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# Cryptocurrencies and the threat versus the act event of geopolitical risk

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ABSTRACT

We examine the reactions of the cryptocurrency market to two events that occurred during the escalation of the Russia–Ukraine war in February 2022. Using hourly data, we find that the escalation exerted a negative influence on both liquidity and returns. Interestingly, the actual escalation triggered a more pronounced drop than the threat of escalation shortly before. This contrasts with the stock market, where threats of geopolitical events are found to have a greater impact. Post-escalation, we observe indications of increased demand for cryptocurrencies, potentially as a means to circumvent Western sanctions imposed on Russia or to provide aid to Ukraine.

## 1. Introduction

The distinction between geopolitical threat and act events was established by Caldara and Iacoviello (2022) and has since been employed to assess the impact of these occurrences on financial market performance. Caldara and Iacoviello (2022) defined geopolitical risk as the inability of parties to resolve power disputes over territories peacefully and democratically. This concept encompasses the danger associated with wars, terrorist acts, and conflicts between nations, which disrupt the normal and peaceful conduct of international affairs. Moreover, geopolitical risk is independent of the business cycle and lacks an economic cause, setting it apart from other types of systematic risks, such as economic policy uncertainty (EPU).[1] Caldara and Iacoviello (2022) considered *threats* of adverse geopolitical events to include, for example, the risk of war, fear of war, military threats, threats of war, and threats of terrorism. On the other hand, the authors considered *act events* to be the actual realization of adverse geopolitical events, such as the beginning of a war, air strikes, heavy casualties, and terrorist acts.

Even though geopolitical risks are unrelated to the business cycle and lack an economic basis, the impact of geopolitical threat and act events on financial markets has been extensively documented in the literature. For instance, Salisu et al. (2022) showed that stock markets have been disproportionately harmed by the threats of events compared to their actual occurrences. Furthermore, in their analysis of the recent Russia–Ukraine War (RUW), Kamal et al. (2023) documented that the Australian stock market experienced a more pronounced negative impact on February 21, 2022, the day when Russia recognized Ukraine's Donetsk and Luhansk regions as independent republics, compared to the date of the actual invasion of Ukraine on February 24, 2022. This implies that the threat

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[1] Caldara and Iacoviello (2022) have repeatedly demonstrated that geopolitical risk has a weak correlation with EPU and other related indices.

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of escalation had a greater impact on financial markets compared to the actual invasion itself. Additionally, Fiorillo et al. (2023) found that the expectation and threat of geopolitical tensions exert a greater influence on stock liquidity than the actual realization and escalation of such tensions.

In this study, we investigate the reactions of the cryptocurrency market to a threat versus an actual occurrence of a major geopolitical event. Our investigation contributes to the existing literature, as while there is substantial evidence on the difference in impact of geopolitical threat versus act events on stock markets, the difference in impact on cryptocurrency markets has received little attention. To explore this difference, we examine two major events from the ongoing RUW. First, as a threat event, we use Russia's recognition of Ukraine's Donetsk and Luhansk regions as independent republics on February 21, 2022, at 7 pm GMT.[2] Second, as an act event, we use the first blasts on Kyiv at 2 am GMT on February 24, 2022, which occurred shortly after Russia's president publicly declared the invasion had begun.[3] These events provide a suitable test setting as they occur within a short timeframe, minimizing the possibility that any observed differences in effects we observe are influenced by other factors.

Our analyses are particularly interesting due to the limited knowledge regarding how cryptocurrencies are influenced by the RUW. On the one hand, given that cryptocurrencies are perceived as speculative investments (Cheah and Fry, 2015), investors may choose to sell their cryptocurrencies to allocate funds to safer assets due to the uncertainty caused by the ongoing conflict. On the other hand, the RUW could potentially result in increased demand for cryptocurrencies as a means to circumvent Western sanctions imposed on Russia and provide immediate donations to Ukraine.[4] The few studies that have investigated the impact of the RUW on the performance of cryptocurrencies include (Khalfaoui et al., 2022), who discovered a negative association between cryptocurrency returns and public sentiment towards the RUW, as indicated by Google searches on specific keywords. Furthermore, Mohamad (2022) found a negative effect of Russia's invasion on February 24 on the returns of the three major cryptocurrencies Bitcoin, Ethereum, and Litecoin, along with evidence of herding behavior between these cryptocurrencies and energy commodities. Additionally, in an event study using daily data with February 24, 2022, as the event date, Diaconaşu et al. (2022) found no statistically significant effect on Bitcoin returns. Moreover, when comparing pre- and post-war scenarios, Patel et al. (2023) found significant impacts of the RUW on the connectedness between socially responsible investments (SRI) and cryptocurrencies. However, none of these studies on cryptocurrencies have specifically investigated differences in the impact of threat compared to act events. In contrast, prior literature has explored the differential effects of threats and acts of geopolitical events on stock markets. Thus, we compare our findings on cryptocurrencies with this earlier research on stocks. Furthermore, despite the numerous differences between stocks and cryptocurrencies, these asset classes also share many similarities. These shared traits serve as additional motivation for limiting the comparison of our results to those found in the stock market.

