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Impact of media hype and fake news on commodity futures prices: A deep learning approach over the COVID-19 period

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ABSTRACT

We investigate the reactions of eight commodity futures to media hype and fake news during COVID-19, utilising the Ravenpack news database, along with deep learning algorithms. Results identify a significant impact on commodity prices of media hype and fake news, with this reaction amplified during COVID-19. Compared to alternative deep learning algorithms, bi-directional long-short-term memory is adaptive to forecasting the returns of the commodity futures contracts with lower mean absolute error and root mean square error. Findings, confirmed by Diebold-Mariano testing, as well as alternative data partitioning, show commodity markets are susceptible to fake news and media hype.

1. Introduction

At least since De Bondt and Thaler (1985), finance scholarship has been interested in how asset classes respond to information signals (Defond and Zhang, 2014; Miwa, 2019).[1] Studies have focused on equity markets (Hu et al., 2021; Goodell et al., 2022) and the cryptocurrency market (Li et al., 2021). However, commodity markets and associated futures contracts have received limited attention concerning reactions to media despite being susceptible to uncertainties. The price informativeness of commodity markets reflects the role of concerned agents in physical commodity trading as vehicles of information (Cheng and Xiong, 2014; Eckwert and Zilcha, 2001; Goldstein and Yang, 2017).

While the relationship between cryptocurrencies and investor attention has received much focus (Dastgir et al., 2019; Shen et al., 2019; Zhang and Wang, 2020; Li et al., 2021), as the role of social media in distorting equity markets, particularly regarding Reddit and GameStop (Lyócsa et al., 2022; Klein, 2022; Umar et al., 2021), the role of social media in influencing commodity markets has so far been only lightly investigated, despite this topic presenting uncertainty about expectations. On the one hand, commodities are driven by highly professional, informed traders comparatively better able than equity markets to discern and quickly process genuine

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[1] See also Banerjee et al., 2023.

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information (Ashok et al., 2022). On the other hand, commodities reflect changes in uncertainty and geopolitical sentiments (Corbet et al., 2020) and are expected to be vulnerable to news trends.

Literature on commodity prices has typically focused on speculative activity and market efficiency (Charles et al., 2015; Dimpfl et al., 2017; Bohl et al., 2020), excess comovement (Ohashi and Okimoto, 2016; Le Pen and Sévi, 2018), and the influence of macroeconomic and news sentiments (Elder et al., 2012; Miao et al., 2014; Smales, 2017; Akyildirim et al., 2022). Studies have also examined the relationship between the financial crisis and commodity price imbalances (Caballero et al., 2008). However, less literature examines the response of commodity prices to a sudden spurt in new information or uncertainty shocks caused by fake news or media hype.

News certainly moves markets (Banerjee et al., 2020; Banerjee and Pradhan, 2021), even to spike trading activity (Soroka, 2006; Wei and Zhou, 2016). Certainly, fake news and media hype can be considered possible catalysts of abnormal market fluctuations and investor overreactions. Further, we consider this an important focus of investigation as the financialisation of commodity markets has increased financial uncertainties (Adams and Glück, 2015; Huynh et al., 2020). Accordingly, as commodity markets are impacted by fake news, so too is overall financial uncertainty impacted.[2]

Further, excessive speculative trades in these markets may dampen informational efficiency, and in periods of great uncertainty, they can make the markets noisy and fluctuating (Bohl et al., 2020; Moews and Ibikunle, 2020). Overall, exploring the impact of fake and media-hype news on commodity markets is important.

Further, as the onset of COVID-19 engendered uncertainty in global markets, this period affords a special opportunity to investigate the role of media 'hype' on commodity futures.[3] Uncertainty might impact futures markets differently than spot markets as information assimilation likely differs between spot and futures markets (Xu and Wan, 2015; Banerjee et al., 2020; Banerjee, 2021; Banerjee et al., 2021). Accordingly, this study uses the futures market to test the impact of media hype and fake news on commodity prices. In doing so, we utilise a deep learning approach to predict the behaviour of commodity futures returns during the COVID-19 pandemic.

