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Cryptocurrencies as a vehicle for capital exodus: Evidence from the Russian–Ukrainian crisis

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ABSTRACT

Cryptocurrencies provide an escape from the conventional financial system and its regulations and could therefore become increasingly popular in the midst of geopolitical uncertainties. We analyze the linkage of the Russia–Ukraine conflict and the trading volume of 16 major cryptocurrencies via event study methodologies, based on a geopolitical risk index. The results show that the trading volume of most cryptocurrencies is positively affected by the events of the conflict. This is especially true for payment tokens and most utility coins. Interestingly, stablecoins show only fewer trading volumes before the actual event. Among utility tokens, Ripple in particular is positively influenced.

1. Introduction

Since the Russian–Ukraine crisis, geopolitical uncertainty[2] around the world has reached new levels, beginning a stormy period of escalating events in which acts of war shake hands with sanctions from various countries. The exclusion of several Russian banks from the Society for Worldwide Interbank Financial Telecommunication (SWIFT) has had a great influence on financial markets. Investors who are thus restricted from participating in cross-border payments may be left with few alternatives, one of which being cryptocurrencies. We investigate the link between certain geopolitical events and the Russian–Ukrainian crisis on the trading volume of cryptocurrencies, as we expect it to be positively influenced mainly due to capital flight across borders or hedging and diversification purposes (see e.g. Bouri et al., 2017, for the last one). Furthermore, in times of crisis, investors seek safe haven assets, such as gold, which do not or negatively correlate with other assets (Baur and Lucey, 2010; Baur and McDermott, 2010). Due to their decentralized setting and their independence from central banks' monetary decisions, crypto tokens may also serve as safe havens, even tough they — in contrast to gold — have no intrinsic value. Empirical evidence on Bitcoin shows support (Baur et al., 2018; Shahzad et al., 2019), but also contradictory findings (Bouri et al., 2017; Klein et al., 2018). The divergent views are

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1 Contributions to this study represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank.

2 Carney (2016) defines the term "geopolitical uncertainty" as one of three types of uncertainty – along with policy and economic uncertainty – that influence economic performance. Following (Caldara and Iacoviello, 2022), the term "geopolitical uncertainty" covers a wide range of events, from wars to climate change, or even economic crises. In our work, we use this term in the context of conflict events during the Russian–Ukrainian conflict.

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not surprising given the high volatility and speculative nature of many crypto tokens. However, investors may believe in the save haven properties of cryptocurrencies and act accordingly.

We contribute to the expanding field of literature on the impact of geopolitical risk on cryptocurrencies and its implications for investments (Bouri et al., 2017; Demir et al., 2018; Aysan et al., 2019; Colon et al., 2021; Theiri et al., 2023). In that context, this work identifies events that are typical for geopolitical uncertainty, particularly the one between Russia and Ukraine. Subsequently, we analyze the effect of selected events on the trading volume of a total of 16 cryptocurrencies. We find that, depending on the type of cryptocurrency, the effect of different conflict events on trading volume varies. Payment tokens, such as Bitcoin (BTC), and selected utility tokens are significantly positively associated with the events, while only ARPA is not affected at all. The lack of increased trading volumes for stablecoins on days with increased geopolitical uncertainty is surprising because stablecoins could serve as a vehicle for capital exodus. This unexpected result contradicts the usual behavior of capital flight, where stablecoins could be expected to see heightened trading activity due to their stability and liquidity. A possible explanation is the stringent U.S. regulation on stablecoins and know your customer requirements, which may have restricted their use and trading during this period.

2. Decentralized finance and uncertainty

Although most of the academic literature on cryptocurrencies focuses on their markets and characteristics (Sovbetov, 2018; Aalborg et al., 2019; Bolt and van Oordt, 2020; Kreppmeier et al., 2023; Kreppmeier and Laschinger, 2023), this study examines how cryptocurrencies react to shocks such as uncertainty and war. Given that uncertainty can have many forms (e.g. political, economy-political, geo-political), economists have relied on a variety of proxies since there is no objective measure of this kind of uncertainty. In this regard, a strand of literature examines global uncertainty in general on Bitcoin returns (Bouri et al., 2017, 2018; Demir et al., 2018; Wang et al., 2019; Panagiotidis et al., 2019; Wang et al., 2020) and volatility of Bitcoin (Klein, 2024; Fang et al., 2019) using different proxies, while others examine the effect of trade policy uncertainty (Baker et al., 2016) on Bitcoin (Gozgor et al., 2019) and other cryptocurrencies (Wu et al., 2021). Furthermore, there are studies exploring the interdependence of Bitcoin and traditional capital markets (Matkovskyy et al., 2020; Mokni et al., 2020; Al Mamun et al., 2020; Ah Mand, 2022; Singh et al., 2022). Although Bitcoin has traditionally dominated investors' and academic attention, a nuanced analysis of various cryptocurrencies offers valuable insights into their diverse applications and potential.

