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Forecasting volatility during the outbreak of Russian invasion of Ukraine: application to commodities, stock indices, currencies, and cryptocurrencies

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Abstract

Research background: The Russian invasion on Ukraine of February 24, 2022 sharply raised the volatility in commodity and financial markets. This had the adverse effect on the accuracy of volatility forecasts. The scale of negative effects of war was, however, market-specific and some markets exhibited a strong tendency to return to usual levels in a short time.

Purpose of the article: We study the volatility shocks caused by the war. Our focus is on the markets highly exposed to the effects of this conflict: the stock, currency, cryptocurrency, gold, wheat and crude oil markets. We evaluate the forecasting accuracy of volatility models during the first stage of the war and compare the scale of forecast deterioration among the examined markets. Our long-term purpose is to analyze the methods that have the potential to mitigate the effect of forecast deterioration under such circumstances. We concentrate on the methods designed to deal with outliers and periods of extreme volatility, but, so far, have not been investigated empirically under the conditions of war.

Methods: We use the robust methods of estimation and a modified Range-GARCH model which is based on opening, low, high and closing prices. We compare them with the standard maximum

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likelihood method of the classic GARCH model. Moreover, we employ the MCS (Model Confidence Set) procedure to create the set of superior models.

Findings & value added: Analyzing the market specificity, we identify both some common patterns and substantial differences among the markets, which is the first comparison of this type relating to the ongoing conflict. In particular, we discover the individual nature of the cryptocurrency markets, where the reaction to the outbreak of the war was very limited and the accuracy of forecasts remained at the similar level before and after the beginning of the war. Our long-term contribution are the findings about suitability of methods that have the potential to handle the extreme volatility but have not been examined empirically under the conditions of war. We reveal that the Range-GARCH model compares favorably with the standard volatility models, even when the latter are evaluated in a robust way. It gives valuable implication for the future research connected with military conflicts, showing that in such period gains from using more market information outweigh the benefits of using robust estimators.

Introduction

Russia launched a full-scale military invasion into Ukraine on February 24, 2022. It was the largest military attack in Europe since the Second World War. The outbreak of the war had a huge impact on financial markets. There has been a fall in the value of most stock indices, an increase in the value of the US dollar and a sharp increase in many commodity prices. A large number of countries began imposing economic sanctions with the aim of crippling the Russian economy. The sanctions were wide-ranging, targeting banks, businesses, monetary exchanges, bank transfers, exports, and imports. Following sanctions, a boycott movement began and many companies and organizations chose to exit Russian markets voluntarily. The boycotts impacted many consumer goods, technology, education, entertainment and sports. Most experts share the opinion that the economic and financial sanctions that have been imposed will lead to a deep recession in Russia, substantially reduce global growth and raise global inflation in the year 2022.

The outbreak of war and the resulting sanctions had wide-ranging impacts on global markets. We study the impacts on the volatility and accuracy of volatility forecasts. Our goals are twofold. First, we investigate the scale of volatility shocks in various markets together with the negative effects on the accuracy of the volatility forecasts produced by standard volatility models. This part of the study refers to the ongoing events and their economic consequences. Second, we examine the methods that have the potential to mitigate the negative effect of the forecast deterioration at times of war. In this context, we focus on two methodological aspects studied broadly in the area of financial econometrics: the robust methods and efficient volatility estimators. These are the aspects which we deem relevant for describing the shock phenomena observed in financial markets during

a military conflict. The use of the robust methods is crucial to cope with outliers, which otherwise undermine the properties of estimators of GARCH parameters. The efficient volatility estimators, in turn, through the better use of the market information, help to handle the extreme volatility dynamics in the wartime. These estimators incorporate, in various forms, the information about daily price ranges. Thus, our long-term contribution is providing a comparison of these methods applied during the military conflict and a discussion of their relative advantages in this context.

The robust methods have been developed as one of the answers to the question whether the mainstream GARCH approach suffices to handle properly shocks of a large scale (Franses & Ghijssels, 1999). In particular, this refers to the shock phenomena characteristic to military conflicts. According to Schwert (1989) U.S. stock volatility is 33 percent lower during wartime and periods of conflict. By contrast, outbreaks of war usually lead to increased volatility and market turmoil. This effect was clearly observed after the Russian invasion of Ukraine. For example, the VDAX volatility index, which tracks the degree of fluctuation expected by the derivatives market for the DAX index, increased from 32.17 on February 23, 2022 to 48.62 during several days. Another peculiar effect of a war outbreak are often huge movements on the commodity market. For instance, during this aggression, the WTI oil price spiked from 92.1 USD on February 23, 2022 to 129.79 USD on March 7, 2022. Such great shocks justify the question of the validity of the use of the standard GARCH model (Bollerslev, 1986). In particular, there are doubts whether the standard model can handle the outliers, which potentially lead to a considerable deterioration of the forecasting accuracy (Catalán & Trivez, 2007; Trucíos & Hotta, 2015). The search for a solution to the problems caused by outliers leads to the robust estimators of the parameters of the volatility models (e.g. Franses & Ghijssels, 1999; Charles, 2008; Boudt *et al.*, 2013; Trucíos, 2019). Following this line, we apply the robust methods of estimation by Muler and Yohai (2008) and Boudt *et al.* (2013) and expect that volatility forecasts from these methods will be more accurate during the turbulent period of the inception of the war.

The use of the range-based volatility models, which incorporate the efficient volatility estimators, is another development which we deem relevant to handle the extreme wartime volatility. This development is connected with the attempts to use the easily-available market information more effectively. It utilizes some information about price fluctuations throughout a day without resorting to the full-scale inclusion of intraday data. At a low cost, this adds a valuable part to the overall picture of the market situation. For example, in the current military conflict, the standard deviation of 5-

minute gold returns raised from 0.506 on February 23, 2022 to 4.420 on February 24, 2022. It shows an unprecedented scale of volatility. Referring to the methodological aspect, such a volatility shock again raises a question about the suitability of the standard approach. The GARCH model based on closing prices, which is commonly used in financial studies, is not able to capture the movements during a day. The range-based models, on the other hand, apply additionally daily low and high prices. The important practical advantage of these models is that for most assets these daily prices are commonly available with closing prices and do not require intraday quotations. We use the modification of the Range-GARCH model of Molnár (2016) and expect that volatility forecasts from this model will be more accurate than forecasts from the traditional GARCH model based on closing prices during the stormy war period.

The rest of the paper is organized in the following way. In the next section, we present the literature review. The subsequent section provides a short description of the applied models and methods. Next, we introduce the applied data, i.e., selected commodities, stock indices, currencies, and cryptocurrencies and present summary statistics. Afterwards, the results of the applied forecasting procedures before and after the outbreak of the Russian invasion of Ukraine are given. This is followed by the discussion of the results. The last section concludes.

