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Russia-Ukraine War and Price Volatility of Global Commodities: The Role of Public Sentiments

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We analysed how public sentiments have affected global commodity market volatility during the Russia-Ukraine war. Using principal component analysis, we created a sentiments index from 30 carefully selected Google trends search keywords related to the war. We tested the predictability of the sentiments index against market volatility. Our results show that while public sentiments increase commodity market volatility, incorporating the sentiment index into our predictive model significantly improves its precision.

I. Introduction

We investigate the response of the market volatility of ten global commodities to Russia-Ukraine war (*RUW*) sentiments. Our analysis hinges on the market efficiency theory, which stipulates that the commodity market responds to information flow. The Russian invasion has heightened economic uncertainty (Anayi et al., 2022) and affected economic fundamentals. Prices of traded commodities have continued to increase, while supply is insufficient (Bachmann et al., 2022; Chepeliev et al., 2022; Fang & Shao, 2022; Gong et al., 2022). The high cost of imports threatens availability, engenders scarcity, and heightens uncertainty. There are studies on the effect of sentiments on commodity return volatility (Chen et al., 2021; Gong et al., 2022; Maghyereh et al., 2020; Price et al., 2017; Qadam & Nama, 2018) and how *RUW* affects energy price fluctuations and trade (Wang et al., 2022; Wicaksana & Ramadhan, 2022).

The study's motivation stems from the under-tapped wealth of quantitative and/or qualitative information on *RUW* sentiments to enhance understanding of the dynamics of commodity market volatility due to external uncertainties (Maghyereh et al., 2020). By examining the commodity market volatility-sentiment nexus, we make threefold contribution to the existing literature. First, we develop a new sentiments index for the *RUW*; second, we test its predictability for market volatility using a model that considers all salient data features; and third, we evaluate the in-sample and out-of-sample forecast performance of our model to establish its robustness. We establish that *RUW* heightens the volatility of commodity markets. Incorporating public sentiments into our predictive model improves the volatility forecasts in the in-sample and out-of-sample periods. In Sections II, III, IV, and V, we discuss data and methodology, empirical results, robustness checks, and the conclusion, respectively.

II. Data and methodology

We employed daily data on commodity future prices (brent, corn, gold, natural gas, nickel, palm oil, platinum, silver, soybeans, and wheat) as the predicted, and the sentiment index as the predictor. The series were obtained from www.investing.com database and Google Trends, respectively, covering February 24, 2022 (commencement of *RUW*) to May 2, 2023. We transformed the commodity prices into realized volatilities by annualizing the 20-day window standard deviation of commodity returns[1]. We selected the sentiments index from gmfus.org[2], which lists prominent keywords associated with the *RUW*. These are "Russia," "Ukraine," "Nato," "oil prices," "kiev," "Vladimir Putin," "Volodomir Zelensky," "Moscow," "G7," "Wheat," "Ukraine invasion," "Russia-Ukraine war," "Russia invasion," "the invasion," "Donetsk," "Kyiv," "sanction," "airstrikes," "cold war," "chemical weapons," "trade sanctions," "armed forces of Ukraine," "missile," "offensive," "NATO weapons," "defensive alliance," "atomic bomb," "response forces," "provocations," and "warplane." We combined the key-

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1 Formular for annualizing is (252*sum of window)/window used

2 https://securingdemocracy.gmfus.org/ukraine-keywords/

words into a composite sentiments index using a principal component analysis (PCA) and normalized it based on Salisu et al.'s (2021) and Olubusoye et al.'s (2021) studies.

Table 1 summarizes the realized volatilities of the commodities and the developed sentiments index. The realized volatilities of nickel and natural gas have the highest and lowest means, respectively. Natural gas has the highest coefficient of variation value, suggesting that it is most unstable, while gold has the lowest variability. Commodities' realized volatilities are positively skewed, except gold and natural gas. The Augmented Dickey-Fuller (ADF) unit root test result is mixed. Brent, Nickel, Wheat, and Sentiments Index are integrated in order one. There is evidence of conditional heteroskedasticity (except for gold, platinum, silver, wheat, and the sentiment index) and serial correlation (except for platinum and silver). All the variables exhibit some degree of persistence.

Therefore, we adopted the Westerlund and Narayan (2015; 2012) type autoregressive distributed lag (ARDL) model, which is based on the feasible generalized least squares (FGLS) regression. The model suitably adjusts for violations such as autocorrelation, heteroskedasticity, and persistence. Recent studies (Salisu et al., 2018; Salisu & Isah, 2018) suggest the need to account for these salient data features in modelling realized volatility. The WN-type model specification is given in Equation (1):

$$\begin{aligned} rv_t =& \propto + \beta rv_{t-1} + \gamma sindx_{t-1} \\ &+ \theta \Delta sindx_t + \sum_{i=1}^{k} \psi_i brk_{i,t} + \epsilon_t \end{aligned} \tag{1}$$

where rv_t is the realized volatility; $sindx_t$ is sentiment index; $\Delta sindx_t$ adjusts for persistence/endogeneity; $brk_{i,t}$ is a break dummy that indicates the i^{th} break point, and k represents the possible number of significant breaks[3]; α, β, γ, θ and ψ are the model parameters; and ϵ is the white noise disturbance term. Accounting for breaks is supported by literature (Salisu et al., 2019; Smyth & Narayan, 2018). The predictability stance is confirmed if the null hypothesis $H_0 : \gamma = 0$ is rejected at a specified level of significance. Our WN-type model was tested with an autoregressive $[AR(1)]$ model.

