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Russia-Ukraine War and Crypto-Currency Returns: An Experiment With New Data

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This study investigates the impact of the Russia-Ukraine War on cryptocurrency returns using the Feasible Quasi Generalised Least Squares technique. Our analysis diverges from conventional approaches by focusing on the susceptibility of cryptocurrency returns to the war and establishes a significant positive relationship. This finding underscores the resilience of cryptocurrencies in the face of geopolitical turmoil. Furthermore, we extend our examination to the predictive content of the war for cryptocurrency returns, employing it for both in- and out-of-sample forecast evaluations of the index against the historical average. We highlight the diversification potential of this asset class during war-induced crises.

I. Introduction

In this study, we examine the impact of Russia-Ukraine War (RUW) on the performance of major cryptocurrencies based on market capitalization. Cryptocurrencies, as highlighted in the work of Brauneis & Mestel (2018), exhibit significant volatility and tend to yield substantial average returns, setting them apart from traditional currencies (W. Liu et al., 2020). These unique attributes, that is, significant volatility and distinct return patterns, underscore their attraction to investors and portfolio managers. Consequently, they are often recognized as a distinct asset class (W. Liu et al., 2020). Plethora of evidence on behaviours of financial markets and the associated assets during crises abound. Particularly, geopolitical crises have been found to impact both global economy (Sharif et al., 2020) and financial markets (Elsayed & Helmi, 2021). During periods of heightened geopolitical tensions, especially those that affect primary commodities including crude oil and precious metals, such as the RUW, investors (regardless of their risk exposure) usually hasten to seek cover from other assets that can guarantee them returns while the crisis lasts, in which case cryptocurrencies have proven useful in recent times (Z. Liu & Shu, 2023). As such, investors are drawn to cryptocurrencies due to their reputation as a 'safe haven' investment (Cheng & Yen, 2020). The foregoing has not only sparked interest among investors, portfolio managers, and scholars, but also has shown evidence that incorporating cryptocur-

rency into investment portfolios can yield substantial returns and enhance risk-adjusted results (Briere et al., 2015).

Basically, the similitude of Crimea annexation by Russia and the subsequent war between Russia and Ukraine in 2014 has once again reoccurred in February 2022. The invasion of Ukraine by Russia has subsequently been greeted by sanctions by superpowers, and the effect on global financial market has been catastrophic. Specifically, the concomitant influence of supply disruption occasioned by the Russia-Ukraine crisis has resulted in high volatility and low returns on investment across the global capital market (Boubaker et al., 2022), hence examining the tolerance and/or susceptibility of cryptocurrency to this crisis would be a worthwhile exercise, albeit with new datasets. While studies have explored the influence of the RUW on major asset classes, the question remains whether the adopted measures of the crisis could adequately capture the risk it portends. This gap is filled by constructing an index informed by the dynamics of this crisis.

Akin to the foregoing, this study seeks to assess the behaviour of major cryptocurrencies during the Russia incursion into Ukraine using a new dataset. Our contribution to the literature on the RUW and cryptocurrencies is hinged on both in- and out-of-sample predictability of our new data for cryptocurrency returns.

The reminder of the paper is structured as follows. Data and methodology, results and discussion, and conclusion are discussed in Sections II, III, and IV, respectively.

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II. Data and Methodology

Our datasets consist of four cryptocurrencies, namely Bitcoin, Ethereum, Binance coin, and Ripple, in addition to a measure of the RUW. The daily data of the top four cryptocurrencies by market capitalization were sourced from www.investing.com. As at the time of data extraction, the selected cryptocurrencies/coins/tokens each had a market capitalization ranging from 28 billion to 535 billion USD and are perceived to have large dominance and representativeness of the dynamics of the cryptocurrency market. Various events that have shaped the RUW are searched from the Google Trends¹ to compute our measure of the conflict using the principal component analysis (PCA). This is done to reduce the complex dataset to a lower dimension, thereby generating a series (IDX) to measure the RUW. To test whether our results are robust to an alternative measure of the geopolitical tension, the geopolitical risk (GPR) by Caldara & Iacoviello (2023) is adopted.² The datasets span from 25th February, 2022 through 7th September, 2023, totaling about 560 data points. The start and end dates are informed by the day Russia invaded Ukraine through the end date suggested by the Google Trends.

We construct a bivariate predictive model using the Feasible Quasi Generalised Least Squares (FQGLS) technique of Westerlund & Narayan (2015) to examine the response of cryptocurrency returns to the RUW. The attraction to this technique is premised on its ability to solve the inherent biases, such as unit root (persistence) and endogeneity, among others, typical of high frequency data. Thus, our estimation model follows:

$$r_t = \alpha + \beta ruw_{t-1} + \varphi(ruw_t - \rho_0 ruw_{t-1}) + e_t \quad (1)$$

where r_t is the cryptocurrency return, α is the constant intercept, ruw is the measure of the RUW and e_t is the zero-mean idiosyncratic error term. The slope coefficient β shows the response of cryptocurrency returns to the RUW. In essence, two specific outcomes are discernible: the susceptibility or resilience of cryptocurrency returns to the RUW. Thus, the former holds when $\beta \leq 0$ while the latter indicates $\beta > 0$. Our focus is on the signs as well as the statistical significance of the β -adjusted coefficients of the model before embarking upon the forecasting exercise.

