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Jim Hanly*

ABSTRACT

This paper carries out a comparative analysis of managing energy risk through futures hedging, for energy market participants across a broad dataset that encompasses the largest and most actively traded energy products. Uniquely, we carry out a hedge comparison using a variety of risk measures including Variance, Value at risk (VaR), and Expected Shortfall as well as a utility based performance metric for two different investor horizons; weekly and monthly. We find that hedging is effective across the spectrum of risk measures we employ. We also find significant differences in both the hedging strategies and the hedging effectiveness of different energy assets. Better performance is found for West Texas Intermediate Oil and Heating Oil while the poorest performer in hedging terms is Natural Gas.

Keywords: Energy, Futures, Hedging, Risk Management, Value at Risk

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1. INTRODUCTION

Energy market participants carry a significant level of price risk given the innate volatility and susceptibility of energy products to political, economic and weather events. Futures contracts were created in large part to facilitate the management of these types of risks, and hedging of spot exposures using futures has become a relatively simple and cost effective way to manage energy price risk. A broad literature has developed on managing risk through hedging, with a majority focused in the main on foreign exchange (Kroner and Sultan, 1993), equities (Cotter and Hanly, 2006) and agricultural commodities (Lien and Yang, 2008). The findings in the literature tend to show that futures' hedging is generally quite effective in terms of reducing risk as measured by the variance.

A significant body of work has also examined volatility and risk management within energy markets, particularly with regard to Oil and Natural Gas. Aloui (2008), states that energy commodities tend to be significantly riskier than the majority of assets traded while Aloui and Mabrouk (2008) relate this to the existence of fat tails, asymmetry and long memory in energy markets. Addressing such risks via hedging, one of the earlier studies by Brinkmann and Rabinovitch (1995) find that the hedging efficacy of Natural Gas hedges is region specific, with Henry Hub futures providing an effective hedge for East coast but not West coast exposures. Bolinger, Wiser and Golove (2006) similarly find that Natural Gas hedge efficiency suffers because of the existence of a location basis differential. Ripple and Moosa (2007) estimated minimum variance based hedges for crude oil. Their findings focused on the impact of contract maturity and they found evidence

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of higher correlations and therefore higher hedging effectiveness for near month contracts as opposed to longer dated futures.

Chang, McAleer and Tansuchat, (2011) focus on Crude Oil hedging using both West Texas Intermediate (WTI) and Brent Oil contracts. They carry out a broad comparison using a number of different GARCH type methodologies and find differences in the optimal hedge strategies for the different Oil contracts depending on the model used. They attribute the differences in part to the difference in the quality of the different Oil contracts. They also find large differences in hedging effectiveness, with Brent Crude Oil hedges showing variance reductions of the order of 57% as compared with around 80% for WTI hedges. More recently, Pan, Wang and Yang (2014) have explored a strategy of hedging crude oil using refined products. They applied a regime switching asymmetric DCC GARCH model and found that heating oil significantly outperformed gasoline in a hedging context. We note however, that within the Oil hedging literature as with the more general hedging literature, utility based hedging incorporating utility based performance metrics has not been applied.

A number of papers have also looked at interactions between the Oil and Natural Gas markets. Marzo and Zagaglia (2008) find strong correlation between crude and refined oil but less so for natural gas, indicating potential differences in terms of hedging approaches and efficacy between Oil and Natural Gas. In contrast, Brown and Yucel (2008) show that crude oil price movements can help shape Natural Gas prices once certain factors such as weather conditions and inventory are taken into account. Aloui, Ben Aissa, Hammoudeh and Nguyen (2014) find that while the oil and Natural Gas markets tend to commove closely, they are much more highly correlated for bull markets than for bearish markets. Comparing these two assets in hedging terms, Cotter and Hanly (2011) use a utility based approach and find that Oil hedges tend to outperform Natural Gas hedges by the order of about 30% in terms of variance reduction and about 35% when Value at Risk (VaR) is the criterion used.

In energy markets, futures trade in six major products; West Texas Intermediate (WTI) and Brent Oil, Heating Oil, Gasoil, Gasoline, and Natural Gas. Outside of the benchmark Crude Oils and Natural Gas, there has been little work on the efficacy of other energy products in terms of their hedging effectiveness. This may relate to the fact that since correlations between energy assets are high, it is assumed that if one energy product can be effectively hedged then so too can others. However, it doesn't necessarily follow that hedging effectiveness will be the same for different energy assets. To our knowledge, no study has carried out a broad based comparison of the hedging effectiveness of futures contracts for the major energy contracts. Furthermore, of the studies that have examined energy hedging, few have incorporated some of the newer risk metrics that are of importance to investors¹ and regulators. This is of particular relevance given that risk is one sided in nature, which means that hedgers will be focused on one side of the return distribution only whereas traditional risk metrics such as the variance are two sided in that they assign equal weight to positive and negative outcomes. Furthermore, the facilitation of energy risk management is a key policy issue for regulators, policy makers and market participants given the inherent susceptibility of energy markets to volatility via political changes and weather events.

This paper contributes to the literature on energy markets by addressing these issues. We estimate and compare optimal hedge ratios (OHR's) using some of the most commonly applied

1. VaR is used in banking regulation and Expected Shortfall is being considered under Basel III recommendations. See Basel Committee on Banking Supervision, Consultative Document: Fundamental Review of the Trading Book (May 3, 2012) (available at <http://www.bis.org/publ/bcbs219.pdf>).

strategies including a constant hedge ratio estimated using Ordinary Least Squares (OLS) and two time-varying GARCH methodologies. We carry out a comparison of the hedging efficacy of futures across all six energy markets using three well known and applied risk measures; Variance, VaR, and Expected Shortfall. We also incorporate a utility based performance metric to evaluate the hedging effectiveness of energy hedges. Given the importance of the time horizon to hedging strategies, (see Juhl, Kawaller and Koch, 2012) we estimate hedge strategies across two time horizons, weekly and monthly. Taken together, this approach allows us to make a detailed and broad based comparison of the effectiveness of futures as a risk management tool in energy markets and to highlight their relative effectiveness across a broad range of different energy commodities and refinery products.