The literature on cryptocurrency markets' reactions to geopolitical conflicts has expanded significantly. Recent studies provide substantial insights into how geopolitical events, such as the Russia–Ukraine war, impact cryptocurrencies. For instance Appiah-Otoo (2023), finds that the Russia–Ukraine war negatively affects Bitcoin trading volume, while Bampinas and Panagiotidis (2024) highlight how the war influences cross-market linkages between stock and cryptocurrency returns. Hamouda et al. (2024) and Poddar et al. (2023) further explore the dynamics and connectedness of cryptocurrency markets during such conflicts, revealing increased integration and volatility. Velip and Jambotkar (2024) analyze the asymmetric effects of the US dollar index (USDX) on cryptocurrencies amid the conflict, and Yousaf et al. (2024) examines the linkages between environmental and policy uncertainties and cryptocurrency markets. This body of work underscores the growing recognition of cryptocurrencies' roles in times of geopolitical stress and offers a more comprehensive understanding of their behavior during such periods. Bedowska-Sójka et al. (2022) analyze the hedging properties of various assets, including Bitcoin and Ethereum, during wars in terms of returns concluding that the Russian invasion disrupted connections between geopolitical risk and asset prices. Ayed et al. (2022) study abnormal cryptocurrency returns to war shocks, such as the Russian invasion, finding that the top cryptocurrencies by market capitalization reacted negatively.[3] Both studies primarily examine abnormal returns, providing information on price reactions, but failing to capture broader market behavior. Khalfaoui et al. (2023) investigate the co-movement of returns of stocks and cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple) during the war period, using quantile cross-spectral analysis to show that geopolitical tensions are driving investors toward liquidity, causing recent price declines. Theiri et al. (2023) examine Bitcoin and Ether liquidity during the war, finding that liquidity rose shortly after the invasion but returned to normal levels, indicating no long-term destabilization. They focus on liquidity, but limit their scope to Bitcoin and Ethereum, neglecting the broader cryptocurrency market.

Our study fills this gap by analyzing trading volume responses across various cryptocurrency types, arguing that trading volume more accurately reflects investor activity and capital movement than price-based measures. This approach reveals how different cryptocurrencies may serve as vehicles for capital transfer during geopolitical crises, particularly in the case that sanctions restrict access to traditional financial tools.

Payment coins, mainly used for transactions, may show mixed reactions during uncertainty. Increased adoption could boost demand, while market volatility could cause outflows as investors seek stable assets. The net effect depends on market sentiment and the perception of cryptocurrencies as a store of value versus a medium of exchange (Ammous, 2018). In times of uncertainty, demand for stablecoins rises as investors move their capital out of local currencies to avoid capital controls and protect against economic instability. Stablecoins, pegged to stable assets like the U.S. dollar, offer a secure way to preserve value, maintain liquidity, and bypass restrictions, making them a vital tool for safeguarding wealth during turbulent periods. However, the stablecoins within this sample, Binance USD and Tether USD, are heavily dependent on the US market and, therefore, need to comply with US regulations, sanctions and know your customer procedures. Therefore, it is not clear whether they are the preferred vehicle in terms of capital exodus (Arner et al., 2020; Kosse et al., 2023).

[3] This is especially true for stablecoins, which are expected to maintain their value relative to the pegged currency without deviation.

