

2018

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Recommended Citation

Hanly, J., Morales, L. & Cassells, D. (2018). The Efficacy of Financial Futures as a Hedging Tool in Electricity Markets. *International Journal of Finance & Economics*, vol. 23, no. 1, pp. 29-40. doi: 10.1002/ijfe.1600.

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The Efficacy of Financial Futures as a Hedging Tool in Electricity Markets

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Abstract

This paper estimates and applies a risk management strategy for electricity spot exposures using futures hedging. We apply our approach to three of the most actively traded European electricity markets, Nordpool, APXUK and Phelix. We compare both optimal hedging strategies and the hedging effectiveness of these markets for two hedging horizons, weekly and monthly using both Variance and Value at Risk (VaR). Our key finding is that electricity futures can effectively manage risk only for specific time periods when using hedging strategies that have been very successful in financial and other commodity markets. More generally they are ineffective as a risk management tool when compared with other energy assets. This is especially true at the weekly frequency. We also find significant differences in both the Optimal Hedge Ratios (OHR's) and the hedging effectiveness of the different electricity markets. Better performance is found for the Nordpool market, while the poorest performer in hedging terms is the Phelix market.

Keywords: Hedging; Risk Management, GARCH, Electricity Futures.

JEL classification: G10, G12, G15.

1. INTRODUCTION

Following the deregulation and liberalisation of electricity markets in Europe, several power markets exchanges now facilitate the trading of electricity. This process has resulted in power companies shouldering the risk of adverse price movements as regulators no longer automatically allow them to transfer risk to their customers through price increases. In turn this has generated a demand for derivative products to allow for hedging those price risks. Hedging with futures contracts has become a standard way of managing commodity price risk, particularly with reference to energy markets, and standardised futures contracts are now traded on many power exchanges.

A large literature has documented the use and effectiveness of futures as a hedging tool since early work by Ederington (1979). This literature has examined equities (Cotter and Hanly, 2012, Kanas, 2009), various commodities (Chen and Sutcliffe, 2012, Wu, Guan, and Myers, 2011), foreign exchange (Kroner and Sultan, 1993, Röthig, 2011) portfolio products such as exchange traded funds (Alexander and Barbosa, 2008) and energy commodities such as Crude oil and Natural Gas, (see for example, Chang, McAleer and Tansuchat, 2011, Brinkmann and Rabinovich, 1995, Fraser and McKaig, 2000). The general results from the literature are that hedging is generally very effective as measured by risk reductions of the order of 60% – 90% depending on the underlying asset being hedged. Some assets have shown better hedging effectiveness, notably stock indices and certain oil contracts such as West Texas Intermediate which have shown hedging effectiveness above 95% in some instances.

There has been relatively little work which has examined electricity price hedging using futures within the European context as the power exchanges are still relatively new¹. Another reason is that there are challenges associated with electricity spot price modelling given the characteristics of electricity prices such as high volatility and price spikes which arise because of non-storability and seasonality (Wickens and Wimschulte, 2007, Botterud, Kristiansen, and Ilic, 2010, Xiao, Colwell and Barr, 2014).

One of the first papers to look at electricity futures hedging was Tanlapco, Lawarrée and Liu (2002). They looked at both cross and direct hedging using data from the US electricity market. They estimated optimal hedge ratios (OHRs) in the range 0.25 to 1.35 and found a significant difference between the Naïve hedge ratio and the OHR as estimated using OLS.

¹ The oldest exchange Nordpool was established in 1996, with APXUK and EEX more recent again in 1999 and 2002 respectively.

They found reductions in risk as measured by the standard deviation ranging from about 3% up to a maximum of 38% depending on the market being hedged. Bystrom (2003) looked at hedging in the Nordpool market using weekly data, for the period 1996 – 1999. He found that hedging effectiveness from Naïve (1:1 ratio), OLS and GARCH models was typically of the order of 10% – 20%. He also found that for specific periods or models hedging effectiveness was as high as 29% but also noted that there were cases where hedging actually increased the variance. Zanotti, Gabbi and Geranio (2010) use similar methods to analyse hedging for Nordpool, Phelix and Powernext markets. Their findings which are based on daily data indicate that model choice has a significant impact on hedging efficiency. They also find that daily hedges are relatively ineffective with typical variance reductions of around 2% - 3%. Frestad (2012) also analyses hedging in the Nordpool market but uses a more extensive dataset ranging from 2000 – 2010. Using an OLS model and a moving window to allow for time variation he documents relatively poor performance using a measure based on accumulated gain but notes that this may relate to ambiguity about the goals of a hedging strategy whereby risk minimisation may not be the main objective. More recently Sanda, Olsen and Fleten, (2013) look at company level hedging for hydro based electricity companies and find that over 90% of aggregate production is hedged. They use cash flow at risk rather than the variance as their measure of hedging efficacy and find that only one of twelve companies showed a significant reduction in monthly cash flow variance.

Given the lack of depth in terms of coverage of electricity hedging we address some issues that are pertinent. A key contribution of this paper is that we examine the efficacy of electricity futures markets within the context of the existing literature of futures hedging. We do this by applying proven futures based hedging strategies that have shown good performance when applied within other energy markets. Our key contribution over the existing literature is that we track the time varying performance of electricity futures hedges period by period using data at two frequencies, weekly and monthly. This allows us to focus on where hedging strategies are effective and where they show poor performance. This is important given the existing work in this area has reported hedging effectiveness as an average of many hedges and this has tended to underestimate the efficacy of electricity futures hedges. Our approach also allows us to track how OHR's and hedging effectiveness have changed as the markets have developed through both tranquil and intensely volatile periods. This paper also contributes by drawing comparisons from the broader hedging literature using both the commonly applied variance reduction criterion as well a downside risk measure – Value at Risk, to account for non-normality. Finally, we look at whether model choice matters in terms of hedging effectiveness.

