

Determinant Factors Influencing the Commodity Futures Market Returns in India: A Markov Regime Switching Approach

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Tables 1 to 9 are available in the Supplementary Files section.

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Abstract

The study analyses the factors influencing returns in the Indian commodity futures market. It capitalises on various uncertainty factors, including global economic conditions, global real economic activity indices, the Indian volatility index (VIX), world industrial production, geopolitical risk (GPR), Indian economic policy uncertainty (IEPU), and oil price uncertainty (OPU). Further, the study uses monthly futures closing prices for eleven actively traded agricultural and non-agricultural commodity futures. Next, we consider the monthly uncertainty factors data from January 2012 to March 2024. The study employs the dynamic Markov Regime Switching model and Transition Probability. The results document mixed outcomes in the low- and high-volatility regimes.

Keywords: Commodity futures market, geopolitical risk, volatility index, economic policy uncertainty, regime switching

1. Introduction

In recent years, interest in commodity investment has heightened the relationship between commodity prices and economic factors, thereby increasing the influence of economic factors on commodity prices through the dynamics of global economic interconnectedness (Reboredo and Uddin, 2016). Further, commodity price fluctuations have attracted significant attention from stakeholders, including investors, academics, and policymakers (Tan and Ma 2017). Besides, the global economy has suffered dramatically in recent years due to the frequent occurrence of unprecedented events. For instance, the global financial crisis of 2008, the COVID-19 pandemic, the March 2020 drop in global oil prices, and the Russia-Ukraine war have all increased the risk to stock and commodity markets (Apergis et al., 2020). On the other hand, the financialization of commodity markets began in the early 2000s when a handful of investors flocked to these markets in search of speculative gains and diversification advantages (Dudda et al., 2024). Since financialization has increased comovement among commodities (Basak and Pavlova, 2016; Le Pen and Sevi, 2018), it is difficult to identify the determinants of returns across different commodity futures markets. However, capital market knowledge helps commercial traders improve their hedging choices, enhances the accuracy of market research outlooks, and allows financial investors to assess portfolio diversification more precisely. In addition, investor sentiment, including fundamental, economic, and financial factors, as well as uncertainty, significantly affects stock markets and can be a driver of commodity returns (Shahzad et al., 2017). Hence, investors could verify these drivers before making any investment decisions. The finance literature is well-documented that investor sentiment plays a significant role in stock and commodity markets. For instance, Pindyck and Rotemberg (1990) document that the macroeconomic factors do not explain the comovements of commodities. Most recently, Baumeister et al. (2020) provide an alternative indicator, global economic conditions, to measure energy markets and oil price pressures. Followed by Chiaie et al. (2022), who present evidence that global economic activity mostly explains commodity price movements. Li et al. (2023) identified that the EPU is a significant risk factor influencing the commodity market volatility and price fluctuations. On the one side, increasing geopolitical risk substantially impacts different industries and commodity prices (Bouri et al., 2023). Moreover, the linkage between uncertainty shocks and commodity prices has attracted widespread attention from the academic community. Most studies have confirmed that the uncertainty shocks significantly impact the volatility of commodity prices (Bakas and Triantafyllou, 2018). It is also noted that a handful of studies examine the impact of only individual uncertainty factors on commodity markets (Bakas

and Triantafyllou, 2020; Wang et al., 2015; Xiao et al., 2019). Furthermore, a few studies consider multiple uncertainty factors to investigate the impact of commodity markets (Bakas and Triantafyllou, 2018). Few studies have examined in depth the relationship between economic policy uncertainty and commodity markets (Reboredo and Wen, 2015; Wang, Zhang, Diao and Wu, 2015; Yin and Han, 2014). Several studies have examined the impact of geopolitical risk on commodity markets. Studies such as Baur and Smales (2020), Huang et al. (2021), and Yilanci and Kilci (2021) consider precious metals. Abdel-Latif and El-Gamal (2020) and Alqahtani and Klein (2021) verify the energy commodities.

The present study addresses the important research question: What are the potential drivers of commodity futures markets? To address this question, the present study comprehensively examines the drivers of commodity futures markets in India. It also provides a comprehensive overview of the most important fundamental, financial and uncertainty-related drivers for individual commodity futures. The study also examines the factors that affect the future returns of a wide range of commodities. However, no extensive study has been conducted in India to examine the impact of prominent factors on the commodity futures markets. This chapter investigates the impact of fundamental, financial, and uncertainty factors on commodity futures markets in India. The study considers 11 actively traded commodities on the MCX in India and employs a Markov regime-switching regression model with multiple regimes. Hence, the present study aims to fill this critical research gap by considering the wide range of fundamental, financial, and uncertainty factors to verify their impact on commodity futures market returns in India.