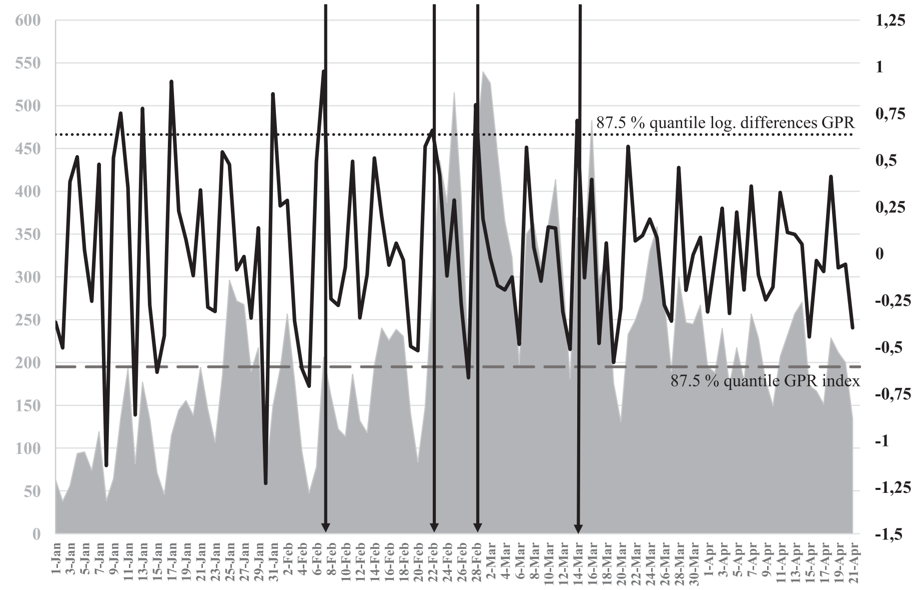

Fig. 1. Event identification based on GPR index. *Notes:* The geopolitical risk index (GPR) is indicated by the gray shaded area (left axis) and the GPR logarithmic differences are shown by the black line on the right axis. In the event period from January to April 2022, both measures must simultaneously exceed their 87.5 quantiles (of the entire observation period January 2021 to April 2022) to identify the day as an event.

Utility coins, which serve functions beyond transactions, may have mixed responses during geopolitical unrest. The increased demand for Decentralized Finance (DeFi) tokens and smart contract applications could lead to inflows, while perceived risks or regulatory restrictions could cause outflows as investors seek safer assets (Momtaz et al., 2019). The net flow depends on the perceived utility and resilience of blockchain ecosystems.[4]

DeFi/Meme coins, known for speculative and community-driven dynamics, may experience increased volatility during geopolitical unrest. Speculative traders might pursue quick gains, while increased risk aversion could lead to liquidations and outflows. Net flow depends on the sentiment of the speculative community and the appetite for risk on the market (Yousaf et al., 2023).

In summary, expected inflows or outflows of each type of cryptocurrency during conflict events or uncertainty are influenced by factors such as perceived stability, adoption as a medium of exchange, utility beyond transactions, and speculative sentiment within the cryptocurrency market. Understanding these dynamics highlights the need for a deeper exploration of various cryptocurrencies and their roles as speculative assets, aiding informed decision-making and risk management in the evolving digital asset landscape.

3. Data & Methodology

3.1. Data

We analyze the daily trading volume in USD of 16 cryptocurrencies from CoinMarketCap, which aggregates data from 250 exchanges.[5] To apply a suitable calibration period prior to the Russian invasion on February 24, 2022, we consider a timeframe between January 1, 2021 and April 20, 2022. On 21 April 2022, the largest crypto exchange Binance announced that it will limit its service to Russian residents and institutions to comply with the fifth package of restrictive measures against Russia. Therefore, this date ends the observation period. The sample used is highly representative of the overall crypto market as CoinMarketCap considers all major exchanges, like Binance, Gemini, and Coinbase.

3.2. Event identification

For the identification of events, we follow the requirements compiled by Sorescu et al. (2017), according to which quality, clarity, timing, and data sources must be taken into account. Therefore, we use the daily geopolitical risk index (GPR) introduced by Caldara and Iacoviello (2022) in our objective event identification process. The GPR index is based on search results from 10 major US newspapers that cover the following aspects. Threats related to war, peace, nuclear and terror acts, or military build-ups. In addition, actual events such as the beginning of war, subsequent escalation, and terror acts are being addressed. The index is a reliable source in numerous studies (Colon et al., 2021; Aysan et al., 2019; Bedowska-Sójka et al., 2022; Singh et al., 2022).

