Risk management and hedging approaches in energy markets

Jim Hanly
Technological University Dublin, james.hanly@tudublin.ie

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Risk Management and Hedging Approaches in Energy Markets

Jim Hanly

Abstract

Energy based assets are showing increased susceptibility to volatility arising out of geo-political, economic, climate and technological events. Given the economic importance of energy products, their market participants need to be able to access efficient strategies to effectively manage their exposures and reduce price risk. This chapter will outline the key futures based hedging approaches that have been developed for managing energy price risk and evaluate their effectiveness. A key element of this analysis will be the breadth of assets considered. These include Crude and Refined Oil products, Natural Gas, and wholesale Electricity markets. We find significant differences in the hedging effectiveness of the different energy markets. A key finding is that, that Natural Gas and particularly electricity futures are relatively ineffective as a risk management tool when compared with other energy assets.

Keywords: Hedging; Risk Management. Energy; Futures; Oil; Natural Gas; Electricity.

Jim Hanly,
Senior Lecturer in Finance,
College of Business,
Dublin Institute of Technology,
Dublin 2,
Ireland.
Tel +353 1 402 3180,
E-mail james.hanly@dit.ie.

1.0 Introduction and Context.

The importance of energy markets within the global economic framework cannot be overstated. They underpin and significantly impact all economic activity and are also important as an asset class within the investment context. However, it is also a fact that they are particularly affected by a variety of events such as political change, weather, technological change and of course economic growth. Given their importance, an analysis of the price movements and associated risks of the major energy products is essential as an aid to understanding energy markets. Furthermore, an ability to manage these risks is key if investors and more generally firms are to engage and participate confidently with energy products and markets. This chapter sets out to examine the energy market by breaking it down into the key products. We compare the price volatility of these key products as well as their correlation and co-movement characteristics. This is done with a view to showing how volatility and associated risk can be managed through the use of futures hedging strategies. We focus on futures given their broad presence and application to energy markets and because for most products they can be effectively applied to reduce risk in an efficient manner. This is true not just for energy markets but for the broader financial markets where effective hedging strategies have been documented. This literature has examined equities (Cotter and Hanly, 2006), various commodities (Lien and Yang, 2008, Wu, Guan, and Myers, 2011), foreign exchange (Kroner and Sultan, 1993, Brooks and Chong, 2001) and exchange traded funds (Alexander and Barbosa, 2008).

Looking more specifically at the literature on energy market hedging, a number of papers have examined the efficacy of hedges for various products. Crude Oil, Gasoline and Heating have all been examined has generally had the most attention with many papers finding useful hedging outcomes. For example, Alizadeh, Nomikos and Pouliasis (2008), Chang, McAleer and Tansuchat, (2011) and Pan, Wang and Yang (2014) all found that hedging oil or oil products generally yielded risk reductions of the order of 50% or above. While results from the literature indicate very good outcomes in respect of crude oil and its derivatives the results in terms of other energy assets aren't as strong. For example, Cotter and Hanly (2012) in a comparison between Oil and Natural Gas hedges find that Oil hedges tend to outperform Natural Gas hedges by around 30% - 35%. More recently, Hanly (2017) showed that Natural Gas hedges tended to return risk reductions of less than 40% on average. The case for electricity price risk management using futures is weaker again. Papers that have examined futures based electricity hedging include: Tanlapco, Lawarrée and Liu (2002). Bystrom (2003) and Zanotti, Gabbi and Geranio (2010). The results from these studies vary widely with hedging effectiveness measuring as low as 2% to a high of 38% depending on market under study and the methodology employed.

This chapter will investigate the volatility and hedging characteristics of the various energy markets using some of the most broadly applied methodologies and evaluation metrics. We begin by focusing on the correlation dynamics between the different products before moving on to analyse volatility with the GARCH framework. We then estimate and compare futures hedging efficacy thus facilitating an up to date analysis across the major markets and products. For the purposes of our study we will constrain ourselves to an analysis using a weekly data to reflect a useful time horizon that reflects many energy market participants and that allows for volatility persistence.

2.0 Energy Products

Energy markets for the most part consist of Oil and its various derivative products, Natural Gas and of course Electricity. For the purposes of this chapter we will initially consider these general markets for which an active futures market exists. These are West Texas Intermediate (WTI) and Brent Oil[1], Heating Oil, Gasoil (Diesel), Gasoline(Petrol), and Natural Gas. We also examine electricity for which we proxy by using the electricity price from the European Nordpool Market. Taken together, these products account for about 84% of total energy consumption in the EU[2].

