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Russia-Ukraine War and Return Forecast of Global Commodity: The Role of Public Sentiments

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Abstract
The study investigated how sentiment has affected commodity returns in this current war between Russia and Ukraine war. The study used Principal Component Analysis to generate sentiment index based on 30 carefully selected 29 keywords. The predictability of sentiment was tested against the commodity returns. The results showed that while sentiment increases returns, integrating the sentiment in our model significantly expands its precision.

Keywords: Public sentiment; commodity returns predictability.

Introduction

Political tension and war usually spin instability and uncertainty and induce public sentiments that affect market behaviour, especially returns on global commodities. The heightened tension and uncertainty that have lingered since the Russia-Ukraine war (RUW) started on February 24, 2022 have major consequences on returns of certain commodities traded in the global market such as oil, gas, sunflower and wheat (Anayi et., 2022; Azeez et al., 2024). Russia ranked as the second major supplier of crude oil in the global market. Largely, this dominance espouses the potential role of Russia in the determination of crude prices. Hence, it is impracticable to isolate the disruption induced by the RUW and the associated public sentiment from the performance of commodities traded in the market. The disruption has major implications for the supply chain of the global commodity market. This study examines how public sentiments influence the response of global commodity returns to the disruptions induced by the on-going Russia-Ukraine war.

The study hinges on the behavioural finance theory, which argues that biases and psychological factors play vital role in market outcomes. Prices of commodities traded at the global market have been constantly witnessing increases, with little supply (Chepeliev et al., 2022; Gong et al., 2022). The incidental costs associated with bringing goods to present place of use portends the readiness, provokes dearth and amplifies doubt. Some previous studies consider the effect of sentiments on commodities' return (Maghyereh et al., 2020; Ji and Guo, 2015a) and how sentiment impact on future prices of commodities (Huang et al., 2018; Qadan and Nama, 2018; Balcilar et al., 2017). These studies pre-date the Russia-Ukraine war and, thus, consider non-war induced sentiments. Therefore, since RUW-induced public sentiments data are available, the motivation for this study twigs from the dearth of studies on the influence RUW-induced sentiments on global commodities' returns. Recent study that relates to this is by Azeez et al. (2024). However, the focus is on public sentiments in relation to global commodity prices, not commodity returns. Therefore, in line with Maghyereh et al. (2020), this study increases the understanding of the dynamics of commodity returns due to public sentiments. Thus, this study contributes to literature in three folds. First, we develop an index from relevant keyword associated with Russian Ukraine war. Second, the predictive nature of commodity return is tested, using suitable model that accommodates data features that are salient. Third, both out-of-sample and in sample are evaluated to ensure robustness. The study confirms that the disruption increases commodity returns with exception to gold, natural gas, soybean, and platinum. Incorporating public sentiments into our model further improves returns in both in-sample and out-of-sample periods. In section II, III, IV, and V, we focus on literature and empirical review, data and methodology, empirical results, robustness, and conclusion, respectively.

Literature Review

The behavioural finance theory emphasises the importance and role of investor sentiment on commodity prices (De Long et al., 1990). The theory recognises the risk inherent with different classes of asset along with overall sentiment of negativity and positivity towards risk (Qadan and Nama, 2018). The theory concludes that investors' disposition to risk is defined on their beliefs in the future prospect of cash flow and risk associated with investment. (Brown and Cliff, 2004). Specifically, the theory sees the possibility whereby sentiments trail in the individual perception towards commodity prices and risks (Han et al., 2007).

Additionally, Price et al. (2017) reiterate the role of sentiments in mitigating investors' risks and commodity performance. They concluded that sentiment plays major role in the demand for investments and the investors make choices based on investment that matches their sentiment. Investors who are risk takers may opt for investments with profitable outcome not for the sake of protection but based on profitable attributes, which are taken in order to define safety (Qadan and Nama. 2018). Once sentiment changes, it reflects in commodity performance and risk tolerance level.