2. Review of Literature

The academic finance literature has been flourishing by exploring newly proposed global risk factors and their impact on equity and commodity markets worldwide. It is also observed that, since the global financial crisis of 2008, many studies have focused mainly on equity and bond markets. In recent years, most studies have considered the global risk factors such as economic policy uncertainty and geopolitical risk. They document that the policy uncertainty and political conditions significantly affect the equity and commodity markets (Antonakakis et al., 2014; Caldaray and Iacoviello, 2016; Kang et al., 2017). Andreasson et al., (2016) examine the dynamic linkage between economic policy uncertainty and commodity futures returns. The study employs both linear and nonlinear causality tests. The study documents that most commodity futures exhibit strong linear and nonlinear unidirectional causality, particularly in agricultural and energy commodities. On the other hand, Reboredo and Uddin (2016) apply quantile regression to

examine the effects of financial stress and policy uncertainty on metal and energy commodities traded in the United States (US). The authors find no association or causality between financial uncertainty and commodity prices. The study documents a substantial association between commodity prices and financial stress in the middle and upper quantiles. Tan and Ma (2017) use a threshold VAR model to examine the impact of macroeconomic uncertainty on commodity prices. The study highlights that positive macroeconomic uncertainty adversely impacts the commodity returns. Besides, Shahzad et al. (2017) and Bahloul et al. (2018) employ a nonparametric causality-in-quantiles method to study the predictability of commodity returns and volatility. They capitalise on news-based uncertainties and conclude that they have a significant effect on predicting commodity returns or commodity volatility. However, Frankel (2008), Anzuini et al. (2015), and Apergis et al. (2020) investigate the impact of the monetary policy shocks on commodity prices. They find considerable effects of monetary policy on commodity prices. Bakas and Triantafyllou (2018) investigate how uncertainty shocks affect commodity price volatility. The study asserts that the uncertainty shocks have a greater effect on energy commodity markets. In addition, Lyu et al. (2021) investigate the impact of economic uncertainty shocks on crude oil futures markets. The authors find a more substantial impact of EPU shocks on bad volatility than on good volatility. Sun et al. (2018) find a weak short-term correlation between economic policy uncertainty and oil prices, but this gradually strengthens over the long run. On the contrary, Hailemariam, Smyth, and Zhang (2019) and Zhang and Yan (2020) report that economic policy uncertainty adversely influences the oil prices during the study period. Qin et al. (2020) report mixed results: economic policy uncertainty both positively and negatively influences oil prices.

Jacks and Stuermer (2018) explore the impact of aggregate commodity demand & supply shocks, storage, and other commodity-specific demand shocks on 12 commodity prices using a structural vector autoregression (SVAR) model. The study results show that the commodity demand shocks substantially dominate supply shocks in influencing commodity prices over long-term horizons. Commodity demand shocks have received more attention than commodity supply shocks. Lee, Lee, and Lien (2019) apply an instrumental-variable quantile regression model to analyse how country risk and financial uncertainty affect energy commodity futures prices. The findings show that the country's risk and financial uncertainty significantly affect the returns of energy commodity futures contracts with different expiry dates. Misecka et al., (2019) employ the Autoregressive Distributed Lag (ARDL) model to examine the effect of attention drivers' behaviour on three internationally traded agricultural commodity prices. They used weekly data for corn, wheat, and soybeans from 2009 to 2015. The study finds a permanent and causal

relationship between Google search queries and the agricultural commodity prices of corn and wheat. Prokopczuk et al. (2019) assess the linkage between economic and financial uncertainties and the volatility of the commodity market. They discovered that the volatility of commodity markets is strongly correlated with financial and economic uncertainties during the crisis period. Cunado et al. (2020) use the TVP-SVAR model to test the effect of geopolitical risk on oil prices. The study documents that geopolitical risk negatively affects oil prices. Similarly, Mitsas et al. (2022) found that geopolitical risk negatively affects the returns of gold, platinum, silver, and crude oil. Karabulut et al. (2020) verify the relationship between commodity prices and world trade uncertainty using wavelet transforms, wavelet power spectra, and wavelet coherencies. The authors document a positive correlation between the commodity price index and world trade uncertainty during the study period. Kim and Kwon (2021) test whether economic uncertainty affects the US and Chinese commodity futures markets. The study uses the Fama-French (2015) five-factor asset pricing model. The study found no significant impact of economic uncertainty on commodity futures markets. Ding, Huang, and Zhang (2021) assess the time-varying impact of financial uncertainty and geopolitical factors on commodity markets. The study results show that the impact of geopolitical risk and financial uncertainty factors on commodity markets is concentrated in the short-term horizons. Frimpong et al. (2021) studied the impact of global economic policy uncertainty (GEPU) on agricultural commodities prices. The study employs wavelet coherence and partial wavelet coherence analysis and found that GEPU drives agricultural commodity prices. Further, it can influence the price movements of agricultural commodities. Nam (2021) assesses the impact of climate uncertainty on international commodity markets. The study finds that climate uncertainty produces adverse supply shocks.

Few studies explore the Chinese commodity markets. For example, Xiao et al. (2019) investigate the effect of economic policy uncertainty on Chinese grain futures prices. The study findings indicate that economic policy uncertainty substantially impacts China's grain futures prices. Lyu et al. (2021) and Yin, Chang and Wang (2023) explore the dynamic impact of Chinese economic policy uncertainty on commodity prices. The results reveal that uncertainty in Chinese economic policy significantly affects commodity markets. Similarly, Zou, Ouyang, and Li (2024) studied the effect of economic, geopolitical, and climate policy uncertainty on Chinese agricultural futures markets. The authors discovered a strong, significant relationship between EPU and CPU for the future of agricultural commodities. On the other hand, there is a weak association with geopolitical uncertainty. On the contrary, Zhu et al. (2020) document that domestic EPU has a substantial adverse effect on agricultural futures returns during the bearish markets. More recently, Ren et al. (2022) examined how the EPU nonlinear risk spillover occurs in the US

commodity futures markets. The study finds that silver has the highest risk transmitter after the corn futures. Further, grain and soft commodity risk spillovers are more sensitive to economic policy uncertainty. Thilaga and Rajkumar (2025) examine the dynamic relationship between EPU and geopolitical risk on commodity futures markets in India. The study employs wavelet power spectra and wavelet coherence and documents substantial comovement between the US EPU and commodity futures returns, except for silver and mentha oil. At the same time, geopolitical risk is weakly associated with gold, lead, zinc, natural gas, and crude oil.