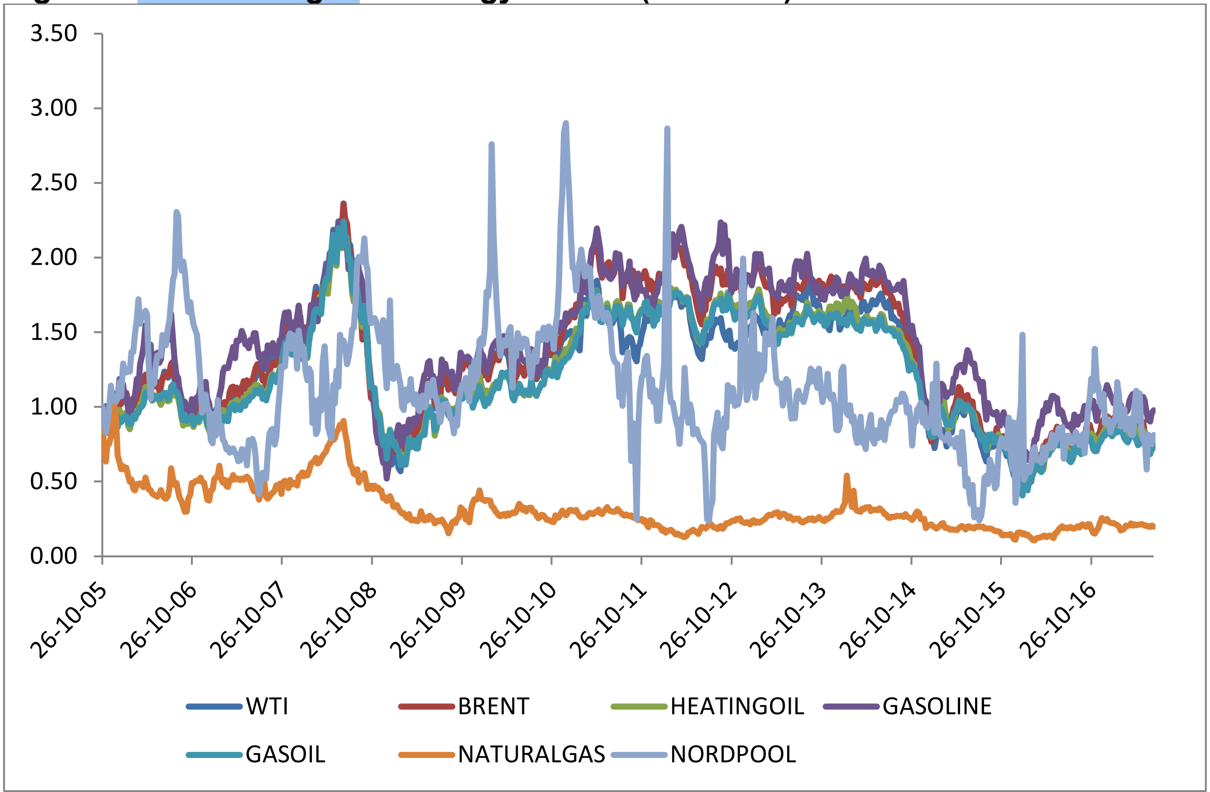
2.1 General Characteristics and Comparisons

From figure 1 a number of key findings emerge. Firstly there is a considerable divergence between the prices of Crude Oil and its derivatives on the one hand, and both Natural Gas and Electricity. Secondly, both of the Crude Oils and each of the derivatives, namely Heating Oil, Gasoline and Gasoil, while moving broadly together still show obvious differences in terms of their price behaviour. Table 1 presents price correlations across three different frequencies, daily weekly and monthly that support this view. Of particular note are the low correlations between the Oil based assets and both Natural Gas and Electricity. This is useful to highlight as it shows investors that all energy assets are not the same despite their substitutability and similarities. Also worth noting is that price correlations across different time horizons are broadly similar.

[1] These are two of the global pricing benchmarks. Further contract details on each of the energy products are available as follows:
WTI, Brent, https://www.theice.com/global-crudes
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
http://www.nordpoolspot.com/Market-data1/#/nordic/table

[2] Source. http://ec.europa.eu/eurostat/web/energy

Figure 1 Price Changes of Energy Assets (Rebased)



Notes: Prices based on weekly data are rebased for comparison purposes

Table 1 Price Correlations

DAILY

	WTI	BRENT	HEATINGOIL	GASOLINE	GASOIL	NATURALGAS	NORDPOOL
WTI	1.000						
BRENT	0.964	1.000					
HEATINGOIL	0.962	0.987	1.000				
GASOLINE	0.937	0.977	0.963	1.000			
GASOIL	0.966	0.987	0.996	0.962	1.000		
NATURALGAS	0.301	0.148	0.213	0.116	0.222	1.000	
NORDPOOL	0.312	0.248	0.248	0.183	0.253	0.241	1.000

