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Safe flight to which haven when Russia invades Ukraine? A 48-hour story[☆]

Azhar Mohamad

Department of Finance, Kulliyyah of Economics and Management Sciences, International Islamic University Malaysia, 53100 Kuala Lumpur, Malaysia

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ABSTRACT

We examine the flight-to-safety phenomenon from ruble (risky asset) to other safe-haven assets at the onset of the Russian invasion of Ukraine on 24 February 2022. We find evidence of flight-to-safe-haven occurrences from the ruble to the USD, yen, silver, Brent, WTI and natural gas as indicated by negative dynamic conditional correlations between these assets. Price discovery surrounding the invasion is found to be dominated by Brent and bitcoin. Further, we observe the presence of herding behaviours between energy commodities (Brent, WTI, gasoline and natural gas) and cryptocurrencies (bitcoin, ethereum and litecoin).

1. Introduction

The latest Russian invasion of Ukraine on 24 February 2022 has given 'flight-to-safety' or 'flight-to-safe-haven' a new meaning. Russia's currency the ruble has tumbled to a record low, and its equity market has plunged about 33%, erasing almost $200 billion in value.[1] On the other hand, crude oil prices have surged 8%, with Brent reaching $105 immediately after the attack, the highest level since 2014.[2] Russia and Ukraine have been in conflict since November 2013. The tension reached its peak when Malaysian Airlines flight MH017 was shot down on 17 July 2014. During the conflict, the Russian and Ukrainian equity markets have dropped by 0.21% and 0.30% after a 1% increase in escalation, proxied by possibility of sanctions by the European Union (Hoffmann and Neuenkirch, 2017). Apart from examining the war/conflict's impact on equity prices and returns, two strands of research have emerged, looking at (a) herding and (b) price discovery. A 'flight-to-safety' is defined as a situation in which investors suddenly fear that the assets they are currently holding may bear higher risks than before, hence prompting them to sell the higher-risk investments in exchange for a safe haven (lower-risk or safe investment). In so doing, investors strive for lower risks, which may result in lower profits. This phenomenon typically happens during periods of market stress or financial turmoil. During episodes of financial chaos, the scramble for a safe haven can wreak havoc on the financial markets—funds will flow together in herds to the most attractive safe havens and leave the unattractive risky assets high and dry. The coefficient value of a tumbling market essentially indicates herding in a flight-to-safety (Demirer and Kutan, 2006). In an earlier work, Santos (2002) hypothesised that the US Civil War (1864–1865) had disrupted the country's transportation and communication systems and increased the volatility of commodities, hence destabilising the agricultural commodities' price discovery process.

In the words of Alan Greenspan, former US Federal Reserve chairman, "when confronted with uncertainty, especially Knightian uncertainty, human beings invariably attempt to disengage from medium- to long-term commitments in favour of safety and liquidity. Because economies, of necessity, are net long (that is, have net real assets) attempts to flee these assets cause prices of equity assets to fall, in some cases dramatically" (Greenspan, 2004, p.38). The pursuit of a safe haven is usually sparked by

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E-mail addresses: dr@azharmohamad.asia, m.azhar@iium.edu.my.

1 See https://www.bloomberg.com/news/articles/2022-02-24/ruble-extends-slump-in-offshore-trading-as-ukraine-crisis-grows.

2 See https://www.reuters.com/business/energy/oil-rises-us-says-russian-attack-ukraine-may-occur-soon-2022-02-24/.

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Table 1
Descriptive statistics.

Instrument	Mean (%)	Median (%)	Max (%)	Min (%)	Std Dev	Skewness	Kurtosis	Jarque–Bera	ARCH 1–5	ADF
Ruble	−0.0027	0.0000	1.95	−2.25	0.20	−1.42	36.4	135202***	62***	−67***
USD	0.0002	0.0000	0.04	−0.05	0.01	−0.05	6.4	1367***	53.6***	−54.8***
Yen	0.0001	0.0000	0.22	−0.32	0.03	−0.42	17.3	24510***	14.8***	−35.8***
Tbill	0.0003	0.0000	1.27	−0.13	0.03	16.99	624.5	46513075***	0.0013	−54.7***
Btc	0.0010	0.0000	2.36	−0.80	0.14	1.72	34.1	117630***	62.4***	−34.6***
Eth	0.0003	0.0000	2.42	−0.88	0.16	1.50	23.7	52595***	19.6***	−34.2***
Ltc	−0.0003	0.0000	2.11	−1.16	0.17	0.73	15.3	18458.95***	21.7***	−50***
Gold	0.0002	0.0000	0.29	−0.40	0.04	−1.26	16.9	24038.56***	74.4***	−52.8***
Silver	0.0002	0.0000	0.35	−0.85	0.06	−1.36	20.0	35591.82***	21.9***	−55***
Brent	0.0003	0.0000	0.77	−1.37	0.10	−1.40	22.5	46453.03***	4.6***	−56.2***
WTI	0.0012	0.0000	0.58	−0.71	0.11	−0.51	8.9	4267.81***	35.9***	−56.8***
Gasoline	0.0016	0.0000	1.80	−0.70	0.09	1.74	52.7	297964.9***	1.24	−54.8***
Natgas	0.0010	0.0000	0.74	−1.12	0.14	−0.48	10.5	6774.857***	29***	−52.6***