For our empirical analysis, we utilize hourly cryptocurrency data for two subsamples: the Top 5 and Top 100 cryptocurrencies based on their market capitalization. We consider the timeframe from 48 h before the threat event (February 21, 2022, at 7 pm GMT) to 48 h after the act event (February 24, 2022, at 2 am GMT). Our results reveal that both the threat and act events were associated with a decrease in liquidity and returns for cryptocurrencies. However, the magnitude of this decrease in liquidity and return differed between the threat and act events. Notably, the act event on February 24 exhibited the most significant decline in liquidity and return, indicating a greater decrease in liquidity and return following the actual occurrence of war escalation compared to the threat of it. Additionally, we observe that the immediate effects of these events on return and liquidity were weaker for the Top 5 cryptocurrencies compared to the Top 100 cryptocurrencies, although the differences were marginal.

Our study makes several contributions to existing research in various areas. Firstly, to the best of our knowledge, we are the first to investigate the short-term impact of geopolitical risk on both the return and liquidity of cryptocurrencies. This expands the discussion on the influence of geopolitical risk on asset pricing, especially on cryptocurrencies, building upon previous studies that has focused on the general effect of geopolitical risk on cryptocurrencies' returns (Long et al., 2022), hedging capabilities (Xu and Kinkyo, 2023), connectedness with SRI (Patel et al., 2023), co-movement with other assets (Diaconaşu et al., 2022; Khalfaoui et al., 2022), among other aspects. For instance, Long et al. (2022) conducted a study on the cross-sectional pricing of cryptocurrencies. They used daily excess returns on these assets to estimate a beta coefficient, which is associated with daily percentage changes in the geopolitical risk index provided by Caldara and Iacoviello (2022) from March 2, 2014, to December 12, 2021. Their analyses revealed that investors tend to pay a premium to hold cryptocurrencies with high and positive beta values, likely because these indicate the potential for these assets to serve as risk hedges. While (Long et al., 2022) used the RUW as a context, their research, centered on the role of geopolitical risk in the cross-sectional pricing of cryptocurrencies, does not cover the specific threat and act events of February 2022 derived from the RUW that we investigate in our study.

Secondly, to the best of our knowledge, we are the first to provide empirical evidence of the differences in reactions in the cryptocurrency market to threat versus act events during periods of extreme geopolitical risk. While some studies have investigated the market reactions of a limited number of major cryptocurrencies alongside other assets solely in the context of geopolitical act events (e.g., Diaconaşu et al., 2022; Mohamad, 2022), our approach stands in contrast. We consider a large sample of cryptocurrencies and examine the market reactions in terms of return and liquidity during both a geopolitical threat and a geopolitical act event.

Finally, our findings reveal a noteworthy pattern in the cryptocurrency market, with negative abnormal returns in the first hours following the geopolitical threat and act events. Furthermore, we observe more pronounced negative abnormal returns triggered

[2] The president's address was released at 10:35 pm Moscow time: http://en.kremlin.ru/events/president/news/67828.

