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The impact of WTI futures on Shanghai crude futures: identifying spillover effects on crude oil prices using the multiplicative error model

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Abstract

Purpose – This study quantifies volatility spillovers between WTI and INE, assessing their time-varying nature and INE's sensitivity to external shocks. It evaluates INE's integration with global markets and its role as a regional benchmark, offering insights into emerging energy markets' resilience.

Design/methodology/approach – This study examines the volatility spillover dynamics between WTI and Shanghai (INE) crude oil futures launched in 2018 to establish a regional benchmark and stabilize China's currency. Using high-frequency data, a Multiplicative Error Model (MEM) quantifies spillovers, while a Markov-switching extension captures regime-dependent effects across the pre-pandemic, pandemic (2020–2021), and post-COVID phases. Robustness checks control for geopolitical risks (e.g. US–China tensions) and RMB exchange rate fluctuations.

Findings – The results show unidirectional spillovers from WTI to INE, with no reverse effect, highlighting WTI's dominance. Spillovers intensify during high-volatility regimes, peaking during the pandemic but declining post-COVID. INE demonstrates resilience to geopolitical and currency risks, reflecting its regional focus. The Markov-switching framework confirms regime-dependent spillovers, indicating a structural market shift.

Originality/value – This study pioneers the use of MEM with Markov-switching to analyze WTI–INE spillovers, challenging static assumptions in prior research. It provides practical insights for Asian policymakers and investors, clarifying INE's role as a regionally focused yet globally influenced contract. INE's insulation from non-energy risks offers novel perspectives on the stability of emerging energy markets, informing risk management in poverty-dependent economies.

Keywords Shanghai INE crude oil futures, Volatility spillover, Multiplicative error model, Markov-switching model, Time-varying effect

Paper type Research article

1. Introduction

Historically, oil price volatility has generated substantial imbalances affecting stability not only in the stock market (Wang *et al.*, 2013; Pandey and Vipul, 2018; Chancharat and Sinlapates, 2023), but across the whole economic system (Hamilton, 1983; Kilian and Park,

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2009; Yating *et al*., 2022), detrimentally affecting economic growth (Van Eyden *et al*., 2019; Salisu *et al*., 2023; Mo *et al*., 2019), and displaying bidirectional causality in the U.S. economy (Zhang *et al*., 2022a). Such volatility significantly affects major oil– importing and –exporting countries, with adverse spillover effects on inflation and long–term growth (Wang *et al*., 2022). Similarly, day–to–day oil price fluctuations negatively affect the current account balance of oil–importing emerging economies (Chang *et al*., 2023). Moshiri and Kheirandish (2024) emphasize the significance of international trade in mitigating the asymmetric effects of oil price shocks on oil–exporting and oil–importing countries. Ferraro *et al*. (2015) showed an ephemeral causality between oil prices and exchange rates, which disappeared when the time frequency was lowered. Oil instability shocks have a significant impact on the exchange rates of oil exporters and importers (Chatziantoniou *et al*., 2023).

The Chinese economy's reliance on oil is significant, as the country is the world's second–largest consumer and primary importer of oil (BP, 2023). In 2018, the need to mitigate currency risks for Chinese refiners and consumers, who have been exposed to significant exchange rate fluctuations between the U.S. dollar and renminbi, and to establish a supply–and–demand–based contract in the Asian region prompted China to introduce an RMB–denominated crude oil futures contract product to the Shanghai International Energy Exchange (INE). For China, this move launched a new era of increasing the importance of the RMB in the foreign exchange market and mitigating exchange rate risks (Ji and Zhang, 2019). This innovative financial instrument has as its underlying asset crude oil varieties that are widely used throughout Asia and is intended to establish a benchmark for Asian oil trading. Unlike the major oil futures contracts, it focuses on heavy high–sulfur crude oil, which is the predominant type of oil imported and used by countries in the Far East. The INE crude oil futures contract has swiftly ascended the ranks of global significance to become the third most prominent futures contract worldwide. In stature it trails only the well–established West Texas Intermediate (WTI) and Brent crude oil futures, which are the benchmarks for the U.S. and European markets, respectively (Okoroafor and Leirvik, 2022; Yu *et al*., 2023b).

The integration between oil price dynamics and returns and volatility has been examined in the economics literature since Adelman's (1984) seminal paper, with the conclusion that fully integrated markets exist when an asset "swims" in one large pool. However, recent research has suggested an asymmetric relationship, owing to partial and unidirectional spillover effects. According to Zhang (2019), Liu *et al*. (2023) and Duan *et al*. (2023), INE crude oil futures act as a net risk receiver in the global crude oil system.

In this study, we examine crude oil volatility by focusing on the conditional expectation of a volatility proxy, such as the high–low range, using intraday data; this contrasts with traditional GARCH models, which use daily squared returns. We rely on an extension of the Multiplicative Error Model (MEM) (Engle, 2002): specifically, the Spillover Asymmetric MEM (SAMEM) proposed by Otranto (2015). The MEM is a class of models for non–negative processes used to describe the dynamics of financial market– related phenomena, such as volatility. The MEM provides a highly flexible model because it is intrinsically heteroskedastic, meaning that the conditional volatility of the process, and not only the conditional mean, is time–varying (capturing the *volatility of volatility*). Furthermore, it can provide the conditional expectation of the variable of interest rather than just the expectation of its logarithm. The SAMEM has the further advantage of distinguishing and quantifying the proper and transmitted volatility components; it can thus capture and measure the volatility explained by other variables.

In our analysis, we identify a unidirectional spillover effect from WTI to INE crude oil futures. Moreover, we enhance the SAMEM by adding a Markovian dynamic to the spillover effect, allowing it to be state–dependent. Indeed, there is evidence that spillover effects are higher during high–volatility periods than during low–volatility periods (e.g. Bauwens and Otranto, 2016).

