672	−0.056	2.925	−16.27**
US10YT	0.262	2.615	8.498	−7.430	−0.051	3.405	−15.55**
USDX	0.029	0.595	1.639	−2.139	−0.451	3.759	−15.58**

Notes: The ** indicates the rejection of non-stationary in series at the 5% significance level.

Table 3. Unconditional correlation between cryptocurrency and treasury securities.

	US5YB	US10YB	US30YB	US10YN	USDX
BTC	−0.089	−0.069	−0.036	−0.126	−0.315
ETH	−0.054	−0.029	0.013	−0.085	−0.296
USDT	0.028	0.002	−0.021	0.008	0.050
USDC	−0.049	−0.070	−0.079	−0.054	0.020
BNB	−0.078	−0.059	−0.027	−0.120	−0.274
BUSD	0.023	−0.001	−0.042	0.009	0.092
XRP	−0.007	0.023	0.058	−0.026	−0.242
ADA	−0.072	−0.051	−0.013	−0.115	−0.301
DOGE	−0.046	−0.045	−0.026	−0.078	−0.151
MATIC	−0.096	−0.063	−0.005	−0.117	−0.288

same statistics taking values 0.263% (US10YB), 0.262% (US10YN), 0.206% (US30YB) and 0.029% (USDX) for a minimum risk sweep between 0.595% to 2.842%. This occurrence indicates with the perseverance of higher risk, the investors have shifted their asset allocation from cryptocurrencies into safe govt. securities. In the table, the kurtosis and skewness values present the cryptocurrencies and treasuries return distribution are heavy-tailed and asymmetric. The ADF test statistics of Said and Dickey (1984) suggest that all variables are free from the unit root and are significant at a 5% level. Additionally, the heteroscedasticity condition in all the variables is necessary to employ the DCC GARCH model, which is also satisfied [3].

In Table 3, we report the correlation between cryptocurrency and treasury security returns. During the invasion period, we notice that govt. securities are generally negatively correlated with cryptocurrencies. This meets the criteria of Baele *et al*. (2020), who stated the FTS days are when there is a high frequency of negative correlation between two assets. However, even when the correlation between cryptos and securities is negative, the coefficient value indicates the strength of FTS from former to latter remains low. Specifically, the BTC and USDX (-0.315) followed by ADA and USDX (-0.301), showed the highest negative correlation value. While the correlation between BUSD and US10YB (-0.001), followed by MATIC and US30YB (-0.005), report the lowest negative correlation. However, some opposite signs of correlation with XRP, BUSD and USDT, govt. securities seem to be appealing as a portfolio diversifier.

4.1. Flight-to-safety analysis in DCC GARCH

Table 4 summarizes the GARCH (1,1) results. Table 5 displays the incidences of FTS through a dynamic correlation between cryptocurrencies and treasury securities from 24/02/2022 to 23/02/2023. The (DCCα) indicates the short-run volatility estimates and (DCCβ) unveils the long-run time-varying volatility spillover effect. From the table, several noteworthy observations have emerged. It may be noted that the extent of the volatility effect from cryptocurrencies to safe-haven assets differs across the investment horizon of safe-asset traders. Of the 30 (DCCα), 25 coefficients depict the sign of negative conditional volatility, out of which 23 turn significant. In particular, our results highlight a negative and significant short-term volatility spillover from; USDT, BNB, BUSD, ADA and DOGE to US5YB; BNB and DOGE to US10YB; BTC, ETH, USDC, XRP, DOGE and MATIC to US30YB; and USDT, BNB, DOGE and MATIC to US10YT. A large negative volatility effect directs to support the notion of short-lived flight-to-safety to the investors from riskier cryptocurrencies to less risky govt-backed securities. More specifically, during the invasion period, all fixed-income securities (US5YB, US10YB, US30YB and US10YT) could have served as a safe asset when the cryptocurrencies, particularly BNB and DOGE, took a tumble. There is also some evidence

Table 4. GARCH model estimates.

