Information Transmission and Volatility-Based Trading Strategies in Commodity Futures and Options Markets

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Abstract

How is volatility transmitted between options and futures contracts, and can this information transmission be used to generate profitable trading strategies? We examine the bidirectional relationship in volatility between commodity options and futures markets for key commodities to learn about how each market influences the other. To this end, we estimate volatility forecasting models using random forests and we calculate connectedness and spillover measures. We find that futures volatility has a strong but short-lived impact on option volatility, while option volatility has a longer lasting effect on futures volatility, confirming a bidirectional volatility transmission. We further document important net spillovers from options to futures. Moreover, predictive analysis shows that option markets generally lead futures markets in terms of providing information that is relevant for trading strategies. We obtain more accurate futures volatility predictions and trading strategies generate superior economic gains.

Keywords: commodities; futures; options; volatility; realized; random forests; trading strategies; spillovers; connectedness; information transmission; bidirectional.

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1. Introduction

The relationship between option pricing and the underlying asset's volatility is defined within the Black and Scholes (1973) framework. Option vega quantifies the change in an option's price relative to a one percent change in the underlying asset's implied volatility. All else being equal, an increase in volatility leads to higher option prices, as the option is more likely to be in the money at the expiration date. What is more, trading in the options market can anticipate or even accelerate changes in the volatility of the underlying market. This can occur through hedging and speculative trading. Large movements in options can lead market participants to adjust their positions in the underlying assets (e.g., instances of "gamma squeezes" reported by the financial press), thus feeding back into the underlying asset (Arkorful et al., 2020; Wu et al., 2022). Thus, the dynamics between volatility in option markets and volatility in the underlying market is expected to be bidirectional.

How is volatility transmitted between options and futures contracts, and can this information transmission be used to generate profitable trading strategies? While this question has received some attention in equity option markets, very little is known in the setting of commodity futures and options markets. Therefore, we investigate the potentially bidirectional nature of volatility transmission and its consequences for volatility forecasting and trading strategies. We examine the direct impacts of changes in the underlying market on option volatility as well as the reciprocal effects of option market dynamics on the underlying commodity futures volatility.

Studying the interaction between these markets is important as there has been considerable growth in commodity futures and options. This is especially true since the Commodity Futures Modernization Act in 2004, which made it easier to trade these derivatives. Over this period, daily trading volume and open interest have steadily increased, reflecting a more widespread demand for the products beyond traditional commodity market participants. A further outcome of the financialization of commodities is that, by increasing liquidity in both the underlying asset and the option market, it has plausibly affected volatility spillovers. This issue also has broader relevance for risk management, trading strategies, and market stability. Indeed, a better understanding of the relationship between option and futures volatility could lead to more accurate option pricing, since volatility is an essential input for option pricing models. What is more, hedging strategies could be improved by adjusting hedges based on observed and predicted volatility transmission.

This issue also has implications for policymakers. For regulators, monitoring option and futures markets interconnections and addressing potential market instabilities is of outmost importance. The Flash Crash of May 6th, 2010, for instance, made it clear there is a critical need to monitor the interconnections between options and futures markets. On that day, major U.S. stock indices experienced a rapid and severe decline, with the Dow Jones Industrial Average plummeting about 1,000 points within minutes before rebounding shortly thereafter. A joint investigation by the U.S. Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) revealed that the crash was triggered by the automated execution of a large sell order in the E-mini S&P 500 futures market. This action led to a cascade of trading activities across various markets, including options, exacerbating the option market's volatility. To this end, improving models to capture the lead-lag relationship in volatility may help in detecting early signs of market crashes or economic downturns, allowing for planning and mitigation.

Our empirical design first aims to determine whether a volatility spillover effect exists between commodity futures and option markets. We generate and examine the impulse response functions (IRF) between the options and futures markets for a sample of six commodities, namely crude oil, natural gas, gold, corn, wheat, and lean hogs. We build on the IRF results by adding evidence from a directional spillover analysis framework (Diebold and Yilmaz 2012). Second, we assess whether current and past futures contract volatility can predict option volatility. Recent research finds that the random forest model consistently outperforms alternative models to predict returns on commodity options (e.g., Aka, Gagnon and Power 2024). Therefore, we use a random forest model to predict each market's one-week ahead realized volatility (RV). For each market, RV is computed using futures or option returns over a one-week period. The model's predictors consist of past RVs from both options and futures markets.

Third, we provide evidence on which market leads the other in terms of volatility, which relates to information transmission across markets. After estimating the models, we generate full and constrained forecasts. The full forecast uses the entire set of predictors, while the constrained forecast uses only the own-market information. Applying this constraint is equivalent to assuming a univariate process. Next, we measure and describe, statistically and economically, how predictive information is transmitted between options and futures markets. We use criteria such as variation in RMSE and in Sharpe ratios for option trading strategies that we design based on the model forecasts.

Our main results are as follows. First, the IRF analysis reveals that a shock in futures volatility has a more pronounced, but shorter-lived impact on option volatility, than on itself. In contrast, a shock in option volatility has a weaker but more persistent impact on futures volatility. Second, results from the Diebold and Yilmaz (2012) analysis show that option markets are a net transmitter of volatility shocks, while futures markets are a net receiver.[1] Third, we find two profitable strategies in commodity option markets that use the predicted option and futures realized volatilities. For the first strategy, we show that a portfolio of options sorted on higher predicted RVs consistently delivers a superior risk-adjusted economic performance than the market portfolio. Then, for the second strategy, we show that shorting a portfolio of straddles[2] that have the highest difference between the one-week predicted futures RV and the current IV ($\mathrm{i.e.}, RV - IV$) consistently generates higher risk-adjusted returns than shorting the market portfolio, across all commodity markets in our sample.

[1] This result is consistent findings for other asset classes, such as Patel et al. (2020) who find that options markets lead spot markets in incorporating new information, particularly around information events.
[2] This strategy consists of holding long positions in both a call option and a put option with the same maturity and strike price.

Lastly, on cross-market predictability, we find that adding option predictors to a strategy based on forecasting futures RV leads to higher economic gains than does the addition of futures predictors to a strategy based on option RV, and this is true across commodities. This finding relates to Bohmann et al. (2019), who find that option markets reflect new information due to increased speculative activity. In the specific setting of soybean markets, Hao et al. (2021) find that price discovery tends to occur in options before futures markets.

2. Background and literature review

While the literature on volatility spillovers is vast, it focuses on the relationship between spot and futures markets, or between asset classes or country market indexes. In contrast, how volatility is transmitted between options and futures is much less studied, especially in commodity markets. This line of research consistently finds that price discovery occurs in futures markets rather than spot markets. Antonakakis et al. (2016) examine the dynamic spillovers between spot and futures market volatility in the UK (FTSE 100) and the US (S&P 500). They find that directional spillovers between spot and futures volatilities are equally informative, with shares of 50% each. In Chinese equity markets, Hou & Li (2020) identify significant volatility spillovers from futures to spot prices, while Zhou et al. (2021) show that news significantly affects the correlation between the index futures and spot equity markets, with bidirectional volatility spillovers. Sehgal et al. (2015) find bidirectional spillovers between spot and futures prices for key currency exchange rates, with futures typically leading in the short run.

In the energy and commodity space, Magkonis & Tsouknidis (2017) find evidence of large and time-varying spillovers in crude oil-related spot and futures prices, with futures as the net volatility transmitter. Tsuji (2018) shows, using a VAR-GARCH-DCC approach, that crude oil volatility spillovers go from equities to futures contracts. Kim & Lim (2018) find that futures markets lead spot markets in China in price discovery and in volatility transmission. Many further studies examine spot and futures markets for individual commodities (An et al., 2020; Balash & Faizliev, 2024; Bonato, 2019; Dahl et al., 2020; Green et al., 2018; Nazlioglu et al., 2013). A common limitation of this literature is that little or no economic analysis is produced to assess the consequences of volatility spillovers, such as potential trading strategies for example.

Therefore, this paper fills a gap by investigating the economic outcomes of volatility spillovers and connectedness between commodity options and their underlying futures. To assess economic performance, we design and implement trading strategies that rely on volatility forecasts from each market. To our knowledge, our paper is the first to analyze volatility spillovers and related trading strategies for a representative sample of commodity options and futures. Indeed, we describe a profitable option trading strategy based on volatility forecasts that use the combined information from the two asset types. In particular, we document a new pattern in the weekly returns of commodity option straddles.

3. Empirical framework and methodology

3.1. Overview

Our methodology is divided into two parts: a connectedness analysis (in-sample) and a predictive information flow analysis (out-of-sample).

3.1.1. Connectedness analysis

First, we describe the connectedness analysis. We begin by estimating a GARCH model on futures returns and raw option returns. Raw option returns are computed as the profit from a strategy that involves buying an option, holding it for one day, and selling it the following day. Consider a return r_{t_0,t_1} over the period $[t_0, t_1]$ such that O_{t_1} is the option price at t_1 and O_{t_0} is the option price at t_0. Then, the return is $r_{t_0,t_1} = \frac{O_{t_1}}{O_{t_0}} - 1$. Once the model is estimated, GARCH volatilities are obtained and incorporated into a VAR model. The VAR estimation is followed by an analysis of impulse response functions (IRFs) to explore interactions between options and futures. Then, we apply the spillover framework due to Diebold and Yilmaz (2012) and examine directional and total connectedness between the volatilities of the two markets.

3.1.2. Predictive information flow analysis

The second part involves predictive information flow analysis. We begin by computing one-week realized volatilities (RV) separately for options and futures. Then, we use a random forest model to generate out-of-sample forecasts for these realized volatilities, using a set of predictors consisting of historical RVs from both markets. The focus on RV warrants some explanations. The realized volatility (RV) of option returns and implied volatility (IV) measure different quantities. Option IV measures the anticipated, risk-neutral volatility of the underlying asset (e.g., futures) over the remaining life of the option, while the RV of option returns measures fluctuations in the option's returns over a given period (in our case, one week). Since our objective is to examine how fluctuations in the returns of the underlying asset affect fluctuations in option returns and vice versa, the appropriate measure of volatility for options is the RV of option returns. Once the model is estimated, two types of forecasts are computed, namely constrained and full. Full forecasts use the entire set of predictors, while constrained forecasts set the past RVs of the other market to zero. Based on these forecasts, we compute two measures to capture the predictive information flow from a statistical perspective:

- **Change in RMSE** ($\Delta RMSE$), which is the difference in Root Mean Squared Error (RMSE) when going from a constrained to a full forecast to predict option or futures RV.
- **Net information transmission (NIT)**: This is defined as the $\Delta RMSE$ for predicting futures RVs minus the $\Delta RMSE$ for predicting options RVs.

In addition, the forecasts are used to implement two option trading strategies. Two further metrics are computed to measure predictive information flow from an economic perspective:

- **Change in Sharpe ratio (SR)** (ΔSR): The change in the Sharpe ratio when moving from a constrained to a full forecast.
- **Sharpe net information transmission (NIT)**: This is the difference between the change in the Sharpe ratio for the strategy based on the futures RV and the change in the average return for the strategy based on the option RV.

