Natural Gas Price, Market Fundamentals and Hedging Effectiveness

Song-Zan Chiou-Wei
Professor
Department of International Business
National Kaohsiung University of Science and Technology
Kaohsiung, Taiwan
chiouwei@nkust.edu.tw

Sheng-Hung Chen*
Associate Professor
Department of International Business
National Kaohsiung University of Science and Technology
Kaohsiung, Taiwan
shchenib@nkust.edu.tw

Zhen Zhu
Professor
Department of Economics
University of Central Oklahoma
Edmond, OK, USA
zzhu@uco.edu
and
Consulting Economist
C.H. Guernsey and Company
Oklahoma City, OK, USA
Zhen.zhu@guernsey.us

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* Corresponding author.

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Abstract

How to effectively manage risk is an important issue that the financial and commodity industries face. One of the issues is the estimation of the financial and consumption asset price volatility and estimation of the optimal hedge ratio. Our study examines whether it is important to incorporate fundamental variables in estimating price returns and volatility by studying the U.S. natural gas market. In doing so, we explain the spot and futures returns and volatilities based on market fundamental variables such as weather, gas underground storage, oil price and macroeconomic news. We find significant impacts of most of these variables on gas price. In addition, we calculate the optimal hedge ratio based on the price and volatility estimations. Our empirical evidence suggests that, as expected, the optimal hedge ratio was not constant but fluctuated significantly during the sample period. Incorporating time-varying hedge ratio has improved hedging effectiveness by a large percentage. In addition, incorporating market fundamental variables further improves the hedging effectiveness significantly. Our empirical results support the proposition that it is important to incorporate fundamental market variables in analyzing commodity price movement and improving hedging effectiveness.

Keywords: Natural Gas Market; Hedge Ratio; Volatility; Weather; Macroeconomic News; DCC-MGARCH; VECM

JEL classification: G13; Q40

1. Introduction

Asset and commodity prices are volatile. Hedging has been used to mitigate price risks. For example, futures contract prices have been used as a hedging tool to reduce risks involving spot transactions. In order for futures contract to be used effectively in managing spot price risk, optimal hedge ratio needs to be estimated. There is a sizable literature on the estimation of the optimal hedge ratio. Among others, Baillie and Myers (1991) estimated the optimal hedge ratio for six commodities, beef, coffee, corn, cotton, gold and soybean, using a bivariate GARCH (BGARCH) model for futures and spot prices, recognizing that the conventional regression method such as Ederington (1979) may not be appropriate. Zainudin (2013) employed a regime switching model to estimate the optimal hedge ratio for the crude palm oil (CPO) market. In a more recent study, Park and Jei (2010) examined the optimal hedge ratio estimation using a different variation of the BGARCH models. Liu et al (2014) estimated optimal hedge ratio for China's copper and aluminum markets. Harris and Shen (2003), Choudhry (2003) estimated optimal hedge ratio for the stock futures, among other studies of hedging in the stock market. Balea (2014) reviewed in the crude oil risk management process the evolution of the optimal hedge ratio and hedge effectiveness. Salisu and Oloko (2015) used the adopted model to compute optimal portfolio weight and hedge ratios between oil price and US stocks using different sample data based on the break date. Their empirical evidence suggested that ignoring breaks exaggerated the hedging effectiveness. There are many studies estimating hedge ratios for other assets and commodities.

This paper makes contributions in two aspects. Even though other studies focused on methods used to estimate the optimal hedge ratio, our paper studies the importance of including fundamental economic variables in explaining price returns and volatilities to improve hedging effectiveness. In addition, we provide a study that focuses on a growingly important market – the natural gas market. The hedge ratio estimation and hedging effectiveness literature for energy markets including electricity, oil and natural gas is limited. Haigh and Holt (2002) estimated optional hedge ratio and examined the effectiveness for hedging crack spread by linking the crude oil, heating oil and unleaded gasoline futures contracts. They found that accounting for volatility spillovers between the markets leads to significant reduction in uncertainty. Chen and Sutcliff (2012) studied the cross hedging between stock and crude oil markets.

Ederington and Salas (2008) investigated the cross-hedging effectiveness in the natural gas market for 17 hubs using the linear regression method and found that incorporating expected changes in the spot-futures relationship could increase efficiency and reduce bias. Woo et al. (2011) developed a linear regression model using natural gas futures as a cross hedge against electricity spot price risk. They found that hedge ratios varied substantially from month to month even though they did find that the natural gas cross hedge provided an effective tool to reduce electricity price risk. Martinez and Torro (2015) investigated the hedging strategies for the European natural gas market and considered seasonality in the estimation of the mean and volatility equations. They found that incorporating seasonality slightly improved the hedging effectiveness. Finally, Cotter and Hanly (2012) incorporated risk aversion in energy hedging and revealed that significant differences exist for optimal hedges based on the utility function.

This paper adds to the literature of optimal hedge ratio estimation and hedging effectiveness for the financial assets and commodity markets in general and the natural gas market in particular. Natural gas price is one of the most volatile commodity prices. Figure 1 shows the plot of natural gas futures and spot prices. Gas prices could spike to more than \$10 followed quickly by prices as low as \$3. Such a large price swing in relatively a short time period suggests that it is imperative to hedge the price risk and maintain an effective hedging strategy. How to effectively model gas price and volatility becomes an important step in maintaining a successful hedging program. To this end, we incorporate fundamental factors available to the market participants in the price and variance equations and estimate the optimal hedge ratio using the DCC-MGARCH models to account for non-linearity and non-constancy of the hedge ratios. Specific factors considered include natural gas storage, crude oil price, weather information and macroeconomic news. In doing so, we emphasize the importance of these variables in influencing natural gas price and price volatility, and how hedging effectiveness can be improved. Our empirical results suggest that several fundamental market variables had significant effects on the level and volatility of the gas price, and optimal hedging ratio was time varying. The hedging effectiveness could improved significantly by incorporating time-varying hedging ratio models and incorporating market fundamental variables, suggesting the importance of utilizing more complicated econometric models and market fundamental variables to effectively manage the commodity risk.

The discussion in the next section provides the motivation for the including of several economic variables in modeling natural gas price. Section 3 discusses the data. Section 4 provides a discussion of estimation models and lays out the specification of several different models. Section 5 explains the estimation results and the last section concludes.

2. Determinants of Natural Gas Prices

2.1 Storage Impact

Natural gas storage affecting gas price is a theoretically valid proposition and empirically observed regularity. The relationship between storage and the commodity price has been discussed since the theory of storage emerged in 1933 by Holbrook Working. Brennan (1958) pointed out the connection between the value of storage commodity and the amount of commodity in storage and showed the importance of how storage would influence the yield of holding the commodity. Deaton and Laroque (1992, 1996) and Chambers and Bailey (1996) presented an elaboration of the theory of storage and suggested that the changing amount of a commodity under storage can generate price variability of that commodity.

Linn and Zhu (2004) focused on natural gas supply and demand conditions as reflected in the natural gas storage injections or drawdowns. Linn and Zhu investigated how gas storage injection or drawdown would have an impact on the residual volatility in natural gas futures prices. In addition, Chiou-Wei el al. (2014) provided empirical evidence that supports the significant influence of storages on natural gas price and its volatility.

Gay, Simkins, and Turac (2009) investigated analyst forecasts in the natural gas storage market and studied the analysts' role in facilitating price discovery in futures markets. They indicated that the market appeared to condition expectations regarding a weekly storage release on the analyst forecasts and found that the market appeared to place greater emphasis on analysts' long-term accuracy than on their recent accuracy.

Inventory announcements have also played a crucial role in stimulating the price dynamics of energy products. Halova, Kurov, and Kucher (2014) examined the effect of oil and gas inventory announcements on energy prices and suggested that energy prices were more strongly influenced by unexpected changes in inventory than shown in previous research. Moreover, recently, Bjursell, Gentle, and Wang (2015) identified jumps in daily futures prices and intraday jumps surrounding inventory announcements of crude oil, heating oil and natural gas using intraday data from January 1990 to

January 2008. They found that large jump components were often associated with the Energy Information Administration's inventory announcement dates, and volatility and trading volume were higher on days with a jump at the inventory announcement than on days without a jump at the announcement.

2.2 Oil price

Oil and natural gas are connected as they are both hydrocarbons. They are substitutes in consumption as in the industrial production as well as consumption process, oil and gas can be substituted to a certain degree. Oil and gas are also related on the production side. Oil wells often produce associated gas. Natural gas liquids are also considered to be close substitutes to oil. Oil price has long been shown to be related to natural gas prices. For example, Brown and Yucel (2008) convincingly established the linkages between oil price and gas price and showed evidence that oil price was a prominent factor that drove natural gas price even during the period after 2008 when oil and gas prices showed some obviously diverging trends. Perifanis and Dagoumas (2018) showed that there were significant price and volatility spillovers between the oil and gas markets. Therefore, it is imperative to consider the impact of oil price on gas price.

2.3 Weather Factors

Weather is clearly behind the pricing of many agricultural and energy commodities. Hansen, Hodges, and Jones (1998) showed that one weather event, ENSO (El Niño–Southern Oscillation), influenced crop production and was associated with low grain yield. Moral-Carcedo and Vicens-Otero (2005), as well as Koirala et al. (2015) all examined the relationship between weather and commodity prices. Their findings showed that weather factors, especially temperature variable, had significantly influenced the commodity prices. Lee and Oren (2009) showed that energy and agriculture were good example of weather sensitive industries. They found that the profit of each industry shared some common factors, and retail price, cost, and demand all were affected by weather. They also pointed out that the energy industry was especially exposed to weather risk on the ground as the energy demand was highly dependent on weather condition. For example, according to Considine (2000), the demand for gasoline and jet fuel had a strong seasonal factor, but it was not sensitive to temperature. Electricity, natural gas, and heating oil consumptions, however, are greatly sensitive to weather. Hong, Chang and Lin (2013) also suggested that weather had a significant impact on electricity demand and energy use and directly influenced the price of electricity. Despite the importance of weather in determining demand for natural gas, few have studied the direct role of weather in the natural gas market (an exception is Mu (2007)). Given that the U.S. natural gas market has evolved from a highly regulated market to a largely deregulated market in more recent history, natural gas prices driven by weather made natural gas market one of the most volatile markets.

To capture the impact of the weather on gas prices, we utilize several weather variables including temperature and relative humidity with an assumption that these variables directly affect demand for natural gas. This is fairly reasonable as natural gas is used in the U.S. mainly in spacing heating in the winter and electricity generation in the summer. Therefore, colder temperature in winter, higher temperature in summer as well as higher relative humidity in summer would increase the demand for natural gas.

2.4 Macroeconomic News

Earlier studies suggested that macroeconomic news was significantly related to the commodity prices and was a well-known key driver for asset prices. Frankel and Hardouvelis (1985) and Barnhart (1989) focused on the effect of monetary variables and revealed that surprises in interest rate and declines of money supply caused commodity prices to increase. Fleming and Remolona (1999) found that economic news announcement had a great influence on commodity prices and trading activity when public information arrived, and it was so especially when uncertainty was high. According to Ederington and Lee (1993), Hess and Hautsch (2002) and Bartolini et al. (2008), financial market price responses to macroeconomic news announcements were generally the strongest for the employment situation summary, the GDP advance release report, the Institute for Supply Management's Manufacturing Report, Consumer Sentiment, Consumer Confidence and Retail Sales. More recently, Tang and Xiong (2012) presented evidence to support the claim that commodity prices had been exposed to market-wide shocks, and they suggested that macroeconomic announcements had a substantial influence on commodity prices.

Recent studies such as Hess, Huang, and Niessen (2008), Christie–David, Chaudhry, and Koch (2000) assumed that commodity price's sensitivity to the announcements was symmetrical and constant over time. However, Kilian and Vega (2011) suggested that it was reasonable to question these assumptions. They presented two possible factors that might have an impact on the response of commodity prices to news announcements. They found that the good news and bad news factors had different influences on the commodity price.

Recently, Karali and Ramirez (2014) analyzed the time-varying volatility and spillover effects in crude oil, heating oil, and natural gas futures markets by incorporating changes in important macroeconomic variables, including major political and weather-related events into the conditional variance equations. These authors showed the presence of asymmetric effects in both random disturbances and macroeconomic variables, while crude oil volatility was found to increase following major political, financial, and natural events. In addition, Basistha and Kurov (2015) examined the effect of monetary policy surprises on energy prices and found a significant response of energy prices to surprise changes in the federal funds target rate in an intraday window immediately following the monetary announcement.

