Market conditions, trader types and price-volume relation in energy futures markets

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Abstract

We investigate the asymmetric relations between trading volume and price changes, and trading volume and price volatility of energy futures contracts across maturities and under different market conditions. Using a relatively long sample of daily observations, we examine whether the impact of trading volume on returns and volatility of futures contracts can be time-varying and dependent on the market condition. We differentiate the market condition based on the slope of the forward curve into backwardation and contango. The results indicate that trading volume and returns are positively related when the market is in backwardation and negatively related when the market is in contango. In addition, the positive relation between changes in trading volume and volatility of futures contracts seem to be stronger when the market is in backwardation than when it is in contango. Finally, the results indicate that, to a certain extent, trade participation and trading activities of agents in energy futures markets can be explained by the slope of the forward curve which reflects the market condition and sentiment.

Key words: Market condition, Volume, Volatility, Energy Futures, Trade participation

JEL Classification: G01, G12, G20, C30

1. Introduction

Understanding the true relationships between trading activity and price changes, and trading volume and volatility in futures markets is important from both trading and regulatory points of view, for a number of reasons. First, knowledge about the nature of such relationships can help market participants to assess and implement their trading activities, hedging strategies, and portfolio construction and rebalancing. Second, from a regulatory point of view, trading activity, traders' positions and their impact on prices and volatility are important factors that regulators monitor to set trading limits or caps to address concerns on speculative bubbles and irregular trading activities.[1] Finally, understanding the true relationships between trading volume, price change and volatility can be useful in defining more appropriate and accurate econometric models for forecasting and risk management applications.

The relation between trading activity and price change in financial market has been the subject of debate for many years and a number of studies have put forward theories and provided empirical evidence on the nature of this relation. A large number of studies have been devoted to examine this relationship in different markets, using different sample periods and functional forms. The general consensus is that there is a positive relationship between trading volume and price change in financial and commodity markets. A number of theoretical frameworks have been proposed to define the positive relation between trading activity and price change as well as trading volume and volatility including the Mixture of Distribution Hypothesis (MDH) by Clark (1973), the Sequential Information Flow (SIF) by Copeland (1976), and Motivation Driven Trades by Wang (1994) and Llorente et al. (2002). In addition, the relation between trading volume and price volatility has been the subject of many studies and the overall empirical evidence suggests that there is a positive relation between trading activity and market volatility in different markets (e.g. Lamoureux and Lastrapes, 1990, Najand and Yung, 1991, Foster, 1995, Moosa and Silvapulle, 2000, Moosa, Silvapulle and Silvapulle 2003, and Chevallier and Sevi, 2012, among others).

In the first instance, this study provides new empirical evidence on the relationship between volume and price change, and volume and volatility, of energy futures contracts under different market states, as indicated by the slope of the forward curve. The rationale for such analysis is that the market participants may implement different hedging or trading strategies given the forward curve dynamics, which consequently affects the behaviour of price and volatility of the underlying asset. Secondly, we investigate the relationships between volume and price change and, volume and volatility, over different contract maturities to examine if there is any difference in the volume-price relationship. It is well known that trading volume decreases as maturity of futures contracts increases, while volatility increases as maturity decreases. In addition, the forward curve as an indicator of market sentiment may influence the position which different traders take over the forward curve to optimise the risk-return of their portfolio. Thirdly, to confirm our observation on the role of the slope of the forward curve in relation to the behaviour of market participants, we use trade participation data to examine whether forward curve dynamics can explain changes in trading positions of market participants. In this respect, we explore the role of the trading strategies of

[1] The U.S. Commodity Futures Trade Commission (CFTC) sets limits on the size of positions in the futures and swaps for different commodities, including energy commodities, as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act that regulates financial and commodity markets.

market participants as well as the sentiment of hedgers and their hedging activities according to the slope of the forward curve.

The study makes several contributions to existing literature. Firstly, whereas previous studies may have looked at the relations between returns and trading volume, and volatility and trading volume of energy futures contracts, our approach examines these relations under different market conditions as indicated by the slope of forward curve. Secondly, we perform the analysis across futures contracts with different maturities (2, 3, and 4-month) as opposed to previous studies, which use only near-month futures contracts and aggregated trading volume and open interest data. The reason for performing our analysis over contracts with different maturities is because trading in near-month contracts is mainly for closing or rolling over positions; hence, our analysis and comparison of the volume-price and volume-volatility relations over different maturities can reveal useful information on how trading activity is related to price change and volatility. Thirdly, we investigate whether market conditions in the form of the forward curve slope can explain the trading behaviour of market participants (whether hedgers or speculators) and whether the asymmetry in the volume-price relation is in line with this trading behaviour. Finally, we test whether there are any differences in trading activities as market conditions change and suggest some explanations on the asymmetry in the trading volume and price relation as well as volume and volatility relation.

The remaining of the paper is structured as follows. Section 2 reviews the theoretical and empirical literature on the volume-price relationship. Section 3 presents the econometric models used to examine the volume-price and volume-volatility relationships under different market conditions. Section 4 discusses the properties of the data. The empirical results and discussion on findings are presented in section 5. Section 6 presents the results of market condition and traders' positions. Final conclusions are drawn in section 7.

2. Literature Review

Investigating the nature of the underlying relation between trading volume and price change has been the focus of many studies in the financial economics literature. A number of studies examine the relationship between trading activity and price change in different financial and commodity markets, using different sample periods, estimation techniques and functional forms. Perhaps the most important study, which brings together the results of several earlier studies in different markets, is the survey by Karpoff (1987). He also argues that, although many researchers use linear monotonic models to investigate the price change–volume relationship, there might be some form of asymmetry in this relationship. Karpoff (1987) points to the theories proposed to explain the positive price and volume relation; that is, the Mixture of Distribution Hypothesis (MDH) of Clark (1973) and the Sequential Information Flow (SIF) of Copeland (1976).

The MDH of Clark (1973) is based on the assumption that both price change and trading volume follow a joint probability distribution. Consequently, price change and trading volume should be positively correlated because they jointly depend on a common underlying variable, which is normally interpreted as the random flow of information to the market. This means that both price and trading volume simultaneously respond to the new information and they are contemporaneously correlated. Additional evidence in support of the MDH is also provided by Epps and Epps (1976) who suggest that price changes follow a mixture of distributions, with transaction volume being the mixing variable. The SIF hypothesis proposed by Copeland (1976) and discussed further in Jennings et al. (1981), assumes that information is disseminated in the market sequentially and randomly. Therefore, informed traders who obtain the information first, take positions and adjust their portfolios accordingly, which results in shifts in supply and demand and a series of transitory equilibria. Once the information is fully absorbed by all traders, informed and uninformed, then equilibrium is restored. This sequential dissemination of information initiates transactions at different price levels during the day, the number of which increases with the rate of information flow to the market. Consequently, both trading volume and movement in price increase as the rate of arrival of information to the market increases which implies the existence of a positive relationship between the two variables.

It can be noted that both the MDH and the SIF attempt to justify the existence of a positive relationship between price changes and trading volume. However, they differ in that the MDH assumes that dissemination of information is symmetrical and all traders view changes in supply and demand simultaneously, which results in an immediate restoration of equilibrium, whereas in the SIF hypothesis, it is assumed that information is disseminated asymmetrically and equilibrium is restored gradually. Therefore, under the latter hypothesis, the trading volume affects subsequent price changes and volatility.

Empirical studies by Crouch (1970), Cornell (1981), Grammatikos and Saunders (1986), Harris (1986), Chatrath et al. (1996), and Malliaris and Urrutia (1998) provide further evidence in support of this argument and report a positive contemporaneous relation between absolute returns and aggregate volume in different markets. Other studies investigate the relationship between trading volume and price volatility. For instance, Grammatikos and Saunders (1986) for futures markets and Harris (1986) for US equities, also report the existence of a positive relationship between trading volume and volatility of returns. Other studies such as Lamoureux and Lastrapes (1990) on stocks, Najand and Yung (1991) on treasury bond futures, Bessembinder and Seguin (1993) on various financial and commodity futures markets, Foster (1995) on oil futures, and Chen et al. (2001) on stock indices, recognise the fact that many asset returns are characterised by time-varying distributions and hence utilize Generalized Autoregressive Conditional heteroskedasticity (GARCH) type models [Engle (1982) and Bollerslev (1986)] to capture the time variability in the conditional second moments of price returns. In general, the evidence in the literature points to positive price–volume and volume–volatility relationships.

An alternative theory, based on the information content of trading volume, is proposed by Blume et al. (1994). Based on the assumption that trading volume is a proxy for the quality and precision of information in the market and consequently contains information about price movements, they suggest that trading volume plays an important role in the price formation process. As a result, they propose that technical trading based on both the information in price movements and trading volume may produce superior results, which implies that there must be some form of inefficiency in the price determination process.

Wang (1994) and Llorente et al. (2002) argue that volume and return dynamics depend on the motivation behind the trade. Based on the trade motivation argument, Wang (2002) discusses two different hypotheses, namely Liquidity Driven Trade (LDT) and Information Driven Trade (IDT) hypotheses. Under the LDT hypothesis, a reversal in consecutive returns is likely if the trading by informed traders is driven by changes of investment opportunities outside the market. In this case, trading volume will contribute positively to the subsequent volatility. Under the IDT hypothesis, it is argued that the momentum in consecutive returns is a consequence of the informed investors' trade due to better private information. This is because when a subset of informed investors sells (buys) because they have unfavourable (favourable) private information; the asset price decreases (increases), reflecting the negative (positive) private information about its payoff. Since this information is usually only partially incorporated into the price at the beginning, the negative (positive) return in the current period will be followed by another negative (positive) return in the next period. Thus this trading volume leads to lower subsequent volatility since these two period returns tend to be of the same sign, which means that high trading volume will be followed by a low volatility; that is, trading volume and subsequent volatility are negatively related. Llorente et al (2002) also show that "hedging trades", which are liquidity-driven trades, generate negatively auto-correlated returns, while "speculative trades", which are information-driven trades, generate positively auto-correlated returns. Moreover, Diagler and Wiley (1999) examine the volatility-volume relation in futures markets using volume data categorised by type of trader. They report that positive relation between volume and volatility is driven by general (public) traders who do not have information on order flows, whereas trading activities by traders with information on trade flows tend to decrease volatility.

A number of studies have also examined the volume–volatility relation in a dynamic framework using GARCH-type models, where trading volume is used as a proxy for the rate of information flow to the market. For instance, Lamoureux and Lastrapes (1990) examine the volume–volatility relation for a number of stocks in the US. They use contemporaneous trading volume as an explanatory variable in the variance equation and find that the inclusion of volume eliminates the persistence in the volatility. However, they also suggest that adding contemporaneous volume into the variance equation might cause 'simultaneity bias' since volume is endogenous to the system. Therefore, they also use the lagged volume in variance equation which is found to be insignificant in most cases. Najand and Yung (1991) perform similar analysis using Treasury bond futures and find that lagged volume explains volatility better than contemporaneous trading volume. However, Chen et al. (2001) report that the persistence in volatility is not eliminated when lagged or contemporaneous trading volume level is incorporated in the GARCH model, a result contrasting the findings of Lamoureux and Lastrapes (1990).

The trading volume and price relationship has also been widely investigated in the energy market. For instance, Foster (1995) examines the temporal price–volatility relationship in the oil futures market considering the simultaneity problem. In fact, using a GARCH model he estimates time-varying variances and incorporates the volatility along with volume in a simultaneous equation model. His results indicate that not only lagged volume is positively related to volatility, but also there is a positive contemporaneous relationship between trading volume and price volatility. Herbert (1995) reports that the volume of trade rather than maturity explains the variance of the volatility of natural gas futures traded in NYMEX. His results also indicate that past levels of volume of trade influence current variability of price volatility but that past variability of price volatility has much less of an influence on current levels of trading. Moosa and Silvapulle (2000) investigate the price–volume relationship in the crude oil futures market using linear and non-linear causality tests. Their results provide support for the sequential information arrival hypothesis, the effect of noise traders, and the presence of maturity and liquidity effects. Girma and Mougoue (2002) study the relation between petroleum futures spread variability, trading volume, and open interest. They find that contemporaneous and lagged volume and open interest can explain futures spreads volatility and lagged volume and open interest substantially reduce the persistence of volatility. Their results support the SIF and imply a degree of market inefficiency in petroleum futures spreads. Moosa, Silvapulle and Silvapulle (2003) present empirical evidence on the temporal asymmetry in the price-volume relationship in the crude oil futures market. They use 3 and 6 month futures prices and trading volumes and find that the price-volume relationship is asymmetric, since negative price and volume changes have stronger effects (on each other) than positive changes.