Our key result indicates that electricity market participants can only obtain good results on a period by period basis but that they can obtain only relatively minor risk reductions on average when compared with other energy or financial market participants. This result raises some questions about the *raison d'être* of electricity futures markets given that the major justification for futures markets is their ability to offer risk management opportunities to market participants. We now outline the hedging models used in this paper.

2. METHOD

There are a number of frameworks that can be used to examine optimal hedging. The most generally applied is the variance minimisation framework (see for example, Ederington, 1979, Alexander and Barbosa, 2008,) which assumes that futures prices are martingales and hence ignores the return component of a hedged portfolio. In this framework the OHR is the ratio of futures relative to spot that minimises the variance of the hedged portfolio. Other papers have incorporated expected return into the estimation of the optimal hedge via utility maximisation (deVille deGoyet, Dhaene and Sercu, 2008). This allows a number of different characterisations of investor utility to be applied. In this paper we adopt the variance minimisation approach given the widespread use of the variance as a risk measure; its dominance in the hedging literature and its twin advantages of relative ease of calculation and interpretation. It also allows us to draw comparisons between the hedging effectiveness of electricity futures and the hedging effectiveness of other assets which many papers (see for example, Chang, McAleer and Tansuchat, 2011, Chen and Sutcliffe, 2012) have examined using the variance minimisation paradigm.

We use two methods to estimate the OHR. The first model we use is an OLS regression based hedge which yields a constant hedge ratio over the period for which it is estimated. This is given by:

$$r_{st} = \alpha + \beta r_{ft} + \varepsilon_t \quad (1)$$

where r_{st} and r_{ft} are the spot and futures returns respectively for period t . The OLS model has been extensively used since it was first applied to futures markets by Ederington (1979); however it assumes a constant variance despite evidence that many economic time series are heteroskedastic. GARCH models following Bollerslev (1986), address this issue by allowing the conditional distribution of spot and futures returns to vary over time. Therefore, the second model we use is the Constant Correlation or CCGARCH model introduced by

Bollerslev (1990)². This model has been applied extensively in a hedging context, is easy to estimate and provides good estimation characteristics even for relatively small samples which is a useful characteristic where monthly data are being used as there are relatively few data points. The model is specified as follows:

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

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

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 $t = 1 \dots n$. $R = E(\eta_t \eta_t' | F_{t-1}) = (\eta_t \eta_t')$ where $R = \rho_{ij}$ for $i, j = 1, \dots, m$. $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, $D_t = (\text{diag} Q_t)^{1/2}$ 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.

$$h_{it} = \omega_i + \sum_{j=1}^r \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^s \beta_{ij} h_{i,t-j} \quad (4)$$

2.1 Risk Measures

We use two risk measures to compare the effectiveness of the OLS and CCGARCH hedge strategies. The first risk measure is the variance and the hedging effectiveness is measured as the percentage reduction in the variance of a hedged portfolio as compared with the variance of an unhedged portfolio which is simply the unhedged spot return.

$$\%Variance_Reduction = 1 - \left[\frac{VARIANCE_{HedgedPortfolio}}{VARIANCE_{UnhedgedPortfolio}} \right] \quad (5)$$

Despite its broad ranging use, a key problem with the Variance as a risk measure, is that it cannot differentiate between upside and downside risk, as it gives equal weight to positive and negative returns. Given that electricity time series are non-normal as evidenced by skewness and kurtosis characteristics we have also included a downside risk metric to

² We also estimated a Naïve or 1:1 model but it underperformed the OLS model in all cases. Also, alternative parameterisations of the GARCH family of models were applied including the DCC GARCH model (Engle, 2002). We report the best performing model which is the CC GARCH model, but our other results are available on request.

measure hedging effectiveness. There are a number of risk metrics that have the ability to measure risk in one tail of the distribution including Lower Partial Moments, Semi Variance and Expected Shortfall, however we have chosen to use VaR given its broad application in the regulatory framework, ease of estimation and intuitive interpretation. VaR estimates the maximum expected loss for a given confidence level and for a specified time period. The VaR at confidence level α is

$$VaR_{\alpha} = q_{\alpha} \quad (6)$$

where q_{α} is the quantile of the loss distribution. We calculate VaR using the 5% confidence level. The performance metric employed is the percentage reduction in VaR.

$$\%VaR_Reduction = 1 - \left[\frac{VaR_{5\%HedgedPortfolio}}{VaR_{5\%UnhedgedPortfolio}} \right] \quad (7)$$

3 DATA AND DESCRIPTIVE STATISTICS

Electricity markets are very different from other energy commodities markets because of the non-storability of electricity. Spot markets for electricity are generally managed by Power Exchanges and prices are set by a process whereby bids are submitted by market participants for the day following the bid process. Equilibrium is established and a market clearing price is set for the following day and for this reason, spot markets are in effect day ahead markets. Electricity spot prices exhibit a number of key characteristics including volatility clustering, mean reversion, price jumps or spikes and seasonality. The demand and supply characteristics of the electricity market can change rapidly and therefore seasonal factors such as time of day, calendar, weather, and economic activity will all have an impact. Because these factors are time dependent, the frequency of the data will have an important impact on the price behaviour. Some of these characteristics present a unique challenge in terms of obtaining an efficient hedging solution to electricity price risk.

In this paper we are seeking to determine the efficacy of hedging as a risk management strategy for electricity market participants. Our analysis is also focused on the volatility characteristics of the European Electricity futures markets and the evolution of these markets which are still quite new as compared with longer established energy commodity markets. We therefore choose three different contracts to represent three different markets. The markets used are Nordpool for Scandinavia, European Energy Exchange for

Germany (Phelix) and Amsterdam Power Exchange (APX) UK for the United Kingdom. These were chosen given their liquidity³ and because they are some of the most long standing electricity futures contracts available. In each case we obtained day-ahead auction prices which we use as spot prices. Note that the spot market for physical delivery of electricity is different than for other commodity markets and is based on an auction system that matches bids with generation and sets a price for market participants 24 hours prior to the delivery. Therefore spot prices are in effect a day-ahead futures contract⁴. For the futures contracts we used base load average reference prices for which a continuous series was formed using a rollover process. Our full sample is for a 10 year period and includes data from 15/09/2004 to 10/01/2014. We include data at two different frequencies; weekly (5-day) and monthly (20-day) to allow for a broad ranging analysis that reflects the time horizons of different market participants. Descriptive statistics are given in Table 1.