After the rigorous review process, we find significant research gaps. First, prior studies have mainly focused on commodity futures markets in developed countries. Second, few studies examine the effects of newly proposed global risk factors on commodity futures markets in emerging countries such as India. Third, the study employs Hamilton's (1989) Markov regime switching regression model to examine the nonlinear effects of uncertainty shocks on commodity futures markets. Fourth, this could be the maiden study to comprehensively examine the impact of financial and economic uncertainty shocks on commodity futures markets in the Indian context.

3. Data and methodology

3.1 Data

The present study uses the monthly closing prices of near-month futures contracts for actively traded commodities on the Multi-Commodity Exchange (MCX). The study uses 11 commodities, classified into precious metals (gold and silver), base metals (aluminium, copper, lead, nickel, and zinc), agricultural commodities (cotton and mentha oil), and energy commodities (crude oil and natural gas). Next, the study considers the newly proposed news-based uncertainty variables such as global economic conditions (GECON), global real economic activity index (GREa), Indian economic policy uncertainty (IEPU) constructed by Baker et al., (2016), geopolitical risk (GPR) proposed by Caldara and Iacoviello (2022), and oil price uncertainty (OPU). The study also uses the Indian volatility index (VIX) and world industrial production (WIP). We use monthly data from January 2012 to March 2024. The commodity futures closing prices were gleaned from the Multi-Commodity Exchange website. The study obtains the IEPU, GPR, and OPU data from the policy uncertainty website (<https://www.policyuncertainty.com/>). GECON and WIP data are extracted from the Baumeister and Hamilton (2019) website <https://sites.google.com/site/cjsbaumeister/research>. GREa data are downloaded from Kilian (2009) and corrected in 2019 from the website <https://fred.stlouisfed.org/series/IGREA>. The VIX data is collected from the Centre for Monitoring Indian Economy (CMIE) Prowess database.

3. 2 Methodology

The present study employs the Markov regime switching model proposed by Hamilton (1989) to study the dynamic behaviour of news-based uncertainty variables, world industrial production, volatility index, and its impact on commodity futures returns. It is considered one of the most widely used nonlinear time-series models, which permits time-varying impacts across states. Such types of models are highly effective when exogenous events drive most of the adjustments. It involves multiple structures that can exhibit time-series behaviour across different regimes and help capture complex dynamic patterns. In recent years, there has been rapid growth in nonlinear time series models; however, to study the dynamic behaviour of news-based uncertainty variables, the present study employs a Markov regime-switching model, which assumes that the impact of transition variables on commodity futures returns is state-dependent. (s_t). The unobservable Markov chain describes the transitions between regimes. Therefore, as shown in the equation below for the Markov regime dynamic regression model.

$$R_{i,s,t} = \gamma_{0,i,s_t} + \gamma_{1,i,s_t} COMFR_{i,t} + \gamma_{2,i,s_t} GECON_{i,t} + \gamma_{3,i,s_t} GREA_{i,t} \\ + \gamma_{4,i,s_t} WIP_{i,t} + \gamma_{5,i,s_t} VIX_{i,t} + \gamma_{6,0,s_t} IEPU_{i,t} + \gamma_{8,0,s_t} GPR_{i,t} + \gamma_{8,0,s_t} OPU_{i,t} + \varepsilon_{i,t} \quad (1)$$

where s denotes regime states, $COMFR_{i,t}$ represents commodity futures returns for time t . $GECON_{i,t}$, $GREA_{i,t}$, $WIP_{i,t}$, $VIX_{i,t}$, $IEPU_{i,t}$, $GPR_{i,t}$, and $OPU_{i,t}$ Refer to global economic conditions, global real economy activity index, world industrial production, volatility index, economic policy uncertainty, geopolitical risk, and oil price uncertainty, respectively. $\varepsilon_{i,t}$ Indicates error term. Further, this model allows all variable coefficients to shift between the different regimes.

However, the Markov regime-switching model estimation procedure and methods are based on Hamilton (1989, 2015) and Agnello et al. (2015). Regarding regime shifts, the present study considers high- and low-volatility regimes. Moreover, we assume that the stochastic regime-generating process follows an unobservable first-order Markov chain with two states and time-varying transition probabilities. Next, the maximum likelihood method is used to estimate the time-varying transition probabilities of the Markov regime switching model (Diebold et al., 1994; Kim and Yoo, 1995).

