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War and cryptocurrency markets: An empirical investigation

Mohamed Arouri
Université Côte d'Azur, GRM, 24 ave. Des diables bleus, Nice 06300, France

Sabrine Ayed
Léonard de Vinci Pôle Universitaire, Research Center, 92916 Paris La Défense (France)

Mathieu Gomes
Université Clermont Auvergne, CleRMa, 11 bd Charles de Gaulle, Clermont-Ferrand 63000, France

Adel Barguellil
Université Côte d'Azur, GRM, 24 ave. Des diables bleus, Nice 06300, France

Abstract

Using daily returns on the top ten cryptocurrencies and the event study methodology, we estimate cryptocurrency abnormal returns around the 2022 Russian invasion of Ukraine. Our findings indicate that except for Binance coin, cryptocurrencies have negatively reacted to the war, but at different scales. For Binance coin, positive abnormal returns are reported. Our findings hold over the post war announcement period and when using alternative measures of abnormal returns based on different asset pricing models.

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Contact: Mohamed Arouri - mohamed.arouri@unice.fr, Sabrine Ayed - sabrine.ayed@devinci.fr, Mathieu Gomes - mathieu.gomes@uca.fr, Adel Barguellil - adel.barguellil@etu.univ-cotedazur.fr.
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1. Introduction

Cryptocurrencies have attracted a lot of attention from investors, scholars and regulators. Their decentralized nature and associated features (trust, potential anonymity, independence from monetary authorities) make them an interesting topic to investigate. The bulk of research on cryptocurrency markets has focused on understanding their characteristics (Bolt and van Oordt, 2016), their links with traditional financial markets (Baur et al. 2018a,b), their implications for investment and portfolio diversification and their uses for illegal transactions (Gandal et al., 2018). Previous research works have also studied the reaction of cryptocurrency markets to uncertainty and shocks such as the Covid 2019 pandemic, cyberattacks on cryptocurrency exchanges, terrorist attacks, and economic policy uncertainty (Elasayed et al., 2022; Chen et al., 2022; Almaqableh et al., 2022).

Our paper contributes to this recent literature by empirically investigating the impact of the Russia-Ukraine military conflict on cryptocurrency markets. While this conflict has generated strong effects across financial, currency, energy and food markets around the globe (Boubaker et al., 2022), we still know little about its social, economic and behavioural implications. The numerous Western sanctions that have been imposed on Russia (e.g., banning major Russian banks from the SWIFT international payment system) have led various experts to suggest cryptocurrencies could be used by agents in Russia, China and other countries as an alternative tool to settle international transactions. Cryptocurrencies were created with the intention of bypassing established financial institutions. Because of their decentralized nature, transactions conducted using cryptocurrencies bypass the traditional financial plumbing (Nakamuto, 2008). Given this, European Union officials mentioned in March 2022 that crypto mining and trade could be used to circumvent sanctions against Russia, which is the world's third-largest Bitcoin miner. Such strategies have already been used by Iran[1] and North Korea[2], and Venezuelan authorities have been evaluating the possibilities presented by cryptocurrencies to face the economic and financial constraints exacerbated by Western-imposed sanctions (Antonopolous et al., 2019).

Further, according to some recent papers, cryptocurrencies could be considered as a safe-haven asset amid times of heightened economic and political uncertainty followed by extreme market downturns. While many researchers have studied the properties of gold as a safe-haven asset (Baur and Lucey, 2010; Conlon et al., 2018; Gomes et al., 2023), recent investigations have hinted toward the possibility of cryptocurrencies playing a similar role. Indeed, gold and cryptocurrencies share some similar characteristics, mainly the scarcity of supply and the absence of centralized control (governments have no authority over either of them since both assets are mined by a large number of independent operators and corporations around the world). Selmi et al. (2018) evaluate the roles of Bitcoin and gold as a hedge or a safe-haven under various market conditions and find that Bitcoin would serve as a safe-haven during political and economic crisis periods. Dyhrberg (2016) shows that Bitcoin can be a useful risk management tool. Shahzad et al. (2019) find that the safe-haven features of Bitcoin are time-varying and dependent upon the stock market considered. Luther and Salter (2017) and Gil-Alana et al. (2020) recognize Bitcoin's potential as an investment refuge amid a market crisis triggered by major events like pandemics and terrorist attacks. Other research works argue that cryptocurrencies have the potential to be safe-haven assets due to their low

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[1] https://www.reuters.com/business/finance/iran-makes-first-import-order-using-cryptocurrency-tasnim-2022-08-09/

[2] https://www.nytimes.com/2022/06/30/business/north-korea-crypto-hack.html

association with traditional financial assets and their independency from monetary policies (Conlon and McGee, 2020). However, the existing literature does not consistently support cryptocurrencies' safe-haven features. For instance, Baur et al. (2018b) highlight the speculative nature of Bitcoin-related investing, which leads to panic selling during significant market turmoil due to major event. Focusing on the Chinese stock market, Corbet et al. (2020) show cryptocurrencies did not act as hedges or safe havens during the Covid-19 crisis.