Note: This table presents the descriptive statistics of minute-by-minute returns of all the 13 instruments examined in this study. ***, ** and * denote significance at 1%, 5% and 10%, respectively. #Obs=2881. ADF stands for Augmented Dickey–Fuller unit root test. ARCH 1–5 refers to the ARCH LM test up to five lags.

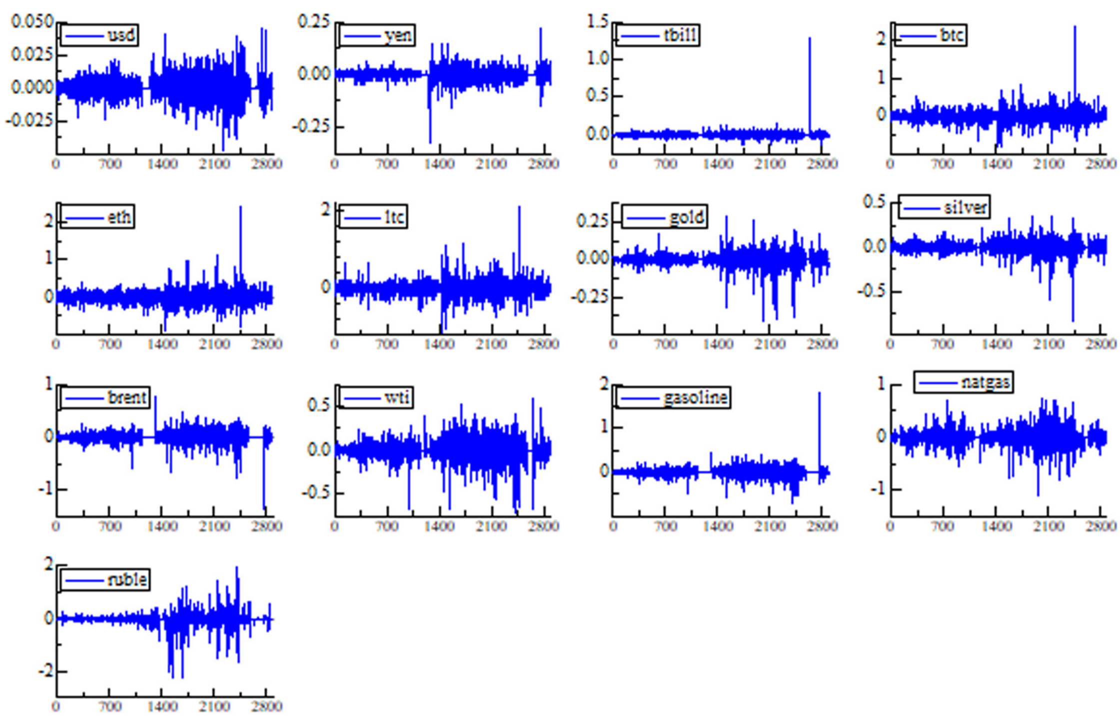

Fig. 1. Return behaviour. This figure presents minute-by-minute natural log return behaviour (in percentage) 24 h before and after the start of the Russian invasion of Ukraine.

sudden and unanticipated events (Caballero and Krishnamurthy, 2008), such as a financial crisis or war. Baur and Lucey (2010) define a safe haven as "an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil" (p.219). Thus, due to the negative correlation, the investors would be compensated for any losses as any drop in another asset would be evened up by a rise in the safe haven's price. Baur and Lucey (2010) also describe a haven as "a harbor or port, a place of safety" (p.219). Therefore, a safe haven can shelter investors and provide them with non-negative returns during a period of financial turmoil.

To this end, we ask whether there was a flight to a safe haven, i.e. from the ruble to other assets, during the 24 h before and 24 h after the Russian invasion of Ukraine. We also ask whether herding was present among the safe-haven assets and whether the safe-haven assets dominated the price discovery process before and during the invasion.