Furthermore, we adopt the approach of Lewellen (2004) and Westerlund & Narayan (2015) to address any issues with the endogeneity bias resulting from the correlation between the predictor series and the error term as well as any potential persistence effect, as modeled in Equation (1). In addition, to resolve the issue of conditional heteroscedasticity effect in the error term, Westerlund & Narayan (2015) suggest pre-weighting all the data with the inverse of the standard deviation obtained from a typical GARCH-type model (i.e. $\frac{1}{\sigma_t}$) and estimating the resulting equation with the OLS.

Utilising both conventional Root Mean Square Error and Clark & West (2007), additional analyses covering both the in- and out-of-sample – using 50:50 data split – forecast evaluation of our predictive model are also offered.

III. Results and Discussion

A. Pre-estimation results

As pre-tests, we subject our data to some preliminary analyses, such as the persistence test, heteroskedasticity, and serial correlation biases, to ascertain our choice of technique. While the serial correlation bias is evident at higher order of the Q-statistic (Q^2 -Statistic) for the return series, it is significant for our geopolitical tension proxies. Similarly, the heteroscedasticity bias is also prominent for all the series, while persistence is also observed in the predictor variable (IDX and GPR). Hence, we find support for our choice of method (FQGLS) which has been considered adequate to solve these biases (see Westerlund & Narayan, 2015).

B. Results

The results of the predictability analysis and forecast evaluation using both the Clark and West as well as the Root Mean Square Error (RMSE) are presented in [Table 2](#). As offered in the preceding section, the predictability results show the susceptibility (or otherwise) of the returns of our cryptocurrency choice to the RUW (IDX). The evidence of significant positive relationship between our RUW index and our return proxies (in Panel A) shows the resilience of these cryptocurrencies to the RUW. As a form of robustness check, these set of cryptocurrencies are exposed to global geopolitical risk index of Caldara & Iacoviello (2023) and similar results are observed. Hence, the resilience of the returns of our cryptocurrency choices to alternative measures of geopolitical tensions. Our results align with that of Abakah et al. (2023), who document a positive impact of RUW on FinTech stock.

Furthermore, the predictive content of the RUW for cryptocurrency returns is extended to cover both the in- and out-of-sample forecast evaluation of the index compared to the historical average (see Panel B). We show that inclusion of the RUW index enhances the in- and out-of-sample forecast performance of the currency market, given the statistical significance of our Clark and West results (see also Appiah-Otoo, 2023). In the same vein, the results obtained from the GPR index also buttressed this. In other words, a model that includes a measure of geopolitical tensions enhances the performance of the cryptocurrency returns. Our results suggest the diversification potential of cryptocurrency during war-induced crises. Thus, investors seeking protection for their portfolio during heightened

¹ The search items include Putin, Russia, Russian, Zelensky, Ukraine, Ukrainian, war, Russia-Ukraine War, Russo-Ukraine War, NATO, and sanctions.

² <https://www.matteoiacoviello.com/gpr.htm>

Table 1. Persistence, conditional heteroscedasticity & autocorrelation tests

	Persistence	Q-Statistic			Q ² -Statistic			ARCH		
		K = 3	K = 6	K = 12	K = 3	K = 6	K = 12	K = 3	K = 6	K = 12
Returns										
Bitcoin		0.02	-0.02	0.03	0.08***	0.05***	0.01***	9.4***	5.04***	2.77***
Ethereum		0.05	0.01	0.05	0.14***	0.09***	0.04***	18.5***	10.03***	5.74***
Binance		0.05	-0.01	0.03	0.05***	0.04***	0.004***	10.1***	5.74***	2.94***
Ripple		0.04	0.04	0.01	0.003***	0.01***	-0.012***	0.1	0.06	0.04
Geopolitical tension										
IDX	0.88***	0.14***	0.03***	0.10***	0.003***	0.06**	-0.004***	4.6***	2.65**	4.20***
GPR	0.68***	-0.003	0.10	-0.07***	0.09***	0.14***	0.08***	22.8***	9.00***	7.41***

IDX is the index generated from our principal component analysis of the Russia-Ukraine War searches. GPR on the other hand is the geopolitical risk index developed by Caldara and Iacoviello (2023). The reported figures are *F*-statistics for the ARCH test and Ljung–Box *Q*-statistics for the autocorrelation test, considered at three different lag lengths ($k = 3, 6$, and 12). The null of no conditional heteroscedasticity and serial correlation are tested for ARCH and autocorrelation tests, respectively. ***, **, and *, represents statistical significance at tests at 1%, 5%, and 10% levels, respectively.