All in all, it seems that the expected reaction of cryptocurrency markets to extreme events such as international military conflicts is rather unclear, and is worth further investigation. The paper closest to ours is Khalfaoui et al. (2023) who study the impact of attention on the Russia-Ukraine war (proxied by Google Trends) on four cryptocurrencies (BTC, XRP, ETC, and LTC). They use quantile cross-spectral analysis and show that co-movements between war attention and cryptocurrencies depends on investment horizon and market state. Our paper differs from theirs as it uses an event study methodology to investigate the behavior of ten cryptocurrencies surrounding the Russian invasion of Ukraine on February 24th, 2022. As such, our focus is not on assessing the impact of "attention" to war but on determining how the war event itself has influenced the behavior of cryptocurrencies. Our investigation is in that regard complementary to theirs.

The remaining of this paper is organised as follows. Section 2 introduces the data and our methodology. Section 3 discusses our main empirical findings. Robustness checks are provided in Section 4. Section 5 concludes.

2. Data and methodology

We consider the top ten cryptocurrencies by market capitalization as of April 2022, namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Luna (LUNA), Cardano (ADA), Avalanche (AVAX), Solana (SOL), Binance Coin (BNB), Dogecoin (DOGE) and Polkadot (DOT). The data is sourced from coinmarketcap.com and covers the period from August 3rd, 2021 to April 15th, 2022. We also use a world stock market index (MSCI world) obtained from Bloomberg and the CRIX cryptocurrency market index introduced by Trimborn and Hardle (2018). The CRIX index is often used as the benchmark index for cryptocurrencies as it tracks the performance of the whole cryptocurrency market while dealing with the issue of disproportionate capitalization between the different cryptocurrencies and the dominance of Bitcoin (Elasayed et al., 2022).

To investigate the impact of the war on cryptocurrency markets, we use the standard event study methodology (MacKinlay, 1997) which enables us to detect abnormal returns and cumulative abnormal returns for each of the ten cryptocurrencies. The methodology makes sense in our context as it enables us to measure the effects of a specific event (in our case, the start of Russia's "special military operation" in Ukraine) on cryptocurrency returns using a relatively short time period. If we assume rationality in the marketplace, the effects of the studied event should be reflected very rapidly in prices. The event-study methodology has been used in many recent papers focused on understanding the behavior of cryptocurrencies (e.g., Ante, 2023; Joo et al., 2020; Yousaf et al., 2023).

We calculate daily returns as the first natural logarithmic difference of each cryptocurrency prices. The use of the event study methodology allows us to detect the cumulative abnormal returns of cryptocurrencies during the event window. Our baseline event window starts on February 17th, 2022 and ends on March 03th, 2022. As in Boubaker et al. (2022), we include one week before February 24th as many nations had already accused Russia of planning the invasion of Ukraine. We also consider alternative event windows.

The abnormal returns for each cryptocurrency i = 1, 2, 3… 10 across t = 1, 2, 3… T days is calculated as follow:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{1}$$

where $R_{i,t}$ is the daily observed return on the cryptocurrency i and $E(R_{i,t})$ is the daily expected (normal) return on the cryptocurrency i. As in Almaqableh et al. (2022), the daily expected return at time t, for cryptocurrency i, is computed using the Capital Asset Pricing Model (CAPM) as follows:

$$E(R_{i,t}) = \widehat{\alpha_\iota} + \widehat{\beta_\iota} R_{mt} \tag{2}$$

where R_{mt} is the daily return of the MSCI World Index at time t, $\widehat{\alpha_\iota}$ and $\widehat{\beta_\iota}$ are the estimated coefficients from a rolling CAPM over the estimation window (142 days prior to the event window) which starts from August 03rd, 2021 and ends the day prior to the event window.

We compute the cumulative abnormal return for each cryptocurrency during the event window in the following way:

$$CAR_{i,p-q} = \sum_{t=p}^{q} AR_{i,t} \tag{3}$$

where $CAR_{i,p-q}$ is the cumulative abnormal return for each cryptocurrency for the event window (p-q).

3. Main findings

3.1. Preliminary analysis

Table 1 reports descriptive statistics on the ten cryptocurrencies over the total period of our analysis starting on August 3rd, 2021 and ending on April 15th, 2022. While the average daily return of the MSCI World index was negative, average returns were positive for 6 out of 10 cryptocurrencies, leading to a positive return on the CRIX index. Avalanche shows the highest return followed by Luna. Yet, all the studied cryptocurrencies are riskier than the world stock market. Luna features the highest volatility followed by Avalanche. Min-Max intervals also suggest that investments in cryptocurrencies are significantly riskier than investments in stocks. Beta coefficients suggest that all the studied cryptocurrencies can be considered as very aggressive assets as their betas are significantly higher than 1. Polkadot shows the highest systematic risk followed by Cardano. Betas calculated based on the CRIX market index confirm that Polkadot is the riskiest cryptocurrency in our sample.