WEEKLY

	WTI	BRENT	HEATINGOIL	GASOLINE	GASOIL	NATURALGAS	NORDPOOL
WTI	1.000						
BRENT	0.963	1.000					
HEATINGOIL	0.962	0.987	1.000				
GASOLINE	0.938	0.978	0.963	1.000			
GASOIL	0.967	0.987	0.996	0.963	1.000		
NATURALGAS	0.293	0.137	0.206	0.105	0.214	1.000	
NORDPOOL	0.327	0.266	0.266	0.200	0.271	0.235	1.000

MONTHLY

	WTI	BRENT	HEATINGOIL	GASOLINE	GASOIL	NATURALGAS	NORDPOOL
WTI	1.000						
BRENT	0.962	1.000					
HEATINGOIL	0.961	0.986	1.000				
GASOLINE	0.939	0.979	0.963	1.000			
GASOIL	0.966	0.987	0.995	0.963	1.000		
NATURALGAS	0.278	0.130	0.203	0.106	0.206	1.000	
NORDPOOL	0.340	0.292	0.291	0.239	0.298	0.196	1.000

Notes: Correlations between prices of the different energy assets are presented for the period 26/10/2005 to 21/06/2017

Table 2 – Stationarity

	Price	Returns
WTI	-1.77	-9.00**
BRENT	-1.59	-8.75**
HEATINGOIL	-1.41	-10.12**
GASOLINE	-2.08	-8.96**
GASOIL	-1.52	-9.77**
NATURALGAS	-2.21	-11.98**
NORDPOOL	**-3.80***	-13.63**

Critical values: 1%= -3.44 5%= -2.86

Notes: Stationarity is testing using the Augmented Dickey Fuller test with 4 lags. * Denotes a stationary series at the 5% level. **Denotes a stationary series at the 1% level.

Broadly speaking, each of the price series is non-stationary with the possible exception of Electricity for which there is some small predictability; however each of the returns series is stationary. Therefore to further examine the characteristics of each series we use log returns.

Table 3 presents correlations between the returns of the different assets. A number of findings emerge from Table 3, chief amongst them is that the correlations for the returns are generally below the correlation between prices. The other findings of note are that again, the oil based assets are broadly similar whereas both Natural Gas and particularly electricity show only very small similarities in terms of how they move together. We also note that the correlations are much higher at lower frequencies. This is to be expected as using lower frequency data has a smoothing effect. From our initial analysis, we will next look at volatility before estimating and analysing some risk management strategies using futures hedging. Given our initial findings, we propose to narrow down our dataset and exclude those assets that are broadly similar. We will therefore carry out further analysis using Brent Crude Oil, Gasoline, Natural Gas and Nordpool (Electricity). We now provide some detail on our general methodological approach to volatility and hedging analysis.

Table 3 Returns Correlations molto piu basso della correlazione tra prezzi!

DAILY

	WTI	BRENT	HEATINGOIL	GASOLINE	GASOIL	NATURALGAS	NORDPOOL
WTI	1.000						
BRENT	0.601	1.000					
HEATINGOIL	0.527	0.418	1.000				
GASOLINE	0.607	0.485	0.506	1.000			
GASOIL	0.697	0.653	0.562	0.607	1.000		
NATURALGAS	0.060	0.131	0.090	0.046	0.111	1.000	
NORDPOOL	-0.018	0.010	0.027	-0.022	-0.012	0.060	1.000

WEEKLY

	WTI	BRENT	HEATINGOIL	GASOLINE	GASOIL	NATURALGAS	NORDPOOL
WTI	1.000						
BRENT	0.790	1.000					
HEATINGOIL	0.605	0.651	1.000				
GASOLINE	0.665	0.701	0.596	1.000			
GASOIL	0.826	0.855	0.698	0.698	1.000		
NATURALGAS	0.135	0.177	0.273	0.144	0.187	1.000	
NORDPOOL	-0.003	0.052	0.108	0.006	0.017	0.018	1.000

MONTHLY

	WTI	BRENT	HEATINGOIL	GASOLINE	GASOIL	NATURALGAS	NORDPOOL
WTI	1.000						
BRENT	0.962	1.000					
HEATINGOIL	0.961	0.986	1.000				
GASOLINE	0.939	0.979	0.963	1.000			
GASOIL	0.966	0.987	0.995	0.963	1.000		
NATURALGAS	0.278	0.130	0.203	0.106	0.206	1.000	
NORDPOOL	0.340	0.292	0.291	0.239	0.298	0.196	1.000