[Table 1 here]

Each series displays a positive mean for the period under study. The electricity price data also shares many of the same characteristics of other energy series such as the presence of significant Skewness and Kurtosis. The Jarque-Bera (J-B) statistic indicates that each of the series is non-normal but also that departures from normality are more pronounced for higher frequency data. Indeed the descriptive statistics in general show that electricity spot prices tend to be much more volatile and have larger departures from normality than other financial, commodity, or energy assets. For example, weekly standard deviations are in the range 15% to 30% as compared with a typical weekly standard deviation for crude oil of about 5% or 2.5% for equities. This presents a particular challenge from a hedging perspective. Unit root tests indicate that all series are stationary while we also find the presence of significant ARCH effects in most cases. Also of interest is that while the correlation between spot and futures prices ranges from 70% to 90% depending on the electricity market, the attendant returns show much lower correlation. We also note that the correlations are higher at lower frequency indicating that hedging performance should be significantly better for lower frequency hedges.

³ Liquidity on all three contracts has grown substantially since their inception and the open interest ranges from 1 – 10 terawatt hours (TWH) per day.

⁴ See the following for more detailed information:

<http://www.apxgroup.com/trading-clearing/apx-power-uk/>

<http://www.nordpoolspot.com/How-does-it-work/Day-ahead-market-Elspot-/>

<https://www.eex.com/en/products/power/power-derivatives-market>

3.1 Estimation Procedure

Our in-sample period is from 14/09/2005 to 05/09/2012. For this period we estimated a constant hedge ratio using OLS and a time-varying hedge ratio using the CCGARCH model. The spot return was then hedged using the following

$$+r_{st} - \beta r_{ft} \quad (8)$$

where r_s and r_f are spot and futures returns respectively, and β is the OHR. In this way we generated 368 t-period hedges in-sample at the weekly frequency and 92 at the monthly frequency for the period October 2005 to December 2012, these were formed into a single portfolio on which we based our hedging effectiveness estimates. We also retained a subsample of two years of data for the period 12/09/2012 to 01/10/2014 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. Because we also wish to track how hedging effectiveness changed over time, we carried out an additional estimation based on a rolling window OLS model. The initial OHR was estimated using a window length equivalent to one year of data for the period October 2004 to October 2005. The hedging effectiveness was then estimated for this portfolio of returns using the % reduction in the variance criterion before rolling the window forward. This was done by adding an observation and removing the oldest observation thus keeping the window length unchanged. The process was then repeated. In this way we obtained 368 hedged portfolios at the weekly frequency (92 monthly) each with a different estimate of hedging effectiveness.

4. EMPIRICAL RESULTS

In this section we report our empirical findings. We first look at volatility of the different electricity markets and discuss the key determinants that contribute to this. We next look at the optimal hedging strategies as obtained from our models. Finally, we examine the hedging efficacy for the different markets and strategies.

4.1 Volatility

Results of our volatility analysis are presented in Table 2, while Figure 1 illustrates the volatility graphs obtained from fitting a GARCH (1, 1) to the electricity return series. The most obvious difference is the large difference in the magnitude of volatility between spot

and futures markets. For other financial assets these would typically mirror each other however for electricity the spot volatility is notably higher for the reasons discussed earlier. In terms of a comparison, some differences emerge across the different spot series, most notably the Nordpool series is the least volatile, followed by APXUK and PHELIX. Differences in spot volatility probably reflect the production structure and generational fuel mix in each market. For example, Norway has a very large hydro generation capacity which is relatively flexible whereas the German market has relied on both nuclear and coal fired generation which is less flexible and therefore more prone to spikes. An additional cause of volatility in the German market is the unpredictable behaviour caused by the massive recent installation of renewables such as wind and solar and their attendant feed in tariff structure. For the futures series the volatility between the markets is broadly similar.

[Figure 1 here]

[Table 2 here]

The coefficients from the GARCH (1, 1) model for electricity are quite different from those typically found at weekly and monthly frequencies for other financial or energy assets. For example, volatility persistence is very high not only at the weekly but also at the monthly frequencies. Only the Nordpool series displays a volatility persistence structure that is similar to other assets with persistence declining as the time horizon lengthens whereas for both APXUK and PHELIX the volatility persistence remains very high at weekly and monthly frequencies. These results are in line with the stylised facts for electricity markets and are similar to those found by other studies such as Gianfreda (2010). We now go on to look at the results from the hedging models.

4.2 Optimal Hedges

Figure 2 presents the OHR's for each of the three markets examined for both weekly and monthly data. The first thing to note is the volatility of the CCGARCH OHR's for each market but especially for the weekly hedges. For example the Phelix market has an OHR in excess of 3 on a number of occasions and on one occasion it goes as high as 8.9.

[Figure 2 here]

For monthly data the time-varying hedges are somewhat lower but are still large in comparison to those obtained from other assets which typically have OHRs in the range 0.5 to 1.5 (Cotter and Hanly, 2012). The second thing to note is the difference between the

OHR's for the different markets. For example at the weekly (monthly) frequency the OLS based OHR's are 0.56 (0.89) for Nordpool, 1.02 (0.72) for APXUK and 0.94 (0.92) for Phelix. These results reflect the different volatility and correlation dynamics between spot and futures for the different markets.