Figure 1 provides a graphical illustration of each step in our methodology. The following subsections delve deeper into each step, offering detailed explanations.

3.2. Connectedness Analysis

3.2.1. Daily GARCH-based volatility

We estimate a GARCH (1,1) model using the daily option and futures returns. Then, we specify and estimate parameters of the conditional variance σ_t^2 equation given by $\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$ with ω, α and β needing to be estimated. After estimating this model using maximum likelihood estimation, the daily volatility is calculated as the square root of the fitted variance over the sample.

3.2.2. DY spillover measures

The Diebold & Yilmaz (2012) connectedness measures are a set of metrics developed to quantify the degree of interconnectedness among multiple time series of financial variables. This approach has been extensively used to study spillover effects among banks (Ribeiro & Curto, 2017), equity markets (Tsai, 2014), currencies (Hameed et al., 2021) , commodities (Magkonis & Tsouknidis, 2017), and cryptocurrencies (Yi et al., 2018), providing insights into how shocks in one area can affect others. To compute the Diebold and Yilmaz (2012) connectedness measures between the variables X_i and X_j, we first estimate a VAR model on these variables. After estimating the VAR parameters, we use the Generalized Forecast Error Variance Decomposition (GFEVD) proposed by Koop et al. (1996) to compute the own and cross-variable variance contribution shares. The GFEVD is computed as:

$$\theta_{ij}^{H} = \frac{\sum_{h=0}^{H-1} \sigma_{ii}^{-1} (e_j^{'} \ \Phi_h \ \Sigma \ e_i)^2}{\sum_{h=0}^{H-1} (e_j^{'} \ \Phi_h \ \Sigma \ \Phi_h{}' e_j)} \qquad (1)$$

In this equation, Φ_h denotes the *h*-step-ahead forecast error coefficient matrix derived from the VAR model, Σ is the covariance matrix of the innovations from the VAR, e_i is a selection vector for the *i-th* variable, and σ_{ii}^{-1} is the variance of the *i-th* innovation. The numerator captures the contribution of the *i-th* variable's shock to the forecast error variance of the *j-th* variable, scaled by the variance of the *i-th* shock. Since the own and cross-variable variance contribution shares do not sum to one under the generalized decomposition, each entry of the variance decomposition matrix is normalized by its row sum, such that : $\theta_{ij}^{H,norm} = \theta_{ij}^{H} / \sum_{k=1}^{n} \theta_{ij}^{H}$. Finally, the connectedness measures are computed as follows:

$$TCI = \frac{\sum_{i \neq j} \theta_{ij}^{H,norm}}{\sum_{i,j} \theta_{ij}^{H,norm}} \times 100 \qquad (2) \qquad\qquad FROM_i = \frac{\sum_{i \neq j} \theta_{ij}^{H,norm}}{\sum_{j} \theta_{ij}^{H,norm}} \times 100 \qquad (3)$$

$$TO_i = \frac{\sum_{i \neq j} \theta_{ji}^{H,norm}}{\sum_{j} \theta_{ji}^{H,norm}} \times 100. \qquad (4) \qquad\qquad NET_i = FROM_i - TO_i \qquad (5)$$

where TCI is the total connectedness index, $FROM_i$ is the contribution of the *i-th* variable's shock to the forecast error variance of the *other* variables, TO_i is the contribution of the other variable's shock to the forecast error variance of the *i-th* variable and NET_i is the net contribution of the *i-th* variable to the system.

3.3. Predictive information flow analysis

3.3.1. Weekly realized volatility

We compute the realized volatility (RV) of option and futures returns over a period of one week. The choice of a weekly frequency is due to the source data being daily returns. Moreover, weekly realized volatility provides a more up-to-date reflection of market conditions than monthly realized volatility. RV is the square root of realized variance, which is calculated as the variance of daily returns in a window of five days. Formally, the realized volatility over the week t is given by:

$$RV_t = \sqrt{\frac{1}{5}\sum_{i=1}^{5}\left[r_{t,j} - \bar{r}\right]^2} \qquad (6)$$

where $r_{t,j}$ represent the j^{th} daily returns of the week t.

3.3.2. Predicting realized volatility

3.3.2.1. Futures realized volatility

To forecast futures RV, we use current and past observations of futures RV as well as current and past values of the realized volatility for different option portfolios. We consider 11 portfolios of options that capture different aspects of the option market. Our approach uses portfolios of various types of options, including call options, put options, in-the-money options, at-the-money options, out-of-the-money options, as well as options categorized by implied volatility (low, medium, high) and option delta (low, medium, high). More formally, the anticipated realized volatility at time $t + 1$ for the return on futures contract i ($FRV_{i,t+1}$) is defined by the following equation:

$$FRV_{i,t+1} = \mathcal{G}\left(FRV_{i,t}, \cdots, FRV_{i,t-h}; OPRV_{i,j,t}, \cdots, OPRV_{i,j,t-h}, \dots\right) + \epsilon_{i,t+1}, \qquad (7)$$

where $FRV_{i,t-h}$, $h = 1,2$ represent past values of the futures realized volatility and $OPRV_{i,j,t-h}$, $h = 1,2$; $j = 1, \dots, 11$ are the past values of the realized volatility for the different option portfolios $j = \{1, \dots, 11\}$. We choose $\mathcal{G}$ to denote the predictive function from the random forest method (Breiman, 2001).

3.3.2.2. *Option realized volatility*

To predict option RV, we use current and past values of the option RV, as well as current and past values of the underlying futures RV. Thus, we may write anticipated option RV at time $t+1$ for the return on option *i* ($ORV_{i,t+1}$) using the following equation:

$$ORV_{i,t+1} = \mathcal{G}(ORV_{i,t}, \cdots, ORV_{i,t-h}; FRV_{i,t}, \cdots, FRV_{i,t-h}) + \epsilon_{i,t+1}, \qquad (8)$$

where $ORV_{i,t-h}, h = 1,2$ are the past values of the option RV while $FRV_{i,t-h}, h = 1,2$ are past values of the futures RV.

3.3.3. Option trading strategies

3.3.3.1. *Strategy 1: Trading based on option RV forecasts*

Our first option trading strategy involves buying the portfolio of options with the highest predicted realized returns, thereby selecting options that are expected to show high price movements (up or down) over the next week. At each week t, we consider all options, including every maturity and strike price available on that day after applying our filters. We rank them into ten portfolios from the lowest predicted RV portfolio to the highest predicted RV portfolio. We then buy the portfolio of options with the highest predicted realized volatility. Finally, we evaluate our strategy by computing the realized return at the week $t+1$.

3.3.3.2. *Strategy 2: Trading based on futures RV forecasts*

The second option trading strategy is based on the information contained in the difference between the current implied volatility and the one-week predicted realized volatility of futures contracts. The one-week predicted futures contract RV is annualized to match the scale of the time-t implied volatility. Our straddle strategy consists in shorting the portfolio of the straddle with the highest difference between predicted RV and current IV. Specifically, in each week *t*, we consider all straddles available. We rank them into ten portfolios from the lowest to the highest, based on the difference ($\widehat{RV}_{i,t+1} - IV_{i,t}$). We then take a short position in the portfolio of straddles with the highest difference. Finally, we assess our strategy by computing the realized return at week $t + 1$. Our strategy differs from the one used by Goyal & Saretto (2009), as ours is implemented weekly and uses the difference between the one-week predicted RV and the current IV as the trading signal. In contrast, in Goyal & Saretto (2009), returns on straddles are computed monthly and the signal for the strategy is the difference between the one-year historical RV and the current IV.

The two strategies are therefore option trading strategies as they are applied to option markets. The difference between them comes from the indicator used to trade. In the first (option RV based strategy), trading decisions are made by looking at the predicted option RV while in the second (futures RV-based strategy), trading decisions are made by looking at the difference between the option IV and the predicted one-week futures RV. Strategy 1 enables us to assess the economic performance of option RV forecasts, while Strategy 2 allows us to evaluate the economic performance of futures RV forecasts.

3.3.4. Predictive information transmission metrics

To determine whether predictors from one market affect volatility forecasts for the other market, we consider two hypotheses (null and alternative) described as follows:

Futures RV model

H0:
$$FRV_{i,t+1} = \mathcal{G}\left(FRV_{i,t}, \cdots, FRV_{i,t-h};\right) + \epsilon_{i,t+1}, \tag{9}$$

vs.

H1:
$$FRV_{i,t+1} = \mathcal{G}\left(FRV_{i,t}, \cdots, FRV_{i,t-\mathrm{h}}; OPRV_{i,j,t}, \cdots, OPRV_{i,j,t-\mathrm{h}}, \ldots\right) + \epsilon_{i,t+1}, \tag{10}$$

Under the null (H0), past option RV has no predictive power to forecast futures RV.

Option RV model

H0:
$$ORV_{i,t+1} = \mathcal{G}(ORV_{i,t}, \cdots, ORV_{i,t-\mathrm{h}}) + \epsilon_{i,t+1}, \tag{11}$$

vs.

H1:
$$ORV_{i,t+1} = \mathcal{G}(ORV_{i,t}, \cdots, ORV_{i,t-\mathrm{h}}; FRV_{i,t}, \cdots, FRV_{i,t-\mathrm{h}}) + \epsilon_{i,t+1}, \tag{12}$$

Under the null (H0), past futures RV has no predictive power to forecast option RV.

We then generate forecasts of realized volatility under the null (H0) and alternative (H1) hypotheses, referred to as ***constrained forecasts*** and ***full forecasts,*** respectively. Full forecasts use a model estimated with all available predictors. Constrained forecasts use only historical values of option realized volatilities (RV) for predicting option RV, and only past values of futures RVs for forecasting futures RV.

3.3.4.1. Statistical measures of information transmission

After generating the full and constrained forecasts, we use them to compute two statistical measures of information flow: the change in RMSE and the net information transmission (NIT). We first compute the RMSE for each forecast type across option and futures realized volatilities (RVs) as follows:

$$\boldsymbol{RMSE} = \frac{\mathbf{1}}{\boldsymbol{N_{T_3}}} \sum\nolimits_{(\boldsymbol{i},\boldsymbol{t})\in \boldsymbol{T_3}} \left(\boldsymbol{RV_{i,t+1}} - \widehat{\boldsymbol{RV}}_{\boldsymbol{i,t+1}}\right)^{\mathbf{2}}, \tag{13}$$

where T_3 refers to the test sample, N_{T_3} is the number of observations in sample T_3, $RV_{i,t+1}$ is realized volatility, and $\widehat{RV}_{i,t+1}$ is the predicted realized volatility. Then, the change in RMSE and the NIT are calculated as follows:

$$\Delta RMSE = \frac{RMSE_{full}}{RMSE_{constrained}} - 1, \tag{14}$$

$$NIT = \Delta\, RMSE_{fut} - \Delta\, RMSE_{opt}, \tag{15}$$

The change in RMSE is the resulting decrease in RMSE (i.e., smaller forecast errors) when going from a constrained forecast to a full (unconstrained) forecast. Net information transmission (NIT) measures the difference between the futures $\Delta RMSE$ and the options $\Delta RMSE$. The former quantity represents the information flow from options to futures, while the latter represents the flow from futures to options. Thus, if $NIT > 0$, option markets are more informative to predict futures markets volatility than vice versa. A positive sign for NIT is predicted based on the literature on informed trading in option markets (e.g., Easley, O'Hara and Srinivas, 1998).

