Innovations

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

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Abstract: *We investigated how public sentiment has affected ten selected commodity returns in the current war between Russia and Ukraine for the period February 24, 2022, to July 31, 2024. Our predictor series is a public sentiment with structural breaks. We used Principal Component Analysis to generate the public sentiment index based on 29 carefully selected keywords, while the predicted series were returns generated from ten global commodity prices. Using an autoregressive model and having accounted for structural breaks, the predictability of the sentiment index was tested against the commodity returns. The results showed that while sentiment increases returns, integrating the sentiment index into our model significantly expanded its precision. In addition, our post-estimation tests confirmed the robustness of the model. The study further affirmed the role of public sentiment in commodity returns in an economy that is full of uncertainty.*

Keywords: *Commodity returns predictability; Commodity Price, Forecasting Public sentiment, Global Commodity Markets, Russia-Ukraine War*

1. **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. This dominance espouses Russia's potential role in the determination of crude prices. Hence, isolating the disruption induced by the RUW and the associated public sentiment from the performance of commodities traded in the market is impracticable. The disruption has major implications for the supply chain of the global commodity market. Therefore, this study examine show public sentimentsinfluence the response of global commodity returns to the disruptions induced by theongoing Russia-Ukraine war.

The study hinges on the behavioural finance theory, which argues that biases and psychological factors play a vital role in market outcomes. Prices of commodities traded in 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 the present place of use portend the readiness, provoke dearth and amplify doubt. Some previous studies consider the effect of sentiments on commodities'returns (Maghyereh et al., 2020; Ji & Guo, 2015a) and how sentiment impacts the future prices of commodities (Huang et al., 2018; Qadan & 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 sentiment data are available, the motivation for this study stems from the dearth of studies on the influence of RUW-induced sentiments on global commodities' returns. However, a related recent study focused on public sentiments in relation to global commodity prices, not commodity returns (Azeez et al., 2024). Therefore, in line with Maghyereh et al. (2020), this studyincreases the understanding of the dynamics of commodity returns due to public sentiments.Thus, this study contributes to the literature in three folds. First, we develop an index from relevant keywords associated with the Russian-Ukraine war. Second, the predictive nature of commodity return is tested using a 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 the exception of 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 sections II, III, IV, and V, we focus on literature and empirical review, data and methodology, empirical results, robustness, and conclusion, respectively.

2. Literature Review

The behavioural finance theory emphasizes the importance and role of investor sentiment on commodity prices (De Long et al., 1990). The theory recognizes the risk inherent in different classes of assets along with the overall sentiment of negativity and positivity towards risk (Qadan & Nama, 2018). The theory concludes that investors' disposition to risk is defined by their beliefs in the prospect of cash flow and risk associated with investment(Brown & 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 public sentiments in mitigating investors' risks and commodity performance. They concluded that sentiment plays a major role in the demand for investments and that investors make choices based on investment that matches their sentiment. Risk-takers investors may opt for investments with profitable outcomes not for the sake of protection but based on profitable attributes, which are taken 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 & Srivastava, 2013).Specifically, finance literature emphasizes equity returns and the starring role of stockholder sentiment. Empirical studies in the past have researched 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 a search volume index from the Google search engine, found that the lag value of sentiment has a high predictive content on both gold and crude oil returns,and the predictability has a decreasing effect on commodity returns. Based on information obtained through the Internet, the sentiment associated with investors is negatively related to commodity returns (Ji & Guo, 2015a, 2015b) studied the role of sentiment on the volatility of oil prices within major events such as the global financial crisis, the Libya war, the hurricanes and OPEC symposiums. The study affirmed that volatility in oil prices responds to the sentiment related to the oil price era. In a similar study, Balcilaret al. (2017) reveal that sentiment plays a significant role in oil price return and volatility when compared with the return on gold traded in the commodity market.

New evidence is documented using new metrics on the sentiment index suggested by Thomson Reuters. Huang et al. (2018) investigated the role of investor sentiment in selected five commodities traded in the central asset platform. The study concluded that one's own sentiment influences commodity. Qadan's and Name's (2018) findings differed, suggesting divergent results in both short-run and long-run periods. The study was based on using nine proxies of sentiment on the volatility of oil prices. The result revealed a 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 the price volatility of precious metals and market sentiments. The result affirms that investor sentiment aggravates volatility in both silver and gold prices at the time of worldwide financial crunch and thereafter. Smales and Lucey (2019) departon the use of a new method of measuring investor sentiment, such as an index developed on financial stress by the Saint Louis Federal Reserve. The outcome suggested that sentiment impacts the liquidity of the commodities (silver and gold) and other instruments at the time when sentiment is experienced at the lowest. Ji et al. (2019) review the spillover effect between the sentiment index of investors and oil prices. The index was derived from investors' positions regarding swap deals, producers, risk-takers, and lesser dealers. The study established that sentiment intensifies oil price volatility.