Following Joo and Choi (2018), we use a bidirectional long short-term memory (BDLSTM). This technique combines a recurrent bidirectional network with long short-term memory (LSTM). As research supports that LSTM models outperform ARIMA in forecasting (Namin and Namin, 2018; Jia et al., 2019), this combination adds to the advantage of LSTM consideration of feedback for the next layer (Althelaya et al., 2018). Results show that the bi-directional LSTM is adaptive to forecasting returns of commodity futures contracts with lower mean absolute errors (MAE) and root mean square errors (RMSE). Further, Diebold-Mariano testing confirms the robustness of our findings.

The paper's conclusions highlight the commodity market's inefficiencies and overreaction to fake and media hype news. The paper has critical implications for different market participants by highlighting the risk and complexity in strategy building for fund managers. The second signal is for policymakers to devise regulations to avoid rigging and excessive speculations, which are detrimental to market efficiencies. The remainder of this paper is as follows: Section 2 presents the data and descriptive statistics. Section 3 details our methodology. Section 4 presents the results. Section 5 concludes.

2. Data and descriptive statistics

We test the predictive power of bi-directional LSTM to forecast the returns of eight commodity futures contracts, gold, silver, copper, lead, nickel, zinc, crude oil, and natural gas traded in the Multi Commodity Exchange (MCX) and the National Commodity Exchange (NCDEX) in India. The study period coincides with the COVID-19 crisis. We check whether the spread of fake and media-hype news caused any change in the dynamics of these contracts, using daily closing prices from January 01, 2020, to May 31, 2021. All the commodity futures prices are in the Indian rupee and extracted from the Bloomberg terminal. COVID-19 news is from the Ravenpack database.[4]

We choose the futures market against the cash market as in Indian markets, and the price assimilation happens in the futures market and spillover to the spot market (Banerjee and Padhan, 2017; Banerjee, 2021). Moreover, for the current study, we choose precious metals like gold and silver and base metals of copper, lead, nickel, and zinc, and lastly, energy contracts of crude oil and natural gas for their criticality for hedging and portfolio diversification abilities and serving as crucial raw materials for industrial usage (see Kang et al., 2017; Chen and Tongurai, 2021; Liu et al., 2023). Moreover, these contracts are mostly traded instruments in both of these exchanges. Lastly, we want to restrict the analyses only to the first two waves of the COVID-19 pandemic.

Table 1 presents the descriptive returns statistics for all eight series, whereas Figs. A1 and A2 present the price and return series, respectively, for all the futures contracts. Prices show a constantly rising trend, while returns display extreme moments during the sudden increase in cases of COVID-19 in India. Table 2 reports unit root tests for stationarity. Optimal lag length selection is based on the Akaike Information Criterion (AIC). Tests reveal stationarity for all the return series.

Table 3 presents descriptive statistics of media hype and fake news sentiment index. While media hype news has a higher standard deviation, the fake news index shows excessive skewness and kurtosis. Fig. 1 presents the media hype and fake news index during the study period. Clearly, the flow of media hype and fake news grew as India experienced the first wave of COVID-19 (March and April 2020).

[2] Also see Banerjee et al., (2022)

[3] The impact of COVID-19 on different markets and asset classes see Banerjee et al. (2022), Banerjee (2022).

[4] RavenPack develops and distributes structured data products from unstructured content. The firm is the leader in news analytics which involves turning news into numbers so they can be easily processed and consumed by quantitative models and trading programs.

Table 1
Descriptive statistic of commodity returns.

Metal	Mean	Median	Stdev	Skewness	Kurtosis
Gold	0.0012	0.0015	0.0088	-0.0477	-0.3276
Silver	0.0016	0.0020	0.0169	-0.1493	0.2364
Copper	0.0021	0.0019	0.0106	0.0405	0.1640
Lead	0.0005	0.0000	0.0138	-0.0001	0.5645
Nickel	0.0011	0.0012	0.0129	-0.0790	-0.2367
Zinc	0.0012	0.0025	0.0119	-0.2236	-0.2803
Crude Oil	0.0010	0.0017	0.0265	-0.2501	1.6003
Natural Gas	-0.0000	-0.0016	0.0284	0.1720	0.1042

Note: the descriptive statistics are for the entire study period, from January 01, 2020, to May 31, 2021.

Table 2
Unit root tests for returns.