Previous studies focused on the role of sentiment in asset returns and volatility **(**Maghyereh et al., 2020; Rao and Srivastava, 2013). Specifically, finance literature emphases on equity returns and starring role of stockholder sentiment. Empirical studies in the past have researched on the impact of sentiment on commodity returns and volatility, with various measures for sentiment indices derived from different information sources such as Wire messages, Facebook, and others. Rao and Srivastava (2013), using search volume index from Google search engine, found that lag value of sentiment has a high predictive content on both gold and crude oil returns. The predictability appears to have decreasing effect on commodity returns. Based on information obtained through the internet, the sentiment associated with investor is negatively related with the commodity returns (Ji and Guo, 2015a). Ji and Guo (2015b) studied the role of sentiment on the volatility of oil price within major event such as the global financial crisis, the Libya war, the hurricanes and OPEC symposiums. The study affirmed that volatility in oil price responds to the sentiment related to oil price era. In a similar study, Balcilar *et al.* (2017) reveal that sentiment play significant role on oil price return and volatility when compared with return on gold traded in the commodity market.

Using new metrics on sentiment index as suggested by Thomson Reuter, new evidence is documented. Huang et al. (2018) investigated the role of investor sentiment in selected five commodity traded in main asset platform. The study concluded that commodity is influenced by own sentiment. Qadan's and Name's (2018) finding differed, suggesting divergent result in both short-run and long run periods. Their study was based on the use of nine proxies of sentiment on the volatility of oil prices. The result revealed strong and positive relationship between sentiment and oil price changes in the short run. This further suggested that sentiment aggravates price volatility. Pan (2018) investigated the link between precious metals price volatility and market sentiments. The result affirms that investor sentiment aggravates volatility in both silver and gold prices at the time of world-wide financial crunch and thereafter. Smales and Lucey (2019) depart on the use of a new method of measuring investor sentiment such as index developed on financial stress by the Saint Louis Federal Reserve. The outcome suggested that sentiment impacts on liquidity of the commodities (silver and gold) and other instruments at the time when sentiment is experience at the lowest. Ji *et al*. (2019) review the spill over effect between sentiment index of investor and oil price. The index were derived from investors' position with regards to swap deal, producer, risk-taker and lesser dealers. The study established that sentiment intensifies oil price volatility.

Li et al. (2019) examine the role of sentiment on global oil price market. The study found that sentiment has high predictive content on the West Texas Instrument future oil price. The study also confirm that other oil price measure such as Brent future oil price, WTI spot price, Dubai spot price are negatively impacted by sentiment. Shahzad et al. (2019) contend that crude oil prices impact on investors' sentiment. This suggests that investment managers can establish appropriate policies that disaggregate between positive and negative partial sum of the oil price. Huang et al. (2019) advance the frontier of knowledge by confirming that sentiment sways price of gold only when the threshold establish is exceeded. This outcome is noticed in the period before the financial crisis of the 2008, a confirmation that gold can be used to hedge against economic risk.

Summarily, these studies investigated the role of sentiment on commodity returns and price volatility. The conclusions arrived are not straightforward with regards the relationship. Rather, it report varied outcome and indecisive evidence. A few previous studies have employed Thomson Reuter approach in the measure of sentiment in relation to commodity return. Also, the previous studies have focused on certain commodities like gold, crude oil and metal, but giving less attention to other unavoidable commodities. This justifies the motive for the study which focuses on Russia-Ukraine war and return forecast of global commodities: the role of public sentiment. By examining the commodity returns sentiment nexus, we sort threefold input to the body of knowledge. Firstly, we develop sentiment index, using search keyword related to Russian Ukraine War; secondly, we test the prospect for commodity returns with the use of model that accommodate noticeable data features; and thirdly, we test using in-sample and out-of-sample forecast evaluation of the model in order to ascertain its robustness.

Data and Methodology

This study deploys daily data points on future global commodity prices as the predicted variables (Wheat, Soybean, Corn, Silver, Nickel, Platinum, Gold, Brent and Natural gas), while sentiment index is used to proxy for predictor. Both the predicted and predictor series were generated from the data base of investing.com (www.investing.com) and Google trend search engine for the period February 24, 2022 (commencement date of the current Russia-Ukraine war) to July 31, 2024. We generated returns series from the global commodity prices. The keywords used to generate sentiment index were carefully selected from gmfus.org, which summarises major and relevant keywords related with the Russia-Ukraine war. The keywords are: Airstrike', 'Armed forces', 'Atomic bomb', 'Chemical weapons', 'Cold war' 'Defensive alliance', 'Donestk', 'G7','Kyiv', 'Missile', 'Moscow', 'Nato', 'Nato weapons', 'Nuclear weapon', 'Offensive', 'Oil prices', 'Provocations', 'Russia', 'Russia invasion', 'Russia Ukraine war', 'Sanction', 'The invasion', Trade sanction', 'Ukraine', 'Ukraine invasion', 'Vladimir Putin', 'Volodymyr Zelenskyy','War plan', and 'Wheats' We employed principal component analysis (PCA) in generating the sentiments index. In addition, we normalised the score in line with Olubusoye et al., (2021) and Salisu et al., (2021).