Notes: Correlations between log returns of the different energy assets are presented for the period 26/10/2005 to 21/06/2017

3 General Method and Models

For the purposes of this chapter we define the optimal hedge (OHR) as the ratio between the futures and the spot that minimises the risk of the hedgers position. Risk is defined as the variance of the hedged portfolio whose returns are given as

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

where r_s and r_f are returns on the spot and futures respectively, and β is the OHR. To estimate the OHR we use two different models that have been broadly applied across many literatures. The first is a Naïve or 1:1 hedge ratio. The second model we use is the Constant Correlation or CCGARCH model introduced by Bollerslev (1990). The model is specified as follows:

$$y_t = E(y_t|F_{t-1}) + \varepsilon_t, \varepsilon_t = D_t\eta_t \tag{2}$$

$$\mathrm{var}(\varepsilon_t|F_{t-1}) = D_t R D_t \tag{3}$$

where $y_t = (y_{1t}...y_{mt})'$, $\eta_t = (\eta_{1t}...\eta_{mt})'$ is a sequence of independent and identically distributed random vectors, F_t is the information set at time t, $D_t = diag(h_1^{1/2},...h_m^{1/2})$, m is the number of returns and $t = 1..n$. $R = E(\eta_t\eta_t'|F_{t-1}) = (\eta_t\eta_t')$ where $R = \rho_{ij}$ for $i, j = 1,...,m$. $\varepsilon_t\varepsilon_t' = D_t\eta_t\eta_t' D_t$ $D_t = (diagQ_t)^{1/2}$ 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.

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_i^2,_{t-j} + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j} \tag{4}$$

These models were chosen as they are broadly used in the literature, have shown good performance in many applications and also because they range in complexity from the very simple Naïve hedge to the somewhat more complex CCGARCH model. We have left out many models that are commonly applied such as the OLS model and many different specifications of GARCH models on the basis that both of the models we use cover the spectrum of models and have in many cases shown the best performance. See Alexander and Barbosa (2008) or Hanly (2017) for more detail.

We primarily compare hedging performance using measures based on Variance because it is a standard measure of risk in finance and because of its prominence in the literature. We also use Value at Risk (VaR) to allow for a demonstrated economic or currency based analysis of hedging efficiency. VaR estimates the expected loss for a given confidence level and a specified time period. The VaR at confidence level α is

$$VaR_{\alpha} = q_{\alpha} \tag{5}$$

Where q_{α} is the quantile of the loss distribution. We calculate VaR using the 5% confidence level. For both risk metrics we measure hedging efficiency be measuring the percentage reduction in the metric for a hedged as compared to an unhedged position.

4 Data for Hedging and Volatility Analysis

Our data consist of three of the largest and most important energy products that trade on either CMEGROUP or the Intercontinental Exchange (ICE). These are:[3], Brent crude oil, Unleaded Gasoline and Natural Gas. We also analyse Electricity using Nordpool as our data proxy. 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 June 28th 2017. The data is analysed at the weekly interval which comprises 1 observation per week. The prices used are closing spot prices on a Wednesday. 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 (J-B) statistics indicate non-normality for each series. Heteroskedasticity is present at the weekly frequency for all assets. 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 using the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests with the single exception of Nordpool which

[3] 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

shows evidence of non-stationarity about a trend. In terms of volatility, the most volatile series as measured by standard deviation is Electricity followed by Natural Gas. This is to be expected given the supply considerations and non-storability of electricity.

Table 4: Summary Statistics

	Mean %	Stdev %	Skewness	Kurtosis	JB	LM	KPSS
Crude Oil Brent	-0.04	4.70	-0.009	2.24*	117.2*	546.19*	C 0.184* T 0.055*
Gasoline	0.01	5.06	-0.394*	1.24*	50.25*	75.57*	C 0.123* T 0.039*
Natural Gas	0.10	7.61	0.445*	4.12*	414.9*	42.24*	C 0.037* T 0.035*
Electricity	-0.15	17.96	-0.665*	12.95*	3957.5*	60.41*	C 0.014* C 0.717

Note: Summary statistics are presented for the log returns of each spot and futures series. The mean and standard deviation (Stdev) are in percentages. The total sample period runs from 26/10/2005 until 28/07/2017.Weekly returns are 5-day. Jarque and Bera (J–B) statistic measures normality. LM with four lags is the Lagrange multiplier test for ARCH effects proposed by Engle (1982); it is distributed as $\chi 2$. Stationarity is tested using the KPSS test, which tests the null of stationarity against the alternative of a unit root. Critical values for the KPSS test at the 1% level are 0.739 and0.216 for the constant (C) and trend (T) statistics respectively.

