Is Bitcoin a better safe-haven asset for individual investors than Gold? – Evidence from sanctioned Russia

Lu Zhang[a], Christian C.P. Wolff[b,*]

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[a] *University of Luxembourg*
[b] *University of Luxembourg and Centre for Economic Policy Research (CEPR)*

Abstract

Extensive research on safe-haven assets has been conducted in the literature. An important finding is that safe-haven assets are frequently used by institutional investors, such as pension funds and investment banks, to ride out high volatility. However, the issue of whether individual investors can benefit from it during a financial crisis has not been adequately addressed. Using the case of sanctioned Russia, we attempt to study whether Bitcoin as a decentralized asset can play a more useful role than gold to protect individual investors when the majority of safe-haven assets are restricted from transactions. Our main results show that both assets exhibit intraday weak safe-haven properties against the ruble. However, gold saw a waning trend compared with its historical performance, whereas Bitcoin's capability increased during this period. Further sentiment analysis demonstrates Russian investors' positive attitudes regarding Bitcoin boosting its price in response to the ruble's depreciation. The return on gold is more likely to be impacted by international investors who are concerned about global uncertainties.

JEL classification: G11; G14; G41

Keywords: Hedging performance; Dynamic conditional correlation; Sentiment analysis

1. Introduction

Throughout the history of humankind, the problem of how to transfer economic value across space and time has persisted. To overcome space issues, the payment methods have gradually shifted from cash payments to intermediate payments. However, both forms of payment have apparent limitations. The cash payments, which are carried out instantly and directly between two entities, need the physical presence of both parties in the same location at the same time. Thanks to the development of telecommunication, individuals are no longer confined to the physical domain of direct contact and have more flexibility through intermediate payments. These transactions, as implied by its name, must be carried out by a trustworthy third party, therefore inevitably increasing the vulnerability of the underlying security and bringing in surveillance by authorities. It reduces people's control over their savings and exposes them to the risk of authorities blocking their transactions for reasons of security, terrorism, or money laundering. The currency history has

* Corresponding author. Tel.: + 352-4666446663
Email address: christian.wolff@uni.lu (Christian Wolff)

also evidenced the plundered ownership. An evident example is the 2007-2008 financial crisis when the subprime mortgage crisis broke out and the US government overissued paper dollars causing the crisis to be dispersed worldwide. Stemming from distrust of government and banks, the concept of Bitcoin was created by Satoshi Nakamoto (2008) to overcome the inherent weakness of the trust-based model. Nevertheless, overshadowed by long-established international monetary practice, the advantages of Bitcoin have probably not yet been fully documented. The research hitherto concentrates on the illegal activity financed by Bitcoin's decentralization and anonymity (Foley, Karlsen and Putniņš, 2019; Fletcher, Larkin and Corbet, 2021). However, decentralized finance is far more than negative effects and further exploration of the positive side seems interesting and warranted.

In this paper, we aim to investigate the safe-haven property of Bitcoin for individual investors against the ruble in sanctioned Russia. Despite the safe haven topic having been extensively studied in the literature (e.g., Baur and Lucey (2010), Ranaldo and Söderlind (2010)), a question that remains unsolved is how individual investors can shelter their savings when they have limited access to conventionally defined safe-haven assets during a financial crisis. Typically, when a legal tender is expected to depreciate, investors are eager to hedge by exchanging for other underlying stable assets, such as gold or the US dollar, to protect their wealth. The strategy works well to hedge inflation risk. However, a sudden sharp depreciation may trigger a bank run. In order to maintain financial stability and avoid depletion of foreign reserves, central banks usually restrict foreign currency exchange under such circumstances. Consequently, protection wealth from through financial hedging is virtually non-existent during such a crisis. This has happened repeatedly in history. For example, in the 1997 Asian financial crisis, people in Thailand, Hong Kong and South Korea lost their life savings. Similar cases happened when Brazil, Argentina and Uruguay plunged into a financial crisis in 2002. Recently, Sri Lanka and Nepal are suffering the same trouble in 2022. Yet, a decentralized financial asset such as Bitcoin may provide alternative options to protect people's wealth. The case of sanctioned Russia in 2022 is an interesting case to illustrate this alternative.

Russia's invasion of Ukraine has triggered a series of international sanctions. For example, the Bank of Russia, the central bank of the Russian Federation, was blocked from accessing more than $400 billion in foreign-exchange reserves held abroad. Political unrest inevitably spread and eventually resulted in erratic financial outcomes on domestic markets, reflected especially in the plummeting of the Russian ruble. Russian investors panicked and attempted a flight to safety, aiming to find a store of value and liquidity in international markets in order to preserve their savings. However, satisfying liquidity demand became challenging as domestic markets were segregated from foreign markets to a large extent under sanctions. Specifically, the EU, the U.S., Canada, and the UK, among others, decided to ban selected Russian banks from the Society for Worldwide Interbank Financial Telecommunications (SWIFT) international payment messaging system two days after the start of the war. These sanctions made it difficult to purchase foreign currency or take money out of the country and created concerns about the security of overseas accounts held by Russians. Moreover, as the ruble plummeted to reach record lows, the Bank of Russia issued an order on March 8 further restricting access to dollars and other hard currencies for the next six months, to prevent the ruble's value from falling further. Given this situation, some assets such as the euro, Swiss franc, dollar, and related products, which may possess safe-haven characteristics (Ranaldo and Söderlind, 2010; Grisse and Nitschka, 2015; Hager, 2017), are excluded because of the extraordinary illiquidity. It thus compels people to reevaluate their demand for a valuable and decentralized universal equivalent that transcends authorities' measures.