2. Data

We obtain minute-by-minute data for the ruble, USD index, yen index, US treasury bill (tbill), bitcoin (btc), ethereum (eth), litecoin (ltc), gold, silver, Brent, WTI, gasoline and natural gas (natgas) from Thomson Reuters Eikon and Bloomberg, in the 24 h before and 24 h after Russia's invasion of Ukraine, that is, from 23 February 2022 at 5am to 25 February 2022 at 5am, Ukraine time.[3] At first, we also considered Ukraine's currency, the hryvnia, but did not proceed with it due to the unavailability of minute-by-minute data. We utilise the natural log return, $r_t = ln(p_t/pt - 1)$, and present the descriptive statistics in Table 1. The ruble is the most volatile asset, with a 0.20% standard deviation, and yields

[3] According to CNN and other sources, the first blasts on Kyiv were heard around 5am, on 24 February 2022, shortly after President Putin's televised address. Thus, we identify this time (minute) as event period 0. See https://edition.cnn.com/2022/02/23/europe/russia-ukraine-putin-military-operation-donbas-intl-hnk/index.html.

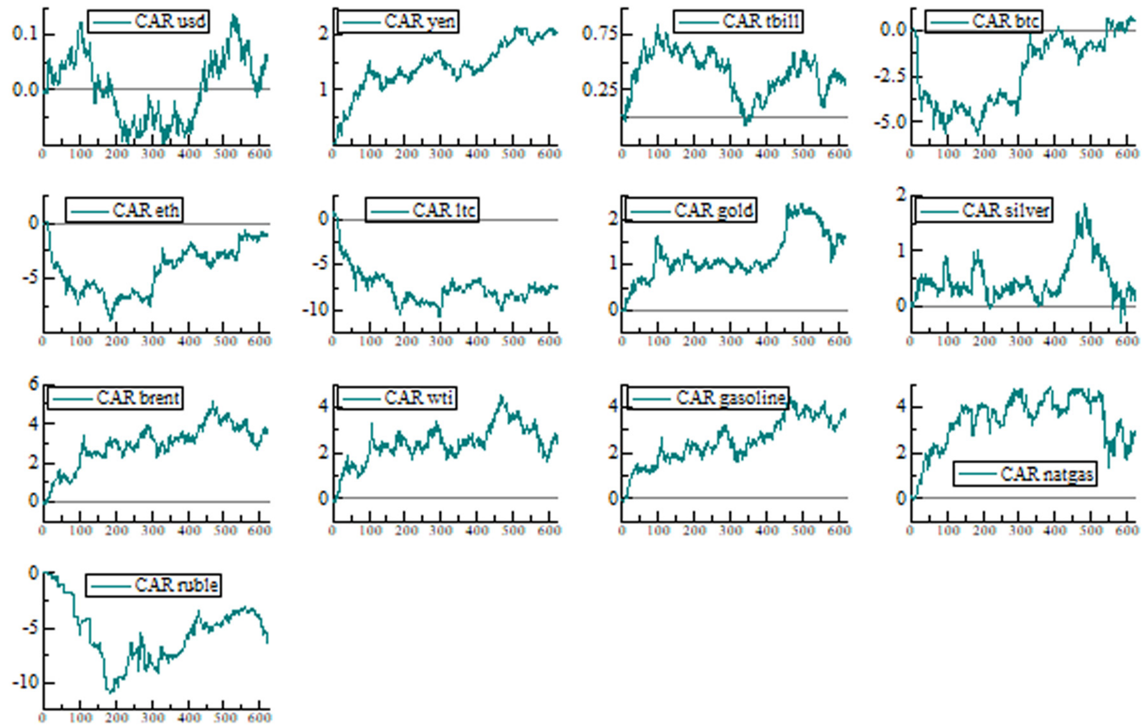

Fig. 2. Cumulative abnormal returns (CARs). This figure shows the CARs in percentage from min −20 to +600. Event period 0 marks the start of the Russian invasion of Ukraine at 5am, 24 Feb 2022 Ukraine time.

the biggest 1-min loss (−2.25%), while ethereum registers the highest gain (2.42%). The 1-min log return behaviour shown in Fig. 1 generally indicates increased volatility of the returns of almost all assets after the start of the invasion.

3. Analysis

We start the analysis by calculating cumulative abnormal returns (CARs) based on the event study methodology. The expected return is the mean return (mean return model) over about four hours (min −240 to −21) before the invasion (event). We then derive abnormal returns for about 10 h (min −20 to +600) after the attack and show the CARs in Fig. 2. We observe similar patterns for Brent, WTI, gasoline and natural gas. Yen displays a consistently up-trending CAR, while the USD's CAR appears to drop for the first three hours, before rising. The ruble's CAR, on the other hand, falls by about 10% in the first two hours before showing a slight rebound.