We employed only 75% of the full data for the in-sample and out-of-sample forecast evaluation using the Clark and West (2007) test, which is appropriate when the compared models are nested. It determines whether the forecast error difference between paired competing models is statistically different from zero. The CW procedure is:

$$\begin{aligned} \hat{f}_{t+h} =& \left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2 \\ &- \left[\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2 - \left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2\right] \end{aligned} \tag{2}$$

where h represents the forecast period, and $\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$ and $\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2$ represent the squared errors for the benchmark and our predictive models, respectively. The adjusted squared error, $\left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2$, is the CW incorporated term to correct for noise associated with the larger model's forecast. The equality of the contending models' forecast was tested by regressing $\hat{f}_{t+h}$ on a constant. Significance implies inequality in the performances; positive (or negative) CW statistics favours our predictive (benchmark) model.

III. Empirical Results

Table 2 presents the predictability (using the full data) as well as the forecast evaluation (using 75% of the full data) results. We found predictability in the sentiment index for commodity market volatility, with a positive nexus (except for soybeans, wheat, and natural gas). This is consistent with some recent studies (Gong et al., 2022; Maghyereh et al., 2020; Qadam & Nama, 2018). The uncertainty occasioned by the *RUW* aggravates the market volatility for the examined commodities, except soybeans, wheat, and natural gas, which corroborates some previous studies (Chen et al., 2021; Gong et al., 2022). The markets become highly unstable despite plausible feats of higher returns as the tension lingers. Similar to Gong et al. (2022), soybean, wheat, and natural gas markets are resilient to the *RUW*, perhaps owing to global adjustments from other exporter countries to mitigate the resultant scarcity. Our predictive model consistently outperformed the benchmark across commodity markets and specified forecast horizons. The sentiment index improves commodity market volatility forecasts.

IV. Robustness Check

We ascertained the sensitivity of our results using weekly data and maintaining the main estimation process. The predictability results support a positive nexus between market volatility and the sentiment index (Table A.2 in the appendix), indicating that increased public sentiments intensify the volatility of the commodity markets as the war lingers. Except for soybeans, wheat, and natural gas, the results align with the main estimation results. The CW procedure retains outperformance in most of the commodity markets and forecast horizons. Hence, our results are robust to the forecast horizons.

V. Conclusion

We examined the realized volatility-sentiment index nexus for ten commodity markets using the WN-type distributed lag model that adequately accommodates all salient data features. Based on the 30 carefully selected keywords, we tested the predictability of the PCA-facilitated sentiments index for market volatilities. We used daily and weekly data to confirm the aggravating impact of the *RUW* on commodity market volatility in about 70% and 100% of cases. The forecast evaluation results confirm the

3 The significant break points are determined by the Bai-Perron multiple breakpoint test. The dates are presented in the appendix on Table A.1 for daily and weekly frequencies.

Table 1. Descriptive Statistics and Preliminary Analysis

Commodities	Mean	Coef. of Variation	Skewne	Kurtosis	Jarque-Bera	Conditional Heteroscedasticity		Serial Correlation				Pers	Unit root
						arch5	arch10	Q(5)	Q(10)	Q2(5)	Q2(10)		
Brent	95.08	13.70	0.44	2.17	16.34***	19.69***	14.30***	18.51***	24.94***	106.29***	127.18***	0.97***	-4.45***c *I(0)*
Corn	688.49	8.40	0.47	2.31	15.11***	3.95***	2.07**	8.43	12.62	24.60***	26.52***	0.98***	-16.61***c *I(1)*
Gold	1832.56	5.69	-0.02	2.10	9.12**	2.05*	1.51	4.99	14.2	12.33**	21.53**	0.98***	-17.84***c *I(1)*
Natural gas	5.69	39.64	-0.21	1.85	16.82***	2.89**	1.96**	9.85*	11.91	19.05***	27.01***	0.99***	-18.28***c *I(1)*
Nickel	26371.99	21.70	4.18	34.91	12109.26***	36.83***	109.99***	4.21	12.21	89.05***	89.26***	0.84***	-4.03***c *I(0)*
Palm oil	4705.48	27.34	1.11	2.60	56.93***	6.13***	5.22***	21.87***	33.85***	46.61***	86.80***	0.98***	-15.75***c *I(1)*
Platinum	966.49	7.33	0.11	2.42	4.23	0.5	0.72	2.05	6.72	2.72	7.71	0.96***	-16.78***c *I(1)*
Silver	21.96	10.43	0.06	1.87	14.35***	0.61	0.54	3.74	9.71	3.16	7.16	0.98***	-16.82***c *I(1)*
Soybean	19.13	39.36	4.09	23.40	5372.56***	4.57***	2.35**	4.18	10.65	22.19***	24.42***	0.98***	-16.25***c *I(1)*
Wheat	260.93	14.86	0.19	2.45	5.02*	0.38	1.44	3.57	9.53	2.89	16.79*	0.99***	-4.05***c *I(0)*
Sentiment index	19.13	39.36	4.09	23.40	5372.56***	0.55	1.33	37.73***	39.15***	26.24***	26.25***	0.84***	-8.33***b *I(0)*