For each of the energy products we formed hedged portfolios using equation (1) with the OHR as estimated from using the Naïve and CCGARCH models. The procedure generated 488 t-period hedges in-sample at the weekly frequency for the period October 2005 to February 2015, upon which we based our hedging effectiveness estimates. We also retained a subsample equivalent to two and a half years of data for the period February 2015 to July 2017 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 Figures 2a and 2b and in Table 5. Figure 2 illustrates a number of clear findings. Firstly Electricity and to a lesser extent Natural Gas clearly standout in terms of showing markedly larger volatility than both of the Oil based series. A second element is that the volatility spikes are not aligned for the most part between the series. This shows that even similar series such as Crude Oil and Gasoline have different triggers for market volatility. For the most par these can be traced to supply concerns and refinery bottlenecks. Also looking at a comparison of Crude Oil and Gasoline, we can see that volatility is higher for Gasoline.

FIGURE 2a: Energy Product Volatility

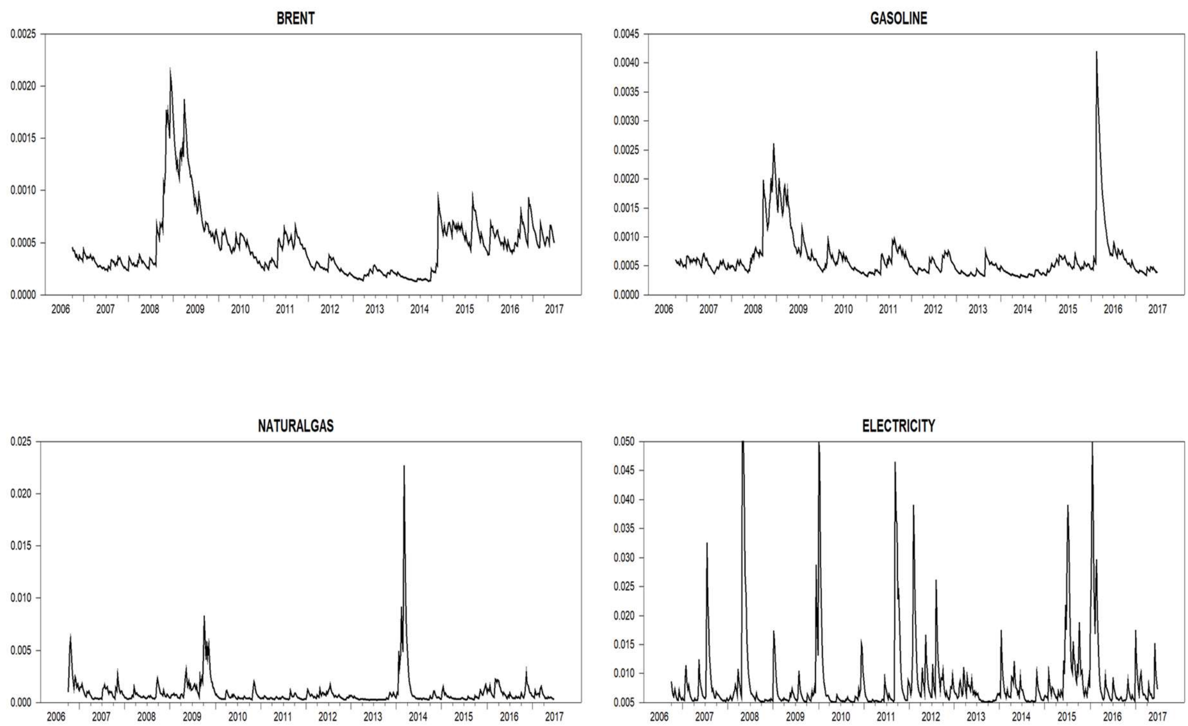
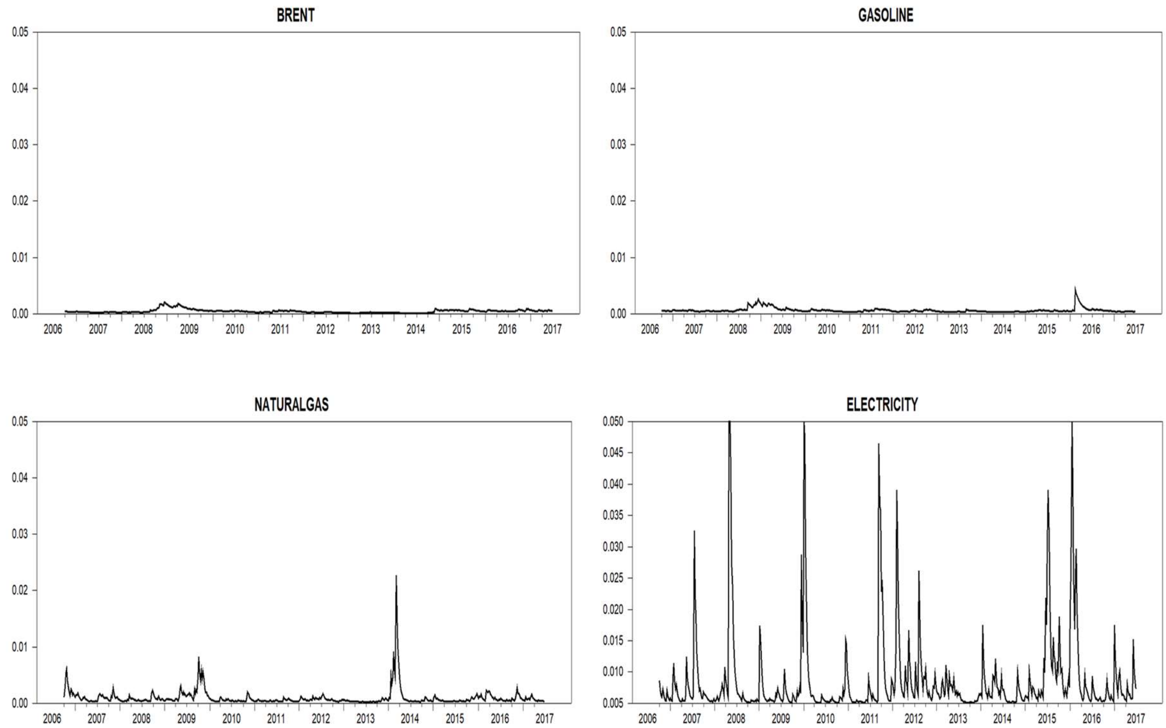