More recently and with the availability of intraday data, a number of studies investigate the volume and volatility relation using high frequency observations. For instance, Ripple and Moosa (2009) use a range-based volatility measure and examine the effect of intra-day trading volume and open interest on crude futures contracts. They report the positive and significant role of trading volume in the determination of volatility as well as the importance of the open interest, which has a significant negative effect on volatility. Chevallier and Sevi (2012) investigate the relation between trading volume and price volatility in the crude oil and natural gas futures markets using various measures of realised volatility. They report existence of a contemporaneous and largely positive relationship between trading volume and price change. They also argue that the volatility-volume relationship is symmetric in relation to positive and negative realised semivariance, in the sense that the information content of negative realized semivariance is higher than for positive realised semivariance. Halova (2012) also examines the intraday volume and volatility relationship in the crude oil and natural gas futures markets using high frequency data. Based on a series of Granger-causality tests using conditional and absolute volatility measures, she reports that trading volume seems to drive volatility, which supports the SIF hypothesis. In a recent study, Rannou and Barneto (2016) investigate the volume-volatility relation in the European emission market by distinguishing trading activities in the OTC market and on screen trading platform. They report that one way causality from OTC to futures volume is driven by heterogeneous investor beliefs since trading volume provides an indication on how (private) information is dispersed and held at different levels rather than proxying information signal itself.

Furthermore, it has been argued that the supply and demand balance for trading in the shape of Limit-Order Book may contain information on volatility or volume-volatility relations. For instance, Næs and Skjeltorp (2005) using equity market data document negative and strong relation between volume-volatility and the limit order book slope, even in the presence of different liquidity measures. They argue that the order book slope can be considered as a proxy for disagreement among investors and their empirical results support the notion that investor heterogeneity intensifies the volume-volatility relation.

Overall, the results of the previous literature point to the existence of a positive relationship between price volatility and trading volume in different financial and commodity markets.

Additionally, there is evidence that a causal relationship exists between trading volume and price changes although the direction of causality seems to differ depending on the period and the market under investigation. However, it seems that the importance of the market condition and the type of trader have not been taken into account when investigating the relations between price and trading activity or volatility and trading volume. Therefore, this study aims to fill this gap by investigating the trading volume, price change and volatility relation under different market conditions as indicated by the slope of forward curve. The asymmetry in the volume-price relationship is then explained using information on trading activities and hedging requirements of market participants.

3. Methodology

In order to investigate the relation between price change and trading activity as well as volatility and trading volume in the energy futures complex, we use an amended Exponential Generalised Autoregressive Heteroscedasticity (EGARCH) model (Nelson, 1991).[2] The EGARCH model allows for asymmetric impact of shocks on price volatility and relaxes the non-negativity assumptions on the parameters of the variance equation. The first EGARCH-X(1,1) model used as the benchmark includes changes in trading volume as an explanatory variable in the mean and variance equations, specified as

$$\begin{aligned} &r_t = \alpha_0 + \alpha_1 dbm_t + \alpha_2 \Delta v_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim \mathrm{GED}(0,\sigma_t^2, v) \quad ; \quad z_t = (\varepsilon_t / \sigma_t) \\ &\sigma_t^2 = \exp\left(\beta_0 + \beta_1 |z_{t-1}| + \beta_2 z_{t-1} + \beta_3 \log(\sigma_{t-1}^2) + \delta_1 dtm_t + \delta_2 dbm_t + \delta_3 \Delta v_t + \gamma s_{t-1}^2\right) \end{aligned} \tag{1}$$

where r_t is the return on futures contract calculated as the logartimic changes of futures price,[3] σ_t^2 is the conditional variance, dbm_t is the dummy variable for the roll-over-day of the contract, dtm_t is the dummy variable counting the days to roll-over date, Δv_t is the change in trading volume, and s_t is the slope of the forward curve constructed as the log difference between 6-month and near-month futures prices, $[\log(F_{t,t+6}) - \log(F_{t,t+1})]$.[4] The EGARCH-X(1,1) model can be augmented to incorporate the variable, Δv_t^B ($\Delta v_t^B = \Delta v_t$ when the market is in backwardation and zero otherwise) in both mean and variance equations to account for the effect of market condition - as indicated by the slope of the forward curve - on the returns-volume and volatility-volume relations.

$$\begin{aligned} &r_t = \alpha_0 + \alpha_1 dbm_t + \alpha_2 \Delta v_t + \alpha_3 \Delta v_t^B + \varepsilon_t \quad ; \quad \varepsilon_t \sim \mathrm{GED}(0,\sigma_t^2, v) \quad ; \quad z_t = (\varepsilon_t / \sigma_t) \\ &\sigma_t^2 = \exp\left(\beta_0 + \beta_1 |z_{t-1}| + \beta_2 z_{t-1} + \beta_3 \log(\sigma_{t-1}^2) + \delta_1 dtm_t + \delta_2 dbm_t + \delta_3 \Delta v_t + \delta_4 \Delta v_t^B + \gamma s_{t-1}^2\right) \end{aligned} \tag{2}$$

[2] A number of studies in the literature (e.g. Bessembinder and Seguin, 1993, Wang, 2002) follow an iterative method for estimating conditional volatility proposed by Pagan and Schwert (1990) to measure the impact of trading volume on volatility. However, we use an EGARCH framework to simultaneously assess the relations between volume and returns, and volume and volatility.

[3] In this paper the term “return” on futures prices is the logarithmic changes in price and not the actual realised return by taking futures position, which is calculated due to changes in the margin account.

[4] As suggested by an anonymous referee, we also used different specifications for determining the slope of forward curve to allow for possibile inconsistencies in the shape of forward curve for some commodities. In particular, we used the difference between 4-month and near month, as well as the difference between 3-month and near month futures, as slope of forward curve. However, the results, not reported here due to space constraint, are generally the same.

In this EGARCH-X(1,1) specification, the relation between return and trading volume, as well as volatility and trading volume, is dependent on the state of the market. For instance, when the market is in contango, the relation between price change and trading volume is picked up by α_2 , and when the market is in backwardation by $(\alpha_2+\alpha_3)$; hence, significance of estimated coefficient of α_3 means that there is a difference in the price change and trading volume relation under different states of the market. Similarly, the difference in the relation between price volatility and trading volume under different market conditions is picked up by δ_3, and if the estimated coefficient of δ_3 is significant is means that volatility and trading volume interact differently under different market conditions.

A number of studies in the literature distinguish between anticipated and unanticipated changes in trading volume and open interest on price volatility (Bessembinder and Seguin, 1993, Wang, 2002, Girard et al., 2008). They justify this distinction by arguing that the traders may adjust their positions and trading strategies based on anticipated trading activities as well as price and volatility of the underlying asset. To distinguish the unanticipated and anticipated trading volume, we estimate a simple ARMA model for changes in trading volume.

$$\Delta v_t = \beta_0 + \beta_1 dbm_t + \sum_{i=1}^{p} \beta_{1,i} \Delta v_{t-i} + \sum_{i=1}^{p} \beta_{2,i} u_{t-i} + u_t \quad ; \quad u_t \sim \mathrm{iid}(0,\sigma^2) \tag{3}$$

where, dbm_t is a dummy variable for the day before the last trading day of the nearby contract or the rollover date. It is important to include this rollover day dummy in the trading volume model since trading activity tends to change significantly over the roll over period. Next, the expected and unexpected trading volume ($\Delta\hat{v}_t, u_t$, respectively) are used to estimate the effect of trading volume on returns and volatilities of energy futures contracts with different maturities by extending the EGARCH-X model of equation (2).

$$\begin{aligned} r_t &= \alpha_0 + \alpha_1 dbm_t + \alpha_{21}\Delta v_t + \alpha_{22} u_t + \alpha_{31}\Delta v_t^B + \alpha_{32} u_t^B + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{GED}(0,\sigma_t^2,v) \quad ; \quad z_t = (\varepsilon_t / \sigma_t) \\ \sigma_t^2 &= \exp\left(\beta_0 + \beta_1 |z_{t-1}| + \beta_2 z_{t-1} + \beta_3 \log(\sigma_{t-1}^2) + \delta_1 dtm_t + \delta_2 dbm_t + \delta_{31}\Delta v_t + \delta_{32} u_t + \delta_{41}\Delta v_t^B + \delta_{42} u_t^B + \gamma s_{t-1}^2\right) \end{aligned} \tag{4}$$

Once again expected and unexpected trading volume series are classified according to the market condition into backwardation and contango states using the slope of the forward curve as the indicator. Therefore, coefficients of α_{21} and α_{22} in equation (4) measure the effect of anticipated and unanticipated changes in trading volume on futures returns when the market is in contango, whereas, when the market is in backwardation, the effect of anticipated and unanticipated trading volume on futures returns are measured by $\alpha_{21}+\alpha_{31}$ and $\alpha_{22}+\alpha_{32}$, respectively. Similarly, coefficients of δ_{31} and δ_{32} measure the effect of anticipated and unanticipated changes in trading volume on volatility when the market is in contango, whereas, when the market is in backwardation, the effect of anticipated and unanticipated trading volume on volatility are measured by $\delta_{31}+\delta_{41}$, and $\delta_{32}+\delta_{42}$, respectively.

4. Description of Data

The data set used in this study comprises daily futures prices and trading activities for four main energy commodities traded on the New York Mercantile Exchange (NYMEX); namely, WTI Crude Oil, New York Harbour Heating Oil Number 2, New York Harbour Gasoline, and Henry Hub Natural Gas Futures. Futures price and trading volume series for different maturities are obtained from Datastream and cover the period 3rd January 1994 to 30th September 2015. After filtering the data for holidays, missing values and non-trading dates, the final sample contains 5441 daily observations. Having a long data set is crucial in this analysis to ensure sufficient number of observations under different market conditions; that is, periods when the market is in contango or backwardation. To construct a continuous series out of monthly contracts, each month prices and trading volumes are rolled over to the next trading month once trading activity of the near month contract is stopped.[5] Consequently, for each energy commodity, continuous futures price and trading volume series with 1 to 6 months to maturity are constructed.

In addition, weekly trade participation data, as well as continuous futures price and trading volume series are collected to examine the effect of market condition on trading activities of commercial and non-commercial market participants, reported by the Commodity Futures Trading Commission (CFTC). Trade participation data are based on the aggregate open interest of commercial and non-commercial participants. According to Buyuksahin and Harris (2011), CFTC classifies a trading entity as Commercial when it files a statement with the CFTC that indicates it is commercially engaged in business activities hedged by the use of the futures or option markets. Similarly, non-commercial entities are mainly financial traders, such as hedge funds, mutual funds, and floor brokers and traders whose positions are reported even though they are not registered with the CFTC under the Commodity Exchange Act (CEA). CFTC also reports data on the positions of non-reporting traders, which include speculators, proprietary traders and smaller traders. This category includes the difference between total open interest and the aggregate positions of reporting traders. It is important to recognize the role of the positions that commercial and non-commercial traders take under each market condition as their objective of trading, view and expectations about the market are different.

Summary statistics of daily returns (logarithmic first-differences) of 1, 2, 3 and 4 months to maturity futures contracts for the four energy commodities over the full sample period are presented in Table 1. Mean and standard deviation of returns are annualised. Average returns for all energy futures and maturities are positive varying from 6.3% for 4-month ahead heating oil futures to 12.2% for 1-month ahead natural gas futures contracts. The relatively high average annualised returns, across all four markets, indicate significant increase in prices over the sample period. The unconditional volatility of returns declines as maturity increases, which confirms the Samuelson effect and the term structure of volatility of energy prices due to mean reversion. Also, comparisons

[5] To construct continuous futures price and trading volume series for each futures contract a rollover technique is used. The technique takes the nearest to maturity series position until the delivery month, at which time the position is closed and a position is opened in the following nearest to month futures contract. The same procedure is applied to construct 2nd to 6th month to maturity price and trading volume series. Changes in trading volume and prices series are calculated based on constructed series.

of volatilities across commodities suggest higher fluctuations in Natural Gas prices compared to Crude Oil, Heating Oil and Gasoline prices over the sample period.