Li et al. (2019) examine the role of sentiment on the global oil price market. The study found that sentiment has a high predictive content on the future oil price of West Texas Instrument. The study also confirms that other oil price measures, such as Brent's future oil price, WTI spot price, and Dubai's spot price, are negatively impacted by sentiment. Shahzad et al. (2019) contend that crude oil prices impact investors' sentiment. This suggests that investment managers can establish appropriate policies that disaggregate between the positive and negative partial sum of the oil price. Huang et al. (2019) advance the frontier of knowledge by confirming that sentiment sways the Price of gold only when the threshold established is exceeded. This outcome was noticed in the period before the financial crisis of 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 at are not straightforward with regard to the relationship. Rather, it reports varied outcomes and indecisive evidence. A few previous studies have employed the Thomson Reuters approach to measure sentiment in relation to commodity return. Also, previous studies have focused on certain commodities like gold, crude oil, and metal but have given less attention to other unavoidable commodities. This justifies the motive for the study, which focuses on the Russia-Ukraine war and returns 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 a sentiment index using search keywords related to the Ukraine War; second, we test the prospect for commodity returns with the use of a model that accommodates 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.

3. 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 the sentiment index is used to proxy for the predictor. Both the predicted and predictor series were generatedfrom the database of investing.com (www.investing.com) and Google trend search engine for the period from February 24, 2022 (the commencement date of the current Russia-Ukraine war) to July 31, 2024.We generated a returns series from the global commodity prices. The keywords used to generate the sentiment index were carefully selected from gmfus.org, which summarises major and relevant keywords related to 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 'Wheat' We employed Principal Component Analysis (PCA) in generating the sentiments index. In addition, we normalized the score in line with Olubusoye et al. (2021) and Salisu et al. (2021).

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

In order to capture salient data features exhibited in the exploratory outcomes, we adopt Westerlund and Narayan's (2015) autoregressive distribution lag (ARDL) model, which shares features of the FeasibleGeneralized Least Squares(FGLS) regression. The model accommodates violations 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:

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

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

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

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

h denotes a period of

forecast, while $(rt+h\text{-}r2t+h)^2$ and $(rt+h-rt+h)^2$ depicts the squared errors of both the 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 outperforms the benchmark.

4. Results

We present the outcomes of the predictive series in Table 3 (see the Appendix), using the full sample series and 75% of the full sample series for the forecast evaluation outcomes. The outcomes revealed that the sentiment index has predictive content on commodity returns, with a noticeable positive relationship with all commoditiesexcept 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 intensified the market returns for all commodities studied, with the exception of 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, soybeans, and platinum appeared to be negatively responsive to the Russian-Ukraine War. Perhaps this is due to the level of response of another exporter at the global level to fill the gap in the supply side. Our model outperforms the benchmark at both in-sample and out-of-sample horizons. The returns of the commodity market are positively influenced by the sentiment index.

5. Robustness Check

We confirmed the main analysis result using weekly data series along with the estimation procedures 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).This suggests that public sentimentssignificantly promote commodity returns as the region continuously experiences war, except for Gold, Natural Gas, Soybean and platinum. These outcomes align with the main estimation outputs. The Clark and West test procedure maintains outperformance in the commodity market and forecast horizons. As such, our outcomes are robust to the forecast horizon.

6. Conclusion

We studied the return-sentiment index for thirty commodities using the Westerlung and Narayan model, which accommodates all data salient features. Using Principal Component Analysis, we examined the sentiment index's predictive nature on market returns on selected commodities. Daily and weekly data were used for the main analysis and robustness check. The out-of-sample forecast results confirm the potential of the sentiment 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.