Where the conditional probability of a specific regime t , mainly depends on the regime observed before the time, $P\{S_t | S_{t-1}\}$ and the transition from one state to another depends on the observation of a transition variable, m_t so that $P\{S_t | S_{t-1}\} = P\{S_t | S_{t-1}, m_t\}$. Moreover, we describe the time-varying transition probabilities of a dynamic Markov regime-switching model as follows.

$$Z_t = \begin{cases} p_{11}(m_{t-k}) = \frac{\exp(a_1 + b_1 m_{t-k})}{1 + \exp(a_1 + b_1 m_{t-k})}; p_{22}(m_{t-k}) = \frac{\exp(a_2 + b_2 m_{t-k})}{1 + \exp(a_2 + b_2 m_{t-k})}, \\ p_{12}(m_{t-k}) = 1 - p_{11}(m_{t-k}); p_{21}(m_{t-k}) = 1 - p_{22}(m_{t-k}) \end{cases} \quad (2)$$

where $p_{ij}(m_{t-k})$ is the probability of moving from state i to state j and conditional on the dynamics of the transition variable k before time periods. The transition probability $p_{ij}(Z_{t-k})$ enables the estimation of the expected duration for each regime, as shown in Equation (3).

$$D_{ij} = (1/1 - p_{ij}) \quad (3)$$

The maximum likelihood method is used to estimate the time-varying transition probabilities of the Marv regime switching model. Thus, the study describes a vector of observed independent variables and transition variables up to period t $\psi_t = (x_t, m_{t-k})$. Also, the study explains the vector of historical values of the endogenous variable $\xi_t = (y_t, y_{t-1}, \dots, y_1)$. With designating θ . We describe the conditional likelihood function of the observed data, ξ_t , as follows:

$$L(\theta) = \pi_{t-1}^T f(y_t | \psi_t, \xi_{t-1}, \theta) \quad (4)$$

where

$$f(y_t | \psi_t, \xi_{t-1}; \theta) = \sum_i \sum_j f(y_t | S_t = i, S_{t-1} = j, \psi_{t-1}, \xi_{t-1}, \theta) \quad (5)$$

Applying Bayes' rule, we recursively estimate the weighted probability with Equation (6).

$$p(S_t = i | S_{t-1} = j, z_t) p(S_{t-1} = j | \psi_t, \xi_{t-1}; \theta) = p_{ij}(z_t) (S_{t-1} = j | \psi_t, \xi_{t-1}; \theta) \quad (6)$$

We also have the following,

$$p(S_t = j | \psi_{t+1}, \xi_t; \theta) = p(S_t = j | \psi_t, \xi_t; \theta) \times \frac{1}{f(y_t | \psi_t, \xi_{t-1}; \theta)}$$

$$\sum_j f(y_t | S_t = i, S_{t-1} = j, \psi_{t-1}, \xi_{t-1}, \theta) \times p(S_t = i, S_{t-1} = j, \psi_t, \xi_{t-1}, \theta) \quad (7)$$

Hereafter, to complete and explain recursion in Equations (6) and (7), we specify the regime-dependent conditional density functions as follows:

$$f(y_t | S_t = 1, S_{t-1} = j, \psi_{t-1}, \xi_{t-1}, \theta) = \frac{\varphi\left(y_t - \frac{\dot{x}_t \beta_1}{\sigma_1}\right)}{\sigma_1 p_{1j}(z_t)} \quad (8a)$$

$$f(y_t | S_t = 2, S_{t-1} = j, \psi_{t-1}, \xi_{t-1}, \theta) = \frac{\varphi\left(y_t - \frac{\dot{x}_t \beta_2}{\sigma_2}\right)}{\sigma_2 p_{2j}(z_t)} \quad (8b)$$

4. Empirical results

Table 1 presents the descriptive statistics for commodity futures returns, news-based uncertainty variables, world industrial production, and the volatility index across the study period. The mean returns of all commodity futures are positive, except for mentha oil and crude oil. The mean return for natural gas (0.958) is the highest among the commodity futures, followed by zinc (0.569). Interestingly, the news-based uncertainty variables, such as GECON, GREA, and IEPU, show negative mean values. VIX also report a negative mean value, while GPR and OPU show positive mean values. Natural gas has the highest standard deviation (13.557), followed by crude oil (10.230), mentha oil (7.449), nickel (6.858), and silver (6.028), respectively. At the same time, the gold (4.253) has the lowest standard deviation. Next, the study considers skewness (asymmetry), Kurtosis (leptokurtic), and the Jarque-Bera test. The findings indicate that the commodity futures return series are non-normally distributed, asymmetric, and fat-tailed.

Please insert Table 1

Table 2 presents the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root test results. Both results show that all variables are stationary at the level.

Table 3 provides correlation matrix results. The coefficients for commodity futures returns, news-based uncertainty variables, world industrial production, and the volatility index under the threshold limit. The results clearly show that gold and mentha oil are negatively correlated with global economic conditions (GECON), while silver, aluminium, copper, zinc, cotton and crude oil are positively and statistically significantly correlated, except for nickel. Commodities such as nickel, crude oil, and natural gas are positively and statistically significant. Whereas gold, silver, lead, and zinc are negatively correlated with the global economic activity index (GREA). On the other hand, silver, cotton and crude oil are positive and significantly correlated with world industrial production (WIP). While gold and mentha oil are negative and insignificant. The volatility index (VIX) is positively correlated with all commodities except copper, zinc, mentha oil, and crude oil. Similarly, Indian economic policy uncertainty (IEPU) is positive and insignificant for all commodities except cotton, mentha oil, and crude oil. With regard to geopolitical risk (GPR) is negatively correlated with gold, lead, and zinc. Whereas all commodities are negatively correlated with oil price uncertainty (OPU), except mentha oil, in which gold is statistically significant.