4.3 Hedging Effectiveness

In this paper we sought to establish the hedging effectiveness of futures hedging strategies for electricity market participants in Europe and to make inter market comparisons to see whether any significant differences emerged. Accordingly, Table 3 shows in-sample results for the three electricity markets we examine; Nordpool, APXUK and Phelix. Two risk measures, Variance and VaR are presented together with the percentage reduction in those risk measures using two frequencies, Weekly and Monthly⁵.

From Table 3, the standout result is that hedging effectiveness is quite low for each of the electricity markets and especially so at the weekly frequency. Taking the best performing model for each market for example, hedging effectiveness as measured by variance reduction ranges from 8.03% for Phelix to 8.19% for APXUK and 8.77% for the best performer which is Nordpool. Using the VaR criterion, the results are even poorer with reductions ranging from 4.11% (Phelix) to 4.52% (Nordpool). To put this in economic terms, for an exposure in the electricity market of €1 million, for the best performer which is Nordpool, hedging would reduce the value at risk from €395,288 to \$377,892 – a reduction of just €17,396. These results are worse than those reported by Bystrom (2003) who found weekly hedging efficiency of about 17% for the Nordpool market. However we examine a much larger time period and two additional markets. Moving on to look at hedges within a monthly time horizon, the results are significantly better, with hedging effectiveness for the best performing model ranging from 17.77% for the APXUK hedges to 24.02% for Phelix and 27.37% for Nordpool which is again the best performing market. VaR reductions are also improved but are still quite low. For example the best hedging performance using VaR is in the Nordpool market (15.39%) while the worst is APXUK (9.02%). The results from VaR which is a tail specific measure indicate that the volatility and non-normality of electricity price data presents a particular challenge in terms of obtaining a good hedging outcome. 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.

⁵ We also estimated but do not present detailed results for Daily hedges as hedging effectiveness was extremely poor in all cases averaging about 1.3% across all assets⁵. This is comparable to results for daily hedges found by Zanotti, Gabbi and Geranio (2010).

[Table 3 here]

We also compare the hedging performance of the OLS and CCGARCH models using a bootstrap process (Efron, 1979) whereby we resampled the hedged returns from each portfolio to facilitate t-tests of the differences between the performances of the different hedging models. The models generated significantly different performance for APXUK and Phelix at the weekly frequency and for Nordpool and Phelix at the monthly frequency. The differences were especially marked for the Phelix market which yielded very large performance differentials depending on the model used to estimate the OHR. In terms of the best model, the OLS was the better performer in all cases at the weekly frequency and also performed best in 50% of cases at the monthly frequency. In those cases where the CCGARCH model outperformed the OLS model, there was a significant difference only in the case of the Nordpool hedge at the monthly frequency. The relatively poor performance of the CCGARCH model may relate to an inability of GARCH models to handle large and frequent jumps in the basis as are typical for electricity markets. This has been found by other studies for even less volatile series such as Oil (Alexander, Prokopczuk and Sumawong, 2013) and Equities (Lee and Yoder, 2007). From these results we conclude that an OLS model is perfectly adequate in that it provides the best chance of obtaining good hedging effectiveness.

Next, we formally compare the performance of the different markets in Table 4 using both Variance and VaR metrics on a model by model basis. Taking Monthly data as an example and using the Variance as our risk metric we can see that there is a significant difference of 7.13% (t-stat 8.78) between the hedging performance of the Nordpool and APXUK markets using the OLS model. Overall we make 24 comparisons. Of these there are significant differences between the hedging performances of the different electricity markets in 67% of cases. This indicates that futures tend to work better as a hedging tool depending on the electricity market they are based on.

[Table 4 here]

4.4 Rolling Window Portfolio Results

Our initial estimates from the OLS and CCGARCH models for hedging effectiveness indicated relatively poor performance. To investigate this further we generated a series of rolling window OHR's together with a time dependent hedging effectiveness measure to allow us to track hedging performance in the different markets through different time periods.

Results for this estimation are presented in Table 5 and in Figure 3. The most noteworthy point is that there is a large variation in the hedging effectiveness across time. For certain time periods, hedges are quite effective and in some cases comparable to other energy markets. This is particularly the case for the monthly hedging frequency and for the Nordpool market which shows a maximum % reduction in the variance of 82.9%. For APXUK it is 72.3% and for Phelix it is 64.3%.

[Table 5 here]

[Figure 3 here]

These figures would constitute reasonably effective hedges for any asset, however as shown in Figure 3, there are also periods for which there is no appreciable benefit to hedging. It would appear therefore that hedges only seem to be effective for short time periods during which the spot and futures returns are highly correlated. However, the fundamentally volatile nature of electricity markets means that this is a relatively rare occurrence and of course is difficult to predict.

Table 6 reports the out-of-sample results which are based on a one step-ahead forecast of the OHR's as described in section 4. As for the in-sample results, the hedging effectiveness is generally low. We can also see that in some cases hedging yields an increase in risk as compared with a no-hedge scenario. For example, a CCGARCH hedge at the weekly frequency marginally increases the variance of a Nordpool position from 1.60% to 1.67%. Also the out-of-sample results confirm the finding that monthly hedges significantly outperform weekly hedges. Finally the results show that the hedging efficiency for the in sample period is generally higher than for the out-of-sample period. Across all markets, models and both risk metrics, the in-sample average hedging effectiveness is 1.6% higher at the weekly frequency and 4.4% higher at the monthly frequency. Given the results of our rolling window portfolio estimation which showed a wide variation in hedging effectiveness, we attribute this difference to the time period examined.

[Table 6 here]

5. CONCLUSION

We examine the volatility characteristics of three of Europe's most deeply established electricity markets and estimate risk management strategies for those markets using futures hedging. We look at two different hedging horizons and apply both constant and time varying approaches. Using a two sided risk measure - the variance, as well as a downside risk measure – VaR to evaluate the hedging effectiveness of these hedge strategies. We also track the conditional hedging performance over a time period spanning 2005 – 2014 which allows us to make a comprehensive comparison of the relative hedging performance of the different markets through different market conditions.

