HEDGING WITH FUTURES IN A CONTEXT OF HIGH TIME VARYING VOLATILITY: AN APPLICATION OF GARCH CORRELATION MODELS TO EUROPEAN ELECTRICITY MARKETS

Abstract

In the last few decades European electricity markets have been subject to a broad deregulation process. The first European exchange for electricity trading has been the Nordic Power Exchange (Nord Pool) that exists since 1996. In 1998 with the EU's directive 98/20/EC, which was then replaced by the directive 2003/55/EC, the deregulation process began in the EMU countries. Since spot electricity prices are characterized by high volatility most markets started to quote futures as long as spot contracts so to allow market player to hedge their positions. This paper investigates how electricity futures can be used to hedge spot position. We compare the performance of the hedge ratio estimated with traditional naïve and OLS (Ordinary least squares) method with more elaborate GARCH models. We concentrate on correlation GARCH models and we test if correlations models perform better than traditional models in a context of high time varying volatility as the case of electricity markets. Our results shows that futures hedging reduce the variance of the portfolio depending on the model choose to estimate the hedge ratio. In some cases traditional hedging lead to an increase on the variance of the hedged portfolio due to the change in correlation between the in sample and the out of sample estimation period. This explains why the correlation structure should be taken into consideration.

1. Introduction

In the last few decades European electricity markets have changed their status from a regulated monopoly to a competitive open market. The first European exchange for electricity trading has been the Electricity Pool In England and Wales[1] created in 1990 followed by the Nordic Power Exchange (Nord Pool) in 1996. In 1998 with the EU's directive 98/20/EC, which was then replaced by the directive 2003/55/EC, the deregulation process began in the EMU countries. In Germany, the European Energy Exchange (EEX) was founded in 2002 as a result of the merger of Leipzig Power Exchange (LPX) and European Power Exchange (EPX) both founded in 2000. In France, the European Directive was implemented into the French Law the 10th of February 2000 and the French electricity market (Power Next) was created in 2001. Similar patterns occurred in the rest of Europe (table 1 and 2 in Appendix).

The liberalisation process has grown the attention of electricity producers and distributors on financial performances and risk management. In a regulated monopoly, the rates, the customer base and the revenues are defined and controlled by the regulator. In a competitive open market, rates and return are instead subject to competition and market movements. Compared with other traded commodities such as gold, coffee or crude oil, electricity poses two distinct challenges. Firstly it is not possible to store electricity in any significant quantity so there is a need to match instantaneous demand with instantaneous generation and secondly the demand and supply are pretty inelastic.

This explain why energy prices are characterized by high volatility, large prices changes that cannot be controlled using inventories. Futures contract traded in some electricity markets as long as spot contracts may allow market players to minimize the effect of adverse movements in spot prices on their portfolios.

Implementing an hedging strategy with futures require several features: define the delivery date of the futures to be used for hedging; define the optimal amount to hedge and estimate the optimal hedge ratio. In this paper we focus on this second feature and we investigate different methodology to estimate the optimal hedge ratio. This is a relevant topic for electricity hedging where the high volatility of electricity price, the non perfect arbitrage opportunities and the not irrelevant transaction costs, can make the basis risk quite significant.

In this paper we compare different model to estimate the hedge ratio focusing on correlation models. Traditional hedging strategies do not consider correlations on the estimation of the hedge ratios. We believe that this may lead to poor hedging performance in a context of high time varying volatility. To prove this we test the performance of different hedging models in different time periods and different markets

The paper is organized as follows. In section 2 we describe our methodology and present econometric models we will use in the empirical analysis. Section 3 review the literature In section 4 we describe the data used in this analysis. Section 5 presents our results. Section 6 concludes.

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[1] The Electricity Pool defines the market trading rules and procedures but does not itself act as market maker buying or selling electricity.

2. Methodology

The hedge ratio indicates how many futures contract should be bought or sold to hedge the underlying spot position so to minimize the portfolio variance. There are different ways to estimate the hedge ratio.

2.1 Naïve one to one Hedge Ratio

The most naïve approach to futures hedging is the a one-to –one (zero basis) hedge ratio. In this approach for any given spot position, an equal amount of futures positions are undertaken.

This hedge ratio is very easy to calculate: each spot contract is offset by exactly one future contract. If both the space and grade basis as well as the time basis are zero, we call this hedging zero basis. In this hedging model, since the two prices converge, the covariance between them equals the futures variance, that is :

$$(1)\quad h_t = \frac{\operatorname{cov}_t\left(r_{st}, r_{ft}\right)}{\operatorname{var}_t\left(f_t\right)} = 1$$

Where h_t is the minimum variance hedge ratio, and r_{st} and r_f are the spot and futures returns..

2.2 OLS Estimated Hedge Ratio

In most applications, to recognize the existence of possible different volatilities in the spot and in the futures markets, the optimal futures position is calculated by minimizing the variance of the spot-future portfolio. The optimal hedge ratio is then given by the ratio of the covariance between the spot and the futures returns and the variance of the futures return. A traditional method to estimate this hedge ratio is to run an OLS regression where the spot returns are the dependent variable and the futures returns are the independent variable. The OLS estimator of the slope provides the optimal hedge ratio.

$$(2)\quad r_{st} = a + b r_{ft} + e_t$$

where r_{st} and r_{ft} are, respectively, the spot and futures returns for period *t*. The OLS estimator of ß provides an estimate for the minimum-variance hedge ratio. This approach has been extensively applied in the literature but the OLS estimator assumes the second moment are constant over time.

In this paper we estimate two OLS Models.

The first model is the *Full Period Hedging*. This is an OLS regression over the whole dataset of spot and futures returns.

$$(3)\quad r_{st} = a + b r_{ft} + e_t$$

where t, in our case, is unique for each time series (EEX: June 2000 – February 2006; PowerNext: June 2004 – February 2006; NordPool: January 2000 – February 2006.)

This is a static solution. The hedge ratio is computed once and remains the same for the full period.

The second model is a *Rolling Periods Hedging*. This is a similar approach of the full period, with a regression re-estimated *n*-times over *n* times intervals. Samples are overlapped to each other and the equations are the following ones:

(4) $r_{st(i)} = a + b r_{ft(i)} + e_t$

This strategy generates a spot-future portfolio with a vector of hedge ratios depending on time.

A major problem with the OLS hedge ratio is its assumption of constant variance that may be difficult to justify for high volatilities prices such as the energy prices. So an hedge ratio estimated in a dynamic framework taking into account the time-varying nature of second moments could improve hedging performances.

2.3 GARCH Hedging

To model heteroskedasticity often encountered on spot and futures prices, hedge ratio using GARCH models are estimated. Numerous variants and extensions of GARCH models have been proposed and there is not a unique answer to what should be the ideal specification of a multivariate GARCH. On one hand a GARCH model should be flexible and able to represent the actual dynamics of variances and covariances. On the other hand as the flexibility and the number of parameters increase, the complexity of the estimation increases as well.

A standard multivariate GARCH model may be defined as:

(5) $r_t = H_t^{1/2} h_t$

Where r_t is a stochastic vector process with dimension *Nx1* such that Er_t=0. H_t is the conditional covariance matrix of r_t and h_t is an i i.d vector error process such that $Eh_t h_t^{'} = I$. This is a general multivariate GARCH framework with no linear dependence structure in r_t. What has to be specified is the matrix process H_t.

The first proposed multivariate GARCH model, the VEC model of Bollerslev, Engle,and Wooldridge (1988) is a generalization of the univariate GARCH. In this model every conditional variance and covariance is a function of lagged conditional variances and covariances, lagged squared returns and cross-products of returns. The model ca be written as:

(6) $vech(H_t) = c + \sum_{j=1}^{q} A_j vech(r_{t-j} r_{t-j}^{'}) + \sum_{j=1}^{p} B_j vech(H_{t-j})$

where C is a N x (N+1)/2 x 1 column vector, Aj and Bj are Nx(N+1)/2 × Nx(N+1)/2 matrices and vech is an operator that stacks the columns of the lower part of its argument square matrix. .