Literature review

So far, the effects of the Russo-Ukrainian war on world markets have been presented in the literature mainly from the point of view of the impact on specific markets. The negative impact on the largest stock markets is presented by Boungou and Yatié (2022). Yousaf *et al.* (2022) discuss its evolution in time and show importance of factors like geographical region or proximity to military operations. Lo *et al.* (2022) indicate the influence of another factor, which is the dependence of the economy on the Russian commodities. Boubaker *et al.* (2022) add belonging to NATO as another factor influencing the reaction of the stock markets. Umar *et al.* (2022) concentrate on Russian and European markets and their connectedness, showing that the relationships among these markets changed during the war. The currency markets are analyzed by Chortane and Pandey (2022), who show the negative impacts of war on the main global currencies as well as on the currencies from the regions close to war like the Polish zloty. Lyócsa and Píhal (2022) try to explain intraday realized variance of the Russian ruble based on implied volatility and google searches. The litera-

ture examining the reactions in cryptocurrency markets is rather scarce. The exceptions are the papers by Long *et al.* (2022), who examine cryptocurrency exposure to the geopolitical risk and Mohamad (2022), who studies the flight to safety and finds the herding behavior among cryptocurrencies after the war outbreak

Alongside the financial markets, the war impacts is also analyzed in the commodity markets. Due to their large exposition to this specific conflict, the main analyzed markets are agricultural, metal and energy ones. Fang and Shao (2022) study the channels through which these markets were affected and find the importance of both the economic and financial channel. Wang *et al.* (2022) and Adekoya *et al.* (2022) report the changes in the spillover effects in these markets. The changes in connectedness among commodity and leading stock markets are investigated by Alam *et al.* (2022).

Unlike previous studies, we do not concentrate on any specific market. Instead, we choose representatives of the stock, currency, cryptocurrency and commodity markets and analyze the volatility shocks caused by the war. We compare the shocks observed in various markets and the effects of the war outbreak on the accuracy of volatility forecasts.

Our study also fits into the more general line of research devoted to the analysis of shocks in time series related to armed conflicts. The shock phenomena and their wide-ranging impacts on financial markets have been observed many times in the past in the aftermath of wars. Charles and Darne (2014) detect large shocks in volatility of the DJIA index in years 1928–2013 and find that many of them were connected with the following wars: the Spanish Civil War, the Second World War, the Korean War, the Gulf War. Antonakakis *et al.* (2017) analyze the influence of the Geopolitical Risk Index on the stock and oil markets relation and identify such events as the First and Second World Wars, the 1956 Suez Canal Crisis, the 1973 Arab–Israeli War, the Gulf War and the invasion of Iraq. Many studies explore the impact of wars on financial markets, such as Choudhry (1997), Frey and Kucher (2000, 2001), Rigobon and Sack (2005), Schneider and Troeger (2006), Choudhry (2010), Guidolin and La Ferrara (2010), Kollias *et al.* (2010), Meulemann *et al.* (2014), Brune *et al.* (2015), Hanedar *et al.* (2015), Hudson and Urquhart (2015). There is, however, a lack of research on the accuracy of volatility forecasts during a war period. The exception is the paper by Naimy *et al.* (2020), who compare the GARCH and EGARCH models for American, Russian, and Chinese stock markets during the Syrian war. We try to fill this research gap and perform the comparison of various volatility forecasting methods during the outbreak of the Russian invasion of Ukraine. We, however, choose a different

research path. Instead of comparing GARCH specifications, which describe various properties of volatility, we decide to concentrate on two methodological aspects, which have the potential to handle the extreme wartime volatility and thus improve the accuracy of forecasts: the robust methods and efficient volatility estimators.

Extremely large observations are often found to affect volatility less than the standard GARCH model would predict (Andersen *et al.*, 2007; Bauwens & Storti, 2009; Carnero *et al.*, 2012). The usage of the standard GARCH model in such a situation leads to an overestimation of volatility for the days following the event. There are two main approaches, classified in the literature as the robust methods for the GARCH models, developed to overcome this problem and receive more precise estimates and forecasts of variances. The first of them is to use the robust estimators to obtain parameter estimates that are not affected by atypical observations and also to mitigate the effect of outliers on the conditional volatility (e.g. Park, 2002; Muler & Yohai, 2008; Mancini & Trojani, 2011; Carnero *et al.*, 2012; Boudt *et al.*, 2013). In this approach, the robustness depends on the choice of the form of the objective function as well as the choice of the threshold parameters of the objective function. Another aspect is the choice of the distributional form. It has been shown that maximizing the likelihood based on a heavy tailed distribution mitigates the negative influence of outliers (e.g. Sakata & White, 1998; Carnero *et al.*, 2007). In the second approach belonging to the robust methods, outliers are identified, corrected and then the standard volatility models are applied (e.g. Franses & Ghijssels, 1999; Charles & Darné, 2005; Grane & Veiga, 2010; Gregory & Reeves, 2010). The review of the robust methods for the GARCH models can be found in Hotta and Trucíos (2018). According to our knowledge, the robust volatility models have not been applied to analyze crises periods related to wars so far. We investigate this issue, applying the robust estimators of GARCH parameters at times of the Russo-Ukrainian conflict.

Typically, volatility models of financial instruments are based solely on closing prices, whereas daily low and high prices are left unused. These prices, however, significantly increase the amount of information about the variation of returns during a day. Models constructed with high and low prices, or with their difference, i.e., the price range, are called the range-based models. In the last dozen or so years numerous univariate dynamic volatility models have been constructed based on such prices. Some of them describe the conditional variance (or standard deviation) of returns (e.g. the REGARCH model by Brandt & Jones, 2006 or the RGARCH model by Molnár, 2016), some depict the conditional mean of the price range (e.g. the range based SV model by Alizadeh *et al.*, 2002; the CARR

model by Chou, 2005; the TARR model by Chen *et al.*, 2008). The review of the range-based volatility models is given in Chou *et al.* (2015) and Petropoulos *et al.* (2022). The forecasts from such models are usually more accurate than the forecasts from the models based on only daily closing prices (see e.g. Chou, 2005; Brandt & Jones, 2006; Li & Hong, 2011; Fiszeder & Perczak, 2016; Molnár, 2016; Fiszeder *et al.*, 2019; Fiszeder & Fałdziński, 2019). The application of low and high prices can be beneficial even compared to the use of high frequency data (see Degiannakis & Livada, 2013; Lyócsa *et al.*, 2021a; 2021b). According to our knowledge, the range-based volatility models have not been applied to analyze crises periods related to wars so far. Our study tries to fill this gap and examine the approach based on the range-based estimators, alongside the robust approach, as another way to improve the accuracy of the volatility forecasts at times of the military conflict.