3.3.4.2. Economic measures of information transmission

After computing full and constrained forecasts, we apply them to our two trading strategies and calculate the resulting Sharpe ratios (SR) for each strategy and type of forecast. We then assess two economic measures of volatility transmission: the change in Sharpe ratio and economic net information transmission. Thus, the change in SR and NIT are calculated as follows:

$$\Delta \ in \ SR = \frac{SR_{full}}{SR_{constraint}} - 1, \quad (16)$$

$$ENIT = \Delta \ in \ SR_{fut:S2} - \Delta \ in \ SR_{opt:S1}, \quad (17)$$

Equation (16) refers to the change in a Sharpe ratio when we go from the constrained to the full forecast. A positive value, which we expect to see, indicates that using the full information set delivers economic gains. The economic net information transmission ($ENIT$) shown in equation (17) is the difference between the change in the futures strategy Sharpe ratio and the change in the option RV Sharpe ratio. When $ENIT > 0$, the option market can be said to lead the futures market, since the futures RV strategy benefits more from adding options information than the option RV strategy benefits from adding futures information. The reverse interpretation follows from the case when $ENIT < 0$.

4. Data

We use end-of-day (EOD) futures options data obtained from the Chicago Mercantile Exchange (CME) and futures data from Refinitiv Datastream. Our sample includes all available EOD option contracts on the CME for six commodity futures markets: NYMEX WTI crude oil, NYMEX Henry Hub natural gas, COMEX gold, CBOT corn, CBOT wheat, and CME lean hogs. Table 1 provides detailed information about these commodities, such as first and last trade dates and sector classifications. For each commodity, we construct six generic futures contracts labeled M1 through M6, where M1 represents the nearest futures contract at any given time, M2 the second nearest, and so forth. Only options linked to these generic contracts are analyzed.

To address potential liquidity concerns, we apply well-established filters from the literature (Back et al., 2013; Jacobs & Li, 2023; Trolle & Schwartz, 2009). First, we exclude options with an open interest below 100 for crude oil, gold, and natural gas, and below 25 for corn, wheat, and lean hogs. Second, we eliminate options whose prices fall outside the bounds typical of American-style options and with a remaining time-to-maturity under five days. Third, we remove options priced less than 10 times the minimum price fluctuation due to price discreteness. Fourth, we exclude options for which the moneyness ratio is either below 0.8 or above 1.2. Finally, we discard options with an implied volatility that exceeds 300%.

Each option dataset contains details such as settlement prices, maturities, strike prices, total volume, open interest, implied volatilities (IVs), and deltas. However, IVs and deltas are only accessible from November 2011 onwards. For earlier data, we compute IVs and deltas using the binomial tree method, and we verify that our calculated IVs align with those supplied by the CME over the period of availability (from November 2011 to August 2022). The futures dataset includes settlement prices, total volume, and open interest.

Table 2 gtrc 4de

5. Results

5.1. Connectedness results

We begin by discussing our analysis of the impulse response functions (IRFs), examining how option (futures) volatility reacts to shocks in futures (option) volatility markets. Subsequently, we present a table of results on spillovers, constructed according to the connectedness framework established by Diebold and Yilmaz (2012).

5.1.1. Impulse response functions (IRF) analysis

Here, we explore the effect of a volatility shock in one market on the volatility forecasts in another. We calculate impulse response functions (IRFs) for six commodity markets, using daily GARCH-based volatility as our volatility measure. We consider each commodity separately to focus on the response of futures market volatility to a shock in option market volatility, and vice versa. Most impulse response functions in Figure 2, shown as sub-figures, indicate that the reaction to a shock begins strong and decreases over time, suggesting that the shock's influence wanes as time passes. The steep decline of the curves indicates a swift and significant initial impact, which diminishes over time, showing a quick adjustment to changes.

Focusing on the reaction of option volatility to shocks in futures contract volatility, there is a noticeable immediate response. The sharp initial decrease in most of the response curves for options highlights a strong but short-lived effect. Except for natural gas, most responses do not persist beyond 100 days, suggesting the strong but fairly short-lived sensitivity of option volatility to changes in futures volatility. Conversely, when examining how futures volatility responds to shocks in option volatility, we find that the initial reaction is less intense, but the effect is sustained over a longer period. The extended tails along the horizontal axis in the futures response graphs indicate that while the initial impact fades, a residual effect persists for at least 200 days. From this section, we conclude that the responses of option volatility are more pronounced but shorter-lived. In contrast, futures volatility shows a weaker initial response but lasts longer.

5.1.2. Spillover analysis

Table 3 presents the Diebold & Yilmaz (2012) connectedness measures for the six commodity markets (crude oil, natural gas, gold, corn, wheat, and lean hogs) detailing the spillovers between option volatility and futures volatility in both short-term ($H = 12$ days) and medium-term ($H = 22$ days). In the crude oil market, both short-run and medium-run spillovers show that each market (options and futures) is predominantly influenced by its own past shocks, with the net spillover slightly favoring a net spillover from options to futures (net 1.3% short-run; net 2.3% medium-run). The total connectedness index (TCI) values, which are 28.2% in the short run and 28.9% in the medium run, suggest a moderate level of connectedness.

In contrast, natural gas displays a higher self-influence on option volatility with a notable net spillover from options to futures (5.7% short-run; 9.8% medium-run), particularly increasing in the medium run. The TCI for natural gas shows a moderate and increasing connectedness (28.4% short-run; 29.2% medium-run). Gold maintains a more balanced interaction between its markets with a net spillover slightly favoring options to futures (3.2%). Gold shows the highest TCI (36.9% short-run; 36.7% medium-run), suggesting a strong overall market connectedness that diminishes slightly over time. Commodities like corn and wheat show a moderate net spillover, and moderate TCIs suggesting lower overall market connectedness compared to other markets such as gold. Contracts on lean hogs are an interesting case with a very high self-influence on option volatility (93.9% short-run; 94.0% medium-run) and significant net spillovers to futures (6.7% short-run; 11.9% medium-run), especially in the medium run, despite a low TCI (9.4% short-run; 12.0% medium-run). This indicates a strong directional connectedness from options to futures that is not mirrored in the total connectedness of the market.

Our Total Connectedness Index (TCI) varies from 9.4% for the least connected market, lean hogs, to 36.9% for the most connected market, gold. These figures fall within the same range as those found by Diebold and Yilmaz (2012) for volatility spillovers across different asset classes (stocks, bonds, commodities, and foreign exchange). Indeed, they report a TCI of 12.6% over their entire sample period. Additionally, when exploring dynamic spillovers throughout their sample period, they observe a TCI ranging from 5% to 30%, which aligns closely with our findings. For net pairwise spillovers, we observe values ranging from 0.8% to 12% while Diebold and Yilmaz (2012) report values ranging from 0% to 6%.

Antonakakis et al. (2016), who examine the dynamic spillovers between stock index spot and futures volatilities in the UK and the US, report values for net pairwise spillovers from spot to futures between 2.3% for the UK and 1.5% for the US. Magkonis & Tsouknidis (2017), who examine the crude oil spot-futures market, find a net pairwise spillover from futures to spot markets of around 10.6%. Our larger net spillovers suggest a plausible level of volatility transmission between options and futures across each commodity. Although we are not examining the same assets, these comparisons help validate our results and show that our results are within a reasonable range. In summary, net spillovers tend to favor a stronger information flow from option to futures markets. Finally, we find that TCI varies across commodities, with higher values in gold, indicating a stronger interconnectedness within those markets.

5.2. Quantifying the predictive information flow

In this section, we present evidence to help explain which market, options or futures, is the leader in terms of transmitting volatility information, according to statistical measures. We evaluate two types of forecasts: *full forecasts* and *constrained forecasts*.[3] By comparing the performance of these

[3] *Full forecasts* use a model estimated using all available predictors. *Constrained forecasts* use only historical values of option realized volatilities (RV) for predicting option RV, and only past values of futures RVs for forecasting futures RV (see section 2.2.4 for details).

forecasts, we showcase the importance of additional information, particularly how information from one market affects RV forecasts in the other market. Table 4 presents results on the RMSE values for predicting futures RV and option RV, the changes in these RMSE values, as well as the net information transmission.

5.2.1. From futures to option markets

We examine the change in Root Mean Squared Error ($\Delta RMSE$) for predicting option realized volatilities (RVs) when moving from a constrained forecast to a full forecast, across the commodities in our sample. This measure offers insight into the incremental value of additional information. Table 4 shows that going from a constrained to a full forecast consistently improves RMSE for predicting option realized volatilities (RVs), particularly for shorter horizons ($H = 1$). Crude oil, gold, and corn show steady reductions in RMSE across all horizons, with improvements diminishing over time, ranging from −5% at $H = 1$ to −1% at $H = 3$. Natural gas and wheat exhibit mixed results, with only marginal improvements or slight increases at longer horizons ($H = 2, 3$), indicating a limited benefit from using past futures RV as additional predictors to forecast option RV for these commodities. For lean hogs, improvements are small or inexistant, suggesting no predictive power of past futures RV to forecast option RV. Overall, using past futures RV as additional predictors to predict option RV leads to an improvement in predictive performance, which means there is a transmission of information from futures market to option market.

5.2.2. From options to futures markets

We analyze the change in Root Mean Squared Error (RMSE) for predicting futures realized volatilities (RVs) as we go from constrained forecasts to full forecasts for each commodity. Table 4 shows consistent reductions in RMSE when moving from a constrained to a full forecast, indicating greater predictive accuracy. The improvements are more pronounced than those observed for options RVs in the previous sub-section. Crude oil, gold, and corn exhibit steady RMSE reductions across all horizons, ranging from −8% at $H = 1$ to −5% at $H = 3$. Natural gas shows the largest improvements, with reductions as high as −30% at $H = 1$ and still substantial (−29%) at longer horizons ($H = 2, 3$), highlighting the value of past option RVs to inform predictions of futures RV. Wheat and lean hogs also show consistent RMSE reductions, but of smaller magnitudes (−2% to −14%) across horizons. Overall, incorporating past option RVs as additional predictors significantly enhances the predictive performance for forecasting futures RVs. This indicates a substantial flow of information from the options market to the futures market.