Our findings indicate that there are significant differences between the volatility characteristics, OHR's and the hedging performance for the different energy markets we examine. We also find that the time period and underlying volatility characteristics of the electricity market have a very significant impact on the hedging efficacy. Of particular note is the poor hedging performance of electricity hedges for all markets at the weekly frequency. The implication of this is that electricity market participants may struggle to reduce their exposure using futures hedging over short time horizons. The relatively poor performance of electricity futures as risk management tools raises questions as to the role and utility of electricity futures markets.

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Table 1 Descriptive Statistics

	Index	Mean	Std Dev	Skewness	Kurtosis	JB	LM	STATIONARITY				Correlation	
		%	%					ADF	PP	KPSS		Price	Return
										CONSTANT	TREND		
NORDPOOL													
DAILY	Spot	0.0063	7.87	0.30*	11.20*	13730.8*	212.8*	-24.1*	-53.7*	0.010	0.008*	0.900	0.09
	Futures	0.0052	3.51	1.27*	17.08*	32541.9*	5.0	-23.6*	-48.1*	0.032*	0.022*		
WEEKLY	Spot	0.0314	15.53	-0.28*	19.11*	7976.5*	84.2*	-9.2*	-26.0*	0.016*	0.012*	0.894	0.28
	Futures	0.0262	8.19	0.34*	3.52*	280.0*	32.3*	-26.0*	-24.1*	0.039*	0.026*		
MONTHLY	Spot	0.5776	29.34	0.38*	11.22*	638.1*	33.9*	-5.8*	-16.6*	0.057*	0.028*	0.8957	0.49
	Futures	0.0702	15.83	-0.38*	2.12*	25.5*	7.2	-5.8*	-10.9*	0.033*	0.030*		
APXUK													
DAILY	Spot	0.0268	15.47	0.32*	6.39*	4496.8*	149.2*	-31.7*	-78.6*	0.009*	0.005*	0.8020	0.16
	Futures	0.0201	2.75	2.17*	24.76*	68997.8*	47.3*	-23.8*	-48.1*	0.051*	0.043*		
WEEKLY	Spot	0.1339	20.99	-0.31*	5.38*	640.5*	45.8*	-14.5*	-36.6*	0.029*	0.015*	0.8010	0.28
	Futures	0.1003	6.09	0.26*	4.93*	536.7*	54.3*	-7.5*	-22.8*	0.043*	0.036*		
MONTHLY	Spot	1.8892	25.72	0.54*	6.42*	213.6*	14.0	-4.3*	-16.7*	0.263*	0.055*	0.8250	0.38
	Futures	0.4499	13.18	-0.66*	3.88*	84.5*	33.7*	-4.9*	-8.1*	0.047*	0.033*		
EEX PHELIX													
DAILY	Spot	0.0151	23.33	-0.05	13.97*	21312.5*	575.3*	-31.8*	-84.0*	0.004*	0.003*	0.7110	0.07
	Futures	0.0029	3.32	2.07*	38.43*	163061.6*	9.2	-22.8*	-49.6*	0.042*	0.019*		
WEEKLY	Spot	0.0756	29.34	-1.17*	11.93*	3227.3*	59.7*	-14.4*	-40.6*	0.015*	0.011*	0.7431	0.29
	Futures	0.0146	7.56	0.49*	5.21*	613.2*	28.0*	-11.1*	-23.4*	0.044*	0.020*		
MONTHLY	Spot	1.6047	36.73	0.27*	4.31*	95.0*	31.5*	-6.3*	-19.4*	0.341*	0.054*	0.7568	0.41
	Futures	0.1281	15.41	-0.12	0.24	0.6*	12.7	-4.9*	-12.0*	0.058*	0.030*		
1% C.V						9.21	13.23	-3.43	-3.43	0.74	0.22		

Note: Descriptive 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 15/09/2004 until 01/10/2014. 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. PP is the Philips Peron test for stationarity. Stationarity is also tested using the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test which tests the null of stationarity against the alternative of a unit root. The correlation coefficient between each set of cash and futures is also given for both price and log returns. * denotes significance at the 1% level.

Table 2: Volatility

Market	Frequency		ω	α	β	$\alpha+\beta$
						Volatility Persistence
NORDPOOL	DAILY	Spot	0.0004	0.331	0.653	0.984
		Futures	0.0003	0.068	0.907	0.975
	WEEKLY	Spot	0.0021	0.329	0.610	0.939
		Futures	0.0017	0.236	0.525	0.761
	MONTHLY	Spot	0.0511	0.212	0.105	0.317
		Futures	0.0156	0.382	0.003	0.385
APXUK	DAILY	Spot	0.0014	0.241	0.726	0.967
		Futures	0.0003	0.273	0.718	0.991
	WEEKLY	Spot	0.0049	0.410	0.537	0.947
		Futures	0.0001	0.142	0.841	0.983
	MONTHLY	Spot	0.0031	0.173	0.782	0.955
		Futures	0.0005	0.296	0.701	0.997
EEX PHELIX	DAILY	Spot	0.0029	0.292	0.695	0.987
		Futures	0.0004	0.046	0.560	0.606
	WEEKLY	Spot	0.0118	0.602	0.394	0.996
		Futures	0.0002	0.066	0.909	0.975
	MONTHLY	Spot	0.0010	0.128	0.823	0.951
		Futures	0.0011	0.129	0.824	0.953

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 : $h_{it} = \omega_i + \sum_{j=1}^r \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^s \beta_{ij} h_{i,t-j}$. The sum of $\alpha + \beta$ measures volatility persistence. The model was run

constraining $\alpha + \beta \leq 1$ which is equivalent to an IGARCH specification to avoid explosive volatility