Bera and Jarque (1980) tests indicate significant departures from normality for the return series of 1-, 2-, 3- and 4-month contracts across all commodities. The Ljung and Box (1978) statistic for the 10th autocorrelation function is significant in all commodities and maturities indicating certain degree of autocorrelation in return series. However, autocorrelation seems to be in the higher lagged orders rather than lower ones. Engle's (1982) ARCH tests, carried out as the Ljung-Box tests on the squared return series, indicate the existence of strong ARCH effects in 1-, 2-, 3- and 4-month return series across all commodities. Finally, the Phillips and Perron (1988) unit root test and the Kwiatkowski et al. (1992) test for stationarity suggest that all return series are stationary. Similar results regarding autocorraltaion, ARCH and stationarity are also obtained for changes in trading volaume across all commodities and maturities.

The state of the market for the four energy commodities over the sample period is illustrated in Figure 1, as the plot of the slope of the forward curve. The slope of forward curve is measured as the difference between the log of 6th-month and the near-month futures prices for each energy commodity. A positive slope suggests that the market is contango and a negative slope suggests that the market is in backwardation. It can be seen that in all markets there are periods of backwardation and contango over the sample period. Moreover, the variation of the slope of the forward curve tends to differ across commodities.

Table 2 reports the proportion of trading activity of the four energy futures contracts from near month to 6-month to maturity.[6] It can be noticed that, for all commodities, more than 40% of the trading activity is concentrated on the near month contract and it declines to between 2-3% for contracts with 6 month to maturity. This said, a large proportion of the trading on the near month contract is due to closing and roll over trading activities for positions that traders or hedgers established previously in longer term contracts. Also, the percentages indicate that more than 95% of the trading in energy futures contracts is concentrated in 1 to 6 months forward contracts.

5. Empirical Results

To analyse the dynamics of trading activities across the maturity spectrum of energy futures contracts, we first estimate the correlation between changes in trading activities for contracts with different time to maturity. Table 3 presents the correlation coefficients between changes in trading volume across different maturities for the four energy commodities under consideration. There are some interesting observations. First, the estimated coefficients of correlation between changes in trading activities of near month futures contracts and contracts with longer maturities are generally low, with the exception of natural gas futures. For instance, the correlation between changes in trading volume of near month and 2nd, 3rd and 4th month futures for WTI crude oil range from -0.224 to 0.167. However, the estimated correlation coefficients between contracts with longer time to maturity (2 to 6 months) seem to be positive and relatively higher ranging from 0.243 between 2 and 6 months to maturity, to 0.673 between 2 and 3 months to maturity contracts. Similar results can be

[6] The proportion of trade is measure relative to the total trading volume for contract from 1 to 12 months.

observed for correlation coefficients of gasoline and heating oil futures. The lower correlation between near month and longer maturity contracts suggests that participants trade futures contracts across different maturities for different purposes and the arrival of information may result in dissimilar trading patterns across the maturity spectrum. The trading activity in the near month contract is generally for the purpose of closing or rolling over a previously traded position or day-trading activities. Thus, trading volume of the near month contract may not reflect the trading objectives or strategies of participants in terms of hedging or speculation. On the other hand, positive and higher correlation coefficients between contracts with longer maturities could be attributed to fact that these contracts are mainly used by market participants for the purposes of building positions for speculation or hedging. For this reason, we concentrate our investigation mainly on the relation between price and trading volume for contracts with 2 to 4 months to maturity.

WTI Crude Oil Futures

Starting with the estimation results of WTI crude oil futures reported in Table 4, there seem to be some signs of autocorrelation and ARCH effects in the standardised residuals. Since these effects could not be removed even with inclusion of more lagged standardised error terms or variance in the model, standard errors are corrected using Newey and West (1987) method. The Jarque-Berra test statistics for normality indicate that standardised residuals are not normally distributed in all models. This is also depicted by the significance of the shape parameter (*v*) of the models, with the estimated values of 1.250 to 1.365 of the GED distributions allowing for deviation from normality. Moreover, the estimated parameter of the roll-over-day dummy variable, α_1, is negative and significant across all models and maturities, with the exception of the 2- and 3-month contracts in model 3. The estimated coefficients of changes in trading volume, α_2, are negative and significant for the 2-month contract when the market condition is not considered in model 1. However, when the market condition is considered, the estimated coefficients of change in trading volume in the mean equation (α_2 and α_3 in equation 2) are significant with opposite signs, revealing an asymmetric effect in the volume and price relation. For instance, coefficients of changes in trading volume when the market is in contango (α_2) are -0.054, -0.096, and -0.057, for 2, 3 and 4 months to maturity contracts, respectively, while the estimated coefficients when the market is in backwardation (α_3) are 0.078, 0.147, and 0.147. Similarly, when we distinguish between anticipated and unanticipated changes in trading volume under different market conditions, the estimated coefficients of trading volume seems to be negative and significant when the market is in contango and positive when the market is in backwardation, again revealing an asymmetric volume-return relationship. The possible cause of such an asymmetry is explained by the trading activities of market participants discussed in section 6.

Turning to the variance equation, negative and significant coefficients of the lagged standardised error terms, β_2, confirms the asymmetric impact of shocks with different sign on volatility. Although, it is generally expected that in commodity markets positive shocks to have greater impact on volatility than negative shoks, we find evidence to the contrary.This is in line with Mohammadi and Su (2010) and might be due to the fact that crude oil futures contracts are now considered more as financial assets rather than physical consumption assets. The relatively large and significant coefficients of lagged variance, β_3, across all models and maturities suggest high volatility persistence in crude oil futures prices. Moreover, positive and significant coefficients of lagged squared slope, γ, in all models and across all maturities reveal a convex relationship between the slope of forward curve and volatility. This is in line with previous literature (Kogan et al, 2009, and Alizadeh and Talley, 2009) and implies that the steeper the slope of the forward curve the higher is the volatility of futures prices.

More importantly, the estimated coefficients of changes in trading volume in the variance equation, δ_3, are positive and significant across all maturities when the market condition is not considered, in model 1. The positive relation between trading volume and volatility is consistent with the previous literature (Foster, 1995, and Bessembinder and Seguin, 1993, and Wang 2002). However, when we allow for changes in the market condition, as in model 2, positive and significant coefficients of δ_{41}, reveal that the relation between changes in trading volume and volatility is dependent on the slope of forward curve. For instance, the estimated values of 1.777, 3.527, 9.845, and 17.950 for δ_{41}, in model 2 for 1, 2, 3 and 4 month maturity contracts, respectively, means a greater degree of association between the trading volume and volatility when the market is in backwardation. Finally, when we allow for the type of volume shock (anticipated and unanticipated) as well as market condition, as in model 3, positive and significant coefficients of δ_{31} and δ_{32}, suggest that both anticipated and unanticipated changes in trading volume are positively related to volatility when the market is in contango. However, positive and significant coefficients of anticipated and unanticipated changes in volume when the market is in backwardation, δ_{41} and δ_{42}, indicate that the trading volume-volatility relation is much stronger when the slope of WTI crude oil forward curve is negative compared to when the slope is positive.[7]

This finding, assuming change in trading volume is a proxy for the flow of information according to the SIF hypothesis, suggests that crude oil futures prices are more sensitive to arrival of information when the market is in backwardation than when it is in contango. The reason for such sensitivity could be attributed to the fact that a backwardated commodity market is an indication of shortage of physical commodity which makes the market more responsive to arrival of information.

Gasoline Futures

The estimation results of EGARCH-X models for Gasoline futures with different maturities are reported in Table 5. All EGARCH-X models for Gasoline futures returns are well specified and there is no sign of autocorrelation and ARCH effects in the standardised residuals of most models. The estimated values of the shape parameter (v) in all models suggest high excess kurtosis in all residuals, which is captured by the use of GED distribution. Moreover, the estimated parameter of the roll-over-day dummy variable in the mean equation, α_1, is negative and significant across all models and maturities, indicating a negative average roll-over yield. Meanwhile, in model 1 the estimated coefficients of change in trading volume in the mean equation, α_2, are positive but not significant for all maturities. Estimated coefficients of changes in volume in model 2, α_{21} and α_{31}, are mostly positive and insignificant. In contrast, when we distinguish between anticipated and

[7] As pointed out by an anonymous referee, the recent revolation in shale gas and oil production may have resulted some structural changes in the industry and hence price linkages. Therefore, we also used a binary dummy variable (which takes a value of zero before 2010 and 1 after 2010) to take this effect into account. However, the results, not reported here, indicate a small reduction (between 1% to 2%) in volatility of futures contracts for crude oil and natural gas due to increase in shale gas production but no significant effect on price-volume and volume volatility relations.

unanticipated changes in trading volume under different market conditions, model 3, the estimated coefficients of anticipated change in trading volume (α_{21} and α_{31}) are negative and significant when the market is in contango and positive when the market is in backwardation, which is consistent with what is observed in the case of crude oil futures. However, the estimated coefficinets of unanticipated change in trading volume (α_{22} and α_{32}) are statistically insignificant across all maturities.

The estimated coefficient of the lagged squared slope in the variance equation, γ, is positive and significant for 2nd and 3rd month to maturity across all models suggesting a quadratic relation between the slope of forward curve and the volatility of futures contracts. Negativity and significance of coefficients of lagged standardised error terms, β_2, in all models point to a certain degree of sign asymmetry in the variance models. More importantly, the estimated coefficients of changes in trading volume in the variance equation, δ_{31}, are positive and significant across all maturities when the market condition is not considered (model 1). Additionally, when we allow for market conditions, as in model 2, the estimated coefficients of changes in volume when the market is in backwardation, δ_{41}, are positive and significant for 1, 3, and 4 month futures contract, indicating stronger linkage between volume and volatility when the market is in backwardation. However, when we distinguish between the anticipated and unanticipated changes in trading volume under different states of the market, according to model 3, the estimated coefficients of δ_{41} and δ_{42} are not significant, suggesting there is no asymmetry in the volume-volatility relation in the Gasoline futures market. This is somehow different from what is observed in the WTI crude oil futures market.

Heating Oil Futures

Table 6 presents the estimation results of EGARCH models for heating oil futures with different maturities. Generally, all EGARCH models seem to be well specified and there is no sign of autocorrelation and ARCH effects in the residuals. Once again, significance of the estimated values of the shape parameter (v) in all EGARCH models for heating oil futures indicate high excess kurtosis in all residuals, which is captured by the GED distribution. Moreover, the estimated parameter of the roll-over-day dummy variable in the mean equation, α_1, is positive and significant only for near-month contract. Meanwhile, the estimated coefficients of change in trading volume in the mean equation, α_2, are negative and significant for all maturities except the 3-month contract, when the market condition is not considered (model 1). However, significant and opposite signs of the estimated coefficients of change in volume in model 2, α_{21} and α_{31}, indicate a negative volume-pice change relation when the market is in contango and positive volume-price relation when the market is in backwardation. For instance, when the market is in contango coefficients of change in volume for 2, 3, and 4 month maturity contracts are -0.121, -0.321, and -0.285, respectively; whereas, when the market is in backwardation the coefficients explaining the relation between changes in trading volume and return are 0.059 (0.180-0.121), 0.085 (0.406-0.321), and 0.087 (0.372-0.285) for 2, 3, and 4 month contracts, respectively. In addition, when we distinguish between anticipated and unanticipated changes in trading volume under different market conditions, as in model 3, the estimated coefficients of anticipated trading volume in the mean equation, α_{21} and α_{31}, are negative and significant at the 10% level when the market is in contango and positive and significant at the 1% level when the market is in backwardation. Similarly, the estimated coefficients of unanticipated trading volume in the mean equation, α_{22} and α_{32}, for all maturities are negative and significant when the market is in contango and positive and significant (for the 2nd and 3rd month) when the market is in backwardation.

