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Price Discovery and Time-Varying Causality Dynamics in Energy Markets: Futures Versus ETFs

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Abstract

This paper investigates price discovery and time-varying causality between energy futures and exchange-traded funds (ETFs) across three major markets: WTI crude oil, natural gas, and gasoline. Drawing on a unique dataset spanning almost two decades, the analysis employs rolling Information Leadership Share (ILS) measures with Monte Carlo simulation bands and recursive time-varying Granger causality (TVGC) tests to trace the evolution of leadership dynamics between ETFs and their underlying assets. The results provide novel empirical evidence that futures generally dominate price discovery under stable market conditions, reflecting their superior liquidity and informational efficiency. In contrast, ETFs assume a more prominent role during episodes of market turbulence, such as the 2014–2016 oil price collapse and the COVID-19 crisis, where they shift from being passive followers to active price setters. Bidirectional, time-varying causality emerges in the WTI–USO and natural gas–UNG pairs, particularly during crisis periods, whereas gasoline markets exhibit a more conventional futures-led process. The study contributes to applied computational economics by illustrating how simulation-based and recursive estimation methods can uncover dynamic leadership patterns in financial markets. It further advances the understanding of financialisation in commodity markets, offering insights into how ETFs reshape information transmission during periods of heightened uncertainty.

Keywords Price discovery · Time-varying causality · Energy futures · Energy ETF · Crude oil

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1 Introduction

Over the past two decades, exchange-traded funds (ETFs) and futures contracts have transformed the way financial markets absorb and transmit information. ETFs represent a significant innovation in financial engineering, functioning both as securities and investment vehicles that replicate the performance of underlying indices or asset classes at relatively low cost (Lettau & Madhavan, 2018). Their rapid growth has democratised access to diversified portfolios, increased trading volumes, and broadened investor participation (Ben-David et al., 2018). In commodity markets, the financialisation of energy assets has accelerated this trend, with the launch of oil, natural gas, and gasoline ETFs providing investors with stock-like instruments to gain exposure to energy price movements (Chincarini & Moneta, 2021; Liu et al., 2020).

The rise of ETFs has reshaped price discovery dynamics. While futures markets are traditionally regarded as the dominant venues for incorporating new information owing to their liquidity and leverage advantages (Fernandez, 2010; Kavussanos et al., 2008), the growing role of ETFs has raised questions about whether they may also act as price makers, particularly in times of stress (Mohamad, 2025). Evidence from equity and carbon markets suggests that ETFs can influence underlying assets by concentrating order flows and enhancing informational efficiency (Fu & Jiang, 2023; Shrestha, Naysari et al., 2023). At the same time, concerns remain that ETF-driven flows may exacerbate volatility and transmit liquidity shocks (Ben-David et al., 2018; Lin et al., 2024).

Energy markets provide an especially relevant laboratory for addressing these issues. Over the last twenty years, they have been shaped by multiple crises and structural shocks, including the Global Financial Crisis, the shale oil revolution, the 2014–2016 oil price collapse, the COVID-19 pandemic, and the Russia–Ukraine war (Bhar & Malliaris, 2011; Fantazzini, 2016; Gharib et al., 2021; Mohamad, 2022, 2024a; Mohamad & Fromentin, 2023; Mohamad & Inani, 2022; Mohamad & Stavroyiannis, 2022; Sifat et al., 2022). These events have amplified volatility, altered market participation, and created opportunities for ETFs to emerge as active contributors to price discovery. Understanding the dynamic interaction between energy ETFs and futures during such episodes is therefore of central importance.

This study contributes to the growing literature on energy markets in several important ways. First, while the price discovery function has been extensively studied, most research has focused on spot and futures markets (Elder et al., 2014; Foster, 1996; Moosa, 2002; Shao & Hua, 2022; Silvério & Szklo, 2012; Yu et al., 2023). The distinct role of ETFs in this process, particularly during episodes of heightened volatility, has received limited attention. To the best of our knowledge, this paper is among the first to examine leadership in price discovery between energy ETFs and their underlying futures over an extended daily dataset spanning from ETF inception nearly two decades ago through September 2024. Our results show that futures markets (WTI, natural gas, and gasoline) typically dominate under normal conditions, consistent with their liquidity and informational efficiency (Fernandez, 2010; Kavussanos et al., 2008). However, ETFs gain influence in periods of stress, such as during the COVID-19 pandemic, when they contribute more substantially to price discovery. This is noteworthy given that futures markets are more liquid and allow for greater leverage than ETFs (Arunanondchai et al., 2020).

Second, we extend the analysis by assessing time-varying causality between futures and ETFs. Despite extensive research on causality and price discovery in energy markets, little is known about the dynamic interaction between these two market segments. To date, the only comparable study is by Shrestha et al. (2023), who examine carbon ETFs and report shifts in price discovery during the COVID-19 crisis. By contrast, our study examines the three major US energy markets and provides evidence of bidirectional causality between WTI futures and the USO ETF, as well as between natural gas futures and the UNG ETF, particularly during crises. This suggests that ETFs can influence futures prices and not merely follow them, especially in turbulent periods. In the gasoline market, however, causality is predominantly unidirectional, with futures consistently leading the UGA ETF, consistent with a more traditional price discovery structure.

Finally, the study contributes methodologically by applying rolling Information Leadership Share measures with Monte Carlo simulation bands alongside recursive time-varying Granger causality with bootstrap inference. This combination of simulation-based and recursive estimation techniques provides a more robust and computationally intensive framework than static models, allowing us to uncover dynamic patterns that would otherwise remain obscured.

Our findings reveal that futures generally dominate price discovery under normal market conditions, reflecting their superior liquidity and ability to absorb new information efficiently. However, ETFs play a more prominent role during episodes of turbulence such as the 2014–2016 oil price collapse and the COVID-19 crisis, when they shift from passive followers to active leaders. Bidirectional causality is particularly evident in the WTI–USO and natural gas–UNG markets during crises, whereas the gasoline market exhibits a more traditional one-way pattern of futures leadership.

The remainder of the paper is structured as follows. Section 2 reviews the literature on price discovery and time-varying causality in energy markets. Section 3 describes the data and methodology. Section 4 presents the empirical results, and Sect. 5 concludes.

2 Literature Review

Research in energy markets primarily focuses on the interaction between exchange-traded funds (ETFs) and futures markets, particularly with regard to price discovery and time-varying causality. Price discovery can be defined as the process by which asset values absorb all available information and is, therefore, essential for market efficiency. In energy markets, futures contracts frequently substantially influence spot prices or ETFs.

2.1 Price Discovery in Energy Markets

Price discovery in crude oil markets is a complex process influenced by various factors, including market structure, trading behaviour, and external economic conditions. Price discovery is crucial as it explains how price is discovered in the market. Earlier works (Elder et al., 2014; Foster, 1996; Moosa, 2002; Silvério & Szklo, 2012) have examined price discovery between spot and futures, looking at WTI or Brent and later studies (Shao & Hua, 2022; Yu et al., 2023) investigate spot-futures price discovery of Shanghai crude oil. Elder (2014) investigated information share price discovery between WTI and Brent futures over a sample period from 2007 to 2012 – and found that WTI dominated price discovery by 80% information share over Brent. Earlier, Foster (1996) examined the price discovery behaviour of crude oil spot and futures markets in the UK and USA during the 1990-91 Gulf conflict and found that such price discovery relationships are intensely temporal. Moosa (2002) examined price discovery between crude oil spot and futures using the Garbade & Silver (1983) model and found that the futures market performs about 60 per cent of the price discovery function.