This model is a very general one but this generality has some disadvantages: the number of parameters to estimate is large unless N is small and there exist only rather restrictive conditions in which the conditional covariance matrices are positive definite. Finally parameters estimation is computationally demanding. So subsequent literature has tried to develop more parsimonious models. Her we present and discuss pros and cons of alternatives GARCH models used in our estimations.

3.1 BEKK MODEL

A first model that try to overcome the computational difficulties of the general VEC is the BEKK model proposed by Baba, Engle, Kraft and Kroner (1995). In this model the conditional covariance matrices are positive definite by construction. In fact, the decomposition of the constant term into a product of two triangular matrices ensure positive definiteness of the conditional covariance matrix.

$$(7)\quad H_t = CC' + \sum_{j=1}^{q}\sum_{k=1}^{K} A'_{kj} r_{t-j} r'_{t-j} A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K} B'_{kj} H_{t-j} B_{kj}$$

Where A_{kj}, B_{kj} and C are NxN parameter matrices and C is lower triangular[2]. Several version of the BEKK models have been proposed in literature.

The number of parameters in the full BEKK model is still quite large[3] and the computations heavy. Obtaining convergence may be difficult because is not linear in parameters. The advantage of this model is that the structure automatically ensures positive definiteness of H_t. Partly because numerical difficulties are so common in the estimation of BEKK models, it is typically assumed A_{kj}, B_{kj} are diagonal matrices. This imply that the conditional variance of the spot returns are affected by its own history and the history of the squared innovations in the spot returns. Similar structures apply to the conditional variance of the futures returns and the conditional covariance between the spot and futures returns. Even if reduced[4] the number of parameters to estimate is still quite large. To further reduced the number of estimation we introduce Conditional Correlation models.

3.2 Conditional correlation model

This is s a family of models based on the decomposition of the conditional covariance matrix into conditional standard deviations and correlations. They are alternative specifications to resolve the problem of a possible non-positive semidefinite conditional variance-covariance matrix.

The simplest multivariate correlation model is the Constant Conditional Correlation (CCCGARCH) model of Bollerslev (1990). This models simplify the Garch model by assuming that the conditional correlation matrix is time invariant and can be expressed as

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[2] Several versions of BEKK models have been proposed. The discussion of these different versions is behind the aim of this presentation.

[3] $(p+q)KN + N(N+1)/2$ in the full BEKK .

[4] $(p+q)KN + N(N+1)/2$

(8) $H_t = D_t R D_t$

Where D_t is a (NxN) matrix with the conditional standard deviations on the diagonal and R is a (NxN) matrix containing the conditional correlations.

The CCC-GARCH model imposes restrictions on the general vector GARCH (VGARCH) model to achieve parameter parsimony while maintaining the positive semi-definiteness property. Kroner and Sultan (1993) applied this model to obtain the minimum-variance hedge ratios of currency futures. Park and Switzer (1995) adopted it to estimate the minimum-variance hedge ratios of stock index futures. Empirical results concerning the performance of GARCH hedge ratios are generally mixed. Within-sample comparisons show that, in some cases, dynamic hedging generates much better performance in terms of risk reduction but in others the benefits seem too minimal to warrant the efforts.

One of the main problem on using CCC-GARCH model is the empirical evidence that suggest that the assumption of constant conditional correlations may be too restrictive.

Engle and Sheppard (2001) proposed a model that is easy to estimate as the CCC-GARCH model but allows for non constant correlations. In this models univariate GARCH are estimated for each asset series and then, using the standardized residuals resulting form the first estimation, a time varying correlation matrix is estimated using a simple specification. The dynamic correlation structure of this models (GARCH DCC) differs from CCC in allowing R, the correlation matrix, to be time varying:

(9) $H_t = D_t R_t D_t$

One possible specification of the correlation matrix is the exponential smoother, that is a geometrically weighted average of standardized residual.

$$[R_t]_{i,j} = \frac{\sum_{s=1}^{t-1} l^s e_{i,t-s} e_{j,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1} l^s e_{i,t-s}^2\right)\left(\sum_{s=1}^{t-1} l^s e_{j,t-s}^2\right)}}$$

This equation will produce a correlation matrix at each point in time. Or, in other terms, a way to construct the correlation matrix is through exponential smoothing.

(10) $q_{i,j,t} = (1 - l)(e_{i,t-1}, e_{j,t-1}) + l(q_{i,j,t-1})$

where q is a proxy of covariance among normalized returns. Conditional correlation can be obtained normalizing $q_{ij,t+1}$ as follows:

(11) $r_{i,j,t} = \dfrac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}}$

for each i,j. This way, we ensure correlation's interval is (-1,+1).

An alternative, to make the correlation be mean reverting is the *GARCH (1,1)* model. The covariance proxy q can be modelled with a GARCH (1,1)

$$(12)\quad q_{i,j,t} = \overline{r}_{i,j} + a\,(e_{i,t-1}, e_{j,t-1} - \overline{r}_{i,j}) + b\,(q_{i,j,t-1} - \overline{r}_{i,j})$$

Rewriting

$$(13)\quad q_{i,j,t} = \overline{r_{i,j}}\left(\frac{1-a-b}{1-b}\right) + a\sum_{s=1}^{\infty} b^{s} e_{i,t-s}, e_{j,t-s}$$

To obtain conditional correlation we must normalize

$$(14)\quad r_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}}$$

for each i,j.
The correlation estimator $r_{i,j,t}$ will be positive definite as long as Q_t is a weighted average of a positive definite and a positive semidefinite matrix. This model is mean reverting as long as $a + b < 1$.

Matrix versions of these two models are

$$(15)\quad Q_t = (1-l)(e_{t-1}, e'_{t-1}) + l\,Q_{t-1}$$

And

$$(16)\quad Q_t = S(1-a-b) + a\,(e_{t-1}, e'_{t-1}) + bQ_{t-1}$$

Where S is the unconditional correlation matrix of the standard residuals deriving from the first stage of estimation. The coefficient α and β are also obtained from univariate GARCH models. This models are estimated in two steps: a set of univariate GARCH estimate and then the correlation estimate. They have the flexibility of general GARCH models but not their computational complexity.
The appeal of this model is that they model conditional variances and correlations instead of straightforward modelling the conditional covariance matrix.

3. Literature review

Several paper have investigated the optimal hedge ratio estimation methodology starting with the Figlewski paper of 1984. Applications of Garch model to hedge ratio estimation have been quite common as well. Baillie and Myers (1991) estimate the optimal hedge ratio for six different commodities. They model commodity price movements using the GARCH and analyse how a bivariate GARCH model can improve hedge ratios estimation. They find that GARCH models provide a good description of the distribution of changes in commodity prices. Hedging performances tests indicate that the assumption of a constant hedge ratio is quite costly, in terms of higher return variance, for some commodities but not for others. Kroner and Sultan (1993) estimate the risk minimizing futures hedge ratios with a bivariate error-correction model with a GARCH error structure, showing that the GARCH model provides greater risk reduction than traditional models.

Lien, Tse and Tsui (2002) compare the performance of hedge ratios estimated using different models on three currency futures contract, five commodity futures and two stock index futures contract in the period from January 1988 through June 1998. Their results shows that GARCH strategy cannot outperform the OLS hedge strategy. In one case GARCH strategy gives 20% more risk than OLS strategy. Based on this, authors conclude that given the high computational costs for the GARCH model there is no reason to consider these models for hedging purposes. GARCH models may however be useful for data description.

Rossi and Zucca (2002) proposes an optimal hedging strategy for a portfolio of Btp (Italian long term government Bonds) hedged with futures contracts traded at Liffe. They perform out-of-sample comparison on three different hedging model to verify if using multivariate models is possible to obtain a reduction of ex-ante portfolio variance than naïve strategies. Their results shows that GARCH hedging strategy is more effective than that of the traditional method.