Intuitively, Bitcoin comes to mind. Its algorithm was built with a fixed overall supply while equipped with a declining issuing rate. The limited production prevents Bitcoin from depreciating as a result of over-issuance like fiat money. Meanwhile, Bitcoin is designed to deliver value using a distributed peer-to-peer network. It brings the desirable characteristics of physical cash to the digital realm, enabling transactions without the involvement of a third party. Ideally, no external force could manipulate the currency to undermine its advantage to the holder. Perhaps the biggest obstacle to it becoming a safe-haven asset is its high historical volatility. Nevertheless, as shown in the study of Mather and Lighthall (2012), individuals under stress tend to emphasize positive information and discount negative information. Hence, investors under panic may focus the positive side of Bitcoin's decentralization property and discount its high volatility. In the sanctioned environment, Bitcoin readily jumps to mind when investors look for alternative safe-haven assets. Chainalysis [1] reported that the trade volume for the ruble-denominated cryptocurrency trading pairs increased immediately following the war, growing over 900% to more than $70 million between February 19 and 24. Nevertheless, there is no evidence that Bitcoin was being used on a large scale to evade sanctions. As Russia's capital outflows reached a record $151.5 billion in 2014 under sanctions, severe situation in 2022 may cause greater capital outflows. The market capacity of cryptocurrency is too small for Russian institutional investors to escape the punishment. It is more likely to be used by individual investors to shelter their savings. Its advantages for the general public therefore can stand out in this event.

One may also wonder: did we not already have gold as a decentralized asset that could be considered a safe haven and less volatile than Bitcoin? In actuality, gold is not as completely a decentralized asset as one might think. Despite the fact that no single institution has complete control over the gold mining industry, the main gold purchases are conducted via claims on gold, by which investors can settle the traded gold with a designated third-party gold custodian. This type of gold claim was invented to increase the marketability of gold across scales, space, and time, but it also inevitably brings government oversight. History has witnessed an increasing amount of concentration of gold being held by banks. By June 2022, global central banks owned approximately one-fifth of all the gold ever mined[2]. The integrity of the sovereign and the demand for liquidity cannot be satisfied simultaneously in any asset from the point of view of Russian investors. It is further illustrated by the G7 summit's agreement, made on June 26, 2022, to prohibit imports of Russian gold. Before then, given the devaluation of the ruble and the Russian individual investors' rising desire for a hedge, most of the pressure may have been directed toward gold due to the lack of other adequate hedging channels. In order to cope with the increased demand for precious metals from households, the Russian central bank suspended its gold purchases from credit institutions starting on 15 March 2022. Whereas, the ruble's trough was around March 10, it is clear that the implementation of this policy lagged behind the market. Since the restricted gold supply fell short of fully satisfying the demand of Russian individual investors, apparently part of the pressure would be shifted to Bitcoin. There were not many alternatives in this context, it is worth exploring whether Russian investors regarded Bitcoin as a superior safe haven compared to gold.

In our empirical analysis, we therefore investigate (i) whether Bitcoin and gold acted as a diversifier, hedge or safe haven against the ruble during the war period; (ii) how their performances

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[1] https://blog.chainalysis.com/reports/cryptocurrency-ukraine-russia-sanctions/

[2] https://investingnews.com/daily/resource-investing/precious-metals-investing/gold-investing/top-central-bank-gold-holdings/

varied compared with their historical records; (iii) what types of investors use Bitcoin or gold as a safe haven during this financial stress period.

By attempting to provide answers to these questions, this study contributes to the existing literature in three aspects. Firstly, our study clarifies from a different point of view whether Bitcoin can function as a safe-haven asset. While some studies claim that Bitcoin is too volatile to serve as a safe-haven asset (Klein, Thu and Walther, 2018; Smales, 2019), others show that it can be used in some circumstances as a safe haven (Shahzad et al., 2019; Urquhart and Zhang, 2019). Since the Bitcoin market is still in its infancy, relatively high volatility is probably inevitable. We may not be able to settle the debate until the market matures. Our research utilizes a particular period when investors are more likely to focus on the advantages of Bitcoin and discount its high volatility because of the lack of alternatives. Our results will demonstrate that, despite initially serving only as a diversifier, Bitcoin turned into a weak safe haven for the ruble during this period. While gold, which had formerly been a strong safe haven, had waned into a weak safe haven. Secondly, while other studies seem to end after obtaining the statistical results of whether assets are safe havens against one or several currencies, we specifically distinguish effects on the role of various investors in driving assets into safe-haven assets. It is crucial to understand the factors that could impact on the performance of safe-haven assets because their response to large shocks is dynamic and inconsistent (Baur and McDermott, 2016). Our research examines three kinds of potential investors' sentiments that could impact the underlying safe-haven assets during the war period. The outcome shows that Russian investors' positive attitudes toward Bitcoin enhance its price movement against the ruble's depreciation and thus facilitate the weak safe-haven property. On the other hand, the influence of Russian investors is insignificant with respect to gold relative to international investors who are concerned about global uncertainties during the war. Furthermore, these results together imply a weakness of the authority-based financial system. Individual investors who have restricted choices under the system during a financial crisis may change their perceptions, which will have a profound impact on their decision-making in the future.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents and describes the data. Section 4 introduces the methodology. Section 5 reports empirical results. The concluding remarks are given in Section 6.