Table 3: In Sample Hedging

		1	2	3	4	5	6
			WEEKLY			MONTHLY	
		NO HEDGE	OLS	CCGARCH	NO HEDGE	OLS	CCGARCH
NORDPOOL	VARIANCE	2.88%	2.63%	2.64%	10.20%	7.69%	7.41%
	VaR	-€ 395,288	-€ 377,439	-€ 377,892	-€ 742,901	-€ 646,834	-€ 628,562
	% Variance Reduction	0.00%	8.77%[^]	8.40% [^]	0.00%	24.65%*	27.37%
	% VaR Reduction	0.00%	4.52%[^]	4.40% [^]	0.00%	12.93%*	15.39%
APXUK	VARIANCE	5.36%	4.92%	5.03%	6.76%	5.58%	5.56%
	VaR	-€ 538,258	-€ 515,979	-€ 524,230	-€ 603,683	-€ 549,238	-€ 551,779
	% Variance Reduction	0.00%	8.19%*[^]	6.17% [^]	0.00%	17.51%	17.77%
	% VaR Reduction	0.00%	4.14%*[^]	2.61% [^]	0.00%	9.02%	8.60%
PHELIX	VARIANCE	7.77%	7.15%	7.79%	9.79%	7.44%	9.81%
	VaR	-€ 648,492	-€ 621,841	-€ 650,505	-€ 735,341	-€ 641,252	-€ 720,118
	% Variance Reduction	0.00%	8.03%*[^]	-0.19%	0.00%	24.02%*	-0.15%
	% VaR Reduction	0.00%	4.11%*[†]	-0.31%	0.00%	12.80%*	2.07%

Notes: We present hedging performance measures Variance and VaR for each of the three electricity markets for weekly and monthly hedging horizons. Three hedge ratios are examined (Columns 1 - 3). They are a hedge ratio of zero (no hedge), constant hedge (OLS), and time varying hedge (CCGARCH). Hedging performance is measured explicitly as the % reduction in each risk measure from both OLS and CCGARCH hedge strategies as compared with a no hedge strategy. Using weekly data on the Nordpool market for example, the OLS strategy reduces the variance by 8.77% and the VaR by 4.52% as compared with a no hedge strategy. Best performing model is in bold. Two statistical comparisons are made. First we compare the hedging strategies across time horizon for each hedge strategy. Using Nordpool for example, and reading across, The OLS model yields a 4.52% reduction in the VaR which is significantly lower than the equivalent figure for the monthly frequency which is 12.93%. We also compare the hedging performance between the OLS and CCGARCH models. [^] and [†], denotes significance at the 5% and 10% levels for and weekly vs. monthly comparisons respectively. * and ** denotes significance at the 5% level and 10% levels for OLS model vs CCGARCH model comparison.

Table 4: Hedging Performance Comparison

	WEEKLY			MONTHLY			
	OLS			OLS			
VARIANCE	NORDPOOL	APXUK	PHELIX	NORDPOOL	APXUK	PHELIX	
	NORDPOOL	0.00%	0.58%	0.74%	0.00%	7.13%*	0.63%
			(1.23)	(1.59)		(8.78)	(0.64)
	APXUK		0.00%	0.16%		0.00%	6.50%*
			(0.36)			(7.78)	
PHELIX			0.00%			0.00%	
	CCGARCH			CCGARCH			
	NORDPOOL	APXUK	PHELIX	NORDPOOL	APXUK	PHELIX	
NORDPOOL	0.00%	2.23%*	8.59%*	0.00%	9.60%*	27.52%*	
		(5.55)	(32.91)		(12.42)	(51.35)	
APXUK		0.00%	6.36%*		0.00%	17.92%*	
			(26.10)			(39.66)	
PHELIX			0.00%			0.00%	
	OLS			OLS			
	NORDPOOL	APXUK	PHELIX	NORDPOOL	APXUK	PHELIX	
NORDPOOL	0.00%	0.38%	0.41%	0.00%	3.91%*	0.14%	
		(0.32)	(0.33)		(3.30)	(0.07)	
APXUK		0.00%	0.03%		0.00%	3.78%**	
			(0.02)			(1.87)	
PHELIX			0.00%			0.00%	
	CCGARCH			CCGARCH			
	NORDPOOL	APXUK	PHELIX	NORD	APXUK	PHELIX	
NORDPOOL	0.00%	1.79%*	4.71%*	0.00%	6.79%*	13.32%*	
		(2.22)	(5.73)		(7.39)	(11.55)	
APXUK		0.00%	2.92%*		0.00%	6.53%*	
			(3.53)			(5.61)	
PHELIX			0.00%			0.00%	
VAR	OLS			OLS			
	NORDPOOL	APXUK	PHELIX	NORDPOOL	APXUK	PHELIX	
NORDPOOL	0.00%	0.38%	0.41%	0.00%	3.91%*	0.14%	
		(0.32)	(0.33)		(3.30)	(0.07)	
APXUK		0.00%	0.03%		0.00%	3.78%**	
			(0.02)			(1.87)	
PHELIX			0.00%			0.00%	
	CCGARCH			CCGARCH			
	NORDPOOL	APXUK	PHELIX	NORD	APXUK	PHELIX	
NORDPOOL	0.00%	1.79%*	4.71%*	0.00%	6.79%*	13.32%*	
		(2.22)	(5.73)		(7.39)	(11.55)	
APXUK		0.00%	2.92%*		0.00%	6.53%*	
			(3.53)			(5.61)	
PHELIX			0.00%			0.00%	

Note: Table 4 shows a comparison between the hedging performance for the different electricity markets. Taking Monthly data for example, there is a significant difference (7.13%) between the hedging performance of the OLS model for the Nordpool and the APXUK markets. T-statistics are in parentheses. *, ** denotes significance at the 5% and 10% levels respectively.