Other works that have analyzed volatility transmission within the MEM framework include Engle *et al*. (2012), Otranto (2015), and Khalifa *et al*. (2017). The first of these distinguishes between specific periods *a priori*, whereas the other two do not account for the time–varying impact of a volatility shock originating in another market, even though the overall component is time–varying. Our use of Markovian dynamics means that in our specification, regime changes are endogenously determined by data.

The remainder of this paper is structured as follows: Section 2 provides an overview of the literature on the impact of transmission effects on oil futures contracts; Section 3 describes the empirical approach used to investigate the direction of shock propagation; Section 4 describes the data; and Sections 5 and 6, present the findings and conclusions of the study, respectively.

2. Background literature

The literature on commodity price co–movement, particularly within crude oil markets, offers valuable insights into market integration, volatility spillovers, and the influence of external factors such as exchange rates and geopolitical risks. Nonetheless, significant debates persist regarding the degree of global oil market integration, the asymmetric and time–varying nature of volatility spillovers, the impact of major disruptions such as the COVID–19 pandemic, and other external factors. While some studies advocate for full market integration, others emphasize regional segmentation and dynamic interdependence. Similarly, the direction and intensity of volatility spillovers remain contentious, especially during crises, and the influence of exchange rates and geopolitical risks raises unresolved questions about causality and feedback effects. This section reviews these debates through thematic sub–sections: market integration and price co–movement (2.1), volatility spillovers in crude oil futures (2.2), the impact of major shocks, such as COVID–19 and the role of exchange rates and geopolitical risks (2.4). These discussions frame the research questions of this study, which aims to elucidate the extent, dynamics, and external influences of volatility spillovers between WTI and INE crude oil futures.

2.1 Market integration and price co–movement

The theoretical foundation for commodity price co–movement stems from the law of one price, which predicts a strong pricing relationship for identical commodities across different markets (Protopapadakis and Stoll, 1983). This principle underpins Adelman's one–pool hypothesis, which asserts that global oil markets are fully integrated, with price shocks in one region swiftly impacting other regions (Adelman, 1984). However, empirical studies present conflicting evidence. Some research supports full market integration, indicating that information is disseminated freely and prices align across regions (e.g. Liao *et al*., 2014). Conversely, other studies reveal a time–varying network structure in oil markets, suggesting that integration is not static but adapts to market conditions (An *et al*., 2020; Liu and Lee, 2021; Sun *et al.*, 2023). Conversely, an alternative perspective underscores the significance of regional segmentation. Weiner (1991) contends that regional characteristics predominantly influence oil market dynamics, resulting in localized price behaviors. Similarly, Fattouh (2010) and Mastroeni *et al*. (2021) observe weak short–term price co–movements, whereas Liu *et al*. (2013) and Joo *et al*. (2021) indicate stronger co–movement over the long term. These discrepancies underscore a pivotal debate: do global oil markets operate as a cohesive system, or are they fragmented by regional factors? The shale boom, as highlighted by Plante and Strickler (2021), further complicates this debate by altering global supply dynamics and refining capacities, potentially reinforcing regional differences. This study addresses this debate through our first research question (RQ1), which investigates whether WTI futures volatility affects INE crude oil futures and examines the extent of market integration.

2.2 Volatility spillovers in crude oil futures

The financialization of commodity markets has amplified volatility spillovers across interconnected markets (Křehlík and Baruník, 2017; Dahl *et al*., 2020). Studies on INE crude oil futures reveal an asymmetric volatility relationship with global markets, indicating that the INE primarily acts as a net recipient of spillovers rather than as a global driver (Yang *et al*., 2021; Liu *et al*., 2023; Cui and Maghyereh, 2023). Wang *et al*. (2023) found that volatility spillovers from WTI to INE are significantly stronger than the reverse flows, suggesting a hierarchical structure in global oil markets. This asymmetry raises questions about the influence of dominant benchmarks, such as WTI, and the regional role of the INE. Moreover, volatility spillovers are not constant and vary with market conditions. Research shows that these spillovers intensify during periods of high volatility compared to more stable periods (Forbes and Rigobon, 2002; Bauwens and Otranto, 2020, 2023, 2025). This time–varying variability is critical because it implies that market interconnectedness is contingent upon the context. The second research question (RQ2) in this study investigates the dynamic nature of WTI–to–INE volatility spillovers, exploring how these effects evolve during turbulent periods. Furthermore, RQ3 quantifies the magnitude of the impact of WTI volatility on INE using the SAMEM framework with Markov switching extensions, addressing the need for precise modelling of the transmitted volatility.

2.3 Impact of major shocks: the COVID–19 pandemic

Disruptions such as the COVID–19 pandemic significantly impact financial market dynamics, including crude oil futures. Malik *et al.* (2022) reports volatility spillovers between BRICS and U.S. stock markets during the pandemic, indicative of increased financial interconnectedness. In oil markets, Zhang *et al.* (2022b) identifies a shift from a unidirectional U.S.–to–China volatility spillover pre–COVID–19 to a bidirectional relationship during the pandemic, with increased spillovers from Chinese markets. Similarly, Li *et al.* (2022) show that the pandemic intensified volatility transmission from global crude oil markets to China's energy futures markets, including INE. The findings highlight a significant issue: external shocks have the potential to alter the structure of volatility spillovers and challenge the stability of market relationships. The conflicting evidence regarding the direction and intensity of spillovers during crises reveals a gap in the understanding of how such shocks reshape market dynamics. The fourth research question (RQ4) of this study addresses this gap by investigating the impact of pandemic–induced shocks on WTI–to–INE volatility spillovers and how these shocks modify spillover dynamics.