We believe there can be connections between macroeconomic conditions and demand for natural gas. Even though we have argued that weather is one of the major factors that would influence the demand for natural gas through demand from the residential, commercial and power sectors, economic conditions could have a major impact on industrial demand for natural gas. Thus any news on economic conditions would be expected to have some impact on gas price and volatility. The empirical study of macroeconomic news on natural gas price and volatility is rare (exceptions include Chan and Gray (2017)). News releases regarding economic variables are many. As a full investigation of the impact of all economic variables on natural gas is not the objective of this study, we have only selected a few representative economic news releases, namely advance retail sales, business inventory, changes in nonfarm payroll, housing starts, industrial production and construction spending, to study the effects of the economic news announcement on gas price levels and returns, with an emphasis on hedging effectiveness.

To summarize, in an attempt to estimate the optimal hedge ratio and hedge effectiveness, we consider several weather factors, storage, oil price and several macroeconomic news announcements in modeling natural gas price and volatility. Our empirical evidence shows that the inclusion of these variable improves the hedging effectiveness significantly.

3. Data

We obtained the weekly and daily oil price (West Texas Intermediate or WTI), natural spot prices (at Henry Hub) and futures contract prices, and storage data from the

US Energy Information Administration (EIA). The sample period starts in January 2000 and ends in December 2013. EIA releases a weekly survey report of the actual level and changes of natural gas storage in the United States regularly on Thursday morning at 10:30 AM Eastern Time; and it gives an updated storage data as of the previous Friday. If the EIA weekly storage report contained a revision, we would omit the observation and also the previous week's observation.

The EIA storage report reveals important information about natural gas market supply and demand balance. Since storage contains such critical information, industry players usually monitor gas flows from pipeline nominations and transportation or survey a limited number of storage operators. As a result, industry players are able to access the storage information thoroughly and promptly. As storage is such an important piece of information in the gas market, market participants anticipate the storage report and news agencies collect analysts' forecast and disseminate to the market. We use Bloomberg's storage survey as the measure of market expectation.

Our weather data were obtained from National Climate Data Center (NCDC) which is the division of the National Oceanographic and Atmospheric Administration (NOAA). The daily and weekly data span the period of January 1, 2000 to December 31, 2013. NOAA's National Climatic Data Center (NCDC) is the world's largest climate data archive and offers climatological services and data to not only every sector of the United States economy but also to users worldwide. NCDC's reports range from paleoclimatology data to data less than an hour old. The Center maintains these data and makes them available to the public, business, industry, government, and researchers. NCDC's stations, land-based, collect the climate data from instruments sited at locations on every continent. The observations include temperature, dew point, relative humidity, precipitation, wind speed and direction, visibility, atmospheric pressure and types of weather occurrences. NCDC provides service with wide level that is associated with land-based observations. Data are available on daily, weekly and multi-year timescales. We compiled our weather data for the following cities: Dallas, Baton Rouge, Atlanta, Chicago, Los Angeles, Phoenix, Saint Louis, New York, Philadelphia, Oklahoma City and Salt Lake City. These cities represent the major gas consumption regions. We computed an average day temperature by daily T_max, T_min measured from midnight to midnight. We then computed a Cooling Degree Day (CDD) measure, a Heating Degree Day (HDD) measure for each day and each week. We also compiled information on relative humidity (RH).

We used Bloomberg as our source to collect the macroeconomic news data during the period of January 1, 2000 to December 31, 2013. Bloomberg provides a description of any announcement releases, including the number of observations, the agency that reports the news, and the release time (see Table 1 for the news items we selected). Our data includes retail sales (ARS), business inventories (BI), changes in nonfarm payrolls (CNP), housing starts (HS), industrial production (IP), and construction spending (CS).

[Insert Table 1 Here]

4. Methodology

4.1 Modeling the Storage Surprises of Natural Gas

EIA reports the survey result of the storage as of the previous Friday on each Thursday morning at 10:30 EST. If Thursday falls on a holiday, then the report will be announced either on Wednesday or Friday and these changes are announced ahead of time to the market so the market knows the report time exactly. Bloomberg collects the storage forecast from gas market analysts and makes them available ahead of the EIA announcement. For our study, we define the storage surprise as the difference between the storage estimated reported by EIA and the survey result by Bloomberg ($EStorage_t$).

$$\Delta NGS_t = Storage_t - EStorage_t \tag{1}$$

4.2 Modeling Related Weather Factors

Next, we define the temperature measures by cooling degree days (CDD) and heating degree days (HDD). When actual temperature minus 65°F is greater than zero then it is defined as the cooling degree day. We set heating degree day as 65°F minus actual temperature when actual temperature is lower than zero. The following shows the definition of HDD and CDD.

$$TD_t = \frac{Tmax_t + Tmin_t}{2} \tag{2}$$

$$CDD_t = \max(0, TD_t - 65F) \tag{3}$$

$$HDD_t = \max(0, 65F - TD_t) \tag{4}$$

where TD_t is the temperature for day t, $Tmax_t$ is the daily maximum temperature, and $Tmin_t$ is the daily minimum temperature on date t. We calculate daily HDD and CDD first, and then the weekly HDD and CDD are the weekly accumulation of daily CDDs and HDDs for the week, respectively.

In addition to the temperature variation, we define a relative humidity factor. We model the relative humidity enthalpy latent days as defined by Huang el al (1986).

$$RH_t = \frac{1}{24}\sum_{i=1}^{365}\sum_{j=1}^{24}(\alpha_{tij})\{E_{tij} - E_{tij}^0\} \tag{5}$$

where RH_t is the relative humidity enthalpy latent days of week t, E is the enthalpy and ^{0} is the enthalpy at the humidity ratio of 0.0116 and the temperature measured.

4.3 Measuring Surprises on Macroeconomic News

In this study, we have selected six news items related macroeconomic issues which are Advanced Retail Sales (ARS), Business Inventory (BI), Change in Nonfarm Payroll (CNP), Construction Spending (CS), Housing Start (HS), and Industrial

Production (IP). These variables represent various aspects of the real economic activities and are expected to have influences on consumers' demand for natural gas. For example, ARS and CNP represent economic activities, which are expected to have a positive impact on natural gas demand through industrial and commercial demand for gas. HS and CS may be directly related to the demand for natural gas in space heating, and IP is expected to be an indicator of demand for natural gas from industrial sectors.

All of these news items are announced monthly. Based on Anderson et al. (2003), the macroeconomic news surprise component is computed as followed:

$$NRS_{i,m} = \frac{A_{i,m} - F_{i,m}}{STD}, \tag{6}$$

where $NRS_{i,m}$ is the news release shock (i=1 to 6, each corresponding to an economic news item), *STD* is the standard deviation, $A_{i,m}$ is the actually released value, and $F_{i,m}$ is the median analyst forecast. This standardization affects neither the statistical significance of the estimated response coefficients nor the fitness of the regressions. This procedure facilitates a comparison of the estimated coefficients. The standardized surprise $NRS_{i,m}$ is used in our empirical analysis.

4.4 Econometric Model

As we model the natural gas spot and futures prices together, we use both the Multivariate GARCH (MGARCH) Model specified by Bollerslev et al. (1988) and Vector Error Correction Model (VECM) proposed by Engle and Granger (1987) to examine returns and volatility spillover effect between spot and futures natural gas markets. In particular, we rely on the use of two relatively flexible volatility models that explicitly incorporate the direct transmission of shocks and volatility across spot and futures markets. This section begins with the presentation of the conditional means in the VECM–MGARCH framework, and then introduces the MGARCH specifications under consideration.

4.4.1. VECM Model for the Conditional Mean Specification

For the empirical analysis on return spillovers across the futures and spot markets, we assume that the conditional mean of returns on the spot and futures markets can be described by a vector autoregressive (VAR) model. In the two-variable case, a VAR model can be set up as in Equations (7) and (8) below. The appropriate lag length of the VAR model is determined using several measures including AIC, SIC and others. See also Table 4 for more details. The base model shown below shows that the futures and spot prices depend on their lagged values. Particularly, we consider there would be only one cointegration relationship between spot and futures prices in natural gas markets, we apply the following specification for the mean equations to model the returns spillover within two markets:

$$\begin{aligned}\Delta NG_t^{Futures} = \mu^{Futures} + \psi^{Futures} \times ECM_{t-1} + \sum_{i=1}^{p-1}\left(\alpha_i^{Futures} \times \Delta NG_{t-i}^{Futures}\right) \\ + \sum_{j=1}^{q-1}\left(\beta_j^{Spot} \times \Delta NG_{t-j}^{Spot}\right) + \xi_t^{Futures}\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta NG_t^{Spot} = \mu^{Spot} + \psi^{Spot} \times ECM_{t-1} + \sum_{j=1}^{q-1}\left(\alpha_j^{Spot} \times \Delta NG_{t-j}^{Spot}\right) \\ + \sum_{i=1}^{p-1}\left(\beta_i^{Futures} \times \Delta NG_{t-i}^{Furures}\right) + \xi_t^{Spot}\end{aligned} \tag{8}$$

where $\Delta NG_t^{Futures}$ and ΔNG_t^{Spot} are the logarithmic returns of the futures and spot natural gas price series, respectively. The error correction term (ECM), ECM_{t-1} is included in each equation (7) and (8), to capture the cointegrating relationship. If the cointegration equation is $\Delta NG_t^{Futures} = \pi_0 + \pi_1 \times \Delta NG_t^{Spot}$, then ECM_t is defined as $ECM_t = \Delta NG_t^{Futures} - \pi_0 - \pi_1 \times \Delta NG_t^{Spot}$. The residuals, ξ_t are assumed to be serially uncorrelated, but the covariance $E(\xi_t^{Spot}, \xi_t^{Futures})$ needs not be zero. The coefficients α^{Spot} and $\alpha^{Futures}$ provide the measures of own-mean spillovers, whereas the coefficients β^{Spot} and $\beta^{Futures}$ measure the cross-mean spillovers between the logarithmic returns of the spot and futures natural gas prices.

4.4.2. MGARCH Models for Conditional Variance

We model the dynamics of the conditional volatility and volatility interdependence between the logarithmic returns of the spot and futures prices for natural gas. In the DCC model, which assumes a time-dependent conditional correlation matrix $R_t = (\rho_{ij,t})$, $i, j = 1, 2$, the conditional variance–covariance matrix H_t is defined as

$$H_t = D_t R_t D_t \tag{9}$$

where

$$D_t = diag\left(\sqrt{h_{11,t}}, \ldots\ldots, \sqrt{h_{22,t}}\right) \tag{10}$$

$h_{ii,t}$ is defined as a GARCH(1,1) specification, i.e. $h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t}$, i=1, 2, and

$$R_t = diag\left(q_{ii,t}^{-1/2}\right) Q_t \, diag\left(q_{ii,t}^{-1/2}\right) \tag{11}$$

with the 2×2 symmetric positive-definite matrix $Q_t = (q_{ij,t})$, i, j=1, 2, given by

$$Q_t = (1 - \lambda_1 - \lambda_2)\overline{Q} + \lambda_1 u_{t-1} u_{t-1}' + \lambda_2 Q_{t-1} \tag{12}$$

and $u_{it} = \varepsilon_{it} / \sqrt{h_{ii,t}} \cdot \overline{Q}$ is the 2×2 unconditional variance matrix of u_t, and λ_1 and λ_2 are non-negative adjustment parameters satisfying 0< λ_1 + λ_2 <1. Q_t basically resembles an autoregressive moving average (ARMA) type process which captures short-term deviations in the correlation around its long-run level. The variance–covariance matrix defined in Eq. (10) permits us, then, to model the degree of volatility interdependence between markets across time.