Brooks, Henry and Persand (2002) employ 3580 daily observations on the FTSE 100 stock index and stock index futures over the period January 1985- April 1999 to estimate optimal hedge ratio allowing for time variation and asymmetry across the variance-covariance matrix of return. In this context the hedge ratio became sensitive to size and sign of the change in prices resulting from information arrival. They find that asymmetric models, that is models that allow positive and negative information to affect volatility differently, yield improvements in forecast accuracy in sample but not on hedging performances out of sample.

Yang and Awokuse (2003) examine the risk minimization hedging effectiveness of different models for major storable and non storable agricultural commodity futures markets. They use daily cash and futures prices of corn, soybean, wheat, cotton and sugar (as storable commodities) and lean hogs, live cattle and feeder cattle (as non storable commodities) over the period 1/1/1997 to 31/12/2001. Using bivariate Garch approach they find that hedging effectiveness is strong for all storable commodities but weak for non storable commodities.

Kenourgios, Samitas, Drosos (2005) investigates the hedging effectiveness of the S&P500 futures contract for the period July 1992 - June 2002. They first focus on the implementation of a model to estimate the hedge ratio so to minimize portfolio returns. Then they test the hedging effectiveness and the stability of optimal hedge ratios through time. Finally they perform an in-sample forecasting analysis in order to examine the hedging performance of different, constant and time varying, econometric models. Their findings suggest that in terms of risk reduction the error correction model provides better results than convention OLS and other GARCH models. This model also provides better forecasts than others. As far as the issue of stability of the estimated hedge ratio is concerned the error correction model still prove to be the best model and suggest that the hedge ratio remains stable over time.

Copeland and Zhu (2006) compute dynamic hedge ratios for contracts on the major stock market index of six countries (Australia, Germany, Japan, Korea, UK and USA) from March 1995 to March 2005. They then compare the dynamic hedge ratios performance with the hedge ratios based on simpler models. The results are extremely mixed so authors conclude that although in principle the more sophisticated models should outperform simpler models, in practice the benefit is likely to be very small or even negative.

Ahmed (2007) in a study applied to Us Treasury Market shows that time-varying hedge ratio have superior hedging performances compared to the traditional duration-based constant ratio. Time-varying hedge ratio, estimated using CCC-GARCH model of Bollerslev (1990), shows a clear advantage in minimizing the variance of portfolio returns over a period of 10 years.

As far as hedging electricity prices is concerned we are aware of only two paper investigating the effectiveness of hedging strategies performed using different hedge ratios model estimation. Bystrom (2003) analyses variances and covariances of Nord Pool electricity price returns over the period January 1996- October 1999 and investigates how the time variation affects short term hedging performance. He compares traditional models with two different GARCH models: the constant correlation bivariate GARCH model introduced by Bollerslev (1990) and a multivariate GARCH model, the Orthogonal GARCH model (Ding (1994)). Bystrom finds that short term hedging of electricity spot prices with electricity futures, using different estimates of the optimal hedge ratio, reduces the variability of the portfolio returns. The results confirm that variances and hedge ratios vary significantly over time. However the traditional simpler hedging models perform as well as more elaborated models when the performance of the hedges are evaluated on the basis of their ability to reduce the portfolio variance. Pekka Malo and Antti Kanto (2005) analyse the hedging performances of a broader range of multivariate GARCH models and they focus on the tests of different multivariate GARCH model specifications. Their aim is to consider different parameter stability tests in order to check the robustness of the selected models. Their findings shows that overall all the models performs well as measured by conditional moments tests, even though the models produces quite different estimates for the conditional covariance matrix. The results of the conditional and unconditional models hedging performances are in line with Bystrom results (GARCH hedges outperform the other hedges).

Our paper focus on the optimal model to forecast hedging ratio on electricity markets. To the best of our knowledge, no previous papers investigate volatilities and hedge ratio of different European electricity spot and futures markets. Three are the markets we focus on: the Nord Pool, the German electricity market (EEX), and the French one (Power next). Furthermore we test the hedging performance of not previously tested model such, the Garch Dynamic Conditional Correlation (Garch-DCC) and the Exponential Smoothing Conditional Correlation (Expsmo-DCC). We believe in fact that dynamic correlation may be a first issue to consider on hedging electricity prices above all in the context of highly volatile markets. No to consider correlation structure on hedging choice could lead, in our view, to underperforming hedging strategies.

4. Data

As described in previous section, the liberalization process is fairly recent in Europe. This limits our empirical analysis to those market for which data are available on a useful size both for the spot and futures markets: Nord Pool, EEX and PowerNext. In most European markets, in fact a futures derivatives still not exists. Also for those countries where both market exist the spot market opened well before the futures one.

We used daily baseload spot prices[5] from 8 April 2003 to 14 February 2006 for the NordPool market, from 01/07/2002 to 14 February 2006 for EEX and from 21 June 2004 to 14 February

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[5] These are equally weighted average prices of the 24 hours prices during a day.

2006 for Powernext. The starting date is given by the introduction on the derivative market of the monthly futures contract.

We used baseload daily settlement prices Monday to Friday. We eliminated the weekends since trades of electricity during weekend and week days respond to very different pattern. This allow us not to consider weekly and hourly seasonality that strongly affect electricity prices. The hourly and weekly seasonality are explained by change in industry demand over the day and over the night. In fact more electricity is requested during peak hours and during week days. Electricity prices are also effect by a seasonality effect that we do not model in this paper since we are interest on short term hedging performance that are not effected by seasonal long-term effect.

For Futures prices we had to consider that each day a number of futures contract with different maturities are available and can be chosen ad hedging instruments. In our analysis we used as hedging instruments futures contract with one month to expiration. This because short term instruments are generally more liquid than long term and our focus is on short term hedging performance. To create a time series of futures prices and avoid delivery effects we roll over to the next one month futures contract one week before the expiration of the previous future contract.

Tables 1,2 and 3 give summary statistics and unit root tests of the spot and futures prices returns for the three analyzed markets. For all the three markets both the spot and the futures returns mean are not significantly different from zero. The volatility is really high if compared to other assets class. The standard deviation of the Nord Pool is lower than the standard deviation of the other two markets. This may be explained by the higher efficiency and liquidity of this older markets compared to the other two younger market. If this is the right explanation it seems that liberalization should lead to higher efficiency at least in terms of lower standard deviation. The high Kurtosis level, the skewness and the high Jarque-Bera test confirms that both spot and futures return are not normally distributed. The test for a autocorrelation indicate that no autocorrelation is present in the spot market while some auto-correlation exists at long lags in the future market.

From the tables reported below is it also possible to note that spot returns volatility is significantly higher than futures returns volatility. This relation holds on the full sample volatility as well as for the GARCH (1,1) and 20 days moving averages volatilities.

Table 1: Return Statistics: Nord Pool market (daily data)

	Mean	St dev	Kurtosis	Skewness	B-J	Q(6)	Q(18)
Spot	0.000434	0.050578	11.67387	0.458999	2269.683	31.916	53.213
Futures	0.000456	0.027286	7.879383	0.867539	800.0964	10.749	40.460

B-J is the Jarque-Bera test for non linearity and Q (..) it the Ljung-Box test for autocorrelation.
99% critical value for Jarque-Bera is 9.21. 99% critical values for Ljung-Box are 16.8 and 34.8.
See appendix one for other statistics related to NordPool market

Table 2: Return Statistics: EEX Next market (01/7/2002-14/02/2006)

	Mean	St dev	Kurtosis	Skewness	B-J	Q(6)	Q(18)
Spot	0.001422	0.321346	14.04389	0.631853	4870.495	158.86	218.80
Futures	0.001129	0.041377	30.96879	1.98212	31485.06	9.9622	24.137

B-J is the Jarque-Bera test for non linearity and Q ( ) it the Ljung-Box test for autocorrelation.
99% critical value for Jarque-Bera is 9.21. 99% critical values for Ljung-Box are 16.8 and 34.8.
See appendix one for the statistic related to EEX market

Table 3: Return Statistics: Power Next market

	Mean	St dev	Kurtosis	Skewness	B-J	Q(6)	Q(18)
Spot	0.002234	0.168953	8.819029	0.143896	610.9895	50.567	67.299
Futures	0.001871	0.029464	11.32722	-0.401778	1259.788	9.2490	21.294

B-J is the Jarque-Bera test for non linearity and Q ( ) it the Ljung-Box test for autocorrelation.
99% critical value for Jarque-Bera is 9.21. 99% critical values for Ljung-Box are 16.8 and 34.8.
See appendix one for the statistic related to NordPool market

Table 4, 5 and 6 report the Philips Perron stationarity test on log prices. In our sample spot but not futures prices are stationary.