Furthermore, as in the case of models for crude oil and gasoline futures, the estimated coefficient of the lagged squared slope in the variance equation, γ, are positive and significant for 2nd and 3rd month to maturity across all models (except the 2nd month in model 3). Again, negative and significant coefficients of lagged standardised error terms, β_2, in all models point to certain degree of sign asymmetry in the variance models. The estimated coefficients of changes in trading volume in the variance equation, δ_{31}, are positive and significant across all maturities when the market condition is not considered (model 1). However, when the market condition is considered, as in model 2, the estimated coefficients of change in volume when the market is in backwardation, δ_{41}, are not significant. Finally, when we distinguish between the anticipated and unanticipated changes in trading volume on volatility under different states of the market, according to model 3, the estimated results suggest that there is no asymmetry in the volume-volatility relation in the Heating oil futures market. However, comparison of estimated coefficients of anticipated and unanticipated trading volume reveals a greater association between anticipated trading activity and volatility compared to unanticipated trading volume and volatility relation. This is similar to what is observed for crude oil and gasoline futures too.

Natural Gas Futures

Lastly, we turn to the estimated models for natural gas futures, presented in Table 7. The diagnostics indicate that there are some ARCH and Autocorrelation effects which could not be removed even with inclusion of more lagged standardised error terms in those models, therefore, standard errors are corrected using Newey and West (1987) method. The coefficient of the roll-over-day dummy variable is positive and significant across all models and maturities for Natural Gas futures indicating a positive average roll over yield over the sample. Once more, the estimated coefficient of the shape of the GED distribution, v, is significant and below 2, which means that standardised residuals of the estimated models show excess kurtosis. The estimated coefficients of change in trading volume are positive for all contract maturities, but significant only for the 1, 3 and 4-month contracts, when the state of the market is not considered. When we allow for market condition, the coefficient of changes in trading volume in the mean equation is positive and significant only for the 1 and 4-month contracts when the market is in contango. In contrast, the estimated coefficients of α_{31} are positive and significant for 2, 3, and 4 month contracts when the market is in backwardation. When anticipated and unanticipated changes in volume are considered, the resulst are somewhat mixed. For instance, coefficints of anticipated changes in volume (α22) are positive and statistically significant when the market is in backwardation, with the exception of 2-month contract, while coefficints of anticipated change in volume are positive and significant in the model for 2 and 3-month contracts when the market is in backwrdation. Nevertheless, the overall results indicate stronger volume and price change relation for natural gas futures contacts when market is in backwardation.

In theh variance equation, as expected, the estimated coefficients of lagged squared slope, γ, are all positive and significant. Also, negative and significant coefficients of the dummy variables for days to maturity, indicate that volatility tends to increase as maturity of contracts approaches; while positive and significant coefficients of roll-over-day indicate a higher level of volatility on these days.

Positive and significant coefficients of lagged standardised error terms, β_2, in all models point to a certain degree of positive sign asymmetry in the variance models for natural gas futures, which is opposite to what is found for crude oil and product futures. Therefore, it seems that in the natural Gas futures market, negative shocks tend to have a relatively lower impact on volatility compared to positive shock with the same magnitude. Estimated coefficients of lagged variance, β_3, seem to be stable across all models and range from 0.947, for 3-month to 0.972 for 4-month forward contracts, which suggest that volatility persistence increases as maturity increases.

Finally, the estimated coefficients of changes in trading volume in the variance equation, δ_{31}, are positive and significant across all maturities when the market condition is not considered in model 1. When the market condition is considered, as in model 2, the estimated coefficients of change in volume, δ_{31} and δ_{41}, are all positive, with the exception δ_{41} for 4-month contract. However, coefficients of change in volume when the maket is in backwardation (δ_{41}) are not statistically significant revealing that there is no asymmetry in the volume-volatility relation in the natural gas futures market. However, it seems that the volume-volatility relation becomes stronger when we move from 2- to 4-month contracts as indicated by greater value of coefficients of δ_{31} (18.838, 20.720, and 53.573 for 2-, 3- and 4-month contracts, respectively). Furthermore, when we distinguish between the anticipated and unanticipated changes in trading volume on volatility under different states of the market, according to model 3, again the estimated results suggest that there is no asymmetry in the volume-volatility relation. Nevertheless, both anticipated and unanticipated changes in volume are positively related to volatility for all maturities when the market, and the strength of the volume-volatility relation increases with maturity, as estimated coefficients of indicate.

Overall, the results suggest that the relation between futures returns and changes in trading volume of energy commodities is negative when the market is in backwardation and positive when the market is in contango. Moreover, the estimation results for crude oil futures market reveal some degree of asymmetry in the relation between volatility and changes in trading volume depending on the state of the market; that is to say, the volume-volatility relation is stronger when the market is in backwardation compared to when the market is in contango. The intuition behind this is that commodity prices can be more sensitive to the arrival of news (trading activity) when there is a shortage of the physical commodity and the market is in backwardation. However, the results for other three energy commodities (gasoline, heating oil and natural gas) do not seem to suggest any asymmetric volume-volatility relation depending on the state of the market.

6. Trade participation and market conditions

To investigate the effect of the state of the market on the trading activities and positions of participants, we use the data on trade positions of commercial and non-commercial traders. According to CFTC, commercial participants are those with some physical interest who are believed to use the futures contracts for hedging purposes, whereas non-commercial participants, such as hedge funds and other financial institutions, may use energy futures for speculative or diversification purposes. The data on commercial and non-commercial trade positions published by CFTC are in the form of aggregate weekly open interests for the entire maturity spectrum of each commodity, i.e. without specific open interest data for individual futures contracts. Therefore, our analysis will be based on weekly time series of trade interest, futures price change and price volatility. According to Hirshleifer (1988), and De Roon et al. (2000), the net position of commercial traders in futures market can be considered as proxy for hedging pressure. We construct the "*net position*" for each trader type – commercial and non-commercial - using the relative long and short positions as

$$y_t^i = \frac{(OI_{long,t}^i - OI_{short,t}^i)}{(OI_{long,t}^i + OI_{short,t}^i)} \tag{5}$$

where $OI_{long,t}^i$ and $OI_{short,t}^i$ are the long and short open interests of trader type *i* (*i*= commercial or non-commercial) at time *t*. Note that we use the difference between long and short positions in the numerator as opposed to Hirshleifer (1989) and De Roon et al (2000). The impact of market condition on the trading activity of commercial and non-commercial participants is examined by regressing the net position of each type of trader, y_t^i, on the lagged volatility, σ_{t-1}, and the slope of forward curve, S_{t-1}, as well as lagged dependent variable in the following form

$$y_t^i = \alpha_0 + \sum_{i=1}^{k} \alpha_i y_t^i + \delta S_{t-1} + \gamma \sigma_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{iid}(0, \sigma^2) \tag{6}$$

The estimation results of equation (6) for each energy commodity over the sample period March 1995 to September 2015, presented in Table 8, indicate that the coefficient of lagged standard deviation,γ, is only statistically significant in the case of commercial and non-commercial equations for crude oil futures. This is not surprising as increases in volatility might increase the participation of commercial traders with both long and short physical market exposures, which in turn may not change the net position of commercial traders. Similarly, changes in futures market volatility may attract non-commercial traders as speculators, who may take long or short positions depending on their views, but may not change their overall net positions.

More importantly, the estimated coefficients of lagged slope, δ, are positive and significant in equations for the net position of commercial participants across all commodities, whereas the same coefficients are negative and statistically significant in all equations for the net position of non-commercial participants. This finding is important as it reveals that commercial and non-commercial traders adjust their net trading positions according to the slope of the forward curve and consequently market conditions. The results are in line with Lehecka (2013) who provides evidence on the relation between trade positions and price changes in commodity markets. Lehecka shows that price changes tend to lead traders' hedging and speculative activities and hence their net positions. Our results support the argument that it is the state of the market and the shape of forward curve that affect the trading strategies of traders and their net positions.

Furthermore, Figure 2 presents the scatter plot of the relative holding positions of commercial and non-commercial participants against the slope of forward curve for four energy futures markets. It can be seen that there is negative relation between the relative holding positions of non-commercial traders and the slope of forward curve across all four commodities, while there is a positive relation between the relative holding positions of non-commercial traders. However, the strength of the relation seems to be different across commodities.

To examine whether the traders' net positions cause the slope of forward curve to change or the dynamics of forward curve are used by traders to rebalance their positions, we use a Granger-causality test. The Granger-causality test is performed on VAR models with slope of forward curve and trader types' net position as endogenous variables. The results of the tests for all four energy commodities are reported in Table 9. It can be seen that for both commercial and non-commercial trader types, the Wald test statistics reject the null hypothesis that the slope of the forward curve does not Granger cause the net position of traders. Whereas, the Wald test statitics reject the null hypothesisthat tradrers' net position affects the slope of forward curve across all commodities and trader types at the 5% significance level, with the exception of non-commercial traders for natural gas futures. This results confirm that traders tend to use the information content and dynamics of the forward curve of energy commodities.

The slope of the forward curve is utilised by participants in the futures market to assess the expected price change, adjust their portfolio and set up their trading and hedging strategies. For instance, when the market is in backwardation (contango), speculators may utilise a rollover trading strategy by buying (selling) long maturity contracts and rollover or close the contacts as their maturity approaches to benefit from rising (falling) prices. The profit or loss from such a strategy is known as roll over yield. Another, strategy could be long-short trade along the forward curve (e.g. buy long maturity-sell short maturity when the market is in deep backwardation) to benefit from corrections (adjustment) of forward curve as the forward curve tilts. Such behaviour and trading activities can put upward (downward) pressure on long maturity contracts when the market is in backwardation (contango). At the same time, hedgers tend to observe the state of the market as indicated by the slope of the forward curve and establish their hedging strategies depending on their views and requirements. For instance, when the market is in backwardation, long hedgers (consumers who are short the physical asset) might be willing to take long hedge positions to avoid paying higher spot prices in the future; whereas, producers who are short hedgers tend to resist hedging as the futures prices are less than the spot price. Such hedging activity can exert an upward pressure on futures contracts. Similarly, when the market is in contango, short hedgers (producers with long physical position) might be willing to take short hedge positions to avoid receiving lower spot prices in the future; whereas long hedgers (consumers) resist hedging as they may expect prices to fall in the future. In other words, it seems that hedgers pay attention to the slope of the forward curve as an indicator of the state of the market, placing more weight on spot price level relative to futures price in deciding to hedge.

7. Conclusions

In this paper we investigated the asymmetric relations between trading volume and price changes, and trading volume and price volatility for four energy futures contracts under different market conditions. The state of the market conveys important information which hedgers and traders use to assess the expected price change, adjust their portfolio and set up their trading and hedging strategies, and hence can affect the price-volume relation. In contrast to previous literature, where mainly nearby contracts are used to analyse the price-volume relation, we performed the analysis on contracts with different maturities.

Our results, which are overall consistent across all maturities considered, show that the relationship between futures returns and changes in trading volume in energy commodities is negative when the market is in backwardation and positive when the market is in contango. Such asymmetry in the relationship between futures returns and changes in trading volume is explained by the trading position of commercial and non-commercial traders. In addition, we find evidence on the asymmetry in volatility and changes in trading volume of energy commodities according to the state of the market. More precisely, the relationship between volatility and changes in trading volume is stronger when the market is in backwardation compared to when the market is in contango. This is attributed to the fact that energy commodity prices can be more sensitive to arrival of information in the form of changes in trading activity when the market is in backwardation.

Furthermore, we analysed the net position of commercial (hedgers) and non-commercial (speculators) in relation to market volatility and the slope of forward curve. The results reveal a statistically significant relationship between traders' net positions in futures contracts and the slope of forward curve. In fact, the results suggest that commercial traders tend to maintain net short positions when the market is in contango and net long positions when the market is in backwardation. On the other hand, it seems that non-commercial traders tend to maintain net long positions when the market is in backwardation and net short positions when the market is in contango. The results are consistent with Hirshleifer (1988) and De Roon et al. (2000) who argue that the net position of commercial traders in futures market can be considered as proxy for hedging pressure. However, we argue that hedging pressure can be dependent on the market condition as indicated by the slope of the forward curve.