[3] https://www.cnn.com/2022/02/23/europe/russia-ukraine-putin-military-operation-donbas-intl-hnk

[4] https://www.economist.com/finance-and-economics/why-crypto-is-unlikely-to-be-useful-for-sanctions-dodgers/21808188

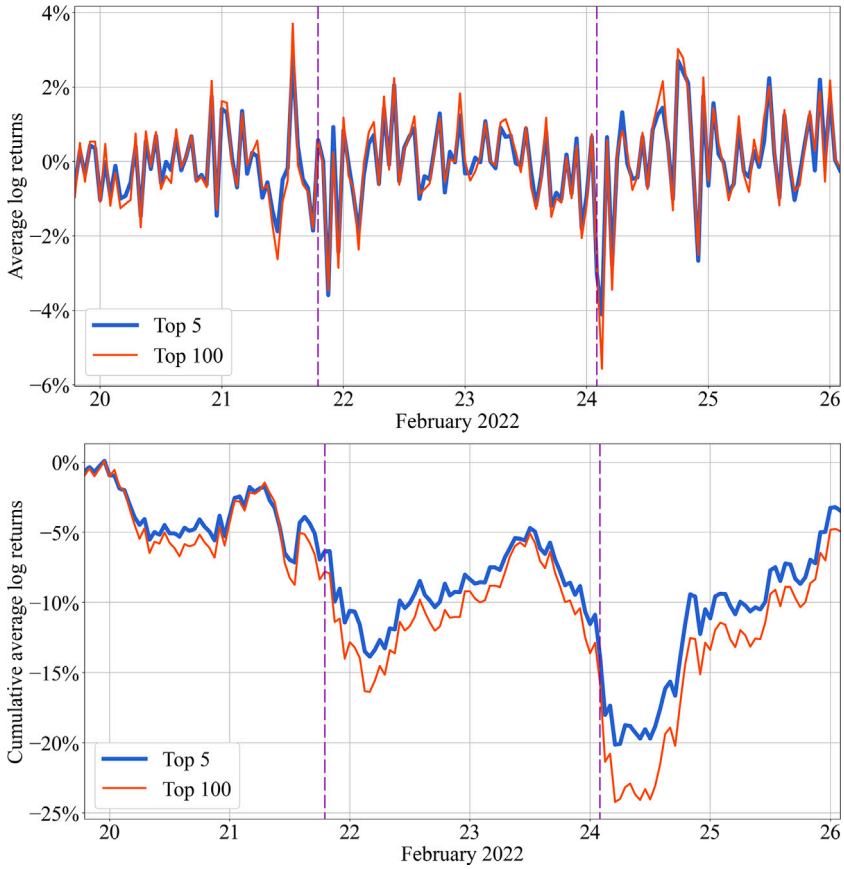


**Fig. 1.** Top panel: Hourly log returns averaged across the Top 5 and Top 100 cryptocurrencies. Bottom panel: Cumulative hourly log return. The vertical dashed lines represent the events.

by the act event as compared to the threat event. This finding contrasts with the evidence observed in the stock market (see, e.g., Kamal et al., 2023). Moreover, our results contrast with those found in the event study by Umar et al. (2022), who identified positive abnormal returns on clean energy stocks and metals coinciding with our act event on February 24, 2022. In sum, our study contributes to the rapidly expanding literature on the economic and financial consequences of the RUW.

The remainder of this paper is structured as follows. Section 2 presents the data used in this study, while Section 3 describes the empirical approach and presents the findings. Finally, the conclusions are provided in Section 4.

## 2. Data

We collect hourly cryptocurrency data for 2022 from the exchange Binance for the two subsamples of the Top 5 and Top 100 cryptocurrencies based on their market capitalization. Fig. 1 displays the average log returns for both groups, spanning from 48 h before the threat event (February 21, 2022, at 7 pm GMT) to 48 h after the act event (February 24, 2022, at 2 am GMT). As expected, we observe increased volatility in returns around the event hours.

## 3. Empirical approach and results

We evaluate the impact of both the threat and act events on cryptocurrencies across two key dimensions. Firstly, we assess the effect on liquidity to understand how investors respond to the arrival of information. Secondly, we analyze the impact on abnormal returns to determine whether these events have immediate or lasting effects on the perceived value of cryptocurrencies among investors. In this section, we will describe the methods employed and present the corresponding results.

We share the code for running all our analyses and generating results at: https://cryptocurrencies-2023.ranik.no We are not allowed to share the data due to restrictions from the provider. However, the shared code includes instructions on how to download all the data we used directly from the data provider.

