Dynamics of the Forward Curve and Volatility of Energy Futures Prices

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ABSTRACT

The shapes of forward curves of energy commodities are believed to contain information on the volatility of futures prices for these commodities. The slope of the forward curve not only reflects temporal supply and demand conditions, but also the relationship between current and expected market conditions. However, no empirical investigation exists in the literature on whether utilising information on the slopes of the forward curves of energy commodities can improve one's ability to capture the dynamics of the volatility of the futures prices of these commodities. The aim of this study is to undertake such an investigation. Daily energy futures prices traded on the New York Mercantile Exchange (NYMEX) over the period January 1997 to December 2006 are used to estimate the parameters of an augmented transition EGARCH model that allows for changes in the model's parameters based on the forward curve. The forecasting performance of the model is compared to that of other models in predicting the volatility of energy futures prices over the period January 2007 to December 2008. The results provide strong support in favour of a convex relationship between the volatility of energy futures prices and the forward curve.

Key words: Energy Futures, Volatility, Forward Curve, Forecasting, VaR.
JEL Classification: C01, C12, C53, G13, G32, Q41, Q47.

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1. Introduction

In 2008 the world's energy consumption reached its highest record level: 11,295 million petroleum tons (crude oil, oil products, and natural gas), coal, and nuclear and hydro electricity, representing 59%, 29% and 12% of this consumption, respectively.[1] The dependence of the world economy on energy commodities has been highlighted in numerous studies, e.g., studies by Lee et al. (1995), Ferderer (1996), Huang et al. (1996), and Sadorsky (1999, 2003). In recent years, competition to secure supplies of energy commodities by developed and developing economies and the growth in international trade and its transportation have contributed to substantial increases in the price and price volatility of energy commodities. Also, world political events have impacted energy markets and thus energy prices and price volatilities, e.g., the price of natural gas imported by Europe from Russia via Ukraine increased in the winter of 2008 following a dispute between Europe and Russia.

Also in recent years, energy commodities have become an important asset group for investors and traders who use such commodities for diversification, speculation and investment purposes. This occurrence has been the impetus for a large body of literature that models the behaviour and dynamics of the volatility of energy prices (mainly oil and oil products). Wilson et al. (1996) found that there were three major shifts in the volatility of world oil prices during the 1984-1992 period, attributed to the nature and magnitude of the exogenous shocks – OPEC policy changes, Iran-Iraq conflict, Gulf War and extreme weather conditions. Fong and See (2002) found that the volatility of oil prices can vary with market conditions.

Sadorsky (2006) in examining the forecasting performance of GARCH and Threshold GARCH (TGARCH) type models in predicting volatility of daily oil prices concludes that no one model is the best predictor. Further, non-parametric models perform better than parametric models based upon back-testing. This is expected because of the deviation of the oil price distribution from normality and the existence of excess kurtosis as observed by Chan et al (2007). Narayan and Narayan (2007) report that asymmetric impact of shocks on the volatility of oil prices and the persistence of this volatility can be different depending on sample period considered. Fan et al. (2008) propose a Generalised Error Distribution (GED) GARCH approach to estimate Value-at-Risk of WTI and Brent crude oil prices. They argue that this approach is more appropriate as it can address deviations from normality. Alizadeh et al. (2008) examine the performance of Markov Regime Switching GARCH (MRS-GARCH) models for hedging WTI Crude Oil, Heating Oil, and Gasoline futures contracts traded in NYMEX, and report that regime switching hedge ratios are generally perform better than other dynamic hedge ratios.

In a recent study, Kang, Kang and Yoon (2009) examine the specification of different GARCH type volatility models in capturing, forecasting and identifying stylized features of volatility of crude oil prices for WTI, Brent and Dubai grades. They find that Component GARCH (CGARCH) and Fractionally Integrated GARCH (FIGARCH) models are better

[1] BP Statistical Review of World Energy 2009.

equipped to explain the persistence of volatility of crude oil prices compared to simple GARCH and IGARCH models. In the natural gas market, Suenaga et al. (2008) examine the dynamics of volatility of NYMEX Natural Gas prices and report that while volatility tends to increase in winter, volatility persistence and correlation between concurrently traded contracts exhibits certain degree of seasonality. They also argue that ignoring such behaviour in volatility dynamics can result in sub-optimal hedging strategies. Models that have been used to investigate the volatility of energy prices, in turn, have been used for deriving hedge ratios (e.g. Haigh and Holt, 2002, Alizadeh et al, 2008), risk monitoring and Value-at-Risk estimations (e.g. Sadorsky, 2006, Sadeghi and Shavvalpour, 2006, Hung et al., 2008, and Marimoutou et al., 2009), asset allocation (e.g. Alizadeh and Nomikos, 2008, Liao, et al., 2008) and derivatives pricing (Brennan and Schwartz, 1985, and Schwartz, 1997, and Anderluh and Borovkova, 2008).

An aspect of the volatility of energy prices that has not been considered heretofore in the literature is the slope of the energy forward curve – a proxy for market condition - that can explain the dynamics of volatility of the energy prices. Whilst the theoretical underpinning of energy forward curve has been discussed by Litzenberger and Robinowitz (1995), Carlson et al. (2007) and Kogan et al. (2009), the nature of the curve and its importance to our understanding of the dynamics of the volatility of energy prices have not been examined in the literature. The purpose of this study is to empirically investigate whether incorporating the slope of the forward curve in energy price volatility models can improve their ability to capture the dynamics of second moments of the futures prices as well as to improve the forecasting performance of these models.

This study contributes to the literature on modelling the volatility of energy prices in several ways. First, it provides empirical evidence of the existence of a strong convex relationship between the slope of forward curve and the volatility of energy prices. Second, it establishes that the dynamics of the volatility of energy prices depends on the market conditions defined by the shape of the forward curve. Third, using short-term energy futures prices, it assesses the impact of the shape of forward curve on 1, 2, and 3 monthly maturity futures energy price volatilities. Finally, it compares the forecasting performance of energy price volatility models that incorporate the shape of the forward curve with conventional volatility models that do not include the shape of the curve as well as measures the asymmetry of the forecasts. The study's findings are expected to have important implications for traders and other participants in energy futures markets by allowing them to accommodate asymmetry in risk assessment and loss functions measurement of these markets.

The study is structured as follows. The next section reviews the theoretical background on the relationship between the market condition for energy commodities (as reflected by the slope of the forward curve) and the volatility of energy commodity prices. Section 3 presents proposed statistical models to be used in investigating the relationship between the forward curve and volatility of energy prices. Section 4 describes the data that are to be used in the estimation of the parameters of these models. Then, the estimation results are presented in section 5, while sections 6 and 7 discuss the forecasting performance and accuracy of VaR estimates of different volatility models, respectively. In the final section, conclusions of the study are found.

2. Theoretical background

Market prices for energy commodities are determined via the market clearing supply-demand process. However, since energy commodities are exhaustible natural resources, the market clearing supply-demand process for these commodities will differ somewhat from the market clearing process of commodities with infinite supply. Theoretical models of the dynamics of energy prices and their volatilities have developed through a series of studies that have taken two different approaches in this development. The first approach is based on statistical models of commodity price dynamics where convenience yield is assumed to be exogenous, stochastic, and correlated with price (e.g., studies by Brennan and Schwartz 1985, Brenan 1991, and Schwartz 1997). In the second approach, an endogenous price process is derived from an equilibrium price framework, where production, demand, storage, and inventories are considered (e.g., studies by Litzenberger and Robinowitz, 1995, Routledge et al., 2000, Carlson et al., 2007, Geman and Ohana, 2009, and Kogan et al., 2009).[2]

Litzenberger and Robinowitz (1995) note that energy prices exhibit strong backwardation, i.e., discounted futures prices are below spot prices. Assuming that price and production are uncertain, they argue that holding commodity extraction rights is similar to a call option with a strike price (a proxy for extraction cost) and that price backwardation arises from an equilibrium trade-off between exercising the option or keeping it alive. That is to say, if discounted futures prices are higher than spot price and the cost of extraction was to increase, all producers would postpone extraction, thereby resulting in an increase in the spot price and weak price backwardation. Litzenberger and Robinowitz (1995) thus claim that the existence of weak price backwardation in energy markets is a necessary condition for current production. In addition, due to the production capacity constraint, they show that there is a positive and linear relationship between the volatility of energy prices and the degree of price backwardation. Assuming a mean reverting demand process and the resulting equilibrium inventory dynamics, Routledge et al. (2000) derive spot and forward energy prices. They show that their model in utilizing a backwardation forward curve captures the impact of low stock levels and high consumption of energy commodities.

A study by Carlson et al. (2007) develops a general equilibrium model for a market for an extractable resource, where both prices and extraction costs are determined endogenously. The study argues that production adjustment costs result in endogenous extraction choices that, in turn, cause higher price volatility both at high and low demand levels. Further, the Carlson et al. (2007) model allows for a nonlinear U shape relationship between the slope of forward curve and price volatility due to production and extraction choices and adjustments. Geman and Ohana (2009) in using the slope of the forward curve as a proxy for inventory levels of energy commodities finds a negative correlation between price volatility of oil prices and oil inventory levels. This negative correlation however prevails only during periods of scarcity when oil inventory levels are below the historical.

More recently, Kogan et al. (2009) argue that models such as that of Litzenberger and Robinowitz (1995), based on competitive storage and changes in inventory for future price determination, ignore the production side of the economy. This shortcoming is addressed by developing a model for determining energy futures prices in an equilibrium production economy with stochastic demand. Kogan et al. (2009) show that irreversibility and maximum investment rate constraints can affect the investment, output and supply decisions of energy

[2] Also, see studies by Deaton and Laroque (1992, 1996), Williams and Wright (1991), and Chambers and Baily (1996).

commodity firms, and therefore, the volatility of futures prices of energy commodities. Kogan et al. (2009) also conclude that the relationship between the forward curve and price volatility is non-monotonic and V shape. Their theoretical argument to support this relationship is as follows: if the capital stocks for energy commodity firms are much higher than the optimal level (for a given demand level), the firms' decisions would be to postpone investment and irreversibility constrains binds. However, when capital stocks are below the optimal level, firms tend to increase their investment rate and the investment rate constraint will be binding. Therefore, in both cases (extremes), the supply curves for energy commodities will become inelastic and therefore futures prices will become more volatile.

Energy commodities tend to have highly price inelastic demand curves, since they are necessaries as opposed to luxury commodities, i.e., they are needed not only for day to day life such as transportation and heating, but also as an input into many industrial production processes (see Figure 1). On the other hand, supply curves for energy commodities tend to have highly price elastic and inelastic sections (see Figure 1). In region B in Figure 1, the demand curve is highly price inelastic and the supply curve is highly price elastic. An increase (decrease) in demand in this region will result in a pronounced increase (decrease) in supply and a relatively small increase (decrease) in price. In fact, at such price and demand levels, producers (suppliers) are able to adjust production (supply) and respond to changes in demand. This includes reducing production, using storage facilities to stock up excess production, adjusting refining output, reducing flow of gas through pipelines, and other methods. At the same time, when market recovers and demand start to increase, the excess capacity can be utilised to boast production to meet excess demand. In region C in Figure 1, both the demand and supply curves are highly price inelastic. The supply curve is price inelastic due to limited production capacity. A pronounced increase in price is needed to obtain the same increase in output that occurred in region B from a relatively small increase in price. In region A in Figure 1, both the demand and supply curves are again highly price inelastic. However, the supply curve is now price inelastic, mainly due to the irreversibility of capital investment in up- and down-stream oil and gas producing firms. Also, the costs of reactivating a production site following a shutdown are expected to be high. Further, in certain instances, reactivation of a production site may not be possible. Thus, energy commodity firms may continue to produce, even at relatively low prices.