FIGURE 2b: Energy Product Volatility (Comparison to Scale)



Note: Volatility in modelled using a GARCH (1, 1) process. Figure 2b shows each volatility series using the same scale on the y axis to illustrate starkly how the volatility of Electricity and to a lesser extent Natural Gas is significantly higher than the other energy products.

questo è esattamente quello che mi dice il modello GARCH su py!

Table 5: Volatility of Energy Products GARCH (1, 1)

	ω	**α**	**β**	**α+β** Volatility Persistence	**Volatility** Unconditional
BRENT	0.000008	0.077	0.908	0.985	0.057%
GASOLINE	0.000036	0.088	0.858	0.946	0.067%
NATURAL GAS	0.000085	0.273	0.643	0.916	0.101%
ELECTRICITY	0.002139	0.192	0.574	0.766	0.914%

Note: Volatility is measured as the unconditional volatility estimated using $\omega_i / 1(-\alpha - \beta)$ from a univariate GARCH (1, 1) process as in equation (5): $h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_i^2,_{t-j} + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j}$. The sum of $\alpha + \beta$ measures volatility persistence.

These findings are supported in Table 5 with unconditional volatility highest for Electricity at 0.914%. Natural Gas at 0.101% compared with the next highest which is Gasoline which is 0.067% and finally Crude Oil showing just 0.057% - the lowest in our dataset. Also worth noting is that for volatility persistence the pattern is reversed with the effect of shocks showing highest for Brent at 0.985 followed by

Gasoline (0.946), Natural Gas(0.916) and Electricity (0.766) in that order. Across the energy sector we can see that the effects of shocks can remain in the market for long periods. For energy hedgers this illustrates the importance of managing volatility given its persistence in energy markets.