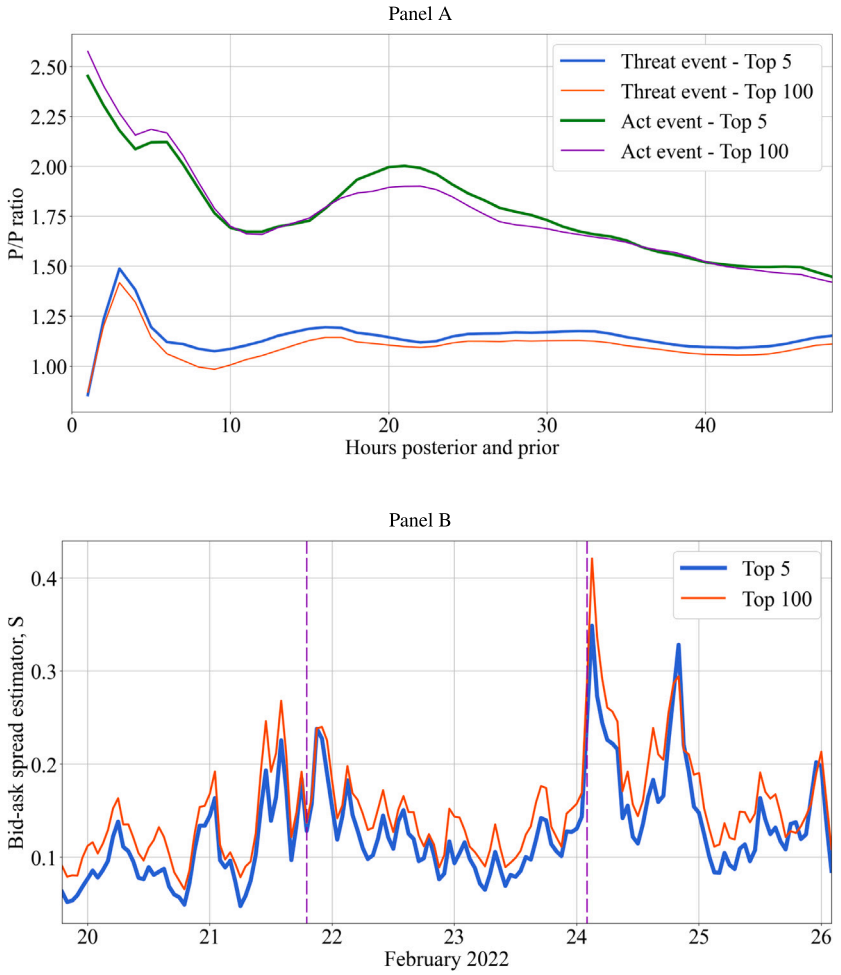


**Fig. 2.** Panel A shows the P/P ratios averaged over the Top 5 and Top 100 cryptocurrencies for both events. Panel B presents the evolution of $S$, with vertical dashed lines representing the events.

### 3.1. Liquidity

We quantify liquidity for cryptocurrency $i$ by the bid–ask spread estimator $S_{i,t}$ of Corwin and Schultz (2012), given by

$$\begin{aligned} S_{i,t} &= 2\left(e^{\alpha_{i,t}} - 1\right) / \left(1 + e^{\alpha_{i,t}}\right) \\ \alpha_{i,t} &= \frac{\sqrt{2\beta_{i,t}} - \sqrt{\beta_{i,t}}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma_{i,t}}{3 - 2\sqrt{2}}} \\ \beta_{i,t} &= E\left\{\sum_{j=t}^{t+1}\left[\ln\left(\frac{H_{i,j}}{L_{i,j}}\right)\right]^2\right\} \\ \gamma_{i,t} &= \left[\ln\left(\frac{H_{i,t,t-1}}{L_{i,t,t-1}}\right)\right]^2 \end{aligned} \tag{1}$$

where $H_{i,t}$ and $L_{i,t}$ are the maximum and minimum prices for hour $t$, and $H_{i,t,t-1}$ and $L_{i,t,t-1}$ are the maximum and minimum prices over both hours $t-1$ and $t$. Further, we measure the effects of the threat and act events on liquidity using the ratio of $S$ averaged over $\theta$ hours posterior divided by $\theta$ hours prior to event hour $\tau$:

$$\mathrm{P/P}_i = \frac{\frac{1}{\theta}\sum_{t=\tau+1}^{\tau+\theta} S_{i,t}}{\frac{1}{\theta}\sum_{t=\tau-\theta}^{\tau-1} S_{i,t}} \tag{2}$$

A narrower spread, that is, a lower $S$, indicates more liquidity. Thus, a P/P ratio above one indicates that liquidity is higher before than after the event.