Research methods

Volatility models and their estimation

The volatility of commodities and financial instruments is usually modeled with the use of the GARCH-type class of models. Following this convention, we use the basic representatives of this class alongside the extensions and modifications that we find relevant to the wartime period. The basic GARCH(p, q) model introduced by Bollerslev (1986) can be presented as:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t), \quad (1)$$

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j}, \quad (2)$$

where ε_t is the innovation process from the conditional mean equation of returns, ψ_{t-1} is the set of all information available at time $t - 1$, N is the conditional normal distribution and h_t is the conditional variance.

We rely on the standard restrictions $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$ (for $i = 1, 2, \dots, q; j = 1, 2, \dots, p$), however weaker conditions for non-negativity of the conditional variance can be assumed (see Nelson & Cao, 1992). For covariance stationarity the following condition has to be satisfied $\alpha_1 + \dots + \alpha_q + \beta_1 + \dots + \beta_p < 1$. Next to the conditional normal distribution in the equation (1), we use the Student's t-distribution in order to better describe

fatter tails and leptokurtosis of unconditional distributions of the analysed asset returns (Bollerslev, 1987).

Parameters of the GARCH models are usually estimated by maximum likelihood (ML). The standard ML estimators, however, are not robust to outliers, thus are not suitable in the wartime volatility period. A way to overcome this problem and receive more precise forecasts of variances is to employ the robust estimators of the parameters. We consider two such estimators, namely, the bounded M-estimator (BM) of Muler and Yohai (2008) and the bounded variance targeting estimator (BVT) by Boudt *et al.* (2013). The BM estimator is defined by the minimization of a conveniently modified likelihood function and includes the volatility-filtering technique, which is the additional mechanism for restricting the propagation of the effect of one outlier on the next estimated conditional variances. We consider two versions of this estimator. The first one applies the normal distribution and the second one, which is more robust, uses the Student's t-distribution. Boudt *et al.* (2013) modified the volatility-filtering mechanism in the BM estimator in a way that ensures that the conditional expectation of the weighted squared unexpected shocks is still the conditional variance in the absence of jumps. Additionally, their BVT estimator integrates the reweighted estimates of the mean and variance into the forecasting procedure. The selected BM and BVT estimators belong to the most popular robust estimators used for the GARCH models (see Trucíos *et al.*, 2017; Hotta & Trucíos, 2018). We expect the volatility forecasts from these methods to be more accurate than those from the standard models during the turbulent period of war.

The traditional GARCH model is based only on closing prices. As such, it limits the available daily information to one value. A more effective use of the information about the volatility of prices during a day is possible through the range-based models, which use additionally daily low and high prices. The largest improvements attainable by the use of the range-based models are expected in periods of increased volatility and turbulence on the market. An implementation of this approach was proposed by Molnár (2016), who introduced the Range-GARCH model. We propose a slight modification of this model and in place of the Parkinson estimator (Parkinson, 1980) we suggest to use the Garman-Klass estimator (Garman & Klass, 1980). The latter one is a significantly more efficient estimator because it is based, not only on low and high prices, but also on opening and closing prices. The proposed RGARCH-GK(p, q) model can be formulated as:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t), \quad (3)$$

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \sigma_{GK,t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j}, \quad (4)$$

where $\sigma_{GK,t}^2$ is the Garman-Klass estimator calculated as $\sigma_{GK,t}^2 = 0.5[\ln(H_t/L_t)]^2 - (2\ln 2 - 1)[\ln(C_t/O_t)]^2$, O_t, H_t, L_t and C_t are opening, high, low and closing prices over a day, respectively.

The similar conditions to those in the traditional GARCH model have to be imposed on the parameters of the RGARCH model. As with the standard GARCH model, we use the Student's t-distribution alongside the normal distribution in equation (3). We expect the volatility forecasts from the RGARCH model with the Student's t-distribution to be the most accurate during the war.

To assess formally the relative performance of the considered models, we apply the model confidence set (MCS) procedure, developed by Hansen *et al.* (2011). This procedure serves to establish whether the models have statistically different predictive abilities. The objective of the MCS test is to identify the set of best models (Superior Set Models, SSM). Starting with the full set of models, the MCS procedure sequentially eliminates the models that are found to be significantly inferior until the null hypothesis of equal forecast accuracy is no longer rejected at the assumed significance level. According to our aims, we apply the procedure separately for the before-war period and the time after the war outbreak.

Data applied

We use the considered models to various classes of assets: commodities, stock indices, currencies and cryptocurrencies. We analyze the following commodities: crude oil WTI (New York Mercantile Exchange, NYMEX), wheat (Chicago Board of Trade, CBOT), gold (New York Mercantile Exchange, NYMEX, COMEX Division), stock indices: S&P 500, DAX, FTSE 100, currency pairs: EUR/USD, EUR/JPY, USD/PLN (forex market) and cryptocurrency pairs: BTC/USD (Bitcoin), ETH/USD (Ethereum), XRP/USD (Ripple). All data come from Refinitiv Eikon. The choice of the assets reflects our attempt to capture the effects of the Russian aggression on various segments of commodity and financial markets. Russia belongs to the largest world producers of the crude oil and wheat, and due to the imposed sanctions it has difficulty in delivering them to global markets. Ukraine is also a significant exporter of this grain and will not be able to ensure the expected sales volume due to the war. Thus, these markets currently experience volatility growth of an unusual scale. The effects in the gold market are common to many crisis situations. During times of market turmoil, investors turn to gold given its perceived safe haven status. The

selected stock indices and currency pairs belong to the most widely followed. Additionally, we analyze Polish zloty which suffers one of the greatest losses in the currency market due to Poland's neighborhood with Ukraine and the massive outflow of the foreign capital. Moreover, there is a debate in the literature as to whether Bitcoin and other cryptocurrencies are safe-haven assets or can be used, alongside gold, for hedging during the turbulent periods (see references in review papers Corbet *et al.*, 2019; Bariviera & Merediz-Solà, 2021; Kayal & Rohilla, 2021). For this reason, we analyze also three cryptocurrencies chosen among those with the highest market capitalization.

We compare the forecasting results before and after the outbreak of the Russo-Ukrainian war. We analyze the initial stage of the war and use the sample from February 24, 2022, to March 25, 2022 (it includes 22 daily quotations). For comparison purposes, we take the same number of observations before the launch of the war. This sample includes data from January 25, 2022, to February 23, 2022. For all assets, we examine data from Monday to Friday, without weekends. Prices of commodities, currencies, cryptocurrencies and values of stock indices are presented in Figure 1. We show also the values of the realized variance calculated as the sum of squares of 5-minute returns. The use of the intraday data in our study, however, serves solely the purpose of evaluating the forecasting performance of the competing models. In the process of estimation, we stick to the rule that we rely only on the easily-available daily data.