2. Literature review

Generally, a reliable safe-haven asset can transfer economic value across time and space under any circumstances. For the first point, the assets must have the ability to hold value into the future, also known as the store-of-value property. Ammous (2018) points out that the stock-to-flow ratio of an asset is a critical indicator in determining the value of storage. The stock is its existing supply in circulation, which is made up of all prior production, and deducts all consumption and destruction, while the flow is the additional output that will be produced in the future. An asset with a high stock-to-flow ratio is more likely to retain its value over time. Gold is a typical example. Indeed, Bitcoin's algorithm also demonstrates this trait since it is built for a maximum supply of 21 million coins and productivity halves roughly every four years. Although it may take a long time before the advantages of Bitcoin can be fully appreciated, the confidence in Bitcoin as a value storage vehicle is increasing (Janson and Karoubi, 2021).

The superiority of transmitting value across space should be reflected in all circumstances, including the worst scenario. Both gold and Bitcoin face no obstacles to circulating in most situations. In extreme circumstances, however, particularly under the sanctioned case that we examine in this paper, the liquidity of gold may not be greater than that of Bitcoin. Because, as we previously mentioned, much of the gold trade is governed by the Russian government, which has lagged in responding to the market demand. As a result, Bitcoin's decentralized architecture may provide circulation advantages in this regard.

Based on their fundamental concepts, both Bitcoin and gold have safe-haven potential, yet the literature has diverse viewpoints on them. It is controversial whether Bitcoin can be accepted and utilized as a safe haven. Smales (2019) investigates the asset characteristics of Bitcoin and reveals that, under normal market conditions, Bitcoin returns are more volatile, less liquid and costlier to transact than other assets, including gold. Therefore, until the market reaches maturity, it is not worthwhile to regard Bitcoin as a safe-haven asset because it is unlikely to enhance these results during periods of market turbulence. Klein, Thu and Walther (2018) also show that, in contrast to gold's flight-to-quality role in times of market distress, Bitcoin behaves in the exact opposite direction in downward markets. On the other hand, some researchers find that Bitcoin can be statistically utilized as a safe haven in some circumstances. Bouri et al. (2017) present that Bitcoin is a poor hedge, but can serve as a strong safe haven against Asian-Pacific stocks in weekly rather than daily data. To further explore how the frequency of data matters to Bitcoin properties, Urquhart and Zhang (2019) assess the relationship between Bitcoin and six main developed currencies at the hourly frequency data and discover that Bitcoin does act as an intraday hedge, diversifier and safe haven for certain currencies. The findings were extended to cover more developing countries' stock indices, regional indices and commodity series by Stensas et al. (2019). They conclude that while some commodities and developed countries can use Bitcoin as a diversifier, the majority of developing countries cannot. Moreover, they take certain events into account and find that Bitcoin can also act as a safe-haven asset for both the US and non-US countries during specific events, such as the US election in 2016, the Brexit referendum in 2016, and the burst of the Chinese market bubble in 2015. Whereas previous research generally focuses more on evaluating Bitcoin's characteristics during specific periods, Shahzad et al. (2019) take into account the dynamic interaction between financial assets that changes over time. Their findings show that Bitcoin is a time-varying weak safe haven.

Our research reconciles these perspectives and provides a new angle to explain the question. In the sanctioned scenario, volatility is less relevant than liquidity since domestic markets provide limited safe-haven options. Moreover, during this period, liquidity is rather concerned with free trade than some metrics such as trading volume, bid-ask spreads and transaction costs (e.g., Goyenko, Holden and Trzcinka (2009), Amihud and Noh (2021)). Many assets that are prohibited from trading due to sanctions cannot meet this criterion. Bitcoin, therefore, gets a ticket to the safe-haven arena.

In contrast to Bitcoin, the role of gold as a safe haven during stress periods is considerable. The study of Baur and McDermott (2010) shows that gold can be a safe haven for major European and US stock markets but not for large emerging markets. Baur and Lucey (2010) find that gold is a safe haven in extreme times for stock markets but not for bond markets. However, from the study of Baur and McDermott (2016), we can learn that gold is riskier than other safe-haven assets such as US government bonds. It is the behavioral biases associated with gold's history that make gold a safe-haven asset ingrained in investors' minds. Inspired by this finding, we aim to investigate investors' perceptions of gold and Bitcoin during our unusual timeframe. The conclusion may hold implications for the roles of Bitcoin and gold in the future.

Furthermore, we attempt to investigate whether individual investors can benefit from these two assets during financial turmoil. Or in other words, who actually use these assets as safe havens? To answer this question, we employ sentiment analysis to check for the influence of three kinds of investor groups on Bitcoin (gold) returns. As one of the world's largest social media platforms, Twitter has been extensively researched in the sentiment analysis field (e.g., Behrendt and Schmidt (2018), Gu and Kurov (2020)). We employ the number of related tweets from Twitter as proxies for investors sentiment and analyze the relationship between sentiment and asset returns. According to the conclusion of Shen, Urquhart and Wang (2019), the number of tweets may drive Bitcoin realized volatility and volume, but not return. Therefore, if we can observe significant results in the relationship between the straightforward indicators of sentiment and asset returns, we may uncover a link with assets' performance as a safe haven.