**Table 1**
P/P ratios averaged over the Top 5 and Top 100 cryptocurrencies. We conduct a standard two-sided $t$-test for the null hypothesis that the mean of the reported ratio is equal to unity.

| Hours | Threat event | | | | Act event | | | |
|---|---|---|---|---|---|---|---|---|
| posterior | Top 5 | | Top 100 | | Top 5 | | Top 100 | |
| and prior | P/P | T-test | P/P | T-test | P/P | T-test | P/P | T-test |
| 1 | 0.86 | −2.64* | 0.87 | −10.19*** | 2.45 | 5.74*** | 2.58 | 25.06*** |
| 2 | 1.23 | 2.52* | 1.20 | 11.27*** | 2.31 | 5.30*** | 2.40 | 23.97*** |
| 3 | 1.49 | 3.72** | 1.42 | 18.90*** | 2.18 | 5.61*** | 2.27 | 23.68*** |
| 4 | 1.38 | 2.39* | 1.32 | 14.65*** | 2.09 | 5.93*** | 2.16 | 24.07*** |
| 5 | 1.20 | 1.31 | 1.15 | 7.28*** | 2.12 | 6.39*** | 2.19 | 26.36*** |
| 6 | 1.12 | 0.88 | 1.06 | 3.34*** | 2.12 | 6.63*** | 2.17 | 28.11*** |
| 7 | 1.11 | 0.79 | 1.03 | 1.61 | 2.01 | 6.80*** | 2.06 | 27.25*** |
| 8 | 1.09 | 0.60 | 1.00 | −0.29 | 1.89 | 6.96*** | 1.92 | 25.40*** |
| 9 | 1.07 | 0.51 | 0.98 | −0.98 | 1.77 | 6.56*** | 1.79 | 22.69*** |
| 10 | 1.09 | 0.59 | 1.01 | 0.36 | 1.69 | 6.61*** | 1.70 | 21.22*** |
| 11 | 1.10 | 0.71 | 1.03 | 2.03** | 1.67 | 6.78*** | 1.66 | 21.45*** |
| 12 | 1.12 | 0.83 | 1.05 | 3.20*** | 1.67 | 6.92*** | 1.66 | 22.63*** |
| 15 | 1.19 | 1.30 | 1.13 | 7.68*** | 1.73 | 8.23*** | 1.74 | 25.66*** |
| 17 | 1.19 | 1.41 | 1.14 | 8.80*** | 1.86 | 8.81*** | 1.84 | 26.68*** |
| 19 | 1.16 | 1.36 | 1.11 | 7.50*** | 1.97 | 10.12*** | 1.88 | 28.06*** |
| 21 | 1.13 | 1.32 | 1.10 | 6.93*** | 2.00 | 10.85*** | 1.90 | 28.21*** |
| 23 | 1.12 | 1.50 | 1.10 | 7.22*** | 1.96 | 11.21*** | 1.88 | 27.84*** |
| 25 | 1.16 | 2.08 | 1.13 | 8.53*** | 1.87 | 11.17*** | 1.80 | 26.22*** |
| 30 | 1.17 | 2.42* | 1.13 | 8.61*** | 1.73 | 11.76*** | 1.69 | 24.62*** |
| 35 | 1.15 | 2.54* | 1.10 | 7.73*** | 1.63 | 13.73*** | 1.62 | 23.70*** |
| 40 | 1.10 | 2.14* | 1.06 | 5.13*** | 1.52 | 13.89*** | 1.52 | 21.94*** |
| 45 | 1.11 | 2.64* | 1.07 | 6.38*** | 1.50 | 11.43*** | 1.46 | 21.96*** |
| 48 | 1.15 | 3.45** | 1.11 | 8.98*** | 1.45 | 10.43*** | 1.42 | 21.10*** |

*Significance at the 10% levels.
**Significance at the 5% levels.
***Significance at the 1% levels.