Table 4: Hedging Effectiveness of Portfolio of Rolling Window OHR's

	(1)	(2)	(3)
	NORDPOOL	APXUK	PHELIX
WEEKLY			
MEAN	13.3%	7.9%	11.3%
MIN	0.1%	0.0%	0.1%
MAX	43.8%	25.2%	33.4%
STDEV	11.2%	4.9%	7.4%
MONTHLY			
MEAN	39.2%	20.6%	24.3%
MIN	0.0%	0.0%	1.0%
MAX	82.9%	72.3%	64.3%
STDEV	21.4%	19.8%	14.3%

Summary statistics of the hedging effectiveness of a portfolio of hedges estimated using a rolling window based on variance minimisation.

Table 5: Out-of-Sample Hedging

		1	2	3	4	5	6
			WEEKLY			MONTHLY	
		NO HEDGE	OLS	CCGARCH	NO HEDGE	OLS	CCGARCH
NORDPOOL	VARIANCE	1.60%	1.61%	1.67%	3.94%	3.30%	3.27%
	VaR	-€ 292,168	-€ 293,653	-€ 298,790	-€ 454,238	-€ 411,451	-€ 405,111
	% Variance Reduction	0.00%	-0.45% ^{*^}	-3.92% [^]	0.00%	16.31%	17.10%
	% VaR Reduction	0.00%	-0.51% ^{*^}	-2.27% [^]	0.00%	9.42% [*]	10.82%
APXUK	VARIANCE	1.46%	1.38%	1.36%	2.82%	2.40%	2.57%
	VaR	-€ 282,349	-€ 275,671	-€ 272,936	-€ 391,726	-€ 363,695	-€ 373,904
	% Variance Reduction	0.00%	5.33% ^{*^}	6.66% [‡] ,	0.00%	14.78% [*]	8.85%
	% VaR Reduction	0.00%	2.37% [‡]	3.33%	0.00%	7.16% [*]	4.55%
PHELIX	VARIANCE	13.52%	12.34%	12.20%	27.86%	25.01%	25.40%
	VaR	-€ 857,703	-€ 816,565	-€ 810,242	-€ 1,205,944	-€ 1,133,608	-€ 1,141,122
	% Variance Reduction	0.00%	8.79% [*]	9.80%	0.00%	10.22% ^{**}	8.82%
	% VaR Reduction	0.00%	4.80%	5.53%	0.00%	6.00%	5.38%

Notes: We present hedging performance measures Variance and VaR for each of the three electricity markets for weekly and monthly hedging horizons. Three hedge ratios are examined. They are a hedge ratio of zero (no hedge), constant hedge (OLS), and time varying hedge (CCGARCH). Hedging performance is measured explicitly as the % reduction in each risk measure from both OLS and CCGARCH hedge strategies as compared with a no hedge strategy. Best performing model is in bold. [^] and [‡], denotes significance at the 5% and 10% levels for and weekly vs. monthly comparisons respectively. * and ** denotes significance at the 5% level and 10% levels for OLS model vs CCGARCH model comparison.

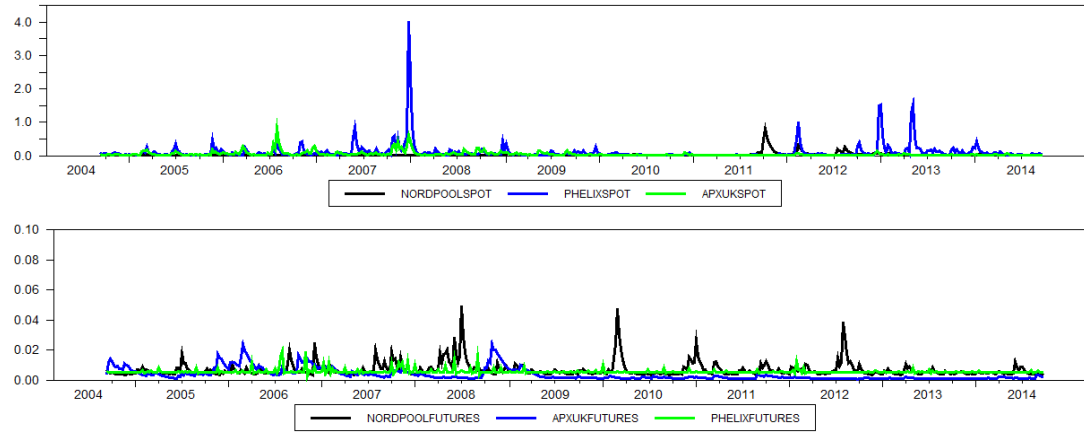


Fig1. Volatility of NORDPOOL, APXUK AND PHELIX Electricity Spot and Futures using Weekly data. Note the Spot and Futures are to difference scales.