By the same token, Silverio & Szklo (2012) documented that WTI futures led price discovery in crude oil markets, especially between 2003 and 2008 and again after the start of 2009. Both studies by Shao and Hua (2022) and Yu et al. (2023) explore price leadership in China's crude oil market. The former study found that Shanghai oil futures contribute approximately 50% to price discovery, roughly equal to the spot market. The latter study by Yu et al. (2023) evaluates the effectiveness of Shanghai crude oil futures in price discovery by comparing them with the market prices of 19 different types of Asian crude oil that may or may not be delivered. Meanwhile, by examining China's crude oil options and futures markets, Zou et al. (2024) find that futures lead options in price discovery.

ETFs have become increasingly popular in the financial markets as they provide exposure to energy commodities. The price discovery process for ETFs involves the interaction between ETF prices, the underlying assets' net asset value (NAV), and the prices of the relevant futures and spot markets. As reported in a recent study (Shrestha, Philip et al., 2023), the authors mentioned that in energy markets, the price could be discovered in either spot or futures market, suggesting that energy ETFs, which often track futures, play an essential role in price discovery. On a similar note, Ben-David et al. (2017) documented that while ETFs can improve price discovery through arbitrage activities, ETFs can also introduce non-fundamental volatility, hence distorting the price discovery process. In addition, trading activity in ETFs significantly impacts their price discovery efficiency. Buckle et al. (2018) support this notion, pointing out that ETFs have increasingly taken over the price discovery role of traditional futures contracts, especially in major US markets. Their analysis showed that ETFs actively adjust prices based on pre-market information, emphasising their importance in the price discovery process. Price discovery in exchange-traded carbon funds (ETFs) has become a topical research area, significantly as efforts to combat climate change intensify. Carbon ETFs are designed to provide investors with exposure to carbon credits and related financial instruments, and understanding their price discovery mechanisms is critical for both market participants and policymakers. Very recently, Shrestha, Naysary, et al. (2023) scrutinised the carbon ETF price discovery. The authors report that carbon futures often dominate the price discovery.

2.2 Time-Varying Causality Dynamics in Energy Markets

The causality dynamics in energy markets reflect the complex interaction of many economic factors, geopolitical events, and market conditions. Recent research has used advanced approaches, such as time-varying Granger causality tests, to explain how economic variables and vice-versa influence energy commodities.

Dhifaoui et al. (2023) adopt a time-varying partial-directed coherence method to examine the causal relationship between global economic conditions and energy prices. This study emphasises the influence of declining global economic conditions on energy costs, indicating a dynamic link that develops over time. Meanwhile, by employing time-varying Granger causality tests, Mensi et al. (2024) assess the relationships between spot and futures of natural gas, crude oil, and gasoline. The authors observe significant linkages and reciprocal spillovers among these markets, particularly during economic instability. Balcilar et al. (2015) conducted a time-varying examination of the correlation between spot and futures prices of crude oil. Their application of a regime-switching methodology indicates that the predictive relationship between spot and futures prices fluctuates temporally, corresponding with major geopolitical and economic occurrences.

Cryptocurrencies, clean energy, and crude oil all have dynamic spillover effects, and Lu et al. (2024) examine how these effects change over time in relation to the media's coverage of COVID-19. Their results suggest that media coverage significantly amplifies spillover effects during turbulence such as the pandemic, with crude oil acting as a net sender of spillover effects, while cryptocurrencies and clean energy are net receivers. Correspondingly, Coronado et al. (2023) examine time-varying causality between US Treasury bond yields and oil using over 150 years of data. They observe bidirectional spillover effects between these markets, with volatility spillover effects from oil to corporate bonds. Bampinas and Panagiotidis (2015) discovered that the causality dynamics before the crisis were unidirectional, from oil to gold. In a similar tone, Raggad and Bouri (2023) analyse the time-varying causality relationship between gold and crude oil prices under different market conditions - only to find the causality is bidirectional in terms of returns.

The relationship between energy prices and financial markets is also a research focus. Cevik et al. (2018) analyse the causal relationships between oil prices and the stock markets of the G7 countries during the global financial crisis. Applying tests for time-varying causality in the mean and causality in the variance, they find that causal relationships between oil prices and stock returns are not static but fluctuate significantly over time, especially during periods of economic turmoil. Jammazi et al. (2017) adopt a multiscale approach in a similar way to investigate the time-varying causal links between stock returns and oil price fluctuations in various key oil-importing nations, discovering notable bidirectional causation across many time horizons. Using time-varying Granger causality tests, Lu et al. (2014) look at the information flow between global crude oil markets, especially on Brent, WTI, Dubai and Tapis crude oil. The findings indicate that, especially Brent and WTI, which dominate, big events like wars and economic crises, magnify the direct causal impacts of these crudes.

Wang et al. (2022) investigate the asymmetric causality between economic policy uncertainty, the oil volatility index and the time-varying relationships between the clean energy, carbon and green bond markets. The results reveal complex relationships between these markets, with EPU and oil volatility acting as significant predictors, especially during periods of market turbulence. Accordingly, Nakhli et al. (2023) investigate the time-varying bidirectional causality between investor sentiment and oil prices. Using data from 1987 to 2020 and applying time-varying Granger causality tests show asymmetric causal relationships, suggesting that bearish and bullish investor sentiment affect oil prices differently during major economic and political events.

2.3 Price Discovery Between Futures and ETFs

Price discovery reflects how trading venues aggregate dispersed information under market frictions. In normal conditions, energy futures tend to absorb new information first because they offer deep limit-order books, low marginal trading costs, and leverage that attracts informed traders (Fernandez, 2010; Kavussanos et al., 2008). Within a standard market microstructure perspective, lower transitory noise and tighter spreads reduce adverse selection premia, so the futures price adjusts quickly to news and inventory shocks. ETFs typically follow because their prices are kept close to net asset value through the creation–redemption mechanism, which transmits signals from the underlying futures to the ETF share price via authorised participants' arbitrage (Arunanondchai et al., 2020).

During stress episodes the hierarchy can change. Three mechanisms support temporary ETF leadership. First, arbitrage constraints tighten. Heightened volatility, balance-sheet limits, or funding and margin pressures can impair authorised participants and futures market-makers. When arbitrage capacity is constrained, ETF premiums and discounts can reflect order imbalances and risk sentiment more rapidly than futures, allowing ETFs to incorporate information from retail and institutional flows before complete convergence occurs (Ben-David et al., 2018). Secondly, liquidity migration can occur. When futures depth thins or margins rise, part of informed and hedging activity may shift to ETFs because they provide stock-like access, netting across investors intraday, and comparatively lower operational frictions for some participants (Glosten et al., 2021; Fu & Jiang, 2023). Thirdly, in commodity markets with storage and term-structure frictions, dislocations of the cost-of-carry and convenience yield can widen the basis across the curve. In such conditions, ETFs that roll systematically may register the changing risk–return trade-off through their prices as investors rebalance exposure, producing the bidirectional patterns we document in oil and natural gas during crises (Berk & Çam, 2020; Rostami & Rahimpour, 2023).

These mechanisms are consistent with an adaptive view of market behaviour. In tranquil periods, futures dominate because liquidity and leverage concentrate informed trading there (Fernandez, 2010; Kavussanos et al., 2008). In turbulent periods, constraints and risk management shift where information is first impounded, so ETFs can temporarily act as price makers, after which arbitrage gradually restores the usual ordering (Arunanondchai et al., 2020). This framework explains why we observe persistent futures leadership in gasoline, but more frequent leadership shifts in WTI and natural gas where flows and frictions are larger, and where creation–redemption and margin dynamics bind more often.

This conceptual discussion complements our empirical results. It clarifies why futures usually lead, why ETFs sometimes lead, and why these roles vary across markets and over time, without requiring a new theoretical model. In line with our empirical focus, we retain the formal analysis to simulation-based rolling ILS and recursive time-varying Granger causality, while pointing to regime-dependent or nonlinear extensions as valuable directions for future research.