Table 4: Stationarity of logprices : Nord Pool Market

	Philips Perron (no trend)	Philips Perron (trend)
Spot Prices	-3.604046	-4.347614
Futures Prices	-1.554141	-2.451107

Note: The 99% values for the Philipps-Perron test with and without trend are -3.44 and -3.97. The 95% values for the Philipps-Perron test with and without trend are -2.86 and -3.41. The 90% values for the Philipps-Perron test with and without trend are -2.56 and -3.13.

Table 5: Stationarity of logprices : EEX Market

	Philips Perron (no trend)	Philips Perron (trend)
Spot Prices	-15,26952	-21.85232
Futures Prices	- 1.439456	-3.626325

Note: The 99% values for the Philipps-Perron test with and without trend are -3.44 and -3.97. The 95% values for the Philipps-Perron test with and without trend are -2.86 and -3.41. The 90% values for the Philipps-Perron test with and without trend are -2.56 and -3.13.

Table 6: Stationarity of logprices: Power Next Market

	Philips Perron (no trend)	Philips Perron (trend)
Spot Prices	-2.561254	-4.606263
Futures Prices	-0.994048	-3.005572

Note: The 99% values for the Philipps-Perron test with and without trend are -3.4453 and -3.97. The 95% values for the Philipps-Perron test with and without trend are -2.86 and -3.42. The 90% values for the Philipps-Perron test with and without trend are -2.57 and -3.13.

Finally in figure 1 to 3 we plot 20 days rolling and GARCH(1,1) volatilities for the three markets. Two points is worth noting. As already underlined spot volatility is higher than futures volatility. Volatility change over time and the assumption of identically independent normally distributed results seems not valid.

Further statistical data are reported on Appendix 2.

Figure 1: Volatility spot and futures market :Nord Pool

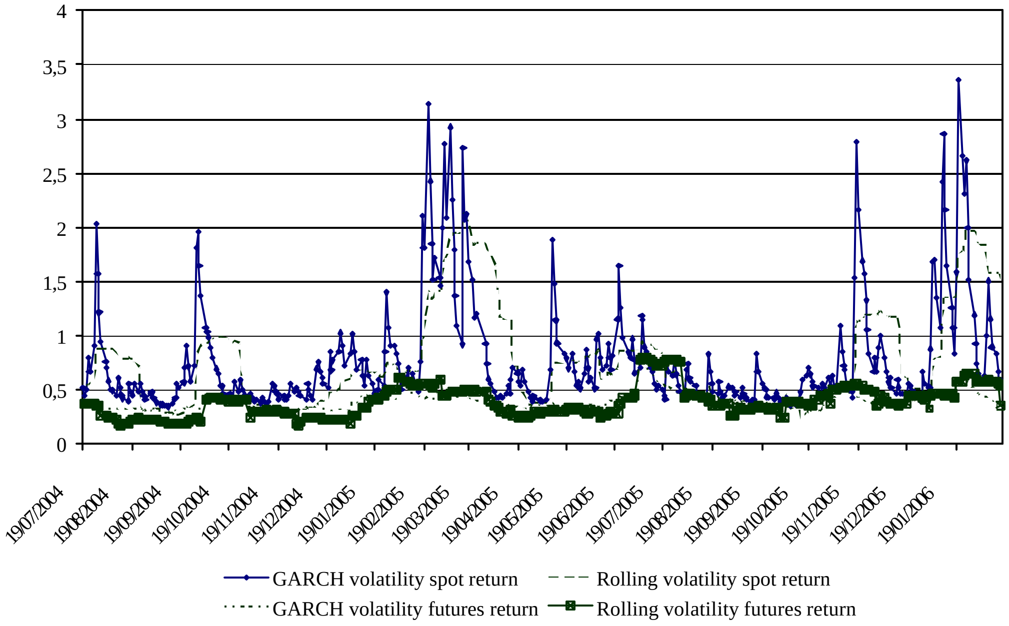


Figure 2: Volatility spot and futures market :EEX

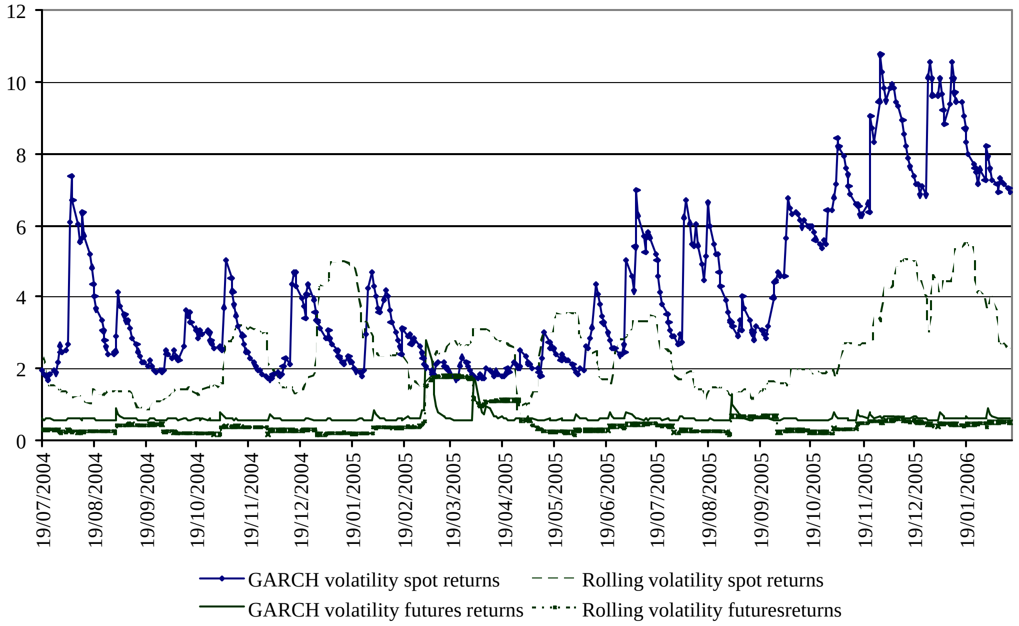
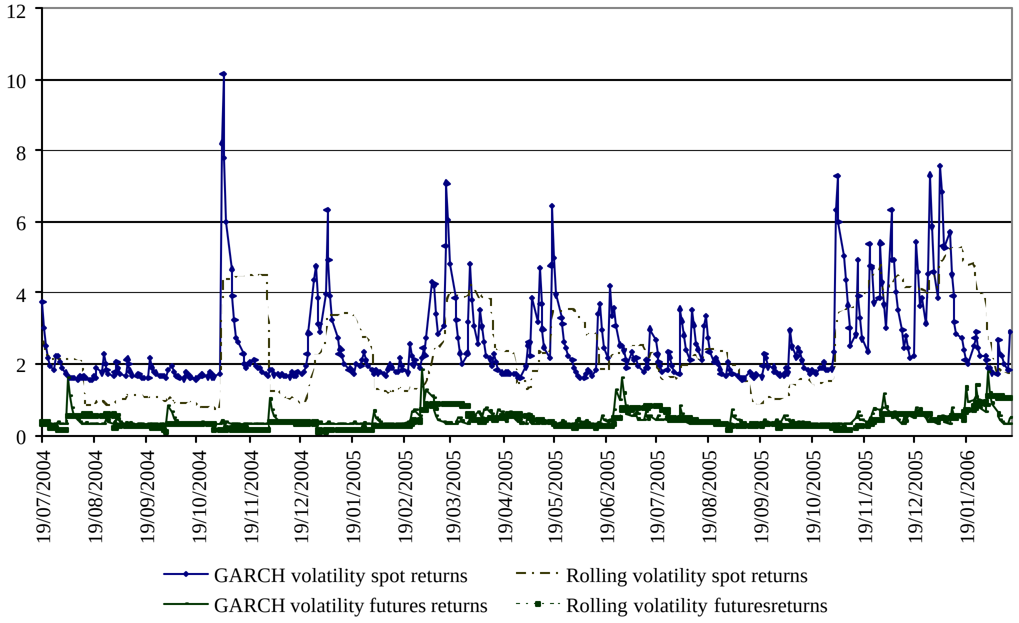