Further, we examine the price discovery between the assets in the 24 h before and 24 h after the invasion. There are four popular price discovery measures, namely the Information Share (IS; Hasbrouck, 1995), Component Share (CS; Gonzalo and Granger, 1995), Modified Information Share (MIS; Lien and Shrestha, 2009)[4] and Information Leadership Share (ILS; Putniņš, 2013. Hasbrouck (1995) defines the IS as the percentage of the variance within the common efficient price innovations that price series innovations can explain. Putniņš (2013) argues that, while price discovery measures essentially attempt to answer the question of 'who moves first', both the IS and CS are susceptible to the diverse noise levels. The author further reiterates that the ILS is arguably a better measure since it favours speed solely instead of noise avoidance. In this study, we estimate the following price discovery measures based on the Vector Error Correction Model (VECM):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{j=1}^{k} A_j \Delta Y_{t-j} + \varepsilon_t,\ \Pi = \alpha\beta^T \tag{1}$$

The CS can be calculated from the normalised orthogonal coefficients of the VECM:

$$CS_1 = \frac{|\alpha_2|}{|\alpha_1| + |\alpha_2|} \text{ and } CS_2 = \frac{|\alpha_1|}{|\alpha_1| + |\alpha_2|} \tag{2}$$

Given covariance matrix Ω from the reduced VECM,

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \tag{3}$$

and its Cholesky factorisation, $\Omega = MM'$, where

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2\left(1-\rho^2\right)^{1/2} \end{pmatrix} \tag{4}$$

the IS can be calculated as follows:

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \quad IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} \tag{5}$$

The MIS can be derived as

$$MIS_i = \frac{\left[(\psi F^*)_i\right]^2}{\psi\Omega\psi^T} \tag{6}$$

where $F^* = \left[G\Lambda^{-1/2}G^T V^{-1}\right]^{-1} \cdot G$ and Λ are drawn from the correlation matrix ε_t.

[4] Lien and Shrestha (2009) propose a different factorisation based on the correlation matrix, yielding a price discovery measure independent of the order of the state variables.

Table 2
Price discovery.

Market	24 h before invasion				24 h after invasion				Change
	IS	CS	MIS	ILS	IS	CS	MIS	ILS	in ILS
RUBLE-usd	0.849	0.166	0.850	0.999	0.388	0.029	0.388	0.998	−0.001
RUBLE-yen	0.001	0.008	0.000	0.007	0.373	0.078	0.373	0.980	0.973
RUBLE-tbill	0.335	0.177	0.335	0.847	0.272	0.091	0.272	0.933	0.086
RUBLE-gold	0.867	0.430	0.867	0.987	0.081	0.059	0.081	0.658	−0.329
RUBLE-brent	0.066	0.205	0.066	0.071	0.044	0.099	0.043	0.147	0.077
RUBLE-btc	0.802	0.767	0.802	0.603	0.085	0.158	0.085	0.195	−0.408
USD-yen	0.676	0.831	0.687	0.153	0.964	0.937	1.000	0.767	0.613
USD-tbill	0.951	0.947	0.951	0.545	0.970	0.965	0.970	0.587	0.042
USD-gold	0.010	0.255	0.010	0.001	0.966	0.966	0.966	0.498	0.498
USD-brent	0.299	0.884	0.299	0.003	0.583	0.937	0.583	0.009	0.006
USD-btc	0.986	0.995	0.987	0.103	0.289	0.918	0.289	0.001	−0.101
YEN-tbill	0.959	0.857	0.960	0.939	0.866	0.800	0.866	0.721	−0.218
YEN-gold	0.569	0.540	0.569	0.558	0.018	0.244	0.017	0.003	−0.555
YEN-brent	0.021	0.285	0.020	0.003	0.633	0.847	0.633	0.088	0.085
YEN-btc	0.101	0.648	0.101	0.004	0.085	0.632	0.085	0.003	−0.001
TBILL-gold	0.536	0.511	0.539	0.550	0.146	0.296	0.139	0.142	−0.408
TBILL-brent	0.001	0.072	0.000	0.000	0.185	0.568	0.184	0.029	0.029
TBILL-btc	0.064	0.624	0.059	0.002	0.286	0.698	0.285	0.029	0.027
GOLD-brent	0.926	0.929	0.928	0.478	0.990	0.997	0.994	0.097	−0.381
GOLD-btc	0.917	0.938	0.921	0.352	0.894	0.910	0.896	0.410	0.058
BRENT-btc	0.444	0.601	0.444	0.219	0.197	0.402	0.197	0.118	−0.101

Note: This table shows price discovery measures (of the assets in capital letters) 24 h before and 24 h after the invasion based on minute-by-minute log prices. IS, CS, MIS, and ILS stand for information share, component share, modified information share, and information leadership share.