Hence, we specify our full model (VECM-DCC-MGARCH) for empirical estimation as follows:

$$\Delta NG_t^{Futures} = \mu^{Futures} + \psi^{Futures} \times ECM_{t-1} + \sum_{i=1}^{p-1}\left(\alpha_i^{Futures} \times \Delta NG_{t-i}^{Futures}\right) + \sum_{j=1}^{q-1}\left(\beta_j^{Spot} \times \Delta NG_{t-j}^{Spot}\right)$$
$$+ \gamma^{Futures} \times \left(\Delta NGS_{t-1}\right) + \pi^{Futures} \times \left(CrudeOil_{t-1}\right) + \sum_{r=1}^{p} \delta_r^{Futures} \times \left(\Delta Weather_{t-1}\right)$$
$$+ \sum_{v=1}^{p} \phi_v^{Futures} \times \left(NRS_{t-1}\right) + \xi_t^{Futures} \tag{13}$$

$$\Delta NG_t^{Spot} = \mu^{Spot} + \psi^{Spot} \times ECM_{t-1} + \sum_{j=1}^{q-1}\left(\alpha_j^{Spot} \times \Delta NG_{t-j}^{Spot}\right) + \sum_{i=1}^{p-1}\left(\beta_i^{Futures} \times \Delta NG_{t-i}^{Futures}\right)$$
$$+ \gamma^{Spot} \times \left(\Delta NGS_{t-1}\right) + \pi^{Spot} \times \left(CrudeOil_{t-1}\right) + \sum_{r=1}^{p} \delta_r^{Spot} \times \left(\Delta Weather_{t-1}\right)$$
$$+ \sum_{v=1}^{p} \phi_v^{Spot} \times \left(NRS_{t-1}\right) + \xi_t^{Spot} \tag{14}$$

and conditional variance equation takes the following form:

$$H_t = CC' + A\xi_{t-1}\xi_{t-1}'A' + BH_{t-1}B' + D\left(\Delta NGS_{t-1}\right)D' + E\left(\Delta Weather_{t-1}\right)E'$$
$$+ F\left(NRS_{t-1}\right)F' + G\left(CrudeOil_{t-1}\right)G' \tag{15}$$

In Equations (13) through (15), ΔNGS_{t-1} stands for the lagged one week (day) of storage surprise for US natural gas, $CrudeOil_{t-1}$ is the lagged one week (day) of WTI spot crude oil return, and we use the shocks of *CDD* (cooling degree day), *HDD* (heating degree day), and *RH* (relative humidity) as a series of weather factors (*ΔWeather*). Moreover, macroeconomic news factors (*ΔNRS*) include shocks of *ARS* (retail sales), BI (business inventories), CNP (change in nonfarm payrolls), HS (housing starts), IP (industrial production), and CS (construction spending), respectively. In Equations (13) and (14), we have specified several lags in the exogenous variables. However, in the estimation, for tractability due to a large number of estimated coefficients, we have included only one lag for each of the exogenous economic variables and three lags each for the spot and futures return.

Therefore, we set up a total of five models for the empirical estimation and they are as follows: Model 1 is the base model only with the ECM term and lagged futures and spot price return values in conditional mean equation and conditional variance equation. Model 2 is based on Model 1 specification plus the lagged storages surprise variable. Model 3 is based on Model 2 and it includes lagged weather shocks. Model 4 is based on Model 3 and it includes lagged macroeconomic news variables. And Model 5 is based on Model 4 and it includes the lagged WTI spot oil price returns. The market fundamental variables enter both the mean and variance equations.

4.4.3 Calculating the Time-Varying Hedge Ratio

The H^* optimal hedge ratio is computed as conditional covariance between spot return and futures divided by the conditional variance of futures return. Thus the minimum variance hedge ratio has now become time-varying as it varies with the changes in conditional covariance matrices as follows:

$$H^* = \frac{h_{sf}}{h_{ff}} \tag{16}$$

where $h_{ss,t} = c_{ss} + \alpha_{ss}\varepsilon^2_{s,t-1} + \beta_{ss}h_{ss,t-1}$, $h_{sf,t} = c_{sf} + \alpha_{sf}\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \beta_{sf}h_{sf,t-1}$, and $h_{ff,t} = c_{ff} + \alpha_{ff}\varepsilon^2_{f,t-1} + \beta_{ff}h_{ff,t-1}$ are specified and estimated as in the above equations.

4.4.4 Evaluating Hedging Effectiveness

Following Ederington (1979), Hedging Effectiveness (HE) is defined as the gain or loss in the variance of terminal revenue due to price changes in an unhedged position relative to those in a hedged position and therefore is defined as:

$$HE_t = \frac{\left[VAR^{Unhedged}(\Omega_t) - VAR^{Hedged}(\Omega_t)\right]}{VAR^{Unhedged}(\Omega_t)} \tag{17}$$

where $VAR^{Unhedged}(\Omega_t)$ and $VAR^{Hedged}(\Omega_t)$ are the variances for the unhedged and hedged positions, respectively. The return of the hedged portfolio during the holding period is defined by $R_t^{Hedged} = R_t^S - H_t \times R_t^F$. According to Eq. (17), the closer HE is to 1, the higher the degree of hedging effectiveness.

5. Empirical Results

5.1 Unit-Root Test

Figure 1 shows the time series plots of natural gas prices and several fundamental variables including CDD, HDD, RH, storage and crude oil price. Both spot and futures gas prices exhibit large volatilities with prices reaching the high of $14 to $15 followed soon by the low of $2 to $3. Such a high price volatility warrantees active price risk management. CDD, HDD and storage show strong seasonal variations while oil price shows a generally upward trend with a major break occurred in 2008/2009.

[Insert Figure 1 Here]

We performed the Augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) unit root tests as well as the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test (Table 2). The results reported in Panel A of Table 2 indicate that all the log-differences of the series were stationary at the 1% level while the log of the spot price was also stationary. We further tested the conditional heteroscedasticity in the second moment of the price series. The Engle (1982) test for conditional heteroscedasticity (Panel B of Table 2) shows that the ARCH effects were significantly present in all the return series, which provides support to our decision to use the GARCH-based approach to examine the return and volatility transmission between the spot and futures natural gas prices in the U.S. market.

[Insert Table 2 Here]

Table 3 shows the conventional Granger causality test to obtain the information about how spot and futures prices were linked to each other. Panel A in table 3 shows that both the weekly spot and futures prices were Granger causing each other. Panel B also suggests that the bi-directional causality existed when we use log daily price differences or gas price returns. However, from both Panel A and Panel B, the null hypothesis of no futures price causing spot price can be rejected at a much higher marginal significance level than the null hypothesis of spot price causing futures price with respective to both the weekly and daily data. This result appears to be consistent with Chiou-Wei et al (2014) which found that futures price moved ahead of spot price when they used daily prices. This is mainly due to different price settings of spot and futures contracts for the same day. Spot transactions are usually done early in a day due to gas nomination for transportation for the next day and futures trading ends the trading day in the afternoon. Therefore, spot prices in the second day usually reacts to information already contained in the previous day's futures price. We also picked up this pattern in the weekly data, suggesting that the nomination and scheduling of the spot transactions could be one of the explanations of futures leading spot slightly ahead of spot leading futures.

[Insert Table 3 Here]

5.2 Return and Volatility Spillovers between Spot and Futures Market for Natural Gas

The selection of the optimal lag of the VAR system is presented in Table 4. We present five statistical tests and three tests (AIC, SC, and HQ) suggested a similar lag order. Therefore, we chose 3 as the optimal numbers of lags for the VAR system of spot and futures prices with respect to both of weekly data (Panel A) and daily data (Panel B).

[Insert Table 4 Here]

5.2.1 Estimations of DCC-MGARCH Models

Table 5 shows the estimation results of the ECM-DCC-MGARCH models with different specifications. Several results stand out. First, there were significant lagged price effect for both the spot and futures returns as many of the lagged futures and spot returns coefficient estimates are statistically significant. This result holds true regardless of the model specification. This suggests that both the futures and spot prices could be predictable to a certain degree. In addition, the one-period lagged futures price influenced futures prices positively (positive feedback effect of own price) while the spot price was negatively affected by own lagged prices (negative feedback effect). The negative feedback effect of the spot price on its own was rather long at all three lags.

[Insert Table 5 Here]

In addition, we do observe some statistically significant cross-price effect. Lagged futures price had a positive effect on spot price while lagged spot price had relatively weaker effects on futures price. Combining the own-price and cross-price effect, it appears that the futures price was mainly affected by own lagged values while the spot price was influenced more by the futures price rather than by own lagged price. This estimation result is consistent across all five models.

The lagged storage surprise effect on both spot and futures prices is significantly negative across various model specifications, indicating that a higher than expected storages decreased gas prices, which is consistent with our expectation and earlier results by Linn and Zhu (2004) and Chiou-Wei et al (2014). Linn and Zhu (2004) found the negative storage effect in the 5-minute data and Chiou-Wei et al (2014) found the same effect using the daily data. In this study, we used the weekly and daily data; and the effect is still detectable with high significances in the weekly data. This piece of evidence simply points to the extreme importance of the storage in influencing natural gas prices.

Oil price had a significantly positive effect on gas price returns, as indicated by Model 5 estimation results. This result holds true for both the spot and futures prices from both the daily and weekly data. The positive connection between oil and gas prices is consistent with the general findings in the literature such as Brown and Yucel (2008).

Weather variables, especially the temperature related variables such as CDD and HDD, had some significant effects on gas prices. Both CDD and HDD significantly increased gas demand as hypothesized. Relative humidity had a less significant effect on gas prices. In the weekly data estimation, none of the RH variable showed up to be statistically significant. In the daily data estimation, however, RH had a significantly positive effect on gas consumption, suggesting that RH is more relevant on the daily basis rather than at the weekly basis.

Macroeconomic news variables had some significant effects on gas price returns though the effects are mixed from the weekly data estimation, but the effects were universally positive from the daily data estimation.

The conditional variance-covariance estimation results presented in Table 5 show that all models had significant GARCH effect, which is not surprising. The economic fundamental variables had significant volatility effects on the gas price variables. Most of the volatility effects of the fundamental variables were positive with the exception of gas storage surprises whose effect turned out to be negative.

Our estimation results across different model specifications appear to be robust.

The significance and estimated signs of various variables remain generally consistent across model specifications and data frequency. The estimation results using the weekly data corroborate well with the estimation results of the daily data.

5.3 Time-Varying Hedge Ratio (HR) and Multiple Structural Breaks in Trend

Figure 2 plots the estimated optimal hedge ratio using different specifications based on DCC-MGARCH (Figures 2-A to 2-E corresponding to Models [1] to [5]) estimated using the weekly data. It is obvious that the estimated HRs fluctuated much more significantly than the rolling OLS HRs which serve as the benchmark. Even though the average values of the DCC-MGARCH HRs are close to 1.0, frequently the HRs deviate significantly from the value of 1.0. Occasionally the values can reach as high as 1.5 or higher and as low as 0.5 or lower. These values are possible as sometimes spot and futures prices can deviate significantly from each other, and the number of futures contracts to be used to achieve minimum variation in the value of the portfolio can change significantly.

[Insert Figure 2 Here]

Figure 3 shows the HR estimation results using daily data. The general conclusions are similar to those estimated from the weekly price data except that there are larger spikes in the HR of the daily price estimations. This can be explained on the basis that daily price fluctuations are larger compared to the weekly average price fluctuation as the weekly average price has eliminated more extreme daily price movement.

[Insert Figure 3 Here]

Table 6 provides the descriptive statistics of the time-varying hedge ratio, and the results of statistical tests for zero mean, median, and variance. We find that the average hedge ratio from DCC-MGARCH ranges from 0.9244 (Model [1]) to 0.9905 (Model [5]) for weekly data. However, the average hedge ratios for daily data are significantly smaller, ranging from 0.3312 (Model [1]) to 0.5253 (model [5]). This suggests much smaller co-movement in the daily prices of spot and futures compared to the weekly prices. The unconditional volatility as measured by the standard deviation ranges from 0.2145 (for Model [1]) to 0.4256 (for Model [5]) for the weekly data but 0.2131 (Model [1]) to 0.2653 (Model [5]) for daily data. The skewness coefficients are positive for all hedge ratio series. The kurtosis coefficients are above three for all the estimated hedge ratio series. These findings indicate that the probability distributions of the hedge ratio are skewed and leptokurtic. The formal tests reject the normality assumption. Finally, we find statistical significance in zero mean, median and variance tests for all specifications.