Please insert Table 2

Please insert Table 3

Table 4 presents the results of the Markov regime switching regression for the full period. We consider two regimes, namely low volatility (regime 1) and high volatility (regime 2), for commodity futures returns. Regimes 1 and 2 are referred to as the low- and high-volatility regimes, respectively. Further, this model examines the impacts of newly proposed news-based uncertainty variables, the volatility index and world industrial production on commodity futures returns. The results clearly show that changes in the news-based uncertainty variables, world industrial production, and the volatility index have mixed impacts on all commodity futures returns, whereas risk exposures vary and depend primarily on the commodity and states. Concerning global economic conditions (GECON), it shows that GECON has positive and highly significant impacts on commodities such as silver, aluminium, copper, and nickel during the low volatility regime, whereas copper is positive and statistically significant during the high volatility regime as well. On the other hand, it has a highly significant positive effect on commodities such as zinc, cotton, and crude oil during the high volatility regime. However, it has an adverse impact on natural gas futures returns during periods of high volatility.

With regard to the effects of the global economic activity index, the study finds that it has a highly significant positive impact on copper, nickel, and natural gas futures returns during the high volatility regime, and that natural gas has a positive, highly significant impact during the low volatility regime. On the contrary, it has negatively affected copper during the low-volatility regime. Meanwhile, it has a negative, highly significant impact on the returns of gold, aluminium, copper, and zinc futures during the low volatility regime. Further, it is found that the significant impact and risk exposures mainly depend on regime states. Hence, the findings imply that the effects of GECON and GREA on commodity futures returns are time-varying, regime-dependent, and heterogeneous.

Regarding the effect of world industrial production (WIP) on silver futures returns, the results show that WIP has a positive and significant impact during the high volatility regime. It positively and significantly influences gold and crude futures returns during the low-volatility regime. Next, the WIP adversely and significantly impacts copper and lead futures returns during the low volatility regime. During the high-volatility regime, natural gas futures returns are negative and are significantly influenced by global industrial production.

Looking at the volatility index (VIX), the coefficients are positive and significant for the returns on gold, aluminium, lead, and nickel futures in the low-volatility regime. In contrast, the VIX negatively and significantly affects nickel futures returns during high-volatility regimes. Similarly, it has a negative impact on mentha oil and crude oil during the high- and low-volatility regimes, respectively. Silver and natural gas are positively and significantly affected by VIX under the high volatility regime.

With reference to the Indian economic policy uncertainty (IEPU) index, the results show that the IEPU have a positive and significant effect on the returns of gold, aluminium, and zinc futures under the low volatility regime. On the contrary, the IEPU negatively and significantly affects zinc futures returns during high-volatility regimes. Additionally, silver had a detrimental effect during the high-volatility regime. However, natural gas was positively affected under the high volatility regime.

Concerning geopolitical risk (GPR), the returns of aluminium and nickel futures have been negatively and significantly affected under the low volatility regime. In addition, the GPR positively and significantly affects the returns on nickel and cotton futures during the high-volatility regime. However, the returns on zinc and natural gas futures are adversely affected by GPR under a high-volatility regime.

Focusing on the effect of oil price uncertainty (OPU), the study finds that gold, aluminium, and crude oil are negatively and significantly affected by OPU during the low volatility regime. Similarly, copper and cotton are adversely impacted under the low volatility regime. On the contrary, OPU has positively and significantly affected it during the high volatility regime. Moreover, the returns on lead and mentha oil exhibit positive, statistically significant effects under both the low and high volatility regimes. Followed by silver and natural gas, have been adversely affected by OPU during high-volatility regimes.

Please insert Table 4

Table 5 presents the results of the Markov regime-switching regression for the pre-COVID-19 period. This model considers two different volatility regimes for commodity futures returns. Regimes 1 and 2 are referred to as the low- and high-volatility regimes, respectively. Further, this model examines the impacts of newly proposed news-based uncertainty variables, the volatility index and world industrial production on commodity futures returns. The results clearly show that changes in the news-based uncertainty variables, world industrial production, and the volatility index have a mixed impact on all commodity futures returns, whereas risk exposures differ across commodities and regimes. Concerning global

economic conditions (GECON), the study finds that GECON has highly significant positive impacts on commodities such as silver, zinc, cotton, and crude oil during the low volatility regime, whereas aluminium, copper, nickel, and zinc exhibit positive, statistically significant impacts during the high volatility regime. On the other hand, it has a highly significant negative effect on commodities such as silver, cotton, and natural gas during the high volatility regime. However, it has an adverse impact on the returns of gold and nickel futures during low-volatility periods.

Regarding the effect of the global economic activity index (GREA) across regimes, the results show that GREA has a positive, significant impact on silver and natural gas futures returns during the high volatility regime. It has a positive and significant influence on nickel futures returns during the low-volatility regime. Next, the GREA have an adverse and significant impact on silver, lead, cotton and natural gas futures returns during the low volatility regime. During a high-volatility regime, the returns on aluminium, copper, zinc, and crude oil futures are negative and are significantly influenced by the global economic activity index.