Meanwhile the IL and ILS can be obtained as follows:

$$IL_1 = \left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right|, IL_2 = \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|; \quad ILS_1 = \frac{IL_1}{IL_1 + IL_2}, ILS_2 = \frac{IL_2}{IL_1 + IL_2} \tag{7}$$

The values of four price discovery measures before and after the invasion are provided in Table 2. The ruble appears to have dominated price discovery against the USD, yen, tbill, and gold, but Brent and bitcoin have led the ruble following the invasion. Interestingly, while Brent seems to lead all assets except bitcoin, bitcoin appears to have dominated the price discovery against all assets following the attack. Regarding the change in the ILS, we observe that the ruble and USD suddenly turn the tide to dominate the yen, after the invasion, by 97.3% and 61.3%, respectively. Thus, to answer the question of 'who moves first', Brent moves first, 24 h before the invasion, whereas bitcoin moves first against other assets within the 24 h after the invasion. Our results are generally in line with Hung (2022) and Mensi et al. (2019), who find that bitcoin serves as a strong transmitter of shocks to other assets. Meanwhile, our Brent analysis is consistent with Ji et al. (2018) and Suleman et al. (2021), who uncover that Brent contributes the most to the positive volatilities of other markets.

Further, to investigate time-varying herding behaviour between the assets, we utilise an augmented version of Chang et al. (2000)'s cross-sectional absolute deviations (CSADs) model, based on 5-min data, as follows:

$$CSAD_t = \alpha_1 + \alpha_2 \left|R_{mt}\right| + \alpha_3^+ \left(R_{mt}^{2,+}\right) + \alpha_4^- \left(R_{mt}^{2,-}\right) + \varepsilon_t \tag{8}$$

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} \left|R_{it} - R_{mt}\right| \tag{9}$$

where $R_{mt}^{2,+}$ and $R_{mt}^{2,-}$ denote the market returns during up and down periods, respectively, taking a value of 1 if the market registers positive (up period) or negative (down period) returns, and 0 otherwise. Coefficients α_3^+ and α_4^- will take negative values if herding is present and positive values if anti-herding is observed.

Following Nakajima (2011), we apply the Monte Carlo Markov Chain (MCMC) method to estimate the posterior distribution of the parameters in the time-varying parameter (TVP) regression model with stochastic volatility, and we present the CSAD time-varying herding results in Fig. 3.[5] In Panel A, we find no evidence of herding between the yen, tbill, gold and silver in the 24 h before and 24 h after the invasion. Meanwhile, Panel C illustrates some herding between Brent, WTI, gasoline and natural gas during upturns and downturns after the start of the invasion, which aligns with Babalos et al. (2015), who observes TVP herding between energy commodities around the 2008 global financial crisis (GFC). In Panel D, we observe herding between bitcoin, ethereum and litecoin during upturns before the invasion, which is in line with Papadamou et al. (2021), who document intense cryptocurrency herding during bull markets.

To examine the dynamic correlations between the ruble and other assets before and after the invasion, we use a two-step dynamic conditional correlations generalised autoregressive conditional heteroskedasticity (DCC-GARCH) model (Engle, 2002), as follows:

$$y_t = \mu_t(\theta) + \varepsilon_t \tag{10}$$

$$\varepsilon_t = H_t^{1/2}(\theta) z_t \tag{11}$$

$$H_t = D_t R_t D_t \tag{12}$$

$$R_t = \text{diag}\left(q_{(11,t)}^{-1/2}, \ldots, q_{(NN,t)}^{-1/2}\right) Q_t \,\text{diag}\left(q_{(11,t)}^{-1/2}, \ldots, q_{(NN,t)}^{-1/2}\right) \tag{13}$$

$$Q_t = \omega + \alpha \mu_t \dot{\mu}_t + \beta Q_{t-1} \tag{14}$$

where $\omega = (1 - \alpha - \beta)\,\overline{Q}$, and the DCC between asset j (ruble) and i (other assets) can be written as

$$\rho_{j,i,t} = \frac{q_{j,i,t}}{\sqrt{q_{j,j,t}\, q_{i,i,t}}} \tag{15}$$

Table 3 provides the estimation results of the univariate DCC-GARCH (1,1). The sum of the coefficients $(\alpha_i + \beta_i)$ is less than 1, which fulfils the DCC-GARCH constraint, and the Ljung–Box Q statistics imply non-existence of linear and non-linear serial

[5] A thorough discussion on Bayesian inference and TVP regression with MCMC is presented by Nakajima (2011).