[4] For more on this topic, see: Drobetz et al. (2019), Fisch and Momtaz (2020) and Momtaz (2020, 2023).

[5] See coinmarketcap.com for more information.

Table 1
Descriptive statistics trade volume in million USD.

Cryptocurrency	N	Mean	SD	Min	Median	Max
Stablecoins:						
Binance USD (BUSD)	475	5,950.69	14,421.66	1,019.54	4,863.23	315,551.10
Tether USD (USDT)	475	85,814.89	37,639.86	33,700.88	77,373.12	279,067.46
Payment coins:						
Bitcoin (BTC)	475	42,486.43	23,696.25	13,736.56	36,541.83	350,967.94
Binance (BNB)	475	2,661.99	1,882.64	450.49	2,120.66	17,982.95
Cardano (ADA)	475	3,583.63	2,843.31	468.47	2,642.05	19,141.98
Ether (ETH)	475	24,483.22	11,626.65	6,533.00	21,589.69	84,482.91
Litecoin (LTC)	475	3,545.47	3,273.85	510.04	2,357.31	17,994.26
Solana (SOL)	475	1,714.73	1,810.81	25.72	1,437.16	17,068.64
Utility coins:						
Algorand (ALGO)	475	399.52	432.38	50.14	291.74	4,812.07
ARPA (ARPA)	475	55.27	115.27	3.12	26.35	1,213.27
Polkadot (DOT)	475	2,128.05	1,389.05	424.25	1,714.83	10,070.00
Polygon (MATIC)	475	1,193.12	1,233.50	9.80	856.59	9,181.25
Ripple (XRP)	475	5,181.58	4,953.00	870.88	3,457.26	36,955.18
DeFi/Meme coins:						
Dogecoin (DOGE)	475	3,409.17	6,247.98	154.39	1,484.99	69,410.68
Fantom (FTM)	475	499.35	544.88	4.99	341.02	3,046.98
TrueFi (TRU)	475	19.47	55.57	0.42	10.78	1,068.68

This table presents the mean, median, standard deviation (SD), minimum, and maximum values of our dataset. All descriptive measures in MM USD. The sample ranges from January 2021 to April 2022.

We identify an event when the following two criteria are met for the GPR index in the period from January 1st, to April 21st, 2022. First, the days on which the index values exceed its quantile of 87.5% of the entire observation period. Second, logarithmic differences in the index must surpass the 87.5% quantile, to account for significant upward movement caused by unanticipated war-related events. The course of the two measures is shown in Fig. 1, which illustrates the event identification process. Consequently we identify four events: February, 07th 2022, February, 22nd 2022, February, 28th 2022 and March, 14th 2022.

In the second step, the possible events are validated for plausibility and possibly interference by using Refinitiv's news monitor and the Google search engine. Hence, the identified events can be confirmed. As expected, the GPR index reacts with a short delay after the invasion due to the natural lag of the newspapers. This is suitable for our analysis, since newspaper publication indicates that the information is available to most investors and is considered validated.

3.3. Descriptive statistics & Methodology

The descriptive statistics of the data sample are shown in Table 1. The stablecoin Tether USD dominates the cryptocurrency market in our observation period with a mean trading volume of 85.8 billion USD. In addition to Tether USD, Bitcoin records the second-largest daily trading volume with a mean of 42.5 billion USD. The smallest mean is given by the TrueFi token with only 19.47 million USD on a daily basis. Because the absolute trading volumes of the cryptocurrencies differ to a great extent in size, we use the daily logarithmic differences of the USD volume.

As this study examines an observation period of low and high geopolitical uncertainty, heteroskedasticity is attributable to these periods. Therefore, we use a GJR-GARCH (1,1) model introduced by Glosten et al. (1993). This model allows error terms to deviate asymmetrically around events and is often used for event studies (see e.g. Hudson et al., 2020; Kreuzer et al., 2021). The model is applied in the following form:

$$v_t = \alpha_0 + \sum_{k=1}^{AR} \alpha_{1,k} v_{t-k} + \sum_{l=1}^{MA} \alpha_{2,l} \varepsilon_{t-l} + \sum_{k=-2}^{2} \alpha_{2,k} E_{t+k} + \varepsilon_t$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \sum_{k=-2}^{2} \beta_{3,k} E_{t+k} + \beta_4 \varepsilon_{t-1}^2 I_{t-1}$$