With regard to the effects of the world industrial production (WIP), the study observes that the WIP has a highly significant positive impact on silver, aluminium, and natural gas futures returns during the high volatility regime, as well as gold, nickel, and natural gas have a positive and highly significant impact during the low volatility regime. Meanwhile, it has a negative, highly significant impact on the returns of silver, aluminium, lead, and cotton futures during the low volatility regime.

Looking at the volatility index (VIX), the coefficients indicate a positive and significant impact on the returns of silver, aluminium, and cotton futures during the low-volatility regime. In contrast, the VIX has a negative, significant impact on aluminium futures returns during high-volatility regimes. Similarly, it has a negative impact on mentha oil and natural gas during the high- and low-volatility regimes, respectively. Zinc is positively and significantly affected by VIX under the high volatility regime.

With reference to the Indian economic policy uncertainty (IEPU) index, the results show that IEPU has a positive and significant effect on the returns of gold, lead, cotton, and natural gas futures under the low volatility regime. On the contrary, the IEPU has a negative, significant impact on the returns of aluminium, lead, and natural gas futures during high-volatility regimes. Besides, silver, nickel, and zinc had a detrimental effect during the low-volatility regime. However, zinc was positively affected under the high volatility regime.

Regarding geopolitical risk (GPR), the returns of gold, silver, and nickel futures have been positively and significantly affected during the low volatility regime. In addition, the GPR has a positive and significant impact on the returns of silver, copper, and cotton futures during the high-volatility regime. However, returns on cotton and crude oil futures are adversely affected by GPR under the low-volatility regime.

Focusing on the effect of oil price uncertainty (OPU), the study finds that aluminium, lead, nickel, and cotton are positively and significantly affected by OPU during the low volatility regime. On the contrary, OPU has negatively and significantly affected aluminium, copper, lead, and cotton during the high volatility regime. Moreover, the returns on silver and crude oil have negative, statistically significant effects during low-volatility regimes. Followed by mentha oil, which has been positively impacted by OPU during the high volatility regimes.

Please insert Table 5

Table 6 presents the Markov regime switching regression results for the post-COVID-19 pandemic period. This model considers two different volatility regimes for commodity futures returns. Regimes 1 and 2 are referred to as the low- and high-volatility regimes, respectively. Further, this model examines the impacts of newly proposed news-based uncertainty variables, the volatility index and world industrial production on commodity futures returns. The results clearly show that changes in the news-based uncertainty variables, world industrial production, and the volatility index have mixed impacts on all commodity futures returns. In contrast, risk exposures differ across commodities and regimes. Concerning global economic conditions (GECON), the study finds that GECON has highly significant positive impacts on commodities such as gold, lead, nickel, and zinc futures during the low volatility regime, whereas gold, aluminium, copper, zinc, cotton, mentha oil, and crude oil are positive and statistically significant during the high volatility regime. On the other hand, it significantly reduces nickel futures returns during the high-volatility regime. However, it has an adverse impact on the returns of copper and crude oil futures during the low-volatility regime.

Regarding the effect of the global economic activity index (GREa) across regimes, the results show that GREa has a positive, significant impact on natural gas futures returns during the high volatility regime. During the low volatility regime, it positively and significantly influences the future returns of nickel, cotton, and mentha oil futures. Next, the GREa significantly and adversely affects the returns on gold, silver, copper, zinc, and crude

oil futures during the low-volatility regime. During a high-volatility regime, the returns on gold, silver, aluminium, copper, zinc, and mentha oil futures are negative and are significantly influenced by the global economic activity index.

With regard to the effects of the world industrial production (WIP), the study observes that the WIP has a highly significant positive impact on lead and zinc futures returns during the high volatility regime, as well as copper, nickel, and crude oil have a positive and highly significant impact during the low volatility regime. Meanwhile, negative and highly significant impacts on lead and mentha oil futures returns during the low volatility regime. Further, it was found that gold, silver, nickel, and mentha oil had a significant, positive impact during the high volatility regime.

Looking at the volatility index (VIX), the coefficients indicate a positive, significant impact on the returns of nickel, cotton, and mentha oil futures during the low-volatility regime. In contrast, the VIX negatively and significantly affects the returns on nickel, lead, zinc, and crude oil futures during high-volatility regimes. Similarly, it has a negative impact on gold, copper, and natural gas during low-volatility regimes. VIX positively and significantly affects gold and aluminium under high volatility regimes.

Regarding the Indian economic policy uncertainty (IEPU) index, the results show that the IEPU have a positive and significant effect on the returns of copper and crude oil futures under the low volatility regime. However, the IEPU negatively and significantly affects the returns on copper, lead, cotton, mentha oil, and crude oil futures during high-volatility regimes. Besides, aluminium, zinc, and cotton had a detrimental effect during the low-volatility regime. However, the high volatility regime positively affected gold, aluminium, and zinc.

Concerning geopolitical risk (GPR), the returns of copper and crude oil futures have been positively and significantly affected under the low volatility regime. In addition, the GPR positively and significantly affects aluminium and zinc futures returns during the high-volatility regime. However, the returns on gold, aluminium, lead, nickel, zinc, mentha oil and natural gas futures adversely impact GPR under the low volatility regime. Similarly, the returns on silver, copper, nickel, cotton, and mentha oil are adversely affected by GPR under the high volatility regime.