5.2 Optimal Hedging Strategies

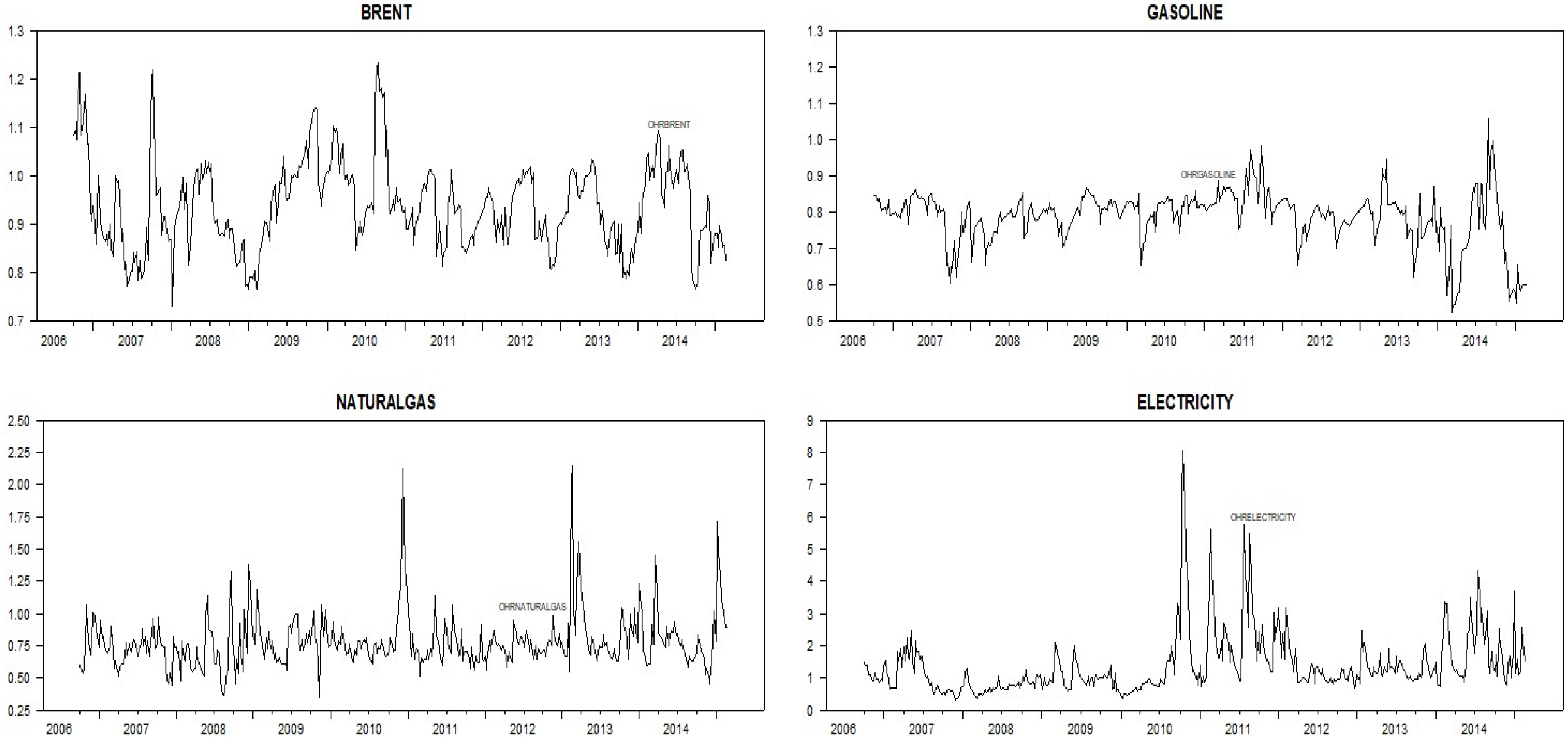
Figure 3 presents a comparison of the Time-Varying OHR's for each energy product. We can see that despite the similarity in the price movements between Brent and Gasoline and the high correlation between them (0.701), the optimal hedge strategies are quite different. This reflects the relationship between the spot and futures of the different assets and the fundamentals of futures pricing having an effect. The differences between the optimal hedges for the Oil based assets and Natural Gas is even starker. The OHR's for the refined oil products for the most part fall within a range of 0.80 to 1.0 whereas the OHR's for Natural Gas tend to a much larger range in the region of 0.50 to 1.50 for the majority of cases. This reflects the higher volatility of Natural Gas. Turning to Electricity we can see that the fundamental differences in terms of Supply and Demand and the non-storability condition which result in very high volatility carry over in terms of optimal hedge estimation. For example the Nordpool OHR's are typically in excess of 1.5 and on one occasion it exceeds 8.0. The interpretation of this would be that for an investor in the electricity market with a long spot position, they would need to go short the equivalent of 8 futures contracts to hedge their exposure. In practical terms this is not a realistic proposition from a risk management perspective however it does serve to highlight that for Electricity Markets, the futures as a hedging tool is suspect.

quello che osservavo: non posso andare short con un ammontare piu alto della commodity

5.3 Hedging Efficacy

The results detailing hedging efficacy are shown in Table 6. Looking first at the In-Sample results a number of key findings emerge. Firstly, for both of the Oil based energy products, futures based hedging is a viable method for managing energy price risk. In terms of the Variance risk metric, risk reductions are in excess of 70% and for VaR around the 50% mark. This result is broadly similar to the large literature that has examined hedging efficacy for Oil and Oil derivatives. For Natural Gas, the results are markedly poorer with the best performing model showing just a 33% risk reduction as measured by the variance, and just under 20% for the VaR metric. The poor performance for Natural Gas hedges relates to a variety of factors including volatility and higher basis risk associated. While quite low in relative terms, these numbers are nevertheless reasonable, as they offer investors the hope of mitigating risk by way of futures hedging. For Electricity however the results are uniformly poor with the best performing model showing a 5.28% reduction in the variance and 2.84% reduction in the VaR. These findings indicate that electricity hedges perform very poorly when compared with the broader hedging literature for which hedging efficiency in the range 50% – 90% is not uncommon. These numbers are so low that we can safely state that futures when using conventionally as a hedging tool are of little use. Indeed we could question the existence of a futures market in electricity markets given this very poor performance when using commonly applied methods for futures markets.