2.4 Exchange rates and geopolitical risks

External factors such as exchange rate fluctuations and geopolitical risks significantly influence crude oil futures markets. Empirical studies consistently report an inverse relationship between USD exchange rates and WTI crude oil prices, where rising oil prices lead to USD depreciation in the currencies of oil–exporting countries (Lizardo and Mollick, 2010). This relationship is elucidated through three mechanisms: wealth transfers that cause current account imbalances (Golub, 1983), inflation–driven exchange rate depreciation in oil–importing countries (Amano and Van Norden, 1998), and hedging strategies that exploit the negative correlation between oil prices and exchange rates (Qiang *et al.*, 2019). Yu *et al.* (2023a) further notes that the pandemic has altered these dynamics, increasing the complexity of spillover effects between exchange rates and oil prices. Geopolitical risks also play a critical role, particularly in China's oil market. Smales (2021) finds that local geopolitical events intensify oil price volatility, while Gong *et al.* (2022) highlights China's vulnerability to supply chain disruptions due to its reliance on suppliers in unstable regions. Conversely, Ivanovski and Hailemariam (2022) reports an inverse causality where oil price volatility affects geopolitical risk, suggesting a feedback loop. Wang *et al.* (2021) argues that RMB–denominated INE futures could mitigate these risks by bolstering China's oil security. The RQ5 examines whether USD/RMB exchange rate fluctuations and geopolitical risk factors affect INE crude oil futures volatility, addressing this critical gap.

3. Empirical strategy

Financial volatility is typically estimated using GARCH models (Bollerslev, 1986). As this approach relies on daily squared returns, it is based only on closing prices and does not consider price movements throughout the day; as a result, it can be ineffective as an estimation of volatility, particularly during periods of turmoil during which there can be abrupt price movements during the course of a day's trading. Volatility proxies based on intraday information — in particular, realized volatility (Andersen *et al*., 2003) and the high–low range (Parkinson, 1980) — have recently been more successful. Realized volatility provides more precise volatility measures but the numerous intraday observations necessary to compute it are not always available; the high–low range is easier to calculate as it requires data only on the maximum and minimum value during the day (Alizadeh *et al*., 2002). As both of these volatility measures are robust to microstructural noise, they are superior to methods based on squared or absolute returns (Chou *et al*., 2015). We adopt the high–low range in this study because we do not have the necessary data to calculate the realized volatility in our empirical application.

Recent methods to model volatility stress the possibility of directly representing the adopted proxies, given as a time series with positive values. Among these, the MEM (Engle, 2002, and further developed by Engle and Gallo, 2006) has had increasing success in the financial literature for estimating volatility because, while maintaining the GARCH structure, it is able to follow the dynamics of volatility with the time–varying behavior of the second moments (the so–called *volatility of volatility*) without an additional equation [1]. The MEM can describe any non–negative process $\{x_t\}$ related to financial market activity, such as volatility, duration, or number of trades, as the product of two positive factors: μ_t, representing its expectation conditional at the information set of the previous period (I_{t-1}), and ϵ_t; a unit–mean error term following a Gamma distribution. The MEM specification is as follows:

$$x_t = \mu_t \epsilon_t, \epsilon_t \sim \text{Gamma}(a, 1/a) \, \forall \, t \mu t = \omega + \alpha x t - 1 + \beta \mu t - 1 \tag{1}$$

where a is the parameter related to the Gamma distribution and ω, α and β are the parameters of the conditional mean equation. In particular, α accounts for the impact of the most recent value of own lagged volatility, and β captures the inertial effect. The constraints $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$ ensure that the process is positive and stationary.

A later extension of the model was proposed by Otranto (2015) with the introduction of SAMEM, which can be considered a special case of the Composite MEM presented by Brownlees *et al*. (2012). SAMEM incorporates the spillover effect, which in our case refers to the portion of volatility caused by the lagged value of the high–low range of another futures contract (z_{t-1}).

The model is defined as follows [2]:

$$x_t = \mu_t \epsilon_t, \epsilon_t \sim \text{Gamma}(a, 1/a) \, \forall \, t \, \mu t = \zeta t + \xi t \, \zeta t = \omega + \alpha x t - 1 + \beta \zeta t - 1 \, \xi t = \delta z t - 1 \tag{2}$$

where δ is the parameter capturing the spillover effect, ζ_t can be interpreted as a *proper* volatility component following MEM dynamics, and ξ_t is the volatility transmitted from another market [3]. The conditional volatility is the sum of these two unobservable volatility components. A large value of z_{t-1} can lead to an undesirable persistence effect by increasing μ_t when added to the conditional mean equation (the second line of Equation (1)).

One of the key benefits of SAMEM is its interpretability, which is further enhanced by its parameterization. This makes it simple to calculate the proportion of volatility caused by spillover effects, using the following formula:

$$tv_t = \frac{\xi_t}{\mu_t} = 1 - \frac{\zeta_t}{\mu_t} \tag{3}$$

From this straightforward specification, we can extract valuable insights about the volatility transmitted from a futures market, which is relevant to our scenario.