3. Methodology

This study models prices of energy commodities via the EGARCH statistical model (Nelson, 1991). 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. Specifically, three versions of the EGARCH model are utilized: 1) Simple EGARCH model, 2) Augmented EGARCH model (EGARCH-X), and 3) Augmented Transition EGARCH model (EGARCH-TX). The Simple EGARCH model is specified as

$$\begin{aligned} r_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_{1,i} r_{t-i} + \varepsilon_t \quad , \quad \varepsilon_t \sim iid\,(0, \sigma_t^2) \\ \sigma_t^2 &= \exp(\beta_0 + \sum_{i=1}^{k} \beta_{1,i} \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{l} \beta_{2,i} \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{i=1}^{m} \beta_{3,i} \ln \sigma_{t-i}^2) \end{aligned} \tag{1}$$

Where r_t represents one period percentage price change in an energy commodity as an Autoregressive process function of its past values; ε_t is an independently and identically distributed random error process with zero mean and variance, σ_t^2. The variance, σ_t^2, is specified as an exponential function of lagged standardised residuals and lagged log of variance. While the main advantage of EGARCH specification is that it allows for asymmetric impact of shocks on price volatility, it also ensures positive definiteness of variances. In equation 1 the $\beta_{1,i}$ coefficients measure the asymmetric impact of shocks (with respect to different magnitudes) on price volatility, while $\beta_{2,i}$ coefficients reflect the asymmetric impact of shocks (with respect to different signs) on price volatility. Coefficients of lagged variance, $\beta_{3,i}$, measure the degree of persistence of price volatility on its past values.

The effect of the slope of the forward curve on volatility of energy prices can be investigated by augmenting the variance equation in the Simple EGARCH model above to include the extra term – the quadratic function of the slope of the forward curve – to obtain the Augmented EGARCH model (EGARCH-X), i.e., equation 2.

$$
\begin{aligned}
r_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_{1,i} r_{t-i} + \varepsilon_t \quad , \quad \varepsilon_t \sim iid(0, \sigma_t^2) \\
\sigma_t^2 &= \exp\left(\beta_0 + \sum_{i=1}^{k} \beta_{1,i} \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{l} \beta_{2,i} \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{i=1}^{m} \beta_{3,i} \ln \sigma_{t-i}^2 + \gamma z_{t-1}^2\right)
\end{aligned}
\tag{2}
$$

where z_{t-1} represents the slope of the forward curve at time *t-1* calculated as the difference between the log of the 6^{th}-month and the near-month futures prices. The quadratic function is included to capture the asymmetric relationship between volatility of energy prices and the slope of the forward curve both in terms of the sign and the magnitude. Also, it is included, because it is believed that this relationship between the slope of the forward curve and volatility of energy prices is non- linear and U shape.[3] The choice of the futures contracts to measure the slope of the forward curve is based on the idea that 6 month differences in futures contracts can present a clear picture with regard to the degree of contago or backwardation of the forward curve.

Once again, $\beta_{1,i}$ coefficients measure the asymmetric impact of shocks (with respect to different magnitudes) on price volatility, while $\beta_{2,i}$ coefficients reflect the asymmetric impact of shocks (with respect to different signs) on price volatility. The coefficient of the slope of the forward curve, γ, measures the relationship between volatility of prices and the market condition for which the slope of the forward curve is its proxy. Furthermore, the use of EGARCH-X specification ensures that the non-negativity constraints on the parameters of the model are not violated, especially since the slope of the forward curve can be negative.

The Augmented Transition EGARCH-X model (i.e., EGARCH-TX) augments the EGARCH-X model by allowing the sign of the slope of the forward curve to be either negative or positive. The EGARCH-TX model is specified as follows

[3] We also used linear specification in the form of absolute value of zt-1, but empirical results and Likelihood Ratio tests strongly supported the quadratic relationship.

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1,i} r_{t-i} + \varepsilon_t \quad , \quad \varepsilon_t \sim iid\,(0, \sigma_t^2)$$

$$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2 +$$
$$\delta_0 S_{t-1} + \delta_1 S_{t-1} \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \delta_2 S_{t-1} \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_3 S_{t-1} \ln \sigma_{t-1}^2) \tag{3}$$

where S_t is a dummy variable taking a value of one when the slope of forward curve is negative, i.e., the market is in backwardation, and a value of zero when the slope of forward curve is positive, i.e. the market is in contango. Therefore, whether the behaviour of price volatility depends on the market condition and the slope of the forward curve can be tested by whether the estimates of coefficients δ_0, δ_1, δ_2, and δ_3 are statistically significant. Furthermore, EGARCH-TX equation (3) can be regarded as a more general specification of the time-varying variance that not only incorporates information regarding changes in market condition and the slope of forward curve, but also allows for the dynamics of the variance to be dependent on the slope of the forward curve.

The above three EGARCH model versions are estimated using futures prices for four main energy commodities. Further, tests will be performed to investigate whether the estimated models capture the dynamics of the time-varying volatility of energy futures prices.

4. Description of data

The data used in this study comprises daily futures prices for four main energy commodities traded on the New York Mercantile Exchange (NYMEX) – WTI Crude Oil, the New York Harbour Heating Oil Number 2, the New York Harbour Unleaded Gasoline, and the Henry Hub Natural Gas Futures – for the period January 1, 1997 to December 31, 2008. The data was obtained from Datastream. After filtering the data for holidays, missing values and non-trading dates, the final sample contains 3,013 daily observations. To construct a continuous series out of monthly traded contracts the contracts were rolled over to the next once trading activity has shifted from the nearest to the second nearest to maturity contract. Consequently, in all cases, three continuous futures series with 1- , 2- and 3-month to maturity were constructed. Data for the period 1st January 1997 to 31st December 2006 (2,509 observations) are used for the in-sample analysis; out-of-sample analysis is carried out using the remaining data for the period of 1st January 2007 to 31st December 2008 (504 observations).

Summary statistics of logarithmic first-differences ("log-returns") of daily prices for the whole period in the four energy markets 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 3.0% to 9.2%. The unconditional volatility of returns declines as maturity increases, which confirms the Samuelsson effect and the term structure of volatility of energy prices due to mean reversion. Also, comparisons 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- and 3- month contracts across all commodities. The Ljung and Box (1978) statistic on the first 10 lags of the sample autocorrelation function is not significant for Heating Oil, Gasoline and Natural Gas returns, revealing that serial correlation is not present. However, the Ljung and Box (1978) statistic indicates some degree of autocorrelation in crude oil return series. The Engle's (1982) ARCH test, carried out as the Ljung-Box tests on the squared return series, indicate the existence of strong heteroscedasticity in 1-, 2- and 3-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.

The state of the market for a given energy commodity over the sample period is illustrated in the plot of the slope of the forward curve measured as the difference between the 6^{th}-month and the near-month futures prices for the four energy commodities. A positive slope suggests that the market is contango and a negative slope suggests that the market is in backwardation. The slopes of forward curves for the four energy commodities are presented in Figures 2 to 5. It can be seen that all in 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 markets.

5. Empirical Results

This section presents the empirical results on the relationship between the term structure and the volatility of energy futures prices. Different EGARCH models that link the dynamics of term structure and volatility are estimated.

The estimation results of the EGARCH(1,1), EGARCH-X(1,1) and EGARCH-TX(1,1) models for the near-month, 2^{nd}-month and 3^{rd}-month return series for WTI Crude, Heating Oil, Gasoline, and Natural Gas are presented in Tables 2 to 5, respectively. Models are estimated using the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992) that yields robust standard errors in the presence of non-normality. The tables include regression statistics and diagnostics tests with respect to specification, validity and in sample performance.

In Table 2 the diagnostic tests of the estimated crude oil futures prices EGARCH models suggest that all the models are well specified and there is no sign of 1^{st} or 10^{th} order autocorrelation or first order ARCH effects in standardised residuals of each model. However, there seem to be some 10^{th} order ARCH effects in models for 2^{nd} and 3^{rd} month futures that could not be removed, even with the introduction of higher-order ARCH terms in variance specifications. The coefficients of size asymmetry, β_1, are positive and significant in all models and across all maturities, thereby suggesting that larger-than-average shocks or news (price changes) have a greater impact on volatility than smaller-than-average shocks. The coefficients of sign asymmetry, β_2, are negative and significant in all models, except in the EGARCH-TX models for 2^{nd} and 3^{rd} month futures, therefore suggesting that bad news (negative price changes) tend to have a greater impact on volatility than good news (positive price changes). The coefficients of lagged volatility are positive and statistically significant and ranging in value from 0.948 to 0.971, thereby indicating high persistence in volatility in all models. More importantly, coefficients of lagged squared slope, γ, are all positive and statistically significant in the EGRACH-X and EGARCH-TX models across all maturities –

indicating a quadratic relationship between the volatility and the slope of the forward curve, meaning that volatility increases at an increasing rate as the market moves deeper into backwardation or contango.

The coefficients of transition in the dynamics of volatility, δ_0, δ_1, δ_2, and δ_3, are negative and statistically significant in the EGARCH-TX models, suggesting that the behaviour of volatility changes as market moves from contango to backwardation. For instance, the negative δ_3 coefficients for all maturities suggest that volatility is lower in a backwardated market than in a contango market. The negative δ_2 coefficients in the 2^{nd} and 3^{rd} month models suggest that negative shocks or bad news tend to a have greater impact on volatility than positive shocks or good news only when the market is in backwardation. Finally, the likelihood ratio, LR, tests for the null of $\delta_0=\delta_1=\delta_2= \delta_3=0$ are rejected for 2^{nd} and 3^{rd} month EGARCH-TX models, suggesting that the dynamics of volatility of crude oil futures are dependent the state of the market.[4]

In Table 3 the diagnostic tests of the estimated gasoline futures prices EGARCH models suggest that all the models are well specified and with no sign of autocorrelation or ARCH effects in residuals. The estimation results for gasoline futures prices indicate that there are significant size effects across all maturities in EGACH and EGARCH-X models, since the coefficients of β_1 are positive and statistically significant. However, the EGARCH-TX estimate for the 2^{nd} month return series suggests that size effects are only present when the market is backwardated since coefficient β_1 is insignificant and the coefficients of δ_1 is positive and significant. At the same time, coefficients of sign effects, β_2, for 2^{nd} and 3^{rd} month futures are negative throughout in the EGARCH, EGARCH-X and EGARCH-TX models and are statistically significant except for the coefficient in the EGARCH-TX model for the 2^{nd} month return series. Moreover, coefficients of lagged squared slope of forward curve, γ, are all positive and significant in EGRACH-X and EGARCH-TX models and across all maturities. Significance of the likelihood ratio tests for the joint significance of δ_0, δ_1, δ_2, and δ_3 in the EGARCH-TX models confirm that these unrestricted models can capture the dynamics of volatility of gasoline futures better than restricted models EGARCH and EGARCH-X models.