Metal	ADF test	PP test
Gold	-6.8228***	-18.1460***
Silver	-7.4812***	-17.9110***
Copper	-6.0584***	-17.9100***
Lead	-6.8023***	-22.1070***
Nickel	-6.4502***	-20.8050***
Zinc	-6.0357***	-19.4720***
Crude Oil	-6.8053***	-18.4830***
Natural Gas	-7.9994***	-19.3460***

Note: ***, **, * significance at 1, 5, and 10 % respectively.

Table 3
Descriptive statistics of the news index.

Sentiment index	Mean	Median	Stdev	Skewness	Kurtosis
Media_hype news	40.1420	41.7550	16.3219	-0.7369	0.6074
Fake news	0.8981	0.5900	1.0096	3.9351	25.7905

Note: the descriptive statistics are for the entire study period, from January 01, 2020, to May 31, 2021.

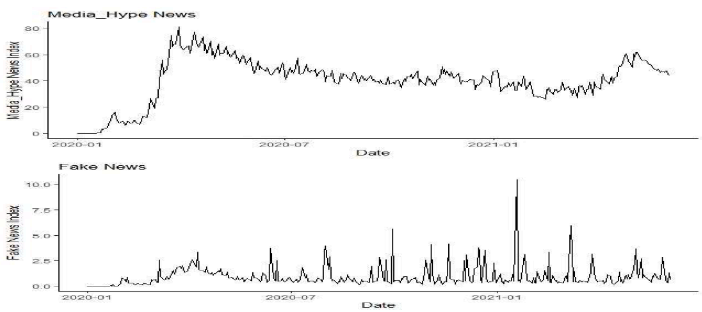

Fig. 1. Media_hype and fake news index.
Note: Fig. 1 shows the flow of media_hype and fake news for the entire study period, from January 01, 2020, to May 31, 2021.

3. Methodology

Recurrent neural networks (RNNs) are a class of artificial neural networks (ANNs) used for financial time series forecasting. The feedback connection between units is connected, forming a directed cycle that allows the signal to travel forward-backwards. In RNN, the representation of information is by the values of synaptic connections between input, hidden, and output layers of neurons. However, RNNs suffer from critical fast gradient descent and convergent problems. To overcome this issue, Schuster and Paliwal (1997) introduce a bidirectional recurrent neural network (BRNN), which extends RNN by introducing additional hidden layers where data are placed in the opposite, negative direction. This hidden layer maintains a hidden state, which can be defined as follows:

$$\overrightarrow{h}_t = \sigma\left(W_{x\overrightarrow{h}} x_t + W_{\overrightarrow{h}\overrightarrow{h}} \overrightarrow{h_{t-1}} + b_{\overrightarrow{h}}\right) \quad (1)$$

For the positive direction and

$$\overleftarrow{h}_t = \sigma\left(W_{\overleftarrow{xh}} x_t + W_{\overleftarrow{hh}} \overleftarrow{h}_{t+1} + b_{\overleftarrow{h}} \right) \tag{2}$$

for the negative direction, W_{xh} represents the weight matrix between input and hidden layers, x_t represents the input vector, W_{hh} represents the weight matrix between two hidden states, b_x represents the bias of the hidden layer, and σ represents the activation function. The output layer is represented as follows:

$$y_t = \sigma\left(W_{\overleftarrow{hy}} \overrightarrow{h}_t + W_{\overleftarrow{hy}} \overleftarrow{h} + b_y \right) \tag{3}$$

where $W_{\overrightarrow{hy}}$ represents the weight matrix between hidden and output layers, while $W_{\overleftarrow{hy}}$ represents the same but opposite direction, and *by* is the bias of the output layer.

A critical issue with BRNN is that it is not fully optimal for complex and noisy financial time series as it suffers from vanishing or exploding gradients. This problem is addressed with bi-directional LSTM meant to suffice the gradient problem by introducing additional gates and using the contextual relation of forwarding and backward time direction in financial time series, thus improving prediction accuracy (Graves et al., 2005). Bi-directional LSTM differs in architecture from the RNN in terms of hidden layers. Bi-directional LSTM has an LSTM cell as a hidden layer, comprising three gates: an input gate, a forget gate, and an output gate. Thus, combining BRNN with LSTM cells can model more complex time dynamics and deal with long-term dependencies. The mathematical representation of LSTM is as follows:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f \right) \tag{4}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{5}$$

$$o_t = \sigma(W_0 x_t + U_0 h_{t-1} + b_i) \tag{6}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh (W_c x_t + U_c h_{t-1} + b_c) \tag{7}$$

$$h_t = o_t \odot \tanh(C_t) \tag{8}$$

In Eqs. (4)–(8) f_t, i_i and o_t represent forget, input, and output gates; *W* and *U* represent the weight matrices; *b* is a bias vector; $\sigma_j$is a sigmoid activation function; tan*h* is the hyperbolic tangent function; C_t is the cell output state; h_t is the layer output; and operator ʘ is the element-wise product of the vectors.