To delve more deeply into the effects of USD/RMB exchange rate volatility and geopolitical risk on INE crude oil futures volatility, we refine the SAMEM by incorporating additional factors. In particular, we add a component to account for the volatility of the USD/RMB exchange rate, which is a natural extension of the model:

$$
\begin{gathered}
x_t = \mu_t \epsilon_t, \epsilon_t \sim \text{Gamma}(a, 1/a) \,\forall\, t \\
\mu t = \zeta t + \xi t + \eta t \\
\zeta t = \omega + \alpha x t - 1 + \beta \zeta t - 1 \\
\xi t = \delta z t - 1 \\
\eta t = \gamma r t - 1
\end{gathered} \tag{4}
$$

where r_t represents the USD/RMB exchange rate volatility, γ is its impact coefficient, and η_t signifies the transmitted volatility component from the same exchange rate volatility. Incorporating the Geopolitical Risk (GPR) Index relationship is not as straightforward because the variables under consideration have different frequencies, with exchange rate volatility measured daily and the GPR Index measured monthly. To resolve this issue, we adopt the MIDAS filter of Ghysels *et al*. (2007), which enables the combination of variables with diverse frequencies within the same analysis. Our model is formulated as follows.

$$
\begin{gathered}
xi, t = \mu i, t \epsilon i, t \\
\epsilon_{i,t} \sim \text{Gamma}(a, 1/a) \,\forall\, i = 1, \ldots, N_t \, and \, t = 1, \ldots, T \\
\mu_{i,t} = \varsigma_{i,t} + \xi_{i,t} + \tau_t \\
\varsigma_{i,t} = \omega + \alpha \S_{i-1,t} + \beta \varsigma_{i-1,t} \\
\xi_{i,t} = \delta z_{i-1,t} \\
T_t = \theta \sum_{k=1}^{K} \varphi_k(\lambda_1, \lambda_2) x_{t-k} \\
\varphi_k(\lambda_1, \lambda_2) = \frac{\left(k/K\right)^{\lambda_1 - 1}\left(1 - k/K\right)^{\lambda_2 - 1}}{\sum_{j=1}^{K}\left(j/K\right)^{\lambda_1 - 1}\left(1 - j/K\right)^{\lambda_2 - 1}}
\end{gathered} \tag{5}
$$

where i represents high frequency (daily) and t low frequency (monthly). x_t is the GPR Index, the weighted K–lagged values of which are allowed to influence the INE crude oil futures volatility dynamics through coefficient θ and τ_t is the respective low–frequency volatility component. The MIDAS filter is based on the weighting beta function $\varphi_k(\lambda_1,\lambda_2)$, with the weights summing to one. We set $\lambda_1 = 1$ and $\lambda_2 > 1$ to ensure a monotonically decreasing pattern, with more recent observations having a higher weight on INE crude oil futures volatility.

In the basic SAMEM (Equation (2)) the spillover effect of z_{t-1} on x_t is considered constant over time. However, we wish to investigate the dependence of the spillover effect on high– and low–volatility regimes. We thus refine the SAMEM by incorporating a state–dependent spillover effect within the Markov switching framework [4]. With this refinement, the coefficient δ depends on a latent state s_t, representing the volatility regime at time t. The resulting Markov–switching (MS) SAMEM is specified as follows:

$$xt = \mu t, st\epsilon t, st, \epsilon t, st \sim \text{Gamma}(ast, 1/ast)\,\forall\, t\ \mu t, st = \xi st + \zeta t$$
$$\xi t, st = \delta stzt - 1 \tag{6}$$
$$\zeta t = \omega + \alpha xt - 1 + \beta\zeta t - 1$$

The latent variable s_t follows a first–order Markov chain. That is:

$$P\{s_t = j | s_{t-1} = i, s_{t-2} \ldots\} = P\{s_t = j | s_{t-1} = i\} = p_{ij}\,\forall\, i, j = 1, \ldots, J \tag{7}$$

where J denotes the number of latent states and p_{ij} are transition probabilities, collected in a $J \times J$ transition matrix. These probabilities represent the likelihood of being in regime j at time t given that the regime is i at time $t-1$. It is important to note that only the most recent value of latent variable (s_{t-1}) has an impact on its current value (s_t). Moreover, these probabilities must satisfy the constraint $\sum_{j=1}^{J} p_{ij} = 1$.

We estimate the parameters of the models discussed above with a maximum likelihood estimator (MLE), maximizing the sample log–likelihood. In the Markov switching model, the log–likelihood is a byproduct of the Hamilton filter (comprehensively described in Hamilton, 1994, ch. 22). However, the log–likelihood above has a quasi–likelihood interpretation, with robust standard errors derived from the Sandwich estimator of the variance– covariance matrix (see White, 1982).

4. Data and variables

We obtained the data for our empirical analysis from Eikon Datastream. Our dataset includes daily high and low prices for INE and WTI crude oil futures from March 26, 2018 to July 19, 2023 [5]. To verify spillover effects from foreign currency to crude oil futures markets, we also obtained daily high and low exchange rates from Eikon Datastream.

To ensure the accuracy of our analysis of the spillover effect in the futures market using the MEM technique, we excluded observations for each series if data for either were missing for a given day. In addition to dealing with unrecorded data, this managed instances of one of the two markets being closed while the other was open. Finally, we excluded the data from April 2020, when WTI futures prices fell below zero due to the Russia–Saudi Arabia oil price war. After this data cleaning, our final dataset contains 1,194 daily observations for each high–low range series.

We determined the daily high–low range used in our analysis as a volatility proxy as follows:

$$\mathcal{X}_t = \sqrt{\frac{\pi}{8}}\left(InP_t^h - InP_t^l\right) \tag{8}$$

where $^{\mathrm{p}}\pi/8$ is the correction proposed by Parkinson P_t^h and P_t^l are the highest and lowest prices, respectively, recorded during day t. Following common practice, the high–low range is expressed as annualized percentage change: that is, it is multiplied by $\sqrt{252} \times 100$.

Table 1 displays the descriptive statistics for the INE and WTI high–low ranges, indicating that the volatility proxies are positively skewed, and their empirical distribution is leptokurtic. This is a common finding for volatility proxies based on intraday data (e.g. Andersen *et al.*, 2001). Specifically, WTI has a higher mean, standard deviation, skewness, and kurtosis value than INE futures. Figure 1 displays several shared peaks in crude oil futures: the impact of COVID–19 on the financial market during the first half of 2020, the uncertainty resulting from the Omicron variant of COVID–19 in November 2021, and the onset of the War in Ukraine in February 2022.