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Table 1: Descriptive statistics of returns and changes in trading volume of energy futures contracts

		Mean	StDev	JB	LB-Q(10)	ARCH(10)	PP	KPSS
WTI Crude Oil								
1-month	r	0.080136	0.3725	4092.3	24.717	65.988	-75.450	0.1300
	Δv	0.000808	0.0596	18262.4	595.833	32.393	-94.911	0.0000
2-month	r	0.072576	0.3377	2740.3	16.457	57.883	-75.845	0.1550
	Δv	0.000587	0.0433	91660.5	294.047	9.002	-83.213	0.0000
3-month	r	0.068292	0.3177	2327.2	18.710	67.534	-76.211	0.1700
	Δv	0.000187	0.0138	18733.3	503.816	71.363	-101.600	0.0000
4-month	r	0.065268	0.3034	2619.1	23.893	67.837	-76.966	0.1810
	Δv	0.00012	0.0088	83992.8	528.538	63.476	-101.776	0.0010
Gasoline								
1-month	r	0.088452	0.4115	8485.8	19.758	36.319	-75.516	0.0930
	Δv	0.00013	0.0096	23393.3	611.894	13.058	-104.855	0.0010
2-month	r	0.075852	0.3525	4610.4	12.189	23.342	-74.095	0.1250
	Δv	0.00011	0.0081	4214.0	656.139	33.419	-95.878	0.0010
3-month	r	0.070056	0.3255	3769.1	18.372	42.124	-75.186	0.1420
	Δv	0.000056	0.0041	14671.1	874.450	93.903	-107.275	0.0030
4-month	r	0.066276	0.3083	2975.7	22.565	41.141	-77.418	0.1540
	Δv	0.000034	0.0025	20673.1	821.710	115.865	-107.523	0.0010
Heating oil								
1-month	r	0.07686	0.3565	8826.7	13.873	19.147	-75.721	0.1070
	Δv	0.000134	0.0099	41488.1	620.895	6.413	-104.635	0.0010
2-month	r	0.069804	0.3238	1527.4	9.067	31.745	-75.958	0.1280
	Δv	0.00012	0.0088	28658.0	429.363	36.558	-95.546	0.0000
3-month	r	0.06552	0.3048	1078.0	9.052	38.854	-76.000	0.1430
	Δv	0.000051	0.0037	27438.0	763.271	117.741	-107.872	0.0010
4-month	r	0.062748	0.2910	1143.9	11.763	41.324	-76.365	0.1540
	Δv	0.000035	0.0026	44817.9	773.350	141.206	-110.755	0.0000
Natural Gas								
1-month	r	0.121968	0.5665	11144.5	30.068	29.100	-76.946	0.0680
	Δv	0.000393	0.0290	13732.1	1301.097	79.855	-119.943	0.0000
2-month	r	0.108612	0.5044	6678.0	26.552	24.386	-77.531	0.0860
	Δv	0.000249	0.0184	75670.1	764.587	31.869	-107.215	0.0000
3-month	r	0.095508	0.4436	13142.8	17.469	9.064	-76.088	0.1110
	Δv	0.000111	0.0082	73201.9	482.960	65.403	-96.404	0.0010
4-month	r	0.084924	0.3944	4992.0	22.657	10.661	-76.589	0.1440
	Δv	0.000069	0.0051	194986.9	1155.160	150.013	-118.192	0.0010

- Sample period: 3 January 1994 to 30 September 2015, total of 5441 observations.
- $r = \Delta f$ is the logarithmic daily return on the futures contract. Mean and Standard deviation of returns are annualised.
- Δv is the change in daily trading volume scaled by 1,000,000.
- JB is the Jarque and Bera (1980) test for Normality which follows a chi-squared distribution with 2 degrees of freedom.
- LB-Q(10) is the Ljung and Box (1978) statistics for 10^{th} order Autocorrelation in the series which follows a chi-squared distribution with 10 degrees of freedom.
- ARCH(10) is the Engle (1982) test for 10^{th} order ARCH effects and follows a chi-squared distribution with 10 degrees of freedom.
- PP is Philips and Perron (1988) test for unit root, , with the 5% critical value of -2.89.
- KPSS the Kwiatkowski et. al. (1992) for stationarity, with the 5% critical value of 0.146.

Table 2: Percentage of trading volume for each contract month relative to the total trading volume over the first 12 monthly futures contracts

	Neat Month	*2nd Month*	*3rd Month*	*4th Month*	*5th Month*	*6th Month*
WTI Crude	47.3%	27.3%	9.7%	4.8%	2.9%	2.1%
Gasoline	42.8%	33.4%	12.4%	6.0%	3.4%	2.0%
Heating Oil	40.2%	30.9%	11.2%	6.0%	3.7%	2.5%
Natural Gas	45.0%	22.4%	10.7%	6.1%	4.1%	3.0%

- Sample period: 3 January 1994 30 September 2015, total of 5441 observations.
- Percentages are calculated as proportion of average trading volume for each forward month over the sample over the total of average trading volumes.

Table 3: Correlation between changes in trading volume across contract maturities

WTI Crude	$\Delta v1$	$\Delta v2$	$\Delta v3$	$\Delta v4$	$\Delta v5$	$\Delta v6$
$\Delta v1$	1					
$\Delta v2$	-0.2238	1				
$\Delta v3$	0.1122	0.6733	1			
$\Delta v4$	0.1670	0.4850	0.6676	1		
$\Delta v5$	0.1973	0.3700	0.5123	0.53580	1	
$\Delta v6$	0.1935	0.2430	0.4244	0.35553	0.3320	1

Gasoline	$\Delta v1$	$\Delta v2$	$\Delta v3$	$\Delta v4$	$\Delta v5$	$\Delta v6$
$\Delta v1$	1					
$\Delta v2$	0.1126	1				
$\Delta v3$	0.1281	0.7919	1			
$\Delta v4$	0.1858	0.6268	0.7766	1		
$\Delta v5$	0.1532	0.5351	0.6560	0.7498	1	
$\Delta v6$	0.1373	0.4562	0.5591	0.5866	0.6832	1

Heating Oil	$\Delta v1$	$\Delta v2$	$\Delta v3$	$\Delta v4$	$\Delta v5$	$\Delta v6$
$\Delta v1$	1					
$\Delta v2$	-0.1034	1				
$\Delta v3$	0.1183	0.6823	1			
$\Delta v4$	0.1159	0.4953	0.6705	1		
$\Delta v5$	0.0752	0.4331	0.5179	0.5913	1	
$\Delta v6$	0.1130	0.2994	0.4303	0.4069	0.4408	1

Natural Gas	$\Delta v1$	$\Delta v2$	$\Delta v3$	$\Delta v4$	$\Delta v5$	$\Delta v6$
$\Delta v1$	1					
$\Delta v2$	0.1592	1				
$\Delta v3$	0.4148	0.6281	1			
$\Delta v4$	0.4041	0.5395	0.6488	1		
$\Delta v5$	0.4163	0.4827	0.5614	0.6097	1	
$\Delta v6$	0.3772	0.4059	0.5175	0.4829	0.5445	1

- Sample period: 3 January 1994 to 30 September 2015, total of 5441 observations.

Table 4: Estimation result of EGARCH-X models for WTI crude oil futures

$$r_t = \alpha_0 + \alpha_1 dbm_t + \alpha_{21}\Delta v_t + \alpha_{22}u_t + \alpha_{31}\Delta v_t^B + \alpha_{32}u_t^B + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{GED}(0,\sigma_t^2,v) \quad ; \quad z_t = (\varepsilon_t / \sigma_t)$$

$$\sigma_t^2 = \exp\left(\beta_0 + \beta_1|z_{t-1}| + \beta_2 z_{t-1} + \beta_3 \log(\sigma_{t-1}^2) + \delta_1 dtm_t + \delta_2 dbm_t + \delta_{31}\Delta v_t + \delta_{32}u_t + \delta_{41}\Delta v_t^B + \delta_{42}u_t^B + \gamma s_{t-1}^2\right)$$

	Model 1				Model 2				Model 3			
Mean	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m
α_0	0.000*	0.001**	0.000**	0.001***	0.000	0.001**	0.000**	0.001**	0.000	0.000	0.000	0.000**
	(1.661)	(2.306)	(2.238)	(2.617)	(1.639)	(2.417)	(2.021)	(2.565)	(1.259)	(1.371)	(1.602)	(2.294)
α_1	-0.002*	-0.006***	-0.005***	-0.004***	-0.002*	-0.005***	-0.005***	-0.004***	0.001	-0.001	-0.003***	-0.004***
	(-1.773)	(-4.347)	(-4.461)	(-4.633)	(-1.849)	(-3.935)	(-4.485)	(-4.665)	(0.780)	(-0.477)	(-2.657)	(-4.620)
α_{21}	-0.006	-0.023***	-0.022	0.005	-0.002	-0.054***	-0.096***	-0.057**	0.003***	-0.070***	-0.257***	-0.253***
	(-1.458)	(-3.831)	(-1.350)	(0.260)	(-0.320)	(-7.880)	(-4.444)	(-2.197)	(3.084)	(-3.416)	(-5.884)	(-4.068)
α_{22}									-0.014***	-0.020***	-0.048**	-0.027
									(-2.823)	(-2.647)	(-2.183)	(-1.120)
α_{31}					-0.010	0.078***	0.147***	0.147***	-0.074***	0.153***	0.501***	0.569***
					(-1.250)	(8.147)	(5.103)	(3.542)	(-5.993)	(10.953)	(9.576)	(6.554)
α_{32}									0.024***	0.016	0.046	0.071*
									(2.716)	(1.332)	(1.604)	(1.897)
Variance												
β_0	-0.014	-0.226***	-0.188***	-0.163***	-0.016	-0.274***	-0.205***	-0.187***	0.136***	-0.372***	-0.253***	-0.179***
	(-0.499)	(-8.493)	(-7.205)	(-5.934)	(-0.550)	(-9.065)	(-7.531)	(-6.410)	(-12.965)	(-10.631)	(-9.163)	(-6.832)
β_1	0.105***	0.097***	0.111***	0.113***	0.109***	0.108***	0.117***	0.119***	0.114***	0.108***	0.112***	0.103***
	(10.172)	(8.931)	(9.887)	(9.900)	(10.070)	(9.193)	(10.101)	(10.011)	(21.906)	(9.010)	(9.671)	(9.248)
β_2	-0.034***	-0.039***	-0.039***	-0.038***	-0.033***	-0.043***	-0.043***	-0.038***	-0.031***	-0.042***	-0.040***	-0.038***
	(-4.892)	(-6.009)	(-5.559)	(-5.368)	(-4.753)	(-6.031)	(-5.891)	(-5.263)	(-4.096)	(-5.835)	(-5.582)	(-5.564)
β_3	0.988***	0.990***	0.989***	0.989***	0.988***	0.986***	0.988***	0.988***	0.989***	0.986***	0.989***	0.990***
	(376.04)	(408.19)	(412.85)	(407.21)	(355.71)	(347.38)	(385.77)	(380.70)	(438.79)	(338.42)	(390.92)	(441.90)
δ_1	-0.016***	0.002**	-0.001	-0.002	-0.016***	0.003***	0.000	-0.001	-0.028***	0.011***	0.004***	0.001
	(-12.556)	(2.049)	(-1.017)	(-1.490)	(-12.577)	(3.047)	(-0.127)	(-1.022)	(-15.041)	(6.683)	(3.132)	(0.350)
δ_2	-0.161**	0.887***	0.420***	0.121	-0.184**	0.909***	0.402***	0.130*	-0.711***	1.479***	0.776***	0.288***
	(-2.098)	(10.267)	(5.293)	(1.571)	(-2.359)	(10.628)	(5.097)	(1.712)	(-8.076)	(10.109)	(9.016)	(3.734)
δ_{31}	5.620***	7.496***	18.052***	14.139***	5.309***	6.787***	15.073***	10.686***	10.588***	13.130***	45.417***	38.345***
	(19.582)	(11.986)	(11.216)	(6.565)	(18.254)	(10.450)	(7.620)	(4.975)	(13.528)	(9.980)	(10.244)	(8.328)
δ_{32}									6.503***	7.818***	23.329***	19.907***
									(18.007)	(11.360)	(10.843)	(7.838)
δ_{41}					1.777***	3.527***	9.845***	17.950***	2.762***	3.754***	12.691**	41.961***
					(4.529)	(5.956)	(5.170)	(4.857)	(3.471)	(4.197)	(2.539)	(5.264)
δ_{42}									1.122***	2.738***	8.973***	20.071***
									(1.750)	(3.934)	(3.563)	(5.120)
γ	0.572***	0.491***	0.459***	0.414**	0.580***	0.641***	0.493***	0.499***	0.540***	0.607***	0.484***	0.388**
	(3.204	(3.073	(2.774)	(2.535)	(3.047)	(3.478)	(2.795)	(2.856)	(2.765)	(3.297)	(2.889)	(2.552)
υ	1.250***	1.284***	1.306***	1.365***	1.252***	1.284***	1.305***	1.353***	1.250***	1.290***	1.282***	1.334***
	(44.548	(43.636	(41.508)	(42.661)	(44.304)	(43.209)	(41.846)	(42.130)	(36.550)	(41.454)	(41.467)	(42.558)