3 Data and Methods

Our dataset includes 18 years of daily front-month futures and ETF prices for WTI and the US Oil Fund (USO), 17 years for natural gas and the US Natural Gas Fund (UNG), and 16 years for RBOB gasoline and the US Gasoline Fund (UGA).[1] This dataset spans from the inception date of each energy ETF (see Table 1) to 16 September 2024. All data is quoted in US dollars sourced from Refinitiv[2] In this study, we chose the USO, UNG and USO ETFs as these ETFs have the most popular energy commodity futures, such as WTI, natural gas and gasoline futures, as underlying assets. The expanded dataset for these six energy assets allows us to comprehensively analyse price discovery, time-varying causality and range-based volatility measures. Table 1 shows the descriptive statistics of daily returns ($ret_t = \ln(p_t/p_{t-1})$). Of the three ETFs, USO had the most considerable assets under management, approximately $1.13 billion and a net asset value of $70.66 per share. The three energy futures are traded on NYMEX, while the three energy ETFs are traded on NYSE Arca. Natural gas futures and UNG are the most volatile instruments, as evidenced by their standard deviation of 3.274 and 3.017, respectively. Correspondingly, WTI futures recorded the highest daily returns of 37.216% and the lowest of ID="MN2">−56.859% during the sample period. The Jarque-Bera tests indicate that none of the series is normally distributed. Meanwhile, the Augmented Dickey-Fuller (ADF) tests show the presence of a unit root in the returns of all assets.

Figures 1 and 2 show daily closing prices and returns evolution over time. In stark contrast to their underlying assets, USO and UNG ETFs have seen a steep downward trend since mid-2008, coinciding with the outbreak of the global financial crisis. WTI futures show the lowest level around April 2020, corresponding to negative pricing for the May 2020 futures contract. The negative pricing for May WTI futures could

[1] Front-month futures are utilised since they are typically the most heavily traded contracts (Entrop et al., 2020).

[2] The Refinitiv Instrument Codes (RICs) for the continuous contracts for WTI, natural gas, and RBOB gasoline futures are CLc1, NGc1, and RBc1, respectively. CL, NG and RB are base ticker symbols for light sweet crude oil, natural gas, and RBOB gasoline futures contracts. “c” stands for continuation, an uninterrupted data series that automatically rolls from the front-month contract to the next as expiration approaches. “1” refers to the first or front-month contract. The roll date for Refinitiv continuous contracts is based on the underlying CME Group futures. It is usually a few days before the last trade date for the front-month contract. See https://www.cmegroup.com/markets/energy/crude-oil/light-sweet-crude.calendar.html;

Table 1 Descriptive statistics of daily returns

	US Oil ETF	US Natural Gas ETF	US Gasoline ETF	WTI futures	Natural gas futures	Gasoline futures
Name	US Oil Fund	US Natural Gas Fund	US Gasoline Fund	WTI crude oil futures	Natural gas futures	RBOB gasoline futures
Asset class	ETF	ETF	ETF	Futures	Futures	Futures
Refinitiv ticker	USO	UNG	UGA	CLc1	NGc1	RBc1
Exchange	NYSE Arca	NYSE Arca	NYSE Arca	NYMEX	NYMEX	NYMEX
ETF Fund family	USCF Investments	USCF Investments	USCF Investments			
ETF Underlying asset	WTI crude oil futures	Natural Gas futures	RBOB gasoline futures			
ETF Inception date	10-Apr-2006	18-Apr-2007	26-Feb-2008			
ETF shares outstanding	16.12B	59.346 M	1.65 M			
ETF Managed Assets ($)	1.139B	870.791 M	98.419 M			
ETF Net asset value ($)	70.66	14.67	59.65			
Management Fee	0.81%	1.11%	0.96%			
Mean (%)	−0.044	−0.139	0.004	0	−0.028	−0.007
Median (%)	0.066	−0.138	0.099	0.104	−0.05	0.095
Maximum (%)	15.415	17.311	17.951	37.216	29.725	21.348
Minimum (%)	−29.189	−21.227	−25.291	−56.859	−19.184	−26.378
Std Dev (%)	2.34	3.017	2.323	2.8	3.274	2.562
Skewness	−1.129	−0.074	−0.801	−1.486	0.296	−0.536
Kurtosis	17.193	5.538	13.405	58.861	6.996	16.202
Jarque-Bera	39919.7***	1181***	19242.3***	604855.4***	2980.4***	30462.3***
ADF t-stat	−67.6***	−68.9***	−64.5***	−44.6***	−71.8***	−65.1***
# Trading days	4639	4384	4167	4639	4384	4167

Note: This table provides descriptive statistics for daily returns and relevant information on the US Oil Fund, US Natural Gas Fund, and US Gasoline Fund ETFs, as well as WTI, Natural gas, and Gasoline futures. Significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively. 'ADF' stands for the Augmented Dickey-Fuller unit root test

be mainly related to the sharp drop in demand due to the COVID-19 pandemic, which led to widespread storage closures and a significant decline in economic activity. As storage facilities reached capacity, traders with physical delivery obligations were forced to pay others to take the oil from them, resulting in negative prices (Fernan-

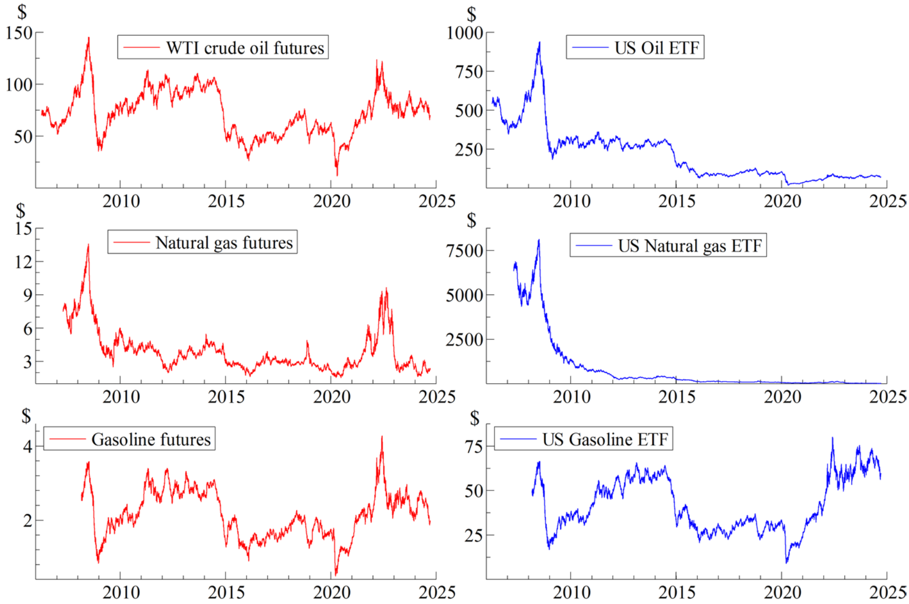

Fig. 1 Time evolution of daily closing prices. Note: This figure shows the time evolution of the daily closing prices of WTI, Natural gas, and Gasoline futures and US Oil, US Natural gas, and US Gasoline ETFs (all in US dollars) from the respective ETF's inception until September 2024