The estimates of the heating oil futures prices EGARCH models are presented in Table 4. Again, the diagnostics tests suggest that the models are well specified, with the exception of the test for normality. Estimated coefficients of size asymmetry, β_1, are all positive and statistically significant, suggesting that larger shocks have a relatively greater impact on volatility than smaller shocks. The statistically significant and positive δ_1 coefficients in the EGARCH-TX model estimates suggest that the impact of larger shocks on volatility is greater than smaller shocks when the heating oil market is backwardation than when it is in contango. Estimated coefficients of β_2 and δ_2 are all insignificant which suggests that there is no asymmetric impact on volatility with respect to shocks of different signs. Coefficients of δ_3 are all negative and significant in the case of 2^{nd} and 3^{rd} month futures, meaning that volatility persistence declines as the market moves from contango to backwardation. The coefficients of γ are all positive and statistically significant in the EGRACH-X and EGARCH-TX models across all maturities. Once again, the likelihood ratio tests reject the restricted EGARCH and

[4] The LR test is a test for joint significance of δ_0, δ_1, δ_2, and δ_3 with the null of $\delta_0=\delta_1=\delta_2= \delta_3=0$. The test statistic is calculated as $LR = 2[LL_{ur} - LL_r]$ where LL_{ur} and LL_r are the Loglikelihood of the *unrestricted* model (EGARCH-TX) and *restricted* model (EGARCH-X). The test statistics follows a chi-squared distribution with 4 degrees of freedom, χ^2_4.

EGACRH-X models in favour of the EGARCH-TX model in the case of near month and 2nd month futures.

Finally, the estimates of the natural gas futures prices EGARCH models are found in Table 5. The diagnostic tests confirm that the models are well specified with no sign of autocorrelation or ARCH effects in residuals. The coefficients of size asymmetry, β_1, are positive and statistically significant in all models across all maturities. The estimated coefficients of δ_1 in the EGARCH-TX models are negative and statistically significant for the near month and second month futures – suggesting that the asymmetric impact of shocks with different magnitudes is less when the natural gas market is in backwardation than when it is in contango. Estimated coefficients β_2 are positive and statistically significant in the EGARCH and EGARCH-X models, suggesting that positive shocks tend to increase volatility more than negative shocks. Conversely, the estimated coefficients of β_2 for the EGARCH-TX models are statistically insignificant. The estimated δ_2 coefficients are positive and statistically, revealing that an asymmetric impact of shocks with different signs on volatility exists when the market is in backwardation. Additionally, the δ_3 coefficients are negative but only significant in the near month series, suggesting similar volatility persistence under backwardation and contango in the near month series. The coefficients of γ are all positive and significant in the EGRACH-X and EGARCH-TX models and across all maturities – again suggesting the existence of a quadratic relation between volatility and the slope of the forward curve but now in the natural gas market. Furthermore, the LR tests reject the restricted EGARCH-X models in favour of unrestricted EGARCH-TX models which allow for changes in the values of parameters and dynamics of volatility of Natural Gas futures prices.

The above estimation results reveal noticeable differences in the dynamics of the volatility of the futures prices of the four energy commodities when the condition of the market is measured via the slope of the forward curve. The volatilities vary with shocks that differ in size and in direction. For instance, negative shocks (or bad news) tend to increase the volatility of crude oil and gasoline futures prices more than positive shocks (or good news), whereas the volatility of natural gas futures tend to increase more following a positive shock than a negative shock. The volatility of crude oil, gasoline and heating oil futures prices depend on the slope of the forward curve, whereas the volatility of natural gas futures prices is independent of market conditions. There are also differences in the degree of dependence of volatility of energy commodities on the slope of forward curve. Figure 6 presents the scatter diagram of slope of forward curve and volatility of near-month futures contract for the four commodities under investigation. The scatter plots and fitted quadratic regression lines illustrate a clear quadratic association between the two variables. However, the degree of this convexity differs among the relationships.

6. Forecasting Performance of Volatility Models

The appropriateness of the above volatility models is examined by investigating their out-of-sample forecasting performance over the period January 2007 to December 2008.[5]

[5] We set the end of our estimation period two years before the end of the sample, i.e. December 2006. This allows us to use the last two years of the sample (January 2007 to December 2008, 504 observations) to examine the forecasting performance of models in predicting volatility of energy futures prices, a practice known as ex-post forecast evaluation technique.

Specifically, the out-of-sample forecast evaluation tests are carried out by comparing the forecasting performance of the one-step-ahead forecasts of the EGARCH(1,1), EGARCH-X(1,1) and EGARCH-TX(1,1) models to those of the Naïve (or Historical Variance) and Exponentially Weighted Moving Average Variance (the RiskMetrics method) models. The Naïve model, which is the simplest method of forecasting variance, is based on the assumption that the best one-period ahead forecast for variance is the current variance, i.e., $\hat{\sigma}^2_{t+1} = \sigma^2_t$, where, $\hat{\sigma}^2_{t+1}$ is the one-period ahead forecast of variance. The RiskMetrics method uses exponentially weighted average of current variance and returns to predict the future variance, $\hat{\sigma}^2_{t+1} = \lambda\sigma^2_t + (1-\lambda)r^2_t$, with a weighting coefficient of λ (e.g. λ=0.95).

The accuracy of the out-of-sample volatility forecasts for different models is investigated using the root mean square error (RMSE), which is the root of the average of the squared differences between forecasted variances and squared realised returns, i.e.,

$$RMSE = \sqrt{\sum_{i=1}^{M} \frac{(\hat{\sigma}^2_i - r^2_i)^2}{M}} \tag{4}$$

where M is the number of forecasts and r^2_i is the square of realized changes in futures prices. The RMSE essentially measures how close the variance estimates track the changes in the square of futures prices. However, RMSE does not provide information on the asymmetry of the variance prediction errors, i.e., if there is a significant difference between variance forecast errors when the variance forecasts over-predict or under-predict the realised variance (changes in futures prices).

Although forecast errors are expected to be unbiased, there might be occasions when a model over-predicts the variance of futures prices relatively more often but the forecast errors are smaller and under predicts the variance relatively less frequently but the forecast errors are larger. A model with symmetric forecast errors should produce about 50% positive and 50% negative forecast errors, with similar positive and negative mean errors. The existence of asymmetric forecast errors is investigated using the Brailsford and Faff (1996) Mixed Mean Error (MME) statistic, which uses a mixture of positive and negative forecast errors with different weights to assess the asymmetry in forecast errors.

$$MME(O) = \frac{1}{M}\left[\sum_{i=1}^{U} |\,\hat{\sigma}^2_{t+i} - r^2_{t+i}\,| + \sum_{i=1}^{O} \sqrt{\left|\hat{\sigma}^2_{t+i} - r^2_{t+i}\right|}\right] \tag{5}$$

$$MME(U) = \frac{1}{M}\left[\sum_{i=1}^{U} \sqrt{|\,\hat{\sigma}^2_{t+i} - r^2_{t+i}\,|} + \sum_{i=1}^{O} |\,\hat{\sigma}^2_{t+i} - r^2_{t+i}\,|\right] \tag{6}$$

MME(O) applies more weight to over-predicted forecast errors in calculating the MME statistic, while MME(U) applies more weight to under-predicted forecast errors in calculating the statistic. By comparing the two statistics, one can assess the relative degree of under-prediction and over-prediction of forecast errors. Asymmetric error statistics in volatility estimation and forecasting have important implications for traders and other participants in energy futures markets, since the statistics enable traders and other participants to address the issue of asymmetry in their risk assessments.

Results of different forecasts evaluation techniques for crude oil futures prices are found in Table 6. A comparison of the RMSE statistics suggests that EGACRH-TX out-performs the other models in terms of predictive accuracy. At the same time, the MME statistics reveal that all models appear to over-predict the variance of futures prices more often than under predicting. However, the mean over-prediction is much lower than the mean under-prediction in all models. The EGARCH model has the lowest MME(U) statistic and the Historical Variance model has the lowest MME(O) statistic. Nevertheless, the sum of the MME(U) and MME(O) statistics for each model reveals that this sum is the lowest for the Historical Variance, thus indicating that it has the best performance in terms of forecasting error asymmetry.

With respect to gasoline futures prices, no model outperforms the other (see Table 6) in predicting the volatility of these prices. The RiskMetrics model has the lowest RMSE statistic, while the EGARCH and Historical Variance models have the lowest MME(O) and MME(U) statistics, respectively. Once again, the sum of the MME(O) and MME(U) statistics is the lowest for the Historical Variance model.

The forecast evaluation technique results for heating oil futures prices in Table 6 suggests that the RiskMetrics model out-performs the other models in terms of predictive accuracy with respect to the RMSE and MME(O) statistics. That is to say, the RiskMetrics model has the lowest RMSE, and MME(O) statistics. However, the RiskMetrics model has the highest MME(U) statistic, while the EGARCH model has the lowest MME(U) statistic. Nevertheless, the sum of the MME(U) and MME(O) statistics for each model reveals that this sum is the lowest for the Historical Variance model, followed by the RiskMetrics model with the second lowest sum value.

For natural gas futures prices, all three EGRACH-type models have the same and lowest RMSE statistic and EGARCH-TX has the lowest MME(O) statistic. The EGARCH model has the lowest MME(U) statistic. However, the sum of the MME(O) and MME(U) statistics is the lowest for the EGACRH-TX model.

7. Value-at-Risk Analysis

VaR analysis that has become an integral part of risk management in financial institutions, trading houses, oil companies and other businesses related to energy markets, is essentially a method of monitoring risk exposure of trading positions and portfolios. By definition, VaR is the possible portfolio loss that might occur over a given time with a given probability. The time horizon over which the VaR is estimated is known as the VaR horizon, typically one day. The probability associated with VaR is the significant level (α), typically taking on values of 1%, 2.5% or 5%. For instance, a 1-day 1% VaR is the possible loss that may occur in one day with a 1% probability.

Let r_{t+k} be the (log) return on an asset over the period t to $t+k$ and (1-α) the confidence level. Then, conditional on the information set available at t, Ω_t, the VaR can be defined as the solution to the following expression:

$$\Pr(r_{t+k} \leq VaR_{t+k}^{\alpha} | \Omega_t) = \alpha \quad \textbf{(7)}$$

The simplest method among several methods for estimating VaR is to use the one-day ahead forecast of volatility, $\hat{\sigma}_{t+1}$, and the α percentile of a parametric distribution such as the standardised normal, Z_α, to obtain $VaR_{1d}^{\alpha\%} = Z_\alpha \hat{\sigma}_{t+1}$. In using this method, the accuracy and forecasting performance of VaR estimates will thus depend on the accuracy of the volatility forecast and the underlying distribution from which the α-percentile is obtained. While the α-percentile can be obtained from parametric distributions, VaR estimates can also be retrieved from the historical distribution of returns or standardised returns. These nonparametric VaR approaches, e.g., the Historical Simulation (HS) and Filtered Historical Simulation (FHS) approaches, obtain percentiles from historical distributions of returns or standardised returns.[6]

To further assess the practical implication of the results in terms of risk assessment and measurement, the VaR estimates of the proposed EGARCH-X and EGACRH-TX models are compared with other competing models using a backtesting procedure. Backtesting is performed by running the model through a given sample to test whether the proportion of times that changes in the variable/portfolio exceeded the VaR level corresponds to the significance level chosen. If such violations of VaR occur, say at α% of the time, then we are assured that the method chosen to estimate the α% VaR is relatively accurate. On the other hand, if changes in the portfolio significantly exceed the α% VaR level, one would not be confident about the predictive performance of the VaR methodology. The most commonly used framework in backtesting VaR models has been developed by Christoffersen (2003) and appears in Appendix A.