5.2.3. Net information transmission

The net information transmission (NIT) metric is calculated as the difference between the futures RV $\Delta RMSE$ and the options RV $\Delta RMSE$ (see section 2.2.4.1). A positive value for NIT indicates that the options market tends to act as a net transmitter of information via volatility. Our empirical analysis of net information transmission highlights the varying degrees of informational advantage for option markets. For crude oil, gold, and corn, the net information transmission is consistently positive across all horizons, ranging from 2% to 7%, indicating a stronger informational flow from the options market to the futures market, as hypothesized from the literature on informed trading in options markets. Natural gas exhibits the largest positive NIT value, particularly at $H = 1$ (27%) and increasing further at longer horizons (29%; 30%), emphasizing the dominant role of options in predicting futures contract volatility. In contrast, wheat shows minimal net transmission, with values close to zero (−1% to 1%), suggesting comparable informational contributions from both markets. Lean hogs show a moderate positive transmission (11%; 14%), reflecting a slightly stronger predictive capacity of the options market.

Overall, the positive net information transmission indicates that for most commodities, the options market is generally more influential in predicting futures volatility than the futures market is in predicting option volatility. This advantage is most pronounced in markets like natural gas and lean hogs, where the improvements in RMSE for futures RV are substantial. In contrast, commodities like wheat exhibit a more balanced informational flow between the two markets. These results are in line with Bohmann et al. (2019) and Hao et al. (2021), who study speculative activity in commodities.

5.3. Economic value of predictive information flow

In this section, we provide additional evidence on information flow by documenting the economic value of more information for trading purposes. We contrast the added economic value from options to futures markets and vice versa. To this end, we apply our trading strategies to the two different forecasts (*full forecasts* and *constrained forecasts*), and analyze the change in the risk-adjusted performance. The following two subsections present the performance of the different option trading strategies, while the last subsection presents the results of the analysis of the predictive information transmission between option and futures volatilities.

5.3.1. Strategy based on option RV forecasts

5.3.1.1. Patterns in average portfolio returns

Table 5 shows a clear pattern of increasing average returns for the sorted decile portfolios from Low to High across commodities. This pattern shows a clear link between the level of predicted option RV and the average strategy returns, suggesting that portfolios comprised of options with higher predicted RVs tend to yield higher returns. For example, in natural gas futures, the average return starts at -1.88% in the Low decile and progressively increases to 19.96% in the High decile, while in the corn futures market, average returns gradually rise from -0.45% in the Low decile to 13.92% in the High decile.

5.3.1.2. Risk-adjusted performance analysis

In comparing the risk-adjusted performance of the high decile portfolio across the commodity markets, natural gas market stands out with the highest Sharpe ratio (0.31) for the high decile portfolio, surpassing the market portfolio's Sharpe ratio of 0.24. This is the most substantial improvement among the commodities in our sample. Other markets, such as crude oil, gold, corn, wheat, and lean hogs, also exhibit improvements in their Sharpe ratios compared with the market but they are less dramatic. Crude oil and lean hogs both see economic gains of 0.06 and 0.05 in Sharpe ratios, respectively, with the high decile portfolios achieving a Sharpe ratio of 0.21. The smallest gain is for the wheat market (0.04), with the high decile portfolio reaching a Sharpe ratio of 0.24. Overall, while all commodities benefit from higher Sharpe ratios in the high decile portfolios, natural gas demonstrates the most substantial relative performance improvement.

Thus, we shed light on a profitable strategy in commodity option markets that uses the predicted realized volatilities of options as the main trading signal. Portfolios sorted on higher predicted RVs consistently deliver superior average returns and Sharpe ratios compared to the market. Using this profitable strategy, we can then evaluate how its performance changes when using option RV *constrained forecasts* rather than *full forecasts*. This change in the risk-adjusted performance will indicate the economic relevance of past futures RV as a predictor for forecasting option RVs.

5.3.2. Strategy based on futures RV forecasts

Table 6 presents some performance statistics for the returns of the market portfolios, and 10-decile portfolios sorted on the difference between the predicted option RVs minus the current implied volatility ($\widehat{RV}_{i,t+1} - IV_{i,t}$) for our six commodity option markets. The strategy consists of shorting the high decile portfolios.

5.3.2.1. Pattern in average returns

Table 6 reveals a clear pattern of decreasing average returns as we move from the sixth to the High decile, for all commodities. Furthermore, the highest decile portfolio consistently has much more negative returns compared to other deciles in general. For the remaining deciles (1 to 5), average returns relative to $\widehat{RV}_{i,t+1} - IV_{i,t}$ do not show any apparent common pattern; rather the trends are commodity specific. Implied volatility (IV) can be seen as the market's forecast (expectation) of a likely movement in the underlying futures price over the option remaining time to maturity. In contrast, realized volatility (RV) refers to the actual volatility of the futures contract observed over a period of one week. In our sample, the difference ($\widehat{RV}_{i,t+1} - IV_{i,t}$) is typically negative. In general, the predicted one-week realized volatility is close to or slightly higher than the current implied volatility.

When the futures realized volatility over the next week ($[t, t+1]$) nearly equals or exceeds the current IV (at time t), it indicates that the underlying asset would fluctuate over the next week more or similarly to what the market, at week t, was expected over the entire life of the option. Given that volatility tends to be mean reverting, a large value for realized volatility in a short period suggests that subsequent volatility may decrease, as the market expects volatility to revert to its mean level. Consequently, the market's expectations of future underlying asset volatility over the remaining life of the option will be lower, leading to a decrease in IV. This reduction in IV will cause the straddle price to drop, resulting in more negative returns for those holding the straddle, as they initially paid a higher price based on the previously higher IV. Our strategy differs from Goyal & Saretto (2009)[4], as explained in section 3.3.3.2. However, both rely on the mean-reverting nature of volatility.

[4] The idea behind their strategy is the fact that IV from an option on a stock should reflect the fact that future volatility will, on average, be closer to its long-run average historical volatility (which is estimated by the 1-year realized volatility) than to its current volatility.

5.3.2.2. Risk-adjusted performance analysis

The comparison of high decile portfolios across commodity markets using the gain in Sharpe Ratio (SR) provides a nuanced view of risk-adjusted performance. The gain in Sharpe ratio is the difference in the SR resulting from shifting from the market portfolio to the High decile portfolio. For crude oil, the high decile portfolio outperforms the market portfolio significantly, with a gain in SR of 0.07, accompanied by the highest net average return of 2.54%. This result suggests that higher risk associated with this portfolio is adequately compensated by higher returns. Wheat also shows a strong performance with a SR gain of 0.06 and a net average return of 2.17%, reflecting a favorable balance between risk and reward compared to its market benchmark. Similarly, for corn there is a Sharpe ratio gain of 0.04 and a net average return of 1.89%, indicating that the short position in the high decile portfolio could yield beneficial outcomes over a strategy that shorts the market portfolio within these commodities. In contrast, natural gas and lean hogs show limited to no improvement in Sharpe ratio gains, at 0.01 and 0.00 respectively, with corresponding modest net average weekly returns of 1.35% and 1.12%. Gold is the only commodity where the high decile portfolio underperforms relative to the market, with a negative Sharpe ratio gain of -0.05 and a minimal net average return of 0.24%. This indicates that the high decile portfolio may take on excess risk without corresponding returns, making it less attractive for risk-averse investors.

Overall, our proposed strategy consistently generates higher and more positive returns than shorting the market portfolio across all examined commodity markets. Regarding risk-adjusted performance, the strategy improves the market portfolio Sharpe ratio in four out of the six commodity markets considered. By employing this profitable strategy, we can assess how its performance varies when we use futures RV-*constrained forecasts* instead of *full forecasts*. The change in risk-adjusted performance will underscore the economic significance of incorporating past option RVs as additional predictors for forecasting futures RVs.

5.3.3. How do options and futures markets inform each other's volatility forecasts?

In this subsection, we assess the predictive information flow in option and futures markets using two metrics: the change in Sharpe ratio and net information transmission (NIT). The change in Sharpe ratio (SR) when shifting from constrained to full forecasts quantifies the valuable information flow for forecasting volatility from one market to another from an economic perspective. The net information transmission is computed as the difference between the change in Sharpe ratio of the futures RV strategy and the change in Sharpe ratio of the option RV strategy. A positive value means that using the full forecasts instead of the constrained forecasts is relatively more beneficial for the futures RV strategy than for the option RV strategy. This would imply that options lead futures in terms of volatility.

Table 8 shows how the change in the Sharpe ratio varies different commodities. For crude oil and gold, the Sharpe ratio for the option RV strategy increases by approximately 3%, and for the futures RV strategy, it rises by about 11%, indicating that both strategies benefit from using more information as provided by full forecasts. In contrast, natural gas and lean hogs show a decrease in the Sharpe ratio for the option RV strategy of 1.7% and 0.5% respectively, but exhibit significant increases of 26% and 10.1% respectively for the futures RV strategy. This notable variation suggests that for natural gas and lean hogs, the futures markets are more sensitive to the influx of additional option information than are the options markets to receiving futures information. For corn, there is a slight increase in the Sharpe ratio for option RV forecasts (0.6%), and a more pronounced improvement for futures RV forecasts (9.7%). Meanwhile, wheat shows modest increases in Sharpe ratios for both strategies—2.5% for the options RV strategy and 3.8% for the futures RV strategy—confirming that the added information has a balanced yet limited effect. Overall, these changes in Sharpe ratios show that full forecasts generally enhance the profitability of the strategies.

The *economic* net information transmission values across each commodity are presented in Table 8. Natural gas stands out with the highest net information transmission among the commodities, at 27.7%. This substantial figure indicates that the option market significantly enhances the predictive accuracy of futures volatility forecasts. The large positive value underscores the option market's important role in providing useful information for forecasting volatility, leading to considerable economic gains when full forecasts are used in the futures RV strategy. Meanwhile, crude oil, gold, corn and lean hogs exhibit moderate net information transmission (ranging from 7.9% to 10.6%), indicating a notable but less dramatic improvement in forecast accuracy and economic gains from using option market data. These commodity option markets play a vital role in enriching the predictive models for the volatility of the futures market, though the impact is less pronounced compared to natural gas. On the other hand, wheat displays a relatively low net information transmission of 1.3%, indicating a minimal yet positive impact of incorporating option market data into futures RV models.

While there is some degree of information spillover from the options to the futures market, the improvement in forecast accuracy and economic gains is modest. The option market does contribute to enhancing the predictive models for futures RV forecasts, but the effect is less significant compared to other commodities. This suggests that, for wheat in particular, the additional information from the options market provides limited incremental value in terms of economic gains and volatility prediction. Overall, the positive values of economic net information transmission across all commodities suggest that the option markets generally lead the futures markets in terms of providing useful information for predicting volatility. This implies that strategies based on full forecasts are more effective in the futures market, where they lead to higher economic gains.