A descriptive summary outcome of the results on both the returns and index series are presented in Table 1 (see the Appendix 1). The commodity returns for nickel and natural gas record the maximum and lowest means, correspondingly. Natural gas account for the highest level of variation, implying that it is the most unsteady, while platinum exhibit lowest level of variation. All commodity returns suggest positively skewed with exception to index. Table 2 (see the Appendix 2) shows the outcome of Augmented Dickey-Fuller unit root test at mix order. Brent, gold, natural gas, silver, soybean, and wheat are integrated at first order, while corn, nickel, platinum, and index stationary at level. There is presence of conditional heteroskedasticity /with exception to gold, platinum, and index, and serial correlation except gold, platinum, and index. All series exhibit amount of persistence.

In order to capture salient data features exhibited in exploratory outcome, we adopt Westerlund and Narayan (2015) autoregressive distribution lag (ARDL) model, which share features of the feasible generalized least square (FGLS) regression. The model accommodate violation such as persistence, autocorrelation and conditional heteroskedasticity. Salisu et al (2018) and Salisu and Isah (2018) underscore the need to account for salient data features in forecasting returns. The model specification as suggested by Westerlund and Narayan is accounted for in equation 1 below:

$$r_t = \lambda + \beta r_{-1} + \gamma index_{t-1} + \sigma \Delta index + \sum_{i=1}^{\kappa} v_i brk_{i,t} + e \ldots\ldots\ldots\ldots\ldots\ldots 1$$

We defined r_t as returns from commodities; $indexx_t$ for sentiment index; $\Delta indexx_t$ persistence adjustment or endogeneity; $brk_{i,t}$ represent break dummy that suggests the i^th point break, and k denotes the possible number of significant breaks; $\lambda, \beta, \gamma, \sigma, and, v$ are parameters to the model with e which denotes disturbance term. Accounting for breaks in the model, improves the model outcome (Salisu et al., 2019; Smyth and Narayan, 2018). Our main model (WN-type) is benchmark with an Autoregressive (AR1) model

We explore 75% of entire data series for the in-sample and out-sample predictability forecast using Clark and West test of 2007, which is suitable when model of interest are nested. The test establishes if error mean rootmen square error generated from the forecast as compared with the benchmark is statistically different from zero. The CW estimation is stated as:

$$f_{t+h} = (rt + h - rt + h)^2 - (rt + h - r2t + h)^2 - (rit + h - r2t + h)^2$$

h denotes period of forecast, while $(rt + h - r2t + h)^2$ and $(rt + h - rt + h)^2$ depict the squared errors of both predictive model and benchmark, respectively. The squared error adjusted, $(rit + h - r2t + h)^2$ is the CW suggestive of correcting noise associated with a larger model's forecast. The CW output statistically which denotes and it outperform the benchmark.

Empirical Results

We present the outcomes of the predictive series in Table 3 (see the Appendix), using full sample series and 75% of the full sample series for the forecast evaluation outcomes. The outcomes revealed that sentiment index has predictive content on commodity returns, with a noticeable positive relationship with all commodities (except Gold, Natural Gas, Soybean and platinum). The outcomes are in line with some previous studies (see: Balcilar *et al.*, 2017; Ji and Guo (2015b; Huang et al., 2018). The political and economic uncertainties occasioned by the Russian Ukraine war intensify the market returns for all commodities studied, with the exception to Gold, Natural Gas, Soybean and platinum. This outcome is in line with some previous studies (Li et al., 2019; Ji *et al.*, 2019). The commodities become highly sensitive to return as the war lingers. On a different note, Gold, Natural Gas, Soybean and platinum appeared responsive negatively to the Russia Ukraine War. Perhaps, this is due to the level of response of other exporter at the global level to fill the gap in the supply side. Our model outperform the benchmark at both in-sample and out-of-sample horizon. The returns of commodity market is positively influenced by the sentiment index.