	μ	ω	α	β	$\alpha+\beta<1$
Panel A: Top ten cryptocurrencies					
BTC	0.168	5.955**	0.305**	0.402**	0.707
ETH	0.267	3.337	0.348**	0.626**	0.974
USDT	0.005**	0.001**	0.446**	0.526**	0.972
USDC	0.001	0.001**	0.378**	0.603**	0.981
BNB	−0.005	3.465	0.056*	0.760**	0.816
BUSD	0.013**	0.002**	0.345**	0.360**	0.705
XRP	0.070	5.583**	0.364**	0.437**	0.801
ADA	−0.025	8.202**	0.319**	0.437**	0.756
DOGE	−0.019	10.170**	0.568**	0.341**	0.909
MATIC	0.428	4.676**	0.464**	0.515**	0.979
Panel B: US treasury securities					
US5YB	0.234	0.843	0.079**	0.803**	0.882
US10YB	0.187	0.091	0.026	0.955**	0.981
US30YB	0.138**	2.256**	0.002	0.466**	0.468
US10YT	0.223*	1.298**	0.139**	0.676**	0.815
USDX	0.031	0.044	0.116	0.759**	0.875

Notes: This table presents the GARCH (1,1) estimates. The ***, ** and * indicates statistical significance at 1%, 5% and 10% level.

Table 5. DCC GARCH model estimates from cryptocurrencies to treasury securities.

	US5YB		US10YB		US30YB		US10YT		USDX	
	DCC(α)	DCC(β)	DCC(α)	DCC(β)	DCC(α)	DCC(β)	DCC(α)	DCC(β)	DCC(α)	DCC(β)
BTC	0.097**	−0.050	0.054*	−0.050	−0.019**	0.990**	0.063**	−0.050	−0.024**	0.811**
ETH	0.012**	−0.050	0.126	−0.028	−0.534*	−0.007**	0.029	−0.050	−0.027**	0.748**
USDT	−0.013**	0.976**	0.106**	−0.050**	0.106**	−0.050	−0.029**	−0.050	−0.036**	−0.050**
USDC	0.157	−0.041	0.143**	−0.050	−0.019**	0.925**	0.142	0.019	0.049	0.748**
BNB	−0.027**	−0.050	−0.025**	−0.050	−0.016	−0.050	−0.023**	−0.050	−0.017*	0.943**
BUSD	−0.025**	0.153**	0.078**	−0.050	0.129	0.616	0.177**	0.557**	0.002	0.006
XRP	0.144	0.036	0.207**	0.086	−0.042**	0.333**	0.161	0.078	−0.013	0.762**
ADA	−0.042**	0.3398	0.021	0.702	0.013	0.823**	0.026	0.197	−0.026**	0.921**
DOGE	−0.018**	−0.050	−0.020**	−0.050	−0.026**	−0.049	−0.026**	−0.019**	0.044	−0.033
MATIC	0.029**	−0.050	0.158*	0.052	−0.034**	0.369**	−0.039**	−0.050	−0.022**	0.629*

Notes: The DCC(α) and DCC(β) represents FTS from cryptocurrencies to US treasury securities in the short-term and long-term horizons. The ***, ** and * indicates the statistical significance and the alternative hypothesis (H_1, H_2 and *H3*) was accepted at 1%, 5% and 10% level, respectively.

of significant positive contemporaneous DCCα coefficients (DCCα = 12), which captures the positive short-run risk transmission effect from; BTC, ETH and MATIC to US5YB; BTC, USDT, USDC, BUSD, XRP and MATIC to US10YB; USDT to US30YB; BTC and BUSD to US10YT. The persistence of the short-run positive volatility effect points out the risk diversification opportunity. In terms of magnitude, for example, a 1-point rise in the BTC explains a substantial percentage of positive volatility in the treasury securities (US5YB = 0.097% (9.7%), US10YB = 0.054% (5.4%) and US10YT = 0.063% (6.3%)), suggesting securities are a diversifier for a BTC.

We also verify the DCCβ coefficients, which describe the long-run volatility dependency among assets. Evaluating such relations portrays crucial financial applications such as portfolio diversification and risk management, asset allocation, price discovery and many more. Regarding the (DCCβ) out of the estimated coefficients, 25 are negative and only 04 are statistically significant at 5%. Some results of the volatility spillover of cryptocurrencies for the negative changes in the volatility of safe haven asset is moderately consistent with the flight-to-safety effect. The significant (USDT – US10YB = - 0.050%; ETH – US30YB = -0.007%; DOGE – US10YT = -0.019%) lends support to the evidence of higher volatility spillover. Pointing out this negative volatility effect, we infer that during the Russia-Ukraine war, investors perceived cryptocurrencies as a risky asset; hence with market fear, selling the crypto investment in exchange for a giant economy of gilt-edged securities. However, cryptocurrencies' more positive volatility effect suggests that securities may be optimal to play a portfolio diversifier role in the long run. More clearly, we observe that the US30YB yield provides higher risk diversification benefits for cryptocurrencies such as BTC, USDC, XRP, ADA and MATIC.