6. Conclusion

This paper investigates the potential bidirectional relationship between commodity options and futures markets at the level of volatility, focusing on six key commodities, namely crude oil, natural gas, gold, corn, wheat, and lean hogs. Our methodology combines impulse response functions (IRF) and connectedness analysis, followed by predictive models using random forest techniques. This allows us to assess spillover effects and predictive information transmission across options and futures markets. Our findings reveal that shocks in futures volatility have a strong immediate impact on options volatility, while shocks in options volatility have a longer-lasting effect on futures volatility. This highlights the bidirectional nature of volatility transmission between these markets. The connectedness analysis further supports these results, showing evidence of self-driven volatility in most commodities, with significant net spillovers from options to futures markets.

The predictive analysis shows that the options market generally holds an informational advantage over the futures market, which means that the options market is generally more important in predicting futures volatility than the futures market is in predicting option volatility. This result suggests that information flow from the options market is crucial for predicting futures market volatility effectively. Furthermore, we establish the economic profitability of using predicted volatilities in option trading strategies. We design two trading strategies based on predicted realized volatilities, which consistently outperform traditional market portfolios. These strategies not only offer superior returns but also showcase the importance of incorporating information from both markets to maximize economic gains. In conclusion, our research provides novel insights into the mechanics of volatility transmission and forecast in commodity option and futures markets. It establishes a clear informational hierarchy, suggesting that an understanding of these dynamics is essential for market participants.

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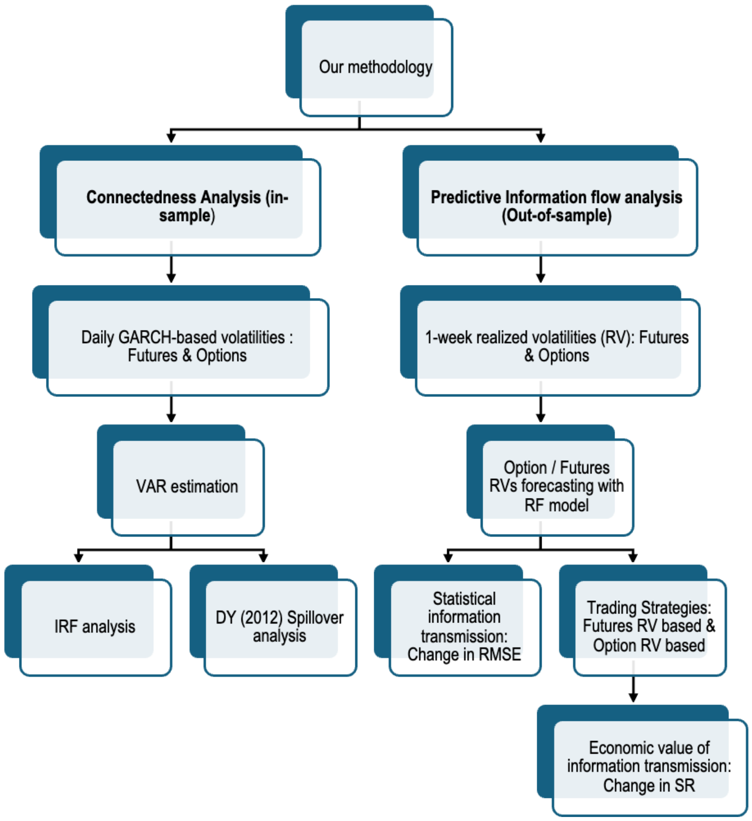
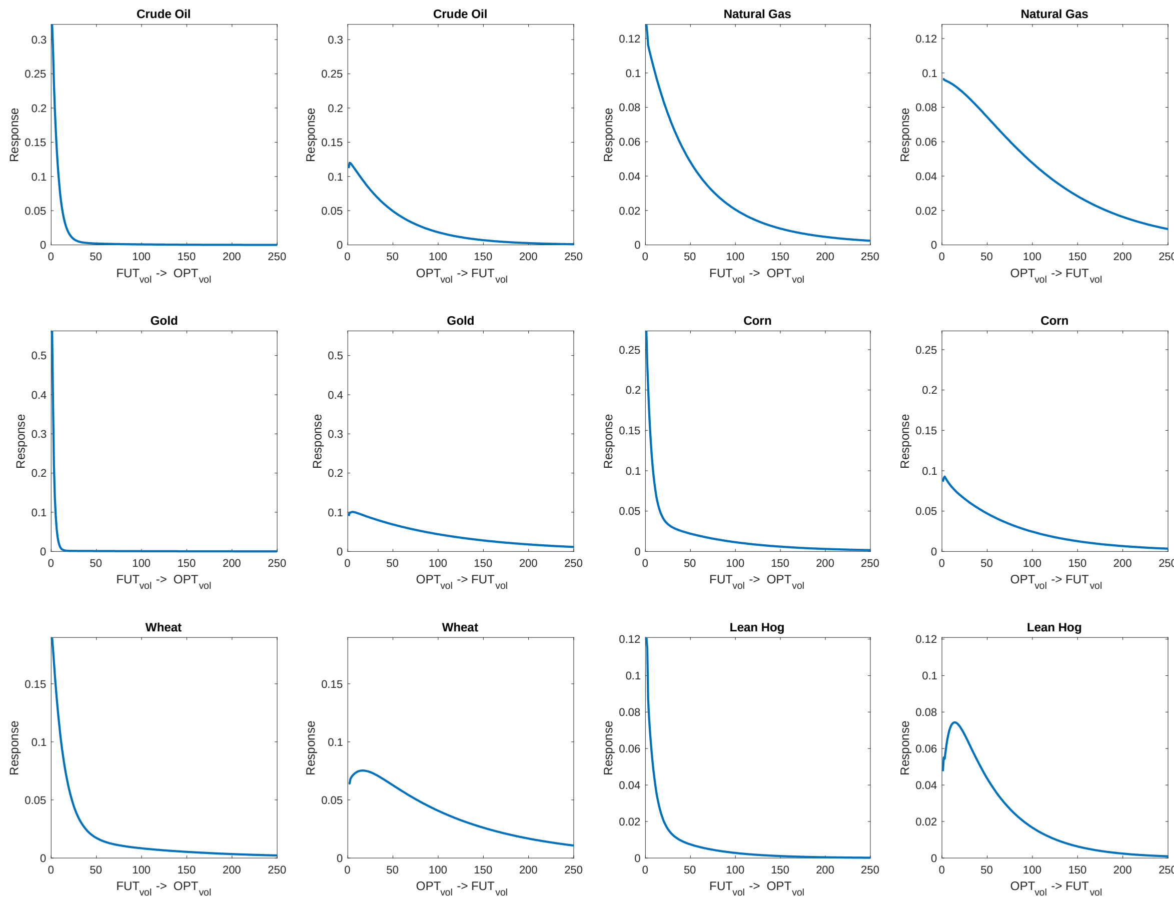
Figures

Figure 1: Methodological framework



Note: This flowchart illustrates the methodological framework used to address our research question. Key abbreviations include VAR (vector autoregressive model), IRF (impulse response functions), and DY (2012) referring to Diebold & Yilmaz (2012). Additionally, RF represents random forest, RMSE denotes root mean squared error, and SR stands for Sharpe ratio.

Figure 2: Impulse function responses (IRF) in commodity futures and options markets



Note: The figure displays impulse response functions (IRFs) for various commodities, showing how option and futures volatilities respond when either futures or option volatilities are shocked. For each commodity, there are two sub-figures. The left sub-figure shows the impact of a futures shock on option volatility, while the right sub-figure shows the impact of a shock in options on the futures volatility. The x-axis measures the number of days after the shock, and the y-axis represents the standardized response value of the volatility, allowing for comparability across different graphs and commodities.

Tables

Table 1: Commodity option contracts

Commodity	Sector	Source	First trade date	Last trade date
Crude Oil	Energy	NYMEX	November 14th, 1986	August 3rd, 2022
Natural Gas	Energy	NYMEX	March 18th, 2004	August 3rd, 2022
Gold	Metals	COMEX	October 4th, 1982	August 3rd, 2022
Corn	Grains	CBOT	February 27th,1985	August 3rd, 2022
Wheat	Grains	CBOT	November 17th, 1986	August 3rd, 2022
Lean hogs	Meats	CME	February 1st,1985	August 3rd, 2022

Note: This table lists commodity options considered in our paper such as Crude Oil, Natural Gas, Gold, Corn, Wheat, and Lean hogs, detailing their sectors, trading sources like NYMEX, COMEX, and CBOT, and trading dates from as early as October 4th, 1982, to a uniform last trading date of August 3rd, 2022.

Table 2: Summary statistics for option returns, straddle returns, option volatility and futures volatility

	Mean	Std.	Q1	Q2	Q3	Skew.	Kurt.
Panel A: Crude oil							
Option returns	0.018	0.421	-0.213	-0.040	0.159	5.72	112.8
Straddle returns	-0.028	0.124	-0.096	-0.034	0.033	0.58	6.0
Option RV	0.131	0.093	0.075	0.111	0.162	4.89	74.4
Futures RV	0.015	0.009	0.009	0.014	0.019	1.63	7.7
Panel B: Natural Gas							
Option returns	0.021	0.363	-0.200	-0.024	0.171	2.63	22.4
Straddle returns	-0.025	0.114	-0.085	-0.029	0.028	0.71	8.0
Option RV	0.119	0.077	0.070	0.102	0.148	2.70	20.4
Futures RV	0.019	0.011	0.012	0.017	0.023	2.48	16.8
Panel C: Gold							
Option returns	0.024	0.510	-0.228	-0.053	0.150	7.05	114.6
Straddle returns	-0.021	0.147	-0.104	-0.036	0.040	1.43	10.7
Option RV	0.135	0.118	0.071	0.108	0.165	7.42	159.3
Futures RV	0.008	0.005	0.005	0.007	0.010	1.92	9.5
Panel D: Corn							
Option returns	0.020	0.345	-0.164	-0.019	0.135	3.32	34.5
Straddle returns	-0.015	0.105	-0.067	-0.016	0.034	0.52	9.5
Option RV	0.110	0.090	0.056	0.088	0.137	5.13	74.8
Futures RV	0.013	0.008	0.007	0.011	0.016	2.17	12.2
Panel E: Wheat							
Option returns	0.035	0.459	-0.211	-0.030	0.181	5.72	98.1
Straddle returns	-0.023	0.123	-0.084	-0.026	0.033	0.84	11.9
Option RV	0.135	0.095	0.075	0.111	0.166	3.37	40.8
Futures RV	0.015	0.008	0.009	0.013	0.018	2.20	17.6
Panel F: Lean hogs							
Option returns	0.024	0.397	-0.190	-0.029	0.160	5.42	110.5
Straddle returns	-0.019	0.132	-0.084	-0.023	0.037	0.91	9.3
Option RV	0.122	0.088	0.065	0.101	0.153	3.36	39.7
Futures RV	0.014	0.011	0.007	0.011	0.016	3.23	20.3

Note: This table presents the summary statistics for option raw returns, straddle returns, option realized volatility (RV) and option realized volatility (RV) across each commodity at a weekly frequency. Mean refers to the average returns or volatility, Std. refers to the standard deviation of the variable. Q1, Q2 and Q3 are the quantile at the level 0.25, 0.5 and 0.75 respectively. Skew. Refers to the skewness of the variables and Kurt. stands for the variable kurtosis.