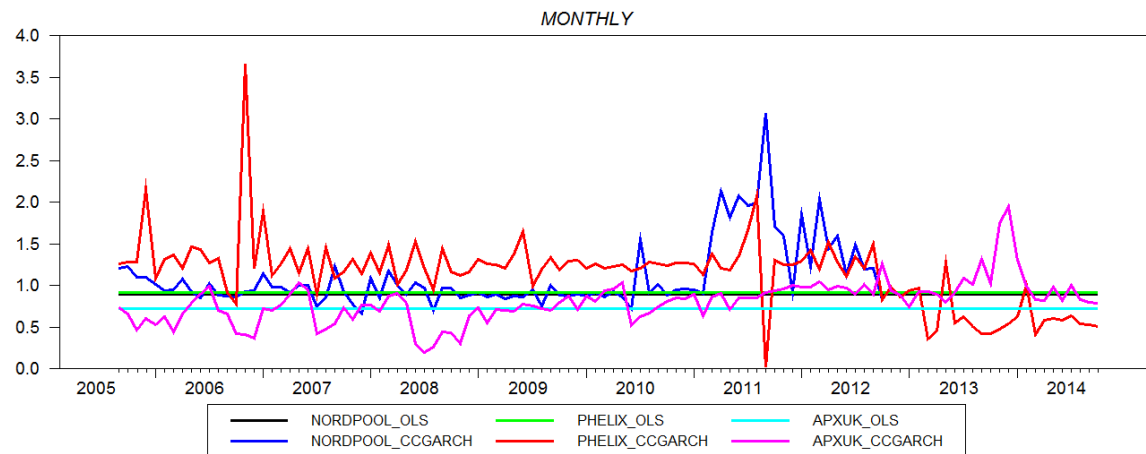
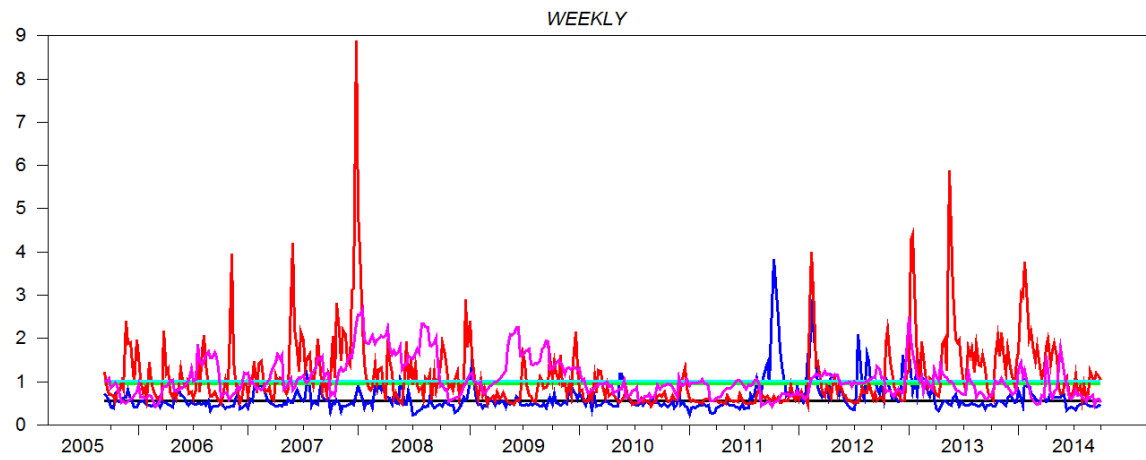


Fig 2. Optimal Hedge Ratios, OLS AND CCGARCH for NORDPOOL, APXUK and PHELIX markets.

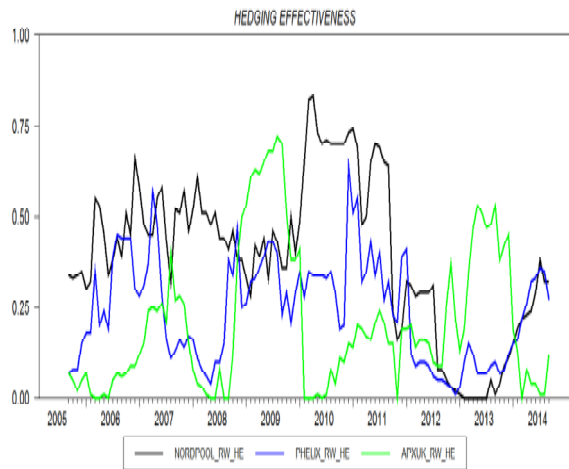
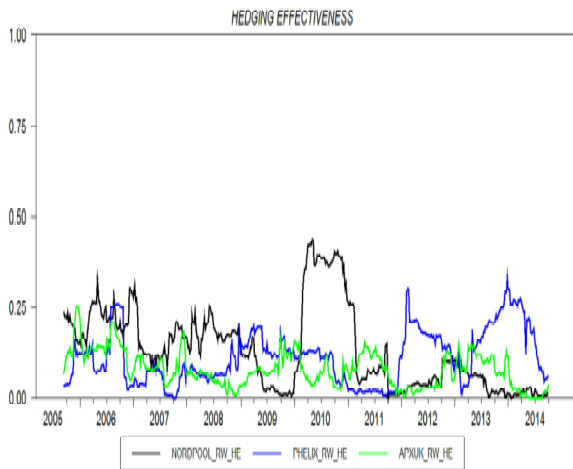
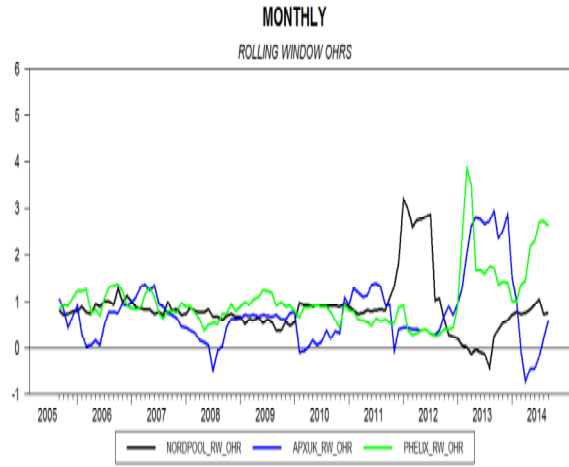
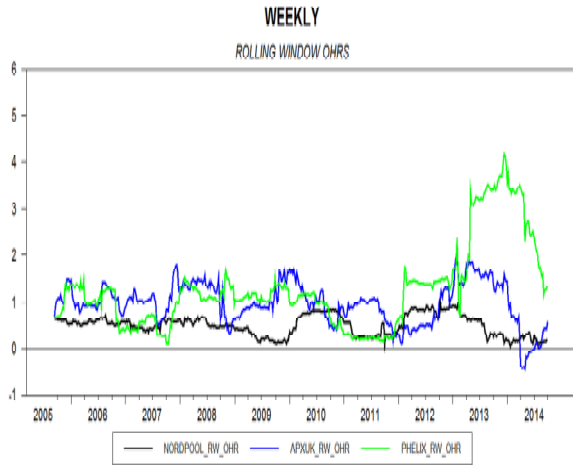


Fig.3 Time Varying Hedging Rolling Window Portfolio OHR's and Hedging Effectiveness.