Eqs. (1)–(7) can be used to estimate the forward and backward layer outputs. The architecture of bi-directional LSTM is presented in Fig. 2. Thus, the backwards layer output sequence is estimated using inputs in a positive sequence, the forward layer output sequence, and reversed inputs. Each element in the output vector of the bi-directional LSTM layer can be calculated as follows:

$$y_t = \sigma\left(\overrightarrow{h_t} \, h_t^{\leftarrow} \right) \tag{9}$$

where two output sequences are combined by utilising the σ function. Past studies have shown that bidirectional networks are more adaptive than unidirectional networks. Furthermore, dropout can be implemented on hidden layers to prevent the network from overfitting.We use bi-directional LSTM to predict price movements of futures contracts of commodities during COVID-19. Like LSTM, we have also used the Gated Recurrent Unit (GRU) networks, which are designed to avoid the vanishing and exploding gradient problems with RNNs. GRUs perform similarly to LSTM in most tasks, to show the superiority in the prediction ability of the Bi-directional LSTM framework.

Additionally, we use two evaluation criteria to evaluate the performance metrics bi-directional LSTM to check prediction accuracy. These performance metrics are mean absolute error (MAE) and root mean square error (RMSE). These are defined are as follows:

$$MAE = \frac{1}{N} \sum_{t=1}^{n} |y_t - \hat{y}_t| \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (y_t - \hat{y}_t)^2} \tag{11}$$

where $y_t$is the true signal and $\hat{y_t}$ is the forecasted signal. Smaller values of performance measures defined by Eqs. (10) and (11) imply better forecasting performance of the model.

4. Empirical results

We use bi-directional LSTM, LSTM and GRU to show the impact of fake news and the media hype news index on the returns of the

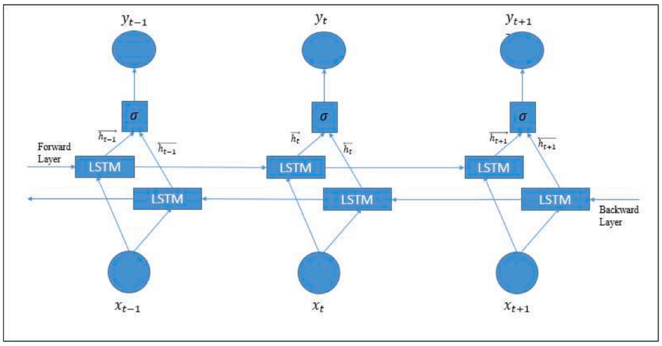

Fig. 2. Bi-directional LSTM architecture.

Note: The architecture of an unfolded BDLSTM with three steps (x: input vector; $\overrightarrow{h}$ hidden state for the positive direction; $\overrightarrow{h}$ hidden state for the negative direction; σ: function used to combine two output sequences; y output vector)

futures prices. These modelings are trained for examining news in isolation to examine the impact on the return series. To check the prediction accuracy, we use the performance metrics of the modelling by estimating the mean absolute error (MAE) and root mean square error (RMSE) of each model. Moreover, we considered the different categories in commodities to avoid overfitting and underfitting, and the datasets partitioned as 80:20 to train, validate and test model performance.

Table 4 presents the MAE and RMSE values of all three models of GRU, LSTM, and bi-directional LSTM. Results indicate MAE and RMSE of all the models are less than the threshold of 10 %. Each news category is factored into the models to improve prediction of impact. Considering competing models of GRU, LSTM, and bi-directional LSTM, bi-directional LSTM is the best model to predict the behaviour of the return of the futures of all the commodities. However, when each news category is factored into the model, the difference in MAE and RMSE values is marginal.