Seeing the huge spike and inverse trend of the US dollar index (USDX) to that of cryptocurrencies, we have also analysed the flight-to-quality of it corresponding to the war period. For the USDX, their short-run volatility response is significant and negative relative to the BTC, ETH, USDT, BNB, ADA and MATIC volatility spillover. We also provide evidence of the negative reaction of USDX to volatility spillover from USDT in the long run. The negative response of USDX to the reported cryptocurrency volatility allows portfolio managers and institutional investors to have a safe short/long-term horizon bet in a US dollar currency. Note that for other cryptocurrencies, USDX acts as a diversifier.

5. Conclusion

In times of market turbulence, investors and portfolio managers reallocate their assets from risky assets to less risky assets. In the financial market, this action is about the investors' flight to safety journey. One of these flights is experienced by cryptocurrency investors. The cryptocurrencies, which had displayed increasing trends even when the market was under the panic of the Covid-19 pandemic (Abdelmalek and Benlagha, 2023), have plunged their astonishing high performance (48.17%) over the period from 01 January 2022 to 26 February 2023. This has cropped a question: during the invasion period, where does this investment shift by the cryptocurrency investors? In light of this, using the DCC-GARCH approach, we test the flight-to-safety from cryptocurrencies to US treasury securities and the US dollar index.

The results of the preliminary unconditional correlation test indicate that the govt. securities are generally negatively correlated with cryptocurrencies. Further, as compared to DCCβ a sizeable negative and significant DCCα volatility coefficients report the short-lived flight-to-safety from cryptocurrencies to securities. This result holds that during the invasion period, investors perceived cryptocurrency as a risky asset. Hence, due to unwavering shock, shift the cryptocurrency investment in exchange for giant economy treasury securities. Specifically, fixed-income securities such as US5YB, US10YB, US30YB and US10YT yield

offer a safety net when cryptocurrencies such as BNB and DOGE are adversely performed. In addition, we have also observed the positive volatility dependencies between some cryptocurrencies and treasuries, particularly in a DCCβ estimate. The persistence of the positive volatility effect points out the substantial amount of risk diversification benefits are visible in the short-term investment horizon. However, the magnitude suggests the benefit intensified in the long-run. One possible example could be that changes in BTC explain a substantial percentage of positive volatility in the gilt-edged securities, suggesting these securities are a short-run risk diversifier for a BTC.

Following a huge spike and an inverse relationship with cryptocurrencies, we also introduce a US dollar index in the analysis. The leading negative short-run volatility effect of BTC, ETH, USDT, BNB, ADA and MATIC on US dollar currency (USDX) complements the flight-to-safety. However, risk-averse investors should note that for other cryptocurrencies, it acts as a diversifier.

We unfolded several surprising implications that could be interesting for various market participants looking for evidence on the behaviour of cryptocurrencies and govt. backed securities during times of market uncertainty. Many researchers labelled cryptocurrencies as a good safe haven tool during the crisis period (Naeem *et al*., 2021), whereas, from a behavioural standpoint, others said it is the most volatile asset and prone to speculative bubbles (Cheah and Fry, 2015). In line with the latter researcher's findings, in the present study, we noticed all cryptocurrencies adversely performed during the invasion period, implying more considerable risk and investment instability to the investors. For the asset and portfolio risk managers in an extreme market condition, as FTS strength of US-backed securities favours can have a safe environment for asset allocation and risk management. In addition, as central Bankers, transfer of investment implies currency appreciation and depreciation and thereby, instability in the financial system. The findings are also critical for policymakers, as independent from central authority, cryptocurrencies are pronounced to higher risk and volatile during the invasion period, demanding regulators to intervene to devise an appropriate and sustainable market strategy.

Notes

1. The rationale behind the selection of giant economy treasury securities and the US dollar index is that these securities' yields showed a large surge when the cryptocurrency market fell during the invasion period.
2. The cryptocurrency market capitalisation lost 48.17% from 01 January 2022 to 26 February 2023 (https://coinmarketcap.com/charts/).
3. The detailed ARCH-LM test results for the heteroskedasticity effect can be provided upon request.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Suraj Velip http://orcid.org/0000-0003-3409-7755
Mrunali Jambotkar http://orcid.org/0000-0002-1317-5075

References

Abdelmalek, W., & Noureddine B. (2023). On the safe-haven and hedging properties of Bitcoin: new evidence from COVID-19 pandemic. *The Journal of Risk Finance*, *24*(2), 145–168. doi:10.1108/JRF-06-2022-0153

Aliu, F., Simona H., & Ujkan Q. B. (2023). Consequences of Russian invasion on Ukraine: evidence from foreign exchange rates. *The Journal of Risk Finance*, *24*(1), 40–58. doi:10.1108/JRF-05-2022-0127