After the start of the war, the prices of commodities increased strongly, whereas the values of stock indices and prices of European currencies came down. Most of the price changes were, however, short-term. After two-three weeks, most stock indices returned to their pre-invasion levels, only the prices of commodities remained higher. The prices of cryptocurrencies rose in a rather moderate scale.

For all assets, the major shock to realized variances occurred on the day of the Russian invasion. However, there were significant differences in the following days. The volatility of the commodities and the DAX index was rising for about two weeks and then it decreased. For the EUR/USD and USD/PLN pairs, the high level of realized variances lasted for approximately two weeks. For the rest of assets, there were only one-day or two-day spikes of volatility.

When transforming prices to returns, we choose to rely on the daily open-to-close returns instead of daily close-to-close returns. This is aimed at avoiding the noise induced by the overnight volatility. For the same reason, when we calculate realized variances, we omit the opening jump. It is a common approach in the realized volatility literature (see e.g. Floros *et*

al., 2020; Reschenhofer *et al.*, 2020, Zhang *et al.*, 2020; Gkillas *et al.*, 2021; Kambouroudis *et al.*, 2021)¹. We use percentage returns calculated as $r_t = 100 \ln(C_t/O_t)$. Their descriptive statistics are given in Table 1.

The summary statistics show that most of the means of returns, except major currency pairs, are positive. It, therefore, suggests that the outbreak of the war had no influence on the prices of assets, except commodities. The major shock is seen in the volatility statistics. The standard deviation of returns of commodities, stock indices and the USD/PLN currency pair increased considerably after the Russian invasion. As opposed to this, the Ethereum and Ripple markets experienced the surprising calm down, as evidenced by their wartime standard deviations. The distribution of all commodities and most stock indices was negatively skewed, whereas the distribution of most currencies and cryptocurrencies was positively skewed.

Results

In this section, we present the forecasting results of the seven volatility models:

1. the standard GARCH model with the normal distribution of the error term and the ML estimator (denoted as GARCH-n),
2. the GARCH model with the Student's t-distribution and the ML estimator (denoted as GARCH-t),
3. the GARCH model with the BM estimator with the normal distribution of the error term (denoted as BM-n),
4. the GARCH model with the BM estimator with the Student's t-distribution of the error term (denoted as BM-t),
5. the GARCH model with the BVT estimator² (denoted as BVT),
6. the RGARCH-GK model³ with the normal distribution and the ML estimator (denoted as RGARCH-n),
7. the RGARCH-GK model with the Student's t-distribution and the ML estimator (denoted as RGARCH-t).

¹ For robustness check we used also close-to-close returns and these results were similar to those presented in the paper (they are available from the authors upon request).

² We also considered the BVT model with the modifications proposed by Trucíos *et al.* (2017). The results were close to those from the BVT model in its primary version, however, in most cases in the analysed period they were in favour of the model with the original BVT estimator (these results are available from the authors upon request).

³ Another model that we considered was the RGARCH model of Molnár (2016) but its performance was inferior to the RGARCH-GK model during the war period.

The models in (6) and (7) are our propositions to modify the RGARCH model of Molnár (2016) by using the more efficient volatility estimator, which is the GK estimator presented in the research methodology section. We implement this model, as well as others⁴, in two versions: with the normal and Student's t-distribution. The latter of these two distributions is expected to be especially useful in the wartime period as it has heavier tails than the normal distribution and gives less weight to larger innovations. For this reason, an estimator based on the maximization of the t-distribution-based log-likelihood can mitigate the influence of atypical observations.

Parameters of all models are estimated separately each day based on a rolling sample of a fixed size (the first period is from January 2, 2019 to January 24, 2022). Lags of order one are applied, i.e. $p = 1$, $q = 1$, for equations (2) and (4). We compute the out-of-sample one-day-ahead forecasts of variance based on each of the selected models. The forecasts are evaluated separately for periods before and after the outbreak of the Russo-Ukrainian war. As a proxy of the daily variance, we use the realized variance calculated as the sum of squares of 5-minute returns. However, very similar results are also attainable with 15-minute returns. The daily forecasts of variances with the corresponding realized variances are presented in Figure 2.

The volatility forecasts in the neighborhood of the war outbreak follow different patterns for traditional markets — the commodity, stock and currency ones — and for the cryptocurrency market. In the first of these two cases, after the outbreak of the war, the dynamics of forecasts gradually adjusts to the extremely changed level of volatility. In the case of the cryptocurrencies, in contrast to this, there is no sudden increase in volatility after the outbreak of the war, but there are significant fluctuations throughout the whole period. All plots depict the inaccuracy of the forecasts obtained from the basic GARCH model, which, after the occurrence of outliers, do not have the ability to return to previous levels. For traditional markets, there are clear differences between the models, suggesting the superiority of the RGARCH models after the outbreak of the war.

After the visual presentation, we proceed to the evaluation of the forecasts based on the mean squared error (MSE)⁵. This, most frequently applied forecasting loss function, has the advantage of being robust to the use

⁴ In the case of BVT, unlike for other models, we only apply the Student's t-distribution, which is in line with the explicit authors suggestion (Boudt *et al.*, 2013).

⁵ For robustness check we use also three other loss functions: the mean absolute error, the logarithmic loss function and QLIKE. Since its results are similar to MSE, we do not present them in the paper (they are available from the authors upon request).

of a noisy volatility proxy (Hansen & Lunde, 2006; Patton, 2011). The values of the MSE are presented in Table 2.

In the first part of the evaluation based on MSE, we compare various models, which serves us to choose the best forecasts. Having evaluated the models, we proceed to the analysis of forecast errors before and after the outbreak of war. According to the MSE measure, for all assets, except the S&P 500 index and the Ripple cryptocurrency, the most accurate forecasts of variance during the war period come from the RGARCH models. Most often, the RGARCH model with the Student's t-distribution turns out best overall. These results differ substantially from those obtained for the peace period. Though the outstanding performance of the RGARCH models can still be noted, this effect is less clear. Before war, RGARCH often gives lowest MSE, but for half the number of assets other models are best according to this criterion.

In the second part of the evaluation based on MSE, we compare the forecasts from the best models before and after the outbreak of the war. For all assets, except the S&P 500 index⁶ and the Ripple cryptocurrency, the values of MSE are much higher after the invasion. These differences between the war and peace periods are especially huge for commodities and the USD/PLN pair. On the other hand, the lowest differences, in relative terms, are for cryptocurrencies.