Our empirical results show that hedging is generally effective in reducing not only the variance of the energy hedgers underlying position, but also in terms of reducing both VaR and Expected Shortfall. We also find that hedging is invariably effective in terms of increasing the energy hedger's utility. We find significant differences in both the hedging strategies and the hedging effectiveness of different energy assets. The best performing energy hedges are for West Texas Intermediate Oil and Heating Oil while the poorest performer in hedging terms is Natural Gas. These differences can be attributed in part to the higher basis risk inherent in natural gas hedges. We also find that hedging effectiveness increases with hedge horizon. The implication is that energy hedgers should tailor their strategy to the particular energy product as a generalised approach is likely to be suboptimal. Furthermore, Natural Gas market participants should be aware of the relatively poor performance of futures hedges in terms of reducing risk, and in particular downside risk as measured using VaR or Expected Shortfall. From a policy perspective this is an interesting result as it points to the need to develop hedging products and strategies designed to minimise Natural Gas price volatility.

2. HEDGING MODELS

The optimal hedge is the ratio of futures contracts relative to spot position that minimises the risk of the payoff of the hedged portfolio² where risk is measured using the variance. The payoff of an energy hedger's portfolio is given as:

$$+ r_{st} - \beta r_{ft} \quad (1)$$

where r_s and r_f are returns on the cash and futures respectively, and β is the estimated OHR. To estimate the OHR we use three³ different methods. We also use a 1:1 or Naïve hedge ratio (1:1) where each unit of the spot contract is hedged with one unit of the futures contract. This approach while simple; may perform well for energy assets where the correlation between spot and futures is very high. The first hedging model we use is a constant hedge ratio estimated using OLS, which is the slope coefficient of a regression of spot on futures returns. This is given by:

2. Or the hedge that maximises the utility of an investor in a utility maximising framework. We approach the hedging problem from the perspective of an energy producer who is naturally long the asset. In terms of risk, they are concerned with price falls and therefore, to hedge their long positions in the underlying asset they sell or go short the futures contract.

3. The three model based measures that we use have been broadly applied in the hedging literature to estimate optimal hedges where optimal is defined in terms of minimising the variance however we would expect them to be reasonably effective in terms of reducing risk defined across a range of measures.

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$$r_{st} = \alpha + \beta r_{ft} + \varepsilon_t \quad (2)$$

where r_{st} and r_{ft} are the spot and futures returns respectively for period t . The OLS model has been extensively used in the literature on hedging since Ederington (1979). A number of papers including Myers (1991) argue that a constant hedge is likely to perform poorly given that it fails to take account of the time-varying nature of volatility, and that methods such as GARCH, which allow the conditional distribution of spot and futures returns to vary over time should be adopted. We therefore use two different parameterizations of the multivariate GARCH model to allow for time varying⁴ effects. The first GARCH model that we use is the Constant Correlation or CCGARCH model introduced by Bollerslev (1990). This model has been applied extensively in a hedging context (see, for example, Cotter and Hanly, 2006). The model is specified as follows:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t, \varepsilon_t = D_t \eta_t \quad (3)$$

$$\text{var}(\varepsilon_t | F_{t-1}) = D_t R D_t \quad (4)$$

where $y_t = (y_{1t}, \dots, y_{mt})'$, $\eta_t = (\eta_{1t}, \dots, \eta_{mt})'$ is a sequence of independent and identically distributed random vectors, F_t is the information set at time t , $D_t = \text{diag}(h_1^{1/2}, \dots, h_m^{1/2})$, m is the number of returns and $t = 1 \dots n$. $R = E(\eta_t \eta_t' | F_{t-1}) = (\rho_{ij})$ where $R = \rho_{ij}$ for $i, j = 1, \dots, m$. $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t = (\text{diag } Q_t)^{1/2}$ and $E(\varepsilon_t \varepsilon_t' | F_{t-1}) = Q_t = D_t R D_t$ where Q_t is the conditional covariance matrix. The model assumes that conditional correlations are constant and therefore the conditional covariances are proportional to the product of the corresponding conditional standard deviations. Each of the conditional variances in D_t has a univariate GARCH (1, 1) specification.

$$h_{it} = \omega_i + \sum_{j=1}^r \alpha_{ij} \varepsilon_{it-j}^2 + \sum_{j=1}^s \beta_{ij} h_{it-j} \quad (5)$$

The assumption of constant conditional correlations while useful, may seem unrealistic for hedging applications, we therefore estimate an additional GARCH model that generalises the CCGARCH model to allow the conditional correlation matrix to be time dependent. This is the Dynamic Conditional Correlation Model or DCCGARCH model of Engle (2002). This is specified as:

$$y_t | F_{t-1} \sim N(0, Q_t), t = 1, 2, \dots, n \quad (6)$$

$$Q_t = D_t R D_t \quad (7)$$

where $D_t = \text{diag}(h_1^{1/2}, \dots, h_m^{1/2})$ is a diagonal matrix of conditional variances and F_t is the information set at time t . The conditional variance is defined as in equation (4), Q_t is the conditional covariance matrix. $R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2}$ where Q_t is a symmetric positive definite matrix given as:

4. We initially estimated the OHR's using a variety of multivariate GARCH models including the Diagonal Vech model and the BEKK models but we report only the two best performing parameterisations which are the Constant Correlation and Dynamic Conditional Correlation models. The other results are available on request.

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1\eta_{t-1}\eta'_{t-1} + \theta_2Q_{t-1} \quad (8)$$

where θ_1, θ_2 are parameters that capture the effects of previous shocks and dynamic conditional correlations on the current dynamic conditional correlation. For $\theta_1, \theta_2 = 0$ the model is equivalent to the CCGARCH model.

This model has shown good performance in hedging applications including for energy based assets (Chang, McAleer and Tansuchat, 2011). Time varying hedges may incur larger transactions costs as compared with a constant hedging strategy given the need to rebalance the hedge however we do not explicitly incorporate such costs as they tend to be very low in futures markets, averaging around 0.033 percent per trade (Locke and Venkatesh, 1997). More specifically, only a small number of papers within the broad literature on hedging have included transactions costs and of those, the findings have been that they are too small to materially affect hedging performance. For example Brooks Cerny and Miffre (2012) find that transactions costs account for just 0.008 of the difference between constant and time varying hedges and conclude that they do not qualitatively affect the relative hedging performance of constant vs time varying approaches.