The performance of models in accuracy and efficiency of VaR estimation are compared for long and short positions of near-month futures prices of different energy commodities. The results of the VaR analysis for the four energy commodities are presented in Tables 7 to 10. In each table 1-day VaR values are reported for long and short positions and different significance levels (1%, 2.5% and 5%). Reported statistics include: number of failures or violations (N_f), percentage of violations (%), and Likelihood Ratio tests for unconditional coverage (LL_{uc}), independence coverage (LL_{ind}), and conditional coverage (LL_{cc}).

The backtesting results for near-month crude oil futures prices that are reported in Table 7 reveal that that the Historical Variance (HV), Historical Simulation (HS), and Filtered Historical Simulation (FHS) models all fail to pass one or more of LR tests in the estimation of VaR for both long and short positions (upside and downside risks). In addition, the RiskMetrics and simple EGACRH models also fail the LR tests with respect to short position when α is 2.5%. The models that pass the backtesting exercise for different levels of α are the EGARCH-X and EGARCH-TX models.

The backtesting results for gasoline futures prices found in Table 8 are mixed, since no model convincingly outperforms the others. For instance, the Historical Variance, HS, and FHS models all fail to pass one or more of the LR tests in estimation of VaR for both long and short positions for different levels of α. At the same time, the EGACRH, EGARCH-X and

[6] See Christoffersen (1998) for more details on nonparametric models for VaR estimation, and Cabedo and Moya (2003) and Costello et al. (2008) for applications of nonparametric VaR estimation in oil markets.

EGRACH-TX models pass the tests when α is 5%, but the EGACRH-TX model fails the test when α is 1% and 2.5%. Overall, the RiskMetrics and EGARCH-X models perform better than other models, i.e., passing more of the LR tests for different levels of α.

In the case of heating oil futures prices, backtesting results reported in Table 9 reveal that the Historical Variance, RiskMetrics and all EGACH models pass the LR tests for all α levels. However, the two nonparametric models fail to pass one or more of the LR tests. The backtesting results for natural gas futures prices reported in Table 10 reveal that all volatility models except the Historical Variance and FHS models pass all LR tests for long and short positions at different levels of α. The historical variance and FHS models also pass the LR tests when α is at 2.5% and 5%. However, when we consider the forecast accuracy and backtesting results together, the EGARCH-TX model performs best in terms of low RMSE values and VaR violations.

8. Conclusions

This paper has investigated the relationship between the dynamics of the term structure of forward curves and the time-varying volatility of the futures prices of energy commodities from estimation of augmented EGARCH models. The rationale for the investigation is that the slopes of forward curves not only reflect temporal supply and demand conditions, but also relationships between current and expected market conditions. Four main energy commodities traded on the New York Mercantile Exchange are used in the investigation; namely, crude oil, gasoline, heating oil and natural gas.

The main findings of the paper are as follows. First, it provides evidence that a convex (U shape) relationship exists between the forward curve and the volatility of energy prices – i.e., the volatility of energy prices increases exponentially as the market moves deeper into backwardation or contango. Second, it provides evidence that the dynamics of the volatility of energy prices and thus the behaviour of energy prices are dependent on the slope of the forward curve. Third, it enhances our understanding of the dynamics of price volatility of specific energy commodities: a) negative shocks tend to increase the volatility of crude oil and gasoline futures prices more than positive shocks; b) the volatility for natural gas tends to increase more following a positive shock than following a negative shock; c) the volatility of crude oil, gasoline and heating oil futures prices depend on the slope of the forward curve, whereas the volatility of natural gas futures prices is independent of market conditions; and d) the degree of the dependence of the volatility of energy prices on the slope of the forward curve differs among energy commodities.

Out-of-sample forecasting performance of the estimated models are somewhat mixed as there is no single model that consistently outperforms others. This might be due to the fact that the volatility of energy prices is an unobservable variable and the metric used as a proxy for this volatility (i.e., squared returns of futures prices) in evaluating forecasting performance might not be an appropriate proxy. Nevertheless, the forecasting evaluation statistics suggest that all models tend to over-predict more often than they under-predict the volatility of energy prices, but the average under-prediction is higher than the average over prediction. However, the backtesting VaR analysis results suggest that in general volatility energy-price models that include the slope of the forward curve, i.e., the EGARCH-X and EGARCH-TX models, perform reasonably well in forecasting energy prices in main energy markets.

Appendix A

A sequence of out-of-sample VaR estimates for a long position is said to be efficient with respect to the information set available at *t-1*, Ω_{t-1}, if the following condition holds:

$$E\left[\Phi_t \middle| \Omega_{t-1}\right] = \alpha \qquad \text{with} \qquad \Phi_t = \begin{cases} 1, & R_t < VaR_t^{\alpha} \\ 0, & R_t \geq VaR_t^{\alpha} \end{cases} \tag{A.1}$$

The above equation implies that the expected VaR failures, $E[\Phi_t]$, should be: 1) on average, equal to the nominal confidence level, α, and 2) uncorrelated with any function/variable in the information set available at *t-1*. The above property is tested using intermediary statistics of unconditional coverage developed by Kupiec (1995), independence, and conditional coverage proposed by Christoffersen (2003). In this respect, the rejection of the model can be categorized as the failure of unconditional coverage, clustering of violations, or both. Christoffersen (2003) defines all three tests as likelihood ratio based tests.

The LR statistic for the correct unconditional coverage is specified as:

$$LR_{UC} = LR_{PF} = 2\left[\log\left(\pi_1^{n_1}(1-\pi_1)^{n_0}\right) - \log\left((1-\alpha)^{n_1}\alpha^{n_0}\right)\right] \sim \chi^2_{(1)} \tag{A.2}$$

where n_1 is the number of 1's in the indicator series, n_0 is the number of 0's in the indicator series, α is the tolerance level of the VaR estimates, and $\pi_1 = n_1/(n_1+n_0)$. The LR statistic for test of independence is specified as:

$$LR_{Ind} = 2\left[\log\left((1-\pi_{01})^{(n_0-n_{01})}\pi_{01}^{n_{01}}(1-\pi_{11})^{(n_1-n_{11})}\pi_{11}^{n_{11}}\right) - \log\left(\pi_1^{n_1}(1-\pi_1)^{n_0}\right)\right] \sim \chi^2_{(1)} \tag{A.3}$$

where n_{ij} is the number of *i* values followed by a *j* value in the indicator series,

$$\pi_{ij} = \Pr\{I_t = i \mid I_{t-1} = j\} \text{ for } i,j = 0,1 \quad \text{and} \quad \pi_{01} = \frac{n_{01}}{n_0},\ \pi_{11} = \frac{n_{11}}{n_1} \tag{A.4}$$

And finally, the LR statistic for the correct conditional coverage is given as the sum of the correct unconditional coverage and the independence test:

$$LR_{\text{CC}} = LR_{\text{UC}} + LR_{\text{Ind}} \sim \chi^2_{(2)} \tag{A.5}$$

The best models are those that generate a coverage rate less than the nominal and a model is considered to be adequate for risk management when it is able to pass both the conditional and unconditional coverage tests.

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Table 1: Descriptive statistics of daily returns on energy futures prices

	Mean	Volatility	Normality	Autocorrelation	ARCH	Unit Root	
		SD	J-B	LB-Q 10th	10th	PP	KPSS
WTI Crude Oil							
1-month	0.045	0.396	2026.4	23.094	393.98	-55.807	0.125
2-month	0.055	0.357	1303.9	17.219	351.19	-55.756	0.130
3-month	0.060	0.335	1023.2	18.572	516.57	-55.911	0.135
Heating Oil							
1-month	0.055	0.392	2642.2	13.431	121.56	-56.744	0.128
2-month	0.058	0.359	548.4	12.153	115.92	-57.275	0.136
3-month	0.062	0.337	321.2	11.660	163.24	-57.178	0.140
Gasoline							
1-month	0.030	0.431	1509.1	8.359	109.89	-53.717	0.111
2-month	0.034	0.378	731.9	8.582	250.65	-54.834	0.136
3-month	0.038	0.344	552.4	16.918	498.24	-55.518	0.148
Natural Gas							
1-month	0.092	0.587	4687.3	8.328	108.82	-56.394	0.026
2-month	0.068	0.531	1505.7	6.627	162.94	-56.741	0.054
3-month	0.078	0.476	4719.9	6.928	57.018	-55.882	0.070

- Sample period: 1st January 1997 to 31st December 2008.
- Mean and standard deviation of returns are annualised.
- JB is the Bera and Jarque (1980) test for normality which follows a $\chi^2_{(2)}$ distribution. The 5% critical value for this test is 5.991.
- ARCH is the Engle (1982) test for 10th order Autoregressive Conditional Heteroscedasticity which follows a $\chi^2_{(10)}$ distribution. The 5% critical value for this test is 18.307.
- LB-Q is the Ljung and Box (1978) test for 10th order autocorrelation which follows a $\chi^2_{(10)}$ distribution. The 5% critical value for this test is 18.307.
- PP is the Philips and Perron (1988) unit root test. The 5% critical value for this test is -2.862.
- KPSS is the Kwiatkowski et al. (1992) test for stationarity. The 5% critical value for this test is 0.463.