Focusing on the effect of oil price uncertainty (OPU), the study finds that lead, nickel, zinc and natural gas are positively and significantly affected by OPU during the low volatility regime. Further, OPU has negatively and significantly affected gold and silver during the high volatility regime. Moreover, the returns on copper and mentha oil exhibit adverse, statistically significant effects under low-volatility regimes. Followed by aluminium, copper, lead, mentha oil and crude oil, which OPU has positively impacted during the high volatility regimes.

Please insert Table 6

Table 7 presents the time-varying probability and expected duration of Markov-switching regression. The study finds that there is a probability of shifting from one state to another. In most cases, the high-volatility regime (state 2) lasts longer than the low-volatility regime (state 1). Further, it is observed that the future returns of commodity futures exhibit considerable volatility between bearish and bullish trends. Commodities such as gold (1.45), aluminium (5.88), lead (3.13) and crude oil (14.29) are in a low-volatility regime in state 1, compared to a high-volatility regime in state 2. Similarly, commodities such as silver (5.88), nickel (3.57), zinc (2.78), cotton (9.09), mentha oil (50), and natural gas (20) exhibit substantial shifts between bullish and bearish trends throughout the study period. Moreover, because of their high volatility, mentha oil (50) and natural gas (20) futures are not the safest investment avenue. Copper shows similar volatility in both regimes, indicating that this commodity's futures returns don't influence the newly proposed news-based uncertainty, world industrial production, and volatility index. However, the study's findings also demonstrate that the shorter-to-more extended period is indicated by 1.64 and 1.45.

Please insert Table 7

Table 8 presents the time-varying probability and expected duration of Markov-switching regression for the pre-COVID-19 pandemic period. The study finds that there is a probability of shifting from one state to another. In most cases, the high-volatility regime (state 2) lasts longer than the low-volatility regime (state 1). Further, it is observed that most commodity futures return moves significantly between bearish and bullish trends. Commodities such as gold (1.45), silver (1.56), lead (-0.21), nickel (7.69), zinc (2.38), cotton (1.16), crude oil (2.86), and natural gas (2.44) are in a low volatility regime in state one as compared to state two, which is a high volatility regime. Similarly, commodities such as aluminium (-33.33), copper (-0.18), and mentha oil (20) exhibit substantial shifts between bullish and bearish trends during the pre-

COVID-19 period. Moreover, because of their high volatility, mentha oil (20) and nickel (7.69) futures are not the safest investment avenue. However, the study's findings also demonstrate that the shorter-to-more extended period is indicated by -0.21 and 1.16.

Please insert Table 8

Table 9 presents the time-varying probability and expected duration of Markov-switching regression during the post-COVID-19 pandemic period. The study finds that there is a probability of shifting from one state to another. In most cases, the high-volatility regime (state 2) lasts longer than the low-volatility regime (state 1). Further, it is observed that the future returns of commodity futures exhibit considerable volatility between bearish and bullish trends. Commodities such as gold 1.49, silver 1.82, copper 1.20, lead 1.78, nickel 2.94, mentha oil 1.61, and crude oil 2.17 are in a low volatility regime in state one as compared to state 2, which is the high volatility regime. Similarly, commodities such as aluminium (20), zinc (1.67), cotton (7.69), and natural gas (11.11) exhibit substantial shifts between bullish and bearish trends throughout the study period. Moreover, because of their high volatility, natural gas futures 20 and cotton futures 11.11 are not the safest investment avenues. Copper shows similar volatility in both regimes, indicating that this commodity's futures returns don't influence the newly proposed news-based uncertainty, world industrial production, and volatility index. However, the study's findings also demonstrate that the shorter-to-more extended period is indicated by 1.20 and 25. Figure 1 presents the smoothed and filtered probability plots for the study variables.

Please insert Table 9

Please insert Figure 1

5. Conclusion

The present study examines the factors that determine commodity futures markets in India. The study considers the most actively traded commodities in the Multi-Commodity Exchange of India (MCX) from January 2012 to March 2024. The present employs a Markov regime-switching regression model. This study considers eleven commodities, classified into precious metals (gold and silver), base metals (aluminium, copper, lead, nickel, and zinc), agricultural commodities (cotton and mentha oil), and energy commodities (crude oil and natural gas), and monthly near-month futures contract closing prices. Next, the study uses newly proposed news-based uncertainty variables: global economic conditions, global economic activity index, Indian economic policy uncertainty, geopolitical risk, and oil price uncertainty. In addition, the study also capitalises on world industrial production and the volatility index. Further, the study period is divided into pre-COVID-19 (January 2012 to December 2019) and post-COVID-19 (January 2020 to March 2024) pandemic periods. The results clearly show that changes in the news-based uncertainty variables, world industrial production, and the volatility index have mixed impacts on all commodity futures returns throughout the study period. In contrast, risk exposures differ across commodities and regimes. The overall results show that time-varying, asymmetric, and regime-switching nonlinear impacts of news-based uncertainty, world industrial production, and the volatility index on commodity futures returns. More specifically, global economic conditions significantly positively affect the returns on silver, aluminium, copper, and nickel futures in the low-volatility regime. It also reports that it significantly and negatively affects energy commodities, such as crude oil and natural gas, during high-volatility regimes. Next, global real economic activity positively and significantly affects cotton and natural gas futures returns in the low volatility regime. On the other hand, it also negatively affects gold, aluminium, copper, and zinc, respectively. Looking at the impacts of global industrial production, it significantly and positively affects gold and crude oil in the low-volatility regime. It negatively affects natural gas futures returns during periods of high volatility. Regarding the impact of the Indian volatility index, this study finds that the volatility index has significant positive effects on gold, aluminium, lead, and nickel futures returns during the low volatility regime, as well as a negative effect on the futures returns of nickel and mentha oil. However, the Indian economic policy uncertainty significantly and positively impacts gold and zinc in the low volatility regime. In a high-volatility regime, it adversely affects the returns on silver and zinc futures. Regarding the geopolitical risk, the low volatility regime reports a positive and significant impact on lead futures returns. However, it negatively impacts nickel and natural gas in a high-volatility regime. Concerning the oil price uncertainty, reports a highly significant and positive effect on lead futures returns, even though it shows an adverse impact on silver, copper, cotton, and natural gas in the high volatility regime.