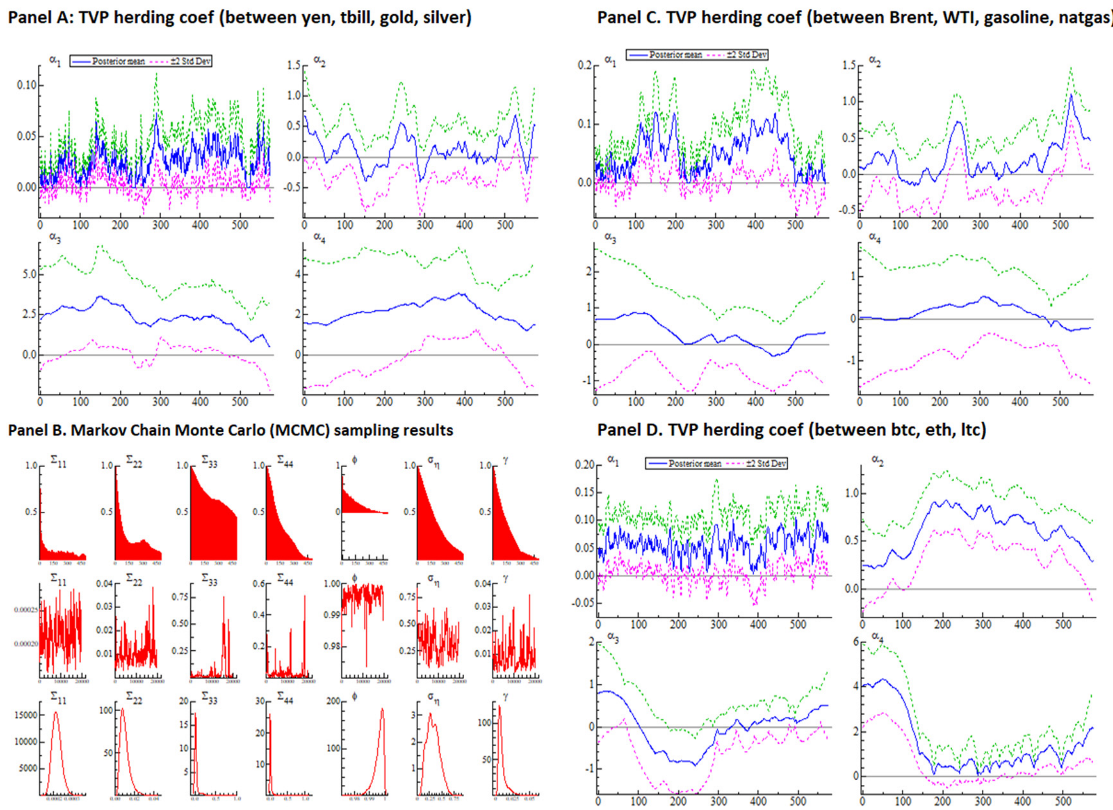

Fig. 3. Time-varying parameter (TVP) herding and MCMC. This figure illustrates the CSAD TVP 5-min regression and the Markov Chain Monte Carlo (MCMC) sampling results, 24 h before and 24 h after the invasion.

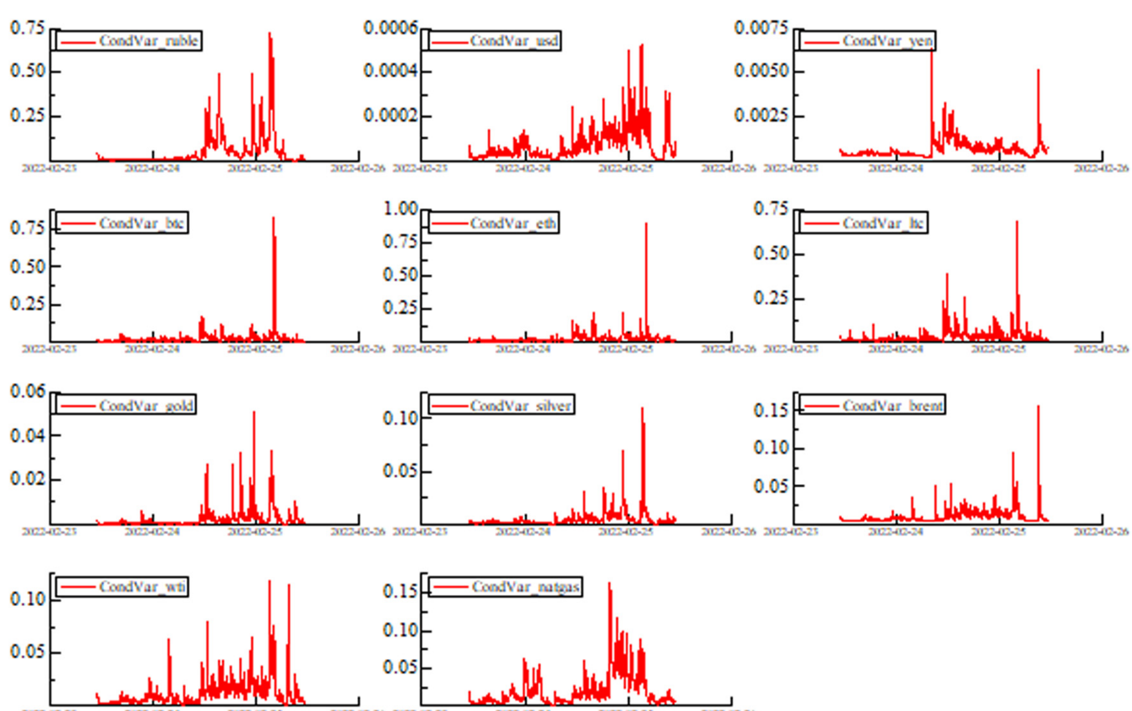

Fig. 4. Conditional variance.