3. HEDGING EFFECTIVENESS

Within the hedging literature, a majority of papers have focused on the estimation of a minimum variance hedge given its simplicity and the wide ranging use of the variance as a risk measure in finance. When return distributions are normal, minimising the variance is sufficient however in many cases returns are non-normal. This means that hedges that may perform well in terms of minimising the variance may not be efficient in terms of other one-sided risk measures such as VaR. A number of papers have addressed this by matching the hedging estimation criterion with the evaluation method. See for example, Harris and Shen (2006) who estimated Minimum VaR hedges or more recently, Cotter and Hanly (2015) who examine various utility based hedges, however these approaches are complex and therefore not widely applied. This paper instead focuses on how well the minimum variance hedges perform in an energy asset context given their broad usage in the literature. We use a variety of risk measures to examine hedging efficiency based on Variance, VaR, Expected Shortfall and Expected Utility. Taken together these provide a comprehensive picture of the hedging effectiveness of energy futures in terms of risk reduction, but also in the case of the utility based measure, incorporates both risk, return, and risk aversion. The first hedging effectiveness measure we use is the variance. The variance metric (HE_1) measures the percentage reduction in the variance of a hedged portfolio as compared with the variance of an unhedged portfolio.⁵

We use the variance despite the fact that it gives equal weight to positive and negative outcomes which intuitively is not how we think about risk. We therefore include some additional one-sided risk measures that focus on a single tail of the distribution and that have become increasingly important in recent years in terms of how risk is measured for regulatory purposes. The first of these is VaR. This estimates the maximum expected loss for a given confidence level and for a specified⁶ time period. The VaR at confidence level α is

5. An unhedged portfolio has a hedge ratio of zero.

6. We used two approaches to calculate VaR at the 5% level. In the first case we use the historical simulation approach which is based on the empirical distribution. We also estimated VaR using the Variance Covariance approach which assumes that returns follow a normal distribution. We report results based on the empirical distribution only given the non-normal

$$VaR_\alpha = q_\alpha \quad (9)$$

where q_α is the quantile of the loss distribution. We calculate VaR using the 5% confidence level under which we would expect losses in excess of the VaR to occur once every 20 weeks (months). The performance metric employed is the percentage reduction in VaR (HE_2).

VaR has been criticised as it is not a coherent measure of risk. This relates to the fact that VaR is not sub additive which implies that the risk of two positions when added together is never greater than the sum of the risks of the two individual⁷ positions. We address this by estimating an additional performance metric; Expected Shortfall. This measures the expected loss, conditional⁸ that we have exceeded the VaR. Expected Shortfall (ES), which is also known as conditional VaR (CVaR) is a useful hedging performance metric because it provides a hedger with an estimate not only of the probability of a loss, but also of the magnitude of a possible loss (for further details, see Tasche, 2002). It is given as:

$$ES = E[L | L > VaR] \quad (10)$$

This measures the expected value of our losses, L , in excess of the VaR. The performance metric we use to evaluate hedging effectiveness is the percentage reduction in the Expected Shortfall (HE_3).

The final metric we use to examine hedging performance incorporates the risk attitude of the investor as expressed in a quadratic utility framework. We choose quadratic utility as it is one of the most broadly applied within the risk management and asset pricing frameworks. This framework is based on a utility maximizing investor whose utility function is defined over the conditional expectation and conditional variance of end-of-period wealth: It is defined as follows:

$$U(W) = W - aW^2, \quad a > 0 \quad (11)$$

Define $U(\cdot)$ as the utility function and W is wealth, a is a positive scalar parameter measuring risk aversion. We use a risk aversion value of 5⁹ which lies within the bounds found by most studies that have measured the risk aversion coefficient. It is worth noting that the expected utility estimate is not readily interpretable, rather it is the ordering of the utilities that matters. Therefore we use the percentage increase in the quadratic utility of a hedged portfolio as compared with the quadratic utility of an unhedged portfolio (HE_4). This enables us to translate the utilities to provide a clear and unambiguous measure to allow us to compare utility based hedging effectiveness.

4. DATA

Our data consist of six of the largest and most important energy products that trade on either CMEGROUP or the Intercontinental Exchange (ICE). These are: West Texas Intermediate

characteristics of the data, but the others are available on request. For more detail on VaR, see Jorien (2006). For the use of VaR in a hedging context see Harris and Shen (2006).

7. For further discussion, see Artzner et al. (1999).

8. The expected shortfall is estimated using the historical simulation approach which is based on the actual returns or empirical distribution as for the VaR.

9. Estimates for the CRRRA have been used in the literature generally fall within the range 1–10. See for example Ghysels, Santa Clara, and Valkanov (2005), Guo and Whitelaw (2006).

Figure 1: Energy Product Spot Price Comparison

Spot prices are rescaled to 1.0 for comparison purposes. WTI is West Texas Intermediate Crude Oil. Brent is North Sea Oil.

(WTI) light sweet crude¹⁰ oil, Brent crude oil, Natural Gas, Unleaded Gasoline, Heating Oil and Gasoil. These products together have highly liquid spot and futures markets and have a significant pricing history. The total sample period runs from October 26th 2005 to December 12th 2013. This timeframe was chosen as it is recent data that covers a number of key energy price events and therefore contains both tranquil and volatile periods. This allows us to compare hedging scenarios that include periods of high volatility as well as both upside and downside movements. We examine hedging at two different frequencies; 5-day (weekly) and 20-day (monthly) to allow for the different holding periods for different market participants. Figure 1 provides a time series plot of energy prices for each of the assets we examine. Table 1 provides descriptive statistics of the data for the full sample period. The data exhibit both skewness and kurtosis as is common for most energy assets. Jarque-Bera (JB) statistics indicate non-normality for each series at all frequencies.