We carried out an additional empirical exercise to determine the effect of geopolitical risk on INE crude oil futures volatility, using the aggregate GPR index provided by Caldara and Iacoviello (2022) and focusing on China. We used the international GPR measures of the same authors.

Table 1. Descriptive statistics of high–low range of INE and WTI's future. Sample period: 26 March 2018–19 July 2023

	Mean	Median	Min	Max	St. dev.	Sk.	Kurt.
INE	33.14	27.00	0.23	251.18	23.69	3.25	21.05
WTI	40.04	32.45	9.13	358.03	32.79	4.84	36.65

Note(s): The table reports the Mean, the Median, the Minimum (Min), the Maximum (Max), the Standard Deviation (St. dev.), the Skewness (Sk.) and the Kurtosis (Kurt.) of the High–Low range. All the variables are expressed in annualized percentage term
Source(s): Eikon Datastream data

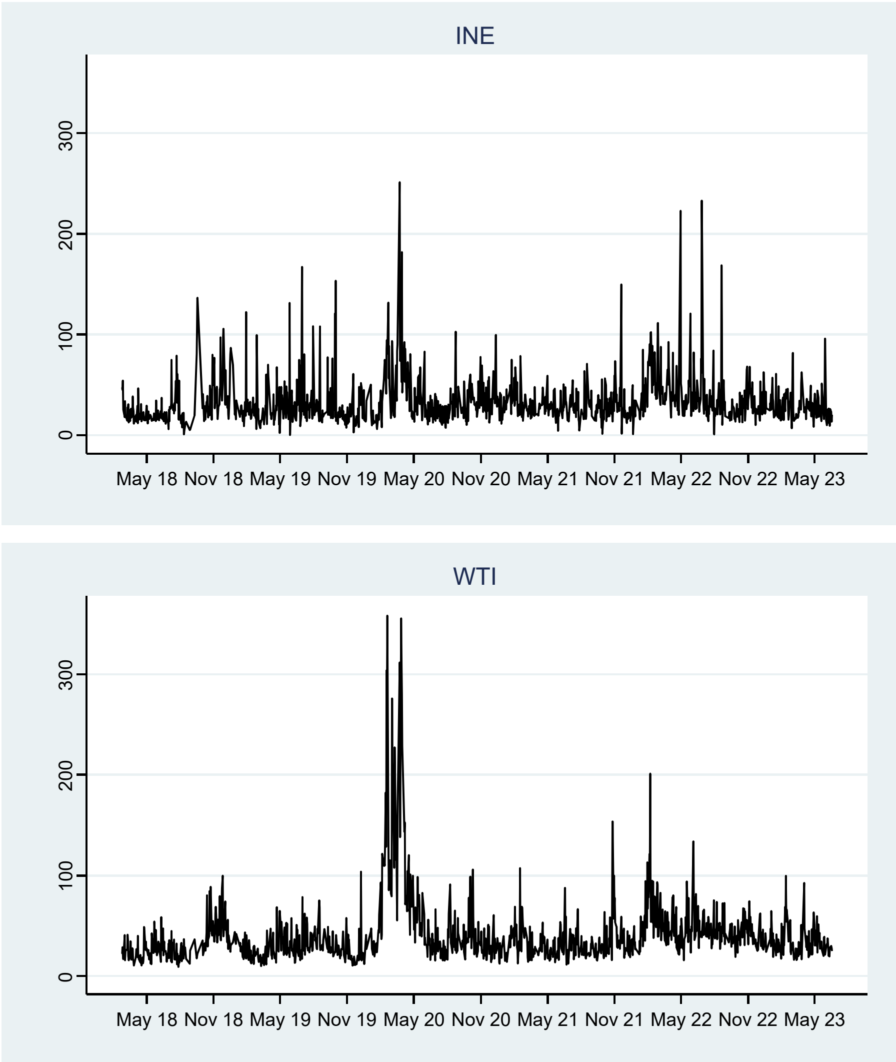

Figure 1. INE (upper panel) and WTI (lower panel) futures high–low range. Sample period: Jan. 26, 2018–Jul. 19, 2023. Source: Authors' own work on Eikon Datastream data

5. Empirical evidence

We fitted three models to the high–low range of INE crude oil futures: the basic MEM, the SAMEM, and the MS SAMEM [6]. The WTI high–low range is the predetermined variable for the latter two models. Table 2 displays the estimation results, including robust standard errors and information criteria. The baseline MEM reveals a value of $\alpha = 0.23$, which accounts for the impact of the most recent high–low range; and a more pronounced value of $\beta = 0.61$, which denotes the inertial effect of past conditional volatility. The SAMEM estimates return lower coefficients, particularly for β, due to the shorter persistence of the proper volatility component represented by $\alpha + \beta$. This effect is attributed to the transmitted volatility component, represented by δz_{t-1}, which serves as a critical factor in explaining the volatility of INE futures. In line with evidence presented in the literature (Yang *et al.*, 2021; Liu *et al.*, 2023; Cui and Maghyereh, 2023), our empirical result answers RQ1 in the affirmative, showing that WTI crude oil futures volatility affects INE crude oil futures. The MEM has a lower Gamma distribution parameter a than that of the SAMEM, resulting in a larger variance of errors. In simpler terms, the transmitted volatility component of the SAMEM identifies volatility dynamics that are not modelled in the MEM specification.