3.2. Event study analysis

The reaction to the war of the ten cryptocurrencies are summarized in Table 2. We consider different event windows. We find that nine out of the ten cryptocurrencies have reacted negatively to the war. The only exception is Binance coin for which the reaction to the war seems to be economically and statistically positive. The magnitude of the negative reaction of cryptocurrencies markets to the Russian invasion of Ukraine seems to change from one cryptocurrency to another. The highest negative reactions are obtained for Avalanche, Polkadot and Solana while the lowest reaction is reported for Bitcoin, the most established cryptocurrency. We also report the change in short-term systematic risk for all cryptocurrencies.

Table 1: Descriptive statistics

	Mean Return	Std..Dev.	MIN Return	MAX Return	Beta (MSCI)	Beta (CRIX)
CRIX	0.001	0.040	-0.130	0.114	2.553	1.000
MSCI Index	-0.001	0.020	-0.081	0.097	1.000	0.088
Bitcoin	0.001	0.040	-0.117	0.111	1.778	0.843
Eutherum	0.001	0.043	-0.160	0.111	2.876	1.055
Binance Coin	0.003	0.056	-0.172	0.220	2.022	0.860
Luna	0.008	0.084	-0.235	0.356	1.851	0.850
Solana	0.003	0.054	-0.235	0.356	3.110	0.965
Ripple	-0.000	0.058	-0.211	0.233	2.213	1.099
Cardano	-0.002	0.305	-2.796	2.715	3.241	0.895
Polkadot	-0.001	0.067	-0.210	0.189	3.452	1.159
Avalanche	0.011	0.083	-0.224	0.246	3.122	1.004
Doge	-0.002	0.057	-0.196	0.234	1.769	1.029

This table presents descriptive statistics for our sample. We report the average, minimum and maximum return, the standard deviation, the beta computed using the market model (Beta MSCI) and the beta using the CRIX index as the market return (Beta CRIX) for each cryptocurrency.

Table 2: Reaction of cryptocurrencies to the outbreak of the Russia-Ukraine conflict

	Bitcoin	Eutherum	Binance Coin	Luna	Solana	Ripple	Cardano	Polkadot	Avalanche	Doge
[-8,+8]	0.040	0.273***	0.698***	-0.069	0.140**	0.043	0.256***	0.175***	0.045	0.034
	(1.082)	(6.179)	(15.243)	(-0.774)	(2.027)	(0.773)	(4.649)	(2.689)	(0.519)	(0.609)
[-7,+7]	0.020	0.294***	0.617***	-0.101	0.182***	0.004	0.275***	0.202***	0.094	0.036
	(0.539)	(6.655)	(13.467)	(-1.137)	(2.641)	(0.066)	(5.000)	(3.103)	(1.090)	(0.644)
[-6,+6]	-0.003	0.156***	0.589***	-0.088	0.055	-0.032	0.192***	0.134**	0.001	0.014
	(-0.086)	(3.523)	(12.85)	(-0.991)	(0.790)	(-0.561)	(3.490)	(2.057)	(0.007)	(0.240)
[-5,+5]	-0.047	0.023	0.526***	-0.119	-0.090	-0.118***	0.030	-0.083	-0.188**	-0.055
	(-1.263)	(0.527)	(11.487)	(-1.331)	(-1.298)	(-2.099)	(0.553)	(-1.277)	(-2.174)	(-0.978)
[-4,+4]	-0.127***	-0.228***	0.426***	-0.171*	-0.321***	-0.270***	-0.223***	-0.341***	-0.420***	-0.164***
	(-3.458)	(-5.155)	(9.302)	(-1.916)	(-4.642)	(-4.797)	(-4.061)	(-5.256)	(-4.864)	(-2.900)
[-3,+3]	-0.124***	-0.283***	0.347***	-0.174*	-0.377***	-0.270***	-0.270***	-0.326***	-0.455***	-0.202***
	(-3.363)	(-6.409)	(7.578)	(-1.953)	(-5.457)	(-4.794)	(-4.904)	(-5.024)	(-5.279)	(-3.574)
[-2,+2]	-0.150***	-0.343***	0.278***	-0.157*	-0.410***	-0.231***	-0.334***	-0.345***	-0.512***	-0.224***
	(-4.077)	(-7.761)	(6.073)	(-1.755)	(-5.929)	(-4.111)	(-6.071)	(-5.314)	(-5.940)	(-3.959)
[-1,+1]	0.001	-0.072	0.235***	-0.008	-0.037	-0.046	-0.031	-0.005	-0.148*	-0.067
	(0.027)	(-1.622)	(5.132)	(-0.092)	(-0.536)	(-0.818)	(-0.568)	(-0.074)	(-1.718)	(-1.181)
T	-0.047	-0.095**	0.035	-0.012	-0.097	-0.080	-0.084	-0.058	-0.132	-0.078
	(-1.267)	(-2.147)	(0.753)	(-0.137)	(-1.402)	(-1.421)	(-1.527)	(-0.891)	(-1.528)	(-1.386)
Change in short-term systematic risk	-0.827**	-2.079***	-0.720	-0.719	-2.351***	-1.115*	-1.473	-2.377***	-2.310**	-0.976
	(-2.10)	(-4.40)	(-1.25)	(-0.76)	-3.16	(-1.82)	(-0.41)	(-3.36)	(-2.48)	(-1.54)

This table reports the cumulative abnormal returns of the 10 cryptocurrencies resulting from the outbreak of the Russia-Ukraine conflict over different windows, ranging from 8 days before the event to 8 days after and the change in short-term systematic risk following the outbreak of the conflict. Cumulative abnormal returns were calculated using the Capital Asset Pricing Model (CAPM). t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% statistical levels, respectively.