Table 3: Diebold & Yilmaz connectedness results for spillovers between commodity option and futures contracts

	Short-run Spillover		Medium-run Spillover	
	From Option Vol.	From Futures Vol.	From Option Vol.	From Futures Vol.
Crude Oil				
To Option Vol.	72.5	27.5	72.2	27.8
To Futures Vol.	28.9	71.1	30.0	70.0
Net	1.3	-1.3	2.3	-2.3
TCI		28.2		28.9
Natural Gas				
To Option Vol.	74.4	25.6	75.7	24.3
To Futures Vol.	31.3	68.7	34.1	65.9
Net	5.7	-5.7	9.8	-9.8
TCI		28.4		29.2
Gold				
To Option Vol.	64.7	35.3	64.5	35.5
To Futures Vol.	38.5	61.5	38.0	62.0
Net	3.2	-3.2	2.5	-2.5
TCI		36.9		36.7
Corn				
To Option Vol.	76.1	23.9	75.3	24.7
To Futures Vol.	24.8	75.2	24.8	75.2
Net	0.8	-0.8	0.1	-0.1
TCI		24.4		24.8
Wheat				
To Option Vol.	76.9	23.1	76.3	23.7
To Futures Vol.	26.4	73.6	27.3	72.7
Net	3.3	-3.3	3.6	-3.6
TCI		24.7		25.5
Lean hogs				
To Option Vol.	93.9	6.1	94.0	6.0
To Futures Vol.	12.8	87.2	17.9	82.1
Net	6.7	-6.7	11.9	-11.9
TCI		9.4		12.0

Note: The table presents data on short-run (horizon = 12 days) and medium-run spillover (horizon = 22 days) effects between option and futures volatilities for various commodities such as Crude Oil, Natural Gas, Gold, Corn, Wheat, and Lean hog. It is structured into sections where each commodity has rows indicating spillover "From Option Vol." and "From Futures Vol." to "To Option Vol." and "To Futures Vol." with corresponding percentages. The main entries of the table are variance shares of each variable to predict option volatility or futures volatility. Additionally, each commodity section includes "Net" spillover values and a "Total Connectedness Index (TCI)" that quantifies overall volatility interaction.

Table 4: Forecast accuracy (RMSE) for option RV and futures RV using full vs constrained models

Predicted variable	Option RV			Futures RV			Net information transmission
Forecast type	*Constrained*	*Full*	*% Δ in RMSE*	*Constrained*	*Full*	*% Δ in RMSE*	
Crude Oil							
H=1	0.1123	0.1064	-5%	0.0098	0.0091	-8%	2%
H=2	0.1369	0.1343	-2%	0.0101	0.0094	-7%	5%
H=3	0.1546	0.1537	-1%	0.0104	0.0096	-8%	7%
Natural Gas							
H=1	0.0793	0.0769	-3%	0.01462	0.0103	-30%	27%
H=2	0.0964	0.0970	1%	0.01490	0.0106	-29%	29%
H=3	0.1226	0.1243	1%	0.01514	0.0108	-29%	30%
Gold							
H=1	0.1224	0.1161	-5%	0.0049	0.0045	-8%	3%
H=2	0.1357	0.1320	-3%	0.0050	0.0046	-8%	5%
H=3	0.1678	0.1659	-1%	0.0051	0.0048	-6%	5%
Corn							
H=1	0.0898	0.0866	-4%	0.0080	0.0075	-6%	2%
H=2	0.1064	0.1042	-2%	0.0081	0.0076	-6%	4%
H=3	0.1324	0.1315	-1%	0.0082	0.0078	-5%	5%
Wheat							
H=1	0.0963	0.0929	-3%	0.0083	0.0081	-2%	-1%
H=2	0.1083	0.1072	-1%	0.0083	0.0081	-2%	1%
H=3	0.1396	0.1391	0%	0.0083	0.0082	-1%	1%
Lean Hogs							
H=1	0.0840	0.0824	-2%	0.0130	0.0113	-13%	11%
H=2	0.0938	0.0934	0%	0.0131	0.0113	-14%	13%
H=3	0.1086	0.1088	0%	0.0133	0.0114	-14%	14%

Note: This table presents the RMSE and the change in RMSE for predicting options RVs and Futures RVs. It displays the RMSE of the two types of forecasts (constrained and full) and emphasizes the change in RMSE when shifting from constrained forecast to full forecast. It also shows the RMSE at different horizons (H=1 day ahead, H=2 days ahead, H=3 days ahead). The *net information transmission* measures the information flow from option market to futures market net of the information coming from futures to option market. It is computed as the change in RMSE for predicting futures RV minus the change in RMSE for predicting option RV. A positive value, NIT>0, means that there is more useful information in option markets to predict futures volatility than there is in futures markets to predict option volatility. NIT>0 indicates that the option market leads the futures market in terms of useful information to predict volatility, while NIT<0 indicates the reverse.

Table 5: Summary statistics of realized returns for the market portfolio, the H-L portfolio and 10-decile portfolios sorted on predicted option RV

	Crude Oil						Natural Gas						Gold					
	Mean	Std.	SR	%DD10	Min	Max	Mean	Std.	SR	%DD10	Min	Max	Mean	Std.	SR	%DD10	Min	Max
Mkt	3.17	22.23	0.14	0.15	-32.0	423.7	4.39	18.09	0.24	0.08	-46.1	119.3	2.53	22.85	0.11	0.19	-33.8	311.8
Low	-1.91	17.14	-0.11	0.26	-62.2	126.8	-1.88	14.86	-0.13	0.26	-52.5	66.3	0.08	23.08	0.00	0.21	-59.3	456.7
2	-1.22	18.70	-0.07	0.24	-53.9	245.8	-0.34	15.74	-0.02	0.22	-45.6	74.9	0.51	27.15	0.02	0.22	-58.3	581.7
3	-0.85	18.32	-0.05	0.22	-56.8	181.4	0.36	17.20	0.02	0.19	-59.0	88.5	0.55	25.99	0.02	0.24	-63.3	499.2
4	0.16	19.68	0.01	0.22	-60.1	200.5	0.56	17.07	0.03	0.19	-58.6	103.8	0.01	21.70	0.00	0.26	-65.8	340.4
5	0.59	24.49	0.02	0.25	-69.5	444.2	1.73	17.95	0.10	0.18	-48.8	96.6	0.40	31.31	0.01	0.27	-58.3	847.8
6	0.97	23.51	0.04	0.25	-62.7	288.3	1.48	18.89	0.08	0.18	-55.8	115.9	1.98	36.59	0.05	0.28	-59.9	792.5
7	2.43	28.42	0.09	0.27	-57.5	480.4	2.48	21.09	0.12	0.21	-49.8	140.6	1.91	31.04	0.06	0.30	-57.9	455.1
8	4.04	35.42	0.11	0.29	-67.6	643.5	4.48	26.00	0.17	0.25	-60.1	202.2	3.89	35.96	0.11	0.34	-61.1	337.8
9	5.71	39.11	0.15	0.34	-71.1	747.5	7.80	31.27	0.25	0.25	-58.3	210.4	5.11	47.33	0.11	0.38	-64.8	614.7
High	15.13	73.52	0.21	0.42	-78.8	1163	19.96	64.49	0.31	0.36	-70.9	395.3	10.53	66.30	0.16	0.43	-78.7	634.5
H-L	17.11	77.28	0.22	0.39	-146	1220	21.90	67.86	0.32	0.34	-137	447.8	10.97	71.15	0.15	0.40	-341	582.4
	Corn						Wheat						Lean Hogs					
	Mean	Std.	SR	%DD10	Min	Max	Mean	Std.	SR	%DD10	Min	Max	Mean	Std.	SR	%DD10	Min	Max
Mkt	2.63	14.56	0.18	0.08	-23.2	231.3	4.15	20.61	0.20	0.13	-24.8	352.4	3.19	19.11	0.17	0.11	-48.4	254.0
Low	-0.45	13.87	-0.03	0.18	-58.1	135.0	-0.74	15.77	-0.05	0.23	-66.3	100.4	-0.30	18.43	-0.02	0.20	-60.0	374.7
2	-0.26	14.62	-0.02	0.19	-65.6	131.7	-0.55	17.81	-0.03	0.23	-60.1	115.5	-0.35	16.41	-0.02	0.20	-59.7	119.3
3	0.43	15.16	0.03	0.15	-71.1	145.6	0.14	17.66	0.01	0.21	-51.6	127.9	0.18	17.12	0.01	0.20	-62.7	106.8
4	0.70	14.90	0.05	0.15	-70.9	189.5	0.74	19.65	0.04	0.22	-52.8	180.8	2.08	20.15	0.10	0.19	-71.0	141.2
5	0.72	16.91	0.04	0.16	-56.8	259.5	1.39	22.80	0.06	0.24	-56.3	365.4	1.07	20.65	0.05	0.23	-71.9	131.8
6	0.36	17.61	0.02	0.20	-75.7	205.1	1.57	25.80	0.06	0.25	-67.0	523.4	0.90	23.49	0.04	0.24	-72.3	225.0
7	1.58	19.99	0.08	0.22	-64.8	180.6	2.01	30.62	0.07	0.29	-74.0	578.7	1.76	30.39	0.06	0.27	-84.1	734.4
8	2.06	23.30	0.09	0.24	-64.0	218.1	4.60	32.97	0.14	0.31	-61.6	397.7	2.11	34.30	0.06	0.31	-71.3	719.5
9	3.79	29.43	0.13	0.29	-64.3	283.1	6.79	42.21	0.16	0.34	-72.3	538.0	4.15	36.25	0.11	0.32	-65.0	311.3
High	13.92	59.49	0.23	0.36	-85.5	709.3	18.30	76.42	0.24	0.39	-85.4	919.1	14.70	68.74	0.21	0.41	-78.7	744.8
H-L	14.32	63.30	0.23	0.36	-155	767.4	19.02	79.64	0.24	0.39	-149	908.2	15.00	69.63	0.22	0.38	-233	748.3

Note: This table presents some summary statistics of the realized returns of the market portfolios, H-L portfolio and 10-decile portfolios sorted on predicted option RVs for six commodity option markets: Crude oil, natural gas, gold, corn, wheat and lean hog. Mean refers to the average realized returns, Std. refers to the standard deviation of the returns of the portfolio, SR refers to the Sharpe ratio of the portfolio, %DD10 refers to the number of times when the return of the portfolio falls below minus 10%, Min is the minimum return and Max is the maximum return of the portfolio. The first row refers to the market portfolio formed by all available options at the trading week. The second to eleventh row refer to the 10-decile portfolio of option based on the predicted option RV. For example, the Low portfolio is formed of available options with the lowest 1-week ahead predicted realized volatility while the High portfolio refers to the portfolio composed of options with highest predicted realized volatility. H-L portfolio is the portfolio resulting in being long the Hi portfolio and short the Low portfolio.