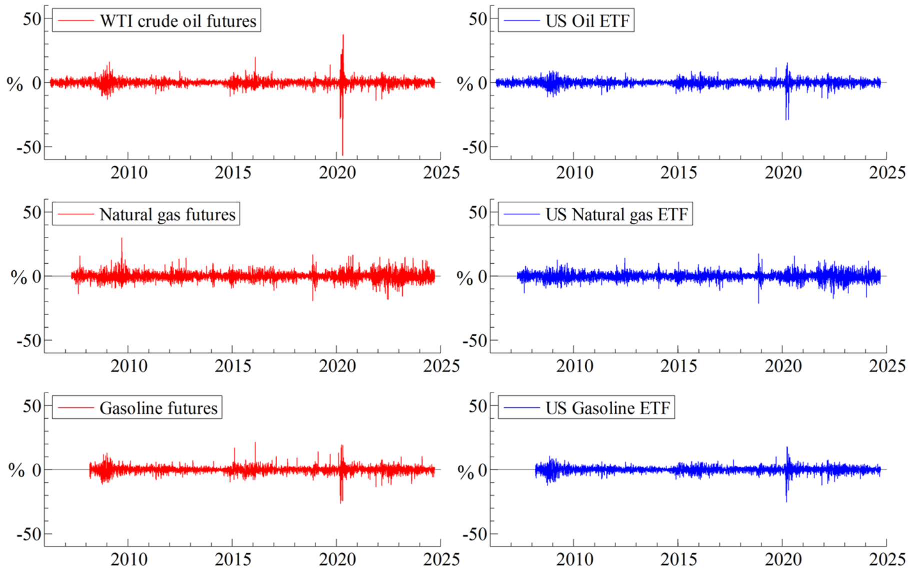

Fig. 2 Time evolution of daily returns. Note: This figure shows the time evolution of the daily closing returns of WTI, Natural gas, and Gasoline futures and US Oil, US Natural gas, and US Gasoline ETFs (all in US dollars) from the respective ETF's inception until September 2024

dez-Perez et al., 2023; Hanieh, 2021). The expiry of the May 2020 futures contracts exacerbated the problem and led to a perfect storm of oversupply and low demand (Fernandez-Perez et al., 2023). Figure 2 shows that around April 2020, WTI futures recorded the largest negative returns of more than -50% and the largest positive returns of more than 30%. Nevertheless, natural gas futures and ETFs (UNG) show the largest return dispersion over the sample period.

3.1 Yang-Zhang Range-Based Volatility

Yang-Zhang volatility measure is regarded as one of the most advanced approaches for approximating the past volatility of a financial asset. It aggregates three distinct forms of volatility: (a) Overnight volatility (close-to-open volatility); (b) Rogers-Satchell volatility (which considers the open, high, low, and close prices); and (c) Open-to-close volatility (Yang & Zhang, 2000). More accurate and efficient than basic approaches like the close-to-close estimator, this combination lets the Yang-Zhang measure manage both opening jumps and price drift. It has been found to be five to fourteen times more efficient than the conventional close-to-close volatility estimator (Li & Hong, 2011).

For volatility analysis, we employ the Yang–Zhang (2000) range-based estimator rather than conditional variance models such as GARCH. This choice is motivated by the structure of energy markets, where volatility is often driven by large overnight information shocks (e.g., inventory announcements, OPEC decisions, or geopolitical events). The Yang–Zhang estimator decomposes volatility into overnight (close-to-open), Rogers–Satchell (high–low–close), and open-to-close components, thereby capturing both intraday and overnight dynamics. By contrast, GARCH-type models estimate conditional variance from squared daily close-to-close returns, which neglects overnight jumps and intraday range information, leading to downward-biased volatility estimates in turbulent periods. Given episodes such as the April 2020 negative WTI pricing, we consider Yang–Zhang a superior measure of realised volatility for our sample, since it reflects the true amplitude of market fluctuations more faithfully.

The Yang-Zhang volatility estimator σ^2_{YZ} can be expressed as follows:

$$\sigma^2_{YZ} = \sigma^2_o + k\sigma^2_c + (1-k)\sigma^2_{rs} \tag{1}$$

where:

$$\begin{gathered}
\sigma^2_o = \frac{Z}{n-1}\sum\left(\ln\frac{O_i}{C_{i-1}} - \mu_o\right)^2 \\
\mu_o = \frac{1}{n}\sum ln\frac{O_i}{C_{i-1}} \\
\sigma^2_c = \frac{Z}{n-1}\sum\left(\ln\frac{C_i}{O_i} - \mu_c\right)^2 \\
\mu_c = \frac{1}{n}\sum ln\frac{C_i}{O_i} \\
\sigma^2_{rs} = \frac{Z}{n}\sum\left(\ln\frac{H_i}{C_i}\ln\frac{H_i}{O_i} + \ln\frac{L_i}{C_i}\ln\frac{L_i}{O_i}\right) \\
k = \frac{0.34}{1+\frac{n+1}{n-1}}
\end{gathered}$$

n is the number of historical prices used for the volatility estimate. Z is the number of closing prices in a year. H_i and L_i are the high and low prices on day *i*. C_i and O_i are the closing and opening prices on day *i*.

3.2 Price Discovery

An examination of current scholarly literature reveals four primary metrics employed in the assessment of price discovery: (IS; Hasbrouck, 1995), Component Share (CS; Gonzalo & Granger, 1995), and Information Leadership Share (ILS; Putniņš, 2013). The IS can be described as the proportion of the variance observed within the joint efficient price innovations that the innovations in a particular price series can explain. Gonzalo & Granger (1995) suggest that the Vector Error Correction Model (VECM) identifies two distinct components within a cointegrated price series: permanent and temporary. Given that energy futures and ETFs differ significantly in terms of liquidity, trading costs, and noise characteristics, relying on either IS or CS alone may result in biased estimates. To address these limitations, we employ the ILS proposed by Putniņš (2013), which combines IS and CS to provide an adjusted measure of price discovery leadership. The ILS accounts for heterogeneous noise structures and offers a more reliable indication of which market incorporates new information first. This measure makes it particularly suitable for our analysis of ETFs and futures, where disparities in market microstructure are central to the research question. The price discovery measures are derived from the VECM framework described below:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{j=1}^{k} A_j \Delta Y_{t-j} + \epsilon_t; \qquad \Pi = \alpha \beta^T \tag{2}$$

where Y_t is the vector of the crude oil price series, and *k* is the optimal lag order, A_j is the function of coefficients of lagged Y_t. The term ΠY_{t-1} is known as the error correction term, where the columns of β contain the m cointegrating vectors, and α the m adjustment vectors given the rank of Π is m, which is greater than 0 and less than full rank in the case of long-term cointegrating relationship.

From the normalised orthogonal coefficients to the VECM, the CS can be determined as follows:

$$CS_1 = \frac{|\alpha_2|}{|\alpha_1| + |\alpha_2|} \text{ and } CS_2 = \frac{|\alpha_1|}{|\alpha_1| + |\alpha_2|} \tag{3}$$

where, CS_1 denotes the price discovery component share for Crude Oil 1 and CS_2 denotes the component share for Crude Oil 2, the total component share is 1.

Based on the following reduced VECM covariance matrix Ω,

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \tag{4}$$

and its Cholesky factorisation, $\Omega = MM'$, where

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\,\sigma_2 & \sigma_2\left(1-\rho^2\right)^{1/2} \end{pmatrix} \tag{5}$$

where σ_1^2, σ_2^2, ρ_{12}, $and\,\sigma_1\sigma_2$ are components of the covariance matrix of the error vector (ϵ_t) in Eq. (3).