Overall, the unprecedented uncertainty around the Russia-Ukraine war and international sanctions imposed on Russia may have led investors to lose faith in the crypto market and rebalance their portfolios toward safer alternatives. However, it appears from our findings that things were completely different for Binance coin on which we report positive abnormal returns. Numerous reports and newspapers articles have reported that Binance was determined to continue servicing Russian citizens who had not been sanctioned[3] and it is possible many Russians have converted their rubles to crypto, mainly Binance coin. This could explain the positive reaction of Binance coin to the Russian invasion of Ukraine.

It is well known that the ability to reliably form statistical inferences can be compromised by failing to account for the ARCH error structure. As such, to make sure our event-study results are not biased by volatility clustering and leptokurtosis, we compute abnormal returns based on a market model which accounts for GARCH(1,1) effects to reflect the heteroskedastic behavior of the error variance over time. Results are reported in Table 3 and confirm that all cryptocurrencies experienced negative abnormal returns following the outbreak of the Russia-Ukraine war, except for Binance coin which experienced positive abnormal returns.

Table 3: Reaction of cryptocurrencies to the outbreak of the Russia-Ukraine conflict using a GARCH (1,1) model

	Bitcoin	Eutherum	Binance Coin	Luna	Solana	Ripple	Cardano	Polkadot	Avalanche	Doge
[-8,+8]	-0.052***	-0.007	0.570***	-0.099***	-0.070***	-0.102***	0,000	-0.101***	-0.181***	-0.108***
	(-5.034)	(-0.574)	(19.801)	(-5.767)	(-3.923)	(-5.801)	(-0.001)	(-4.939)	(-8.715)	(-5.264)
[-7,+7]	-0.054***	0.019	0.515***	-0.068***	-0.040**	-0.076***	0.004	-0.078***	-0.156***	-0.088***
	(-5.236)	(1.599)	(17.919)	(-3.987)	(-2.242)	(-4.345)	(0.013)	(-3.813)	(-7.528)	(-4.315)
[-6,+6]	-0.051***	-0.04***	0.524***	-0.044***	-0.095***	-0.066***	-0.028	-0.082***	-0.146***	-0.071***
	(-4.909)	(-3.431)	(18.227)	(-2.577)	(-5.311)	(-3.764)	(-0.095)	(-4.036)	(-7.043)	(-3.451)
[-5,+5]	-0.06***	-0.051***	0.488***	-0.062***	-0.124***	-0.090***	-0.059	-0.159***	-0.163***	-0.073***
	(-5.784)	(-4.329)	(16.961)	(-3.624)	(-6.910)	(-5.154)	(-0.197)	(-7.792)	(-7.877)	(-3.539)
[-4,+4]	-0.060***	-0.083***	0.463***	-0.049***	-0.116***	-0.126***	-0.088	-0.176***	-0.154***	-0.060***
	(-5.729)	(-7.045)	(16.107)	(-2.847)	(-6.470)	(-7.195)	(-0.294)	(-8.591)	(-7.442)	(-2.919)
[-3,+3]	-0.042***	-0.095***	0.401***	-0.051***	-0.132***	-0.113***	-0.085	-0.113***	-0.158***	-0.077***
	(-4.040)	(-8.037)	(13.953)	(-2.996)	(-7.369)	(-6.460)	(-0.286)	(-5.534)	(-7.640)	(-3.781)
[-2,+2]	-0.034***	-0.058***	0.367***	-0.014	-0.065***	-0.031*	-0.042	-0.026	-0.121***	-0.049**
	(-3.275)	(-4.944)	(12.759)	(-0.800)	(-3.621)	(-1.776)	(-0.139)	(-1.281)	(-5.847)	(-2.374)
[-1,+1]	0.022**	-0.029**	0.246***	0.031*	0.025	-0.001	0.009	0.045**	-0.066***	-0.035*
	(2.080)	(-2.433)	(8.543)	(1.806)	(1.419)	(-0.065)	(0.029)	(2.184)	(-3.182)	(-1.710)
T	-0.026**	-0.044***	0.050*	0.014	-0.035*	-0.043**	-0.033	-0.001	-0.061***	-0.047**
	(-2.473)	(-3.719)	(1.747)	(0.841)	(-1.930)	(-2.475)	(-0.112)	(-0.032)	(-2.924)	(-2.279)

This table reports the cumulative abnormal returns of the 10 cryptocurrencies resulting from the Russian Ukrainian conflict over different windows, ranging from 8 days before the event to 8 days after using the GARCH(1,1) model to estimate stock volatility in the Capital Asset Pricing Model (CAPM). t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% statistical levels, respectively.