Here, v_t represents the logarithmic difference in the trading volume of a cryptocurrency on day t, while v_{t-k} comprises the value on the kth previous day, with AR referring to the maximum number of lags. Regarding the moving average component (MA), ε_{t-l} is the error term of the lth previous day. E_{t+k} represents dummy variables that address a window ±2 days around event days[6]. As a

[6] As robustness considerations, we also use ±5 days time windows. However, due to overlapping time windows, we cannot investigate all events simultaneously in this case. Therefore, we choose the ±2 days window for our main analysis.

Table 2
Results: Relation between conflict-related events and logarithmic difference in trade volume of cryptocurrencies.

Cryptocurrency	AR|MA	−2d	−1d	Event	+1d	+2d	Model
Stablecoins:							
Binance USD (BUSD)	1|1	−0.44***	−0.07	0.03	−0.07	0.05	s
Tether USD (USDT)	1|1	−0.20**	0.12	0.17	−0.02	0.07	s
Payment coins:							
Bitcoin (BTC)	0|2	−0.34***	0.15	0.33**	−0.06	−0.02	s
Binance (BNB)	2|2	−0.04	0.02	0.08	0.08**	0.03	GJR
Cardano (ADA)	1|4	−0.08	0.10	0.32*	−0.10	−0.06	s
Ether (ETH)	0|3	−0.28**	0.14	0.18	−0.05	0.08	s
Litecoin (LTC)	0|2	−0.19	0.03	0.27**	−0.04	0.09	s
Solana (SOL)	1|1	−0.19*	0.08	0.16	−0.08	0.19	GJR
Utility coins:							
Algorand (ALGO)	1|1	−0.19	0.05	0.30**	0.06	0.03	GJR
ARPA (ARPA)	1|1	−0.32	0.23	0.24	0.20	−0.30	s
Polkadot (DOT)	1|1	0.08	−0.02	0.11**	−0.07	0.19	GJR
Polygon (MATIC)	1|1	−0.26**	0.00	0.35***	−0.10	0.08	GJR
Ripple (XRP)	0|2	0.07	−0.24	0.40**	−0.10	−0.05	GJR
DeFi/Meme coins:							
Dogecoin (DOGE)	0|2	−0.32	0.35	0.43*	−0.41***	0.16	GJR
Fantom (FTM)	1|1	−0.12	−0.10	0.22	−0.08	0.01	GJR
TrueFi (TRU)	1|1	0.07	0.02	−0.14**	0.30	0.15	GJR

Results of the GJR-GARCH(1,1) models explaining the logarithmic difference in trading volume for the analyzed crypto token. AR refers to the auto-regressive and MA to the mean average components used. 475 observations used in all specifications. Column Model displays whether a GJR-GARCH model or a sGARCH specification is used.
* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

result, $E_t = 1$ on the day of the event and 0 otherwise. ϵ_t labels the residuals at time t. Note that the AR and MA values are derived for each time series by estimating ARMA models and applying the following rule: Choose the specification with the lowest Bayesian information criterion (BIC), which prevents errors from being auto-correlated (as shown by Ljung–Box tests).

The second equation addresses heteroskedasticity by modeling the conditional variance h_t of the residuals ϵ_t. Therefore, h_{t-1} describes the conditional variance of the previous day and ϵ^2_{t-1} denotes the squared residuals of the previous day. I_{t-1} is a dummy variable that equals 1, if $\epsilon_{t-1} < 1$, or else 0. If an effect can be observed on the day of the event, the regression coefficient $\alpha_{2,0}$ will be statistically significant. Although the GJR-GARCH approach is suitable for many time series, which we consider, our parameterization approach showed an insignificant β_4 for some cryptocurrencies. Consequently, we neglect the β_4 addend and refer to it as sGARCH.

4. Results

Table 2 provides the results of the GJR-GARCH (1,1) and if more appropriate the sGARCH (1,1) regressions on cryptocurrencies. An irregular increase (decrease) in trading volume on a specific date is indicated by significantly positive (negative) coefficients.