3. Data

3.1 Asset data

We first collect the return data of Bitcoin, gold and the ruble during the war period. To mitigate the issue of asynchronism that can lead to the underestimation of return correlations (Martens and Poon, 2001), we collect the hourly price data of XAU/USD (spot gold), BTC/USD from Dukascopy, and the matched RUB/USD data from Yahoo. The timeline is aligned through Coordinated Universal Time (UTC). The ruble and gold trade 24h a day except at weekends, while Bitcoin trades 24 hours a day, 7 days a week, so we filter out Bitcoin weekend data in order to achieve a complete match with other data series. Missing values are filled in using the average of the two values that are closest to it on either side. As we concentrate on the safe-haven performance of Bitcoin and gold against the ruble, we narrow the research period to the first month, from 2022/02/24 to 2022/03/24. This is an episode with high hedging demand from the panic resulting from the collapsed ruble. After that, the ruble steadily recovered to pre-war levels and Russian banks resumed gold purchases at a set price from March 28th. As shown in Figure 1, Bitcoin's price pattern presents a high degree of similarity to the S&P 500 prior to the start of the war. This is consistent with the finding of Conlon and McGee (2020) that the price of Bitcoin declines in lockstep with the S&P 500 during a bear market. However, the price trends of Bitcoin and the S&P 500 begin to diverge two working days after the start of the war. Not until the end of the first month of the war do they converge again. We suspect that this divergence is primarily the result of Russian investors' shifting needs for Bitcoin. Due to a series of sanctions, conventional safe-haven and hedging instruments are unable to function for Russian investors due to a lack of liquidity, whereas Bitcoin, a decentralized and anonymous asset, continues to operate. Consequently, the new variable causes the nature of the relationship between Bitcoin and the S&P 500 index to diverge. This makes the first month of the war an especially interesting time period for our research.

Insert Figure 1 about here

Following the selection of the major research period, we additionally collect one-year of data prior to the war month (2021/02/24 to 2022/02/24) as a reference period to evaluate whether the characteristics of Bitcoin and gold against the ruble had changed during the war period.

Logarithmic returns are employed for each dataset:

$$r_t = \left[ln \frac{P_t}{P_{t-1}}\right] \times 100 \quad (1)$$

where r_t is the logarithmic return, P_t is the asset price at time t and P_{t-1} is the asset price at time $t-1$.

The descriptive statistics of the one-year return before the war and the one-month return during the war are reported in Table 1 where we can see that Bitcoin is always the most volatile one among the three assets. It is clear that during the war, both gold and the ruble's volatility dramatically rose in comparison to their average volatility over the previous year, especially for the ruble, whose average volatility increased more than tenfold from 0.00231 to 0.02435. On the other hand, Bitcoin's average volatility decreased from 0.92779 to 0.86360 and extreme returns movements were smaller in size. All variables experienced considerable skewness and excess kurtosis, which will provide guidance for the distribution choice in the following models.

Insert Table 1 about here

3.2 Sentiment analysis data

To determine what kind of investor sentiment can affect the properties of Bitcoin and gold during the first month of the war, we gather the number of tweets as a proxy for sentiment from Twitter. We concentrate on three categories of investors: 1. Russian investors who are interested in Bitcoin (gold). 2. International investors who care about information concerning both the war and Bitcoin (gold). 3. International investors who are just concerned with the Bitcoin (gold) price movement. Using the Twitter research API, we collect related three different types of tweets from Twitter between 2022-02-24 and 2022-03-24 and then calculate the hourly numbers of each type of tweet. Data on weekends is filtered out to match returns on assets. Taking the data collection for Bitcoin as an example, we apply the following principles:

It is common for the Twitter community to use the hashtag (#) and dollar symbol ($) as a prefix to indicate topics relevant to cryptocurrencies (Kraaijeveld and De Smedt, 2020). Therefore, the first class is collected by searching Russian-written tweets containing any one of the following keywords: "bitcoin", "#btc", "$btc" or "биткоин". These tweets represent the attention of Russian investors who may seek shelter from Bitcoin against the depreciation of the ruble. Using the same logic, the second group collects English-written tweets containing any information about "bitcoin", "#btc" or "$btc" while also including keywords about the Russia-Ukraine war. In our case, the keyword for the war is "Russia" since we find that all the eligible tweets will contain "Ukraine" as well. Since English is a universal language, the second group consists of international investors who may use Bitcoin as a hedge or a form of speculation due to global uncertainty brought on by the war. The final group represents international investors as well, but they are only concerned with the price of Bitcoin and do not necessarily associate this with the war. Thus, only tweets published in English and including Bitcoin-related keywords make up the data set for this group. The case-insensitive principle is applied during the data fetching process to ensure that data including keywords like "Bitcoin" or "BTC" will not be lost. We employ an identical procedure to collect gold-related tweets except for changing the keyword to "gold".

Insert Tables 2 and 3 about here

The descriptive statistics of three different types of tweets related to gold or Bitcoin are reported in Tables 2 and 3, respectively. These tables report numbers of tweets. The average number of tweets written in English is much higher than the average number of tweets written in Russian in both tables. Only approximately 3% of investors who are interested in gold or Bitcoin also attempt to link this with the war. The proportion of Russian investors who pay attention to Bitcoin is greater (0.1444%) in the three groups in Table 2, compared with the proportion of Russian investors who are interested in gold (0.1055%) in Table 3. Comparing Tables 2 and 3, we can see that Table 3 has a lower mean, volatility, maximum and minimum. It shows that Bitcoin-related topics are more popular on Twitter than gold-related topics.

4. Methodology

4.1 Distinguish diversifier, hedge and safe haven assets

We follow the definition of Baur and Lucey (2010) which has become the acknowledged standard in the literature to distinguish between a diversifier, hedge, and safe haven assets. According to their definition, a diversifier is defined as an asset that is positively correlated with another asset, while a hedge is defined as an asset that is uncorrelated or negatively correlated with another asset. An asset that acts as a safe haven is one that is uncorrelated or negatively correlated with another asset in times of market stress or turmoil. Adhering to these specifications, we first employ the Dynamical Conditional Correlation (DCC) model proposed by Engle (2002) to capture the time-varying correlations across return series.