Table 4 reports tests on cumulative abnormal returns calculated for different windows covering the post-war announcement period. Again, except for Binance coin, our findings suggest that the Russia-Ukraine war did not lead to a boost in crypto adoption. However, for Binance coin, the post war announcement effect was positive suggesting that this war has pushed investors

[3] https://www.reuters.com/technology/crypto-exchange-binance-says-it-wont-unilaterally-freeze-accounts-russia-2022-02-28/

to shift from banks and traditional foreign-exchange settlement companies to Binance Coin. Investors could also have overweighed their investments in Binance Coin compared to the other cryptocurrencies. From February 24th to April 15th, the CRIX index has increased by 8.5% from 3 563 to 3 867, Bitcoin by only 5.7% from $38 332 to $40 553 while Binance Coin has increased by more than 15% from $361 to $417.

Table 4: Cumulative abnormal return for the post-event windows

	Bitcoin	Eutherum	Binance Coin	Luna	Solana	Ripple	Cardano	Polkadot	Avalanche	Doge
[0,+1]	-0.026 (-0.703)	-0.125*** (-2.818)	0.099** (2.161)	-0.028 (-0.309)	-0.076 (-1.107)	-0.080 (-1.428)	-0.084 (-1.529)	-0.082 (-1.270)	-0.187** (-2.169)	-0.087 (-1.531)
[0,+2]	-0.026 (-0.703)	-0.125*** (-2.818)	0.099** (2.161)	-0.028 (-0.309)	-0.076 (-1.107)	-0.080 (-1.428)	-0.084 (-1.529)	-0.082 (-1.270)	-0.187** (-2.169)	-0.087 (-1.531)
[0,+3]	-0.144*** (-3.914)	-0.350*** (-7.926)	0.121*** (2.645)	-0.145 (-1.627)	-0.368*** (-5.329)	-0.229*** (-4.065)	-0.306*** (-5.569)	-0.374*** (-5.765)	-0.460*** (-5.337)	-0.213*** (-3.758)
[0,+4]	-0.165*** (-4.487)	-0.368*** (-8.331)	0.094** (2.051)	-0.187** (-2.091)	-0.454*** (-6.572)	-0.290*** (-5.158)	-0.376*** (-6.837)	-0.447*** (-6.877)	-0.542*** (-6.288)	-0.240*** (-4.231)
[0,+5]	-0.146*** (-3.953)	-0.287*** (-6.505)	0.141*** (3.084)	-0.186** (-2.088)	-0.378*** (-5.465)	-0.255*** (-4.531)	-0.296*** (-5.383)	-0.388*** (-5.980)	-0.476*** (-5.518)	-0.203*** (-3.584)
[0,+6]	-0.082** (-2.221)	-0.128*** (-2.895)	0.223*** (4.858)	-0.126 (-1.413)	-0.187*** (-2.704)	-0.145*** (-2.570)	-0.105* (-1.903)	-0.146** (-2.254)	-0.292*** (-3.386)	-0.113** (-1.990)
[0,+7]	-0.080** (-2.169)	-0.031 (-0.691)	0.211*** (4.602)	-0.157* (-1.761)	-0.093 (-1.353)	-0.139** (-2.479)	-0.033 (-0.597)	-0.102 (-1.575)	-0.265*** (-3.073)	-0.107* (-1.891)
[0,+8]	-0.081** (-2.198)	-0.081* (-1.833)	0.266*** (5.803)	-0.199** (-2.230)	-0.159** (-2.308)	-0.175*** (-3.103)	-0.057 (-1.044)	-0.150** (-2.303)	-0.335*** (-3.882)	-0.137** (-2.415)
[0,+36]	-0.023 (-0.615)	-0.165*** (-3.740)	0.057 (1.240)	-0.377*** (-4.230)	-0.443*** (-6.410)	-0.130** (-2.307)	-0.118** (-2.140)	-0.273*** (-4.201)	-0.655*** (-7.595)	0.062 (1.089)

This table reports the cumulative abnormal returns of the 10 cryptocurrencies resulting from the Russian Ukrainian conflict over post event windows ranging from 1 day after the event to 36 days after. t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% statistical levels, respectively.