Panel A of Fig. 2 displays the P/P ratios averaged over the Top 5 and Top 100 cryptocurrencies for up to 48 h posterior and prior to the threat and act events. The P/P ratio values, along with their $t$-statistics, are also presented in Table 1. We observe P/P ratios above one, indicating a decrease in liquidity following both events. This observation is further supported by Panel B of Fig. 2, which shows the evolution of $S$ from 48 h before the threat event to 48 h after the act event. Notably, the decrease in liquidity is most pronounced for the event on February 24, signifying a more substantial decline in liquidity following the act compared to the threat of war escalation. Additionally, we observe that the immediate liquidity effects of the events are relatively weaker for the Top 5 cryptocurrencies compared to the Top 100 cryptocurrencies. However, the differences between the two subgroups are minor. We also observe that the P/P values decrease in the days after the events, suggesting an increase in liquidity. This could be attributed to a heightened demand for cryptocurrencies as a means to circumvent Western sanctions imposed on Russia or to facilitate immediate donations to Ukraine

### 3.2. Abnormal return

Next, we use a standard event study methodology (Fama et al., 1969) to estimate the effects of the threat and act events on cryptocurrency returns. For each cryptocurrency $i$, we calculate abnormal return (AR) by

$$AR_{i,t} = R_{i,t} - E\left(R_{i,t}\right) \tag{3}$$

where $R_{i,t}$ is the hourly log return, and $E\left(R_{i,t}\right)$ is the expected return calculated as the average of $R_{i,t}$ over a 30 days estimation window ending 36 h before the event hours for the threat and act events. Further, we calculate the cumulative abnormal return (CAR) over the event window $\left[\tau_1, \tau_2\right]$ by

$$CAR_i\left[\tau_1, \tau_2\right] = \sum_{t=\tau_1}^{\tau_2} AR_{i,t} \tag{4}$$

We calculate the test statistics for CAR with the estimation period standard deviation, as in Pandey and Kumari (2021).

Table 2 presents the average AR in percent for the Top 5 and Top 100 cryptocurrencies during each hour within the event window [−12, 12] around the event hour (0) for both the threat and act events. Additionally, Table 3 displays the CAR for different event hours surrounding the threat and act events. Fig. 3 illustrates the evolution of CAR over the event window [−36, 36]. We observe negative effects on cryptocurrency returns following both the threat and act events, which aligns with previous literature that focused solely on the act event. For example, Mohamad (2022) found negative CAR following the event on February 24 for the three cryptocurrencies in his investigation (Bitcoin, Ethereum, and Litecoin). Furthermore, we observe a more pronounced negative effect

**Table 2**
Average abnormal return (AR) in percent for the Top 5 and Top 100 cryptocurrencies during each hour within the event window [−12, 12] around the event hours (0).

| | 21 February 2022 at 7 pm GMT | | | | 24 February 2022 at 2 am GMT | | | |
|---|---|---|---|---|---|---|---|---|
| | Top 5 | | Top 100 | | Top 5 | | Top 100 | |
| | AR | T-test | AR | T-test | AR | T-test | AR | T-test |
| −12 | 0.13 | 0.35 | 0.57 | 4.80*** | −1.19 | −3.02*** | −1.26 | −10.29*** |
| −11 | −0.98 | −2.64** | −0.73 | −6.11*** | −0.39 | −1.00 | −0.51 | −4.14*** |
| −10 | −0.57 | −1.52 | −0.62 | −5.23*** | 0.80 | 2.04** | 1.19 | 9.75*** |
| −9 | −1.33 | −3.58*** | −1.71 | −14.37*** | −1.20 | −3.05*** | −1.47 | −12.05*** |
| −8 | −1.88 | −5.07*** | −2.61 | −21.94*** | −0.84 | −2.14** | −0.97 | −7.93*** |
| −7 | −0.50 | −1.33 | −1.07 | −8.94*** | −1.00 | −2.55** | −1.09 | −8.92*** |
| −6 | −0.19 | −0.50 | −0.51 | −4.24*** | 0.19 | 0.48 | 0.12 | 1.02 |
| −5 | 2.82 | 7.58*** | 3.72 | 31.18*** | −0.86 | −2.20** | −0.97 | −7.94*** |
| −4 | 0.41 | 1.11 | −0.08 | −0.71 | 0.62 | 1.59 | 0.44 | 3.63*** |
| −3 | −0.48 | −1.30 | −0.61 | −5.08*** | −1.80 | −4.58*** | −2.04 | −16.66*** |
| −2 | −0.72 | −1.93* | −0.81 | −6.80*** | −0.90 | −2.30** | −1.13 | −9.23*** |
| −1 | −1.86 | −5.02*** | −1.79 | −15.01*** | 0.66 | 1.69* | 0.75 | 6.15*** |
| 0 | 0.57 | 1.53 | 0.57 | 4.75*** | −3.02 | −7.69*** | −2.88 | −23.60*** |
| 1 | 0.00 | 0.01 | −0.12 | −0.97 | −4.11 | −10.48*** | −5.55 | −45.45*** |
| 2 | −3.59 | −9.67*** | −3.46 | −29.01*** | 0.66 | 1.67* | 0.59 | 4.82*** |
| 3 | 0.92 | 2.48** | 0.25 | 2.13** | −2.79 | −7.10*** | −3.43 | −28.04*** |
| 4 | −2.43 | −6.55*** | −2.85 | −23.89*** | 0.07 | 0.18 | 0.23 | 1.92* |
| 5 | 0.84 | 2.25** | 1.19 | 9.95*** | 1.33 | 3.38*** | 0.85 | 6.95*** |
| 6 | −0.07 | −0.19 | −0.37 | −3.13*** | −0.05 | −0.13 | 0.28 | 2.28** |
| 7 | −0.93 | −2.50** | −0.73 | −6.16*** | −0.46 | −1.18 | −0.75 | −6.13*** |
| 8 | −1.91 | −5.15*** | −2.36 | −19.78*** | −0.43 | −1.09 | −0.38 | −3.11*** |
| 9 | −0.38 | −1.03 | −0.05 | −0.41 | 0.67 | 1.70* | 0.79 | 6.49*** |
| 10 | 0.47 | 1.26 | 0.80 | 6.69*** | −0.66 | −1.67* | −0.72 | −5.90*** |
| 11 | 0.70 | 1.90* | 1.07 | 8.99*** | 0.86 | 2.18** | 0.97 | 7.97*** |
| 12 | −0.61 | −1.63 | −0.63 | −5.27*** | 1.26 | 3.21*** | 1.58 | 12.89*** |