[Insert Table 6]

The results presented in Table 7 suggest that there were structural breaks in the hedge ratio series estimated with different model specifications. The null hypothesis of no structural breaks against the alternative of an unknown number of structural breaks is clearly rejected. All test statistics are above their critical values at common levels of significance. As proposed by Bai and Perron (2003), we used the Bayesian information criterion (BIC) to condense the information given by the tests. This criterion is most appropriate in our case, as structural breaks have to be expected a priori. In Panel A, both the LWZ (modified Schwarz criterion) and BIC suggest one or two breaks in the series of estimated hedge ratio based on Models [1] – [5]. The estimation results from the daily data are similar to those from the weekly data even though the detected break dates do not match those from the weekly data exactly. To some extent, this large number of structural breaks may be due to the high level of sensitivity that we chose for our tests. We set the trimming parameter to 10% which results in a minimum length of a segment of 725 days and allows for 5 structural breaks detected in every single series at the maximum. Our results suggest that it is very important to account for the time-varying nature of the hedge ratio and it is also imperative to recognize the structural breaks in the hedge ratio in order to hedge effectively.

[Insert Table 7 Here]

5.4 Hedging Effectiveness (HE)

Our key findings are shown in Table 8 which shows the hedging effectiveness based on variance reduction of hedged portfolios compared to the unhedged positions under different model specifications. The dynamic hedging strategy using DCC-MGARCH models without incorporating any market fundamentals did work for natural gas market with more than 60% of variance reductions for the weekly data. For the daily data, accounting for time-varying nature of the hedging ratio would lead to 33% reduction in the variance of the portfolio. As more market fundamental variables are included in the model (in the order of Model [2] to Model [5]), the hedging effectiveness increases. Incorporating only the storage shock variable in both the mean and variance equations would raise the HE from 65% to 73% for the weekly data and from 34% to 38% for the daily data. However, when all the variables are considered, the HE increases to 85% for the weekly data and 59% for the daily data. For both the weekly and daily data cases, incorporating economic variables increases the HE by more than 20%.

To summarize, incorporating available economic information and engaging in dynamic hedging help to reduce risk. This is evident from the comparison of the HEs generated with models that incorporated fundamental variables to the HEs generated with models that employed only the lagged price variables.

[Insert Table 8 Here]

6. Conclusions

Price risks faced by investors of financial and consumption assets can be large. This is particular true for energy market participants including investors, producers and consumers. How to effectively manage risk is always an important issue.

This paper studies the effect of incorporating fundamental factors in modeling commodity prices with the focus on the U.S. natural gas market. The price and volatility of natural gas have been modeled using various fundamental factors such storage news, oil price, weather information, and macroeconomic news announcement. Our modeling results suggest that incorporating these factors improves the model performance and leads to better estimation of the optimal hedge ratio.

Our estimated results also reveal that the optimal hedge ratio fluctuated quite significantly during the sample period. In addition, there were structural breaks in the estimated hedge ratios. As the result, hedging against price risks in the energy market in general, natural gas market in particular, requires dynamic hedging of the portfolio. Our analysis of hedge effectiveness using various models suggests that hedging using a constant hedge ratio can lead to subpar hedging performances and dynamic hedging using time-varying hedge ratios under the guidance of economic theory can improve hedging effectiveness quite significantly. Our modeling results suggest that the variance of the hedged assets can be more than 65% lower than the variance of the unhedged portfolio from the weekly data and more than 33% lower from the daily data.

Even though the hedging effectiveness can be improved quite significantly by utilizing dynamic hedging and incorporating all economic information, we do note that there could be some practical issues related to the implementation of such approaches. One such issue is the cost of dynamic hedging resulted in from constant rebalancing of the portfolio, which is expected to increase the transaction cost quite rapidly. The second issue is that to effectively model the price and volatility of asset prices, one needs to have reliable information about fundamentals. In the natural gas market, one needs to have reliable information on the fundamental market variables including at least the variables modeled in this paper. In the practice, the successful modeling of the price and volatility requires accurate forecasts of these variables. While the accurate forecasts can be hard to come by, it is beneficial for market participants to actively seek out this information.

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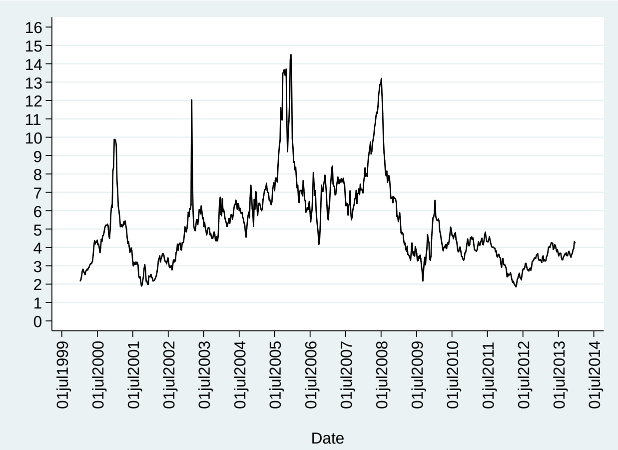
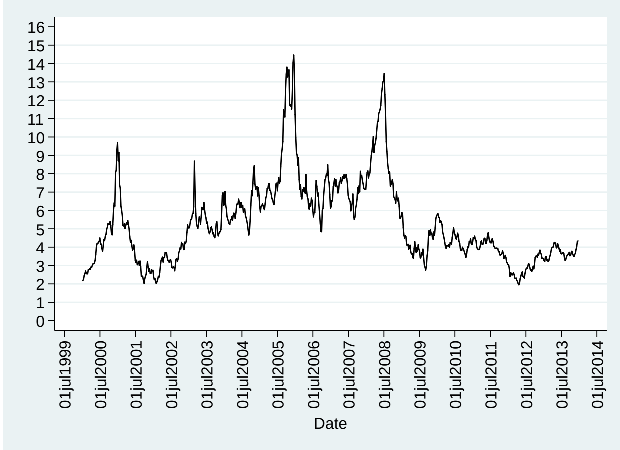
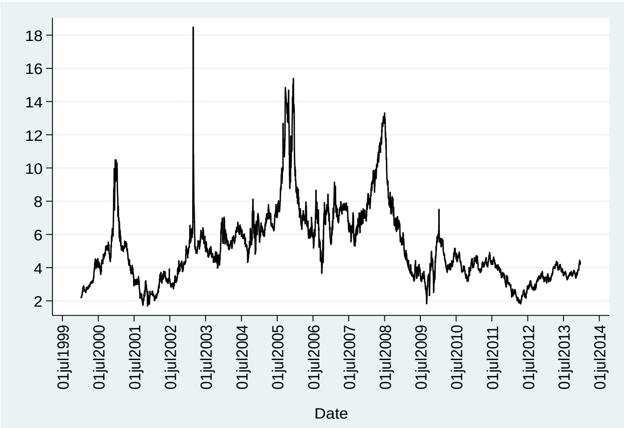


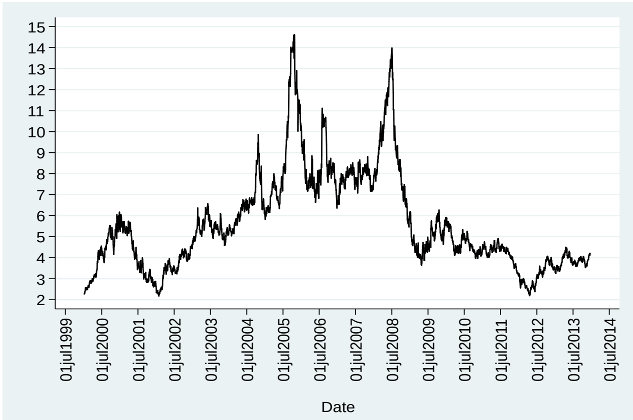
A. Weekly spot price of natural gas



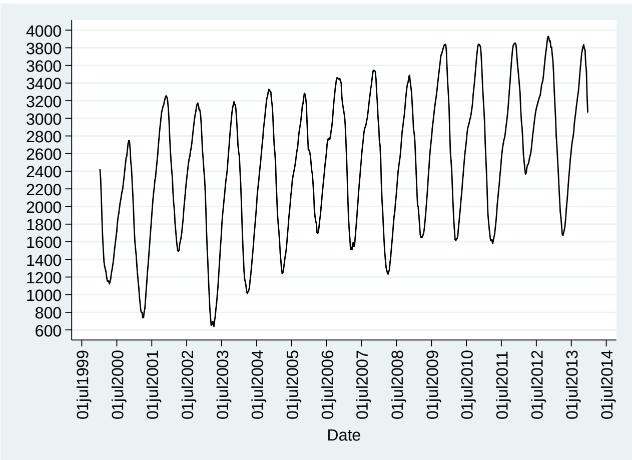
B. Weekly futures price of natural gas



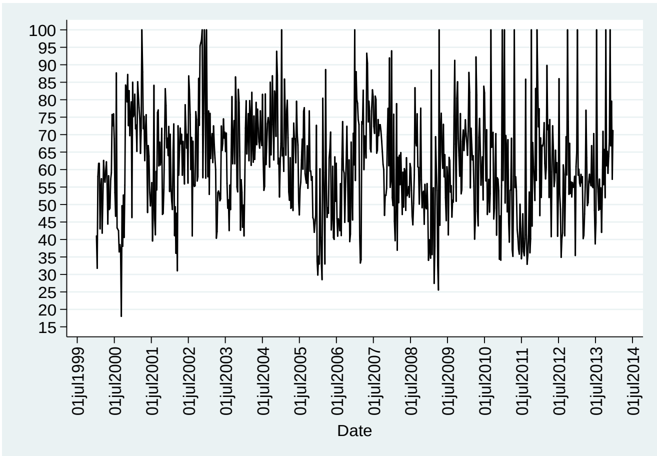
C. Daily spot price of natural gas



D. Daily futures price of natural gas



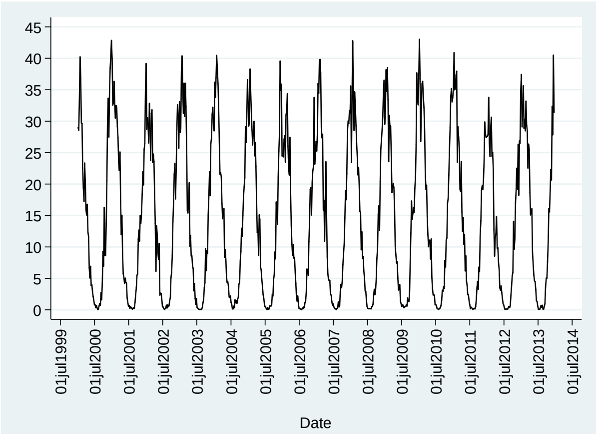
E. Weekly storages of natural gas



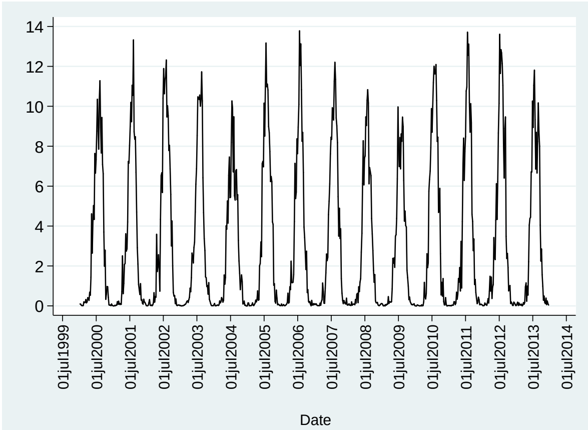
F. Weekly relative humidity

Figure 1

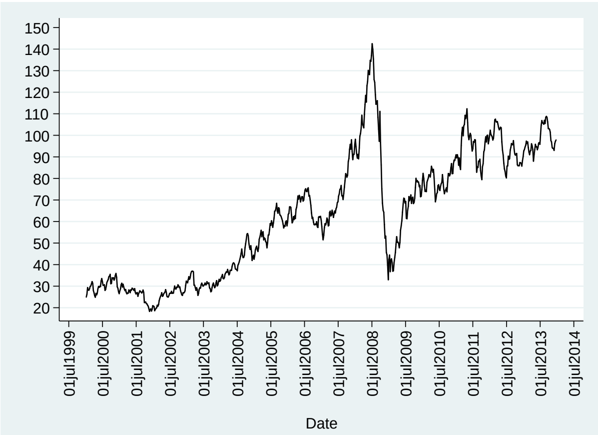
Time-series plot of key variables



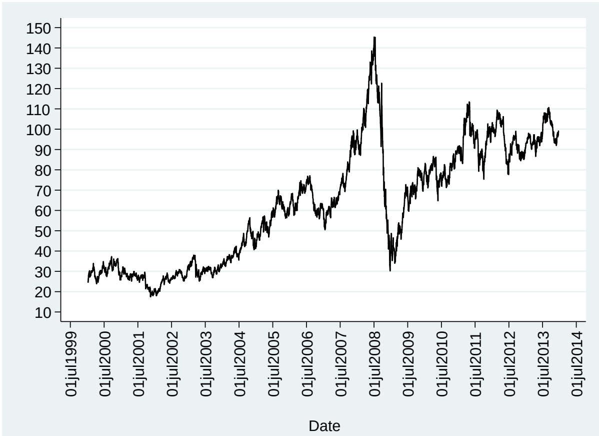
G. Weekly Heating Degree Day (HDD)