The IS can be determined using the various Cholesky orderings as follows:

$$IS_1 = \frac{\left(\gamma_1 m_{11} + \gamma_2 m_{12}\right)^2}{\left(\gamma_1 m_{11} + \gamma_2 m_{12}\right)^2 + \left(\gamma_2 m_{22}\right)^2}, IS_2 = \frac{\left(\gamma_2 m_{22}\right)^2}{\left(\gamma_1 m_{11} + \gamma_2 m_{12}\right)^2 + \left(\gamma_2 m_{22}\right)^2} \tag{6}$$

In addition, the IL (information leadership) and ILS (information leadership share) can be calculated as follows:

$$IL_1 = \left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right|, IL_2 = \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|;\ ILS_1 = \frac{IL_1}{IL_1 + IL_2}, ILS_2 = \frac{IL_2}{IL_1 + IL_2} \tag{7}$$

where, IL_1 denotes the Information Leadership for Crude Oil 1 and IL_2 denotes the Information Leadership for Crude Oil 2. Similarly, ILS_1 and ILS_2 are Information Leadership Share for Crude Oil 1 and Crude Oil 2, respectively.

Following previous research (Bandyopadhyay & Rajib, 2023; Mohamad, 2024b), we calculate rolling ILS to account for the time-varying nature of price discovery between crude oils. The rolling ILS is computed using a rolling window technique, that is, with a 100-day observation period. This step means the ILS is calculated daily based on data from the previous 100 days. In addition, we use a 90-day moving average to smooth out the ILS over time. This method enables researchers to track how the ILS price discovery measure evolves, particularly in reaction to major crises like the COVID-19 pandemic and the Russia-Ukraine war. Furthermore, we also report Monte Carlo confidence bands for 100-day rolling windows to address concerns about small-sample inference. To test for robustness, we also extended the estimation window to 250 days (approximately one trading year)(Bohl et al., 2020). The longer window reduces small-sample issues while preserving the rolling structure. In both cases, 1,000 bootstrap replications were applied per window to obtain pointwise 95% confidence intervals.

3.3 Time-Varying Granger Causality (TVGC)

TVGC can be described as the dynamic evaluation of causal relationships among time-varying variables, especially during extreme events or volatile periods, an essential diagnostic for complex financial systems (Tseng et al., 2024). This concept suggests that causal relationships among variables may fluctuate or develop across various time intervals.

Based on the work of Shi et al. (2018, 2020), this paper examines the time-varying causality relationship between WTI and USO, natural gas and UNG, and gasoline and UGA,. Granger causality's temporal stability can be assessed by using a stationary vector autoregressive (VAR) model or a lag-augmented VAR (LA-VAR) model. Generally, three time-varying methods are offered to identify instability in the causal relationship: recursive evolving, rolling, and forward expanding. However, Shi et al. (2020) express their preference for the recursive estimate of the classic Wald statistic, which can be explained below:

$$y_{1t} = \varnothing_0^{(1)} + \sum_{k=1}^{m} \varnothing_{1k}^{(1)} y_{1t-k} + \sum_{k=1}^{m} \varnothing_{2k}^{(1)} y_{2t-k} + \epsilon_{1t} \tag{8}$$

$$y_{2t} = \varnothing_0^{(2)} + \sum_{k=1}^{m} \varnothing_{1k}^{(2)} y_{2t-k} + \sum_{k=1}^{m} \varnothing_{2k}^{(2)} y_{2t-k} + \epsilon_{2t} \tag{9}$$

where the variables y_{1t} and y_{2t} represent the crude oil being examined. $\varnothing_{1k}^{(1)}, \varnothing_{2k}^{(1)}, \varnothing_{1k}^{(2)}, and\, \varnothing_{2k}^{(2)}$ are the coefficients of the lagged variables, $\epsilon_{1t}\, and\, \epsilon_{2t}$ are the error terms.

The Wald test evaluates the joint significance of $\varnothing_{1k}^{(2)}(k = 1, \ldots, m)$ under the null hypothesis that there is no Granger causality from y_1 to y_2,. The Wald statistics, $[f_1, f_2]$, are calculated using a sample size fraction of $f_w = f_2 - f_1 \geq f_0$, and represented by $W f_2 (f_1)$. Additionally, the supremum Wald statistics can be expressed as follows:

$$SW_f (f_0) = \frac{sup}{(f_1, f_2) \in \widehat{0}, f_2 = f} \{w_{f_2} (f_1)\} \tag{10}$$

where $\widehat{0} = \{(f_1, f_2) : 0 < f_0 + f_1 \leq f_2 \leq 1, \text{and}\, 0 \leq f_1 \leq 1 - f_0\}$.

Further, we can make an estimation of $\widehat{f_e}$ and $\widehat{f_f}$. We will then examine if the test statistics for these estimations fall inside or outside the critical values for the initial and final points of the causal relationship. This test can be done in the following manner:

$$\widehat{f_e} = \frac{inf}{f\varepsilon\, [f_0, 1]} \{f : SW_f (f_0) > scv\} \tag{11}$$

$$\widehat{f_f} = \frac{inf}{f\epsilon \left[\widehat{f_\varepsilon}, 1\right]} \{f : SW_f (f_0) > scv\} \tag{12}$$

Where scv represents the critical values derived from SW_f statistics.

4 Empirical Results and Discussion

4.1 Unconditional (Range-Based) Volatility

Figure 3 illustrates the volatility estimates derived from the Yang-Zhang range-based volatility model. The top, middle, and bottom panels describe the volatility estimates for WTI futures vs. USO ETF, natural gas futures vs. UNG ETF, and gasoline futures vs. UGA ETF, respectively. The top panel shows that the most significant volatility peak occurs in April 2020, especially for WTI futures. This extraordinary volatility

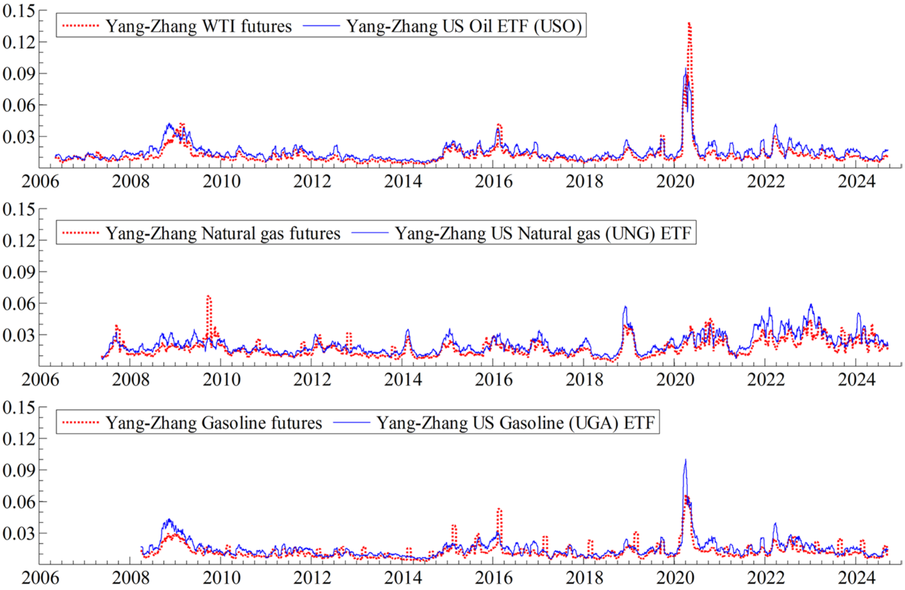

Fig. 3 Range-based volatility measure. Note: This figure depicts the volatility of WTI, Natural gas, and Gasoline futures and US Oil, US Natural gas, and US Gasoline ETFs using the Yang and Zhang (2000) range-based volatility estimator based on daily opening, high, low, and closing prices

can be linked to an unusual event in which WTI futures prices went into negative territory as a result of oversupply, collapsing demand, and limited storage capacity during the early stages of the COVID-19 pandemic (Fernandez-Perez et al., 2023). The USO ETF, which has WTI futures as the underlying asset, generally demonstrated increased volatility, albeit not as much as the futures market.