Figure 3: Volatility spot and futures market :Power next



5. Optimal Hedge ratio estimation and Hedging performance

To evaluate the hedging performances we considered a one-period model.

A the beginning of the period the economic agent is long the underlying asset. To hedge his position and reduce risk exposure he sells futures contract. The number of future contracts is choosed so to minimize the variance of the hedged portfolio. We estimated the hedge ratio in 7 different ways: the naïve one to one hedge ratio where we offset each spot contract by one futures contract; the static OLS hedge ratio were we regressed the spot return over the futures return; the dynamic OLS hedge ratio estimated continuously updating the moving averages (50 days period); a traditional GARCH Model (BEKK); a constant correlation model (CCC); finally two time varying correlations model (dynamich GARCH and Espo GARCH).

We divided our samples in in-sample and out-sample period. We calculated daily spot and futures return as the differenced log prices on the in-sample periods. The optimal hedge ratios are estimated on a day to day rollovers . For the dynamic models the hedge ratio is updated daily. Figure 4,5 and 6 plots the hedge ratio obtained through the different estimation methods Hedge ratio appears to be instable during the period and

Figure 4: Hedge ratio estimation: Nord Pool

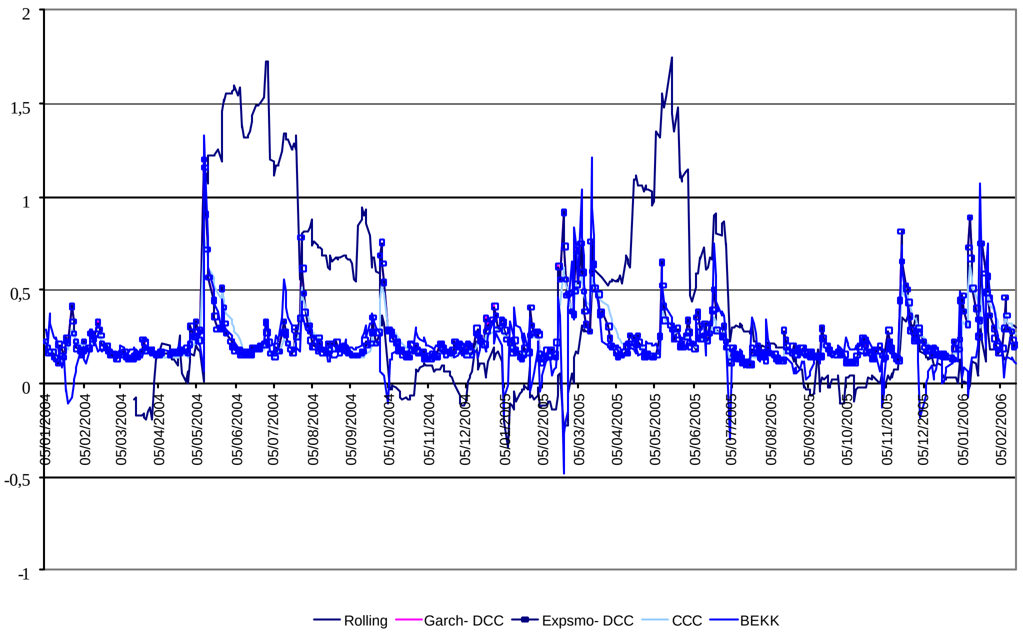


Figure 5: Hedge ratio estimation: EEX

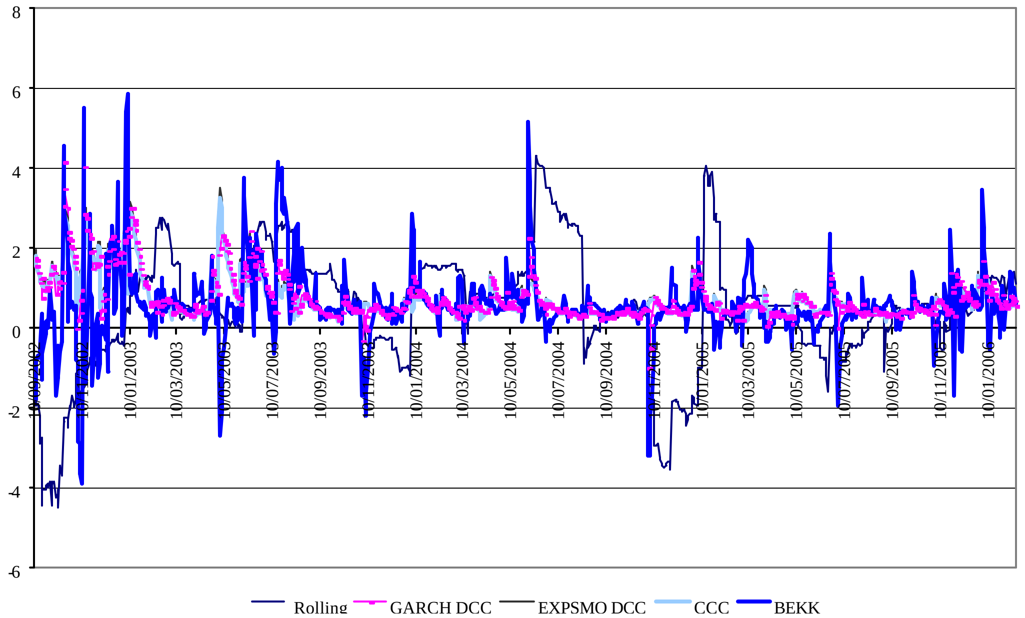
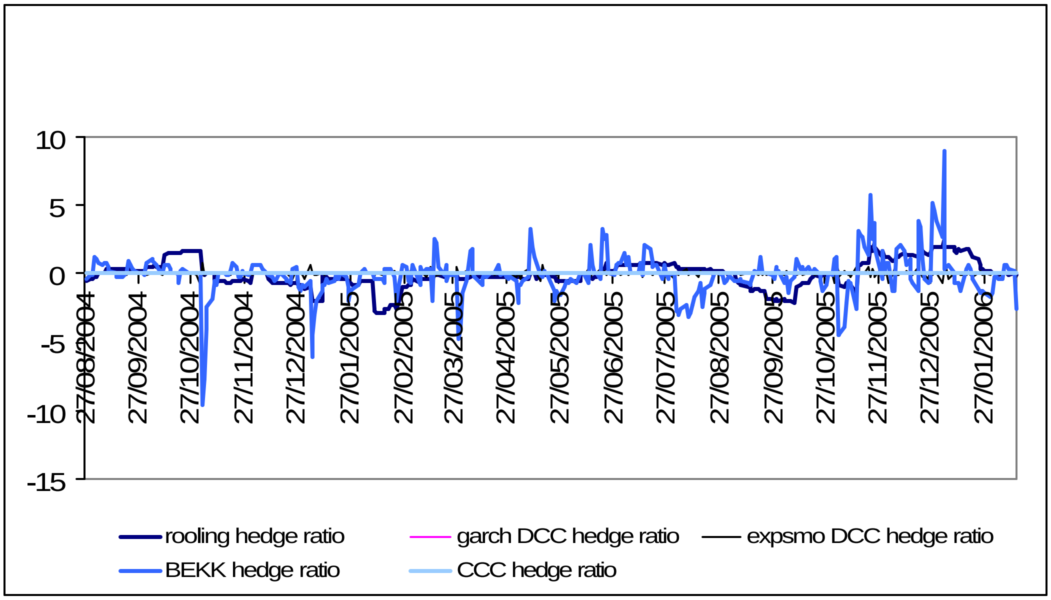


Figure 6: Hedge ratio estimation: Power Next



In tables 7,8 and 9 we report average portfolio returns, standard deviation and the percentage of volatility reduction, compared to spot un-hedged position, obtained through different hedge ratios estimation method. The reason we also report mean return is that the "ideal" best hedging strategies in the one with the biggest volatility reduction and the lowest return reduction.