Table 6: Summary statistics of realized returns for the market portfolio, and 10-decile portfolios sorted on the difference between the predicted option RVs and the current implied vol (RV-IV)

	Crude oil						Natural Gas						Gold					
	Mean	Median	Std.	Min	Max	RV-IV	Mean	Median	Std.	Min	Max	RV-IV	Mean	Median	Std.	Min	Max	RV-IV
Mkt	-2.17	-3.27	8.99	-32.77	40.91	-6.86	-2.36	-3.24	7.82	-25.51	46.49	-5.26	-1.90	-3.46	9.98	-30.33	67.30	-3.67
Low	-1.97	-2.53	11.31	-50.27	48.72	-10.35	-2.54	-2.35	9.32	-43.54	38.76	-9.63	-3.21	-3.45	10.36	-43.49	50.83	-5.99
2	-1.69	-2.38	10.45	-36.69	50.25	-9.35	-2.45	-2.45	9.21	-37.05	55.28	-8.45	-2.66	-3.31	11.30	-46.10	113.25	-4.95
3	-1.67	-2.52	10.02	-35.64	45.14	-8.71	-2.57	-2.63	9.25	-38.03	69.67	-7.27	-2.46	-3.37	11.68	-47.01	98.71	-4.55
4	-1.52	-2.75	9.98	-42.13	51.78	-8.15	-2.15	-2.54	9.49	-36.76	61.68	-6.62	-1.88	-3.16	11.18	-35.54	60.89	-4.18
5	-1.74	-3.03	9.74	-42.45	47.02	-7.62	-2.27	-2.68	9.25	-41.75	52.76	-5.87	-1.73	-3.14	11.72	-38.34	71.99	-3.87
6	-1.51	-2.72	9.93	-41.89	42.89	-7.05	-1.86	-2.64	9.40	-30.59	55.87	-4.79	-1.23	-3.34	12.34	-40.30	67.74	-3.65
7	-1.85	-3.19	10.48	-32.11	70.12	-6.39	-2.23	-2.96	9.23	-29.96	49.96	-4.27	-1.19	-3.00	12.39	-31.28	75.32	-3.40
8	-2.00	-3.21	11.05	-33.29	60.02	-5.75	-2.36	-2.92	10.09	-38.21	64.92	-3.53	-1.34	-3.73	13.39	-49.35	77.25	-3.06
9	-2.00	-3.42	11.91	-38.73	61.25	-5.16	-1.86	-2.94	10.30	-31.91	53.15	-2.65	-1.27	-3.38	13.46	-35.59	75.83	-2.74
High	-4.71	-6.08	15.06	-45.49	90.82	-3.03	-3.71	-4.12	12.55	-46.93	56.09	-0.48	-2.14	-4.45	15.48	-41.24	99.47	-1.81

	Corn						Wheat						Lean Hogs					
	Mean	Median	Std.	Min	Max	RV-IV	Mean	Median	Std.	Min	Max	RV-IV	Mean	Median	Std.	Min	Max	RV-IV
Mkt	-1.27	-1.64	7.16	-22.43	38.66	-6.18	-1.84	-2.88	8.97	-25.76	92.17	-4.03	-1.42	-2.67	8.59	-30.58	73.50	-2.10
Low	-0.64	-1.00	10.16	-36.03	42.32	-12.21	-1.64	-2.42	10.82	-35.35	82.27	-8.91	-1.11	-1.54	11.74	-41.02	72.31	-6.00
2	-0.62	-0.71	9.32	-29.45	42.80	-10.04	-0.88	-1.66	12.33	-33.91	171.24	-7.58	-1.16	-1.95	12.14	-37.82	78.24	-5.01
3	-0.60	-1.11	8.72	-36.93	41.75	-8.93	-1.14	-1.83	11.54	-44.16	165.52	-6.61	-1.26	-2.30	10.98	-34.83	66.89	-4.16
4	-0.29	-0.95	8.51	-35.14	42.74	-7.86	-1.28	-2.05	9.67	-33.07	59.80	-5.70	-1.17	-1.87	11.18	-49.45	78.92	-3.37
5	-0.91	-1.46	7.88	-36.85	37.58	-6.94	-1.40	-2.09	10.74	-40.84	102.14	-4.89	-1.20	-2.23	11.62	-52.44	98.47	-2.79
6	-1.09	-1.17	7.88	-26.06	36.54	-6.19	-1.50	-2.64	10.53	-36.06	106.29	-4.24	-0.85	-2.26	12.08	-43.29	130.40	-2.21
7	-1.11	-1.65	8.48	-32.58	40.65	-5.32	-1.53	-2.48	11.23	-39.02	109.76	-3.25	-0.92	-1.75	11.41	-42.33	56.91	-1.56
8	-1.71	-2.10	8.24	-34.36	40.93	-4.48	-2.06	-2.83	11.63	-46.62	113.13	-2.35	-1.00	-2.35	11.40	-31.92	76.79	-0.90
9	-1.69	-2.27	9.02	-38.16	65.56	-3.26	-2.42	-3.13	11.64	-43.91	76.14	-1.40	-2.08	-2.06	12.57	-53.30	90.98	-0.03
High	-3.16	-3.93	14.47	-59.81	132.90	-0.16	-4.01	-4.94	14.64	-60.62	55.68	1.07	-2.54	-2.76	14.91	-50.09	82.35	1.81

Note: This table presents some summary statistics of the realized returns of the market portfolio, and 10-decile portfolios sorted on the difference between the predicted futures RVs minus the current implied volatility (RV-IV) for six commodity markets: Crude oil, natural gas, gold, corn, wheat and lean hog. Mean refers to the average realized returns, Std. refers to the standard deviation of the returns of the portfolio, Median refers to the median of returns of the portfolio, Min is the minimum return and Max is the maximum return of the portfolio. The first row refers to the market portfolio formed by all available straddle at the trading week. The second to eleventh row refer to the 10-decile portfolio of straddle based on the difference between the predicted futures RVs minus the current implied volatility (RV-IV). For example, the Low portfolio is formed of available straddle with the lowest difference RV-IV while the High portfolio refers to the portfolio composed of straddle with highest difference RV-IV. RV-IV is the average difference for the group.

Table 7: Summary statistics of realized returns for the market portfolio, and 10-decile portfolios sorted on the current implied volatility

	Crude Oil				Natural Gas				Gold			
	Mean	Median	Std.	IV	Mean	Median	Std.	IV	Mean	Median	Std.	IV
Mkt	-2.17	-3.27	8.99	31.06	-2.36	-3.24	7.82	36.64	-1.90	-3.46	9.98	16.56
Low	-3.68	-5.09	14.59	28.19	-1.85	-2.28	10.48	32.14	-2.13	-4.78	16.50	14.43
2	-2.67	-4.18	12.09	29.25	-1.46	-2.01	8.93	32.78	-1.81	-3.95	14.43	15.16
3	-2.02	-3.33	10.85	29.98	-1.84	-2.54	9.52	33.35	-1.16	-3.35	13.96	15.57
4	-1.88	-3.04	10.51	30.45	-2.08	-2.71	9.25	34.30	-1.23	-3.76	13.19	15.89
5	-1.73	-2.90	10.47	30.77	-1.99	-2.66	9.15	35.06	-1.18	-3.13	12.11	16.24
6	-1.82	-3.01	10.26	31.07	-2.07	-2.99	9.94	35.47	-1.44	-3.41	12.11	16.60
7	-1.77	-2.91	10.16	31.46	-2.04	-3.13	9.58	36.78	-1.66	-3.02	11.35	16.76
8	-1.81	-3.23	10.83	31.83	-2.55	-2.79	9.75	37.68	-2.01	-3.22	10.96	17.00
9	-1.93	-2.93	10.75	32.34	-3.07	-3.64	10.17	38.61	-2.66	-3.56	11.15	17.31
High	-2.54	-2.95	12.19	33.96	-3.81	-3.42	11.32	41.18	-2.90	-3.26	9.84	18.79
	Corn				**Wheat**				**Lean Hogs**			
	Mean	Median	Std.	IV	Mean	Median	Std.	IV	Mean	Median	Std.	IV
Mkt	-1.27	-1.64	7.16	25.43	-1.84	-2.88	8.97	26.08	-1.42	-2.67	8.59	22.79
Low	-2.70	-3.11	13.12	20.42	-3.37	-3.93	13.28	21.75	-1.33	-1.65	13.32	19.66
2	-1.89	-2.28	9.85	21.79	-2.42	-3.08	11.91	23.09	-1.76	-2.03	10.97	20.35
3	-1.79	-2.05	8.55	22.65	-2.04	-2.86	10.99	23.96	-0.97	-1.30	10.74	20.92
4	-1.41	-1.98	8.25	23.58	-1.50	-2.33	11.31	24.72	-1.29	-1.75	10.14	21.44
5	-1.59	-1.68	8.12	24.31	-1.37	-2.73	11.43	25.31	-1.02	-1.87	11.23	22.01
6	-1.07	-1.47	8.24	25.09	-1.15	-1.97	10.78	25.88	-1.18	-2.34	12.29	22.50
7	-0.75	-1.12	8.44	25.97	-1.76	-2.57	10.38	26.65	-1.91	-2.55	11.47	22.88
8	-0.71	-1.20	9.30	26.83	-1.67	-2.42	10.81	27.37	-1.57	-2.59	12.14	23.67
9	-0.65	-1.35	9.24	27.84	-1.51	-2.13	12.33	28.22	-1.62	-2.86	13.32	24.19
High	-0.97	-1.30	11.16	31.84	-1.95	-2.62	12.24	30.86	-1.35	-2.26	14.32	26.33

Note: This table presents some summary statistics of the realized returns of the market portfolios, and 10-decile portfolios sorted on the current implied volatility (IV) for six commodity markets: Crude oil, natural gas, gold, corn, wheat and lean hog. Mean refers to the average realized returns, Std. refers to the standard deviation of the returns of the portfolio, Median refers to the median of returns of the portfolio. The first row refers to the market portfolio formed by all available straddle at the trading week. The second to eleventh row refer to the 10-decile portfolio of straddle based on the current implied volatility (IV). For example, the Low portfolio is formed of available straddle with the lowest current implied IV while the High portfolio refers to the portfolio composed of options with highest current IV.

Table 8: Sharpe ratio, change in Sharpe ratio and Economic net information transmission.