Baele, L., Geert B., Koen I., & Min W. (2020). Flights to Safety. *The Review of Financial Studies*, *33*(2), 689–746. doi:10.1093/rfs/hhz055

Bansal, N., Robert A. C., & Chris S. (2010). Regime-switching in stock index and Treasury futures returns and measures of stock market stress. *The Journal of Futures Markets*, *30*(8), 753–779. doi:10.1002/fut.20439

Baur, D. G., & Brian M. L. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *The Financial Review*, 45(2), 217–229. doi:10.1111/j.1540-6288.2010.00244.x

Baur, D. G., & Thomas K. M. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, *34*(8), 1886–1898. doi:10.1016/j.jbankfin.2009.12.008

Beber, A., Michael W. B., & Kenneth A. K. (2009). Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *The Review of Financial Studies*, *23*(3), 925–957. doi:10.1093/rfs/hhm088

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. doi:10.1016/0304-4076(86)90063-1

Boucher, C., & Sessi T. (2019). Stocks and bonds: Flight-to-safety for ever? *Journal of International Money and Finance*, *95*, 27–43. doi:10.1016/j.jimonfin.2019.03.002

Cheah, E., & John F. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, *130*, 32–36. doi:10.1016/j.econlet.2015.02.029

Chiang, T. C., Bang N. J., & Huimin L. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance*, *26*(7), 1206–1228. doi:10.1016/j.jimonfin.2007.06.005

Connolly, R., Chris S., & Licheng S. (2005). Stock Market Uncertainty and the Stock-Bond Return Relation. *The Journal of Financial and Quantitative Analysis*, *40*(1), 161–194. doi:10.1017/S0022109000001782

Corbe, S., Charles L., & Brian L. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, *35*. doi:10.1016/j.frl.2020.101554

Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339–350. doi:10.1198/073500102288618487

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987–1007. doi:10.2307/1912773

Flavin, T. J., Ciara E. M., & Ekaterini P. (2014). Identifying safe haven assets for equity investors through an analysis of the stability of shock transmission. *Journal of International Financial Markets, Institutions & Money*, *33*, 137–154. doi:10.1016/j.intfin.2014.08.001

Jalan, A., Roman M., & Larisa Y. (2021). "Shiny" crypto assets: A systemic look at gold-backed cryptocurrencies during the COVID-19 pandemic. *International Review of Financial Analysis*, *78*. doi:10.1016/j.irfa.2021.101958

Klein, T., Hien P. T., & Thomas W. (2018). Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105–116. doi:10.1016/j.irfa.2018.07.010

Lowen, C., Bilal K., & Thorsten L. (2021). Is this time really different? Flight-to-safety and the COVID-19 crisis. *Plos One*, *16*(5). doi:10.1371/journal.pone.0251752

Mohamad, A. (2022). Safe flight to which haven when Russia invades Ukraine? A 48-hour story. *Economics Letters*, *216*. doi:10.1016/j.econlet.2022.110558

Naeem, A., Saqib F., Faruk B., & Syed J. H. S. (2021). Hedging the downside risk of commodities through cryptocurrencies. *Applied Economics Letters*, *28*(2), 153–160. doi:10.1080/13504851.2020.1739609

Ruzzi, D. (2016). Flight to Safety: Does it matter for volatility forecasting? *available at SSRN 3134374*. doi:10.2139/ssrn.3134374

Said, S. E., & David A. D. (1984). Testing for unit roots in autoregressive-moving average models of unknown order. *Biometrika*, *71*(3), 599–607. doi:10.1093/biomet/71.3.599

Sarwar, G. (2017). Examining the flight-to-safety with the implied volatilities. *Finance Research Letters*, *20*, 118–124. doi:10.1016/j.frl.2016.09.015

Theiri, S., Ramzi N., & Jahangir S. (2023). Cryptocurrency liquidity during the Russia–Ukraine war: the case of Bitcoin and Ethereum. *The Journal of Risk Finance*, *24*(1), 59–71. doi:10.1108/JRF-05-2022-0103

Troster, V., Elie B., & David R. (2019). A quantile regression analysis of flights-to-safety with implied volatilities. *Resources Policy*, *62*, 482–495. doi:10.1016/j.resourpol.2018.10.004

Wiseman, P., & David M. (2022). *Economic dangers from Russia's invasion ripple.* AP NEWS, available at: https://supernet.isenberg.umass.edu/media/BostonGlobe-03022022.pdf. (accessed 24 April 2023)