Table 2: Estimation results of EGARCH(1,1), EGARCH-X(1,1), and EGARCH-TX(1,1) for NYMEX crude oil futures prices

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2)$$

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2)$$

EGARCH-TX $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2 + \delta_0 S_{t-1} + \delta_1 S_{t-1} \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \delta_2 S_{t-1} \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_3 S_{t-1} \ln \sigma_{t-1}^2)$$

	Near month			2nd Month			3rd Month		
	EGARCH	EGARCH-X	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX
Mean									
α_0	0.0003	0.0005	0.0005	0.0004	0.005	0.0005	0.0004	0.0005	0.0005
	(0.777)	(1.085)	(1.076)	(0.979)	(1.260)	(1.305)	(1.087)	(1.281)	(1.430)
Variance									
β_0	-0.217***	-0.404***	-0.286***	-0.333***	-0.404***	-0.331***	-0.309***	-0.343***	-0.314***
	(-4.148)	(-5.387)	(-3.620)	(-4.423)	(-4.757)	(-3.432)	(-3.888)	(-4.263)	(-3.091)
β_1	0.105***	0.090***	0.091***	0.116***	0.098***	0.124***	0.101***	0.091***	0.131***
	(8.026)	(6.739)	(4.846)	(10.399)	(8.532)	(6.348)	(8.595)	(7.909)	(6.608)
β_2	-0.044***	-0.045***	-0.041***	-0.041***	-0.042***	-0.015	-0.035***	-0.033***	-0.012
	(-5.592)	(-4.717)	(-2.929)	(-4.547)	(-4.308)	(-0.957)	(-3.963)	(-3.370)	(-0.785)
β_3	0.971***	0.948***	0.964***	0.956***	0.949***	0.958***	0.960***	0.957***	0.961***
	(139.82)	(97.866)	(92.988)	(80.922)	(88.247)	(77.190)	(95.321)	(95.433)	(74.818)
δ_0			-0.306***			-0.666***			-0.693***
			(-2.679)			(-3.154)			(-2.817)
δ_1			-0.014			-0.040			-0.046
			(-0.529)			(-1.328)			(-1.512)
δ_2			-0.016			-0.078***			-0.068***
			(-0.775)			(-3.428)			(-3.021)
δ_3			-0.041***			-0.086***			-0.088***
			(-2.671)			(-3.138)			(-2.807)
γ		2.345***	2.503***		1.823***	2.752***		1.391***	2.281***
		(5.413)	(5.581)		(5.168)	(5.991)		(4.348)	(5.204)

LR test			5.540			14.260			12.420
p-value			0.2362			0.0065			0.0145
Diagnostics									
R-bar sq	-0.002	-0.002	-0.004	-0.002	-0.002	-0.004	-0.002	-0.002	-0.004
AIC	-6.551	-6.565	-6.567	-6.745	-6.754	-6.760	-6.895	-6.902	-6.907
SBIC	-6.535	-6.546	-6.536	-6.730	-6.736	-6.729	-6.879	-6.883	-6.876
LL	8218.18	8235.39	8238.16	8461.88	8473.48	8480.61	8649.61	8658.39	8664.60
LB-Q(1)	0.139	0.139	0.139	0.064	0.064	0.064	0.033	0.033	0.033
	[0.710]	[0.710]	[0.710]	[0.801]	[0.801]	[0.801]	[0.856]	[0.856]	[0.856]
LB-Q(10)	13.597	13.597	13.597	12.951	12.951	12.951	11.410	11.410	11.410
	[0.192]	[0.192]	[0.192]	[0.226]	[0.226]	[0.226]	[0.326]	[0.326]	[0.326]
ARCH (1)	1.201	0.345	0.472	0.263	0.053	0.035	1.960	1.476	0.715
	[0.273]	[0.556]	[0.492]	[0.608]	[0.817]	[0.851]	[0.169]	[0.224]	[0.398]
ARCH (10)	13.079	14.135	12.809	21.480	22.740	21.442	19.384	19.974	18.845
	[0.219]	[0.167]	[0.235]	[0.018]	[0.012]	[0.018]	[0.036]	[0.039]	[0.042]
JB test	1173.5	1173.5	1173.5	1039.55	1039.55	1039.55	579.65	579.65	579.65
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- Sample period: 1st January 1997 to 31st December 2006.
- z_t is the slope of forward curve calculated as the difference in log of near month and the 6th month futures prices.
- AIC and SBIC are the Akaike and Schwartz Bayesian Information Criteria, respectively.
- LL is the log-likelihood value of the estimated model.
- LR test is the likelihood Ratio test for the joint significance of δ_0, δ_1, δ_2, δ_3.
- LB-Q(1) and LB-Q(10) are the Ljung and Box (1978) tests for the 1st and the 10th order autocorrelation. The 5% critical values for these tests are 3.841 and 18.307, respectively.
- ARCH(1) and ARCH(10) are the Engle (1982) tests for the 1st and the 10th order Autoregressive Conditional Heteroscedasticity. The 5% critical values for these tests are 3.841 and 18.307, respectively.
- JB is the Jarque and Bera (1980) test for normality. The 5% critical value for this test is 5.991.
- Standard errors are corrected using Bollerslev and Wooldridge (1992).

Table 3: Estimation results of EGARCH(1,1), EGARCH-X(1,1), and EGARCH-TX(1,1) for NYMEX gasoline futures prices

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2)$$

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2)$$

EGARCH-TX $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2 + \delta_0 S_{t-1} + \delta_1 S_{t-1} \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \delta_2 S_{t-1} \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_3 S_{t-1} \ln \sigma_{t-1}^2)$$

	Near month			2nd Month			3rd Month		
	EGARCH	EGARCH-X	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX
Mean									
α_0	0.0005	0.0006	0.0006	0.0002	0.0003	0.0003	0.0001	0.0003	0.0002
	(0.990)	(1.291)	(1.229)	(0.378)	(0.674)	(0.703)	(0.327)	(0.659)	(0.592)
Variance									
β_0	-0.304***	-0.502***	-0.455***	-0.135***	-0.193***	-0.169***	-0.203***	-0.293***	-0.288***
	(-4.073)	(-4.834)	(-3.545)	(-3.384)	(-3.833)	(-2.881)	(-2.938)	(-3.454)	(-2.748)
β_1	0.136***	0.134***	0.053*	0.067***	0.076***	0.033	0.087***	0.095***	0.070***
	(9.292)	(8.129)	(1.684)	(5.948)	(5.968)	(1.492)	(6.140)	(6.374)	(2.633)
β_2	0.009	0.0003	0.009	-0.016***	-0.015***	-0.015	-0.025***	-0.024***	-0.030*
	(1.050)	(0.030)	(0.455)	(-2.367)	(-1.936)	(-1.059)	(-3.098)	(-2.625)	(-1.870)
β_3	0.957***	0.933***	0.939***	0.982***	0.975***	0.978***	0.974***	0.963***	0.963***
	(92.965)	(66.580)	(52.942)	(185.53)	(148.49)	(126.19)	(109.99)	(89.798)	(71.553)
δ_0			-0.115			-0.403**			-0.608**
			(-0.765)			(-2.451)			(-2.402)
δ_1			0.115***			0.084***			0.054
			(3.194)			(3.026)			(1.515)
δ_2			-0.023			-0.031			-0.030
			(-0.869)			(-1.431)			(-1.160)
δ_3			-0.015			-0.052**			-0.076**
			(-0.701)			(-2.430)			(-2.351)
γ		1.118***	1.240***		0.325***	0.542***		0.441***	0.802***
		(5.141)	(5.182)		(3.015)	(3.083)		(3.728)	(3.214)

LR test			10.800			7.960			10.900
p-value			0.0289			0.0931			0.0277
Diagnostics									
R-bar sq	-0.002	-0.002	-0.004	-0.002	-0.002	-0.004	-0.002	-0.002	-0.004
AIC	-6.298	-6.309	-6.313	-6.599	-6.6-2	-6.605	-6.822	-6.825	-6.830
SBIC	-6.282	-6.290	-6.262	-6.583	-6.583	-6.574	-6.806	-6.807	-6.798
LL	7900.88	7914.02	7919.42	8277.98	8281.96	8285.94	8557.77	8562.36	8567.81
LB-Q(1)	3.412	3.412	3.412	0.605	0.605	0.605	0.112	0.112	0.112
	[0.065]	[0.065]	[0.065]	[0.437]	[0.437]	[0.437]	[0.738]	[0.738]	[0.738]
LB-Q(10)	13.553	13.553	13.553	10.235	10.235	10.235	13.046	13.046	13.046
	[0.194]	[0.194]	[0.194]	[0.420]	[0.420]	[0.420]	[0.221]	[0.221]	[0.221]
ARCH (1)	1.037	0.660	1.038	3.076	1.862	1.059	1.289	0.584	0.107
	[0.309]	[0.417]	[0.308]	[0.079]	[0.172]	[0.303]	[0.256]	[0.445]	[0.744]
ARCH (10)	10.942	8.701	9.421	11.322	10.359	8.278	11.437	10.655	8.279
	[0.362]	[0.561]	[0.493]	[0.333]	[0.410]	[0.602]	[0.324]	[0.385]	[0.602]
JB test	1541.24	1541.24	1541.24	482.45	482.45	482.45	185.68	185.68	185.68
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- Sample period: 1st January 1997 to 31st December 2006.
- z_t is the slope of forward curve calculated as the difference in log of near month and the 6th month futures prices.
- AIC and SBIC are the Akaike and Schwartz Bayesian Information Criteria, respectively.
- LL is the log-likelihood value of the estimated model.
- LR test is the likelihood Ratio for the joint significance of δ_0, δ_1, δ_2, δ_3.
- LB-Q(1) and LB-Q(10) are the Ljung and Box (1978) tests for the 1st and the 10th order autocorrelation.
- ARCH(1) and ARCH(10) are the Engle (1982) tests for the 1st and the 10th order Autoregressive Conditional Heteroscedasticity.
- JB is the Jarque and Bera (1980) test for normality.
- Standard errors are corrected using Bollerslev and Wooldridge (1992).

Table 4: Estimation results of EGARCH(1,1), EGARCH-X(1,1), and EGARCH-TX(1,1) for NYMEX heating oil futures prices

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2)$$

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2)$$

EGARCH-TX $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2 + \delta_0 S_{t-1} + \delta_1 S_{t-1} \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \delta_2 S_{t-1} \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_3 S_{t-1} \ln \sigma_{t-1}^2)$$

	Near month			2nd Month			3rd Month		
	EGARCH	EGARCH-X	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX
Mean									
α_0	0.0006	0.0007	0.0007	0.0004	0.0005	0.0006	0.0003	0.0005	0.0004
	(1.470)	(1.572)	(1.552)	(1.047)	(1.343)	(1.280)	(0.737)	(1.162)	(1.052)
Variance									
β_0	-0.336***	-0.716***	-0.586***	-0.297***	-0.566***	-0.456***	-0.220***	-0.420***	-0.158**
	(-5.169)	(-4.591)	(-3.637)	(-3.436)	(-3.637)	(-2.915)	(-3.480)	(-3.562)	(-2.339)
β_1	0.162***	0.160***	0.061***	0.102***	0.106***	0.060***	0.085***	0.100***	0.046***
	(10.579)	(7.622)	(2.626)	(7.255)	(5.591)	(2.825)	(6.049)	(5.736)	(3.120)
β_2	0.034***	0.017	0.018	-0.003	-0.007	0.000	-0.005	-0.001	-0.007
	(3.495)	(1.482)	(1.223)	(-0.307)	(-0.689)	(0.000)	(-0.640)	(-0.110)	(-0.771)
β_3	0.954***	0.906***	0.925***	0.961***	0.927***	0.942***	0.971***	0.946***	0.980***
	(109.31)	(44.340)	(44.230)	(85.151)	(46.186)	(46.918)	(119.38)	(63.150)	(114.57)
δ_0			-0.124			-0.390			-0.352**
			(-0.580)			(-1.593)			(-2.018)
δ_1			0.180***			0.119***			0.091***
			(5.333)			(3.358)			(3.144)
δ_2			0.015			-0.006			0.021
			(0.569)			(-0.235)			(1.023)
δ_3			-0.021			-0.054*			-0.047**
			(-0.747)			(-1.678)			(-2.064)
γ		2.002***	1.633***		1.155***	1.255***		0.746***	0.586***
		(6.294)	(4.945)		(4.768)	(4.163)		(4.230)	(3.639)