4. Robustness testing

To check for the sensitivity of our findings to the choice to the CAPM as a model for normal returns, we compute cumulative abnormal returns over the event windows in different ways. First, we use the mean model introduced by Brown and Warner (1985) and we calculate the abnormal returns as follows:

$$AR_{i,t} = R_{i,t} - \overline{R_i} \tag{4}$$

where $R_{i,t}$ is the daily observed return on cryptocurrency i and $\overline{R_i}$ denotes the simple average of each cryptocurrency returns over the estimation period[4]. Second, we calculate cumulative abnormal returns based on the market-adjusted model by using the average market returns to proxy the average normal returns. We proceed as follows:

$$AR_{i,t} = R_{i,t} - R_{mt} \tag{5}$$

where $R_{i,t}$ is the daily observed return on cryptocurrency i and R_{mt} represents the MSCI global index return. Finally, we develop an asset pricing model which considers both the MSCI global index and the CRIX index returns. To avoid multicollinearity issues, we use the returns on the CRIX non explained by the MSCI market model. Precisely, we first estimate the following model:

[4] Our results remain consistent when applying the exponential moving average of each cryptocurrency to compute cumulative abnormal returns.

$$CRIX_t = \beta_i R_{mt} + CRIX\varepsilon_t \tag{6}$$

where $CRIX_t$ is the return of the CRIX index, R_{mt} is the return on the MSCI world index and $CRIX\varepsilon_t$ is the residual of the model, i.e., the returns on the CRIX not explained by the global stock market returns.

We then estimate the following model over our estimation period and use the estimated coefficients to compute normal returns as if the event did not happen:

$$R_{i,t} = \alpha_i + \beta_{1,i} R_{mt} + \beta_{2,i} CRIX\varepsilon_t + \varepsilon_t \tag{7}$$

Finally, we estimate abnormal returns as follows:

$$AR_{i,t} = R_{i,t} - (\widehat{\alpha_i} + \widehat{\beta_{1,i}} R_{mt} + \beta_{2,i}\widehat{CRIX}\varepsilon_t + \varepsilon_t) \tag{8}$$

We compute the cumulative abnormal return for each cryptocurrency during the event window in the same way as in the previous section:

$$CAR_{i,p-q} = \sum_{t=p}^{q} AR_{i,t} \tag{9}$$

where $CAR_{i,p-q}$ is the cumulative abnormal return for each cryptocurrency for the event window (p-q).

Table 5: Cumulative abnormal returns using the constant mean model (Brown and Warner, 1985)

	Bitcoin	Eutherum	Binance Coin	Luna	Solana	Ripple	Cardano	Polkadot	Avalanche	Doge
[-8,+8]	-0.172***	-0.061	0.475***	-0.122	-0.109	-0.218***	-0.166***	-0.238***	-0.102	-0.227***
	(-4.375)	(-1.241)	(9.831)	(-1.347)	(-1.499)	(-3.719)	(-2.760)	(-3.401)	(-1.139)	(-3.901)
[-7,+7]	-0.205***	-0.063	0.376***	-0.188**	-0,105	-0.275***	-0.168***	-0.238***	-0.103	-0.233***
	(-5.235)	(-1.283)	(7.782)	(-2.081)	(-1.440)	(-4.690)	(-2.784)	(-3.393)	(-1.153)	(-3.999)
[-6,+6]	-0.203***	-0.161	0.375***	-0.168	-0.202***	-0.279***	-0.199***	-0.255***	-0.178*	-0.224***
	(-5.167)	(-3.268)	(7.761)	(-1.860)	(-2.771)	(-4.749)	(-3.314)	(-3.648)	(-1.988)	(-3.849)
[-5,+5]	-0.107***	-0.070	0.468***	-0.074	-0.118	-0.193***	-0.104*	-0.203***	-0.149*	-0.149**
	(-2.738)	(-1.421)	(9.691)	(-0.816)	(-1.619)	(-3.286)	(-1.728)	(-2.894)	(-1.665)	(-2.560)
[-4,+4]	0.016	0.009	0.599***	0.067	-0.006	-0.090	0.019	-0.064	-0.048	-0.048
	(0.415)	(0.180)	(12.394)	(0.746)	(-0.076)	(-1.538)	(0.323)	(-0.909)	(-0.539)	(-0.829)
[-3,+3]	0.059	0.016	0.563***	0.085	-0.007	-0.041	0.049	0.028	-0.041	-0.041
	(1.511)	(0.333)	(11.647)	(0.946)	(-0.095)	(-0.701)	(0.819)	(0.405)	(-0.459)	(-0.706)
[-2,+2]	0.122***	0.100**	0.593***	0.176*	0.102	0.108*	0.152	0.182***	0.032	0.032
	(3.108)	(2.023)	(12.273)	(1.949)	(1.396)	(1.838)	(2.518)	(2.607)	(0.354)	(0.544)
[-1,+1]	0.044	-0.001	0.287***	0.066	0.059	0.008	0.041	0.078	-0.033	-0.033
	(1.120)	(-0.016)	(5.942)	(0.732)	(0.814)	(0.131)	(0.675)	(1.117)	(-0.370)	(-0.569)
T	0.002	-0.015	0.091*	0.049	-0.004	-0.019	0.003	0.037	-0.033	-0.033
	(0.055)	(-0.312)	(1.885)	(0.537)	(-0.060)	(-0.325)	(0.049)	(0.526)	(-0.367)	(-0.565)

This table reports the cumulative abnormal returns of the 10 cryptocurrencies resulting from the Russian Ukrainian conflict over different windows, ranging from 8 days before the event to 8 days after. Cumulative abnormal returns were calculated using the constant mean model of (Brown and Warner, 1985). t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% statistical levels, respectively.