H. Weekly Cooling Degree Day (CDD)

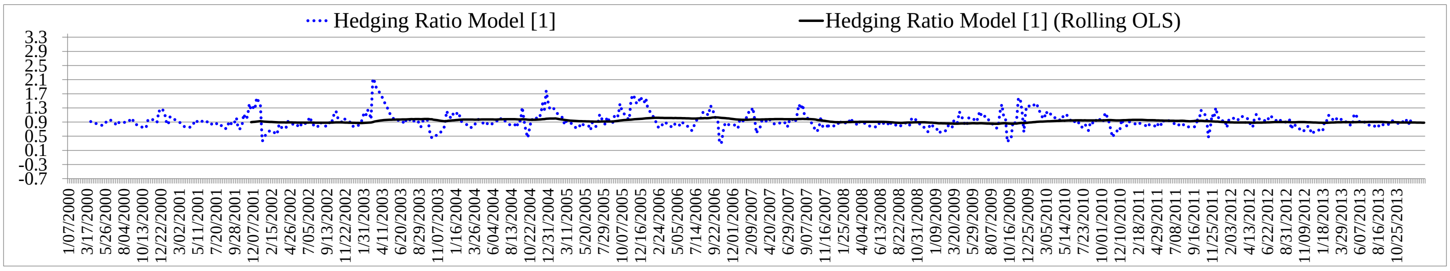


I. Weekly WTI crude oil price

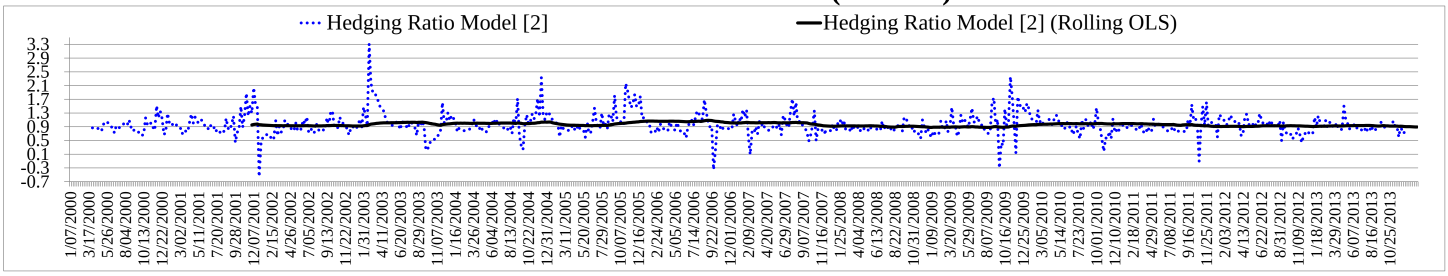


J. Daily WTI crude oil price

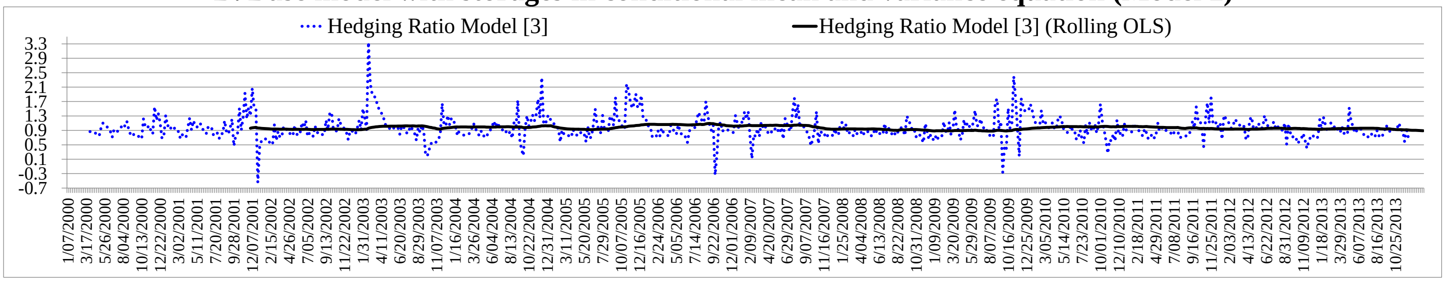
Figure 1. Time series plot of key variables (Continued)



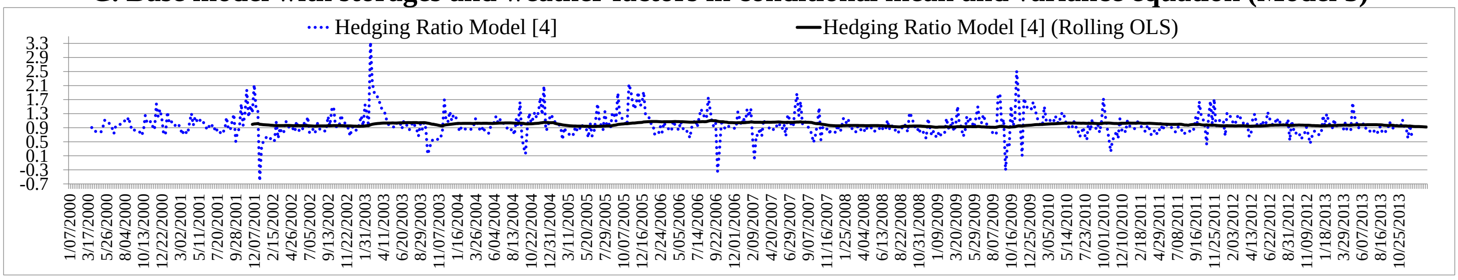
A. Base model conditional (Model 1)



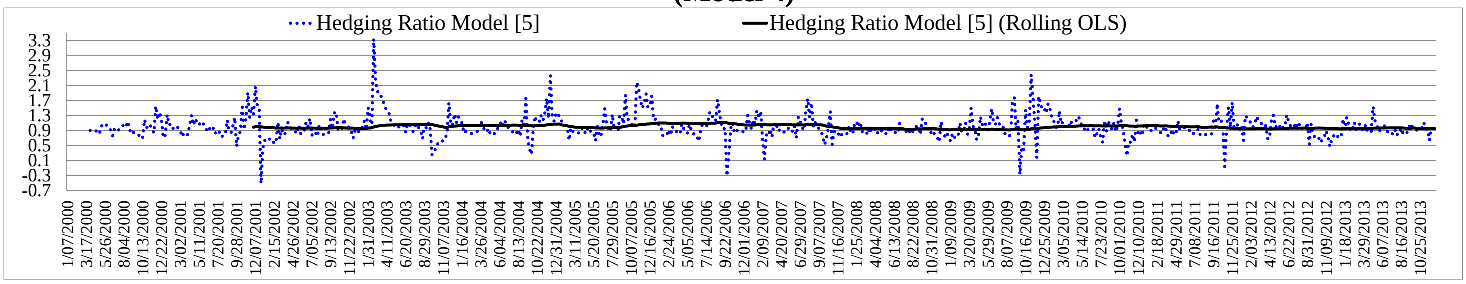
B. Base model with storages in conditional mean and variance equation (Model 2)



C. Base model with storages and weather factors in conditional mean and variance equation (Model 3)

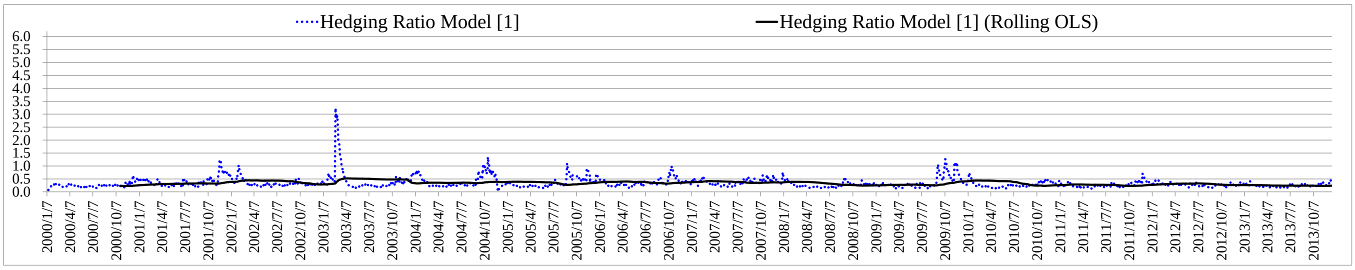


D. Base model with storages, weather factors and macroeconomic news in conditional mean and variance equation (Model 4)

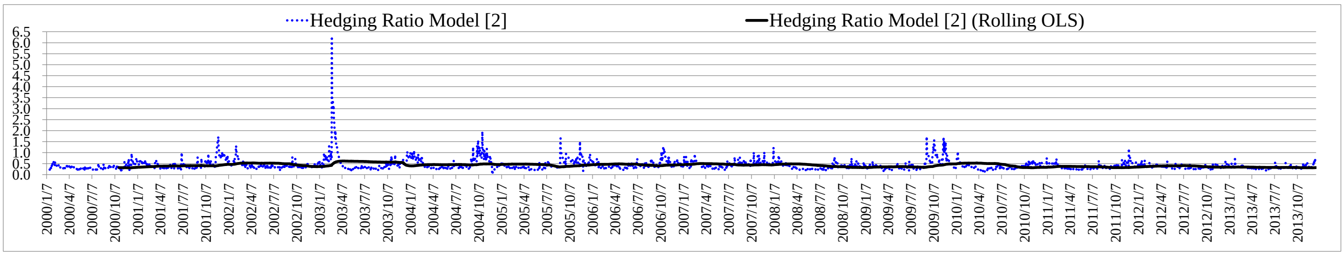


E. Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation (Model 5)

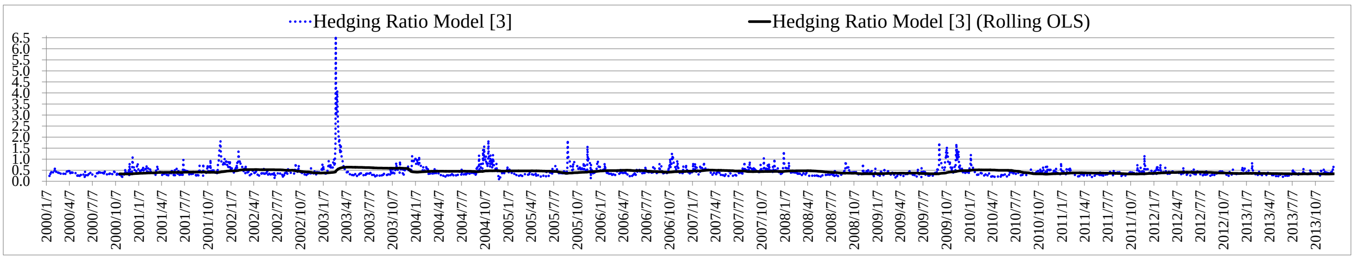
Figure 2
Weekly time-series hedging ratio estimated by DCC-MGARCH under different specifications



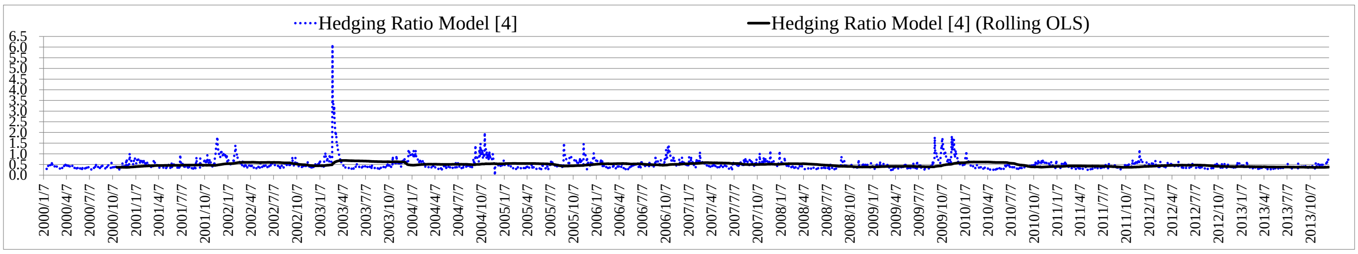
A. Base model (Model 1)