LR test			19.220			8.400			7.000
p-value			0.0007			0.0780			0.1359
Diagnostics									
R-bar sq	-0.002	-0.002	-0.004	-0.002	-0.002	-0.004	-0.002	-0.002	-0.004
AIC	-6.468	-6.487	-6.495	-6.628	-6.638	-6.642	-6.773	-6.778	-6.781
SBIC	-6.452	-6.469	-6.464	-6.612	-6.620	-6.610	-6.757	-6.760	-6.750
LL	8114.11	8138.45	8148.06	8114.71	8327.79	8331.99	8496.10	8503.29	8506.79
LB-Q(1)	1.542	1.542	1.542	3.232	3.232	3.232	2.550	2.550	2.550
	[0.214]	[0.214]	[0.214]	[0.072]	[0.072]	[0.072]	[0.110]	[0.110]	[0.110]
LB-Q(10)	11.975	11.975	11.975	9.589	9.589	9.589	9.261	9.261	9.261
	[0.287]	[0.287]	[0.287]	[0.477]	[0.477]	[0.477]	[0.507]	[0.507]	[0.507]
ARCH (1)	0.028	0.391	0.550	0.743	0.443	0.678	0.030	0.004	0.012
	[0.868]	[0.532]	[0.214]	[0.389]	[0.506]	[0.410]	[0.863]	[0.947]	[0.912]
ARCH (10)	8.673	9.016	9.472	14.256	14.410	12.840	11.751	11.095	13.070
	[0.563]	[0.530]	[0.488]	[0.162]	[0.155]	[0.232]	[0.302]	[0.350]	[0.220]
JB test	2718.24	2718.24	2718.24	510.49	510.49	510.49	262.66	262.66	262.66
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- Sample period: 1st January 1997 to 31st December 2006.
- z_t is the slope of forward curve calculated as the difference in log of near month and the 6th month futures prices.
- AIC and SBIC are the Akaike and Schwartz Bayesian Information Criteria, respectively.
- LL is the log-likelihood value of the estimated model.
- LR test is the likelihood Ratio for the joint significance of δ_0, δ_1, δ_2, δ_3.
- LB-Q(1) and LB-Q(10) are the Ljung and Box (1978) tests for the 1st and the 10th order autocorrelation.
- ARCH(1) and ARCH(10) are the Engle (1982) tests for the 1st and the 10th order Autoregressive Conditional Heteroscedasticity.
- JB is the Jarque and Bera (1980) test for normality.
- Standard errors are corrected using Bollerslev and Wooldridge (1992).

Table 5: Estimation results of EGARCH(1,1), EGARCH-X(1,1), and EGARCH-TX(1,1) for NYMEX natural gas futures prices

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2)$$

EGARCH-X $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2)$$

EGARCH-TX $$\sigma_t^2 = \exp(\beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 \ln \sigma_{t-1}^2 + \gamma z_{t-1}^2 + \delta_0 S_{t-1} + \delta_1 S_{t-1} \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \delta_2 S_{t-1} \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta_3 S_{t-1} \ln \sigma_{t-1}^2)$$

	Near month			2nd Month			3rd Month		
	EGARCH	EGARCH-X	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX	EGARCH	EGARCHX	EGARCH-TX
Mean									
α_0	0.001	0.001	0.0009	0.001**	0.001*	0.001	0.0015***	0.0013**	0.0013**
	(1.638)	(1.782)	(1.437)	(2.043)	(1.705)	(1.117)	(2.736)	(2.391)	(2.363)
Variance									
β_0	-0.132***	-0.198***	-0.200***	-0.107***	-0.269***	-0.262***	-0.085***	-0.267***	-0.248***
	(-4.105)	(-5.146)	(-4.629)	(-5.224)	(-5.318)	(-4.367)	(-4.025)	(-4.605)	(-3.724)
β_1	0.149***	0.122***	0.117***	0.119***	0.107***	0.100***	0.111***	0.113***	0.102***
	(10.495)	(9.941)	(7.474)	(10.463)	(8.326)	(5.861)	(9.565)	(7.597)	(5.171)
β_2	0.025***	0.039***	0.000	0.029***	0.036***	0.007	0.042***	0.035***	0.004
	(3.495)	(6.201)	(0.002)	(4.315)	(4.239)	(0.709)	(6.282)	(4.173)	(0.419)
β_3	0.979***	0.971***	0.971***	0.983***	0.961***	0.963***	0.987***	0.963***	0.966***
	(200.87)	(171.70)	(157.40)	(325.91)	(133.48)	(114.51)	(322.44)	(119.94)	(105.30)
Δ_0			-0.105			-0.082			-0.017
			(-1.633)			(-1.052)			(-0.257)
Δ_1			-0.077***			-0.048*			-0.005
			(-3.024)			(-1.774)			(-0.156)
Δ_2			0.091***			0.075***			0.088***
			(5.973)			(4.371)			(4.978)
Δ_3			-0.018*			-0.014			-0.004
			(-1.772)			(-1.199)			(-0.450)
γ		0.276***	0.282***		0.322***	0.318***		0.278***	0.238***
		(6.984)	(6.335)		(6.658)	(5.365)		(6.242)	(4.584)

LR test			39.040			20.500			20.940
p-value			0.0000			0.0004			0.0003
Diagnostics									
R-bar sq	-0.002	-0.003	-0.004	-0.002	-0.003	-0.004	-0.003	-0.003	-0.004
AIC	-6.671	-6.688	-6.703	-5.835	-5.854	-5.862	-6.078	-6.088	-6.096
SBIC	-6.655	-6.669	-6.672	-5.820	-5.835	-5.831	-6.062	-6.069	-6.065
LL	7114.18	7134.99	7154.51	7320.21	7344.04	7354.29	7624.75	7637.37	7647.84
LB-Q(1)	3.853	3.853	3.853	2.481	2.481	2.481	0.524	0.524	0.524
	[0.050]	[0.050]	[0.050]	[0.115]	[0.115]	[0.115]	[0.469]	[0.469]	[0.469]
LB-Q(10)	9.317	9.317	9.317	7.321	7.321	7.321	10.064	10.064	10.064
	[0.502]	[0.502]	[0.502]	[0.695]	[0.695]	[0.695]	[0.435]	[0.435]	[0.435]
ARCH (1)	0.531	0.253	0.035	0.003	0.004	0.205	0.364	0.644	0.124
	[0.466]	[0.615]	[0.851]	[0.960]	[0.950]	[0.651]	[0.546]	[0.422]	[0.725]
ARCH (10)	12.643	9.644	12.244	13.623	12.935	14.026	7.225	10.968	12.054
	[0.244]	[0.472]	[0.269]	[0.191]	[0.227]	[0.172]	[0.704]	[0360]	[0.281]
JB test	2632.22	2632.22	2632.22	1190.41	1190.41	1190.41	4097.94	4097.94	4097.94
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- Sample period: 1st January 1997 to 31st December 2006.
- z_t is the slope of forward curve calculated as the difference in log of near month and the 6th month futures prices.
- AIC and SBIC are the Akaike and Schwartz Bayesian Information Criteria, respectively.
- LL is the log-likelihood value of the estimated model.
- LR test is the likelihood Ratio for the joint significance of δ_0, δ_1, δ_2, δ_3.
- LB-Q(1) and LB-Q(10) are the Ljung and Box (1978) tests for the 1st and the 10th order autocorrelation.
- ARCH(1) and ARCH(10) are the Engle (1982) tests for the 1st and the 10th order Autoregressive Conditional Heteroscedasticity.
- JB is the Jarque and Bera (1980) test for normality.
- Standard errors are corrected using Bollerslev and Wooldridge (1992).

Table 6: Forecast evaluation and asymmetric bias of volatility forecasts

Crude Oil

	Ave Vol	RMSE	Over Prediction			Under Prediction			Sum
			%	Mean	MME(O)	%	Mean	MME(U)	
Hist. Variance	0.37158	0.00225	64.3%	**0.00034**	**0.01183**	35.7%	-0.00177	0.01200	**0.02383**
RiskMetrics	0.43871	0.00210	66.7%	0.00050	0.01367	33.3%	-0.00158	0.01070	0.02437
EGARCH	0.43436	0.00214	67.9%	0.00049	0.01426	32.1%	-0.00168	**0.01049**	0.02476
EGARCH-X	0.42388	0.00209	67.3%	0.00045	0.01343	32.7%	-0.00168	0.01079	0.02422
EGARCH-TX	0.42862	**0.00208**	65.7%	0.00047	0.01314	34.3%	**-0.00157**	0.01088	0.02401

Gasoline

	Ave Vol	RMSE	Over Prediction			Under Prediction			Sum
			%	Mean	MME(O)	%	Mean	MME(U)	
Hist. Variance	0.40034	0.00174	66.67%	**0.00043**	0.01157	33.3%	-0.00165	**0.01382**	**0.02539**
RiskMetrics	0.44660	**0.00165**	66.87%	0.00055	0.01076	33.1%	**-0.00144**	0.01495	0.02571
EGARCH	0.44830	0.00169	68.65%	0.00056	**0.01056**	31.3%	-0.00156	0.01597	0.02653
EGARCH-X	0.44740	0.00168	68.65%	0.00055	0.01064	31.3%	-0.00156	0.01576	0.02640
EGARCH-TX	0.43472	0.00168	68.25%	0.00051	0.01091	31.7%	-0.00158	0.01488	0.02578

Heating Oil

	Ave Vol	RMSE	Over Prediction			Under Prediction			Sum
			%	Mean	MME(O)	%	Mean	MME(U)	
Hist. Variance	0.32793	0.00103	63.10%	**0.00030**	0.00930	36.9%	-0.00090	0.01083	**0.02013**
RiskMetrics	0.35751	**0.00100**	66.07%	0.00036	**0.00846**	33.9%	**-0.00087**	0.01183	0.02029
EGARCH	0.37816	0.00102	70.63%	0.00040	0.01383	29.4%	-0.00097	**0.00784**	0.02168
EGARCH-X	0.36015	0.00103	69.64%	0.00036	0.01301	30.4%	-0.00100	0.00826	0.02127
EGARCH-TX	0.33641	0.00104	66.87%	0.00031	0.01168	33.1%	-0.00098	0.00890	0.02058

Natural Gas

	Ave Vol	RMSE	Over Prediction			Under Prediction			Sum
			%	Mean	MME(O)	%	Mean	MME(U)	
Hist. Variance	0.50540	0.00446	71.63%	0.00081	0.02002	28.4%	-0.00232	0.01086	0.03088
RiskMetrics	0.48710	0.00442	69.64%	0.00071	0.01819	30.4%	**-0.00212**	0.01076	0.02896
EGARCH	0.51540	0.00441	73.41%	0.00078	0.02016	26.6%	-0.00229	**0.00987**	0.03003
EGARCH-X	0.50491	0.00441	74.01%	0.00073	0.01961	26.0%	-0.00238	0.00994	0.02955
EGARCH-TX	0.47326	**0.00441**	70.63%	**0.00064**	**0.01762**	29.4%	-0.00222	0.01075	**0.02837**

Notes:

The total number of one-step ahead forecasts is 504.

Historical Variance forecast is based on a 126 day rolling variance.