All of the energy products with the exception of Natural Gas exhibit a positive mean which is indicative of the strong price rises for energy over the last decade. The price falls in Natural Gas have been attributed to the increase in fracking which has increased supply. Also, because of the

10. This is the most actively traded energy product in the world and it is used as a pricing benchmark. Further contract details on each of the energy products are available as follows:

Brent, <https://www.theice.com/productguide/ProductSpec.shtml?specId=219>,

Henry Hub Natural Gas, http://www.cmegroup.com/trading/energy/natural-gas/natural-gas_contract_specifications.html

Unleaded Gasoline, <http://www.cmegroup.com/trading/energy/refined-products/rbob-gasoline.html>

Heating Oil, http://www.cmegroup.com/trading/energy/refined-products/heating-oil_contract_specifications.html

Gasoil, <https://www.theice.com/productguide/ProductSpec.shtml?specId=909>

Table 1: Summary Statistics

	Frequency	Mean %	Stddev %	Skewness	Kurtosis	JB	LM	ADF
Crude Oil WTI								
Spot	Weekly	0.11	4.97	0.25*	4.20**	315.9**	60.6**	-7.8**
Futures	Weekly	0.11	4.81	0.13	2.50**	111.8**	76.7**	-7.7**
Spot	Monthly	1.00	10.24	-1.25**	4.23**	98.8**	8.5	-5.2**
Futures	Monthly	1.01	10.12	-1.28**	4.23**	100.0**	9.4	-5.2**
Crude Oil BRENT								
Spot	Weekly	0.14	4.58	-0.26	2.76**	139.6**	77.5**	-7.7**
Futures	Weekly	0.15	4.48	-0.40**	3.52**	230.3**	97.4**	-7.9**
Spot	Monthly	1.12	9.49	-1.62**	6.54**	217.1**	5.3	-4.5**
Futures	Monthly	1.05	9.14	-1.49**	6.54**	210.7**	4.4	-4.5**
Heating Oil								
Spot	Weekly	0.12	4.47	-0.18	1.42**	37.8**	69.1**	-9.2**
Futures	Weekly	0.11	4.35	-0.10	1.82**	59.3**	54.5**	-8.8**
Spot	Monthly	0.91	8.72	-0.95**	3.41**	62.2**	6.0	-3.9**
Futures	Monthly	0.95	8.44	-1.07**	4.24**	92.1**	5.2	-4.1**
Gasoline								
Spot	Weekly	0.13	5.39	-0.44**	1.06**	33.5**	64.6**	-8.1**
Futures	Weekly	0.12	5.29	-0.18	2.01**	73.6**	57.7**	-7.7**
Spot	Monthly	1.01	11.26	-1.09**	2.90**	53.6**	28.9**	-5.0**
Futures	Monthly	0.91	11.30	-1.16**	4.12**	91.3**	20.8	-5.1**
Gasoil								
Spot	Weekly	0.11	4.33	-0.36**	2.54**	122.5**	71.4**	-8.8**
Futures	Weekly	0.11	4.23	-0.07	1.94**	66.6**	51.9**	-8.6**
Spot	Monthly	0.83	8.83	-1.13**	3.60**	73.8**	4.5	-4.0**
Futures	Monthly	0.86	8.62	-1.18**	4.25**	96.5**	2.9	-4.1**
Natural Gas								
Spot	Weekly	-0.29	7.74	0.18	2.26**	92.4**	18.8**	-10.4**
Futures	Weekly	-0.28	7.38	0.37**	1.65**	57.7**	16.3**	-10.1**
Spot	Monthly	-0.40	29.72	0.41	1.48**	11.8**	24.3**	-4.2**
Futures	Monthly	-0.32	29.36	0.40	3.40**	49.9**	13.1*	-4.1**

Summary statistics are presented for the log returns of each spot and futures series. The mean and standard deviation (Stddev) are in percentages. The total sample period runs from 26/10/2005 until 10/12/2013. Weekly returns are 5-day while monthly returns are 20-day. JB is the Jarque-Bera statistic which measures normality. LM, (with 4 lags) is the Engle (1982) ARCH test for heteroskedasticity. ADF is the augmented dickey fuller test (with 4 lags) for stationarity. ** and * denotes significance at the 1% and 5% levels respectively.

lack of adequate facilities to handle large amounts of Natural Gas for export, U.S. Natural Gas prices have fallen below international prices. Heteroskedasticity is present at the weekly frequency for all assets but only for Natural Gas and Gasoline at the monthly frequency.

This provides a strong case for the use of GARCH models to estimate the conditional variance and covariance. All series are stationary as measured using an Augmented Dickey Fuller (ADF) test. Also of note is the similarity in the price movement of most of the energy products with the exception of Natural Gas. In terms of volatility, the most volatile series as measured by standard deviation is Natural Gas followed by Gasoline. This is confirmed by a quick glance at Figure 2 which models each series using a GARCH (1, 1) process. Again Natural Gas tends to move independently of the other energy products which share broadly similar movements.

All series also exhibit periods of marked volatility, most notably the energy price spike and rapid decline of 2008. While some commentators have attributed this spike to speculative activity (see for example Cifarelli and Paladino, 2010), the underlying supply and demand fundamentals of the energy market also seem to have been a contributory¹¹ factor.

For each of the energy products we formed hedged portfolios using equation (1) with the OHR as estimated from each of the four hedging models used; Naïve, OLS, CCGARCH and DCCGARCH. This procedure generated 372 t-period hedges in-sample at the weekly frequency and 93 at the monthly frequency for the period October 2005 to December 2012, upon which we based our hedging effectiveness estimates. We also retained a subsample equivalent to one year of data for the period December 2012 to December 2013 for out-of-sample testing. This was done by generating 1-step ahead forecasts of the OHR for use in period $t + 1$. The OHR's were assumed to follow a random walk process and the 1-step-ahead forecasts for the time varying hedges were generated using a rolling window approach.

5. EMPIRICAL ANALYSIS

5.1 Volatility

Volatility was examined using a univariate GARCH (1, 1) model with results presented in Figure 2 and in Table 2. From Figure 2 there are a number of clear findings. Firstly Natural Gas is again the standout in that it exhibits much larger volatility than each of the other energy products. It is also volatile when many of the other series are relatively tranquil such as during 2009 following large amounts of shale gas from fracking coming to market.

For the other energy products the pattern of volatility is broadly similar with Gasoline showing the largest volatility and Gasoil the lowest. These findings are supported in Table 2 with unconditional volatility again highest for Natural Gas at 5.28% for the weekly frequency (14.39% monthly) as compared with the next highest which is Gasoline which is 5.12% weekly (10.94% monthly). Also worth noting is that volatility persistence is quite high ($> 75\%$) at the monthly frequency for all assets with the exception of gasoline. This indicates that the effects of shocks can remain in the market for long periods. This is particularly true for both Gasoil (95%) and Natural Gas (93%). For energy hedgers this illustrates the importance of managing volatility given its persistence in energy markets.