Following the DCC model, a univariate GARCH (1, 1) model is firstly carried out for each time series of returns. The ARMA (p, q) mean equation of GARCH (1, 1) model is specified in Equation (2).

$$r_t = c + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{2}$$

where r_t is the vector of price return; c is the constant term; and ε_t is a vector of residuals. Then the variance equation for time series i can be defined as:

$$h_{i,t} = \omega_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{i,t-1} \tag{3}$$

where ω_i is the constant; $h_{i,t}$ is the conditional variance; a_i is the parameter that captures the short-run persistence or the ARCH effect; and b_i represents the long-run ppersistence of volatility or the GARCH effect. In the second step, we start with the conditional covariance matrix H_t, which can be decomposed into:

$$H_t = D_t R_t D_t \tag{4}$$

where D_t is a diagonal matrix with time-varying standard variation from the univariate GARCH process:

$$D_t = diag\left(h_{1,t}^{\frac{1}{2}}, \dots h_{n,t}^{\frac{1}{2}}\right) \tag{5}$$

and R_t is the conditional correlation matrix specified as:

$$R_t = diag\{Q_t\}^{-1/2} Q_t \, diag\{Q_t\}^{-1/2} \tag{6}$$

The DCC (1,1) equation is given by Q_t, which is a symmetric positive definite matrix as in Eq. (7):

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \nu_{t-1}\nu'_{t-1} + \beta Q_{t-1} \tag{7}$$

where ν_t is a vector of standardized residuals; $\bar{Q}$ is the unconditional covariance matrix of these standardized residuals. Parameter α represents the effects of previous shocks and β represents the influence of previous DCCs on the current DCC. The elements of R_t will be of the form:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}} \tag{8}$$

where $q_{i,j,t}$, $q_{i,i,t}$ and $q_{j,j,t}$ are the elements of Q_t corresponding to the indices.

The DCC model captures correlation clustering, which assumes the correlation is more likely to be high at time t if it was also high at time $t - 1$. This assumption, however, does not necessarily fit well with an economic environment experiencing a substantial shift, which is typically brought on by influential and unexpected news. For instance, if the correlation is positive at time $t - 1$ but changes to negative at time t as a result of big positive news, the DCC model will fail to capture the real correlation at time t. It may distort the correlation upward and even produce a positive result since the effect of earlier, positive DCCs is taken into account. In our situation, the outbreak of war is a critical piece of information that can instantaneously change the direction of correlation. Therefore, the DCC-GARCH model will be implemented respectively for one-year data prior to the war and the one-month data during the war to mitigate the indicated issue.

Subsequently, the calculated correlations are employed to differentiate between safe-haven, hedging, and diversification properties. We apply the technique of Ratner and Chiu (2013) and Bouri et al. (2017) as in Eq. (9)

$$DCC_t = m_0 + m_1 D(r_{q10}) + m_2 D(r_{q5}) + m_3 D(r_{q1}) + \epsilon_t \tag{9}$$

where DCC_t is the pairwise conditional correlation between ruble and gold or Bitcoin at time t. $D(r_{q10})$, $D(r_{q5})$ and $D(r_{q1})$ are the dummy variables representing extreme return movements in the underlying ruble market at the lower 10th, 5th and 1st percentile of the whole period return distribution respectively. Bitcoin or gold is a diversifier against movements in the ruble if m_0 is significantly positive; Bitcoin or gold is a weak hedge against movements in ruble if m_0 is zero or a strong hedge if m_0 is significantly negative; Bitcoin or gold is a weak safe haven against movements in ruble if m_1, m_2 or m_3 coefficients are insignificantly different from zero, or a strong safe haven if they are negative.

4.2 Sentiment analysis

To examine the relationship between Bitcoin (gold) return and the sentiment of investors, both bi-directional contemporaneous and lead-lag relationship models are employed. We start by examining the contemporaneous model:

$$r_t = \mu + n_1 N_{\text{t,Ru}} + n_2 N_{\text{t,En\_Russia\_Ukraine}} + n_3 N_{\text{t,En}} + \varepsilon_t \tag{10}$$

where r_t is the return of Bitcoin or gold. $N_{\text{t,Ru}}$, $N_{\text{t,En\_Russia\_Ukraine}}$ and $N_{\text{t,En}}$ are the hourly numbers of tweets that respectively represent the sentiment or attention of three different types of investors: Russian investors; English-speaking investors (international investors) who are concerned with the Russia-Ukraine war process; English-speaking investors who do not mention the war in their tweets. In order to be counted, these investors' tweets must also contain information about the underlying asset, either Bitcoin or gold. If the coefficient of n_i is significant, the investors' attention can affect the movement of the underlying asset return, and the sign will indicate aggregate positive or negative impacts. This equation is estimated using OLS and the MM weighted least squares procedure proposed by Yohai (1987).

The Granger causality test developed by Granger (1969) is then employed to capture the lead-lag relationship between assets return and sentiment as expressed below:

$$r_t = \alpha_1 + \sum_{i=1}^{n} \beta_{1,i}\, r_{t-i} + \sum_{i=1}^{n} \gamma_{1,i}\, N_{t-i,j} + \varepsilon_{1,t} \tag{11}$$

$$N_{t,j} = \alpha_2 + \sum_{i=1}^{n} \beta_{2,i}\, N_{t-i,j} + \sum_{i=1}^{n} \gamma_{2,i}\, r_{t-i} + \varepsilon_{2,t} \tag{12}$$

where $N_{t,j}$ represents the number of tweets for different investors, and the lag length n is determined with the aid of the Schwarz Information criteria.