	Strategy based on option RV forecasts			Strategy based on futures RV forecasts			Econ. net information transmission
Forecast type	Constrained	Full	% Δ in SR	Constrained	Full	% Δ in SR	
Crude Oil	0.200	0.206	3%	0.282	0.313	11%	8%
Natural Gas	0.315	0.309	-2%	0.235	0.296	26%	28%
Gold	0.153	0.159	4%	0.124	0.138	12%	8%
Corn	0.233	0.234	1%	0.199	0.218	10%	9%
Wheat	0.234	0.240	2%	0.264	0.274	4%	1%
Lean Hogs	0.215	0.214	0%	0.155	0.170	10%	11%

Note: This table provides the Sharpe ratio, the change in Sharpe ratio for option RV and futures RV strategies as well as the economic net information transmission for each commodity. The % change in mean refers to the change in Sharpe ratio when we shift from using the constrained forecasts to the full forecasts. A positive value means that using the full information set delivers substantial economic gains. The economic net information transmission is computed as the change in average return of the strategy based on futures RV minus the change in average return of the strategy based on option RV. A positive value, ENIT>0, means that using the full forecasts instead of the constrained forecasts in the futures RV strategy leads to a relatively higher added value than does the use of the full forecasts in the option RV strategy. RVs while the constrained forecasts are based on only futures past RVs. A positive economic net information transmission also means that the option market leads the futures market in terms of useful information to predict volatility.

Appendices

A. Characteristics describing options that generate the most impact

In this subsection, we want to shed light on the characteristics of options that impact the most the forecasting of futures RV. The predictors considered include the current and past realized volatilities (RVs) of portfolios composed of : 1-call and 2-put options, 3-at-the-money (ATM) options, 4-in-the-money (ITM) options, 5-out-of-the-money (OTM) options, and 6-low IV options, 7-medium IV options, 8-high IV, 9-low delta options, 10-medium delta options and 11-high delta options. Table 9 presents the percentage changes in mean absolute errors (MAE) when each predictor is removed from the forecasting models. A positive change in this value indicates an increase in forecasting errors, which underscores the significance of the excluded predictor.

By analyzing the results in Table 9, we find that the exclusion of call option realized volatilities (RVs) to predict crude oil futures RV results in a substantial 4.0% increase in mean absolute error (MAE), underscoring their crucial role. Similarly, the realized volatilities of low IV portfolios are also important for crude oil futures RV with a 3.7% rise in MAE. Meanwhile, the volatility predictions for natural gas futures are highly sensitive to almost all considered option portfolio realized volatilities (RVs). Notably, the forecasts are significantly affected by put option RVs, low IV option RVs and ITM option RVs (with change in MAE of 9.4%, 6.7% and 4.6%, respectively). This suggests a strong dependence of natural gas futures volatility forecasts on these option portfolios. In the case of gold futures, volatility showed moderate sensitivity to the removal of both call and put option RVs, which led to increases in MAE of 3.2% and 2.1%, respectively. This reflects a moderate reliance on these option types for accurate volatility forecasting in the gold market. In contrast, corn futures volatility demonstrated lower sensitivity to the RVs of option portfolios considered. The most notable impacts were from call options and out-of-the-money (OTM) options RVs, which led to modest increases in MAE of 0.7% and 0.6%, respectively. Interestingly, wheat futures consistently exhibit negative changes in MAE across most predictors. This pattern suggests that the considered predictors are not individually important for wheat futures volatility.

Finally, lean hog futures displayed the highest sensitivity to the exclusion of several option portfolio RVs. The removal of the RVs of the in-the-money (ITM) and low delta option portfolios leads to the most substantial increases in MAE, at 11.5% and 6.8% respectively, highlighting their importance in forecasting lean hog futures volatility. Additionally, high IV and ATM options also significantly affected the forecasts, with MAE increasing by 5.6% and 5.3%, respectively.

Table 9: Most important option portfolios to predict futures RV

% Δ in MAE	*Crude Oil*	*Natural Gas*	*Gold*	*Corn*	*Wheat*	*Lean Hogs*
Call	4.0%	7.1%	3.2%	0.7%	-0.1%	1.3%
Put	2.0%	9.4%	2.1%	0.2%	0.7%	3.1%
ATM	-0.5%	0.1%	-0.5%	-0.4%	-1.0%	5.3%
ITM	0.5%	4.5%	1.5%	0.4%	-0.5%	11.5%
OTM	0.0%	0.9%	0.4%	0.6%	-0.7%	2.5%
Low IV	3.7%	6.7%	1.9%	0.2%	-0.1%	3.4%
Med IV	0.5%	2.3%	0.7%	0.7%	-0.3%	4.2%
High IV	2.1%	4.0%	1.0%	-0.3%	-0.7%	5.6%
Low delta	0.6%	1.7%	0.4%	0.5%	-0.7%	6.8%
Med delta	0.6%	3.1%	-0.7%	0.3%	-1.1%	2.8%
High delta	1.0%	0.9%	-0.1%	0.4%	-0.8%	4.0%

Note: This table presents how the Mean Absolute Error (MAE) changes in forecasting futures RV when we set one of the predictors from option market to zeros. The option market predictors are the realized volatility of different option portfolios such as Call which is formed of call options or ATM which is formed of ATM options. A positive change means that withdrawing the predictor i yields to an increase in the forecast errors. The more positive the change in MAE, the more important the predictor is.

B. Characteristics describing options that receive the most impact

In this subsection, our goal is to highlight the main characteristics of the least and most impacted options. The least impacted options correspond to the options with the least improvement of the RMSE for predicting their RVs when adding new information from futures markets (current and past values of futures RVs). Analogously, the most impacted options correspond to the options with the largest improvement of the RMSE for predicting their RVs when adding new information from futures markets. Table 10 presents the average feature of the least and most impacted options by futures RVs across different commodities.

We find that the most impacted options typically have a longer time-to-maturity compared to least impacted ones. This suggests that longer maturity may be associated with greater sensitivity to the underlying futures volatility. The least and the most impacted options tend to have moneyness values closer to one, suggesting these are at-the-money (ATM) options. The most impacted options tend to have higher deltas, signifying a stronger sensitivity to price changes in the underlying asset. This increased sensitivity could contribute to their higher impact classification regarding volatility changes. Consistently, most impacted options show lower open interest. This might reflect lesser market participation or liquidity, possibly making these options more susceptible to large swings in prices due to fewer market participants.

Table 10: Characteristics of the Least/Most impacted option by futures RV

	Call type	Time-to-maturity	Moneyness	Implied Volatility	Delta	Open Interest	Option RVs	% change of RV
Panel A: Crude Oil								
Least Impacted	0.530	69	1.004	0.345	0.324	3255	0.154	2.051
Most Impacted	0.465	93	0.989	0.305	0.470	1574	0.154	-0.447
Panel B: Natural gas								
Least Impacted	0.587	60	0.997	0.454	0.346	5387	0.183	1.279
Most Impacted	0.527	89	0.990	0.408	0.488	1885	0.194	-0.596
Panel C: Gold								
Least Impacted	0.454	72	0.990	0.192	0.216	1523	0.164	1.851
Most Impacted	0.621	113	1.007	0.203	0.421	744	0.164	-0.465
Panel D: Corn								
Least Impacted	0.577	82	1.007	0.309	0.308	8422	0.170	1.437
Most Impacted	0.438	151	1.004	0.345	0.484	2565	0.151	-0.605
Panel E: Wheat								
Least Impacted	0.547	73	0.999	0.309	0.285	2185	0.172	1.716
Most Impacted	0.549	101	1.013	0.310	0.374	1224	0.205	-0.410
Panel F: Lean hogs								
Least Impacted	0.564	78	1.016	0.255	0.238	1215	0.174	1.369
Most Impacted	0.498	109	1.004	0.251	0.400	824	0.194	-0.580

Note: This table presents average values of the different characteristics for the least and the most impacted options by futures realized volatilities. Call type refers to the average type of the options in the group. A value around one means a more oriented call option group. Time-to-maturity refers to the average remaining lifetime of the group of options expressed in days. Moneyness is the ratio of the strike price to the underlying futures price. A value around one means that options are at-the-money (ATM). A value far from one means that the options are in-the-money (ITM) or out-the-money (OTM). The % change of RV refers to the future rate of change of the option realized volatility. It is computed as $RV_{t+1} / RV_t - 1$.

Finally, both the least and most impacted options tend to have similar realized volatilities (RVs), but their percentage change in RV (from week *t* to week *t+1*) shows a stark contrast. The least impacted options typically show a positive change, indicating stable or increasing volatility, whereas the most impacted options show a decrease in volatility. Finally, it appears that the most impacted options generally have longer time-to-maturity, higher deltas, and lower open interest compared to the least impacted options. The change in realized volatility also shows a consistent pattern of decrease for the most impacted options across different commodities.

C. Returns on trading strategies: constrained vs. full forecast

Table 11: Summary statistics of the returns of the two trading strategies using the constrained and the full forecasts

	Strategy based on option RV forecasts					Strategy based on futures RV forecasts				
	Mean	Std.	SR	SoR	%DD10	Mean	Std.	SR	SoR	%DD10
Crude Oil										
Constrained	14.44	72.27	0.20	0.67	0.43	4.25	15.10	0.28	0.43	0.13
Full	15.13	73.52	0.21	0.70	0.42	4.71	15.06	0.31	0.49	0.12
Natural gas										
Constrained	20.61	65.47	0.31	1.11	0.35	2.82	12.01	0.23	0.37	0.11
Full	19.96	64.49	0.31	1.05	0.36	3.71	12.55	0.30	0.48	0.10
Gold										
Constrained	10.11	65.98	0.15	0.48	0.42	2.04	16.50	0.12	0.18	0.16
Full	10.53	66.30	0.16	0.49	0.43	2.14	15.48	0.14	0.20	0.14
Corn										
Constrained	13.53	58.15	0.23	0.75	0.36	2.66	13.39	0.20	0.28	0.09
Full	13.92	59.49	0.23	0.76	0.36	3.16	14.47	0.22	0.31	0.11
Wheat										
Constrained	18.18	77.77	0.23	0.84	0.39	3.62	13.74	0.26	0.43	0.12
Full	18.30	76.42	0.24	0.86	0.39	4.01	14.64	0.27	0.44	0.14
Lean hogs										
Constrained	14.76	68.69	0.21	0.67	0.41	2.18	14.11	0.15	0.23	0.12
Full	14.70	68.74	0.21	0.67	0.41	2.54	14.91	0.17	0.26	0.14

Note: This table presents some summary statistics of the returns of the two trading strategies (based on option RV forecasts and based on Futures RV forecasts) using in both cases the *constrained* and the *full* forecasts for six commodity option markets: Crude oil, natural gas, gold, corn, wheat and lean hogs. Mean refers to the average realized returns, Std. refers to the standard deviation of the returns of the strategy, SR refers to the Sharpe ratio of the returns of the strategy, SoR is the Sortino ratio of the strategy returns and %DD10 is the number of times the drawdown of the strategy is higher than 10%. The first row refers to the results of strategies using the constrained forecasts. The second row refers to the results of strategies using the full forecasts.