Our results reveal differences depending on the category of crypto token. In the context of stablecoins, we observe mostly insignificant coefficients. However, there is significantly less trading volume observable two days in advance. We observe a significantly higher trade volume for the non-stable payment token Bitcoin (BTC), Cardano (ADA), and Litecoin (LTC) on the event day, indicating that high level of uncertainty may cause a flight of capital into these cryptocurrencies. Note that we cannot find any significant abnormal trade volume after the event day. Similarly to stablecoins, we find a reduction in trading volume two days in advance for Bitcoin (BTC), Cardano (ADA) and Solana (SOL). An explanation may be that crypto donations made to both belligerents paid in Russian rubles, as all these payment tokens are relatively liquid, which is also supported by Arasasingham and DiPippo (2022). Consequently, Bitcoin, which is the non-stable payment token with the highest average volume, shows an abnormally high trade volume on the day of the event.

For the category of utility tokens, the results are similar. All utility coins, with the exception of ARPA, show increased trading volume during the event period. Note that we observe an increased change in trade volume for the Binance coin (BNB) not exactly on the event day but the day after. Polkadot's (DOT) higher volume might be surprising, as its native token is not primarily designed for

Table 3
Robustness check: Relation between conflict-related events and logarithmic difference in the trade volume of cryptocurrencies with a ±5 days event window.

Cryptocurrency	−5d	−4d	−3d	−2d	−1d	Event	+1d	+2d	+3d	+4d	+5d
Stablecoins:											
Binance USD	0.06	−0.03	−0.21*	−0.41***	0.00	0.17	0.05	0.06	−0.12	0.08	−0.34***
Tether USD	0.05	0.21*	−0.09	−0.30**	0.03	0.31**	0.06	−0.01	−0.04	0.07	−0.24**
Payment coins:											
Bitcoin (BTC)	0.12	0.22	−0.12	−0.49***	0.11	0.44***	0.00	0.04	−0.15	0.16	−0.37**
Binance (BNB)	0.06	0.15	−0.02	−0.08	−0.08	0.15***	0.25**	−0.11	0.01	−0.03	−0.14*
Cardano (ADA)	0.03	0.16	−0.23	−0.25	0.06	0.45**	−0.01	−0.18	−0.09	−0.09	0.03
Ether (ETH)	0.02	0.23	−0.06	−0.46***	0.07	0.31**	0.08	−0.01	−0.07	0.09	−0.30**
Litecoin (LTC)	0.04	0.25*	−0.12	−0.27**	−0.01	0.33**	0.06	−0.03	−0.05	−0.02	−0.21*
Solana (SOL)	0.16	0.65	−0.27	−0.56	−0.02	0.36*	−0.05	0.15	0.04	−0.02	−0.36*
Utility coins:											
Algorand (ALGO)	0.16	0.28	−0.20	−0.18	−0.07	0.48***	0.15	−0.07	0.14	−0.14	−0.23
ARPA (ARPA)	0.03	−0.06	0.10	−0.28	0.24	0.37	0.13	−0.36	0.23	−0.12	−0.04
Polkadot (DOT)	0.07	0.14	0.05	0.00	−0.26	0.27	−0.03	0.01	−0.01	−0.05	−0.14
Polygon (MATIC)	0.02	0.22	−0.10	−0.33	−0.11	0.79***	−0.07	0.01	−0.08	−0.07	−0.34
Ripple (XRP)	0.01	0.04	0.16	0.05	−0.39***	0.48***	0.01	−0.12	−0.16	−0.08	0.03
DeFi/Meme coins:											
Dogecoin (DOGE)	0.07	0.39	−0.11	−0.34*	0.29	0.71**	−0.39*	−0.10	−0.10	0.05	−0.13
Fantom (FTM)	−0.06	0.21	0.05	−0.32*	−0.15	0.47***	0.04	−0.05	−0.12	−0.14	−0.15
TrueFi (TRU)	−0.06	0.51	−0.20	0.07	0.05	−0.15	0.47	0.08**	0.82	−0.30	−0.77**

Results of regression models explaining the logarithmic difference in trading volume for the analyzed crypto token. Model specifications are shown in Table 2. To prevent overlapping event windows, only the following event days were considered: February, 07th 2022, February, 28th 2022 and March, 14th 2022.

* Indicate statistical significance at 10%.