However the average return of the portfolio depend on the underlying trend of the spots and futures return. So we believe that volatility reduction is a much valid ranking criteria.

Table7: Portfolio return, Standard deviation and volatility reduction: Nord Pool

	Mean Return	**Standard Deviation**	**% Volatility reduction**
Spot un-hedged position	0,0020	0,0614	
Naive 1-1	0,0002	0,0643	-4,7587%
OLS Static Hedge	0,0015	0,0609	0,9000%
OLS dynamic hedge	0,0016	0,0621	-1,1575%
BEKK	0,0017	0,0615	-0,1703%
CCC	0,0014	0,0606	1,3586%
GARCH DCC	0,0015	0,0608	0,9891%
ExpDCC	0,0015	0,0608	0,9821%

Table 8: Portfolio return, Standard deviation and volatility reduction: EEX

	Mean Return	**Standard Deviation**	**% Volatility reduction**
Spot un-hedged position	0,0029	0,2457	
Naive 1-1	0,0015	0,2424	1,3585%
OLS Static Hedge	0,0037	0,2506	-1,9968%
OLS dynamic hedge	0,0035	0,2493	-1,4700%
BEKK	0,00319	0,24731	-0,6529%
CCC	0,00205	0,24167	1,6441%
GARCH DCC	0,00219	0,24176	1,6096%
ExpDCC	0,00207	0,24158	1,6805%

Table 9: Portfolio return, Standard deviation and volatility reduction: Power Next

	Mean Return	**Standard Deviation**	**% Volatility reduction**
Spot un-hedged position	0,0048	0,1822	
Naive 1-1	0,0024	0,1844	-1,1951%
OLS Static Hedge	0,0054	0,1826	-0,1874%
OLS dynamic hedge	0,0048	0,1859	-1,9981%
BEKK	0,0035	0,1931	-5,9482%
CCC	0,0048	0,1822	0,0066%
ExpDCC	0,0048	0,1823	-0,0028%
GARCH DCC	0,0048	0,1822	0,0066%

The results obtained show that the best performing strategies are the one based on correlations model. Static traditional models but also GARCH model that do not take in consideration correlations do not perform well. In some cases, using tradition model we drive the conclusion that hedging increase the variance of the portfolio. This may be in fact explained by the impact of correlations. Making reference to EEX market results, in the in-sample correlation of spot and futures return is negative leading to an hedge ratio of -0.577 (for the static model). However the out of sample correlations become positive and explain the unsuccess of the hedging strategy and the increase of volatility. The same apply to other markets

To further increase the statistical significance of our results, we split the out of sample period on two subperiods of equal length and we test the hedging performance over the two subperiods. Tables 10 to 12 give the results.

As can been seen from the tables this analysis further stress the importance of implementing hedging strategies based on correlations models. Another conclusion may also be driven by the subperiods analysis. The performance of correlations models compared to traditional hedging models is stronger in high volatility periods when reducing variance is particularly important.

Table 10: Portfolio return, Standard deviation and volatility reduction in two subperiods: Nord Pool

	Standard Deviation		**% Volatility reduction**	
	subperiod 1	**subperiod 2**	**subperiod 1**	**subperiod 2**
Spot un-hedged position	0,06418	0,05874		
Naïve 1-1	0,06623	0,06261	-3,100%	-6,183%
OLS Static Hedge	0,06322	0,05862	1,512%	0,202%
OLS dynamic hedge	0,06523	0,05908	-1,605%	-0,575%
BEKK	0,06408	0,05907	0,160%	-0,559%
CCC	0,06302	0,05824	1,836%	0,848%
GARCH DCC	0,06334	0,05837	1,330%	0,625%
ExpDCC	0,06334	0,05837	1,322%	0,619%

Table 11: Portfolio return, Standard deviation and volatility reduction in two subperiods: EEX

	Standard Deviation		**Volatility Reduction**	
	subperiod 1	**subperiod 2**	**subperiod 1**	**subperiod 2**
Spot un-hedged position	29,975%	17,557%		
Naive 1-1	29,404%	17,598%	1,944%	-0,231%
OLS Static Hedge	30,587%	17,886%	-1,998%	-1,839%
OLS dynamic hedge	30,259%	18,082%	-0,938%	-2,902%
BEKK	30,196%	17,628%	-0,731%	-0,402%
CCC	29,318%	17,548%	2,243%	0,048%
GARCH DCC	29,345%	17,526%	2,148%	0,177%

ExpDCC	29,299%	17,556%	2,309%	0,007%

Table 12: Portfolio return, Standard deviation and volatility reduction in two subperiods: Power next

	Standard Deviation		**Volatility Reduction**	
	subperiod 1	**subperiod 2**	**subperiod 1**	**subperiod 2**
Spot un-hedged position	14,729%	21,223%		
Naive 1-1	15,010%	21,399%	-1,877%	-0,825%
OLS Static Hedge	14,748%	21,269%	-0,130%	-0,215%
OLS dynamic hedge	14,877%	21,747%	-0,996%	-2,410%
BEKK	15,324%	22,666%	-3,887%	-6,368%
CCC	14,730%	21,220%	-0,007%	0,013%
GARCH DCC	14,729%	21,221%	-0,004%	0,007%
ExpDCC	14,729%	21,223%	-0,005%	-0,002%

Finally, as a variation to the volatility reduction as a criteria to asses the effectiveness of and hedging strategy, we calculate the number of times that the hedge portfolio returns are actually smaller, in absolute term, than the spot return. In fact a large standard deviation may be explained by a relatively small number of large return even if most returns are smaller than the other portfolios. This analysis once again confirm that correlations model performs relatively better than tradition dynamic hedge ratio and BEKK models.

Table 13: Number of days in which the hedged portfolio return is smaller than the unhedged return position: Nordpool

	Number of days	**% full sample**
Spot un-hedged position	0	
Naive 1-1	233	43,55%
OLS Static Hedge	395	73,83%
OLS dynamic hedge	270	50,47%
BEKK	271	50,65%
CCC	272	50,84%
GARCH DCC	272	50,84%
ExpDCC	272	50,84%

Table 14: Number of days in which the hedged portfolio return is smaller than the unhedged return position: EEX

	Number of days	**% full sample**
Spot un-hedged position	0	
Naive 1-1	399	48,96%
OLS Static Hedge	349	42,82%

OLS dynamic hedge	376	46,13%
BEKK	398	48,83%
CCC	408	50,06%
GARCH DCC	408	50,06%
ExpDCC	407	49,94%

Table 15: Number of days in which the hedged portfolio return is smaller than the unhedged return position: Powernext

	Number of days	% full sample
Spot un-hedged position	0	
Naive 1-1	96	40,51%
OLS Static Hedge	110	46,41%
OLS dynamic hedge	102	43,04%
BEKK	103	43,46%
CCC	106	44,73%
GARCH DCC	106	44,73%
ExpDCC	110	46,41%

6. Conclusions

In this paper we analyzed the performance of different hedging models in a context of high time varying volatility such as the one that characterize electricity markets. We estimated the hedge ratio and calculated the reduction obtained by the futures hedging compared to the spot unhedged positions using 7 different models. From the results obtained some interesting conclusions may be driven. The first one is that, in the periods analysed and in the market analysed it has been possible to reduce the variance of electricity markets using futures hedging. However, and this is our second conclusion, the hedging performance depend on the model choosed to estimate the hedge ratio. Finally, we proved that in a context of high volatility and time varying correlations traditional hedging strategies show worse performances that GARCH correlations models.