Superscript "b" and "c" denote that ADF unit root test regressions are model with constant only and model with constant and trend. Autocorrelation and heteroskedasticity tests are tested using LJung- box test Q statistics and Autoregressive conditional heteroscedasticity, respectively, at lags 5% and 10%. Coefficient of variation is computed as = Std/mean, Pers = persistence

Table 2. Parameter Estimation and Forecast Evaluation using Daily Data

Commodity	Coefficient Estimate	Clark and West Test			
		In-Sample	*h* = 5	*h* = 10	*h* = 20
Brent	0.1044*** (0.0195)	284.61***	285.61***	286.32***	289.54***
Corn	0.1127*** (0.0403)	5711.01***	5601.41***	5493.06***	5302.47***
Gold	0.4547*** (0.0891)	836.84***	8830.86***	9497.23***	9954.12***
Natural gas	-0.0005 (0.0017)	2.97***	3.32***	3.74***	4.61***
Nickel	78.8015*** (19.0917)	65895241***	64416888***	63265223***	60580217***
Palm oil	3.7368*** (0.3169)	964204.5***	940351.1***	917309.7***	874545.3***
Platinum	0.8018*** (0.1112)	6471.36***	6851.62***	7090.70***	6857.74***
Silver	0.0231*** (0.0039)	6.17***	6.57***	6.94***	6.95***
Soybean	-0.0087** (0.0035)	31.53***	31.38***	31.54***	32.17***
Wheat	-0.0818*** (0.0124)	2442.41***	2466.25***	2482.31***	2486.97***

The values in each cell under column 2 are estimated coefficients and the corresponding standard errors; columns 3 – 6 are Clark and West Statistics; with *** and ** indicating statistical significance at 1% and 5%, respectively.

statistical importance of the sentiment index for predicting the volatility of commodity markets.

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Appendix

Table A.1. Structural Break Dates

Commodity	Daily	Weekly
Brent	8/3/2022; 11/21/2022; 5/25/2022	8/4/2022; 11/17/2022; 5/26/2022
Corn	7/14/2022; 9/8/2022; 11/8/2022; 4/26/2022	7/14/2022; 4/14/2022; 9/1/2022
Gold	12/20/2022; 7/1/2022; 4/26/2022	6/30/2022; 12/1/2022; 4/28/2022
Natural gas	12/19/2022; 9/23/2022; 4/26/2022; 7/22/2022	10/13/2022
Nickel	5/5/2022; 11/10/2022	4/14/2022; 11/10/2022
Palm oil	6/22/2022; 8/30/2022; 10/27/2022	6/23/2022; 4/21/2022
Platinum	11/7/2022; 6/14/2022; 2/2/2023	11/3/2022; 6/23/2022
Silver	12/1/2022; 4/26/2022; 6/30/2022; 2/2/2023; 10/3/2022	12/1/2022; 4/28/2022; 6/30/2022
Soybean	6/22/2022; 12/5/2022; 10/6/2022	6/16/2022; 4/14/2022; 8/4/2022; 12/1/2022; 10/6/2022
Wheat	6/22/2022; 11/22/2022	6/2/2022; 11/10/2022

Table A.2. Parameter Estimation and Forecast Evaluation using Weekly Data

Commodity	Coefficient Estimate	Clark and West Test			
		In-Sample	h = 5	h = 10	h = 20
Brent	0.37***(0.08)	183.76***	187.38***	187.83***	187.83***
Corn	2.73*** (0.22)	7191.70***	7066.99***	6925.39***	6925.39***
Gold	4.41*** (0.61)	7792.81***	7874.55***	7874***	8142.25***
Natural gas	0.03*** (0.01)	2.17	1.45	0.68	0.68
Nickel	273.94** (98.27)	23071102***	22568002***	21976799***	21976799***
Palm oil	69.60*** (7.77)	472240.4	461934.7	447012.7	447012.7
Platinum	4.95*** (0.97)	6483.03***	6803.21***	7054.35***	7054.35***
Silver	0.13***(0.03)	7.08***	7.24***	7.46***	7.46***
Soybean	0.34***(0.03)	59.95***	58.12***	56.33***	
Wheat	0.65***(0.10)	2332.68***	2350.90***	2373.38***	2373.38***

The values in each cell under column 2 are the estimated coefficients and the corresponding standard errors; columns 3 – 6 are the Clark and West Statistics; with *** and ** indicate statistical significance at 1% and 5%, respectively.