5. Empirical results

5.1 DCC and properties regression result

Specification results based on the Akaike information criterion indicated that an ARMA(1,1) model was sufficient to eliminate the substantial degree of autocorrelation in the returns for pre-war period. ARMA(4,4) of higher orders has been estimated for the war period. As we have found skewness and excess kurtosis in the return distributions reported in Table 1, we counted skew term σ and shape term δ in the distribution model. Table 4 reports the ARMA- GARCH(1,1) DCC(1,1) model regression results. It can be seen that for the one-year data prior to the war, the sum of α and β are close to 1, which means that the conditional volatility is persistent, whereas the results shown in wartime indicate a short-term shock. We do not elaborate on the results in too much detail since the general purpose of DCC modelling is to generate conditional correlations over time, which can be utilized for the following property regression model.

Insert Table 4 about here

We then use Equation (9) to differentiate between safe-haven, hedging, and diversification properties, and the regression results are reported in Table 5. We can see that during the one year before the war, both Bitcoin and gold can act as a diversifier with a positive m_0. The positive and significant coefficients m_1 and m_2 only show Bitcoin is no more than an effective diversifier in the 10% and 5% quantiles respectively. However, as evidenced by the negative and significant coefficient m_2, gold additionally offers a strong safe-haven property against the ruble. Therefore, Bitcoin is uncompetitive compared to gold's reliable safe-haven status during this year, and it appears that investors do not have a tendency utilize Bitcoin as a hedge against the ruble. This changed considerably during the first month of the war. The significant and negative coefficients on the constant term (m_0) indicate that both Bitcoin and gold display a strong hedging capability. Furthermore, the coefficients m_1 and m_3, which are not significantly different from zero, show a weak safe-haven property of gold against the ruble. Similarly, as indicated by the close to zero coefficient m_1, Bitcoin also presents a weak safe-haven property. Compared with their historical performance, the safe-haven property of gold therefore has become weaker rather than stronger during the war period, while Bitcoin emerged from being just a diversifier and displayed weak safe-haven capability against the ruble.

Russian investors' panic led them to find a safe-haven asset to park their savings. Due to sanctions, Russian domestic financial markets are relatively isolated from the global financial market. As a result, the demand for safe-haven assets was probably channeled into gold because of limited options. The amount of gold in circulation fell short of fully satisfying Russian investors' demand, so part of the hedging demand may have shifted to Bitcoin, which is relatively popular in Russia. This could be the reason why Bitcoin has turned into a weak safe haven, next to gold, against the depreciating ruble. To further investigate this interpretation, we employ sentiment analysis in the following phase.

Insert Table 5 about here

5.2 Sentiment analysis results

Our findings in the previous subsection indicate that, during the war, Bitcoin's capacity to act as a safe haven against the ruble grew while gold's ability to do so decreased. To identify the type of investors who specifically sparked this transformation, we collect the number of tweets from three different investor groups as sentiment indicators and regress them onto the return of Bitcoin (gold). These three groups, as described in detail in section 3.2, contain Russian investors who are interested in Bitcoin (gold), international investors who pay attention to both the war and Bitcoin (gold), as well as international investors who only care about Bitcoin (gold) related information. The outcomes of the contemporaneous model are shown in Table 6, where it is clear that different types of investors have distinct effects on the returns of either Bitcoin or gold over the same period. Russian investors who paid attention to Bitcoin during that period can positively affect Bitcoin's return, while international investors who were concerned with global uncertainty brought on by the war in the aggregate had positive attitudes toward gold. Where investors' sentiment is insignificant in the regression model, this is possibly because investors' overall attitudes toward Bitcoin (gold) are ambiguous and/or inconsistent, or their behavior is negligible in comparison to that of other types of investors. One interpretation of our results is that Russian investors who were faced with the ruble dilemma started to recognize the advantages of Bitcoin and revised their perceptions. As a result, they purchased Bitcoin during the war period to protect their holdings and therefore influenced Bitcoin's transformation to a weak safe haven against the ruble. Gold is undoubtedly a prominent hedging option, but due to purchase limitations and the fact that gold is not discussed as frequently on Twitter as Bitcoin, we are unable to determine the total effect of Russian investors' behavior on gold returns with the aid of this simple model.

Insert Table 6 about here

Using the Granger causality model, we then attempt to capture the lead-lag relationship between investors' sentiment and asset returns. The estimation results of Bitcoin and gold are reported in Tables 7 and 8, respectively, where we can see that none of the investors' sentiments can forecast the return on Bitcoin or gold. The return of Bitcoin can affect the sentiment of investors who are only interested in Bitcoin, which shows that this kind of investor depends more on Bitcoin's performance to determine whether to go long or go short. Gold returns can predict the sentiment of international investors who are worried about global uncertainty brought on by the war. Combined with the result in the contemporaneous model, this sort of investor is therefore firstly influenced by the gold price, and then their consequent purchase behavior will affect gold's return on an hourly basis.

Insert Tables 7 and 8 about here

Overall, the results from the contemporaneous model and Granger causality model support the interpretation that Russian investors' positive perceptions of Bitcoin drive up its price and push it to become a weak safe haven against the ruble. Although gold also functions as a safe haven against the ruble, we are unable to discern how this relates to Russian investors' behavior. More intricate sentiment indices may need to be utilized for further analysis.

6. Conclusion

In this paper, we investigate the intraday safe-haven interaction between the ruble and Bitcoin and compare it with gold's performance as a safe haven for the ruble for sanctioned Russia. Employing the DCC model, our results show that both assets' properties against the ruble were influenced by the outbreak of the war in Ukraine in February, 2022. Bitcoin evolved from a just a diversifier to a weak safe haven, while gold waned from a strong safe haven to a weak safe-haven asset.

We employ the number of tweets as a straightforward sentiment proxy and assess the correlations between three kinds of investors' sentiment and Bitcoin (gold) returns. Through bi-directional contemporaneous and lead-lag relationship models, our results demonstrate that Russian investors' positive attitudes toward Bitcoin may be one of the reasons for Bitcoin to become a weak-safe haven. However, it is unclear how the conventional safe-haven asset, gold, worked for these investors. According to our findings, international investors who are concerned with the global uncertainties brought on by the war are more likely to impact on gold's return.