Diagnostics												
R-bar-sqr	-0.002	-0.001	-0.002	-0.002	-0.001	0.008	0.002	0.000	0.008	0.016	0.008	0.002
LL	13512.7	13896.3	14235.8	14472.1	13517.9	13932.5	14254.9	14486.2	13557.2	13964.0	14309.0	14523.0
SBIC	-4.952	-5.093	-5.218	-5.305	-4.950	-5.103	-5.222	-5.307	-4.959	-5.108	-5.235	-5.314
LB-Q (1)	2.813	4.718	6.116	10.364	2.790	4.867	5.810	10.276	3.400	5.191	5.663	9.796
	[0.094]	[0.030]	[0.013]	[0.001]	[0.095]	[0.027]	[0.016]	[0.001]	[0.065]	[0.023]	[0.017]	[0.002]
LB-Q (10)	24.576	16.704	19.196	24.602	24.666	16.947	19.703	24.494	25.671	17.376	18.488	24.130
	[0.006]	[0.081]	[0.038]	[0.006]	[0.006]	[0.076]	[0.032]	[0.006]	[0.004]	[0.066]	[0.047]	[0.007]
ARCH (1)	10.416	3.239	0.965	3.739	9.800	1.841	0.642	2.893	9.596	1.300	0.475	2.693
	[0.001]	[0.072]	[0.326]	[0.053]	[0.002]	[0.175]	[0.423]	[0.089]	[0.002]	[0.254]	[0.491]	[0.101]
ARCH (10)	26.883	27.558	17.557	20.314	29.912	28.900	19.432	19.595	27.319	20.157	27.221	21.337
	[0.003]	[0.002]	[0.063]	[0.026]	[0.001]	[0.001]	[0.035]	[0.033]	[0.002]	[0.028]	[0.002]	[0.019]
JB test	4121.7	2808.6	2368.0	2677.9	4088.9	2805.4	2362.1	2670.4	3991.49	2768.7	2380.4	2695.0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- Sample period: 3 January 1994 to 30 September 2015, total of 5441 observations.
- LL is the log-Likelihood value and SBIC is the Schwarz Bayesian Information Criterion, Schwarz (1978).
- JB is the Jarque and Bera (1980) test for Normality which follows a chi-squared distribution with 2 degrees of freedom.
- LB-Q(1) and LB-Q(10) are the Ljung and Box (1978) statistics for 1^{st} and 10^{th} order Autocorrelation in the series which follows a chi-squared distribution with 1 and 10 degrees of freedom, respectively.
- ARCH(1) and ARCH(10) are the Engle (1982) test for 1^{st} and 10^{th} order ARCH effects and follows a chi-squared distribution with 1 and 10 degrees of freedom, respectively.
- ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 5: Estimation result of EGARCH-X models for gasoline futures

$$r_t = \alpha_0 + \alpha_1 dbm_t + \alpha_{21}\Delta v_t + \alpha_{22}u_t + \alpha_{31}\Delta v_t^B + \alpha_{32}u_t^B + \varepsilon_t \quad \varepsilon_t \sim \mathrm{GED}(0,\sigma_t^2,v) \quad ; \quad z_t = (\varepsilon_t / \sigma_t)$$

$$\sigma_t^2 = \exp\left(\beta_0 + \beta_1 |z_{t-1}| + \beta_2 z_{t-1} + \beta_3 \log(\sigma_{t-1}^2) + \delta_1 dtm_t + \delta_2 dbm_t + \delta_{31}\Delta v_t + \delta_{32}u_t + \delta_{41}\Delta v_t^B + \delta_{42}u_t^B + \gamma s_{t-1}^2\right)$$

	Model 1				Model 2				Model 3			
Mean	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m
α_0	0.001***	0.001**	0.001**	0.001**	0.001***	0.001**	0.001**	0.001**	0.001***	0.001***	0.001***	0.001***
	(3.477)	(2.458)	(2.483)	(2.472)	(3.469)	(2.477)	(2.495)	(2.482)	(3.030)	(2.923)	(3.060)	(2.714)
α_1	-0.007***	-0.008***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.004	-0.009***	-0.009***	-0.007***
	(-4.273)	(-5.597)	(-5.585)	(-6.163)	(-4.481)	(-5.210)	(-5.718)	(-6.127)	(-1.420)	(-4.353)	(-6.416)	(-6.171)
α_{21}	0.001	0.037	0.070	0.120	0.042	-0.057	0.066	0.017	-0.006	-0.478***	-0.648***	-0.746**
	(0.034)	(1.192)	(1.294)	(1.465)	(0.839)	(-1.191)	(0.688)	(0.121)	(-0.046)	(-3.929)	(-2.968)	(-1.995)
α_{22}									0.049	0.027	0.209**	0.142
									(0.944)	(0.506)	(1.973)	(0.872)
α_{31}					-0.068	0.148***	0.007	0.147	-0.175	0.597***	0.663***	0.936**
					(-1.120)	(2.593)	(0.059)	(0.855)	(-1.376)	(5.051)	(2.691)	(2.137)
α_{32}									-0.012	0.035	-0.120	0.022
									(-0.195)	(0.515)	(-0.961)	(0.112)
Variance												
β_0	-0.184***	-0.215***	-0.121***	-0.114***	-0.217***	-0.218***	-0.108***	-0.116***	0.084*	-0.208***	-0.125***	-0.119***
	(-4.346)	(-6.528)	(-4.054)	(-3.749)	(-4.805)	(-6.507)	(-3.823)	(-3.771)	(-1.901)	(-5.952)	(-4.281)	(-3.807)
β_1	0.174***	0.109***	0.096***	0.101***	0.186***	0.109***	0.092***	0.102***	0.161***	0.109***	0.092***	0.102***
	(13.033)	(9.494)	(8.593)	(8.964)	(13.057)	(9.393)	(8.574)	(8.994)	(12.215)	(9.280)	(8.549)	(8.878)
β_2	-0.016	-0.049***	-0.043***	-0.048***	-0.018*	-0.050***	-0.041***	-0.048***	-0.014	-0.049***	-0.039***	-0.048***
	(-1.615)	(-6.763)	(-6.103)	(-6.586)	(-1.776)	(-6.728)	(-5.955)	(-6.586)	(-1.525)	(-6.675)	(-5.701)	(-6.448)
β_3	0.974***	0.982***	0.987***	0.987***	0.971***	0.981***	0.989***	0.987***	0.981***	0.982***	0.989***	0.987***
	(221.85)	(300.40)	(361.53)	(344.67)	(206.84)	(295.99)	(387.34)	(341.81)	(259.39)	(291.93)	(387.36)	(338.03)
δ_1	-0.016***	-0.009***	-0.009***	-0.010***	-0.016***	-0.009***	-0.009***	-0.010***	-0.032***	-0.009***	-0.008***	-0.010***
	(-13.054)	(-8.393)	(-8.507)	(-9.367)	(-12.580)	(-8.221)	(-8.529)	(-9.272)	(-15.977)	(-7.248)	(-6.320)	(-8.950)
δ_2	0.087	1.424***	0.732***	0.687***	0.089	1.413***	0.736***	0.686***	-0.843***	1.283***	0.858***	0.706***
	(1.112)	(15.770)	(9.761)	(9.988)	(1.147)	(15.571)	(9.772)	(9.926)	(-7.382)	(7.888)	(8.824)	(8.780)
δ_{31}	30.399***	46.111***	42.942***	57.686***	24.690***	47.066***	31.752***	56.796***	101.307***	40.671***	73.108***	80.302**
	(13.947)	(14.229)	(6.406)	(5.722)	(8.322)	(10.252)	(3.525)	(3.500)	(12.725)	(4.366)	(3.372)	(2.209)
δ_{32}									34.455***	47.345***	37.814***	60.926***
									(11.275)	(9.937)	(4.027)	(3.543)
δ_{41}					8.980***	-0.999	18.088***	2.116***	-1.161	-1.439	9.131	-7.031
					(3.145)	(-0.228)	(1.885)	(0.121)	(-0.290)	(-0.247)	(0.499)	(-0.195)
δ_{42}									9.859***	-2.037	17.073*	0.329
									(3.163)	(-0.393)	(1.773)	(0.018)
γ	0.705***	0.462***	0.240***	0.133	0.770***	0.470***	0.229***	0.136	0.578***	0.442***	0.228***	0.137
	(4.329)	(4.354)	(2.643)	(1.311)	(4.444)	(4.412)	(2.645)	(1.327)	(4.067)	(4.118)	(2.616)	(1.333)
υ	1.315***	1.319***	1.408***	1.439***	1.306***	1.317***	1.406***	1.438***	1.278***	1.316***	1.409***	1.438***
	(40.063)	(43.696)	(41.362)	(41.853)	(38.925)	(43.595)	(41.215)	(41.754)	(39.675)	(43.250)	(40.930)	(41.379)

Diagnostics												
R-bar-sqr	0.001	-0.003	-0.002	-0.002	0.001	-0.001	-0.002	-0.002	0.001	0.006	0.002	0.000
LL	12938.9	13664.0	14081.3	14379.6	12943.3	13666.9	14083.3	14380.0	12992.0	13676.4	14091.8	14382.3
SBIC	-4.741	-5.008	-5.162	-5.272	-4.740	-5.006	-5.159	-5.268	-4.752	-5.003	-5.156	-5.263
LB-Q (1)	3.091	0.080	1.758	11.862	2.932	0.098	1.750	11.808	2.984	0.015	1.594	11.892
	[0.079]	[0.778]	[0.185]	[0.001]	[0.087]	[0.754]	[0.186]	[0.001]	[0.084]	[0.904]	[0.207]	[0.001]
LB-Q (10)	19.240	10.650	16.584	20.456	19.032	10.443	16.518	20.386	18.940	11.204	16.778	20.763
	[0.037]	[0.385]	[0.084]	[0.025]	[0.040]	[0.403]	[0.086]	[0.026]	[0.041]	[0.342]	[0.079]	[0.023]
ARCH (1)	2.473	0.139	0.867	7.293	2.154	0.104	1.088	6.959	4.411	0.080	1.710	6.589
	[0.116]	[0.709]	[0.352]	[0.007]	[0.142]	[0.747]	[0.297]	[0.008]	[0.036]	[0.778]	[0.191]	[0.010]
ARCH (10)	12.080	8.707	5.208	15.187	10.870	8.471	6.025	14.937	15.697	8.899	7.338	15.072
	[0.280]	[0.560]	[0.877]	[0.125]	[0.368]	[0.583]	[0.813]	[0.134]	[0.109]	[0.542]	[0.693]	[0.129]
JB test	7997.4	4904.5	4110.4	3360.9	7974.2	4726.0	4126.4	3357.3	8006.59	4185.91	3872.11	3246.15
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- See note in Table 4.