Table 6: Cumulative abnormal returns using the market-adjusted model

	Bitcoin	Eutherum	Binance Coin	Luna	Solana	Ripple	Cardano	Polkadot	Avalanche	Doge
[-8,+8]	-0.181***	-0.096*	0.505***	-0.181*	-0.110	-0.276***	-0.148**	-0.224***	-0.130	-0.259***
	(-4.544)	(-1.941)	(11.301)	(-2.019)	(-1.502)	(-4.697)	(-2.445)	(-3.184)	(-1.447)	(-4.439)
[-7,+7]	-0.275***	-0.197***	0.344***	-0.295***	-0.247***	-0.386***	-0.245***	-0.349***	-0.281***	-0.327***
	(-6.917)	(-3.998)	(7.008)	(-3.295)	(-3.370)	(-6.564)	(-4.040)	(-4.969)	(-3.136)	(-5.602)
[-6,+6]	-0.283***	-0.174***	0.271***	-0.274***	-0.207***	-0.366***	-0.246***	-0.341***	-0.300***	-0.300***
	(-7.125)	(-3.515)	(5.521)	(-3.063)	(-2.817)	(-6.226)	(-4.068)	(-4.853)	(-3.346)	(-5.134)
[-5,+5]	-0.146***	-0.122**	0.456***	-0.106	-0.123*	-0.240***	-0.128**	-0.202***	-0.172**	-0.172***
	(-3.662)	(-2.469)	(9.273)	(-1.186)	(-1.676)	(-4.079)	(-2.107)	(-2.875)	(-1.917)	(-2.941)
[-4,+4]	-0.023	-0.033	0.536***	0.019	-0.084	-0.140**	-0.031	-0.105	-0.109	-0.109*
	(-0.580)	(-0.667)	(10.917)	(0.208)	(-1.147)	(-2.378)	(-0.520)	(-1.501)	(-1.213)	(-1.860)
[-3,+3]	0.105***	0.106**	0.576***	0.160*	0.057	0.058	0.107*	0.143**	0.003	0.003
	(2.642)	(2.137)	(11.722)	(1.785)	(0.776)	(0.988)	(1.761)	(2.030)	(0.034)	(0.051)
[-2,+2]	0.096**	0.065	0.469***	0.109	0.060	0.057	0.107*	0.129*	-0.004	-0.004
	(2.426)	(1.315)	(9.540)	(1.222)	(0.816)	(0.966)	(1.775)	(1.831)	(-0.050)	(-0.077)
[-1,+1]	0.106***	0.063	0.410***	0.145	0.099	0.086	0.153**	0.121*	0.027	0.027
	(2.667)	(1.273)	(8.352)	(1.623)	(1.351)	(1.457)	(2.522)	(1.728)	(0.304)	(0.466)
T	0.058	0.033	0.108**	0.033	0.095	0.046	0.068	0.050	0.025	0.025
	(1.449)	(0.662)	(2.197)	(0.368)	(1.290)	(0.790)	(1.123)	(0.716)	(0.284)	(0.436)

This table reports the cumulative abnormal returns of the 10 cryptocurrencies resulting from the Russian Ukrainian conflict over different windows, ranging from 8 days before the event to 8 days after. Cumulative abnormal returns were calculated using the market-adjusted model. t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% statistical levels, respectively.