Thus our proposed bi-directional LSTM deep learning approach model performs well in predicting and capturing the trend in the returns of all sample commodities. Results suggest that commodity prices tended to overreact to the release of media hype and fake news about the COVID-19 pandemic. Further, we use Diebold-Mariano (DM) testing to examine the accuracy of our proposed bi-directional LSTM deep learning algorithm against the other two algorithms. DM testing demonstrates that our proposed model outperforms other competing models in forecasting effectiveness regarding the RMSE loss function.[5]

Further, to check the robustness of our result from another aspect, we apply different partition ratios and clusters during the pandemic period. Results are consistent with our baseline findings.

5. Conclusions

Literature has long been interested in the responses of assets to information, with studies mainly focusing on equity and cryptocurrency markets. However, commodity and futures markets have received less scholarly attention regarding how they respond to information and changes in uncertainty, even though commodities are closely linked to macroeconomic uncertainties.

From one perspective, commodities are driven by highly professional informed traders comparatively better able than equity markets to discern and quickly process genuine information, while from an alternative view, commodities reflect changes in uncertainty and geopolitical sentiments and so are likely responsive to media hype.

We examine the reactions of commodity futures to media hype and fake news, focusing on the period of uncertainty corresponding to COVID-19. We use deep learning models and a state-of-the-art Ravenpack database to predict commodity returns. We find that commodity futures prices react to media hype and fake news with higher frequency and magnitude of reaction during COVID-19. Reactions differ for metals versus energy commodities. Additionally, compared to alternatives, we evidence that bi-directional LSTM modelling is better at capturing the behaviour of commodities to fake news and media hype. Results suggest commodity markets have exploitable inefficiencies despite the identified ability of physical traders to enhance the superior information processing of commodity markets. This study motivates future research. Future research should investigate further commodity market behaviour following releases of fake and media hype. Future research can also examine the commonality of trends in these markets concerning the impact of fake and media news on commodity markets.

Our findings have implications for investors, portfolio managers, and policymakers. For investors and portfolio managers, price overreaction to media hype news implies that commodity markets are inefficient. For policymakers, results suggest that governments should diligently monitor against price manipulation, especially post shocks. As results indicate commodity markets are sensitive to news of fake categories and media hype, these markets may be subject to hoarding and price rigging, impacting market dynamics. Additionally, the hedging abilities of some precious metals can be impaired during crises.

[5] For brevity, results not reported, but shared upon upon reasonable request.

Table 4
Mean absolute and root mean square values of the models.

Metals	Media_hype new index					
	Mean absolute error			Root mean square error		
	GRU	LSTM	Bi_LSTM	GRU	LSTM	Bi_LSTM
Gold	0.0059	0.0058	0.0057	0.0074	0.0073	0.0072
Silver	0.0110	0.0109	0.0108	0.0142	0.0141	0.0140
Copper	0.0089	0.0088	0.0087	0.0106	0.0105	0.0105
Lead	0.0115	0.0115	0.0113	0.0140	0.0139	0.0138
Nickel	0.0158	0.0159	0.0157	0.0206	0.0205	0.0205
Zinc	0.0098	0.0098	0.0097	0.0120	0.0120	0.0119
Crude Oil	0.0162	0.0157	0.0157	0.0222	0.0219	0.0219
Natural Gas	0.0157	0.0159	0.0157	0.0206	0.0206	0.0205
Metals	Fake news index					
	Mean absolute error			Root mean square error		
	GRU	LSTM	Bi_LSTM	GRU	LSTM	Bi_LSTM
Gold	0.0058	0.0058	0.0057	0.0072	0.0072	0.0071
Silver	0.0108	0.0108	0.0106	0.0141	0.0141	0.0139
Copper	0.0093	0.0093	0.0093	0.0115	0.0114	0.0113
Lead	0.0115	0.0115	0.0114	0.0140	0.0140	0.0139
Nickel	0.0117	0.0117	0.0116	0.0140	0.0139	0.0138
Zinc	0.0102	0.0101	0.0101	0.0125	0.0124	0.0123
Crude Oil	0.0165	0.0164	0.0163	0.0224	0.0224	0.0222
Natural Gas	0.0159	0.0159	0.0158	0.0203	0.0202	0.0201

Note: the mean absolute error (MAE) and root mean square error are calculated based on Eqs. (10) and 11.

Author statement

The authors affirm that this work is an original work that is not published or under consideration elsewhere and is a genuine collaboration.

Data availability

Data will be made available on request.