The Markov switching extensions of the SAMEM provide evidence of the time-varying nature of the spillover effect between low– and high–volatility regimes, allowing for the stress testing of RQ2. We observe that the transmitted volatility effect is greater in the less stable high–volatility regime than during quiet periods. Unlike the single–regime model, the MS SAMEM model shows in both regimes a relatively low value for the constant term, a relatively low impact of favorable news, and a higher impact of news from the WTI. Our MS SAMEM results, similar to those of Gallo and Otranto (2015), indicate that low–volatility periods are characterized by higher persistence: the expected duration of low (high) volatility periods, given by $1/(1 - p_{ii})$, is 10 (2) days. In addition, the variances of the error term (proportional to the parameter of the Gamma distribution) are larger during high–volatility periods, which confirms the more accurate estimates provided by the MS models that identify two regimes rather than unique coefficients mediating the two states. By using the Markov switching model, we can determine the regime of the process for each day by relying on the mode of the smoothed probability [7]. A smoothed inference is depicted in Figure 2, in which we observe switching to the second regime during bursts of volatility, such as the period of the COVID–19 pandemic.

The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values displayed in Table 2 indicate that the MS SAMEM model is the best performer in terms of explaining spillover from WTI and time– varying factors that have an impact on the future volatility of INE crude oil futures.

SAMEM permits a rigorous response to RQ3 by enabling the calculation of the proportion of INE futures volatility accounted for by the transmitted volatility component from the WTI futures market. The ratio between the conveyed volatility component and overall conditional volatility, which is represented by ξ_t/μ_t in Eq. (3), provides insight into the extent of this volatility spillover from the WTI. The ratio is generally higher for the time–varying specification and ranges from 0.08 (0.19) to 0.75 (0.89), with a mean value of 0.30 (0.48), for the single (double) regime. Figure 3 displays two ratios that highlight the exceptional contagion that occurred during the pandemic– induced instability in 2020. Overall, INE crude oil futures have a weak degree of diversification with respect to the benchmark. The volatility trough becomes almost complete during the turbulent period of the sample, indicating a strong relationship with severe market shocks.

Figure 4 displays the volatility and spillover effect calculated by the SAMEM and MS SAMEM models. The results highlight the significance of accounting for time–varying transmitted volatility, which is more pronounced during periods of instability such as the bursts of volatility in 2020 due to COVID–19. The markedly more significant spillover during the pandemic dissipates in the post–COVID–19 period, contradicting the assumption of RQ4 that the pandemic cannot be considered a structural break.

Table 2. Parameter estimates for the MEM, SAMEM, and MS SAMEM, information criteria and the maximized value of Log–likelihood; dependent variable: high–low range for the INE; predetermined variable: high–low range for the WTI. Sample period: 26 March 2018–19 July 2023

	ω	α	β	δ_1	δ_2	a_1	a_2	$p11$	$p22$	LOGLIK	AIC	BIC
MEM	5.40	0.23	0.61			3.32				−4994.90	8.37	8.39
	(1.49)	(0.05)	(0.08)			(0.20)						
SAMEM	6.77	0.18	0.44	0.27		3.59				−4942.90	8.29	8.31
	(2.45)	(0.05)	(0.15)	(0.03)		(0.24)						
MS SAMEM	3.72	0.08	0.61	0.34	0.89	8.54	1.30	0.90	0.57	−4796.01	8.05	8.09
	(1.67)	(0.03)	(0.14)	(0.03)	(0.13)	(0.83)	(0.17)	(0.02)	(0.08)			

Source(s): Authors' calculations from Eikon Datastream data

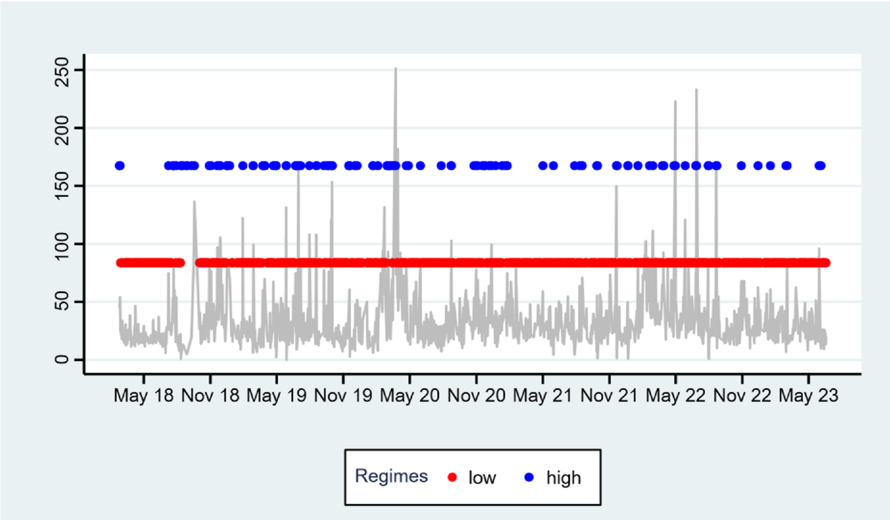

Figure 2. Smoothed inference of MS SAMEM. Volatility proxy: high–low range (gray line). Sample period: Jan. 26, 2018–Jul. 19, 2023. Source: Authors' own work on Eikon Datastream data

We analyze the direction of shock transmission by reversing the SAMEM specification and find that in the reverse direction, δ is non–significant. This finding is consistent with studies that have suggested that INE crude oil is a net receiver of volatility from the U.S. futures market (Zhang, 2019; Liu *et al*., 2023; Duan *et al*., 2023) [8].

Our fifth research question is whether INE crude oil futures are influenced by other elements that contribute to market instability: specifically, geopolitical risk and fluctuations in foreign exchange markets. We use two separate models to test the impact of these potential drivers of volatility. Model (4) estimates the effect of USD/RMB exchange rate volatility on change rate volatility nor the GPR Index has a significant impact on INE crude oil futures volatility [9], thus supporting Smales (2021) in showing that Chinese derivatives are more resilient than WTI crude oil futures against both geopolitical instability and exchange rate shocks.