5.2 Optimal Hedges

Figure 3¹² plots a comparison of the OHR's for each hedging model using weekly data. We can see that despite the similarity in the price movements between many of the energy products and the high correlation between them, the optimal hedge strategies are quite different. This is confirmed if we look at Table 3 which presents the constant OLS OHRs for each of the energy products and Table 4 which shows a statistical comparison of the two time-varying GARCH based OHR's. Looking first at the Constant OLS hedges, we can clearly see large differences between the optimal hedges for the different energy products. For example, the Constant OHR for WTI is 1.017

11. See for example Hamilton (2009)

12. We illustrate OHR's using weekly data for brevity. Monthly OHR's broadly follow a similar pattern and are available on request.

Figure 2: Energy Product Volatility Comparison

Volatility is modelled using a GARCH (1, 1) process. The volatility of Natural Gas is significantly higher than the other energy products. This is followed by Gasoline, WTI, Brent, Gasol and finally Heating Oil has the lowest volatility over the period.

Table 2: Volatility of Energy Products GARCH (1, 1)

	Frequency	ω	α	β	$\alpha+\beta$ Volatility Persistence	Volatility Unconditional
WTI	Weekly	0.0001	0.092	0.871	0.96	4.60%
	Monthly	0.0025	0.242	0.532	0.77	10.44%
BRENT	Weekly	0.0000	0.086	0.889	0.98	4.12%
	Monthly	0.0015	0.300	0.575	0.87	10.87%
Heating Oil	Weekly	0.0000	0.060	0.927	0.99	3.89%
	Monthly	0.0007	0.197	0.720	0.92	8.99%
Gasoline	Weekly	0.0001	0.106	0.864	0.97	5.12%
	Monthly	0.0045	0.3059	0.316	0.62	10.94%
Gasoil	Weekly	0.0000	0.068	0.915	0.98	3.76%
	Monthly	0.0004	0.168	0.780	0.95	8.95%
Natural Gas	Weekly	0.0002	0.173	0.770	0.94	5.28%
	Monthly	0.0014	0.219	0.713	0.93	14.39%

Volatility is measured as the unconditional volatility estimated using $\omega/1(-\alpha-\beta)$ from a univariate GARCH (1, 1) process as in equation (5): $h_{it} = \omega_t + \sum_{j=1}^r \alpha_j \varepsilon_{it-j}^2 + \sum_{j=1}^s \beta_j h_{it-j}$. The sum of $\alpha + \beta$ measures volatility persistence.

as compared with an OHR for Brent of just 0.888. The OHR's for the refined oil products are all broadly similar with values falling between 0.9 and 1.0 whereas Natural Gas is just 0.685. This reflects the lower correlation between Natural Gas Spot and Futures contracts.

Looking next at the monthly hedges, we can see that the OLS hedges are similar across most assets, with values very close to 1, and only Gasoline showing a markedly different OHR of 0.959 as compared with hedges in the range 0.996–1.026 for the other assets. The differences between the OHR's for weekly and monthly data reflect the higher correlation between spot and futures for data at the lower frequency.

Moving on to the time varying hedges; from Table 4 we carry out a statistical comparison between the mean of the time varying OHR's for the different products. Using weekly data and taking the CCGARCH model for example, there is a significant difference of 0.067 (t-stat 11.80) between the OHR for WTI Crude and the OHR for Brent Crude. Overall for comparisons between all models, we find significant differences between the OHR's for the CCGARCH model in 87% of cases. For the DCCGARCH model the figure is higher at 93%. Making a similar comparison for monthly data we find significant differences in 73% and 60% of cases for the CCGARCH and DCCGARCH models respectively. While this is lower than the results for the weekly data, it indicates that hedging strategies should be tailored to the particular energy product and that it is not possible to generalise an optimal hedge strategy from one energy asset to another. These findings are similar to those found in other energy hedging studies such as Chang, McAleer and Tansuchat (2011) who also find differences in the OHR's for WTI and Brent Crude; however we extend their findings given our much broader energy dataset.

5.3 Hedging Effectiveness

Table 5 presents in-sample results for hedging performance for each of the six different energy products. The first thing to note is that hedging is generally very effective in that each of

Figure 3: Optimal Hedge Ratios–Weekly

OLS, CCGARCH and DCCGARCH hedges are presented for each of the different energy products in sample using Weekly data.

the different hedging models yields a large improvement in the underlying risk measure as compared with an unhedged portfolio. For example, for weekly data the average hedging effectiveness for all performance metrics across all assets and hedging models is 68%. Monthly hedges are more effective.

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**Table 3: Estimated Minimum Variance (OLS)
Hedge Ratios**

	WEEKLY OLS	MONTHLY OLS
WTI	1.017	1.009
BRENT	0.888	1.026
GASOLINE	0.916	0.959
HEATINGOIL	0.989	1.006
GASOIL	0.930	1.002
NATLGAS	0.685	0.996

tive again at 81% on average. Turning next to the relative hedging performance of the different energy products, we use our first metric HE (1) which measures the percentage reduction in the variance for each hedging model as compared with a no hedge scenario.

Looking at the weekly hedges and using a no hedge strategy as a benchmark, the WTI and Heating Oil hedges show the largest reductions in the variance of 96.8% and 93.6 % respectively. The poorest performer by some distance is the Natural Gas hedge with just 42.6% reduction in variance using the best performing OLS model. Moving on to look at hedging using VaR, we again see that hedging results in large reductions in this risk measure for most of the energy products with better performance again showing for WTI and Heating Oil, however the reductions in VaR are slightly lower than for the Variance. For example WTI hedges reduce the VaR by about 85% across all hedging models as compared with an average of about 96% for the Variance. Also worth noting is that Brent crude returns notably poorer performance as measured by VaR as compared with WTI crude with reductions of the order of about 48–50%. This may relate to the breakdown in correlations between spot and futures for Brent where tail events occur. For the poorest performer which is Natural Gas, hedging can only reduce the VaR by around 26% on average across the OLS, and GARCH models.