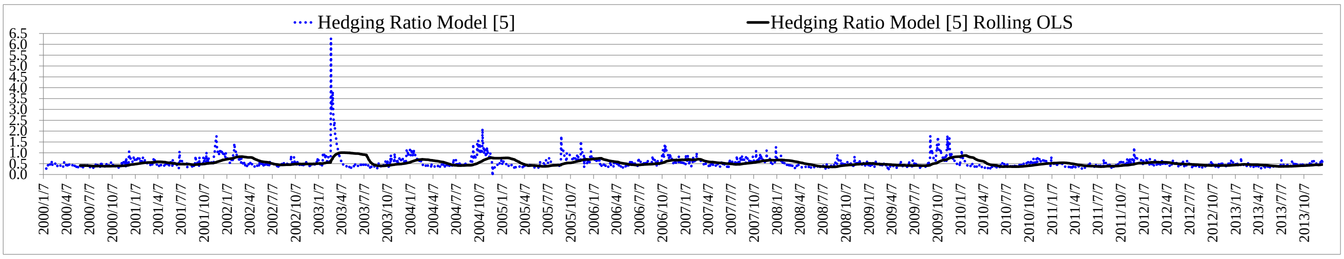
B. Base model with storages, weather factors and macroeconomic news in conditional mean equation (Model 2)



C. Base model with storages and weather factors in conditional mean and variance equation (Model 3)



D. Base model with storages, weather factors and macroeconomic news in conditional mean and variance equation (Model 4)



E. Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation (Model 5)

Figure 3
Daily time-series hedging ratio estimated by DCC-MGARCH under different specifications

Table 1

Announcements of macroeconomic news

Time	New item	Observation (actual value)	Consensus Forecast	Shock	S.D
08:30	Retail sales (ARS)	244	122	18	0.155
08:30	Business inventories (BI)	243	122	168	0.421
08:30	Change in nonfarm payrolls (CNP)	283	142	39	0.145
08:30	Housing starts (HS)	310	155	142	0.413
09:15	Industrial production (IP)	266	133	132	0.335
10:00	Construction spending (CS)	248	124	123	0.375
	Total	**1,594**			

Table 2

Unit root tests and conditional heteroscedasticity test

Panel A. Unit root tests						
Variables	**Weekly data**			**Daily data**		
	ADF	*PP*	*KPSS*	*ADF*	*PP*	*KPSS*
Spot Price of Natural Gas	-3.463**	-3.230*	0.535 [a]	-3.502***	-3.649***	1.169 [a]
	(0.044)	(0.079)	[0.463]	(0.008)	(0.005)	[0.463]
Futures Price of Natural Gas	-2.986	-2.973	0.554 [a]	-2.321	-2.276	1.372
	(0.137)	(0.141)	[0.463]	(0.165)	(0.180)	[0.463]
Log-Difference in Spot Price of Natural Gas	-23.197***	-22.937***	0.066	-47.885***	-55.139***	0.050
	(0.000)	(0.000)	[0.463]	(0.000)	(0.000)	[0.463]
Log-Difference in Futures Price of Natural Gas	-22.304***	-22.184***	0.067	-61.739***	-61.897***	0.233
	(0.000)	(0.000)	[0.463]	(0.000)	(0.000)	[0.463]

Panel B. Conditional heteroscedasticity tests		
Variables	**Weekly data**	**Daily data**
	ARCH-LM Tests	*ARCH-LM Tests*
Spot Price of Natural Gas	436.780[a] (0.000)	23,034.36[a] (0.000)
Futures Price of Natural Gas	1042.634[a] (0.000)	21,936.9[a] (0.000)
Log-Difference in Spot Price of Natural Gas	11.166[a] (0.000)	1080.16[a] (0.000)
Log-Difference in Futures Price of Natural Gas	5.126[a] (0.000)	21.95[a] (0.000)

Note: ADF, PP and KPSS are the empirical statistics of the Augmented Dickey and Fuller (1979), and the Philips and Perron (1988) unit root tests, and the Kwiatkowski et al. (1992) stationarity test, respectively. [a] Denotes the rejection of the null hypotheses of normality, no autocorrelation, unit root, non-stationarity, and conditional homoscedasticity at the 1% significance level. Asymptotic critical values at the 1% level from Kwiatkowski-Phillips-Schmidt-Shin (1992) are reported in brackets. The *P*-values are reported in the parentheses.

Table 3

Pairwise Granger causality tests – log natural gas spot and futures prices returns

Null Hypothesis:	# of Lag	Observations	*F*-Statistic	(*P*-value)
Panel A. Weekly data				
Level				
Spot Price does not Granger Cause Futures Price	3	725	4.477***	(0.004)
Futures Price does not Granger Cause Spot Price	3	725	33.786***	(0.000)
Log-Differences				
Log-Difference in Spot Price does not Granger Cause Log-Difference in Futures Price	3	725	2.948**	(0.032)
Log-Difference in Futures Price of does not Granger Cause Log-Difference in Spot Price	3	725	24.630***	(0.000)
Panel B. Daily data				
Level				
Spot Price does not Granger Cause Futures Price	3	3,494	10.366***	(0.000)
Futures Price does not Granger Cause Spot Price	3	3,494	274.762***	(0.000)
Log-Differences				
Log-Difference in Spot Price does not Granger Cause Log-Difference in Futures Price	3	3,494	12.306**	(0.000)
Log-Difference in Futures Price of does not Granger Cause Log-Difference in Spot Price	3	3,494	141.189***	(0.000)

Note: *, ** and *** indicate a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Table 4

Selection criteria of optimal VAR lag order

# of Lag	LogL	LR	AIC	SC	HQ
Panel A. Weekly data					
0	2222.981		-6.187	-6.174	-6.182
1	2257.824	69.395*	-6.272	-6.234	-6.258
2	2269.141	22.476	-6.293	-6.229	-6.268
3*	2287.408	36.179	**-6.345***	**-6.243***	-6.298
4	2295.837	16.646	-6.338	-6.230	-6.301*
Panel B. Daily data					
0	-22643.9		12.9813	12.9849	12.9826
1	-18063.3	9161.3	10.3579	10.3684	10.3616
2	-18059	8.6128	10.3577	10.3753	10.364
3*	-17987.2	**143.64***	**10.3188***	**10.3435***	**10.3276***
4	-17984.4	5.4785	10.3195	10.3513	10.3309

Note: * indicates lag order selected by the criterion.

Table 5

Estimation results of the VECM-DCC-MGARCH model using different specifications

Variables	Model[1]				Model[2]				Model[3]				Model[4]				Model[5]			
Panel A. Weekly Data																				
	Spot Returns		Futures Returns		Spot Returns		Futures Returns		Spot Returns		Futures Returns		Spot Returns		Futures Returns		Spot Returns		Futures Returns	
Panel A.1 Conditional Mean Equation																				
Constant	-0.210	(-1.111)	-0.108	(-0.562)	-0.006	(-0.031)	-0.019	(-0.099)	-0.046	(-0.258)	-0.017	(-0.089)	-0.237	(-0.707)	-0.419	(-1.184)	-0.003	(-0.020)	-0.116	(-0.644)
ECT $_{t-1}$	0.015**	(2.226)	0.010*	(1.649)	0.009	(1.434)	0.008	(1.249)	0.013*	(1.949)	0.009	(1.485)	0.005	(0.849)	0.004	(0.671)	0.005	(0.761)	0.004	(0.641)
Spot Returns $_{t-1}$	-0.334***	(-4.190)	-0.086	(-1.441)	-0.430***	(-5.997)	-0.136**	(-2.313)	-0.157	(-0.502)	0.326	(1.015)	-0.439***	(-5.955)	-0.105*	(-1.716)	-0.360***	(-5.651)	-0.082	(-1.622)
Spot Returns $_{t-2}$	-0.263***	(-3.749)	-0.035	(-0.560)	-0.037	(-0.521)	0.085	(1.289)	-0.283	(-0.914)	-0.379	(-1.177)	-0.003	(-0.042)	0.105	(1.598)	-0.008	(-0.118)	0.073	(1.247)
Spot Returns $_{t-3}$	-0.192***	(-2.670)	-0.094	(-1.607)	-0.210***	(-3.259)	-0.130**	(-2.270)	-0.180***	(-2.830)	-0.105*	(-1.895)	-0.219***	(-3.435)	-0.144**	(-2.458)	-0.250***	(-4.189)	-0.174***	(-3.375)
Futures Returns $_{t-1}$	0.617***	(8.191)	0.243***	(3.580)	0.721***	(9.646)	0.305***	(4.271)	0.425	(1.333)	-0.180	(-0.547)	0.755***	(9.868)	0.302***	(4.144)	0.644***	(9.560)	0.242***	(3.726)
Futures Returns $_{t-2}$	0.217***	(2.828)	0.019	(0.261)	0.053	(0.694)	-0.064	(-0.854)	0.291	(0.917)	0.400	(1.208)	-0.000	(-0.002)	-0.116	(-1.510)	-0.010	(-0.141)	-0.092	(-1.321)
Futures Returnst-3	0.233***	(2.889)	0.111	(1.534)	0.201***	(2.689)	0.112	(1.573)	0.178**	(2.379)	0.089	(1.270)	0.208***	(2.877)	0.125*	(1.783)	0.287***	(4.061)	0.227***	(3.524)
ΔStorage Surprises $_{t-1}$					-42.221***	(-4.176)	-7.662	(-0.802)	-59.277***	(-5.846)	-19.993**	(-2.112)	-41.077***	(-4.144)	-8.164	(-0.859)	-23.197	(-1.536)	-5.203	(-0.382)
ΔSpot Oil Return $_{t-1}$																	0.281***	(6.528)	0.360***	(8.042)
Weather Factors																				
ΔCDD $_{t-1}$									0.588***	(4.194)	0.262*	(1.746)	0.557***	(4.049)	0.237*	(1.878)	0.350**	(2.331)	0.098	(0.632)
ΔHDD $_{t-1}$									0.232***	(3.957)	0.060	(1.023)	0.240***	(4.042)	0.074	(1.243)	0.151*	(1.649)	0.053	(0.595)
ΔRH $_{t-1}$									0.140	(0.235)	0.201	(0.328)	0.035	(0.060)	0.076	(0.124)	0.474	(0.744)	0.388	(0.582)
Macroeconomic News																				
ΔARS $_{t-1}$													0.185	(0.179)	-0.736	(-0.631)	-0.957	(-1.308)	-0.329	(-0.424)
ΔBI $_{t-1}$													-25.449***	(-4.572)	-11.833**	(-2.410)	0.690	(1.332)	0.474	(0.925)
ΔCNP $_{t-1}$													1.578	(1.339)	2.143*	(1.780)	-0.149	(-0.155)	-0.798	(-0.847)
ΔCS $_{t-1}$													1.587**	(2.061)	1.237	(1.525)	-1.249**	(-2.197)	-1.200**	(-2.119)
ΔHS $_{t-1}$													2.002**	(2.121)	1.868**	(1.980)	-0.844	(-1.437)	-0.185	(-0.317)
ΔIP $_{t-1}$													-1.699*	(-1.807)	-1.560*	(-1.660)	1.140*	(1.788)	0.571	(0.890)
Panel A.2 Conditional Variance-Covariance Equation																				
Constant	2.334***	(3.865)	1.872***	(3.374)	0.929***	(3.844)	1.010***	(3.512)	0.055	(0.140)	0.678**	(2.111)	0.948***	(4.020)	1.177***	(4.198)	1.660***	(3.536)	2.476***	(7.678)
ARCH $_{t-1}$	0.345***	(9.038)	0.249***	(8.179)	0.316***	(8.383)	0.240***	(7.397)	0.288***	(8.269)	0.241***	(7.733)	0.375***	(7.937)	0.291***	(7.058)	0.364***	(7.435)	0.345***	(6.789)
GARCH $_{t-1}$	0.707***	(30.351)	0.764***	(32.607)	0.671***	(23.901)	0.733***	(21.428)	0.721***	(32.036)	0.741***	(24.850)	0.626***	(19.090)	0.676***	(15.600)	0.552***	(14.381)	0.481***	(7.696)
ΔStorage Surprises $_{t-1}$					-54.279***	(-9.604)	-30.799***	(-4.294)	-29.332***	(-2.608)	-7.448	(-0.703)	-57.668***	(-10.230)	-34.997***	(-5.277)	-23.529**	(-2.562)	-10.677	(-1.255)
ΔSpot Oil Return $_{t-1}$																	-0.013***	(-3.930)	-0.011***	(-4.188)
Weather Factors																				
ΔCDD $_{t-1}$									0.403*	(1.727)	0.094	(0.334)	0.105	(0.342)	0.026	(0.089)	0.224**	(2.006)	0.055	(0.597)
ΔHDD $_{t-1}$									0.429***	(8.523)	0.253***	(5.906)	0.465***	(4.883)	0.261***	(4.897)	0.111*	(1.942)	0.122***	(2.671)
ΔRH $_{t-1}$									1.930***	(3.788)	-0.552	(-0.780)	2.590**	(2.497)	0.022	(0.019)	0.456	(0.971)	0.347	(0.838)
Macroeconomic News																				
ΔARS $_{t-1}$													-0.886	(-0.779)	3.074**	(2.493)	0.276	(0.349)	0.463	(0.669)
ΔBI $_{t-1}$													2.490***	(3.875)	1.394**	(2.420)	1.858***	(4.378)	0.345	(0.991)
ΔCNP $_{t-1}$													1.397***	(3.230)	0.902**	(2.092)	1.110**	(2.488)	0.532	(1.358)
ΔCS $_{t-1}$													-1.648***	(-3.693)	-1.546*	(-1.832)	-1.156***	(-2.901)	-0.608	(-1.205)
ΔHS $_{t-1}$													2.892**	(2.116)	1.757*	(1.903)	-1.344**	(-2.201)	-1.035***	(-2.863)
ΔIP $_{t-1}$													-0.145	(-0.316)	-0.352	(-0.961)	3.968***	(2.887)	2.112***	(3.591)
ρ(Spot, Futures)	0.899***	(65.483)			0.911***	(80.748)			0.911***	(83.729)			0.913***	(74.593)			0.921***	(83.900)		
λ_1	0.194***	(7.156)			0.205***	(7.509)			0.205***	(6.597)			0.253***	(7.914)			0.219***	(7.368)		
λ_2	0.652***	(15.522)			0.588***	(12.480)			0.570***	(10.335)			0.567***	(12.697)			0.606***	(14.014)		
HQ(20)	15.106	[0.301]			20.484	[0.116]			16.231	[0.237]			23.108	[0.111]			23.108	[0.111]		
HQs(20)	3.259	[0.196]			11.250	[0.939]			19.913	[0.463]			24.077	[0.239]			24.077	[0.239]		
Mean Absolute Error (MAE)	1.995				3.043				3.042				3.040				3.040			
Theil Inequality Coefficient	0.986				0.940				0.939				0.928				0.928			
Observations	717				717				717				717				717			
Log-likelihood	-4,111				-4,042				-4,088				-4,017				-3,936			
χ^2	194***				271***				301***				370***				476***			