The middle panel shows volatility increased significantly in late 2009, particularly in natural gas futures. This rise coincides with a period of significant change in the US natural gas market, mainly fuelled by the shale gas revolution. By 2009, the rapid rise in shale gas production had considerably boosted natural gas supply, producing significant market uncertainty (Hilaire et al., 2015). In contrast, the UNG ETF experienced a lower volatility peak over this period. Furthermore, in the bottom panel, the largest volatility peak occurred in April 2020, with the UGA ETF exhibiting greater volatility than gasoline futures. This trend could have been influenced by the prevalence of contango in the futures market, which saw future contract prices much higher than near-term prices. UGA suffered significant costs when rolling over its futures contracts due to the wide gap between the expiring and fresh contracts it needed to purchase—this dynamic increased volatility in the ETF.

4.2 Price Discovery

Price discovery requires a stable long-term relationship between ETFs and their underlying futures. Johansen cointegration tests reported in Table 2 confirm the pres-

Table 2 Cointegration test

WTI futures - USO ETF			*Natural gas futures - UNG ETF*			*Gasoline futures - UGA ETF*		
	Trace	L_{max}		*Trace*	L_{max}		*Trace*	L_{max}
$r=0$	137.38***	134.42***	$r=0$	19.08**	17.54**	$r=0$	28.41***	24.01***
$r=1$	2.96	2.96	$r=1$	1.54	1.54	$r=1$	4.4**	4.4**

Note: This table shows the results of Johansen cointegration tests between WTI futures and USO ETF, Natural gas futures and ETF, and Gasoline futures and UGA ETF during the sample period. Trace, $L_{\max}$ and $r=0$ or 1 refer to trace, max-eigen statistics, and the number of hypothesised cointegrating equations (0 or 1), respectively. *** and ** denote 1% and 5% significance, respectively

ence of a single cointegrating vector in each pair, which allows us to proceed with the estimation of information leadership measures.

Figures 4 and 5 present the rolling Information Leadership Share (ILS) with Monte Carlo confidence bands, constructed from 1,000 bootstrap replications at the 95 per cent confidence interval, based on 100-day and 250-day rolling windows respectively. The shorter window captures localised fluctuations in leadership, while the longer window provides a smoother view of broader dynamics. It should be noted that the confidence intervals are pointwise, which by construction allows for occasional excursions of the ILS curve outside the shaded region without necessarily indicating a structural change in leadership.

For WTI futures and the USO ETF, the ILS is consistently above 0.5, indicating that futures dominate price discovery across most of the sample period. Futures leadership remains clear during the COVID-19 outbreak in early 2020, when volatility

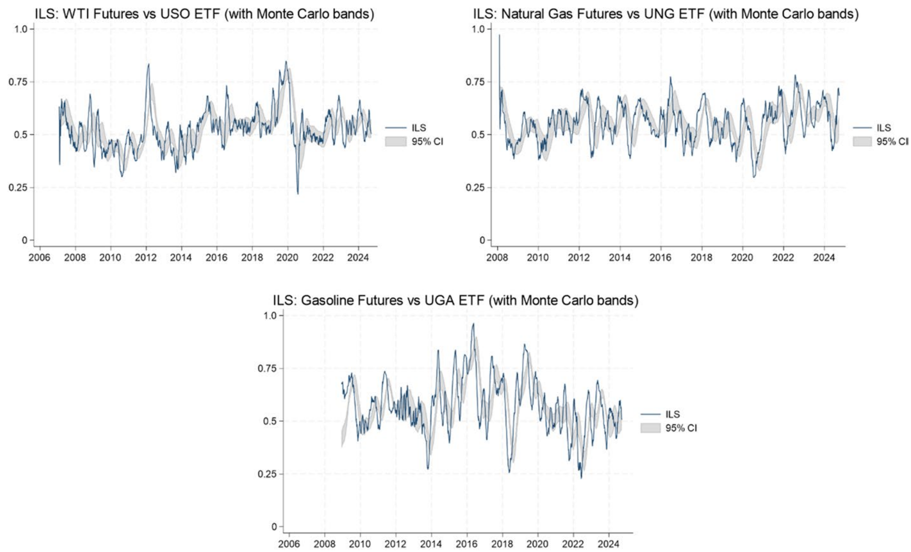

Fig. 4 Price discovery rolling ILS (with Monte Carlo bands, 100-day rolling window). Note: This figure illustrates the rolling Information Leadership Share (ILS) as a measure of price discovery between WTI futures and USO ETF, Natural gas futures and ETF, and Gasoline futures and UGA ETF during the sample period, based on a 100-day rolling window. The shaded regions represent pointwise 95 per cent Monte Carlo confidence bands derived from 1,000 bootstrap replications

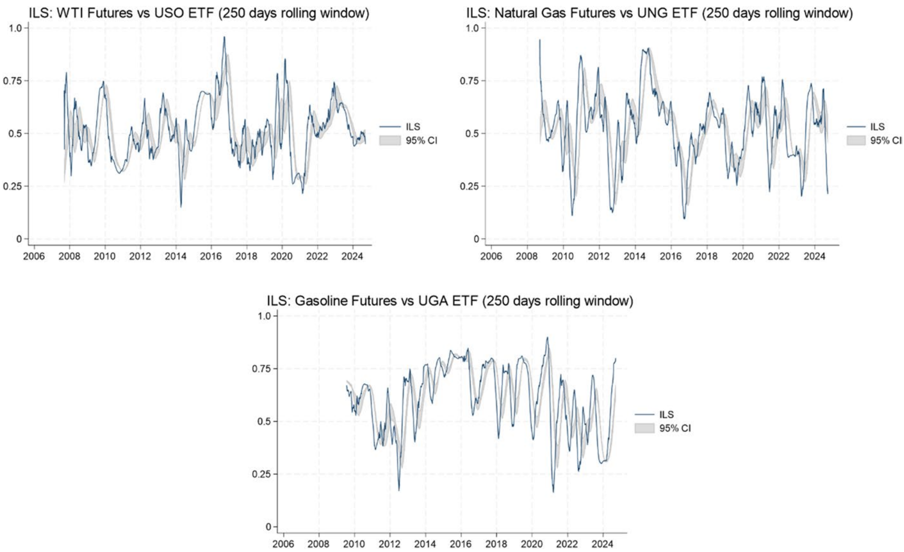

Fig. 5 Price discovery rolling ILS (with Monte Carlo bands, 250-day rolling window). Note: This figure illustrates the rolling Information Leadership Share (ILS) as a measure of price discovery between WTI futures and USO ETF, Natural gas futures and ETF, and Gasoline futures and UGA ETF during the sample period, based on a 250-day rolling window. The shaded regions represent pointwise 95 per cent Monte Carlo confidence bands derived from 1,000 bootstrap replications

was exceptionally high. However, in late 2020 the ILS briefly falls below 0.5, suggesting that the USO ETF assumed leadership during this interval. The Monte Carlo bands confirm that this shift was statistically significant. These results show that ETFs can temporarily act as price makers in conditions of heightened uncertainty, even though futures are generally more liquid and typically absorb new information more rapidly.

In the natural gas market, the ILS demonstrates that futures usually lead the UNG ETF, although the relationship is more variable than in the WTI–USO pair. Episodes such as late 2020 reveal intervals when UNG made a significant contribution to price discovery. This suggests a more dynamic interaction between futures and ETFs in the gas market, reflecting structural shifts and the heightened sensitivity of gas prices to shocks.

The gasoline market provides the clearest evidence of futures dominance. The ILS remains above 0.5 for most of the sample period, but UGA contributes during certain episodes. The most notable shifts occurred between 2014 and 2017, coinciding with the oil price collapse and the disruption caused by Hurricane Harvey. The Monte Carlo bands confirm that UGA's temporary leadership was statistically significant, demonstrating that ETFs played a role in price discovery when futures markets were under stress.