Ethical Declarations

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Consent for Publication

All authors agreed with the content and hereby give explicit consent to submit.

Conflict of Interest

The authors declare that there are no potential conflicts of interest to disclose.

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Figures

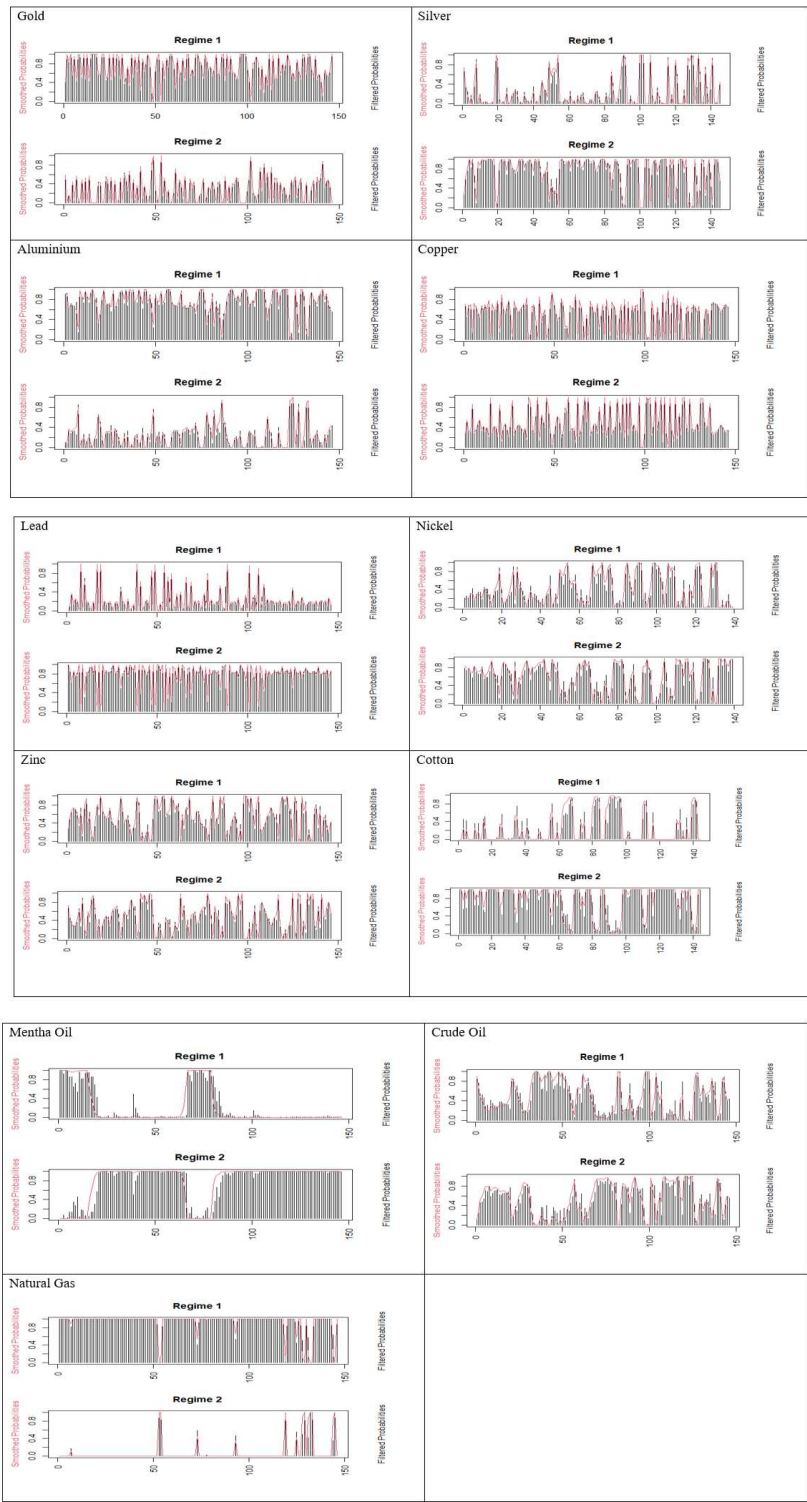


Figure 1

Smoothed and filtered probability plots

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