INE crude oil futures volatility and Model (5) estimates the effect of the GPR Index as a measure of geopolitical instability. The results for these models show that neither USD/RMB exchange. This finding also supports the argument that the introduction of RMB–denominated crude oil futures can enhance China's crude oil security (Wang *et al*., 2021).

6. Concluding remarks

In recent decades, supply and demand shocks in crude oil markets have caused notable fluctuations in business cycles (Ge, 2023). Furthermore, these shocks have spillover effects that disrupt the long–term growth trajectories of developed and emerging economies. In light of the susceptibility of the reference WTI crude oil futures to exogenous shocks that generate multiple instability spillovers, the INE has introduced a crude oil futures contract product denominated in the local currency. This strategy aims to decrease the exposure of this crucial commodity to the volatility of benchmark international futures. The new derivative also serves the purposes of reducing exchange rate risks and minimizing exposure to adverse shocks specific to the U.S. economy.

We use multiple models — the basic MEM, SAMEM, and MS SAMEM — to gain a nuanced understanding of the behavior and interactions of these crude oil futures markets.

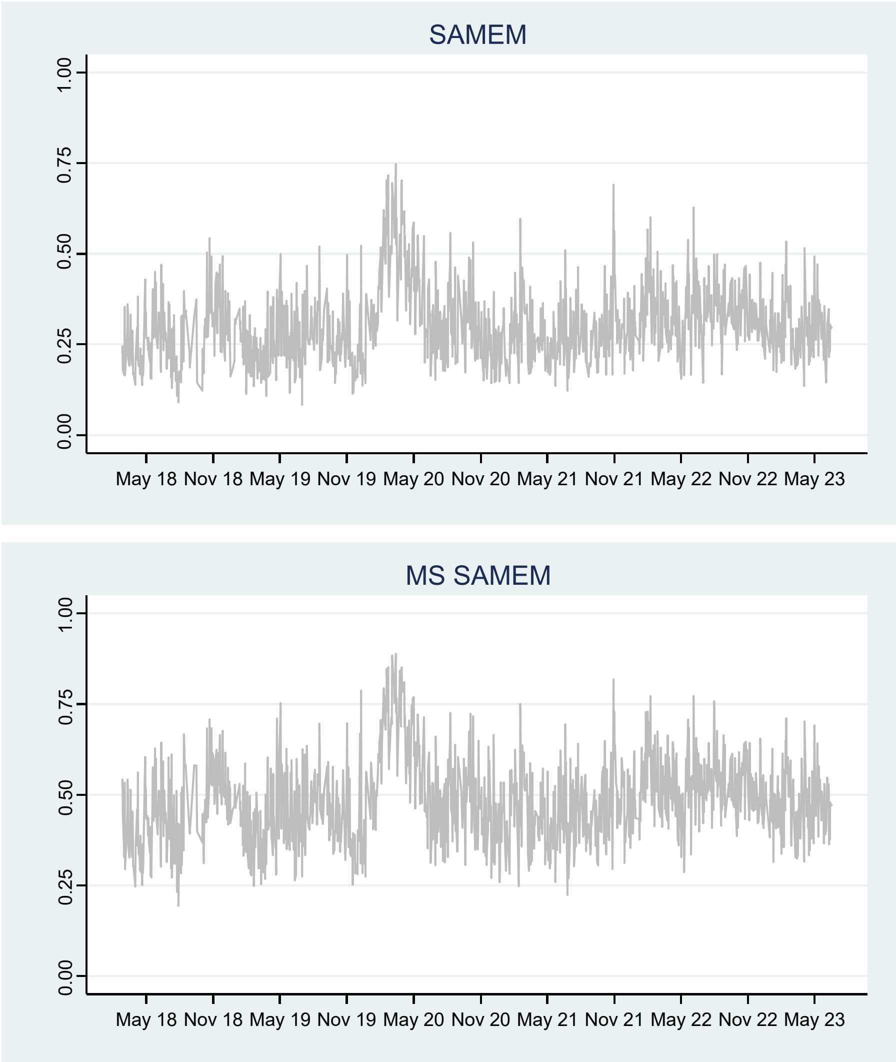

Figure 3. Ratio (gray line) among spillover effect and conditional volatility of SAMEM and MS SAMEM. Volatility proxy: high–low range. Sample period: Jan. 26, 2018–Jul 19, 2023. Source: Authors' own work on Eikon Datastream data

One of our major discoveries is the impact of the WTI crude oil futures market on the INE futures market. The SAMEM model distinguishes the transmitted volatility component and thereby highlights the importance of cross–market spillovers. The model indicates that fluctuations in the U.S. crude oil futures market can have a significant impact on INE crude oil futures volatility, underscoring the interconnectedness of global oil markets. The MS SAMEM model further exposes time–varying spillover effects and demonstrates the significance of taking different market regimes into account. The increased transmitted volatility identified during periods of higher instability highlights the necessity for market participants to be aware of global events that could trigger volatility surges. These findings