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Appendix 1

Table 1 . Deregulation and Electricity Market Opening

	Opened	**Size (TWh)**		**Opened**	**Size**
Austria	100%	44	Schweden	100%	135
Belgium	90%	60	UK	100%	335
Denmark	100%	3	Malta	0%	0
Finland	100%	80	Estonia	10%	1
France Germany	70% 100%	275 500	Latvia Lithuania	76% -	4 -
Greece	62%	29	Poland	52%	50
Ireland	56%	12	Czech R.	47%	25
Italy	79%	225	Slovakis	66%	15
Luxembourg	57%	3	Hungary	67%	22
Netherlands	100%	100	Slovenia	75%	10
Portugal	100%	42	Cyprus	35%	1
Spain	100%	100	Norway	100%	110

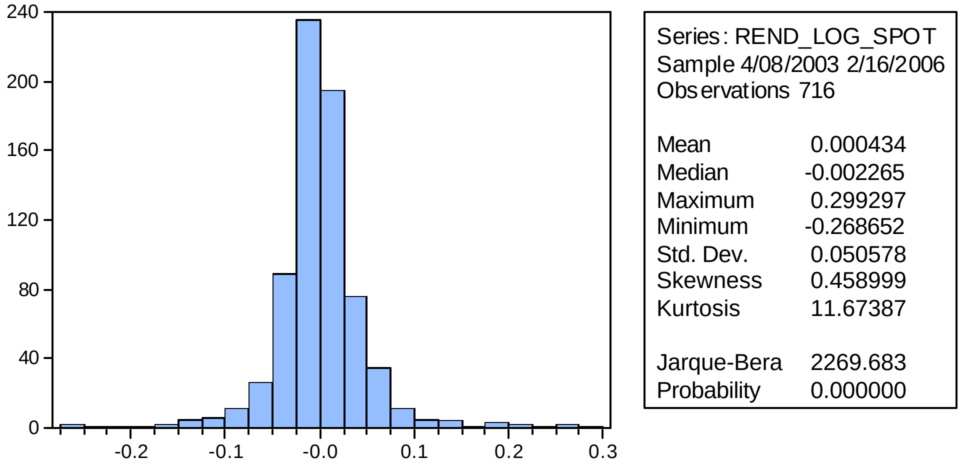
Souce: Technical annexes to the report from the Commission on the implementation of the gas and electricity internal market. Commission of European communities 2005.

Table 2. The European Energy Exchange

Country	**Date**	**Name**
England	1990-1999	Electric ity Pool
	2001	UK Power Exchange (UKPX) now APX Power UK
Holland	1990	Amsterdam Power Exchange (APX)
Norway	1993	Nord Pool Scandinavia
	1998	Nord Pool
Spain	1998	OMEL
Germany	2000	Leipzig Power Exchange (KPX)
	2000	European Power Exchange (EEX)
Poland	2000	Polish Power Exchange (PPX)
France	2001	Powernext
Austria	2002	EXAA
Italy	2004	Mercato Elettrico Italiano (GME)

Appendix 2

Figure 1 : Spot return Nordpool Market

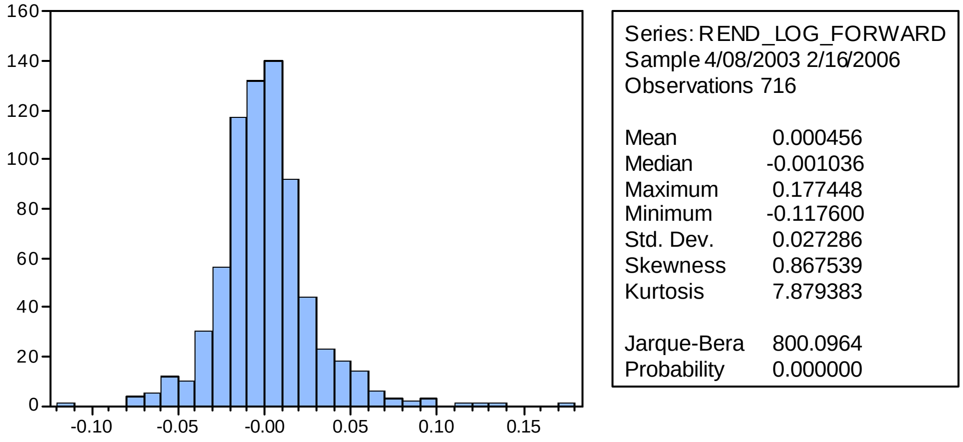


```
Series: REND_LOG_SPOT
Sample 4/08/2003 2/16/2006
Observations 716

Mean          0.000434
Median       -0.002265
Maximum       0.299297
Minimum      -0.268652
Std. Dev.     0.050578
Skewness      0.458999
Kurtosis      11.67387

Jarque-Bera   2269.683
Probability   0.000000
```

Figure 2: Future Returns Nordpool Market



```
Series: REND_LOG_FORWARD
Sample 4/08/2003 2/16/2006
Observations 716

Mean          0.000456
Median       -0.001036
Maximum       0.177448
Minimum      -0.117600
Std. Dev.     0.027286
Skewness      0.867539
Kurtosis      7.879383

Jarque-Bera   800.0964
Probability   0.000000
```

Figure 3: Unit Root Dickey Fuller Test, Spot and Futures Return Nord Pool

Figure 4: Ljiung Box test: Nord Pool Spot Return

```
Date: 02/08/08   Time: 18:17
Sample: 4/08/2003 2/16/2006
Included observations: 716
==============================================================================
   Autocorrelation      Partial Correlation        AC      PAC    Q-Stat   Prob
------------------------------------------------------------------------------
      *|.   |              *|.   |          1  -0.108  -0.108   8.4073   0.004
      *|.   |              *|.   |          2  -0.123  -0.137   19.350   0.000
      *|.   |              *|.   |          3  -0.088  -0.122   24.948   0.000
      .|.   |              .|.   |          4  -0.011  -0.058   25.033   0.000
      .|*   |              .|.   |          5   0.091   0.056   31.038   0.000
      *|.   |              *|.   |          6  -0.116  -0.121   40.713   0.000
      .|.   |              .|.   |          7   0.002  -0.016   40.716   0.000
      .|.   |              .|.   |          8   0.066   0.049   43.844   0.000
      *|.   |              *|.   |          9  -0.066  -0.077   47.016   0.000
      .|.   |              .|.   |         10   0.064   0.052   50.044   0.000
      .|.   |              .|.   |         11  -0.061  -0.040   52.722   0.000
      .|.   |              .|.   |         12   0.030   0.010   53.397   0.000
      .|.   |              .|.   |         13  -0.012  -0.021   53.504   0.000
      .|.   |              .|.   |         14  -0.017  -0.001   53.708   0.000
      .|.   |              .|.   |         15   0.005  -0.025   53.727   0.000
      .|.   |              .|.   |         16  -0.032  -0.025   54.457   0.000
      .|.   |              .|.   |         17  -0.006  -0.026   54.485   0.000
      .|.   |              .|.   |         18  -0.027  -0.051   55.027   0.000
      .|.   |              .|.   |         19  -0.026  -0.040   55.536   0.000
      .|.   |              .|.   |         20   0.033  -0.005   56.362   0.000
      .|.   |              .|.   |         21  -0.037  -0.046   57.400   0.000
      .|.   |              .|.   |         22   0.012  -0.015   57.507   0.000
      .|.   |              .|.   |         23   0.003  -0.004   57.512   0.000
      .|.   |              .|.   |         24   0.036   0.025   58.449   0.000
      .|.   |              .|.   |         25  -0.010  -0.016   58.522   0.000
      .|.   |              .|.   |         26  -0.015   0.003   58.682   0.000
      .|.   |              .|.   |         27  -0.024  -0.036   59.128   0.000
      .|.   |              .|.   |         28   0.039   0.027   60.255   0.000
      .|.   |              .|.   |         29  -0.018  -0.021   60.493   0.001
      .|.   |              .|.   |         30   0.008   0.004   60.545   0.001
      .|.   |              .|.   |         31  -0.022  -0.020   60.903   0.001
      .|.   |              .|.   |         32  -0.002  -0.018   60.907   0.002
      .|.   |              .|.   |         33   0.005  -0.011   60.923   0.002
      .|.   |              .|.   |         34   0.030   0.023   61.586   0.003
      .|.   |              .|.   |         35  -0.003  -0.003   61.592   0.004
      .|.   |              .|.   |         36   0.001  -0.001   61.593   0.005
==============================================================================
```