Overall, the evidence shows that WTI, natural gas, and gasoline futures are the primary drivers of price discovery. Nevertheless, ETFs increase their influence during periods of turbulence, such as the oil price collapse and the COVID-19 pandemic, when they served as convenient vehicles for investors seeking exposure to volatile energy markets. The use of 1,000 bootstrap replications with pointwise 95 per cent confidence intervals provides robust inference and ensures that the observed shifts in leadership are not artefacts of sampling variation.

4.3 Time-Varying Granger Causality (TVGC)

Before estimating the VAR using the LA-VAR framework, it is essential to determine the order of integration of the asset series. Table 3 reports the results of the ADF and ERS–DF–GLS tests based on weekly returns. As is often observed in empirical work, the two tests yield slightly different classifications: the ADF test suggests that some series (e.g., UNG ETF and natural gas futures) are stationary only after first differencing, while the ERS–GLS test indicates that others (e.g., USO, UGA ETFs, and WTI futures) are stationary at levels. These differences arise because the two tests vary in power and sensitivity to sample size and deterministic components.

Importantly, both tests consistently show that all series become stationary after first differencing, implying that the maximum order of integration is one ($d\text{max}=1$). As highlighted by Shi et al. (2020), the LA-VAR framework relies on knowledge of dmax rather than exact pre-classification of each series, and it remains valid as long as no series is integrated of order two or higher. Thus, setting $d\text{max}=1$ accommodates the observed differences across tests and ensures the avoidance of spurious regression results. Moreover, following Toda & Yamamoto 1995, the augmented VAR/VECM approach is robust even when some series are borderline stationary at

Table 3 Unit root test results

	Levels		First-difference		
	Intercept	Trend & Intercept	Intercept	Trend & Intercept	Conclusion
ADF test					
USO ETF	−2.572*	−4.228***	−28.103***	−28.098***	I(0)
UNG ETF	−4.088***	−3.481**	−29.719***	−29.716***	I(0)
UGA ETF	−1.753	−1.842	−27.673***	−27.676***	I(1)
WTI futures	−2.476	−2.555	−32.241***	−32.224***	I(1)
Natural gas futures	−2.977**	−3.105	−28.636***	−28.624***	I(0)
Gasoline futures	−2.591*	−2.583	−28.897***	−28.882***	I(0)
ERS-DF-GLS test					
USO ETF	−0.686	−3.714***	−3.678***	−5.872***	I(0)
UNG ETF	0.475	−0.599	−28.815***	−29.08***	I(1)
UGA ETF	−1.653*	−1.658	−27.591***	−27.415***	I(0)
WTI futures	−2.475**	−2.486	−3.863***	−6.18***	I(0)
Natural gas futures	−0.723	−2.168	−27.494***	−28.064***	I(1)
Gasoline futures	−1.89*	−2.424	−18.65***	−18.568***	I(0)

Note: This table displays the unit root test outcomes for the US Oil Fund, US Natural Gas Fund, US Gasoline Fund ETFs, as well as WTI, Natural gas, and Gasoline futures over the entire sample period, based on weekly closing prices (levels) and returns (first differences). These results are based on the Augmented Dickey-Fuller (ADF) and Elliott-Rothenberg-Stock, Dickey-Fuller generalised least squares (ERS-DF-GLS) tests. Significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively levels, as the inclusion of extra lags secures valid asymptotic inference. Accordingly, the chosen framework remains appropriate despite minor discrepancies in unit root outcomes.

Table 4 shows the TVGC analysis using a recursive evolving (RE) estimation for all six assets derived from 499 bootstrap replications. Remarkably, the maximum RE Wald statistics consistently reject the null hypothesis that there is no time-varying Granger causality at any point in time at a 5% significance level (95th percentile) for all assets except for the UGA ETF at the bottom right. This finding indicates that the UGA ETF does not exhibit Granger causality for gasoline futures, as its Wald test statistic (9.227) is below the critical 95th percentile value of 10.998. Our TVGC results also suggest that there is bidirectional time-varying causality between WTI futures and USO ETF, as well as natural gas futures and UNG ETF, but not between gasoline futures and UGA ETF. The Wald statistic (35,133) also suggests that the USO ETF has the most substantial causal influence on WTI futures of the six assets.

Figure 6 illustrates the TVGC analysis for all six assets over the sample period. The time-varying Wald test statistics and the critical 95% bootstrap values are shown in these plots. In the upper left panel, the t-statistic exceeds the critical value, indicating significant time-varying causality between WTI futures and the USO ETF from mid-2021 onwards. Accordingly, these notable periods of strong causality correspond to the aftermath of the COVID-19 pandemic. Further, the t-statistic in the upper right panel exceeds the critical value even more significantly, indicating stronger time-varying causality between the USO ETF and WTI futures from mid-2021 onwards.

Table 4 Time-varying granger causality wald test based on recursive estimation

1a) Does WTI futures Granger-cause USO ETF?			1b) Does USO ETF Granger-cause WTI futures?		
t-stat	Percentile	Max Wald	t-stat	Percentile	Max Wald
24.972			35.133		
	90th	7.5		90th	7.369
	95th	9.408		95th	9.353
	99th	16.181		99th	15.936
2a) Does Natural gas futures Granger-cause UNG ETF?			2b) Does UNG ETF Granger-cause Natural gas futures?		
t-stat	Percentile	Max Wald	t-stat	Percentile	Max Wald
19.756			17.382		
	90th	7.184		90th	6.096
	95th	9.325		95th	9.014
	99th	13.615		99th	14.629
3a) Does Gasoline futures Granger-cause UGA ETF?			3b) Does UGA ETF Granger-cause Gasoline futures?		
t-stat	Percentile	Max Wald	t-stat	Percentile	Max Wald
17.064			9.227		
	90th	7.481		90th	8.341
	95th	8.98		95th	10.998
	99th	14.585		99th	17.594

Note: This table presents the Wald test t-statistics and critical values from the time-varying Granger causality tests, utilising recursive estimation. The critical values for the 90th, 95th, and 99th percentiles are derived from 499 replications

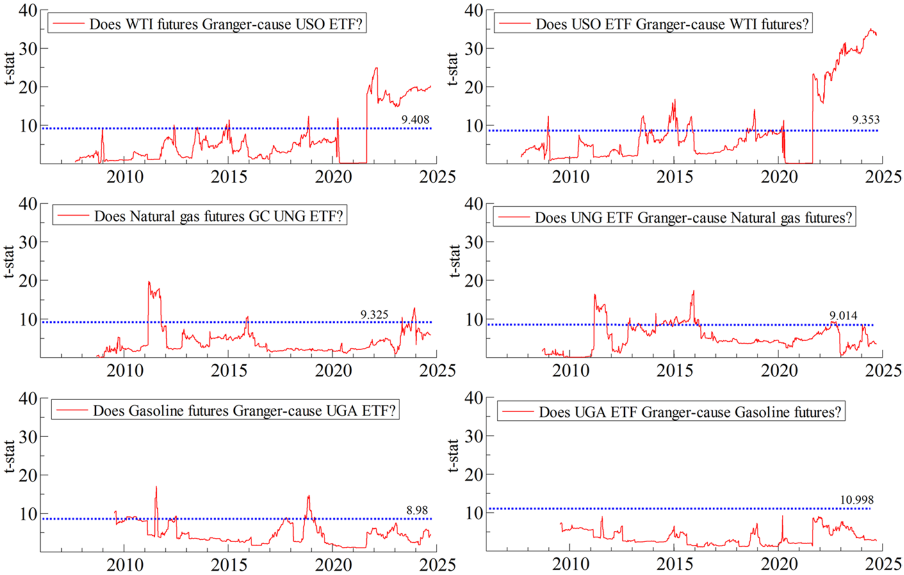

Fig. 6 Time-varying Granger causality (recursive estimation) results. Note: This figure plots the Wald test t-statistics and critical values of the time-varying Granger causality tests, utilising recursive estimation. The horizontal blue dotted lines and the figure above or below the dotted lines mark the 95th percentile bootstrapped critical values based on 499 replications

Hence, this result suggests a bidirectional time-varying causality between USO and WTI futures that only occurs after 2021.