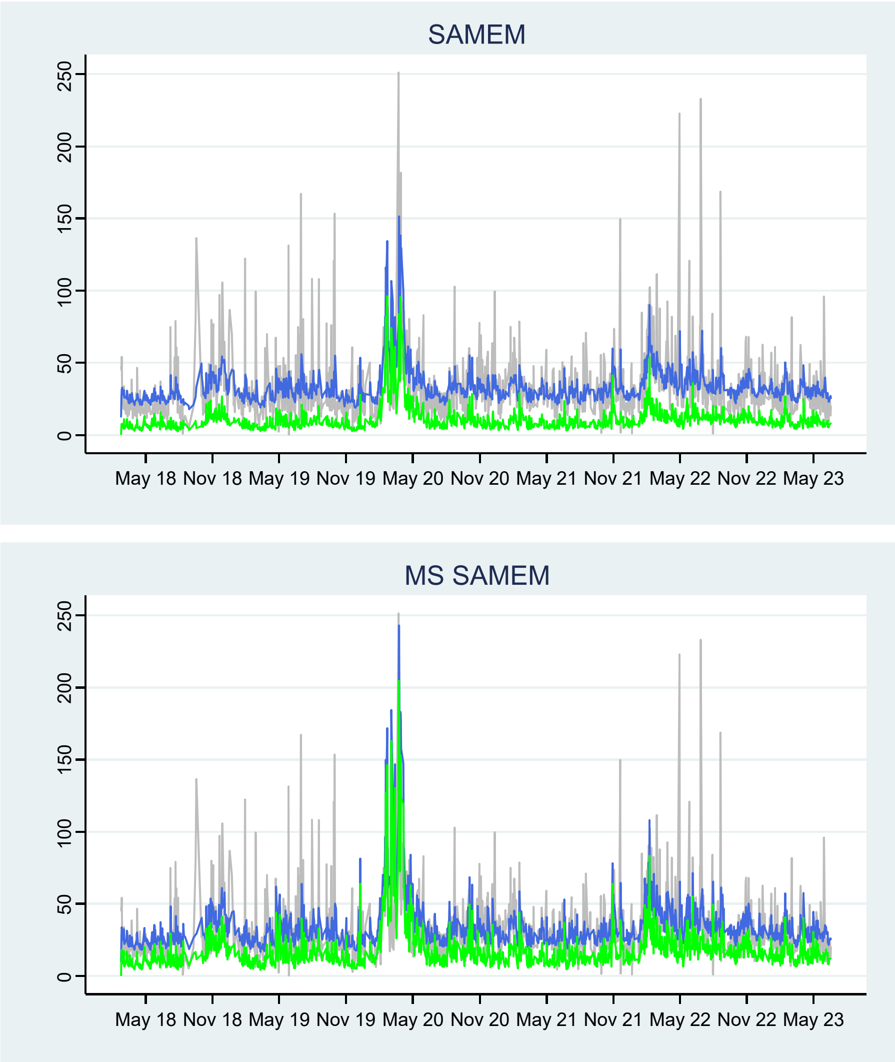

Figure 4. Conditional volatility (blue line), spillover effect (green line), high–low range of SAMEM and MS SAMEM. Sample period: Jan. 26, 2018–Jul. 19, 2023. Source: Authors' own work on Eikon Datastream data

carry significant financial implications for risk management strategies and portfolio diversification, particularly in times of heightened uncertainty.

The outstanding performance of the MS SAMEM model, as demon strated by the information criteria, underscores the importance of considering spillover effects with a time–varying nature in volatility models. This understanding can aid practitioners in selecting suitable modeling strategies to better capture market trends and enhance forecasting accuracy. Moreover, the observed resilience of INE crude oil futures volatility against geopolitical risks and foreign exchange market volatility is noteworthy and suggests that the behavior of INE is influenced by different factors than its global peers. As the INE market grows, market participants and policymakers can draw confidence from its ability to withstand external shocks, which is likely to make it an increasingly attractive financial instrument.

Our findings have important implications for market regulators. The documented volatility spillover from WTI to INE futures, particularly during high–stress regimes, suggests that implementing dynamic margin frameworks could bolster market resilience. Such frameworks might include position– size–adjusted requirements and differentiated treatment for hedged versus speculative positions, similar to mechanisms effectively employed in commodity markets. Simultaneously, developing tailored hedging instruments, such as INE–WTI spread swaps, would allow participants to manage the basis risk inherent to this regional benchmark. These structural refinements, combined with targeted liquidity incentives, could further shield the INE from external shocks while reinforcing its role as Asia's price discovery hub.

Our analysis is influenced by the time frame covered by the available time series, which includes several significant market shocks. It is important to note that this specific timeframe may not capture all possible market scenarios and dynamics. Indeed, future periods of relative market calm could serve as valuable laboratories for analyzing the potential diversification role of INE crude oil futures. Examining how INE crude oil futures behave during these calmer periods will provide a more comprehensive understanding of their ability to stabilize investment portfolios. Such an analysis would provide a broader perspective on the role of INE crude oil futures, beyond the immediate context of market volatility. It is important to continually evaluate the adaptability and strength of financial instruments, including INE crude oil futures, to reveal their effectiveness during turbulent times but also their capacity to enhance portfolio stability and minimize risk when markets are less volatile. The methodology of this study can also be easily applied to other energy–related derivatives introduced in emerging and developed countries.

Notes

1. In other approaches, such as the Heterogeneous AutoRegressive (HAR) model of Corsi (2009), the *volatility of volatility* is captured with an additional GARCH equation for the variance of innovations (Corsi *et al*., 2008).
2. Although the model is called the Spillover Asymmetric MEM, we do not account for asymmetric effects in either the proper or transmitted volatility components, because models that do incorporate asymmetric effects do not outperform our proposed model.
3. We exclude the inertial component ($\beta\xi_{t-1}$) from our specification because in our empirical application, the model that includes the inertial component does not outperform our proposed model. Note that if $\delta = 0$ the model reduces to the MEM (cfr. Equation (1)).
4. See Hamilton (1989) for a general description of MS models and Gallo and Otranto (2015) for the extension to the MEM case.
5. We also procured data for Brent crude oil futures from Eikon Datastream to conduct a standalone analysis of this derivative.
6. The empirical analysis was developed by proposing three new models belonging to the SAMEM family (Otranto, 2015): an SAMEM with the exchange rate volatility effect, an SAMEM–MIDAS, and an MS SAMEM. To save space, we only show the estimation results of the latter model because they are most interesting. The results for the other models are available upon request.
7. For a comprehensive description of the smoothed filter, refer to Kim and Nelson (1999).
8. The results of the reversed SAMEM estimate are available upon request.
9. The detailed results of these estimates are available upon request.

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