Ave Vol is the average annualised volatility over the forecasting period. RMSE is the root mean squared error of volatility forecast compared to squared returns. MME(O) and MME(U) are Mixed Mean Error statistics (Brailsford and Faff, 1996) for comparisons of asymmetries in volatility forecasts. Mean Over (Under) Prediction is the average of forecast errors when predicted volatility is higher (Lower) than the realised one. Percentage is the proportion of under prediction and over prediction over the forecast period. Sum is the sum of the MME(O) and MME(U) statistics.

Table 7: Comparison of forecasts of different volatility models for Near-month NYMEX crude oil futures

Panel A: VaR for 1% and 5% Models Crude Oil

Model	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}
			1.0%					99.0%		
Hist. Variance	10	1.98%	3.833	1.768	5.601	14	2.78%	10.848*	3.731	14.58*
Hist. Sim	16	3.17%	15.288*	2.800	18.088*	17	3.37%	17.706*	2.404	20.11*
Filtred Hist Sim	12	2.38%	6.998*	1.167	8.165*	13	2.58%	8.844*	NA	NA
RiskMetrics	6	1.19%	0.174	3.730	3.904	10	1.98%	3.833	NA	NA
EGARCH(1,1)	6	1.19%	0.174	NA	NA	6	1.19%	0.174	NA	NA
EGARCHX(1,1)	8	1.59%	1.490	NA	NA	8	1.59%	1.490	2.584	4.074
EGARCHTX(1,1)	9	1.79%	2.548	2.144	4.692	9	1.79%	2.548	2.144	4.692
			2.5%					97.5%		
Hist. Variance	25	4.96%	9.775*	2.055	11.83*	25	4.96%	9.775*	2.055	11.829*
Hist. Sim	38	7.54%	34.43*	1.574	36.01*	26	5.16%	11.238*	1.747	12.984*
Filtred Hist Sim	22	4.37%	5.904*	0.962	6.866*	23	4.56%	7.104*	0.764	7.868*
RiskMetrics	13	2.58%	0.013	0.928	0.941	24	4.76%	8.396*	2.394	10.790*
EGARCH(1,1)	14	2.78%	0.154	0.723	0.877	17	3.37%	1.423	5.843	7.266*
EGARCHX(1,1)	15	2.98%	0.442	0.549	0.991	19	3.77%	2.892	1.728	4.620
EGARCHTX(1,1)	17	3.37%	1.423	2.404	3.827	17	3.37%	1.423	2.404	3.827
			5.0%					95.0%		
Hist. Variance	46	9.13%	14.682*	0.177	14.859*	39	7.74%	6.866*	0.000	6.866*
Hist. Sim	54	10.71%	26.479*	1.988	28.468*	47	9.33%	15.999*	0.102	16.100*
Filtred Hist Sim	37	7.34%	5.115*	0.034	5.148	36	7.14%	4.326*	0.806	5.132
RiskMetrics	31	6.15%	1.313	0.619	1.932	33	6.55%	2.326	0.338	2.664
EGARCH(1,1)	26	5.16%	0.026	1.747	1.773	30	5.95%	0.909	0.794	1.703
EGARCHX(1,1)	32	6.35%	1.786	0.467	2.253	31	6.15%	1.313	0.619	1.932
EGARCHTX(1,1)	32	6.35%	1.786	1.756	3.542	30	5.95%	0.909	0.794	1.703

Notes:
The total number of one-step ahead forecasts is 504.
Historical Variance forecast is based on a 126 day rolling variance.
N_f is the number of failures of VaR. LR_{uc} , LR_{ind}, and LR_{cc} are tests for "unconditional coverage", " independence" and "conditional coverage", respectively (see Christoffersen 2003). LR_{uc} and LR_{ind} follow a Chi-Squared distribution with 1 degree of freedom, while LR_{cc} follows a Chi-Squared distribution with 2 degrees of freedom. The 5% critical value for LR_{uc} and LR_{ind} tests is 3.841, and the 5% critical value for LR_{cc} test is 5.991. * indicates rejection of the null and failure of the test.

Table 8: Comparison of forecasts of different volatility models for Near-month NYMEX gasoline futures

Panel A: VaR for 1% and 5% Models Crude Oil

Model	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}
			1.0%					99.0%		
Hist. Variance	15	2.98%	13.00*	0.549	13.55*	7	1.39%	0.687	3.105	3.792
Hist. Sim	10	1.98%	3.833*	NA	NA	13	2.58%	8.844*	0.928	9.772*
Filtred Hist Sim	16	3.17%	15.29*	NA	NA	20	3.97%	25.66*	0.054	25.72*
RiskMetrics	13	2.58%	8.844*	NA	NA	5	0.99%	0.000	4.499	4.499
EGARCH(1,1)	7	1.39%	0.687	NA	NA	4	0.79%	0.233	5.482*	5.715
EGARCHX(1,1)	9	1.79%	2.548	NA	NA	5	0.99%	0.000	4.499*	4.500
EGARCHTX(1,1)	15	2.98%	12.99*	0.549	13.55*	4	0.79%	0.233	NA	NA
			2.5%					97.5%		
Hist. Variance	25	4.96%	9.775*	0.055	9.829*	14	2.78%	0.154	3.731	3.885
Hist. Sim	19	3.77%	2.892	0.109	3.001	25	4.96%	9.775	2.055	11.83*
Filtred Hist Sim	24	4.76%	8.396*	0.020	8.416*	36	7.14%	29.920	0.158	30.08*
RiskMetrics	18	3.57%	2.100	NA	NA	17	3.37%	1.423	2.404	3.827
EGARCH(1,1)	19	3.77%	2.892	0.109	3.001	7	1.39%	3.035	3.105	6.139*
EGARCHX(1,1)	19	3.77%	2.892	0.109	3.001	9	1.79%	1.170	2.144	3.314
EGARCHTX(1,1)	18	3.57%	2.100	0.184	2.284	10	1.98%	0.591	6.353*	6.944*
			5.0%					95.0%		
Hist. Variance	38	7.54%	5.962*	1.574	7.536*	33	6.55%	2.326	0.014	2.340
Hist. Sim	40	7.94%	7.825*	1.084	8.909*	38	7.54%	5.962*	0.007	5.969*
Filtred Hist Sim	46	9.13%	14.68*	0.012	14.69*	45	8.93%	13.41*	0.000	13.41*
RiskMetrics	28	5.56%	0.317	0.251	0.568	32	6.35%	1.786	0.001	1.787
EGARCH(1,1)	27	5.36%	0.132	0.171	0.303	21	4.17%	0.779	1.188	1.967
EGARCHX(1,1)	25	4.96%	0.002	0.055	0.056	22	4.37%	0.446	0.962	1.408
EGARCHTX(1,1)	35	6.94%	3.597	0.093	3.690	24	4.76%	0.061	0.591	0.652

Notes:

The total number of one-step ahead forecasts is 504.

Historical Variance forecast is based on a 126 day rolling variance.

N_f is the number of failures of VaR. LR_{uc} , LR_{ind}, and LR_{cc} are tests for "unconditional coverage", " independence" and "conditional coverage", respectively (see Christoffersen 2003). LR_{uc} and LR_{ind} follow a Chi-Squared distribution with 1 degree of freedom, while LR_{cc} follows a Chi-Squared distribution with 2 degrees of freedom. The 5% critical value for LR_{uc} and LR_{ind} tests is 3.841, and the 5% critical value for LR_{cc} test is 5.991. * indicates rejection of the null and failure of the test.

Table 9: Comparison of forecasts of different volatility models for Near-month NYMEX heating oil futures

Panel A: VaR for 1% and 5% Models Crude Oil

Model	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}
			1.0%					99.0%		
Hist. Variance	8	1.59%	1.490	NA	NA	9	1.79%	2.548	2.144	4.692
Hist. Sim	13	2.58%	8.844*	NA	NA	13	2.58%	8.844*	0.928	9.772*
Filtred Hist Sim	21	4.17%	28.55*	NA	NA	14	2.78%	10.85*	NA	NA
RiskMetrics	9	1.79%	2.548	NA	NA	9	1.79%	2.548	NA	NA
EGARCH(1,1)	6	1.19%	0.174	NA	NA	5	0.99%	0.000	4.499	4.500
EGARCHX(1,1)	8	1.59%	1.490	NA	NA	4	0.79%	0.233	5.482	5.715
EGARCHTX(1,1)	9	1.79%	2.548	NA	NA	6	1.19%	0.174	3.730	3.904
			2.5%					97.5%		
Hist. Variance	17	3.37%	1.423	NA	NA	20	3.97%	3.793	0.054	3.847
Hist. Sim	24	4.76%	8.396*	0.020	8.416*	23	4.56%	7.104	0.003	7.107
Filtred Hist Sim	24	4.76%	8.396*	NA	NA	29	5.75%	16.10*	0.070	16.17*
RiskMetrics	16	3.17%	0.868	NA	NA	18	3.57%	2.100	0.184	2.284
EGARCH(1,1)	10	1.98%	0.591	NA	NA	12	2.38%	0.030	1.167	1.197
EGARCHX(1,1)	11	2.18%	0.218	NA	NA	11	2.18%	0.218	1.445	1.662
EGARCHTX(1,1)	16	3.17%	0.868	0.403	1.271	15	2.98%	0.442	0.549	0.991
			5.0%					95.0%		
Hist. Variance	29	5.75%	0.576	0.347	0.923	36	7.14%	4.326	0.806	5.132
Hist. Sim	43	8.53%	11.03*	1.057	12.08*	39	7.74%	6.866*	0.346	7.212*
Filtred Hist Sim	44	8.73%	12.19*	1.246	13.44*	48	9.52%	17.36*	0.048	17.41*
RiskMetrics	24	4.76%	0.061	NA	NA	33	6.55%	2.326	0.338	2.664
EGARCH(1,1)	17	3.37%	3.156	NA	NA	23	4.56%	0.208	0.764	0.972
EGARCHX(1,1)	24	4.76%	0.061	0.020	0.082	26	5.16%	0.026	0.317	0.344
EGARCHTX(1,1)	36	7.14%	4.326	0.079	4.405	36	7.14%	4.326	0.079	4.405

Notes:

The total number of one-step ahead forecasts is 504.

Historical Variance forecast is based on a 126 day rolling variance.

N_f is the number of failures of VaR. LR_{uc} , LR_{ind}, and LR_{cc} are tests for "unconditional coverage", " independence" and "conditional coverage", respectively (see Christoffersen 2003). LR_{uc} and LR_{ind} follow a Chi-Squared distribution with 1 degree of freedom, while LR_{cc} follows a Chi-Squared distribution with 2 degrees of freedom. The 5% critical value for LR_{uc} and LR_{ind} tests is 3.841, and the 5% critical value for LR_{cc} test is 5.991. * indicates rejection of the null and failure of the test.