Appendix

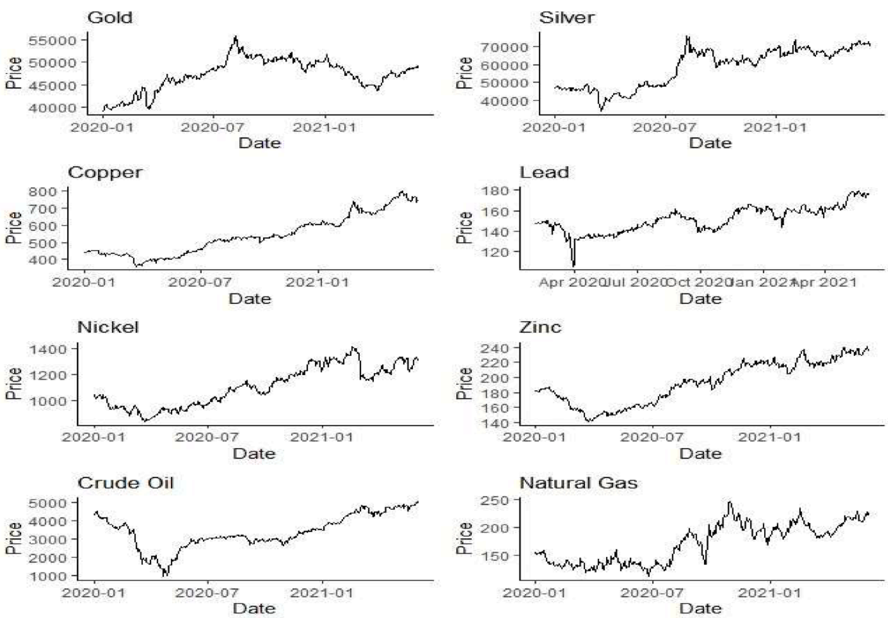

Fig. A1. Prices of different future contracts.
Note: Fig. A1 presents the prices of the future contracts for the entire study period, from January 01, 2020, to May 31, 2021.

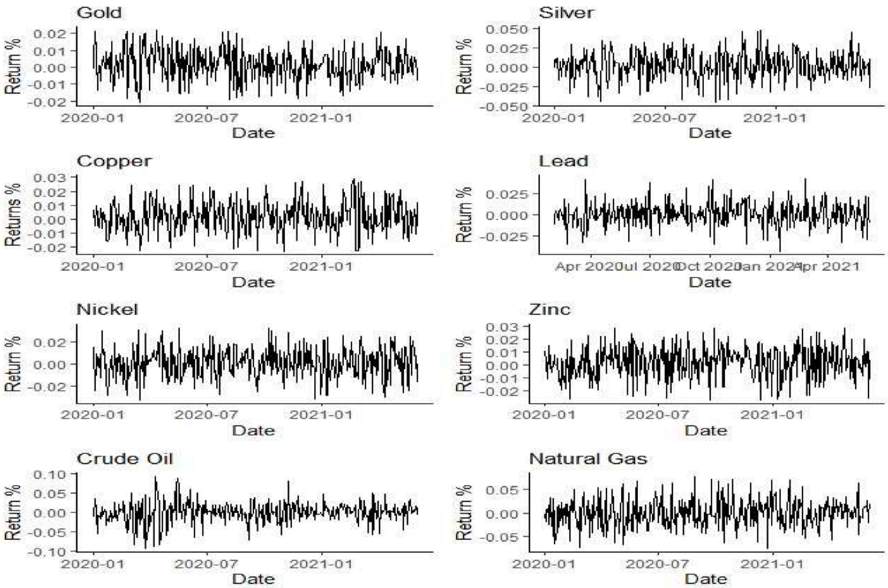

Fig. A2. Returns of the future contracts.
Note: Fig. A2 presents the returns of the future contracts for the entire study period, from January 01, 2020, to May 31, 2021.