Table 6: Estimation result of EGARCH-X models for heating oil futures

$$r_t = \alpha_0 + \alpha_1 dbm_t + \alpha_{21}\Delta v_t + \alpha_{22}u_t + \alpha_{31}\Delta v_t^B + \alpha_{32}u_t^B + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{GED}(0,\sigma_t^2,v) \quad ; \quad z_t = (\varepsilon_t / \sigma_t)$$

$$\sigma_t^2 = \exp\left(\beta_0 + \beta_1|z_{t-1}| + \beta_2 z_{t-1} + \beta_3 \log(\sigma_{t-1}^2) + \delta_1 dtm_t + \delta_2 dbm_t + \delta_{31}\Delta v_t + \delta_{32}u_t + \delta_{41}\Delta v_t^B + \delta_{42}u_t^B + \gamma s_{t-1}^2\right)$$

	Model 1				Model 2				Model 3			
Mean	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m
α_0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.274)	(0.836)	(0.547)	(0.623)	(0.193)	(0.972)	(0.644)	(0.597)	(0.374)	(0.592)	(0.464)	(0.543)
α_1	0.005***	0.002	0.002*	0.001	0.005***	0.001	0.001	0.001	0.005**	0.002	0.002	0.001
	(3.891)	(1.520)	(1.913)	(1.218)	(3.864)	(1.109)	(1.404)	(1.209)	(2.055)	(0.908)	(1.544)	(1.167)
α_{21}	-0.082***	-0.032	-0.113***	-0.130*	-0.096***	-0.121***	-0.321***	-0.285***	-0.027	-0.158*	-0.408***	-0.397*
	(-3.220)	(-1.147)	(-2.063)	(-1.826)	(-3.089)	(-3.683)	(-4.223)	(-2.856)	(-0.310)	(-1.664)	(-2.391)	(-1.751)
α_{22}									-0.096***	-0.064*	-0.263***	-0.257***
									(-2.831)	(-1.645)	(-3.262)	(-2.399)
α_{31}					0.030	0.180***	0.406***	0.372***	-0.066	0.387***	0.764***	0.776***
					(0.639)	(4.223)	(3.851)	(2.647)	(-0.692)	(5.526)	(3.536)	(2.431)
α_{32}									0.065	0.073	0.280***	0.300*
									(1.245)	(1.265)	(2.537)	(1.883)
Variance												
β_0	-0.055*	-0.171***	-0.094***	-0.071***	-0.055*	-0.171***	-0.096***	-0.075***	0.170***	-0.207***	-0.128***	-0.080***
	(-1.850)	(-7.965)	(-4.255)	(-3.464)	(-1.833)	(-7.823)	(-4.356)	(-3.575)	(-4.497)	(8.138)	(5.561)	(3.803)
β_1	0.120***	0.084***	0.085***	0.082***	0.119***	0.085***	0.087***	0.084***	0.121***	0.086***	0.087***	0.082***
	(10.612)	(9.403)	(8.814)	(8.817)	(10.482)	(9.323)	(8.954)	(8.782)	(10.358)	(9.087)	(8.845)	(8.593)
β_2	-0.008	-0.021***	-0.022***	-0.022***	-0.008	-0.022***	-0.023***	-0.023***	-0.009	-0.023***	-0.023***	-0.023***
	(-1.126)	(-3.741)	(-3.807)	(-3.926)	(-1.162)	(-3.891)	(-3.912)	(-4.063)	(-1.210)	(-3.903)	(-3.948)	(-4.050)
β_3	0.987***	0.994***	0.994***	0.995***	0.987***	0.994***	0.994***	0.995***	0.987***	0.994***	0.994***	0.995***
	(398.53)	(600.40)	(572.90)	(619.23)	(399.27)	(587.10)	(553.77)	(605.91)	(410.58)	(572.46)	(557.96)	(610.84)
δ_1	-0.013***	-0.002	-0.005***	-0.006***	-0.013***	-0.002	-0.0051***	-0.0055***	-0.030***	0.000	-0.003***	-0.005***
	(-10.309)	(-1.549)	(-4.871)	(-5.332)	(-10.354)	(-1.546)	(-4.676)	(-5.147)	(-13.729)	(0.378)	(-2.525)	(-4.613)
δ_2	-0.310***	1.466***	0.573***	0.466***	-0.309***	1.439***	0.571***	0.4665***	-1.464***	1.710***	0.792***	0.506***
	(-3.522)	(14.412)	(7.809)	(6.394)	(-3.516)	(14.167)	(7.786)	6.404)	(-10.081)	(10.365)	(8.689)	(6.857)
δ_{31}	31.799***	48.988***	68.107***	71.750***	32.627***	48.343***	73.480***	76.661***	106.933***	64.019***	144.04***	112.961***
	(15.879)	(15.274)	(11.711)	(9.286)	(14.502)	(14.535)	(9.082)	(7.791)	(12.888)	(8.694)	(7.962)	(5.215)
δ_{32}									44.542***	49.953***	87.076***	85.934***
									(17.990)	(13.428)	(9.788)	(8.194)
δ_{41}					-2.015	0.299	-11.663	-14.841	3.073	-1.626	-11.612	-11.552
					(-1.161)	(0.100)	(-1.246)	(-1.189)	(0.925)	(-0.471)	(-0.703)	(-0.480)
δ_{42}									-3.024	0.395	-12.286	-15.763
									(-1.491)	(0.100)	(-1.309)	(-1.249)
γ	0.740***	0.340***	0.226**	0.124	0.742***	0.341***	0.237**	0.132	0.791***	0.332	0.223**	0.125
	(5.797)	(4.015)	(2.460)	(1.364)	(5.806)	(3.944)	(2.530)	(1.431)	(6.599)	(3.797)	(2.426)	(1.370)
υ	1.323***	1.228***	1.294***	1.302***	1.322***	1.228***	1.292***	1.296***	1.281***	1.227	1.287***	1.296***
	(42.781)	(44.201)	(42.287)	(42.104)	(41.838)	(44.358)	(42.161)	(41.000)	(41.688)	(44.037)	(41.792)	(40.490)

Diagnostics												
R-bar-sqr	-0.004	-0.001	-0.001	-0.002	-0.004	0.001	0.001	-0.001	-0.003	0.004	0.001	-0.001
LL	13692.4	14092.7	14342.0	14580.9	13692.9	14099.6	14350.8	14585.2	13743.7	14105.5	14362.4	14588.0
SBIC	-5.019	-5.166	-5.258	-5.346	-5.016	-5.165	-5.258	-5.344	-5.028	-5.161	-5.256	-5.339
LB-Q (1)	3.804	4.867	5.023	6.733	3.783	5.371	5.058	6.601	3.812	5.262	5.001	6.552
	[0.051]	[0.027]	[0.025]	[0.009]	[0.052]	[0.020]	[0.025]	[0.010]	[0.051]	[0.022]	[0.025]	[0.010]
LB-Q (10)	14.404	9.432	9.367	11.955	14.440	9.539	9.255	11.674	14.561	9.205	9.025	11.435
	[0.155]	[0.492]	[0.498]	[0.288]	[0.154]	[0.482]	[0.508]	[0.307]	[0.149]	[0.513]	[0.530]	[0.325]
ARCH (1)	0.343	0.012	0.070	0.756	0.365	0.062	0.069	0.732	0.513	0.198	0.164	0.875
	[0.558]	[0.912]	[0.792]	[0.385]	[0.545]	[0.803]	[0.792]	[0.392]	[0.474]	[0.656]	[0.685]	[0.350]
ARCH (10)	12.988	21.794	15.478	20.524	13.440	21.476	14.916	20.914	15.564	20.502	16.182	21.588
	[0.224]	[0.016]	[0.116]	[0.025]	[0.200]	[0.018]	[0.135]	[0.022]	[0.113]	[0.025]	[0.095]	[0.017]
JB test	10102.9	1598.5	1117.1	1161.5	10049.7	1569.2	1105.7	1150.3	9737.86	1519.48	1095.17	1140.56
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- See note in Table 4.

Table 7: Estimation result of EGARCH-X models for natural gas futures

$$r_t = \alpha_0 + \alpha_1 dbm_t + \alpha_{21}\Delta v_t + \alpha_{22}u_t + \alpha_{31}\Delta v_t^B + \alpha_{32}u_t^B + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{GED}(0,\sigma_t^2,v) \quad ; \quad z_t = (\varepsilon_t/\sigma_t)$$

$$\sigma_t^2 = \exp\left(\beta_0 + \beta_1|z_{t-1}| + \beta_2 z_{t-1} + \beta_3\log(\sigma_{t-1}^2) + \delta_1 dtm_t + \delta_2 dbm_t + \delta_{31}\Delta v_t + \delta_{32}u_t + \delta_{41}\Delta v_t^B + \delta_{42}u_t^B + \gamma s_{t-1}^2\right)$$

	Model 1				Model 2				Model 3			
Mean	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m	1st m	2nd m	3rd m	4th m
α_0	-0.0002	-0.0007*	-0.0001	-0.0001	-0.0001	-0.001**	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.483)	(-1.938)	(-0.482)	(-0.183)	(-0.485)	(-1.969)	(-0.558)	(-0.233)	(-0.530)	(-1.073)	(-0.572)	(-0.198)
α_1	0.017***	0.020***	0.016***	0.011***	0.017***	0.020***	0.016***	0.011***	0.018***	0.017***	0.016***	0.012***
	(8.203)	(9.462)	(9.422)	(7.808)	(8.154)	(9.407)	(9.300)	(7.843)	(8.236)	(5.828)	(9.278)	(8.139)
α_{21}	0.044***	0.019	0.093***	0.183***	0.045***	-0.002	0.052	0.136**	0.039*	-0.107**	-0.128	0.089
	(3.811)	(0.951)	(2.519)	(3.197)	(3.605)	(-0.092)	(1.337)	(2.202)	(1.653)	(-2.027)	(-1.123)	(0.801)
α_{22}									0.041***	0.023	0.073***	0.157***
									(3.025)	(0.956)	(2.166)	(2.432)
α_{31}					-0.014	0.208***	0.214***	0.220*	0.014	0.281***	1.454***	0.314
					(-0.452)	(3.747)	(2.075)	(1.648)	(0.212)	(3.311)	(4.721)	(1.512)
α_{32}									0.005	0.172***	0.047	0.027
									(0.130)	(2.570)	(0.448)	(0.218)
Variance												
β_0	-0.275***	-0.487***	-0.359***	-0.273***	-0.270***	-0.488***	-0.357***	-0.270***	-0.173***	-0.480***	-0.326***	-0.248***
	(-6.670)	(-8.566)	(-6.297)	(-5.876)	(-6.484)	(-8.518)	(-6.275)	(-5.780)	(4.219)	(8.417)	(6.011)	(5.521)
β_1	0.192***	0.169***	0.162***	0.163***	0.191***	0.169***	0.161***	0.164***	0.176***	0.165***	0.158***	0.160***
	(12.624)	(12.672)	(9.549)	(10.532)	(12.374)	(12.636)	(9.514)	(10.518)	(11.315)	(12.366)	(9.622)	(10.617)
β_2	0.054***	0.026***	0.028***	0.029***	0.053***	0.027***	0.027***	0.029***	0.054***	0.027***	0.025***	0.029***
	(6.228)	(2.920)	(3.105)	(3.307)	(6.196)	(2.947)	(3.065)	(3.292)	(6.748)	(3.034)	(2.843)	(3.394)
β_3	0.962***	0.947***	0.956***	0.969***	0.962***	0.947***	0.957***	0.970***	0.966***	0.950***	0.961***	0.972***
	(184.27)	(132.69)	(152.53)	(203.35)	(184.67)	(132.30)	(153.25)	(202.37)	(204.09)	(135.88)	(163.15)	(213.84)
δ_1	-0.017***	-0.009***	-0.013***	-0.013***	-0.017***	-0.009***	-0.013***	-0.013***	-0.022***	-0.008***	-0.013***	-0.013***
	(-14.670)	(-7.631)	(-10.260)	(-10.356)	(-14.526)	(-7.490)	(-10.160)	(-10.302)	(-14.976)	(-5.505)	(-10.209)	(-10.540)
δ_2	0.339***	1.122***	0.664***	0.754***	0.337***	1.119***	0.662***	0.746***	0.189***	1.235***	0.750***	0.812***
	(5.624)	(14.744)	(9.501)	(11.360)	(5.506)	(14.097)	(9.477)	(11.175)	(3.192)	(11.303)	(9.029)	(11.580)
δ_{31}	13.800***	19.248***	22.061***	51.984***	13.684***	18.838***	20.720***	53.573***	23.360***	23.494***	52.894***	98.548***
	(23.148)	(14.351)	(7.939)	(10.640)	(20.544)	(13.795)	(7.118)	(9.634)	(14.756)	(8.910)	(6.560)	(8.630)
δ_{32}									16.384***	20.275***	26.610***	65.437***
									(18.523)	(14.026)	(8.366)	(10.775)
δ_{41}					0.874	1.266	7.456	-9.658	-1.876	-0.629	-15.337	-22.804
					(1.171)	(0.508)	(1.054)	(-1.104)	(-0.966)	(-0.218)	(-0.989)	(-1.288)
δ_{42}									-2.668***	-2.022	4.028	-10.072
									(-2.296)	(-0.745)	(0.562)	(-1.026)
γ	0.386***	0.458***	0.327***	0.155***	0.383***	0.458***	0.328***	0.152***	0.365***	0.435***	0.307***	0.145***
	(6.758)	(7.626)	(6.249)	(3.587)	(6.747)	(7.569)	(6.280)	(3.526)	(7.377)	(7.446)	(6.192)	(3.496)
υ	1.197***	1.269***	1.289***	1.301***	1.197***	1.269***	1.285***	1.299***	1.175***	1.270***	1.274***	1.290***
	(46.054)	(53.134)	(39.125)	(39.803)	(45.959)	(51.392)	(39.163)	(39.552)	(46.053)	(47.045)	(38.652)	(39.014)