The above comparison confronts two non-overlapping samples — the one reaching up to the beginning of the war (containing data only from the peace period, i.e., from January 25, 2022, to February 23, 2022) and the other starting at the day the war broke out (containing data only from the war period, i.e., from February 24, 2022, to March 25, 2022). Next, we examine how the MSE evolved over time between these samples. To this purpose, we calculate the MSE measure based on a rolling sample of a fixed size, starting with the peace period and ending with the war period. The results of this evaluation are given in Figure 3.

The evolution of the forecast errors confirms the previous conclusion about superior performance of the RGARCH models in the war period. In almost all cases, the RGARCH models give visibly the lowest errors, especially when the data from the war period prevail. In some cases, after the war outbreak, the models clearly split into two groups. Then, one of the groups — the one being markedly superior — contains only the RGARCH models. This is particularly evident for the currencies.

⁶ Figure 3, presented further in the paper, shows that for the S&P 500 index MSE rose immediately after the war outbreak (in line with the tendencies observed for other assets), however the month's period was long enough for this effect to disappear.

The analyzed dynamics of the forecast errors, shows specific features within classes of assets. For the currencies, which seem to be most homogeneous, the changes happen gradually with including more data from the war period — the mean errors gradually go up to much higher levels. Similar picture is seen for the stock indices, apart from S&P 500, which does not show clear tendencies. However, for the stock indices, there is a sharper increase at the start, showing a sudden deterioration of the volatility forecasts at the outbreak of the war. The tendencies within the class of commodities are again similar, but they seem most rapid and a little delayed in comparison to those in the stock or currency markets. This is especially evident in the cases of wheat and gold, when there is a dramatic deterioration of forecasts after including data from one- or two-week period after the war outbreak. On the other hand, forecast errors for cryptocurrencies behave completely differently. After a short jump-up at the war outbreak, they come back to their usual levels or even show a decreasing tendency. This, again, exposes the individual nature of these markets.

So far, our results were based on graphical analysis of forecasts and the MSE comparisons of two types: the first among the models and the second between the pre-war and war periods. To assess formally the relative performance of the considered models, we apply the MCS procedure, which identifies the set of superior models (SSM). This procedure is applied separately for the before-war period and the time after the war outbreak. The results of the MCS procedure for the MSE measure are given in Table 3.

According to the MCS test, for all considered assets, the SSM always contains at least one of the RGARCH models during the war time. Moreover, such a result is not observed for any of the other models. The two RGARCH models always take at least one of two leading positions and most often take both of them in the ranking of the models in SSM. For some assets (wheat, stock indices, Ethereum) the set of best models includes additionally the GARCH model with some of the robust methods of estimation. Only in few cases — for the crude oil, Bitcoin and Ethereum — does SSM contain most of the analyzed models. It means that the differences between forecasts are not large enough to be statistically significant in the examined sample. The results for the peace period are substantially different. For as many as seven assets (gold, stock indices and cryptocurrencies), it is not possible to point out best models because all or almost all of them are included in SSM. For the rest of the assets, various models are considered as the most accurate and there is no clear winner.

Discussion

Our results treat various aspects of forecasting volatility during the ongoing Russo-Ukrainian war. The conclusions from all stages of the analysis can be divided into two parts. The first part is connected with the ongoing economic situation, in particular the volatility shocks and increase of forecast errors in various markets. The second part includes the conclusions about the methods applied to mitigate the effect of the forecast deterioration.

Regarding the first aspect, the scale of observed volatility shocks after the outbreak of war confirms that forecasting volatility during such a period is much more difficult than during the peace period. Similar conclusions have been already presented separately for specific markets (for stock markets by Boungou & Yatié, 2022; Yousaf *et al.*, 2022; Lo *et al.*, 2022 and Boubaker *et al.*, 2022; for currency markets by Chortane & Pandey, 2022 and Lyócsa & Plíhal, 2022; for cryptocurrency markets by Long *et al.*, 2022 and Mohamad, 2022; for commodity ones by Fang & Shao, 2022; Wang *et al.*, 2022 and Adekoya *et al.*, 2022). These studies dealt with the effects of the war on the prices, returns or volatilities (sometimes in relation to transition channels or various factors like war proximity or belonging to NATO), however our study is the first to show the effects of war on accuracy of forecasts. Unlike the above-mentioned studies, we do not concentrate on any of the specific markets, but we present a comparison spanning four types of markets: stock, currency, cryptocurrency and commodity ones. Our contribution is, therefore, showing the differences in the scale of the war-driven changes in the forecast errors among assets. Specifically, we show the effect that the ranking of assets regarding their variance predictability is different before and after the war outbreak. Before the invasion, the highest forecast errors are observed for cryptocurrencies, which typically have large fluctuations in volatility. After the outbreak of the war, the highest errors are connected with the wheat and crude oil commodities. What is stable in both periods is the position of currencies, which exhibit the lowest errors. The exception is the USD/PLN pair, affected by the close neighborhood of the military activities, whose errors after the invasion soar up, exceeding even those of the stock indices. Our results expose also the individual nature of the cryptocurrency markets, where the reaction to the outbreak of the war was very limited and the accuracy of forecasts remained at the similar level before and after the beginning of the war. These conclusions, therefore, extend the previous literature connected with the Russo-Ukrainian war.

Our conclusions regarding the suitability of the methods during the war point to the advantages of RGARCH models over the standard GARCH

models, even if the latter ones are estimated in a robust way. This conclusion comes from all parts of the study: the graphical analysis, the MSE comparisons and the MCS test. From the graphical analysis it is clearly seen that the forecasts of volatility based on the RGARCH models are more accurate for high levels of the realized variance after the beginning of the war. The forecast adjustments from the other models are much delayed, which is observed for all commodities and currencies. Moreover, the forecasts from RGARCH models are more precise when volatility decreases sharply after the shocks subside. This is particularly evident for stock indexes — DAX and FTSE 100. Also the MSE measure shows that the most accurate forecasts of variance during the war period come from the RGARCH models. This is observed for all assets except the S&P 500 index and the Ripple cryptocurrency. According to the MSC test results, the set of superior models always contains at least one of two analyzed RGARCH models. These models usually take leading ranking positions in the set of superior models. All these conclusions are novel in the sense that, unlike existing studies on the range-based models (e.g. those done by Chou, 2005; Brandt & Jones, 2006; Li & Hong, 2011; Fiszeder & Perczak, 2016; Molnár, 2016; Fiszeder *et al.*, 2019 or Fiszeder & Fałdziński, 2019), they compare the benefits from using the RGARCH models to the benefits from using the robust approach. This is an important contribution to econometrics literature since both these approaches serve similar purposes (dealing with volatility shocks) and thus both have the potential to handle the extreme conditions of war. It is, therefore, important in practical applications to know what are their relative advantages.