** Indicate statistical significance at 5%.

*** Indicate statistical significance at 1%.

payments. However, DOT is used for transaction fees, governance, and staking within the Polkadot ecosystem. We find that Ripple (XRP) is the token most positively affected by the event. Although Ripple is classified as a utility token, it is closely related to the financial system. Furthermore, the logarithmic differences in the trading volume of the DeFi token Fantom (FTM) have not been influenced by events. TrueFi (TRU) even shows a lower trading volume on event day. This may be because decentralized finance systems, which offer unsecured loans and rely on credit risk evaluation rather than traditional collateral, could be viewed as risky rather than secure by investors seeking safety during times of serious conflict. Dogecoin (DOGE), which is popular among crypto community but not designed for finance purposes, shows a significant positive coefficient on event day and a significant negative coefficient on the following day.

Recall that we apply a ±2 days event window, as otherwise we would not be able to use all identified events due to overlapping time windows. However, it is interesting to look more closely for potential lagged effects, and thus we do a further robustness check, in which we apply the ±5 days window but neglect February 22, 2024 as an event, to prevent an overlapping event bias. The results are shown in Table 3. We see that the robustness check generally supports our main results. Now, all payment tokens exhibit significantly higher trading volume on the event day. In particular, the payment token shows negative coefficients on the fifth day, indicating that the effect is temporary and not a lasting impact.

In summary, we find that the different types of crypto tokens are affected differently by conflict events. However, non-stable payment and utility tokens are positively influenced by the events to a similar extent, with the exception of ARPA. One potential explanation may lie in the fact that ARPA exhibits by far the smallest market capitalization and trading volume compared to the other utility tokens and therefore liquidity considerations may play a role. Ripple stands out since the utility token was probably triggered by the event day due to its function as a real-time payment system. So far, our findings are in line with the results of previous studies that examine the effects of various types of uncertainty on cryptocurrency returns (Demir et al., 2018; Wu et al., 2019, 2021). Our findings also align with Colon et al. (2021), who find that the cryptocurrency market can serve as a hedge against geopolitical uncertainty and threats of geopolitical uncertainty.

5. Conclusion

We analyze the effects of the Russian–Ukraine conflict on the logarithmic differences in trading volumes of crypto tokens by applying an event study methodology to daily trading volumes of 16 cryptocurrencies for an observation period from January 1, 2021, to April 20, 2022. The selection of events is based on the GPR index.

Our results show that the trading volumes of most crypto tokens are positively affected by the conflict events. However, there are significant differences between the individual token categories. Non-stable coins, used for payment purposes, such as Bitcoin, Ardano, and Litecoin, are positively related to the event day and the Binance coin one day later. We observe similar patterns for most utility tokens such as Ripple, Polkadot, Polygon, and Algorand, while ARPA does not show any significant coefficients. Ripple for instance shows the highest effect on the event day, which might be connected to its function as a real-time payment system. Surprisingly, Binance USD and Tether USD exhibit significantly reduced trading volumes two days before the event and no effect in the following days, indicating that anonymity increases attractiveness, especially for risk-prone individuals (Borgonovo et al., 2021). The DeFi/Meme tokens are either not affected at all (Fantom) or negatively affected around the event day.

One potential limitation of our study lies in the selection of events. Although we follow an objective, data-driven approach, alternative methods are possible and could influence the results. Furthermore, we cannot completely exclude the possibility that our results may be influenced to some extent by other factors than the investigated events, which is a common limitation in event studies. We are tackling this issue by applying relatively short event windows and doing robustness checks. Although we consider a wide range of crypto tokens, further research may benefit from extending this selection. Furthermore, comparing the reactions of cryptocurrencies with various kinds of geopolitical uncertainty, such as climate risk or economic crises, is also worth further investigation.

In summary, this study contributes to a deeper perspective on the important issue of how the conflict between Russia and Ukraine affects the different categories of tokens. The insights are helpful for policy makers, as the findings can be an indicator for possible capital flights.

CRediT authorship contribution statement

Christian Kreuzer: Writing – review & editing, Writing – original draft, Supervision, Formal analysis, Data curation. **Ralf Laschinger:** Writing – review & editing, Writing – original draft. **Christopher Priberny:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Sven Benninghoff:** Writing – original draft, Data curation.

Data availability

All data sources are freely accessible.

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