Overall, our results offer some interesting insights for individual investors. In a financial crisis, individual investors are more helpless compared with institutional investors. They may have restricted access to authority-based safe-haven assets to protect their savings. A decentralized universal equivalent like Bitcoin that can transcend authorities' directives can be useful and learning how to use it is important for everyone. Furthermore, our research shows that investors' attitudes toward Bitcoin have been evolving. Given that the behavioral biases associated with gold's history make gold a prominent safe-haven asset ingrained in investors' minds (Baur and McDermott, 2016), the transformation in perceptions could have a profound impact on the role of Bitcoin and similar assets in financial markets.

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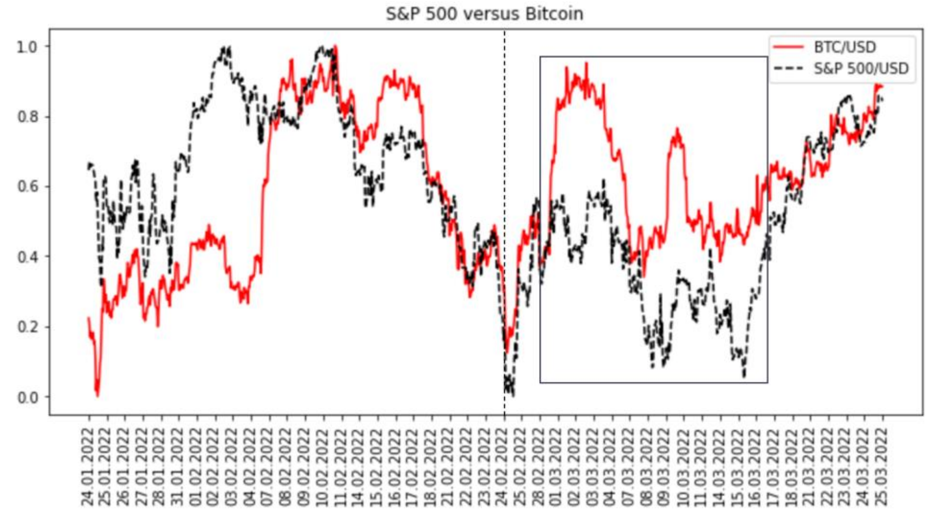

Fig. 1. The S&P 500 and Bitcoin time series price movement patterns from 2022/01/24 to 2022/03/24. Prices are normalized using the min-max method. The dotted line indicates the start of the war. Data comes from Dukascopy.

Table 1. Descriptive statistics of the hourly logarithmic returns for gold, Bitcoin and the ruble. Panel A and Panel B represent the statistics for the year before the war and the first month during the war data respectively.

Panel A – One-year pre-war data						
	Mean	St.Dev	Max	Min	Skew	Kurt
Bitcoin	-0.00418	0.92779	9.00893	-11.9412	-0.59183	17.3585
Gold	0.00089	0.16608	1.26212	-2.00573	-0.67462	12.7752
RUB	-0.00002	0.00231	0.01853	-0.01941	-0.12154	7.64403
Panel B – One-month wartime data						
	Mean	St.Dev	Max	Min	Skew	Kurt
Bitcoin	0.03258	0.86360	4.49751	-4.25873	0.15928	6.03935
Gold	0.00497	0.29723	1.52103	-1.93370	-0.57281	8.69990
RUB	-0.00050	0.02435	0.13933	-0.15967	-0.50400	10.7471

Table 2. Descriptive statistics: number of hourly Bitcoin-related tweets of the three types

	Mean	St.Dev	Max	Min	Skew	Kurt
Russian-written BTC related	9.39081	6.84712	82	0	2.98709	22.0464
English-written BTC & war related	189.405	147.002	988	12	1.34699	2.24234
English-written only BTC related	6291.22	1833.87	13335	3232	0.83470	0.62459

Table 3. Descriptive statistics: number of hourly gold-related tweets of the three types

	Mean	St.Dev	Max	Min	Skew	Kurt
Russian-written Gold related	3.08532	2.93716	21	0	1.74732	4.95897
English-written Gold & war related	86.8571	63.5658	480	17	2.47443	8.18258
English-written only Gold related	2834.49	770.651	8550	1767	2.37837	11.4683

Table 4. The ARMA-GARCH(1,1)-DCC(1,1) results, where $\boldsymbol{c}$ refers to the constant and $\boldsymbol{\varphi_p}$ and $\boldsymbol{\theta_q}$ refer to the AR(p) and MA(q) term in the mean equation. $\boldsymbol{\omega}$ refers to the constant in the variance equation, $\boldsymbol{a}$ refers to the ARCH term, $\boldsymbol{b}$ refers to the GARCH term, $\boldsymbol{\sigma}$ refers to the skew term while $\boldsymbol{\delta}$ refers to the shape term. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ refers to the parameters in the DCC equation. Panel A and Panel B represent the statistics for the year before the war and the first month during the war respectively.