Figure3: Optimal Hedge Ratios



Note: Time Varying (CCGARCH) hedges are presented for each of the different energy products.

Table 6 Hedging Performance

	IN-SAMPLE		OUT-OF-SAMPLE	
	NAÏVE	**CC GARCH**	**NAÏVE**	**CC GARCH**
Variance				
BRENT	76.22	**77.30***	79.67	**80.75***
GASOLINE	71.92	**74.14***	**77.51***	76.61
NATURAL GAS	27.35	**33.10***	35.54	**40.56***
ELECTRICITY	**5.28***	4.78	5.62	**5.25***
VaR 5%				
BRENT	51.14	**51.91***	55.75	**57.13***
GASOLINE	46.69	**49.11***	**52.37***	51.22
NATURAL GAS	16.87	**19.61***	16.56	**19.42***
ELECTRICITY	**2.84***	2.05	3.66	**3.89***

Note: * denotes the best performing hedging model for a given energy product. Figures are in percentages. For example, hedging Brent with the CCGARCH model yields a 77.3% reduction in the Variance as compared with a No-Hedge strategy.

What this means is that for investors, speculators and producers in energy markets, the ability to offset risk is dependent on the underlying asset being hedged. For Oil market participants the results are useful in that they show that almost three quarters of energy price risk can be offset but the use of futures hedging. Natural Gas market participants in particular will only be able to offset about one third of their exposure and for electricity market participants the figure is around one twentieth.

5.4 Hedging Model Performance

In this chapter we applied only two hedging models. The simple Naïve model is applied as it is essentially a 1:1 ratio between the spot and the futures. It requires no estimation and is extremely simple conceptually and in terms of its application. Despite its simplicity is has been advocated as one of the best overall hedging approaches as it delivers good performance and is simple to apply. For this reason it is a benchmark against which other methods can be compared. We also chose to only apply one of the myriad more complex models (CCGARCH) as this model has compared favourably to many of the even more complex approaches in the literature. (see Hanly 2017 for a discussion). In a sense therefore we cover both simple and complex in our hedging approaches. From table 6 we can see that while the CCGARCH model is the better performer overall showing better performance in 75% of cases. The performance differentials are not economically significant particularly as we haven't included the effects of transactions costs or estimation and applications complexity. Our view on this is that while complex models may offer better performance – in most cases this is only theoretical or paper based superiority. When the full cost benefits of complex hedging approaches are considered, they offer little additional advantage to the energy market participant over the very simple 1:1 hedging approach.

6 CONCLUSION

We estimate and compare optimal energy hedges using a variety of two widely applied hedging models and risk measures to capture hedging performance. We Carry out an initial analysis on the relationships between six different energy products which together comprise the majority of the energy traded in energy markets. We then model the volatility and hedging characteristics of a sample of four of the key assets, Crude Oil, Gasoline, Natural Gas and Electricity to show investors how energy price risk can be managed using futures contracts. We also estimate the relative efficacy of these approaches. 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 and to inform the reader of same.

Our findings indicate that there are significant differences between volatility and the hedging characteristics and performance for the different energy products we examine. Of particular note is the relatively poor hedging performance of Natural Gas hedges and the extremely poor ability of conventional futures hedging to yield substantive risk reductions for Electricity markets. The implication of this is that Natural Gas energy and particularly Electricity market participants will struggle to obtain meaningful risk management outcomes from conventional futures based hedging strategies. Our results also show that hedging is generally effective in reducing risk for Crude Oil and its derivatives.

Our results show that energy market hedge strategies should be tailored to the individual energy product being hedged. They also show that for certain assets such as Electricity, managing volatility using futures hedging may only be of little use and alternative approaches should be considered.

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Short Bio

Jim Hanly is a Senior Lecturer in the College of Business in Dublin Institute of Technology. He also works as a financial trainer and consultant. His research interests focus on risk management and hedging, asset pricing, and volatility modelling in financial and commodity markets. He holds a PhD in Financial Economics from University College Dublin.