This picture of relatively poor performance for the Natural Gas hedges is repeated for each of the different performance metrics we use and probably relates to a combination of factors including volatility, but especially the higher basis risk associated with Natural Gas which is difficult to store and transport, has restricted access to export markets and is therefore subject to large price fluctuations making it the most volatile of the energy products. This is especially the case when we look at Expected Shortfall. For example the reduction in the Expected Shortfall of Natural Gas for the best performing OLS model is just 12.89%. This compares with reductions in the region of 77% for WTI, Brent (55%), Gasoline (55%), Heating Oil (77%) and Gasoil (59%). What this means is that it is difficult for Natural Gas producers to limit their exposure to extreme events using hedging. The fourth hedging effectiveness metric we is based on quadratic utility. In terms of the relative ranking of the best energy hedges, again we see WTI and Heating Oil showing the best performance, and while Natural Gas is still the worst performer, its relative performance against the other energy products is not as bad in terms of Utility. For example the DCCGARCH model returns an increase in Utility for Natural Gas of the order of 49.83% which is significantly better than the performance of Natural Gas hedges when measured using the Variance, VaR and Expected Shortfall. What these results show is that irrespective of the risk measure that is used to measure hedging effectiveness, the relative performance for the different energy products is broadly similar.

If we compare the effectiveness of monthly as compared with weekly hedges, in almost all cases with the sole exception of Gasoline and Heating Oil using VaR, the performance improves significantly. This relates to higher correlations at lower frequencies and also that the data are more approximately normal. The most striking improvement is for Natural Gas which now shows similar

Table 4: Comparison of Time Varying Optimal Hedges Ratios across Energy Products

	WEEKLY						MONTHLY					
	CCGARCH						CCGARCH					
	WTI	BRENT	GASOLINE	HEATINGOIL	GASOIL	NATLGAS	WTI	BRENT	GASOLINE	HEATINGOIL	GASOIL	NATLGAS
WTI	0.000	0.067* (11.80)	0.084* (19.51)	0.015* (3.81)	0.079* (17.63)	0.252* (29.13)	0.000	0.031* (3.88)	0.076* (9.53)	0.006 (1.33)	0.036 (10.35)	0.015 (1.40)
BRENT		0.000	0.017* (2.89)	0.052* (9.48)	0.012 (1.96)	0.185* (19.46)		0.000	0.107* (9.49)	0.025* (2.70)	0.067* (7.68)	0.016 (1.21)
GASOLINE			0.000	0.069* (16.98)	0.005 (1.12)	0.168* (19.24)			0.000	0.082* (8.94)	0.040* (4.68)	0.091* (6.80)
HEATINGOIL				0.000	0.064* (15.05)	0.237* (27.78)				0.000	0.042* (7.31)	0.009 (0.75)
GASOIL					0.000	0.173* (19.64)					0.000	0.051* (4.50)
NATLGAS						0.000						0.000
	DCCGARCH						DCCGARCH					
	WTI	BRENT	GASOLINE	HEATINGOIL	GASOIL	NATLGAS	WTI	BRENT	GASOLINE	HEATINGOIL	GASOIL	NATLGAS
WTI	0.000	0.090* (21.31)	0.091* (40.66)	0.013* (5.51)	0.070* (31.68)	0.328* (40.23)	0.000	0.029* (3.40)	0.083* (8.67)	0.011 (2.17)	0.019* (4.19)	0.002 (0.11)
BRENT		0.000	0.000 (0.10)	0.077* (15.90)	0.020* (4.28)	0.238* (25.95)		0.000	0.112* (8.81)	0.018 (1.89)	0.047* (5.01)	0.027 (1.48)
GASOLINE			0.000	0.077* (23.99)	0.021* (6.77)	0.237* (28.17)			0.000	0.094* (8.79)	0.065* (6.18)	0.085* (4.50)
HEATINGOIL				0.000	0.057* (17.64)	0.315* (37.10)				0.000	0.029* (4.53)	0.009 (0.52)
GASOIL					0.000	0.258* (30.64)					0.000	0.020 (1.20)
NATLGAS						0.000						0.000

Table shows a comparison between the time varying OHR's for the different energy products. For the GARCH models we carry out a statistical comparison between the Mean of the time varying OHR's for the different products. Taking weekly data for example, there is a significant difference (0.067) between the OHR for WTI and the OHR for Brent from the CCGARCH model. T-statistics are in parentheses. *Denotes significance at the 1% level.

Table 5: In-Sample Hedging Performance

	WEEKLY			MONTHLY				
	NAIVE	OLS	CCGARCH	DCCGARCH	NAIVE	OLS	CCGARCH	DCCGARCH
HE1 - Variance								
WTI	96.44	96.47	96.60*	96.77*	99.57	99.58	99.59	99.60 ^λ
BRENT	74.25*	75.45**	75.88**	75.84**	96.03*	96.09*	94.45**	95.36**
GASOLINE	78.79*	79.46**	79.40**	78.83*	90.56*	90.72*	90.27*	87.60**
HEATINGOIL	93.62*	93.63**	93.28**	93.11**	97.50*	97.50*	97.51*	97.52 ^λ
GASOIL	82.22*	82.70**	80.98**	82.44*	96.24*	96.24*	96.37*	96.15*
NATURAL GAS	33.55*	42.59**	41.70**	42.23**	87.23*	87.23*	87.70**	87.78**
HE2 - VaR								
WTI	86.39 ^λ	86.16	84.53*	86.33	87.76 ^λ	87.61	87.54*	87.57*
BRENT	49.90*	48.80**	48.68**	51.08**	59.34 ^λ	58.42**	53.20**	54.30**
GASOLINE	65.07 ^λ *	61.37**	60.29**	52.19**	46.19	48.31 ^λ *	44.03*	41.36*
HEATINGOIL	78.57*	78.44*	77.71**	79.44**	76.59 ^λ	76.53*	76.57*	76.59*
GASOIL	58.51*	58.52*	59.15 ^λ *	58.72*	72.05	71.87*	74.94**	66.97**
NATURAL GAS	20.02*	26.16**	26.53**	26.05**	45.67	45.79*	44.85*	46.78*
HE3 - EXPECTED SHORTFALL								
WTI	77.79	77.44	78.82**	78.19	85.77	85.85	86.09	86.16 ^λ
BRENT	52.93*	54.91**	55.12**	53.09*	75.60*	75.94*	70.68**	74.72*
GASOLINE	46.89*	52.61**	55.01**	54.76**	64.48*	64.29*	66.98**	66.28**
HEATINGOIL	75.83*	75.87*	77.08**	75.49*	80.96*	80.69*	81.60*	81.89 ^λ *
GASOIL	58.84*	58.95*	56.33**	59.07*	77.48*	77.60*	77.32*	78.17**
NATURAL GAS	7.99*	12.89**	11.49**	10.64**	33.44*	33.41*	36.35**	36.13**
HE4 - UTILITY								
WTI	95.49 ^λ	95.23	92.15**	93.40**	99.15 ^λ	99.02	97.92*	97.85*
BRENT	62.89*	69.09**	68.87**	69.50**	93.48*	92.62**	97.32**	89.95**
GASOLINE	76.28*	78.88**	78.60**	75.02*	90.79*	91.73**	94.71**	95.08**
HEATINGOIL	94.26	94.59	97.78*	99.09**	99.52 ^λ	99.32	98.14	99.47
GASOIL	76.65*	79.48**	79.63**	86.86**	95.08*	95.02*	98.26*	96.09*
NATURAL GAS	45.80*	47.13*	49.79**	49.83**	88.92*	88.84*	88.99*	88.21*