Table 2. Vulnerability/Predictability and forecast evaluation results

Panel A: Vulnerability/Predictability results								
	Bitcoin		Ethereum		Binance		Ripple	
IDX	0.0419***		0.0174***		0.0388***		0.0474***	
	(0.0109)		(0.0061)		(0.0050)		(0.0105)	
	[3.8361]		[2.8514]		[7.7264]		[4.5137]	
GPR	0.0061***		0.0075***		0.0101***		0.0099***	
	(0.0002)		(0.0001)		(0.0004)		(0.0004)	
	[33.0553]		[71.1975]		[25.3498]		[22.2505]	
Panel B: Forecast evaluations using Clark and West								
In-sample forecast evaluation								
	Bitcoin		Ethereum		Binance		Ripple	
IDX	3.6164***		3.8934***		4.7943***		4.2497***	
	(0.8168)		(1.0413)		(0.9074)		(1.9181)	
	[4.4272]		[3.7388]		[5.2837]		[2.2156]	
GPR	3.6263***		3.8532***		4.5987***		2.9821***	
	(0.6557)		(0.7350)		(0.6595)		(0.6442)	
	[5.5304]		[5.2427]		[6.9731]		[4.6291]	
Out-of-sample forecast evaluation								
	Bitcoin		Ethereum		Binance		Ripple	
	IDX	GPR	IDX	GPR	IDX	GPR	IDX	GPR
h=3	3.6247***	3.6335***	3.9126***	3.8682***	4.8037***	4.6144***	4.2140***	3.0035***
	[4.4711]	[5.5829]	[3.7836]	[5.2963]	[5.3282]	[7.0320]	[2.2140]	[4.6953]
h=6	3.6536***	3.6677***	3.9390***	3.9049***	4.8012***	4.6275***	4.1530***	3.0180***
	[4.5406]	[5.6764]	[3.8381]	[5.3856]	[5.3662]	[7.1042]	[2.1984]	[4.7533]
h=14	3.7011***	3.6869***	3.9826***	3.9149***	4.8408***	4.6614***	4.0364***	3.0412***
	[4.6674]	[5.7758]	[3.9532]	[5.4893]	[5.5089]	[7.2743]	[2.1798]	[4.8822]
Panel C: Forecast evaluation using RMSE								
	Bitcoin		Ethereum		Binance		Ripple	
	IDX	GPR	IDX	GPR	IDX	GPR	IDX	GPR
In-sample	0.9242	0.9337	0.9510	0.9542	0.9121	0.9183	1.0272	0.9747
Out-of-Sample forecast evaluation								
h = 3	0.9241	0.9337	0.9507	0.9541	0.9123	0.9184	1.0272	0.9742
h = 6	0.9231	0.9327	0.9499	0.9533	0.9122	0.9188	1.0277	0.9739
h = 14	0.9229	0.9335	0.9490	0.9537	0.9117	0.9188	1.0282	0.9732

***, ** & * imply statistical significance at the 1%, 5%, & 10% levels, respectively. Values in parentheses denote standard errors while those reported in square brackets are *t*-statistics. For the Clark & West test, the null hypothesis of a zero coefficient is rejected if the *t*-statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test) (see Clark & West, 2007). We equally compare the forecast performance of both the RUW index and the GPR's. The smaller the RMSE value the better the forecast performance of a model.

geopolitical tensions could take cover from cryptocurrency market.

Finally, we compare in Panel C, the forecast performance of our index to that of Caldara & Iacoviello (2023) using the RMSE results. The RMSE values for our RUW index are lower than that of GPR for all the cryptocurrencies barring Ripple, across various forecast horizons. This suggests the superiority of our index over that of GPR while analyzing the response of cryptocurrency returns to geopolitical tensions.

IV. Conclusion

Utilizing the FQGLS technique, this study investigates the repercussions of the RUW on the performance of four major cryptocurrencies based on market capitalization. Our

empirical analysis reveals a significant positive relationship between the returns of the selected cryptocurrencies and the RUW index, underscoring the resilience of this cryptocurrency cohort in the face of geopolitical turmoil.

As a robustness check, we subject this portfolio of cryptocurrencies to examination under a global geopolitical risk index, yielding analogous results. This underscores the implication that the employed measure of geopolitical tensions enhances the overall performance of cryptocurrency returns, thus emphasizing the diversification potential of cryptocurrencies during crises induced by war. The study provides valuable insights into market dynamics during heightened geopolitical tensions and underscores the potential of cryptocurrencies as a diversification asset amid crises associated with warfare.

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