References

1. *Anayi, L., Bloom, N., Bunn, P., Mizen, P., Thwaites, G., & Yotzov, I. (2022). The impact of the war in Ukraine on economic uncertainty. VoxEU. Org, 16. cep r.org*
2. *Azeez, K. A., Hambolu, V. O., Okwu, A. T., & Agboola, B. A. (2024). Russia-Ukraine War and Price Volatility of Global Commodities: The Role of Public Sentiments. Energy Research Letters, 4(Early View).*
3. *Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2017). The effect of investor sentiment on gold market return dynamics: Evidence from a nonparametric causality-in-quantiles approach. Resources Policy, 51, 77-84.*
4. *Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. Journal of Empirical Finance, 11(1), 1–27.*
5. *Chepeliev, M., Hertel, T. W., & van der Mensbrugghe, D. (2022). Cutting Russia's fossil fuel exports: Short-term pain for long-term gain. GTAP Working Paper.*
6. *De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy, 98(4), 703-738.*
7. *Gong, X., Zhang, W., Wang, J., & Wang, C. (2022). Investor sentiment and stock volatility: New evidence. International Review of Financial Analysis, p. 80, 102028.*
8. *Han, S., Lerner, J. S., & Keltner, D. (2007). Feelings and consumer decision making: The appraisal-tendency framework. Journal of Consumer Psychology, 17(3), 158-168.*
9. *Huang, D., Lehkonen, H., Pukthuanthong, K., & Zhou, G. (2018). Sentiment across asset markets. Available at SSRN 3185140.*
10. *Huang, X., Jia, F., & Xu, X. (2019). The threshold effect of market sentiment and inflation expectations on gold Price. Resources Policy, 62, 77-83.*
11. *Ji, Q., & Guo, J. F. (2015). Market interdependence among commodity prices is based on information transmitted on the Internet. Physica A: Statistical Mechanics and its Applications, 426, 35-44.*
12. *Ji, Q., & Guo, J. F. (2015). Oil price volatility and oil-related events: An Internet concern study perspective. Applied Energy, 137, 256-264.*
13. *Ji, Q., Li, J., & Sun, X. (2019). Measuring the interdependence between investor sentiment and crude oil returns: New evidence from the CFTC's disaggregated reports. Finance Research Letters, 30, 420-425.*
14. *Azeez, K. A., Hambolu, V. O., Okwu, A. T. & Agboola, B. A. (2024). Russia-Ukraine war and price volatility of global commodities:The role of public sentiments. Energy Research Letters, 5(2), 1-6.*

15. *Li, S., Zhang, H., & Yuan, D. (2019). Investor attention and crude oil prices: Evidence from nonlinear Granger causality tests. Energy Economics, 84, 104494.*
16. *Maghyereh, A., Abdoh, H., & Al-Shboul, M. (2020). The impact of sentiment on commodity return and volatility. Review of Pacific Basin Financial Markets and Policies, 23(04), 2050034.*
17. *Olubusoye, O. E., Ogbonna, A. E., Yaya, O. S., & Umolo, D. (2021). An information-based index of uncertainty and the predictability of energy prices. International Journal of Energy Research, 45(7), 10235-10249.*
18. *Pan, W. F. (2018). Sentiment and asset price bubble in the precious metals markets. Finance Research Letters, pp. 26, 106–111.*
19. *Price, S. M., Seiler, M. J., & Shen, J. (2017). Do investors infer vocal cues from CEOs during quarterly REIT conference calls? The Journal of Real Estate Finance and Economics, 54(4), 515-557.*
20. *Qadan, M., & Nama, H. (2018). Investor sentiment and the Price of oil. Energy economics, 69, 42-58.*
21. *Rao, T., & Srivastava, S. (2013, May). Modelling movements in oil, gold, forex and market indices using search volume index and Twitter sentiments. In Proceedings of the 5th annual ACM Web Science conference (pp. 336-345).*
22. *Salisu, A. A., & Isah, K. O. (2018). Predicting US inflation: Evidence from a new approach. Economic Modelling, 71, 134–158.*
23. *Salisu, A. A., Ademuyiwa, I., & Isah, K. O. (2018). Revisiting the forecasting accuracy of Phillips curve: the role of oil price. Energy Economics, 70, 334-356.*
24. *Salisu, A. A., Ogbonna, A. E., Oloko, T. F., & Adediran, I. A. (2021). A New Index for Measuring Uncertainty Due to the COVID-19 Pandemic. Sustainability 2021, 13, 3212.*
25. *Salisu, A. A., Swaray, R., & Oloko, T. F. (2019). Improving the predictability of the oil–US stock nexus: The role of macroeconomic variables. Economic Modelling, 76, 153-171.*
26. *Shahzad, S. J. H., Bouri, E., Raza, N., & Roubaud, D. (2019). Asymmetric impacts of disaggregated oil price shocks on uncertainties and investor sentiment. Review of Quantitative Finance and Accounting, 52, 901-921.*
27. *Smales, L. A., & Lucey, B. M. (2019). The influence of investor sentiment on the monetary policy announcement liquidity response in precious metal markets. Journal of International Financial Markets, Institutions and Money, 60, 19-38.*
28. *Smyth, R., & Narayan, P. K. (2018). What do we know about oil prices and stock returns? International Review of Financial Analysis, pp. 57, 148–156.*
29. *Westerlund, J., & Narayan, P. K. (2015). Testing for Predictability in Conditionally Heteroskedastic Stock Returns. Journal of Financial Econometrics, 13(2), 342–375.*

Appendix A: Summary of the results of 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

The 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)

Subscripts "a" "b" and "c" suggest that the Augmented Dickey-Fuller Test (ADF) of unit root regression is a model with none, constant, constant and trend. Conditional heteroscedasticity and auto-correlation tests 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, is 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 columns 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, is 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 columns 4 to 7 are the statistics results of Clark and West

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