Robustness Check

We confirmed the main analysis result, using weekly data series along with estimation process adopted earlier. The outcomes conform to the main analysis result in terms of signs and significance between commodity returns and sentiment index (see Table 4b in the Appendix), suggesting that public sentiments significantly promote commodity returns as the region continuously experience war, except Gold, Natural Gas, Soybean and platinum. These outcomes align with the main estimation outputs. The Clark and West test procedure maintains outperformance in commodity market and forecast horizons. As such, our outcomes are robust to the forecast horizon.

Conclusion

We studied the return-sentiment index for thirty commodities, using the Westerlung and Narayan model that accommodates all data salient features. We examined the predictive nature of sentiments index, using Principal Component Analysis, on market returns on selected commodities. Daily and weekly data were used for the main analysis and robustness check, respectively. The out-of-sample forecast results confirm the potential of sentiments index in predicting commodity returns. Therefore, the key contributions of this study to the knowledge are the sentiment index construct, the predictive nature of sentiments-induces commodity returns and the robustness of the estimates.

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Appendix A: Summary of the results on the returns series

Table 1: Preliminary Analysis (Descriptive Statistics)

	Mean	Coef. Of variation	Skewness	Kurtosis	Jarque-Bera
Brent	88.94	13.06	1.13	3.65	132.97
Corn	579.84	21.02	0.15	1.66	44.86
Gold	1973.54	10.21	0.75	3.03	53.96

N_gas	4.05	56.7	0.91	2.36	89.13
Nickel	22328.5	25.37	2.95	24.41	11801.9
Platinum	957.94	6.49	0.41	2.78	16.81
Silver	23.61	12.92	0.62	3.33	39.42
Index	40.53	38.71	-0.84	4.3	107.75
Soybean	1382.34	11.75	0.29	2.52	13.76
Wheat	728	24.23	1.22	3.06	159.5

Coefficient of variation is derived as the standard deviation/mean.

Table 2: Preliminary Analysis Table

Commodities	Conditional Heteroscedasticity				Serial Correlation								pers	Unit root
	arch5	arch10	arch20	arch30	q(5)	q(10)	q(20)	q(30)	q2(5)	q2(10)	q2(20)	q2(30)		
Brent	43.12***	28.05***	4.39***	3.76***	42.66***	46.08***	55.75***	72.31***	263.48***	332.87***	383.78***	412.61***	0.98***	aI (1)
Corn	5.71***	3.41***	1.77**	1.25	22.63***	25.03***	37.93***	46.96***	38.69***	44.88***	51.09***	55.19***	0.99***	cI (0)
Gold	1.43	12.27	1.16	1.08	6.48	14.07	18.78	29.05	7.32	15.13	25.22	30.18	1.00***	cI (1)
N_gas	12.34***	9.81***	6.05***	5.22***	7.34	8.79	23.06	32.07	88.19***	180.6***	292.51***	448.61***	0.99***	aI (1)
Nickel	186.81***	296.28***	7.34***	4.98***	13.22**	29.55***	34.06**	37.48	243.85***	244.44***	244.45***	244.45***	0.92***	cI (0)
Platinum	0.65	0.48	0.72	1.12	3.94	5.68	21.1	31.29	3.35	5.16	13.76	22.66	0.95***	bI (0)
Silver	5.26***	5.48***	3.25***	2.99***	6.75	14.11	17.7	30.89	32.66***	85.43***	127.98***	143.72***	0.99***	cI (1)
Index	0.25	0.25	0.23	0.2	6.84	18.57**	35.99**	50.42**	2.03	3.12	5.66	7.39	0.93***	cI (0)
Soybean	10.22***	10.29***	5.37***	4.10***	10.67*	16.44*	35.33**	48.34**	80.59***	170.59***	247.29***	300.75***	0.99***	bI (1)
Wheat	118.37***	5.29***	5.57***	4.19***	42.97***	61.66***	80.66***	93.32***	221.01***	231.99***	235.18***	236.01***	0.99***	bI (1)

Subscript ''a'' ''b'' and ''c'' suggest Augmented Dickey-Fuller Test (ADF) of unit root regression are model with none, constant, constant and trend. Conditional heteroscedasticity and auto-correlation test are done based on Ljung box test Q statistics majorly at 5% and 10%.