Figures are in percentages. HE1–HE4 give the percentage reduction in the performance measure from the hedged model as compared with a no hedge position. For example, hedging WTI at the weekly frequency with the Naïve model yields a 77.79% reduction in the Expected Shortfall as compared with a No-Hedge strategy. * Denotes significance at the 1% level for a comparison of the hedging performance for each energy product using a given performance metric. Using the Variance at the weekly frequency for example, WTI has a reduction of 96.44% in the variance from the Naïve hedge strategy. This is significantly larger than each of the other energy products. λ denotes the best performing hedging model for a given energy product. The best performing energy product for a given hedging strategy is highlighted. ^λ Denotes a significant difference at the 5% level for a statistical comparison of the hedging performance of the Naïve Hedging strategy with each of the model based hedges; OLS CCGARCH and DCCGARCH.

performance to the other energy products when measured using the Variance and the Utility measures, and reasonable performance in terms of reducing both VaR and Expected Shortfall by about 45% and 35% respectively.

In Table 5, we also carry out a statistical comparison between the hedging performances of the different energy products using Efrons (1979) bootstrap procedure. This involves the generation of a large number of sample datasets from data for each hedged¹³ portfolio. For example, using weekly data and the (HE1) variance, we compare the best performing energy product which is WTI, with each of the other energy products for each hedging model. We therefore calculated 80 differences between the hedging models, together with their associated t-statistics for each frequency. Of the 80 pairs tested, 78 (97%) are significant at the 1% level in-sample at the weekly frequency, whereas 75 (93%) are significant at the monthly frequency. This indicates substantial differences in the statistical hedging performance for the different energy products.

We next test whether there is a significant difference between the Naïve or 1:1 hedge strategy and each of the other model based hedges to see whether modelling the hedge using OLS or GARCH models can provide significant performance improvements. Taken together across all of the risk metrics employed we carry out 72 comparisons at both weekly and monthly frequencies. At the weekly frequency the model based hedges perform significantly better in 71% of cases with the best performing CCGARCH model outperforming the Naïve model in 88% of cases. At the monthly frequency the performance improvement is just 38% on average, with the best performing model (CCGARCH) showing significant outperformance in 46% of cases. This result reflects the more normal characteristics of the data at lower frequencies.

We also carry out an out-of-sample analysis to examine the extent to which the hedging approaches that we have used would be useful in a real world scenario. The results are summarised in Table 6 and are based on 1-step-ahead forecast OHR's as estimated using the process outlined in section three. In general terms, the results contained in Table 6 support the broad findings in-sample however, a notable change is that the performance differential between the different metrics is much narrower. For example, using the WTI hedges at the weekly frequency, the best performing model reduces Variance by 96.88%, VaR by 90.03% and Expected Shortfall by 90.63%. An interesting finding is that the Natural Gas hedges perform significantly better than for the in-sample period when measured using the VaR and Expected Shortfall metrics. This may relate to the lower volatility for the product during the out-of-sample period (2013). In terms of a comparison across time horizon, the performance improves significantly for all assets as we move from the weekly to the monthly frequency with the exception of Gasoline and Heating oil. The relatively poor performance of these assets at a lower frequency relates to an occasion when the spot and futures movements had opposite signs and this resulted in poor hedging performance.

A key element of this study is the focus on refined energy products in addition to Crude Oil and Natural Gas to enable a broad based hedging effectiveness comparison. What we find is that while hedging is generally effective, the risk reducing ability of futures contracts varies widely depending on the underlying asset that is being hedged. This is clearly demonstrated in Table 7 which presents the average hedging performance for the different energy products across all three risk metrics employed. At the weekly frequency, three distinct groups emerge. WTI and Heating Oil market participants can expect to obtain hedges with effectiveness rates in excess of 85%.

13. We resampled the hedged returns from each portfolio 100 times. This generated 100 performance metrics in each case with an attendant variance which facilitated t-tests of the differences between the performance of the energy products using point estimates of our results.