correlations. Tbill and gasoline demonstrate an absence of the ARCH effect and hence are excluded from the DCC-GARCH model. Fig. 4 shows a marked increase in the conditional variance of all assets after the start of the invasion.

The bivariate DCC-GARCH (1,1) results are presented in Table 4. Coefficients α_i and b_i are significantly different from zero. McLeod-Li tests indicate the absence of both linear and non-linear serial correlations. Further, before the invasion, the ruble–yen

Table 3
Estimation results of univariate DCC-GARCH (1,1).

Asset	Arch (α)		Garch (β)		Q (20)	Q^2 (20)
Ruble	0.046***	(5.921)	0.952***	(45.632)	25.418	7.918
USD	0.117***	(3.249)	0.881***	(31.61)	28.357	7.478
Yen	0.059***	(2.491)	0.907***	(25.93)	24.851	5.565
Btc	0.105***	(5.013)	0.889***	(31.482)	16.670	10.891
Eth	0.122***	(7.569)	0.868***	(45.86)	13.769	3.201
Ltc	0.167***	(7.846)	0.825***	(36.131)	26.909	19.709
Gold	0.173***	(4.747)	0.826***	(34.241)	23.174	14.731
Silver	0.121***	(3.453)	0.873***	(27.309)	18.487	10.314
Brent	0.083***	(4.297)	0.909***	(12.4)	23.173	13.158
WTI	0.082***	(5.166)	0.909***	(27.242)	23.365	19.570
Natgas	0.151***	(7.292)	0.843***	(31.609)	14.556	7.978

Note: Q and Q^2 are Ljung–Box Q-statistics. *** denotes significance at 1%. T-stats are in parentheses.

Table 4
Estimation results of bivariate DCC-GARCH (1,1).

Ruble vs asset	Before invasion $\rho_{j,i}$	After invasion $\rho_{j,i}$	Full sample $\rho_{j,i}$	Alpha (α)		Beta (b)		Q (20)	Q^2 (20)
Ruble-usd	−3.8035	−3.8029	−3.8032	0.088***	(7.22)	0.872***	(14.11)	56.4	29.3
Ruble-yen	−18.86	1.1214	−8.8658	0.045***	(4.43)	0.935***	(22.63)	73.6	17.1
Ruble-btc	2.0064	2.0064	2.0064	0.106***	(5.32)	0.854***	(12.78)	51.8	19.1
Ruble-eth	0.0538	0.0538	0.0538	0.091***	(8.49)	0.869***	(13.91)	78.4	51.9
Ruble-ltc	0.0267	0.0267	0.0267	0.094***	(8.96)	0.866***	(13.64)	52.4	42.6
Ruble-gold	1.8369	1.8377	1.8373	0.112***	(5.74)	0.848***	(12.95)	50.4	45.9
Ruble-silver	−1.0963	−1.1334	−1.1149	0.152***	(6.63)	0.808***	(9.07)	56.6	13.9
Ruble-brent	−1.9095	−2.4535	−2.1816	0.126***	(7.48)	0.834***	(11.71)	77.8	40.7
Ruble-wti	−2.8888	−3.3538	−3.1214	0.219**	(5.69)	0.74***	(8.56)	69.2	35.3
Ruble-natgas	−3.2849	−3.3166	−3.3008	0.048***	(4.98)	0.925***	(20.32)	61.1	21.7

Note: Q and Q^2 are McLeod–Li Q-statistics. T-stats are in parentheses. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