In similar fashion, in the centre left panel, the Wald t-statistic exceeds the critical value, especially in 2011, suggesting that natural gas futures granger-cause the UNG ETF during this period. Apparently, the continued boom in shale gas production in the US has significantly impacted natural gas prices. Advances in hydraulic fracturing (fracking) and horizontal drilling technologies led to an increase in natural gas supply, which put downward pressure on prices (Wang et al., 2014). In addition, we observed strong spikes or increased time-varying causality in the centre-right panel in 2011 and early 2016. The peak in 2011 corresponds to the ongoing boom in shale gas production, and the peak in 2016 corresponds to the collapse of the oil price. Similar to the top panel, there is bidirectional time-varying causality between natural gas futures and UNG ETF in 2011 and 2016.

Correspondingly, in the lower left panel, the Wald t-statistic surpasses the critical value of the 95th percentile in 2011 and 2019, suggesting that gasoline futures are a Granger cause of UGA ETF in these periods. It seems that while the spike in 2011 could be related to the ongoing shale boom, the spike in 2019 could be related to the Atlantic hurricane season – several storms threatened the Gulf Coast, a central hub for US refining capacity. Moreover, these events led to short spikes in gasoline futures due to potential supply disruptions (Rostami & Rahimpour, 2023). In addition, looking at the lower right panel, we can observe that the Wald statistic is below the critical value. This result indicates that UGA is not a significant Granger cause for gasoline futures throughout the sample period. Ostensibly, the TVGC within the gasoline market was rather unidirectional, i.e. from gasoline futures to UGA ETF but not vice versa.

Although our ILS and TVGC analyses capture leadership based on traded prices, ETFs are subject to management fees and roll costs. The three ETFs examined: USO, UNG, and UGA carry expense ratios of 0.81%, 1.11%, and 0.96%, respectively (Table 1). These costs, while modest in daily terms, accumulate over time and reduce net asset value. In addition, in commodity markets that remain in contango, such as natural gas and oil, ETFs incur rollover costs when replacing expiring contracts, which further erodes performance (Chincarini & Moneta, 2021). Thus, while our ILS/TVGC estimates reveal that ETFs may exert notable short-term informational leadership during crises, their effective influence from an investor's perspective is somewhat constrained by these structural frictions. Recognising this limitation refines the interpretation of our findings, showing that ETFs act as influential price makers in volatile periods but with reduced net efficiency relative to their underlying futures.

The empirical findings from this study can be summarised as follows. For starters, futures led price discovery in all three markets (WTI, natural gas, and gasoline). This finding demonstrates the liquidity and effectiveness of futures markets in absorbing fresh information. Having said that, the growing involvement of ETFs in price discovery during periods of significant volatility, such as the COVID-19 outbreak in 2020, indicates that ETFs are playing an increasingly crucial role in influencing futures prices, particularly during times of increased market uncertainty. Second, the presence of bidirectional TVGC in both the WTI-USO and natural gas-UNG markets, particularly after 2020, highlights the changing dynamics of these markets. The expanding prominence of ETFs, particularly in the aftermath of the COVID-19 outbreak, emphasises the need to view ETFs as active price makers in energy markets during turbulent periods rather than passive price takers. Further, the unidirectional causality from gasoline futures to the UGA ETF implies that, unlike in the oil and natural gas markets, ETFs have little influence on futures prices in the gasoline market. This observation could be due to the disparity in size and liquidity between the gasoline futures and ETF markets. Finally, to summarise, our empirical findings synthesise that ETFs play a more prominent role in price discovery during periods of market volatility. For example, during the 2014–2017 oil price crash and the 2020 pandemic, ETFs tend to Granger cause or influence futures prices. This tendency could be fuelled by growing retail investor engagement, especially during market stress when ETFs act as convenient instruments for exposure to volatile commodity markets.

5 Conclusion

This paper has examined price discovery and time-varying causality between energy futures and exchange-traded funds (ETFs) in the WTI crude oil, natural gas, and gasoline markets over nearly two decades of data. By combining rolling Information Leadership Share (ILS) measures with Monte Carlo simulation bands and recursive time-varying Granger causality (TVGC) tests with bootstrap inference, we applied computationally intensive econometric techniques to capture the evolving leadership dynamics between futures and ETFs with a high level of rigour.

Our findings show that futures markets generally dominate price discovery under normal conditions, reflecting their superior liquidity and ability to incorporate new information efficiently. However, ETFs gain importance during episodes of turbulence, such as the 2014–2016 oil price collapse and the COVID-19 pandemic, when they temporarily shift from passive followers to active price makers. This pattern is particularly evident in the WTI–USO and natural gas–UNG pairs, where bidirectional causality emerges during crises. By contrast, gasoline markets display a more traditional one-way leadership structure in which futures remain the primary drivers of price discovery.

The study makes two key contributions. First, it demonstrates the value of applying simulation-based and recursive estimation techniques in applied computational economics, showing how Monte Carlo inference and time-varying causality frameworks can uncover dynamic patterns that static models may overlook. Second, it provides novel empirical evidence on the changing role of ETFs in energy markets, demonstrating that while futures remain dominant, ETFs can play a significant role in information transmission during periods of heightened volatility.

Despite these contributions, the study has limitations. Our analysis focuses on US-based energy ETFs and their corresponding futures (WTI, Henry Hub natural gas, and RBOB gasoline). Global benchmarks such as Brent crude and ICE gasoil are also central to international price discovery, but they are not directly represented here because the ETFs under study do not track them. Nevertheless, the literature documents strong cross-market spillovers between US and international benchmarks, which suggests that the leadership role of ETFs identified in this study may be shaped by broader inter-market dynamics. Future research should extend this framework by incorporating Brent and ICE gasoil to assess whether the leadership patterns we identify are unique to US markets or form part of a wider global structure of information transmission.

The findings of this study carry several practical and policy implications. For traders and institutional investors, the evidence that ETFs can act as price makers during periods of heightened volatility suggests that ETF order flows and pricing dynamics warrant closer monitoring. In particular, ETFs may provide early signals of shifts in market sentiment when futures markets are under stress. Incorporating ETF leadership into trading and hedging strategies could therefore improve responsiveness to information transmission in turbulent conditions.

From a policy perspective, the growing influence of ETFs during crises raises important questions about investor protection and market stability. ETFs provide retail investors with convenient and relatively low-cost exposure to commodity markets, yet their temporary leadership role in volatile periods means that shocks in ETF pricing can reverberate quickly into the underlying futures markets. Such spillovers increase the risks faced by less experienced investors. Regulators may therefore wish to strengthen disclosure practices, promote investor education, and ensure that the risks of ETF trading in turbulent conditions are communicated transparently. Overall, the evidence indicates that ETFs are no longer merely passive vehicles but active participants in price discovery during periods of stress. This conclusion has implications both for how traders formulate strategies and for how policymakers protect retail investors while maintaining orderly energy markets.

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Data Availability Data for this study were obtained under licence from LSEG Refinitiv and are not publicly available. A subscription to the databases is required for access.

Declarations

Ethical Compliance This study did not involve human participants, animal subjects, or any primary data collection requiring ethical approval.

Conflict of Interests The author declares no competing interests, financial or otherwise, that could influence the work reported in this paper.

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