Table 6: Out-of-Sample Hedging Performance

	WEEKLY				MONTHLY			
	NAIVE	OLS	CCGARCH	DCCGARCH	NAIVE	OLS	CCGARCH	DCCGARCH
HE1 - Variance								
WTI	96.56	96.59	96.72	96.88 ^λ	99.57	99.60	99.61 ^λ	99.60
BRENT	74.65*	75.82*	76.24 ^λ **	76.17 ^λ **	90.22*	90.78 ^λ **	91.09 ^λ **	91.07 ^λ **
GASOLINE	78.71*	79.48 ^λ *	79.45*	78.88*	64.90*	67.28 ^λ **	67.37 ^λ **	68.81 ^λ **
HEATINGOIL	93.48*	93.48 ^λ *	93.15*	92.98 ^λ **	88.22*	88.42*	88.32*	88.45 ^λ *
GASOIL	82.46*	82.90 ^λ *	81.25 ^λ **	82.65*	96.36*	96.35*	96.44 ^λ *	96.38*
NATURAL GAS	35.55*	43.99 ^λ **	43.25 ^λ **	43.63 ^λ **	90.64*	90.88 ^λ *	89.84*	90.16*
HE2 - Var								
WTI	90.26	89.30*	90.01	90.03 ^λ	92.92	92.83	92.97 ^λ	93.02
BRENT	60.11*	60.13*	61.85 ^λ *	60.88*	67.61*	68.47*	68.87 ^λ *	68.76*
GASOLINE	80.08 ^λ *	79.14*	79.01*	78.85*	29.04*	30.48*	30.71*	31.33 ^λ *
HEATINGOIL	68.56 ^λ *	68.48*	68.43*	68.43*	60.26*	60.65*	60.44*	60.71 ^λ *
GASOIL	55.07*	55.31*	55.28*	55.36 ^λ *	87.54 ^λ *	87.48*	87.45*	87.49*
NATURAL GAS	54.68*	42.61 ^λ **	44.86 ^λ **	42.41 ^λ **	50.57*	51.35 ^λ *	47.23*	48.59*
HE3 - EXPECTED SHORTFALL								
WTI	90.63 ^λ	89.02*	90.52	90.58	89.16	89.16	89.71 ^λ	89.56
BRENT	72.02 ^λ *	72.02*	71.57*	71.28*	70.31*	70.31*	73.07 ^λ **	72.90 ^λ **
GASOLINE	46.56*	28.45 ^λ **	47.39 ^λ *	47.27*	-9.29 ^b	-9.29	-7.42	-7.00
HEATINGOIL	66.65 ^λ *	66.65*	66.32*	66.24*	66.31*	66.31*	66.71*	66.95 ^λ *
GASOIL	67.16*	67.16*	67.85*	67.93 ^λ *	87.77 ^λ *	87.77*	87.49*	87.67*
NATURAL GAS	54.65 ^λ *	49.53 ^λ **	49.72 ^λ **	45.04 ^λ **	50.55 ^λ *	50.55*	47.54*	48.55*
HE4 - UTILITY								
WTI	95.98	95.02*	95.88	96.79 ^λ	88.16*	92.77 ^λ **	93.04 ^λ **	95.50 ^λ **
BRENT	73.44*	74.67*	74.75 ^λ *	74.21*	84.59*	85.06 ^λ *	84.60*	84.13*
GASOLINE	77.83*	78.74 ^λ *	78.13*	77.35*	60.28*	63.03 ^λ **	62.30*	65.62 ^λ **
HEATINGOIL	91.29*	91.37 ^λ *	90.82*	90.85*	78.79*	78.85 ^λ *	78.82*	78.57*
GASOIL	84.66*	85.45*	83.54*	87.42 ^λ **	110.11*	110.06*	110.39*	111.54 ^λ *
NATURAL GAS	5.10*	32.03 ^λ **	28.31 ^λ **	30.96 ^λ **	133.87	131.69	143.10 ^λ **	140.35 ^λ *

Figures are in percentages. HE1–HE4 give the percentage reduction in the performance measure from the hedged model as compared with a no hedge position. For example, hedging WTI at the weekly frequency with the Naive model yields a 90.63% reduction in the Expected Shortfall as compared with a No-Hedge strategy. The best performing energy project for a given hedging strategy is highlighted. ^b Note that for Gasoline Hedges at the monthly frequency, the best performer is a no-hedge strategy, each of the hedging models actually return a worse expected shortfall. This relates to one occasion when the spot and futures movements had opposite signs. ^{*} Denotes significance at the 1% level for a comparison of the hedging performance for each energy product using a given performance metric. ^λ denotes the best performing hedging model. Percentage increases in utility in some cases are in excess of 100% which results when the hedge changes utility from negative to positive. See Alexander (2008) for more detail. ^α Denotes a significant difference at the 5% level for a statistical comparison of the hedging performance of the Naive Hedging strategy with each of the model based hedges; OLS CCGARCH and DCCGARCH.

Table 7: Average Improvement in Hedging Performance by Energy Product

	Average Risk Reduction	Difference vs Best Performing Contract
Weekly		
WTI	89%*	
HEATINGOIL	86%	3%
GASOIL	70%	19%
GASOLINE	67%	22%
BRENT	62%	27%
NATURAL GAS	31%	58%
Monthly		
WTI	93%*	
HEATINGOIL	89%	4%
GASOIL	85%	8%
BRENT	80%	13%
GASOLINE	73%	20%
NATURAL GAS	64%	29%

The average improvement in hedging performance is based on an average of each of the difference performance metrics used, Variance, VaR and Expected Shortfall as well as Utility across each of the hedging models; Naïve, OLS CCGARCH and DCCGARCH.* denotes best performing contract.

Gasoil Gasoline and Brent form the second group with effectiveness averaging 70% 67% and 62% respectively. The final group is made up of Natural Gas which by itself averages hedging effectiveness of just 31%. In terms of a comparison, WTI outperforms the other products as follows: Heating Oil (3%), Gasoil (19%), Gasoline (22%), Brent (27%), and Natural Gas (58%). What this means is that for investors, speculators and producers in energy markets whose time horizon is weekly, the ability to offset risk depends significantly on the underlying asset being hedged. Natural Gas market participants in particular will only be able to offset about one third of their exposure. For hedgers with monthly time horizons, the picture is somewhat better with average risk reductions in the range 64% (Natural Gas) to 93% (WTI). We note that these figures are based on averages, however, where tail risk as measured by VaR and Expected shortfall was concerned, hedgers will get poorer performance.

6. CONCLUSIONS

We estimate and compare optimal energy hedges using a variety of hedging models and risk measures to capture hedging performance. We apply this approach for six different energy products across weekly and monthly hedging frequencies. This allows us to make a comprehensive comparison of the relative hedging performance of some of the most important energy products trading in the markets.

Our findings indicate that there are significant differences between the OHR's and the hedging performance for the different energy products we examine. Of particular note is the poor hedging performance of Natural Gas hedges at the weekly frequency when evaluating using modern risk management metrics such as VaR and Expected Shortfall. The implication of this is that Natural Gas energy market participants may struggle to reduce their exposure to low probability tail events when they employ conventional hedging strategies. Our results also show that hedging is generally

effective in reducing energy hedgers risk across a variety of risk metrics. We also find that hedging is also effective in terms of increasing the energy hedger's utility.

Taken together these results suggest that energy market hedge strategies should be tailored to the individual energy product being hedged. They also show that for certain assets such as Natural Gas, managing volatility using futures hedging may only be of limited usefulness especially when risk is measured using VaR or Expected Shortfall.

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