*Significance at the 10% levels.
**Significance at the 5% levels.
***Significance at the 1% levels.


**Fig. 3.** Average CAR across the Top 5 and Top 100 cryptocurrencies from 36 h before to 36 h after the events.

on cryptocurrency returns following the act event compared to the threat event. Additionally, Table 2 shows a highly significant negative impact on cryptocurrency AR at the act event hour (0). In contrast, we observe minimal or no impact on AR at the threat event hour (0). However, there is a sharp decline in cryptocurrency returns in the subsequent hours, resulting in an overall negative effect on abnormal returns.

Moreover, we notice that the CAR reverts to its previous level within two days after the onset of the threat and act events. For the actual event on February 24, 2022, specifically, the CAR reverts to its previous level in less than 24 h. This observation aligns with the findings of Diaconaşu et al. (2022), which reveal no statistically significant effect on daily Bitcoin returns in their event study, using the same event date of February 24, 2022. A plausible explanation for the CAR reverting to its previous level could be the increased demand for cryptocurrencies as a means to circumvent Western sanctions imposed on Russia or to facilitate immediate donations to Ukraine. Indeed, shortly after the escalations in the RUW, the Russian ruble plummeted to a record low against the US dollar, suggesting that Russian households and companies rapidly converted their rubles to foreign currencies (Wilson,