Diagnostics												
R-bar-sqr	0.010	0.011	0.005	0.002	0.010	0.018	0.007	0.003	0.008	0.017	0.013	0.002
LL	11340.5	11784.6	12393.4	13005.5	11340.8	11790.6	12396.7	13007.1	11374.0	11794.6	12412.1	13021.4
SBIC	-4.154	-4.318	-4.542	-4.767	-4.151	-4.317	-4.540	-4.764	-4.157	-4.312	-4.539	-4.763
LB-Q (1)	8.901	12.501	4.643	7.025	8.786	11.840	4.607	7.081	8.839	12.642	4.053	6.771
	[0.003]	[0.000]	[0.031]	[0.008]	[0.003]	[0.001]	[0.032]	[0.008]	[0.003]	[0.000]	[0.044]	[0.009]
LB-Q (10)	26.246	22.731	14.818	19.310	26.176	21.833	14.826	19.158	26.039	22.414	14.019	19.013
	[0.003]	[0.012]	[0.139]	[0.037]	[0.004]	[0.016]	[0.139]	[0.038]	[0.004]	[0.013]	[0.172]	[0.040]
ARCH (1)	0.159	18.442	5.877	0.743	0.243	17.710	5.989	0.623	0.297	18.229	4.823	0.440
	[0.690]	[0.000]	[0.015]	[0.389]	[0.622]	[0.000]	[0.014]	[0.430]	[0.586]	[0.000]	[0.028]	[0.507]
ARCH (10)	16.277	32.658	40.435	29.223	15.516	32.732	40.597	28.342	10.503	32.650	37.975	25.486
	[0.092]	[0.000]	[0.000]	[0.001]	[0.114]	[0.000]	[0.000]	[0.002]	[0.398]	[0.000]	[0.000]	[0.005]
JB test	12141.6	7313.3	16053.7	5702.7	12105.9	6360.5	15940.9	5638.6	12251.2	6859.23	14209.7	5652.0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- See note in Table 4.

Table 8: The effect of slope of forward curve and volatility on net position of commercial and non-commercial traders

$$y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i y_{t-i} + \delta S_{t-1} + \gamma \sigma_{t-1} + \varepsilon_t$$

	WTI Crude Oil		Gasoline		Heating Oil		Natural Gas	
	Commercial	Non-commercial	Commercial	Non-commercial	Commercial	Non-commercial	Commercial	Non-commercial
α_0	-0.077***	0.281***	-0.155***	0.498***	-0.072***	0.203**	0.085	-0.148*
	(-2.723)	(3.773)	(-7.373)	(6.001)	(-3.554)	(2.215)	(1.264)	(-1.905)
α_1	0.975***	0.926***	0.931***	0.920***	0.931***	0.920***	0.989***	0.941***
	(131.075)	(64.921)	(84.590)	(65.061)	(75.398)	(69.247)	(210.53)	(91.756)
δ	0.100***	-0.534***	0.063*	-0.452***	0.106***	-0.553***	0.044***	-0.315***
	(3.611)	(-3.087)	(1.914)	(-3.793)	(2.868)	(-2.689)	(3.496)	(-3.989)
γ	0.410**	-2.302**	0.455	-0.506	-0.047	-0.842	-0.022	0.643
	(2.470)	(-2.424)	(1.599)	(-0.415)	(-0.158)	(-0.539)	(-0.255)	(1.183)
$\bar{R}^2$	0.952	0.872	0.870	0.854	0.869	0.853	0.977	0.898

- Sample period: March 1995 to September 2015, 1070 weekly observations.
- Standard errors are corrected for Heteroscedasticity and/or Autocorrelation using Newey and West (1987) method where necessary.
- ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Figure 1: Plots of the slope of forward curve for different energy commodities as the log difference between 6-month and near month futures prices

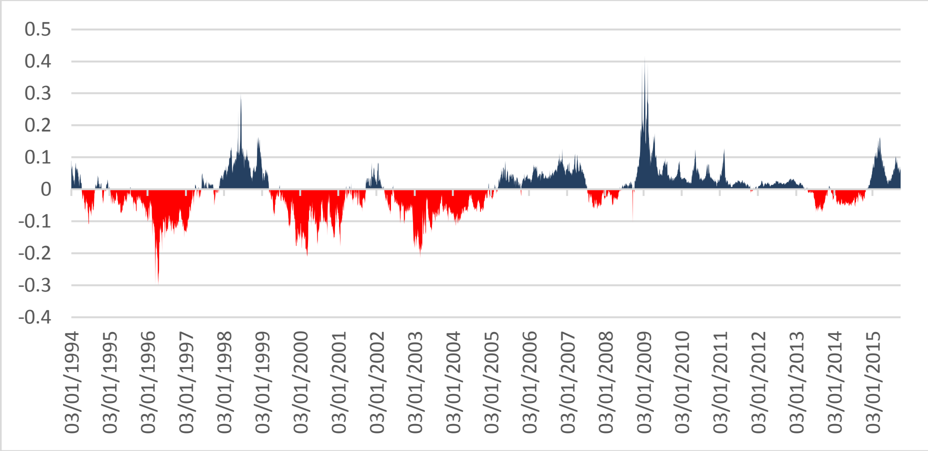
NYMEX WTI Crude Futures

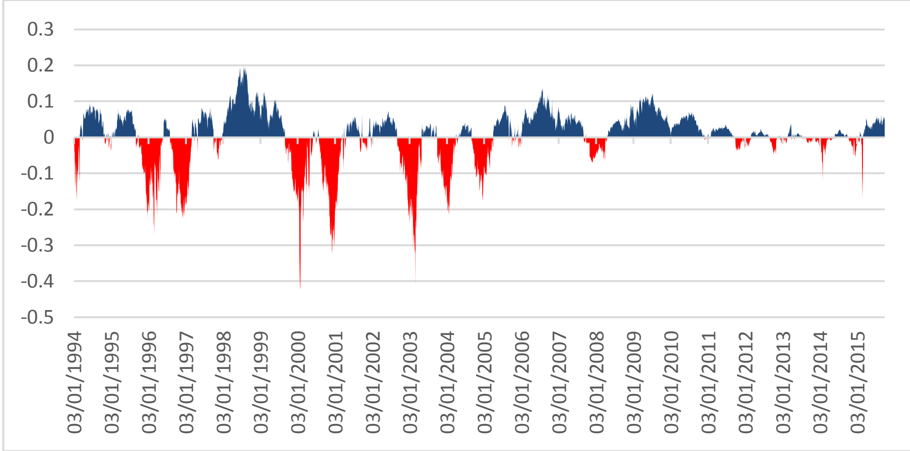
NYMEX New York Harbour Heating Oil No 2

Table 9: Granger Causality test between trader type net position and slope of forward curve

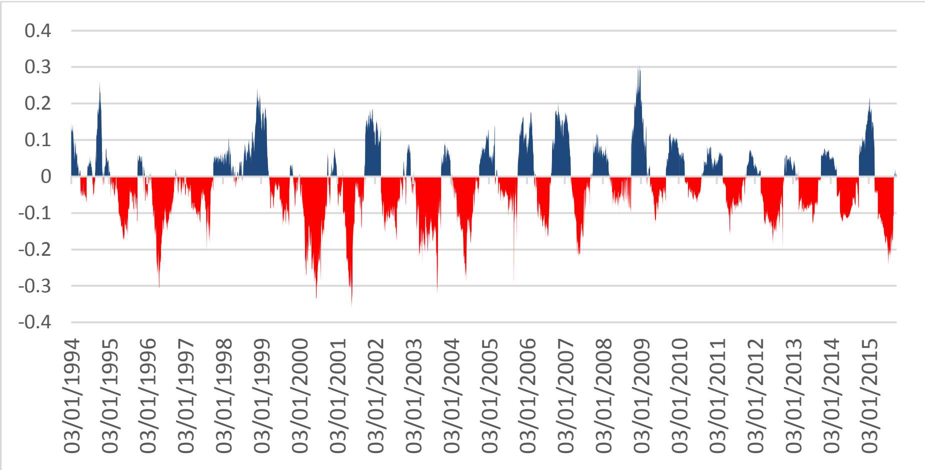
	WTI Crude oil		Gasoline		Heating Oil		Natural Gas	
	Commercial	Non Commercial	Commercial	Non Commercial	Commercial	Non Commercial	Commercial	Non Commercial
Slope Granger Causes Net Position								
Lags	2	2	5	2	3	3	2	2
Wald Test Statistics	11.842	7.267	13.500	14.421	9.234	11.443	10.959	8.334
P-value	[0.003]	[0.026]	[0.002]	[0.001]	[0.026]	[0.010]	[0.004]	[0.015]
Net Position Granger Causes Slope								
Lags	2	2	5	2	3	3	2	2
Wald Test Statistics	1.906	1.436	6.934	0.594	7.749	6.074	3.819	6.945
P-value	[0.86]	[0.488]	[0.226]	[0.743]	[0.052]	[0.108]	[0.148]	[0.031]

- Sample period: March 1995 to September 2015, 1070 weekly observations.
- The Granger-Causality test is performed on VAR models with slope of forward curve and trader types' net position as endogenous variables.
- The lag length for each VAR model is chosen according to the SBIC.
- The Wald test statistics is for the exclusion of the explanatory variable (slope or net position) in a VAR model.





NYMEX New York Harbour Gasoline



NYMEX Henry Hub Natural Gas

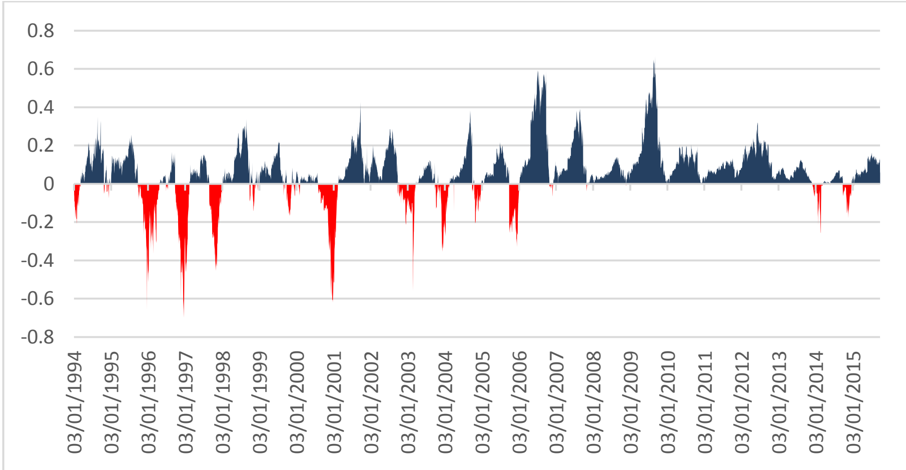


Figure 2: Scatter plot of relative net position (NP) of commercial and non-commercial traders against the slope of forward curve