Panel A – One-year pre-war data					
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
c_{ruble}	0.0000	c_{gold}	0.0024*	$c_{Bitcoin}$	-0.0093
φ_{1_ruble}	0.2648***	φ_{1_gold}	0.9603***	$\varphi_{1\_Bitcoin}$	0.6857***
θ_{1_ruble}	-0.3966***	θ_{1_gold}	-0.9659***	$\theta_{1\_Bitcoin}$	-0.7200***
ω_{ruble}	0.0000	ω_{gold}	0.0127***	$\omega_{Bitcoin}$	0.0051***
a_{ruble}	0.0459***	a_{gold}	0.6979***	$a_{Bitcoin}$	0.0236***
b_{ruble}	0.9479***	b_{gold}	0.3011***	$b_{Bitcoin}$	0.9723***
σ_{ruble}	0.9844***	σ_{gold}	1.0054***	$\sigma_{Bitcoin}$	0.9567***
δ_{ruble}	3.6063***	δ_{gold}	2.6058***	$\delta_{Bitcoin}$	3.1621***
α_{ruble_gold}	0.0068***			$\alpha_{ruble\_Bitcoin}$	0.0080*
β_{ruble_gold}	0.9895***			$\beta_{ruble\_Bitcoin}$	0.9782***

Panel B – One-month wartime data					
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
c_{ruble}	0.0002	c_{gold}	0.0052	$c_{Bitcoin}$	0.0329
φ_{1_ruble}	-0.4729***	φ_{1_gold}	0.3837***	$\varphi_{1\_Bitcoin}$	-0.2399***
φ_{2_ruble}	0.7090***	φ_{2_gold}	1.0612***	$\varphi_{2\_Bitcoin}$	0.6973***
φ_{3_ruble}	-0.5174***	φ_{3_gold}	0.1481***	$\varphi_{3\_Bitcoin}$	-0.0989
φ_{4_ruble}	-0.9559***	φ_{4_gold}	-0.8142***	$\varphi_{4\_Bitcoin}$	-0.8632***
θ_{1_ruble}	0.4737***	θ_{1_gold}	-0.3970***	$\theta_{1\_Bitcoin}$	0.2085***
θ_{2_ruble}	-0.7213***	θ_{2_gold}	-1.0668***	$\theta_{2\_Bitcoin}$	-0.6888**
θ_{3_ruble}	0.5162***	θ_{3_gold}	-0.1780***	$\theta_{3\_Bitcoin}$	0.0737
θ_{4_ruble}	0.9606***	θ_{4_gold}	0.8622***	$\theta_{4\_Bitcoin}$	0.8411***
ω_{ruble}	0.0001	ω_{gold}	0.0020	$\omega_{Bitcoin}$	0.0000
a_{ruble}	0.5996***	a_{gold}	0.0446	$a_{Bitcoin}$	0.0012***
b_{ruble}	0.3994**	b_{gold}	0.9307***	$b_{Bitcoin}$	0.9974***
σ_{ruble}	1.0348***	σ_{gold}	0.9725***	$\sigma_{Bitcoin}$	1.0016***
δ_{ruble}	2.6021***	δ_{gold}	3.3304***	$\delta_{Bitcoin}$	3.6471***
α_{ruble_gold}	0.0000			$\alpha_{ruble\_Bitcoin}$	0.0000
β_{ruble_gold}	0.9253***			$\beta_{ruble\_Bitcoin}$	0.9395**

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

Table 5. Estimation results on the diversification, hedging and safe-haven properties of Bitcoin and gold against ruble.

	Quantile 10 (m_1)	Quantile 5 (m_2)	Quantile 1 (m_3)	Hedge (m_0)
Gold-normal year	0.00004674	-0.01737**	0.09553*	0.03075***
Bitcoin-normal year	0.0098954***	0.0120858***	0.0140708	0.08130***
Gold-war month	-4.937e-08*	2.796e-08	3.970e-08**	-0.04358***
Bitcoin-war month	7.878e-08*	-7.053e-08	3.840e-08	-0.01590***

Table 6. Estimation result of the contemporaneous model. Where $\boldsymbol{N}_{\mathbf{t,Ru}}$ represents the sentiment of Russian investors toward Bitcoin or gold; $\boldsymbol{N}_{\mathbf{t,En\_Russia\_Ukraine}}$ represents the sentiment of international investors (English-speaking investors) who are concerned with both the war process and Bitcoin or gold information; $\boldsymbol{N}_{\mathbf{t,En}}$ represents the sentiment of international investors who only care about Bitcoin or gold.

	μ	$N_{\mathrm{t,Ru}}$	$N_{\mathrm{t,En\_Russia\_Ukraine}}$	$N_{\mathrm{t,En}}$
Coefficient for Bitcoin	0.05010	0.01421***	-0.00009	-0.00002
Coefficient for gold	-0.04414	0.00155	0.00036**	0.00001

Table 7. Estimation result of Granger causality test for Bitcoin

Null Hypothesis	F-statistic	Null Hypothesis	F-statistic
The number of Russian-written and Bitcoin related tweets does not Granger cause Bitcoin return	1.79300	Bitcoin return does not Granger cause the number of Russian-written and Bitcoin related tweets	0.00489
The number of English-written and both Bitcoin & war related tweets does not Granger cause Bitcoin return	1.09672	Bitcoin return does not Granger cause the number of English-written and both Bitcoin & war related tweets	1.96311
The number of English-written and only Bitcoin related tweets does not Granger cause Bitcoin return	1.53747	Bitcoin return does not Granger cause the number of English-written and only Bitcoin related tweets	4.48151**

Table 8. Estimation result of Granger causality test for gold

Null Hypothesis	F-statistic	Null Hypothesis	F-statistic
The number of Russian-written and gold related tweets does not Granger cause gold return	0.04977	Gold return does not Granger cause the number of Russian-written and gold related tweets	2.39429
The number of English-written and both gold & war related tweets does not Granger cause gold return	0.97354	Gold return does not Granger cause the number of English-written and both gold & war related tweets	4.18317***
The number of English-written and only gold related tweets does not Granger cause gold return	0.39569	Gold return does not Granger cause the number of English-written and only gold related tweets	0.02063