References

Adams, Z., Glück, T., 2015. Financialisation in commodity markets: a passing trend or the new normal? J. Bank. Financ. 60, 93–111.
Akyildirim, E., Cepni, O., Pham, L., Uddin, G.S., 2022. How connected is the agricultural commodity market to the news-based investor sentiment? Energy Econ. 113, 106174.
Althelaya, K.A., El-Alfy, E.S.M., Mohammed, S., 2018. Evaluation of bidirectional LSTM for short-and long-term stock market prediction. In: 2018 9th international conference on information and communication systems (ICICS. IEEE, pp. 151–156.
Ashok, S., Corbet, Dhingra, S.D., Goodell, J.W., Kumar, S., Yadav, M.P, 2022. Are energy markets informationally smarter than equity markets? Evidence from the COVID-19 experience. Finance Res. Lett. 47, 102728.
Banerjee, A.K., & Padhan, P.C. (2017). Herding behavior in futures market: an empirical analysis from India. *Available at SSRN 3014561*.
Banerjee, A.K., Pradhan, H.K., Tripathy, T., Kanagaraj, A., 2020. Macroeconomic news surprises, volume and volatility relationship in index futures market. Appl. Econ. 52 (3), 275–287.
Banerjee, A.K., 2021. Futures market and the contagion effect of COVID-19 syndrome. Finance Res. Lett. 43, 102018.
Banerjee, A.K., Pradhan, H.K., 2021. Intraday analysis of macroeconomic news surprises, and asymmetries in Indian benchmark bond. Finance Res. Lett. 45, 102135.
Banerjee, A.K., Dionisio, A., Pradhan, H.K., Mahapatra, B., 2021. Hunting the quicksilver: using textual news and causality analysis to predict market volatility. Int. Rev. Financ. Anal. 77, 101848.
Banerjee, A.K., Akhtaruzzaman, M., Dionisio, A., Almeida, D., Sensoy, A., 2022. Nonlinear nexus between cryptocurrency returns and COVID-19 news sentiment. J. Behav. Exp. Finance 36, 100747.
Banerjee, A.K., 2022. You sneeze, and the markets are paranoid: the fear, uncertainty and distress sentiments impact of the COVID-19 pandemic on the stock–bond correlation. J. Risk Finance 23 (5), 652–668.
Banerjee, A.K., Pradhan, H.K., Sensoy, A., Goodell, J.W., 2023. Assessing the US financial sector post three bank collapses: signals from fintech and financial sector ETFs. Int. Rev. Financ. Anal., 102995
Bohl, M.T., Pütz, A., Sulewski, C., 2020. Speculation and the informational efficiency of commodity futures markets. J. Commod. Markets, 100159.
Caballero, R.J., Farhi, E., Gourinchas, P.O., 2008. *Financial crash, commodity prices and global imbalances* (No. w14521). Natl Bureau Econ. Res.
Charles, A., Darné, O., Kim, J.H., 2015. Will precious metals shine? A market efficiency perspective. Int. Rev. Financ. Anal. 41, 284–291.
Cheng, I.-H., Xiong, W., 2014. Financialisation of commodity markets. Ann. Rev. Financ. Econ. 6 (1), 419–441.
Chen, X., Tongurai, J., 2021. Cross-commodity hedging for illiquid futures: evidence from China's base metal futures market. Glob. Finance J. 49, 100652.
Corbet, S., John, W., Goodell, J.W., Günay, S., 2020. Co-movements and spillovers of oil and renewable firms under extreme conditions: new evidence from negative WTI prices during COVID-19. Energy Econ. 92, 104978.
Dastgir, S., Demir, E., Downing, G., Gozgor, G., Lau, C.K.M., 2019. The causal relationship between Bitcoin attention and Bitcoin returns: evidence from the Copula-based Granger causality test. Finance Res. Lett. 28, 160–164.
De Bondt, W.F., Thaler, R., 1985. Does the stock market overreact? J. Finance 40 (3), 793–805.
DeFond, M., Zhang, J., 2014. A review of archival auditing research. J. Account. Econ. 58 (2–3), 275–326.
Dimpfl, T., Flad, M., Jung, R.C., 2017. Price discovery in agricultural commodity markets in the presence of futures speculation. J. Commod. Markets 5, 50–62.
Eckwert, B., Zilcha, I., 2001. The value of information in production economies. J. Econ. Theory 100 (1), 172–186.
Elder, J., Miao, H., Ramchander, S., 2012. Impact of macroeconomic news on metal futures. J. Bank. Financ. 36 (1), 51–65.
Goldstein, I., Yang, L., 2017. Information disclosure in financial markets. Ann. Rev. Financ. Econ. 9, 101–125.
Goodell, J.W., Kumar, S., Xiao Li, X., Pattnaik, D., Sharma, A, 2022. Foundations and research clusters in investor attention: evidence from bibliometric and topic modelling analysis. Int. Rev. Econ. 82, 511–529.
Graves, A., Fernández, S., Schmidhuber, J., 2005. Bidirectional LSTM networks for improved phoneme classification and recognition. In: International Conference on Artificial Neural Networks. Springer, Berlin, Heidelberg, pp. 799–804.
Hu, Y., Li, X., Goodell, J.W., Shen, D., 2021. Investor attention shocks and stock co-movement: substitution or reinforcement? Int. Rev. Financ. Anal. 73, 101617.
Huynh, T.L.D., Burggraf, T., Nasir, M.A., 2020. Financialisation of natural resources & instability caused by risk transfer in commodity markets. Resour. Policy 66, 101620.