In view of our aims, an important aspect of the results is connected with the differences in suitability of the methods before and after the outbreak of the war. These differences are very clear from the MCS test, where before the war it is often not possible to point out the best models. This happens for as many as seven assets (gold, stock indices and cryptocurrencies). The differences before and after the war outbreak show that the advantages from choosing the RGARCH model increase substantially in the period of the military conflict. These conclusions contribute to the literature on suitability of econometrics methods during military conflicts due to the lack of similar studies including the robust GARCH models and RGARCH models. So far the accuracy of volatility forecasts in the context of war has been studied only with reference to various specifications of GARCH models, like e. g. EGARCH vs basic GARCH (Naimy *et al.*, 2020).

The advantages of the RGARCH models over the GARCH models come from utilizing more market information. This, in turn, is achieved by using the volatility estimator based on the daily range instead of the daily

squared return computed only from closing prices. Our results suggest, therefore, that efficient use of all available information, especially the information giving more insight into daily price fluctuations, in periods of military conflicts is crucial for accuracy of forecasts. This is a valuable contribution to existing literature on forecasting volatility during wars. It indicates that future research dealing with volatility forecasts at times of war should consider the extension of the GARCH models to the RGARCH ones instead of the most common approach, which relies solely of closing prices.

Conclusions

The outbreak of a major international military conflict usually leads to the turmoil in financial markets. This predictable pattern repeated after the Russian invasion of Ukraine of February 24, 2022. The capital markets, seen through their main stock indices, declined, while the gold prices soared. Some shock phenomena, though observed in many situations of military aggression, may be perceived as specific to this conflict. These were mainly the reactions connected with the close neighborhood of the arena of war or the dependence on the Russian or Ukrainian exports. In particular, most of the European stock indices, especially in Central and Eastern Europe, fell sharply. The same happened with the European currencies, which declined against the U.S. dollar. The prices of commodities of which Russia and Ukraine are significant producers, like crude oil, natural gas and wheat, rose severely. Most of the price changes were, however, short-term. After two-three weeks, most stock indices returned to their pre-invasion levels, only the prices of commodities remained higher.

We analyzed the major effects of the outbreak of the Russo-Ukrainian war reflected in the properties of returns of various assets. The most striking of them was the increase in volatility of commodities, stock indices and the USD/PLN currency pair after the Russian invasion. An opposed reaction was observed in some of the cryptocurrency markets, where the Ethereum and Ripple volatility decreased. In fact, there was the increase of volatility but only on the day of the war outbreak and, after that, the calm dawn came surprisingly fast.

We evaluated the forecasting accuracy of volatility models before the invasion and during the first stage of the war. Our results depicted the scale of increase in forecast errors after the war outbreak and showed the differences among various markets. The most striking exception among markets was the cryptocurrency market. For cryptocurrencies, unlike other assets,

the accuracy of volatility forecasts remained at the similar level after the launch of the war.

The employment of various methods relevant to dealing with volatility shocks gave us an insight into their relative advantages in the current conflict. The best volatility forecasts during the war period were obtained from the modified Range GARCH model with the Garman-Klass estimator, which is based on opening, low, high and closing prices. The key issue in forecasting volatility was the problem of outliers, which were present in relatively large number in the turbulent war period. They led to a considerable deterioration of the forecasting accuracy. That is why we applied robust estimators of the parameters of the GARCH model. This approach increased the accuracy only in several cases. The forecasts obtained with the robust methods turned out inferior to those from the range-based volatility models. This surprising result shows that in this specific wartime period the gains from including information on opening, low, high and closing prices outweigh the benefits from employing robust procedures. This conclusion extends existing research on application of econometric methods during armed conflicts and gives a valuable indication for future research on this topic.

A limitation of our study is a small sample size, which influences negatively the possibilities of statistical inference. The choice of such a sample resulted from the fact that extending it with further observations could change its specific nature. We wanted this sample to correspond to the immediate reaction of the market to the outbreak of war and to give an inside into the possibilities of forecasting volatility at times of sudden changes. Its extension would imply entering the next phase of the conflict, characterized by still increased volatility, but without such violent shocks. This would not be in line with the objectives of the study. Therefore, we decided to limit the study to the period of approximately one month of the hostilities and the same time before the outbreak of the war. Although such a short period is a limitation in terms of statistical inference, the MCS test yielded significant results in most cases during the war. In the light of this small sample size, the obtained results give a very strong confirmation of our conclusions regarding the war period. In addition, the significance of the test results during the war confronted with the lack of significance before its outbreak exposes the impact of the outbreak of war on the suitability of examined methods. Such results are in line with the purposes of our study.

Another limitation of our research was the scope of the models chosen for comparison. We chose the two approaches that we deem most suitable for forecasting volatility under the presence of outliers and volatility shocks. As a benchmark, we decided to use the basic GARCH model. This

model has dozens of extensions, whose inclusion could add some value to our study. However, due to employment of two main types of robust GARCH estimators and two types of error term distributions, which gave a large number of comparisons, we decided not to include extensions of the basic GARCH model. We see this as an interesting topic for further studies.

The study can be extended in the future to other variants of the GARCH models which describe other properties of financial time series like leverage effect or long memory. Modelling such features can improve forecasts but this applies to all methods and models applied in this papers, that is, it pertains both to the robust methods and the range-based models. Another interesting continuation of this study would be with the inclusion of the MS-GARCH models. Their performance at times of sudden changes in the market could be compared with those of the RAGRCH models. A natural extension would be a merger of these two approaches, possibly in the form of MS-RGARCH models.