Table 10: Comparison of forecasts of different volatility models for Near-month NYMEX natural gas futures

Panel A: VaR for 1% and 5% Models Crude Oil

Model	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}	N_f	%	LL_{uc}	LR_{ind}	LR_{cc}
			1.0%					99.0%		
Hist. Variance	9	1.79%	2.548	NA	NA	11	2.18%	5.322*	1.445	6.767*
Hist. Sim	6	1.19%	0.174	NA	NA	9	1.79%	2.548	2.144	4.692
Filtred Hist Sim	11	2.18%	5.322*	1.445	6.767*	5	0.99%	0.000	4.499	4.500
RiskMetrics	9	1.79%	2.548	2.144	4.692	5	0.99%	0.000	4.499	4.500
EGARCH(1,1)	5	0.99%	0.000	NA	NA	4	0.79%	0.233	5.482	5.715
EGARCHX(1,1)	5	0.99%	0.000	NA	NA	6	1.19%	0.174	3.730	3.904
EGARCHTX(1,1)	8	1.59%	1.490	NA	NA	7	1.39%	0.687	3.105	3.792
			2.5%					97.5%		
Hist. Variance	18	3.57%	2.100	0.184	2.284	16	3.17%	0.868	0.403	1.271
Hist. Sim	13	2.58%	0.013	NA	NA	16	3.17%	0.868	0.403	1.271
Filtred Hist Sim	20	3.97%	3.793	0.054	3.847	18	3.57%	2.100	0.184	2.284
RiskMetrics	14	2.78%	0.154	0.723	0.877	16	3.17%	0.868	0.403	1.271
EGARCH(1,1)	10	1.98%	0.591	NA	NA	10	1.98%	0.591	1.768	2.359
EGARCHX(1,1)	11	2.18%	0.218	NA	NA	9	1.79%	1.170	2.144	3.314
EGARCHTX(1,1)	15	2.98%	0.442	0.549	0.991	11	2.18%	0.218	1.445	1.662
			5.0%					95.0%		
Hist. Variance	26	5.16%	0.026	0.105	0.131	21	4.17%	0.779	0.019	0.798
Hist. Sim	29	5.75%	0.576	0.070	0.647	26	5.16%	0.026	0.105	0.131
Filtred Hist Sim	44	8.73%	12.194	0.008	12.202	36	7.14%	4.326	1.405	5.731
RiskMetrics	27	5.36%	0.132	1.468	1.601	29	5.75%	0.576	0.347	0.923
EGARCH(1,1)	20	3.97%	1.212	0.054	1.266	25	4.96%	0.002	0.055	0.056
EGARCHX(1,1)	21	4.17%	0.779	0.019	0.798	25	4.96%	0.002	0.055	0.056
EGARCHTX(1,1)	23	4.56%	0.208	0.764	0.972	28	5.56%	0.317	0.132	0.448

Notes:
The total number of one-step ahead forecasts is 504.
Historical Variance forecast is based on a 126 day rolling variance.
N_f is the number of failures of VaR. LR_{uc} , LR_{ind}, and LR_{cc} are tests for "unconditional coverage", " independence" and "conditional coverage", respectively (see Christoffersen 2003). LR_{uc} and LR_{ind} follow a Chi-Squared distribution with 1 degree of freedom, while LR_{cc} follows a Chi-Squared distribution with 2 degrees of freedom. The 5% critical value for LR_{uc} and LR_{ind} tests is 3.841, and the 5% critical value for LR_{cc} test is 5.991. * indicates rejection of the null and failure of the test.

Figure 1: Supply-demand framework for energy commodities

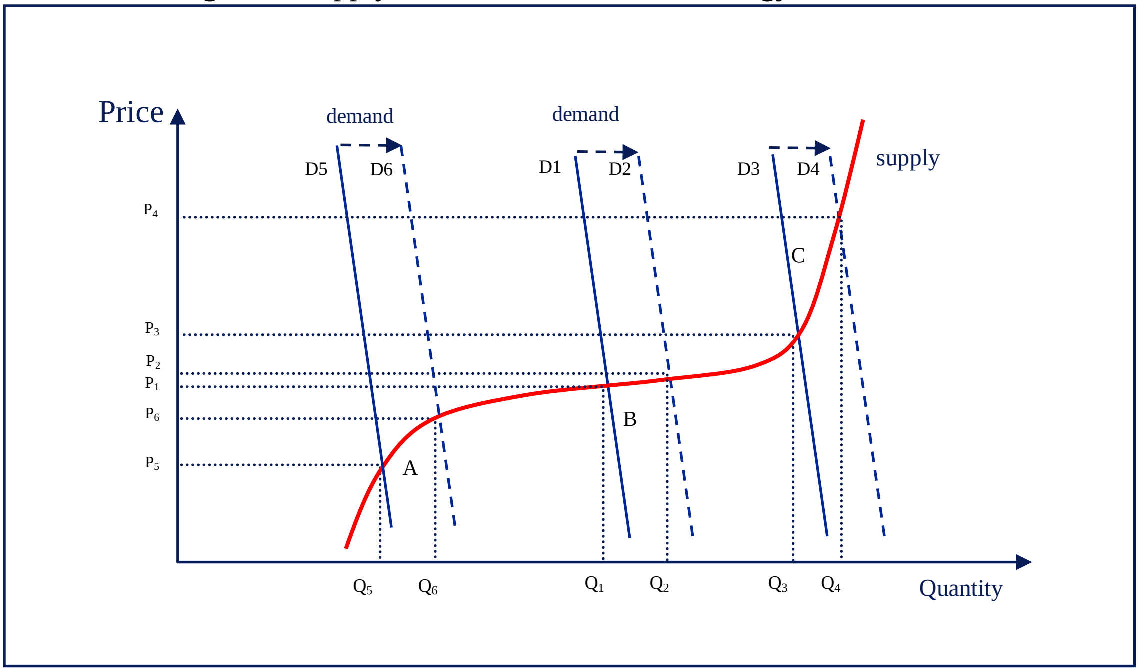

Figure 2: The slope of NEMEX crude oil forward curve

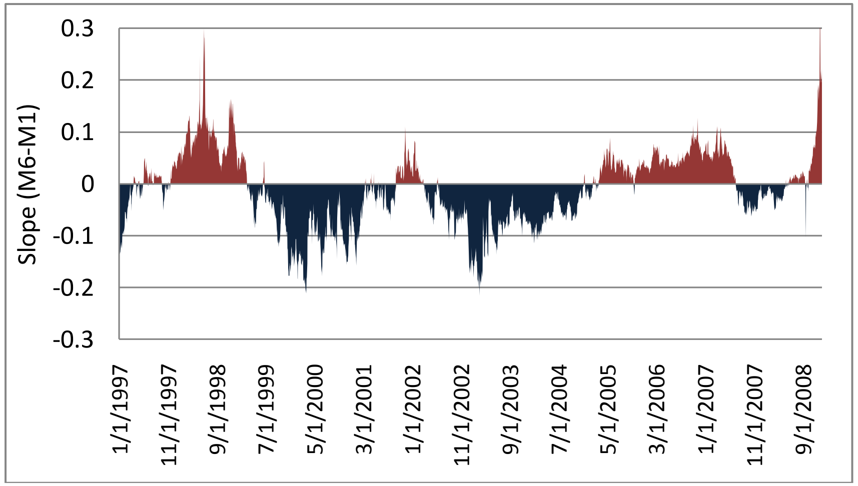

Figure 3: The slope of NEMEX gasoline forward curve

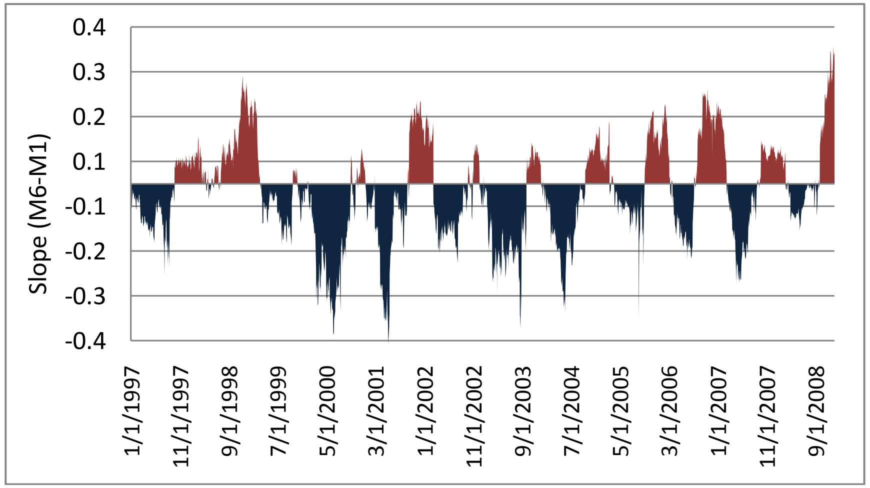

Figure 4: The slope of NEMEX heating oil forward curve

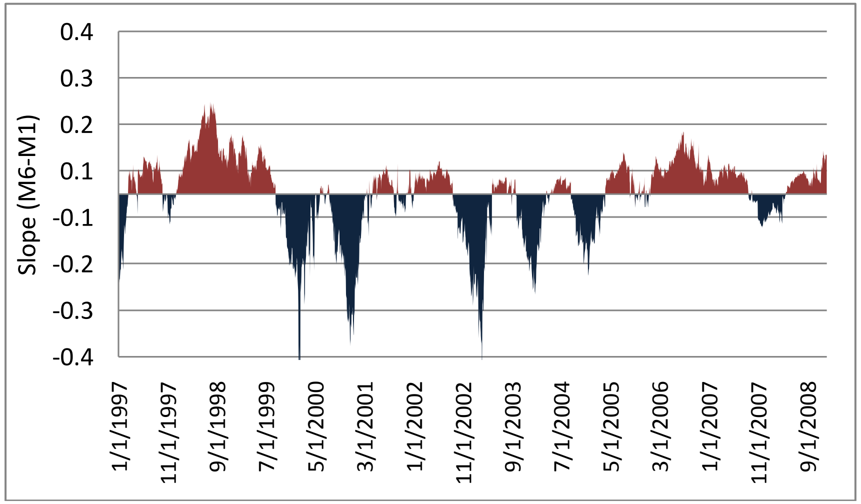

Figure 5: The slope of NEMEX natural gas forward curve

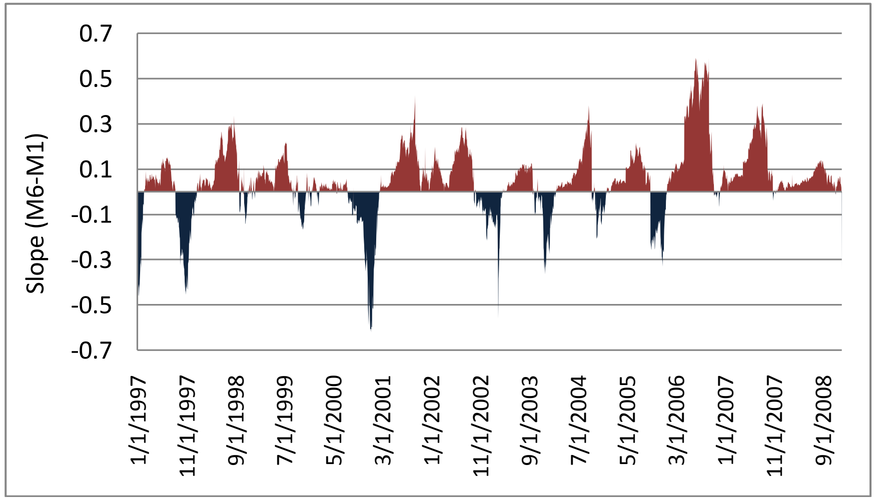

Figure 6: Slope of forward curve and volatility of near month futures prices for different energy commodities