Note: *t*-statistics (*p*-value) are reported in parentheses (brackets), respectively. *, **, *** denoted statistically significant at 10%, 5%, and 1%. ECT represents error coreection terms generated form VECM model. HQ(20) and HQs(20) are Hosking's multivariate portmanteau Q-statistics on the standardized residuals and the standardized squared residuals, respectively. Model [1]: Base model. Model [2]: Base model with storage, weather factors and macroeconomic news in conditional mean equation. Model [3]: Base model with storage and weather factors in conditional mean and variance equations. Model [4]: Base model with storage, weather factors and macroeconomic news in conditional mean and variance equations. Model [5]: Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation.

Table 5 (Continued)

Variables	Panel B. Daily Data																			
	Model[1]				Model[2]				Model[3]				Model[4]				Model[5]			
	Spot Returns		Futures Returns		Spot Returns		Futures Returns		Spot Returns		Futures Returns		Spot Returns		Futures Returns		Spot Returns		Futures Returns	
Panel B.1 Conditional Mean Equation																				
Constant	-0.093**	(-2.309)	-0.038	(-0.927)	-0.113***	(-2.727)	-0.051	(-1.259)	-0.175***	(-3.594)	-0.085*	(-1.653)	-0.196***	(-3.644)	-0.065	(-1.139)	-0.106***	(-2.582)	-0.038	(-0.976)
ECT $_{t-1}$	-1.152***	(-10.812)	-0.400***	(-6.202)	1.105***	(10.485)	-0.439***	(-6.685)	1.030***	(10.007)	-0.450***	(-6.819)	1.040***	(10.114)	-0.446***	(-6.752)	1.097***	(10.603)	-0.427***	(-6.873)
Spot Returns $_{t-1}$	-0.173***	(-8.902)	-0.013	(-1.014)	-0.160***	(-8.026)	-0.007	(-0.550)	-0.166***	(-8.544)	-0.007	(-0.571)	-0.166***	(-8.517)	-0.006	(-0.509)	-0.151***	(-7.506)	-0.011	(-0.878)
Spot Returns $_{t-2}$	-0.163***	(-8.384)	-0.004	(-0.361)	-0.160***	(-8.237)	-0.004	(-0.290)	-0.151***	(-7.902)	-0.002	(-0.183)	-0.151***	(-7.873)	-0.002	(-0.139)	-0.157***	(-7.775)	-0.003	(-0.289)
Spot Returns $_{t-3}$	-0.058***	(-4.043)	0.001	(0.114)	-0.051***	(-3.560)	0.003	(0.295)	-0.036**	(-2.538)	0.004	(0.375)	-0.038***	(-2.701)	0.003	(0.318)	-0.063***	(-4.510)	0.003	(0.327)
Futures Returns $_{t-1}$	0.757***	(42.133)	-0.041**	(-2.277)	0.751***	(41.653)	-0.042**	(-2.310)	0.735***	(42.184)	-0.046**	(-2.536)	0.735***	(42.115)	-0.047**	(-2.572)	0.759***	(40.980)	-0.019	(-1.097)
Futures Returns $_{t-2}$	0.107***	(4.412)	0.002	(0.104)	0.094***	(3.820)	-0.003	(-0.167)	0.101***	(4.262)	-0.003	(-0.140)	0.105***	(4.397)	-0.003	(-0.138)	0.084***	(3.469)	-0.008	(-0.381)
Futures Returns $_{t-3}$	0.157***	(6.716)	-0.001	(-0.035)	0.158***	(6.785)	-0.002	(-0.074)	0.139***	(6.138)	-0.004	(-0.201)	0.137***	(6.056)	-0.005	(-0.242)	0.153***	(6.488)	-0.013	(-0.666)
ΔStorage Surprises $_{t-1}$					-3.476*	(-1.733)	-5.679***	(-2.888)	-8.592***	(-4.016)	-8.834***	(-3.584)	-8.904***	(-4.109)	-8.610***	(-3.457)	-3.588*	(-1.924)	-6.768***	(-3.738)
ΔSpot Oil Return $_{t-1}$																	0.109***	(6.516)	0.322***	(18.447)
Weather Factors																				
ΔCDD $_{t-1}$									0.062***	(2.884)	0.069***	(2.898)	0.063***	(2.954)	0.069***	(2.901)	0.028	(1.193)	0.037	(1.632)
ΔHDD $_{t-1}$									2.353***	(3.846)	1.383**	(2.161)	2.560***	(4.059)	1.295**	(1.964)	3.061***	(5.480)	1.076**	(2.231)
ΔRH $_{t-1}$									0.214***	(7.284)	0.058*	(1.899)	0.217***	(7.273)	0.063**	(2.038)	0.122***	(4.092)	0.013	(0.446)
Macroeconomic News																				
ΔARS $_{t-1}$													0.404	(0.796)	0.173	(0.268)	0.403	(0.761)	1.291**	(2.038)
ΔBI $_{t-1}$													0.536*	(1.695)	0.067	(0.196)	1.254***	(3.335)	0.419	(1.231)
ΔCNP $_{t-1}$													0.413	(0.765)	0.097	(0.170)	0.079	(0.126)	0.509	(0.838)
ΔCS $_{t-1}$													0.819**	(2.284)	0.235	(0.595)	0.038	(0.085)	0.067	(0.169)
ΔHS $_{t-1}$													0.239	(1.310)	0.002	(0.011)	1.180***	(2.941)	0.591	(1.359)
ΔIP $_{t-1}$													0.112	(0.555)	0.017	(0.080)	0.322	(0.715)	0.787	(1.633)
Panel B.2 Conditional Variance-Covariance Equation																				
Constant	0.123***	(4.360)	1.872***	(3.374)	-1.818***	(-7.401)	-2.671***	(-8.152)	-1.955***	(-7.107)	-2.716***	(-8.216)	-1.959***	(-7.063)	-2.718***	(-8.209)	-3.143***	(-7.052)	-2.861***	(-3.762)
ARCH $_{t-1}$	0.179***	(11.778)	0.249***	(8.179)	0.205***	(11.929)	0.052***	(7.789)	0.211***	(12.435)	0.051***	(7.735)	0.213***	(12.542)	0.051***	(7.707)	0.243***	(12.920)	0.066***	(7.613)
GARCH $_{t-1}$	0.838***	(70.104)	0.764***	(32.607)	0.806***	(54.444)	0.939***	(119.553)	0.803***	(55.949)	0.940***	(121.710)	0.801***	(55.603)	0.940***	(121.605)	0.750***	(44.869)	0.918***	(72.558)
ΔStorage Surprises $_{t-1}$					-31.694***	(-13.524)	-24.229***	(-3.423)	-32.620***	(-12.453)	-24.593***	(-3.461)	-32.747***	(-12.457)	-24.572***	(-3.453)	-72.467***	(-10.779)	14.466	(1.479)
ΔSpot Oil Return $_{t-1}$																	0.234***	(5.246)	0.221***	(3.926)
Weather Factors																				
ΔCDD $_{t-1}$									0.105***	(3.155)	0.093	(0.900)	0.020	(0.687)	0.047	(0.845)	0.121***	(3.710)	0.110	(1.148)
ΔHDD $_{t-1}$									0.287	(0.159)	1.840	(0.391)	11.729***	(7.186)	3.041	(0.697)	0.902	(0.636)	3.534	(0.684)
ΔRH $_{t-1}$									0.885***	(6.042)	0.617*	(1.844)	1.072***	(7.700)	0.524*	(1.795)	0.713***	(5.835)	0.185	(0.453)
Macroeconomic News																				
ΔARS $_{t-1}$													0.189***	(11.681)	0.052***	(7.746)	3.548	(1.060)	2.424	(1.204)
ΔBI $_{t-1}$													0.824***	(61.819)	0.939***	(115.954)	5.244**	(2.336)	3.130***	(2.839)
ΔCNP $_{t-1}$													3.538	(0.692)	2.328	(1.142)	0.978	(0.135)	2.983**	(2.004)
ΔCS $_{t-1}$													5.831*	(1.686)	2.999***	(2.809)	0.271	(0.835)	0.161	(0.270)
ΔHS $_{t-1}$													1.387	(0.219)	2.917**	(2.020)	1.970	(0.226)	1.415	(0.707)
ΔIP $_{t-1}$													0.265	(0.920)	0.159	(0.255)	1.477	(0.174)	1.658	(0.792)
ρ(Spot, Futures)	0.365***	(20.796)			0.363***	(20.462)			0.365***	(21.366)			0.364***	(19.898)			0.344***	(17.052)		
λ_1	0.012	(1.633)			0.015**	(2.002)			0.015*	(1.866)			0.020**	(2.483)			0.019***	(2.853)		
λ_2	0.897***	(15.751)			0.890***	(17.160)			0.871***	(13.495)			0.884***	(19.983)			0.919***	(30.725)		
HQ(20)	18.778	[0.224]			32.051	[0.157]			18.752	[0.343]			18.645	[0.230]			35.921	[0.211]		
HQs(20)	19.507	[0.192]			22.326	[0.133]			10.770	[0.292]			8.156	[0.227]			9.140	[0.243]		
Mean Absolute Error (MAE)	1.993				1.994				1.995				1.993				1.990			
Theil Inequality Coefficient	0.967				0.966				0.965				0.967				0.940			
Observations	3,490				3,490				3,490				3,490				3,490			
Log-likelihood	-16,758				-16,720				-16,642				-16,256				-16,981			
χ^2	2,359***				2,301***				2,624***				2,574***				2,759***			

Note: *t*-statistics (*p*-value) are reported in parentheses (brackets), respectively. *, **, *** denoted statistically significant at 10%, 5%, and 1%. ECT represents error coreection terms generated form VECM model. HQ(20) and HQs(20) are Hosking's multivariate portmanteau Q-statistics on the standardized residuals and the standardized squared residuals, respectively. Model [1]: Base model. Model [2]: Base model with storage, weather factors and macroeconomic news in conditional mean equation. Model [3]: Base model with storage and weather factors in conditional mean and variance equations. Model [4]: Base model with storage, weather factors and macroeconomic news in conditional mean and variance equations. Model [5]: Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation.