Jia, M., Huang, J., Pang, L., Zhao, Q., 2019. Analysis and research on stock price of LSTM and bidirectional LSTM neural network. In: 3rd International Conference on Computer Engineering, Information Science & Application Technology. Atlantis Press, pp. 467–473. ICCIA 2019.
Joo, I.T., Choi, S.H., 2018. Stock prediction model based on bidirectional LSTM recurrent neural network. J. Korea Instit. Inform. Electron. Commun. Technol. 11 (2), 204–208.
Kang, S.H., McIver, R., Yoon, S.M., 2017. Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. Energy Econ. 62, 19–32.
Klein, T., 2022. A note on GameStop, short squeezes, and autodidactic herding: an evolution in financial literacy? Finance Res. Lett. 46, 102229.
Le Pen, Y., Sévi, B., 2018. Futures trading and the excess comovement of commodity prices. Rev. Financ. 22 (1), 381–418.
Li, Y., Goodell, J.W., Shen, D., 2021. Comparing search-engine and social-media attentions in finance research: evidence from cryptocurrencies. Int. Rev. Econ. 75, 723–746.
Liu, C., Zhang, X., Zhou, Z., 2023. Are commodity futures a hedge against inflation? A Markov-switching approach. Int. Rev. Financ. Anal. 86, 102492.
Lyócsa, Š., Eduard Baumöhl, E., Tomáš Výrost, T., 2022. YOLO trading: riding with the herd during the GameStop episode. Finance Res. Lett. 46, 102359.
Moews, B., Ibikunle, G., 2020. Predictive intraday correlations in stable and volatile market environments: evidence from deep learning. Physica A 547, 124392.
Miao, H., Ramchander, S., Zumwalt, J.K., 2014. S&P 500 index-futures price jumps and macroeconomic news. J. Futures Markets 34 (10), 980–1001.
Miwa, K., 2019. Trading hours extension and intraday price behavior. Int Rev Econ 64, 572–585.
Namin, S.S., Namin, A.S., 2018. Forecasting economic and financial time series: arima vs. LSTM. Mach. Learn. 119.
Ohashi, K., Okimoto, T., 2016. Increasing trends in the excess comovement of commodity prices. J. Commod. Markets 1 (1), 48–64.
Schuster, M., Paliwal, K.K., 1997. Bidirectional recurrent neural networks. IEEE Trans. Signal Process. 45 (11), 2673–2681.
Shen, D., Urquhart, A., Wang, P., 2019. Does twitter predict Bitcoin? Econ. Lett. 174, 118–122.
Smales, L.A., 2017. Commodity market volatility in the presence of US and Chinese macroeconomic news. J. Commod. Markets 7, 15–27.
Soroka, S.N., 2006. Good news and bad news: asymmetric responses to economic information. J. Polit. 68 (2), 372–385.
Umar, Z., Imran Yousaf, I., Adam Zaremba, A., 2021. Comovements between heavily shorted stocks during a market squeeze: lessons from the GameStop trading frenzy. Res. Int. Bus. Finance 58, 101453.
Wei, J., Zhou, X., 2016. Informed trading in corporate bonds prior to earnings announcements. Financ. Manage. 45 (3), 641–674.
Xu, F., Wan, D., 2015. The impacts of institutional and individual investors on the price discovery in stock index futures market: evidence from China. Finance Res. Lett. 15, 221–231.
Zhang, W., Wang, P., 2020. Investor attention and the pricing of cryptocurrency market. Evol. Inst. Econ. Rev. 17, 445–468.