**Table 3**
Average cumulative abnormal return (CAR) of Top 5 and Top 100 cryptocurrencies around the events.

| | Event | Threat event | | | | Act event | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Window | Top 5 | | Top 100 | | Top 5 | | Top 100 | |
| | | CAR | T-test | CAR | T-test | CAR | T-test | CAR | T-test |
| Pre-event | **[−12,0]** | −4.59 | −3.42*** | −5.68 | −13.23*** | −8.92 | −6.31*** | −9.80 | −22.25*** |
| | **[−9,0]** | −3.17 | −2.70*** | −4.90 | −13.01*** | −8.14 | −6.56*** | −9.23 | −23.89*** |
| | **[−7,0]** | 0.05 | 0.05 | −0.58 | −1.71* | −6.11 | −5.50*** | −6.79 | −19.64*** |
| | **[−5,0]** | 0.73 | 0.80 | 0.99 | 3.40*** | −5.29 | −5.51*** | −5.82 | −19.46*** |
| | **[−3,0]** | −2.50 | −3.36*** | −2.64 | −11.07*** | −5.05 | −6.44*** | −5.30 | −21.67*** |
| | **[−1,0]** | −1.30 | −2.47** | −1.22 | −7.26*** | −2.36 | −4.25*** | −2.13 | −12.34*** |
| Post-event | **[0,1]** | 0.57 | 1.09 | 0.45 | 2.68*** | −7.13 | −12.85*** | −8.44 | −48.82*** |
| | **[0,3]** | −2.10 | −2.83*** | −2.75 | −11.55*** | −9.26 | −11.80*** | −11.28 | −46.13*** |
| | **[0,5]** | −3.70 | −4.06*** | −4.41 | −15.12*** | −7.86 | −8.18*** | −10.19 | −34.05*** |
| | **[0,7]** | −4.70 | −4.47*** | −5.52 | −16.38*** | −8.38 | −7.55*** | −10.66 | −30.85*** |
| | **[0,9]** | −7.00 | −5.95*** | −7.93 | −21.03*** | −8.14 | −6.56*** | −10.25 | −26.53*** |
| | **[0,12]** | −6.43 | −4.80*** | −6.69 | −15.56*** | −6.68 | −4.72*** | −8.42 | −19.12*** |
| Symmetric | **[−1,1]** | −1.29 | −2.01** | −1.34 | −6.48*** | −6.47 | −9.52*** | −7.69 | −36.32*** |
| | **[−3,3]** | −5.17 | −5.25*** | −5.96 | −18.89*** | −11.30 | −10.88*** | −13.69 | −42.33*** |
| | **[−5,5]** | −3.54 | −2.87*** | −3.99 | −10.08*** | −10.14 | −7.79*** | −13.13 | −32.40*** |
| | **[−7,7]** | −5.22 | −3.63*** | −6.66 | −14.44*** | −11.46 | −7.55*** | −14.57 | −30.78*** |
| | **[−9,9]** | −10.73 | −6.62*** | −13.40 | −25.79*** | −13.26 | −7.76*** | −16.60 | −31.16*** |
| | **[−12,12]** | −11.58 | −6.23*** | −12.94 | −21.71*** | −12.58 | −6.41*** | −15.34 | −25.11*** |

*Significance at the 10% levels.
**Significance at the 5% levels.
***Significance at the 1% levels.

2022). This trend likely also impacted the cryptocurrency market, as daily trading volume between the ruble and cryptocurrencies escalated to 15.3 billion rubles (approximately 140.7 million US dollars) within a week after the invasion – a three-fold increase compared to the volume just before the threat of invasion on February 21, 2022. Owing to their decentralized nature and the fact that they are not issued by a single central governmental authority, cryptocurrencies are particularly appealing in developing markets where foreign currencies are in short supply, national currencies are prone to hyperinflation, and international trade is government-restricted (Klasa and Wheatley, 2021). In fact, compared to banks and other regulated intermediaries for currency exchanges, cryptocurrency exchanges like Binance – the world's largest cryptocurrency exchange, which accounted for over 40% of all cryptocurrency trades in rubles at the time of escalation in the RUW in late February 2022 – refused to ban any Russian users unless they were directly targeted by sanctions (Wilson, 2022). Furthermore, despite their renowned volatility, cryptocurrencies may have appeared attractive as a means to preserve savings during the economic turmoil following the RUW escalation (Feeney, 2022).

Finally, our findings may be explained by market efficiency. Behavioral factors such as market sentiment, fear of missing out, and speculative behavior can significantly influence the cryptocurrency market, leading to unpredictable price patterns that challenge the Efficient Market Hypothesis.

## 4. Conclusions

Our findings indicate that the escalation in the RUW in late February 2022 had a negative impact on cryptocurrency liquidity and returns. Interestingly, we observe a more pronounced decrease in liquidity and returns in response to the actual escalation in the RUW compared to the threat of escalation shortly before. This contrasts with previous research on stock markets, which suggests that stock markets are more susceptible to the threat of geopolitical events than their actual occurrences.

Furthermore, we notice indications of increased liquidity and returns in the days following the escalation. This suggests a potential rise in demand for cryptocurrencies, possibly driven by the desire to utilize them as a means to circumvent Western sanctions imposed on Russia or to facilitate immediate donations to Ukraine.

While previous literature has demonstrated the reactions to the actual occurrence of major geopolitical events as compared to mere threats of them in stock markets, we further contribute by examining the impact on the cryptocurrency market. However, there is still a lack of analysis concerning other asset classes such as currencies and commodities. We suggest that future research explore the differences in effects of geopolitical threats and actual events on other asset classes.

## Data availability

We share the code for running all our analyses and generating results at: https://cryptocurrencies-2023.ranik.no. We are not allowed to share the data due to restrictions from the provider. However, the shared code includes instructions on how to download all the data we used directly from the data provider.

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