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Annex

Table 1. Summary statistics of daily returns before and after the outbreak of the Russo-Ukrainian war

| Assets | Mean | Minimum | Maximum | Standard deviation | Skewness | Excess kurtosis |
|------------------|--------|---------|---------|--------------------|----------|-----------------|
| Commodities | | | | | | |
| Crude oil | 0.339 | -3.148 | 4.242 | 1.767 | -0.105 | 0.075 |
| | 0.432 | -12.939 | 10.136 | 5.457 | -0.415 | 0.119 |
| Wheat | 0.098 | -4.119 | 3.906 | 2.22 | -0.104 | -0.799 |
| | 0.177 | -10.91 | 8.255 | 5.563 | -0.654 | -0.592 |
| Gold | 0.111 | -1.593 | 1.822 | 0.802 | -0.068 | 0.225 |
| | 0.039 | -3.181 | 2.823 | 1.392 | -0.176 | -0.017 |
| Stock indices | | | | | | |
| S&P 500 | -0.231 | -2.312 | 2.181 | 1.236 | 0.176 | -0.800 |
| | 0.338 | -2.942 | 3.105 | 1.419 | -0.350 | -0.217 |
| DAX | 0.103 | -1.783 | 1.385 | 0.819 | -0.395 | -0.47 |
| | 0.004 | -3.876 | 3.810 | 1.8 | -0.261 | 0.22 |
| FTSE 100 | 0.103 | -1.783 | 1.385 | 0.819 | -0.395 | -0.47 |
| | 0.004 | -3.876 | 3.810 | 1.800 | -0.261 | 0.22 |
| Currencies | | | | | | |
| EUR/USD | -0.006 | -0.831 | 1.189 | 0.464 | 0.537 | 0.567 |
| | -0.133 | -1.054 | 1.620 | 0.635 | 0.725 | 0.864 |
| EUR/JPY | -0.006 | -1.314 | 1.664 | 0.568 | 0.537 | 0.567 |
| | -0.133 | -1.745 | 1.770 | 0.820 | 0.725 | 0.864 |
| USD/PLN | 0.024 | -1.570 | 2.040 | 0.817 | 0.193 | 0.221 |
| | 0.227 | -3.579 | 2.838 | 1.696 | -0.512 | -0.443 |
| Cryptocurrencies | | | | | | |
| Bitcoin | 0.213 | 8.022 | 9.498 | 3.656 | 0.317 | 1.027 |
| | 1.078 | 6.644 | 10.667 | 4.218 | 0.177 | 0.132 |
| Ethereum | 0.605 | -8.172 | 10.491 | 4.625 | 0.112 | -0.435 |
| | 1.120 | -7.232 | 8.006 | 4.064 | -0.534 | -0.462 |
| Ripple | 0.219 | -8.656 | 17.208 | 5.647 | 0.889 | 2.014 |
| | 0.774 | -4.006 | 9.110 | 3.594 | 0.616 | -0.359 |

Notes: The upper value in each cell is for the sample period before the Russian invasion and includes data from January 25, 2022, to February 23, 2022, the lower value is for the war period from February 24, 2022, to March 25, 2022.

Table 2. Evaluation of variance forecasts based on the MSE measure

| Assets | GARCH-n | GARCH-t | BM-n | BM-t | BVT | RGARCH-n | RGARCH-t |
|---------------|--------------|--------------|--------------|--------------|----------|----------------|-----------------|
| Commodities | | | | | | | |
| Crude oil | 5.643 | 5.498 | 8.014 | 6.821 | 8.145 | 2.172 | 2.248 |
| | 360.398 | 366.491 | 411.240 | 410.971 | 457.726 | 226.251 | 238.247 |
| Wheat | 5.262 | 5.059 | 5.577 | 4.171 | 5.341 | 3.833 | 3.610 |
| | 1506.591 | 1512.333 | 1523.590 | 1490.560 | 1590.858 | 1459.560 | 1451.277 |
| Gold | 0.097 | 0.091 | 0.107 | 0.133 | 0.119 | 0.092 | 0.093 |
| | 3.197 | 3.491 | 4.109 | 4.447 | 3.919 | 3.035 | 2.899 |
| Stock indices | | | | | | | |
| S&P 500 | 1.716 | 1.697 | 1.796 | 1.709 | 1.670 | 1.351 | 1.266 |
| | 1.527 | 1.604 | 1.156 | 1.610 | 1.514 | 1.593 | 1.540 |
| DAX | 0.540 | 0.610 | 0.569 | 0.548 | 0.553 | 0.700 | 0.752 |
| | 4.596 | 6.639 | 4.502 | 4.595 | 3.634 | 2.961 | 2.847 |
| FTSE 100 | 0.530 | 0.518 | 0.555 | 0.507 | 0.524 | 0.619 | 0.631 |
| | 4.343 | 4.809 | 3.587 | 3.756 | 3.676 | 2.755 | 2.727 |

Table 2. Continued

| Assets | GARCH-n | GARCH-t | BM-n | BM-t | BVT | RGARCH-n | RGARCH-t |
|------------------|---------|--------------|----------------|----------------|---------|----------------|----------------|
| Currencies | | | | | | | |
| EUR/USD | 0.019 | 0.018 | 0.019 | 0.016 | 0.017 | 0.022 | 0.022 |
| | 0.138 | 0.137 | 0.140 | 0.133 | 0.142 | 0.099 | 0.097 |
| EUR/JPY | 0.018 | 0.018 | 0.022 | 0.020 | 0.020 | 0.020 | 0.020 |
| | 0.145 | 0.144 | 0.164 | 0.155 | 0.159 | 0.096 | 0.096 |
| USD/PLN | 0.131 | 0.123 | 0.151 | 0.119 | 0.142 | 0.121 | 0.118 |
| | 6.201 | 6.006 | 6.064 | 5.843 | 6.312 | 4.688 | 4.627 |
| Cryptocurrencies | | | | | | | |
| Bitcoin | 54.370 | 100.770 | 59.438 | 56.978 | 63.483 | 36.939 | 43.064 |
| | 154.964 | 193.178 | 173.756 | 172.102 | 183.187 | 145.472 | 144.982 |
| Ethereum | 188.667 | 201.433 | 218.951 | 251.532 | 270.296 | 134.952 | 146.940 |
| | 306.190 | 296.915 | 295.429 | 283.927 | 301.662 | 253.566 | 252.908 |
| XRP | 401.927 | 568.291 | 365.965 | 266.920 | 487.122 | 416.802 | 480.846 |
| | 243.870 | 267.793 | 218.238 | 226.199 | 234.554 | 229.457 | 319.584 |