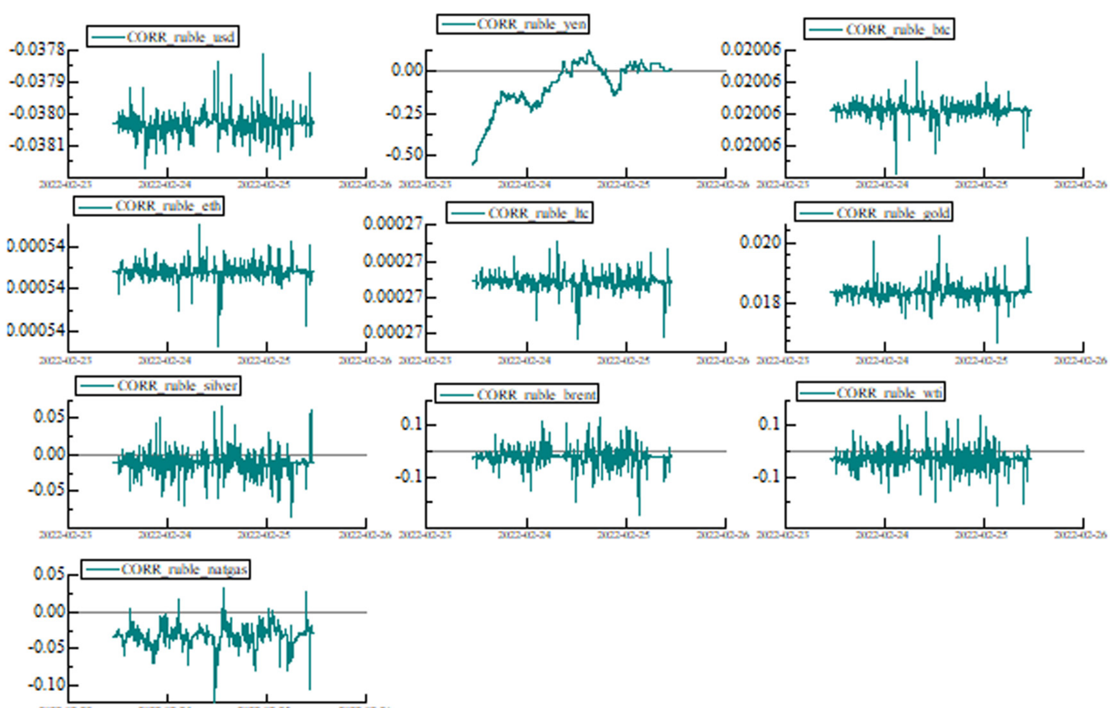

Fig. 5. Dynamic conditional correlations between ruble and other assets.

pair shows the lowest correlation (−18.86), while, after the invasion, the ruble–USD pair exhibits the lowest correlation (3.8032). Looking at the average conditional correlation for the whole sample period, we notice that several ruble pairs register negative correlations. Hence, assets such as the yen, USD, natural gas, WTI, Brent and silver could have served as a safe haven when the ruble took a tumble following the Russian invasion of Ukraine. Fig. 5 visualises the DCCs between the ruble and the other assets. The DCC between the ruble and USD is consistently negative. Correspondingly, the DCCs between the ruble and the yen, silver, Brent, WTI and natural gas also hover below zero and tend to be negative throughout the sample period. As mentioned earlier, negative correlations are desirable as they mean investors will be compensated for drops in the risky asset.

4. Conclusion

This paper presents several fresh findings regarding the flight to a safe haven when Russia invaded Ukraine on 24 February 2022. Generally speaking, our price discovery analysis suggests that Brent and bitcoin dominate the price leadership before and after the start of the invasion—meaning these two assets tend to move first (lead) while other assets tend to be the followers. In the TVP regression using the MCMC sampling procedure, we observe that cryptocurrencies like bitcoin, ethereum and litecoin tend to herd together during upturns before the invasion, whereas energy commodities such as Brent, WTI, gasoline and natural gas are inclined to move together during upturns and downturns after the start of the invasion. These results imply that, in the event of a crisis, assets of a similar characteristic tend to move together in searching for a safe haven. Finally, in the DCC-GARCH analysis, we uncover a shift in investment behaviour indicated by negative correlations between ruble pairs. We infer that, when Russia invaded Ukraine, investors perceived Russia's currency the ruble as a risky asset, hence, as a knee-jerk reaction, selling the ruble in exchange for a safe haven. Among the assets perceived as safe havens during the 24 h before and 24 h after the invasion (based on our DCC-GARCH analysis) are the USD, yen, silver, Brent, WTI and natural gas. By and large, our results are consistent with Chan et al. (2018) and Cho et al. (2020), who find that the USD and yen behave like safe haven currencies. Further, Naeem et al. (2022) conclude that crude oil functions as a safe haven for other commodities prior to the GFC while Bouoiyour et al. (2019) uncover that silver yields positive returns during downturns. Thus, to recap the gist of this research: (a) we find evidence of a flight to a safe haven, from the ruble to other safe-haven assets; (b) some of these assets, such as cryptocurrencies and energy commodities, tend to demonstrate asymmetric time-varying herding behaviour; and (c) price discovery at the onset of the period of financial turmoil caused by the Russian invasion of Ukraine was dominated by Brent and bitcoin. In summary, all these pieces of evidence point to the fact that, during a crisis, not only is there a flight to a safe haven, but some of these assets also tend to herd together and dictate the price discovery process.

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