Table 6

Descriptive statistics on time-varying hedge ratios estimated by different specifications

Statistics	Model Specifications					Test in		
	[1]	[2]	[3]	[4]	[5]	Mean	Median	Variance
Panel A. Weekly data								
Mean	0.9244	0.9551	0.9624	0.9855	0.9905	2.190*	13.298***	17.835***
Median	0.8951	0.9162	0.9167	0.9459	0.9517	(0.087)	(0.004)	(0.000)
Maximum	2.1337	3.3109	3.3445	3.3400	3.3464			
Minimum	0.2936	-0.5561	-0.5438	-0.6203	-0.5207			
Std. Dev.	0.2145	0.3073	0.3156	0.3187	0.4256			
Skewness	1.2795	1.1436	1.2524	1.0275	1.389			
Kurtosis	7.2396	11.3548	10.6330	10.2618	12.831			
Jarque-Bera	732***	1,235	1,923	1,697	2,767			
(Probability)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
Observations	725	725	725	725	725			
Panel B. Daily data								
Mean	0.3312	0.4183	0.4239	0.4812	0.5253	33.854***	24.526 ***	9.030***
Median	0.2779	0.3578	0.3657	0.4157	0.4589	(0.000)	(0.000)	(0.000)
Maximum	3.2342	6.1894	6.5881	6.1336	6.2706			
Minimum	0.0052	-0.2221	0.0292	-0.0126	-0.1945			
Std. Dev.	0.2131	0.2473	0.2559	0.2526	0.2653			
Skewness	5.7015	7.1745	8.1027	6.9447	6.8442			
Kurtosis	58.9737	114.6683	135.6946	104.3247	97.8112			
Jarque-Bera	473***	841***	596***	519***	633***			
(Probability)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
Observations	3,494	3,494	3,494	3,494	3,494			

Note: *p*-value are reported in parentheses. *** denoted statistically significant at 1%. Model [1]: Base model. Model [2]: Base model with storage, weather factors and macroeconomic news in conditional mean equation. Model [3]: Base model with storage and weather factors in conditional mean and variance equations. Model [4]: Base model with storage, weather factors and macroeconomic news in conditional mean and variance equations. Model [5]: Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation.

Table 7

Structural breaks in the time-series hedging ratios using Bai and Perron (2003) approach

Panel A. Weekly data

Specifications: z=1, q=1, p=0, h=72.5, M=5

Estimation models	*Test statistics*						
	SupF_t(1)	SupF_t (2)	SupF_t (3)	SupF_t (4)	SupF_t (5)	*UDmax*	*WDmax*
Model [1]	14.287	24.397	18.319	15.307	10.721	24.397	28.992
Model [2]	10.006	13.315	9.808	8.555	6.355	13.315	15.823
Model [3]	6.411	10.432	8.077	7.212	5.787	10.432	12.700
Model [4]	6.266	8.959	6.932	6.299	5.018	8.959	11.012
Model [5]	10.006	13.315	9.808	8.555	6.355	13.315	15.823
	SupF_t(1|0)	SupF_t (2|1)	SupF_t (3|2)	SupF_t (4|3)	SupF_t (5|4)		
Model [1]	14.287	33.850	5.832	5.895	0.000		
Model [2]	10.006	16.308	2.722	2.885	0.000		
Model [3]	6.411	14.271	3.249	4.500	0.000		
Model [4]	6.266	5.851	2.782	4.054	0.000		
Model [5]	10.006	16.308	2.722	2.885	0.000		

	Number of breaks selected		
	Sequential	LWZ (Modified Schwarz criterion)	BIC (Bayesian information criterion)
Model [1]	1	1	1
Model [2]	2	2	2
Model [3]	2	2	2
Model [4]	2	2	2
Model [5]	2	2	2

	Break dates according to BIC	
	Date [1]	Date [2]
Model [1]	2/17/2006	
Model [2]	2/14/2003	2/17/2006
Model [3]	2/14/2003	2/17/2006
Model [4]	9/27/2002	2/17/2006
Model [5]	11/08/2002	11/11/2005

	Mean hedging ratio according to subsamples proposed by break dates given above		
	Subsample 1 (*t*-statistics)	Subsample 2 (*t*-statistics)	Subsample 3 (*t*-statistics)
Model [1]	0.959***(79.050)	0.898***(27.440)	
Model [2]	0.931***(37.130)	1.057***(32.770)	0.924***(70.370)
Model [3]	0.934***(36.290)	1.053***(31.610)	0.937***(69.210)
Model [4]	0.946***(33.900)	1.067***(36.350)	0.961***(68.700)
Model [5]	0.955***(35.520)	1.086***(37.330)	0.960***(73.240)

Note: Based on Bai and Perron (2003) the Bayesian information criterion (BIC) has to be preferred under the presence of multiple breaks, the modified Schwarz criterion (LWZ) by contrast under H_0: No breaks. *M*: Maximum number of breaks allowed. *h*: Minimum length of a segment (0.1*sample size). *z*: Matrix of regressors whose coefficients are allowed to change. *q*: Number of regressors *z*. *x*: Matrix of regressors with coefficients fixed across regimes. *p*: Number of regressors *x*. Sup$F_t(l)$: *F* statistic for H_0: No structural breaks vs. H_1: Arbitrary number of breaks. Sup$F_t(l+1|l)$: Sequential test, H_0: No breaks vs. H_1: l+1 breaks. *UDmax*: Double maximum statistic ($max_{1\leq l\leq M}$sup$F_T(l)$). *WDmax*: Weighted double maximum statistic ($max_{1\leq l\leq M}\ w_l$sup$F_T(l)$). Newey-West (1987) corrected *t*-statistics appear in parentheses. *, **, *** denoted statistically significant at 10%, 5%, and 1%, respectively. Model [1]: Base model. Model [2]: Base model with storage, weather factors and macroeconomic news in conditional mean equation. Model [3]: Base model with storage and weather factors in conditional mean and variance equations. Model [4]: Base model with storage, weather factors and macroeconomic news in conditional mean and variance equations. [Model 5]: Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation.

Table 7 (continued)

Panel B. Daily data

Estimation models	$\text{Sup}F_t(1)$	$\text{Sup}F_t(2)$	$\text{Sup}F_t(3)$	$\text{Sup}F_t(4)$	$\text{Sup}F_t(5)$	*UDmax*	*WDmax*
	Specifications: z=1, q=1, p=0, h=72.5, M=5						
	Test statistics						
Model [1]	151.806	97.980	83.540	64.916	42.811	151.806	151.806
Model [2]	122.566	80.615	69.568	53.862	36.808	122.566	122.566
Model [3]	99.814	68.685	59.898	46.615	32.080	99.814	99.814
Model [4]	136.163	79.544	70.194	53.788	36.286	136.163	136.163
Model [5]	137.796	88.375	75.238	58.434	38.594	137.796	137.796
	$\text{Sup}F_t(1\|0)$	$\text{Sup}F_t(2\|1)$	$\text{Sup}F_t(3\|2)$	$\text{Sup}F_t(4\|3)$	$\text{Sup}F_t(5\|4)$		
Model [1]	151.806	31.160	26.368	5.444	0.000		
Model [2]	122.566	25.888	29.351	2.624	0.000		
Model [3]	99.814	19.873	30.516	4.354	0.000		
Model [4]	136.163	22.101	39.396	4.071	0.000		
Model [5]	137.796	27.251	23.882	5.290	0.000		
	Number of breaks selected						
	Sequential	LWZ (Modified Schwarz criterion)		BIC (Bayesian information criterion)			
Model [1]	1	1		1			
Model [2]	2	2		2			
Model [3]	2	2		2			
Model [4]	2	2		2			
Model [5]	2	2		2			
	Break dates according to BIC						
	Date [1]	Date [2]					
Model [1]	2/2/2010						
Model [2]	12/31/2002	2/27/2008					
Model [3]	12/31/2002	2/7/2008					
Model [4]	1/24/2003	2/1/2010					
Model [5]	1/24/2003	2/6/2008					
	Mean hedging ratio according to subsamples proposed by break dates given above						
	Subsample 1 (*t*-statistics)	Subsample 2 (*t*-statistics)		Subsample 3 (*t*-statistics)			
Model [1]	0.358***(85.960)	0.261***(22.220)					
Model [2]	0.409***(44.910)	0.483***(51.630)		0.366***(87.560)			
Model [3]	0.416***(44.160)	0.487***(48.630)		0.374***(92.250)			
Model [4]	0.476***(51.790)	0.527***(69.130)		0.403***(129.040)			
Model [5]	0.516***(53.500)	0.575***(71.470)		0.443***(134.830)			

Note: Based on Bai and Perron (2003) the Bayesian information criterion (BIC) has to be preferred under the presence of multiple breaks, the modified Schwarz criterion (LWZ) by contrast under H_0: No breaks. *M*: Maximum number of breaks allowed. *h*: Minimum length of a segment (0.1*sample size). *z*: Matrix of regressors whose coefficients are allowed to change. *q*: Number of regressors *z*. *x*: Matrix of regressors with coefficients fixed across regimes. *p*: Number of regressors *x*. $\text{Sup}F_t(l)$: *F* statistic for H_0: No structural breaks vs. H_1: Arbitrary number of breaks. $\text{Sup}F_t(l+1|l)$: Sequential test, H_0: No breaks vs. H_1: l+1 breaks. *UDmax*: Double maximum statistic ($max_{1\leq l\leq M}\text{sup}F_T(l)$). *WDmax*: Weighted double maximum statistic ($max_{1\leq l\leq M}\, w_l \text{sup}F_T(l)$). Newey-West (1987) corrected *t*-statistics appear in parentheses. *, **, *** denoted statistically significant at 10%, 5%, and 1%, respectively. Model [1]: Base model. Model [2]: Base model with storage, weather factors and macroeconomic news in conditional mean equation. Model [3]: Base model with storage and weather factors in conditional mean and variance equations. Model [4]: Base model with storage, weather factors and macroeconomic news in conditional mean and variance equations. Model [5]: Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation.

Table 8

Hedging effectiveness under different model specifications

Model Specifications	Mean of Hedge Ratio	Variance of Unhedged Portfolio (%)	Variance of Hedge Portfolio (%)	HE (Hedging Effectiveness)(%)
Panel A. Weekly data				
Model [1]	0.9244	0.5665	0.1977	65.1039
Model [2]	0.9551	0.5665	0.1478	73.9121
Model [3]	0.9624	0.5665	0.1194	78.9160
Model [4]	0.9855	0.5665	0.1041	81.6262
Model [5]	0.9905	0.5665	0.0862	84.7795
Panel B. Daily data				
Model [1]	0.3312	0.5210	0.3465	33.5012
Model [2]	0.4183	0.5210	0.3224	38.1260
Model [3]	0.4239	0.5210	0.2951	43.3663
Model [4]	0.4812	0.5210	0.2388	54.1635
Model [5]	0.5253	0.5210	0.2141	58.8996

Note: Model [1]: Base model. Model [2]: Base model with storage, weather factors and macroeconomic news in conditional mean equation. Model [3]: Base model with storage and weather factors in conditional mean and variance equations. Model [4]: Base model with storage, weather factors and macroeconomic news in conditional mean and variance equations. Model [5]: Base model with spot WTI crude oil return, storages, weather factors and macroeconomic news in conditional mean and variance equation.