Table 7: Cumulative abnormal returns using the extended CAPM model

	Bitcoin	Eutherum	Binance Coin	Luna	Solana	Ripple	Cardano	Polkadot	Avalanche	Doge
[-8,+8]	0.089***	0.372***	0.684***	0.004	0.197***	0.087**	0.309***	0.248***	0.090	0.107***
	(4.708)	(15.383)	(20.474)	(0.045)	(3.202)	(2.304)	(6.516)	(4.794)	(1.130)	(2.688)
[-7,+7]	0.049***	0.237***	0.665***	0.013	0.122*	0.086**	0.217***	0.190***	0.098	0.071*
	(2.583)	(9.807)	(19.888)	(0.160)	(1.991)	(2.275)	(4.578)	(3.664)	(1.226)	(1.771)
[-6,+6]	-0.014	0.074***	0.579***	-0.099*	-0.070	-0.070*	0.040	-0.045	-0.083	-0.019
	(-0.748)	(3.071)	(17.328)	(-1.181)	(-1.134)	(-1.846)	(0.844)	(-0.869)	(-1.042)	-(0.475)
[-5,+5]	-0.052***	-0.044*	0.495***	-0.114	-0.177***	-0.131***	-0.048	-0.123**	-0.212***	-0.069*
	(-2.740)	(-1.800)	(14.813)	(-1.360)	(-2.887)	(-3.460)	(-1.018)	(-2.374)	(-2.665)	(-1.720)
[-4,+4]	-0.047**	-0.052**	0.461***	-0.118	-0.139***	-0.111***	-0.043	-0.098*	-0.233***	-0.068*
	(-2.475)	(-2.148)	(13.8)	(-1.407)	(-2.257)	(-2.945)	(-0.899)	(-1.892)	(-2.921)	(-1.703)
[-3,+3]	-0.066***	-0.163***	0.493***	-0.089	-0.194***	-0.155***	-0.118**	-0.219***	-0.295***	-0.086**
	(-3.503)	(-6.728)	(14.766)	(-1.066)	(-3.163)	(-4.102)	(-2.486)	(-4.229)	(-3.697)	(-2.158)
[-2,+2]	0.035*	0.001	0.409***	0.023	0.013	-0.05	0.05	0.044	-0.079	-0.023
	(1.881)	(0.046)	(12.248)	(0.274)	(0.209)	(-1.316)	(1.062)	(0.846)	(-0.994)	(-0.582)
[-1,+1]	-0.026	-0.056**	0.218***	0.003	-0.111*	-0.047	-0.088*	0.005	-0.156*	-0.056
	(-1.380)	(-2.331)	(6.526)	(0.038)	(-1.814)	(-1.251)	(-1.854)	(0.09)	(-1.952)	(-1.400)
T	0.006	0.029	0.116***	-0.001	0.019	0.007	0.035	0.052	0.017	-0.006
	(0.343)	(1.199)	(3.466)	(-0.012)	(0.307)	(0.195)	(0.733)	(1.008)	(0.216)	(-0.154)

This table reports the cumulative abnormal returns of the 10 cryptocurrencies resulting from the Russian Ukrainian conflict over different windows, ranging from 8 days before the event to 8 days after. Cumulative abnormal returns were calculated using the CRIX model. t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% statistical levels, respectively.

Our findings are summarized in Tables 5, 6 and 7. The conclusion that we can draw from those findings remains the same: except for Binance coin, all the studied cryptocurrencies have reacted negatively to the Russia-Ukraine war.

5. Discussion and conclusion

We investigate the impact of the Russian invasion of Ukraine in February 2022 on cryptocurrency markets using an event study methodology. We found that nearly all cryptocurrencies experienced negative CARs because of the war. This corroborates the findings of Kalfaoui et al. (2023) who found that public attention to the Russia-Ukraine war had a strong negative causal effect on short-term cryptocurrency returns. The only exception is Binance coin (which Kalfaoui et al. (2023) did not consider) which showed a positive abnormal return. As Binance had made clear it did not want to sanction non-targeted Russian citizens, it is possible many Russians have converted their rubles to crypto, mainly Binance coin (BNB). In addition, Visa, Mastercard, and American Express cards issued outside of Russia are no longer accepted in Russian stores or ATMs, just as all transactions initiated with Visa cards issued in Russia do no longer work outside of the country[5]. Clients are thus unable to use their Russian cards overseas or to make foreign payments online. This circumstance forced investors and customers to use alternative payment methods, such as the Binance Visa Card, which allows customers to buy online and pay in cryptocurrencies. All these factors may have contributed to a higher demand for Binance coin, leading to positive returns following the outbreak of the Russia-Ukraine conflict.

The negative impact of the war on all other cryptocurrencies may be the result of various mechanisms. First, while some Russians may have tried to liquidate their fiat monies into other safer assets, doing so on a large scale using cryptocurrencies could have posed significant risks (due to the possible tracing of large crypto transactions). In addition, the low liquidity of the cryptocurrency market would have potentially made such attempt futile. This is in line with Theiri et al. (2023) who found no significant change in crypto liquidity after the war broke out. Second, it has been shown that monetary policies influence cryptocurrency returns. For example, Aboura (2022) shows that the March 2020 Fed Funds rate cut was a driver of the ensuing Bitcoin's dramatic increase. While the very accommodative monetary policies of the last decade created a favorable environment for cryptocurrencies, the major monetary shift that happened at the end of 2021[6] (roughly three months prior to the outbreak of the Russia-Ukraine war) removed one of the major tailwinds for crypto-assets, whose non-cash generating features make them "expensive" to hold in periods of higher interest rates.

Overall, our findings have useful implications for investors in that they show that cryptocurrencies —as an asset class— do not seem to act as safe-haven in war time, at least in a tapering/tightening monetary regime. However, our results indicate that it may be relevant to understand the heterogeneity of the various cryptocurrencies. In the Russia-Ukraine war context, Binance has benefited from some of its specific characteristics, e.g., its executives'

[5] https://www.reuters.com/business/finance/visa-suspends-operations-russia-over-ukraine-invasion-2022-03-05/

[6] In November 2021, the Federal Reserve announced that it would begin to "taper" its large-scale asset purchases by $15 billion per month. It later announced in December 2021 that it would double the monthly reduction in purchases in January. In January 2022, the Fed announced that purchases would end in March 2022, at which point its balance sheet will stop growing.

decision to continue servicing Russian clients. As such, it could be interesting to duplicate previous studies using different cryptocurrencies.

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