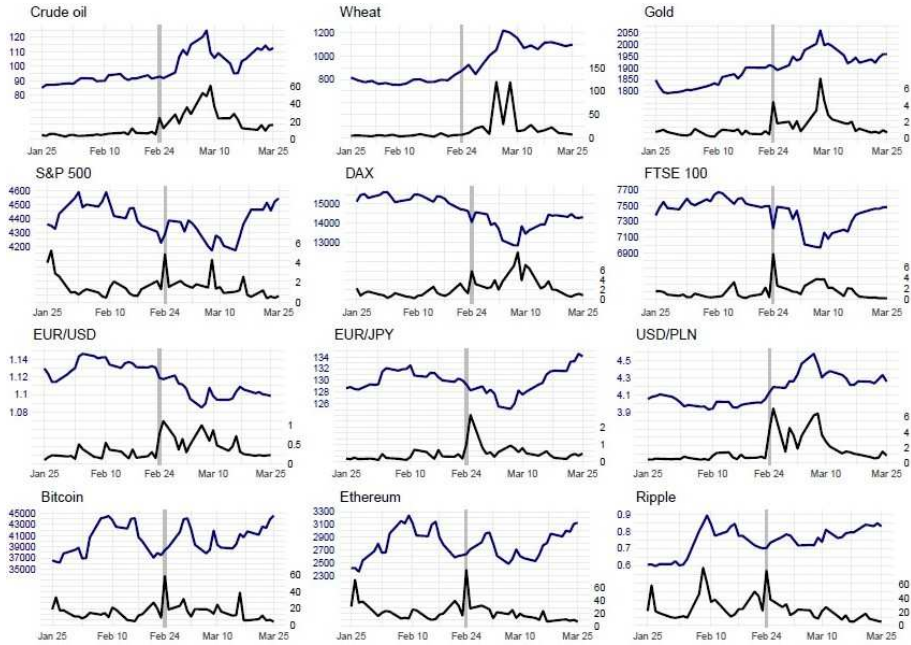
Notes: The upper value in each cell is for the sample period before the Russian invasion and includes data from January 25, 2022, to February 23, 2022, the lower value is for the war period from February 24, 2022, to March 25, 2022. The lowest values of MSE are marked in bold.

Table 3. Evaluation of variance forecasts based on the MCS procedure with the MSE loss function

| Assets | GARCH-n | GARCH-t | BM-n | BM-t | BVT | RGARCH-n | RGARCH-t | MCS test p-value |
|------------------|---------|---------|------|------|-----|----------|----------|------------------|
| Commodities | | | | | | | | |
| Crude oil | – | – | – | – | – | 1 | 2 | 0.856 |
| | 3 | 4 | 5 | 6 | – | 1 | 2 | 0.166 |
| Wheat | – | – | – | 2 | – | – | 1 | 0.143 |
| | 4 | – | – | 3 | 5 | 1 | 2 | 0.222 |
| Gold | 4 | 3 | 5 | – | 6 | 2 | 1 | 0.115 |
| | – | – | – | – | – | 2 | 1 | 0.409 |
| Stock indices | | | | | | | | |
| S&P 500 | 6 | 5 | 3 | 7 | 4 | 2 | 1 | 0.584 |
| | – | – | 1 | – | 3 | – | 2 | 0.192 |
| DAX | 1 | – | – | 2 | 3 | 4 | 5 | 0.260 |
| | – | – | – | – | 3 | 2 | 1 | 0.142 |
| FTSE 100 | 4 | 3 | 5 | 1 | 2 | 6 | 7 | 0.289 |
| | – | – | 3 | – | 4 | 2 | 1 | 0.149 |
| Currencies | | | | | | | | |
| EUR/USD | – | – | – | 1 | – | – | – | 0.036 |
| | – | – | – | – | – | – | 1 | 0.003 |
| EUR/JPY | 2 | 1 | – | – | – | 3 | 4 | 0.166 |
| | – | – | – | – | – | 1 | 2 | 0.901 |
| USD/PLN | – | 4 | – | 2 | – | 3 | 1 | 0.331 |
| | – | – | – | – | – | – | 1 | 0.092 |
| Cryptocurrencies | | | | | | | | |
| Bitcoin | 3 | 7 | 5 | 4 | 6 | 1 | 2 | 0.200 |
| | 3 | 6 | 4 | 5 | – | 2 | 1 | 0.249 |
| Ethereum | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 0.172 |
| | – | – | 3 | – | 4 | 1 | 2 | 0.408 |
| XRP | 3 | 5 | 2 | 1 | – | 4 | – | 0.334 |
| | 4 | 5 | 2 | – | 3 | 1 | – | 0.639 |

Notes: The numbers give the position of a model in SSM according to the MCS test. The dash (–) indicates that the model is outside SSM at the 10% significance level, so its predictive ability is inferior to the models from SSM. The upper number in each cell is for the sample period before the Russian invasion and includes data from January 25, 2022, to February 23, 2022, the lower number is for the war period from February 24, 2022, to March 25, 2022. The MCS p-value stops the MCS procedure, so it gives the minimal type I error probability needed to reject any of the models from the SSM (in the case when the procedure stops with only one model being in SSM, the p-value is from the previous step).

Figure 1. Prices and realized variances before and after the outbreak of the Russo-Ukrainian war



Notes: For each asset, the upper (blue) line presents the prices (the axis is on the left). The lower (black) line presents realized variances (the axis is on the right). The vertical gray line marks the day of the outbreak of the war (February 24, 2022).

Figure 2. Daily forecasts of variances before and after the outbreak of the Russo-Ukrainian war

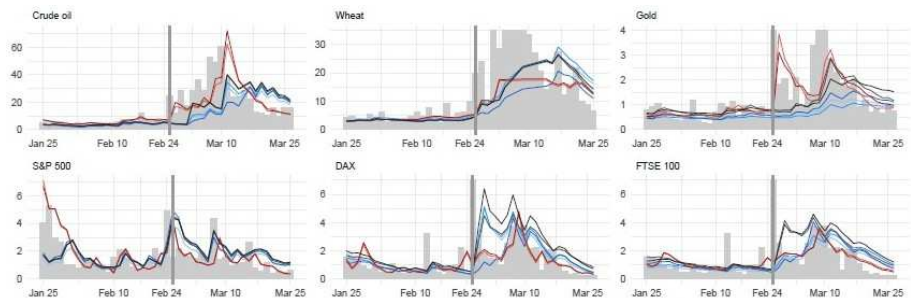
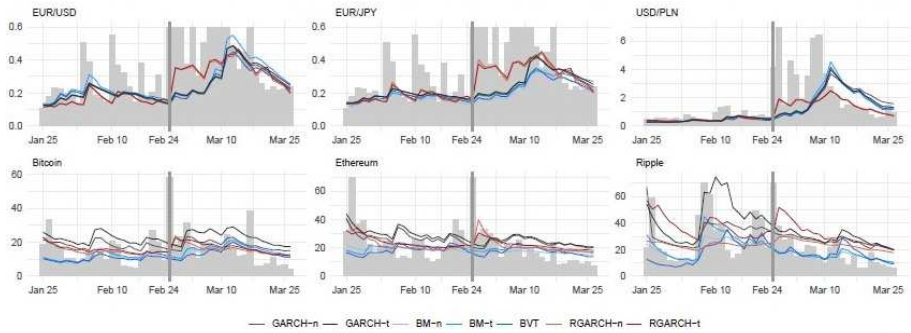


Figure 2. Continued



Notes: Gray bars present realized variances. The vertical gray line marks the day of the outbreak of the war (February 24, 2022).

Figure 3. Comparison of the rolling MSE values