Table 3. Parameter Estimation and Return Forecast Evaluation Using Daily Data

Commodities	**AR 1 Model**	**Coefficient of Estimation**	**Clark and West Evaluation Test**			
			In-Sample	h=20	h=30	h=50
Brent	0.98***	0.01***(0.0012)	208.1427***	221.1287***	241.1453***	251.312***
Corn	0.99***	0.03***(0.0056)	11435***	11452***	11475***	11482***
Gold	0.99***	-0.08***(0.0150)	19524***	19567***	19574***	19592***
N-gas	0.99***	- 0.01***(6.70E5)	7.36***	7.64***	7.90***	7.99***
Nickel	0.90***	4.72***(0.7894)	29423***	29448***	29467***	29484***
Soybean	0.98***	-0.15***(0.0332)	1287***	1293***	1314***	1319***
Platinum	0.96***	-0.07***(0.0045)	3079***	3094***	3114***	3133***
Silver	0.98***	0.01***(0.0004)	5.51***	5.74***	5.84***	5.98***
Wheat	0.99***	0.10***(0.0301)	29483***	29509***	29524***	29433***

The result in cells as contained in column 2 are the coefficient and corresponding standard errors for auto-regressive output; The output in column 3
is the estimate and corresponding standard error for the estimation; from column 4 to 7 are the statistics result of Clark and West with *, **. and
*** suggesting significant statistically at 10%, 5% and 1% respectively.

Table 4(a): Structural Break Dates

Commodities	Daily	Weekly
Brent	11/15/2022; 08/03/2022; 03/14/2023; 07/25/2023	08/28/202; 04/12/20222;

Corn	07/17/2023’ 07/15/2022; 04/04/2023; 10/01/2022	06/25/2023; 07/10/2022; 02/19/2023
Gold	01/18/2023; 06/07/2022’ 04/24/2023; 09/26/2023	01/08/2023; 06/26/2022
N-gas	12/29/2022; 07/12/2022	12/25/2022/; 09/18/2022
Nickel	15/10/2023; 06/08/2022; 11/09/2022; 09/21/2023	05/07/2023; 06/05/2022; 11/06/2022; 09/17/2023
Soybean	04/25/2022; 06/23/2022; 12/07/2022; 08/03/2023	06/26/2022; 07/02/2023
Platinum	10/26/2022; 06/13/2022; 02/13/2023; 09/25/2023; 03/07/2023	10/23/2022; 06/18/2023; 03/19/2023
Silver	12/01/2022; 06/08/2022; 03/27/2023; 08/02/2023	11/27/2022; 06/26/2022; 03/19/2023
Wheat	12/01/2022; 06/23/2022; 04/21/2023; 08/14/2023	11/13/2022; 06/19/2022; 02/19/2023; 08/13/2023

Table 4(b): Parameter Estimation and Return Forecast Evaluation Using Weekly Data

Commodities	**AR 1 Model**	**Coefficient of Estimation**	**Clark and West Evaluation Test**			
			In-Sample	h=20	h=30	h=50
Brent	0.91***	0.07***(0.0178)	89.39***	89.60***	89.76***	89.93***
Corn	0.96***	1.34***(0.1089)	9236***	9243***	9261***	9285***
Gold	0.96***	-1.50***(0.3426)	17098***	17109***	17121***	17143***
N-gas	0.98***	-0.01***(0.0014)	5.69***	5.87***	5.97***	6.14***
Nickel	0.88***	36.08(18.3158)	160***	172***	176***	187***
Soybean	0.93***	-1.76***(0.2863)	9651***	9672***	9688***	9694***
Platinum	0.83***	-0.69(0.8689)	5501***	5521***	5533***	5549***
Silver	0.89***	0.03*(0.0131)	5.01***	5.14***	5.19***	5.26***
Wheat	0.91***	0.09(0.3606)	16127***	16141***	16157***	16173***

The result in cells as contained in column 2 are the coefficient and corresponding standard errors for auto-regressive output; the output in

Column 3 is the estimate and corresponding standard error for the estimation; from column 4 to 7 are the statistics result of Clark and West

with *, **. and *** suggesting significant statistically at 10%, 5% and 1% respectively.