Figure 5: Ljiung Box test: Nord Pool Futures Return

```
Date: 02/08/08   Time: 18:19
Sample: 4/08/2003 2/16/2006
Included observations: 716
```

```
=====================================================================================
 Autocorrelation      Partial Correlation         AC      PAC     Q-Stat    Prob
=====================================================================================
   .|.     |            .|.     |            1   0.001    0.001    0.0002   0.988
   .|.     |            .|.     |            2   0.031    0.031    0.7117   0.701
   .|*     |            .|*     |            3   0.092    0.092    6.7505   0.080
   .|.     |            .|.     |            4   0.006    0.006    6.7807   0.148
   .|.     |            .|.     |            5  -0.004   -0.010    6.7938   0.236
   .|.     |            .|.     |            6   0.033    0.024    7.5846   0.270
   .|.     |            .|.     |            7   0.051    0.051    9.5058   0.218
   *|.     |            *|.     |            8  -0.111   -0.112    18.389   0.018
   .|.     |            .|.     |            9  -0.002   -0.011    18.391   0.031
   .|.     |            .|.     |           10  -0.058   -0.062    20.880   0.022
   *|.     |            *|.     |           11  -0.122   -0.104    31.678   0.001
   .|.     |            .|.     |           12  -0.040   -0.037    32.837   0.001
   .|.     |            .|.     |           13  -0.055   -0.044    35.067   0.001
   .|.     |            .|.     |           14   0.014    0.040    35.208   0.001
   *|.     |            *|.     |           15  -0.094   -0.075    41.668   0.000
   .|.     |            .|.     |           16   0.039    0.040    42.811   0.000
   .|.     |            .|.     |           17  -0.040   -0.029    43.997   0.000
   .|.     |            .|.     |           18  -0.028   -0.016    44.589   0.000
   .|.     |            .|.     |           19   0.062    0.042    47.379   0.000
   .|*     |            .|*     |           20   0.126    0.131    59.190   0.000
   .|.     |            .|.     |           21   0.019    0.002    59.458   0.000
   .|.     |            .|.     |           22   0.024    0.005    59.869   0.000
   .|*     |            .|.     |           23   0.077    0.026    64.224   0.000
   .|.     |            .|.     |           24  -0.055   -0.058    66.495   0.000
   .|.     |            .|.     |           25   0.014   -0.007    66.638   0.000
   .|.     |            .|.     |           26   0.033   -0.007    67.447   0.000
   .|.     |            .|.     |           27  -0.019   -0.013    67.719   0.000
   .|.     |            .|.     |           28  -0.005   -0.003    67.739   0.000
   .|.     |            .|.     |           29   0.018    0.021    67.971   0.000
   .|.     |            .|.     |           30  -0.043   -0.030    69.346   0.000
   .|.     |            .|.     |           31  -0.043    0.010    70.709   0.000
   .|.     |            *|.     |           32  -0.063   -0.070    73.655   0.000
   .|.     |            .|.     |           33  -0.045   -0.021    75.149   0.000
   .|.     |            .|.     |           34   0.001    0.020    75.149   0.000
   *|.     |            .|.     |           35  -0.066   -0.055    78.430   0.000
   .|.     |            .|.     |           36  -0.037   -0.035    79.463   0.000
=====================================================================================
```

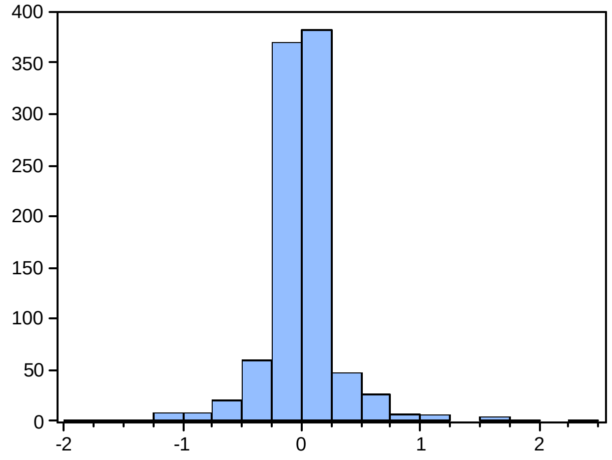
Figure 6: Spot return Power Next

Figure 7: Futures return Power Next

Figure 8: Unit Root Dickey Fuller Test, Spot and Futures Return Power Next

			Spot Returns		**Futures Returns**	
			t-Statistic	**Prob.***	**t-Statistic**	**Prob.***
Augmented Dickey-Fuller test statistic			--29.76455	0.0000	-8.8531	0.0000
Test critical values:	1% level		-3.439268		-3.439345	
	5% level		-2.865366		-2.865400	
	10% level		-2.568864		-2.568882	

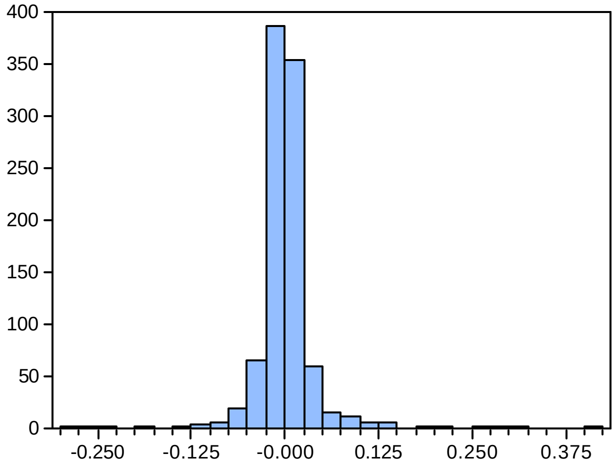
Figure 11: Spot return EEX



Series: SPOT_RETURN_EEX
Sample 7/02/2002 2/14/2006
Observations 946

Mean	0.001422
Median	0.000803
Maximum	2.369608
Minimum	-1.963626
Std. Dev.	0.321346
Skewness	0.631853
Kurtosis	14.04389
Jarque-Bera	4870.495
Probability	0.000000

Figure 12: Future return EEX



```
Series: FUTURES
Sample 7/01/2002 2/14/2006
Observations 946

Mean          0.001129
Median       -0.000923
Maximum       0.421543
Minimum      -0.286835
Std. Dev.     0.041398
Skewness      1.982912
Kurtosis      30.93471

Jarque-Bera   31378.66
Probability   0.000000
```

Figure 13: Unit Root Dickey Fuller Test, Spot and Futures Return EEX

			Spot Return		**Futures Return**	
			t-Statistic	**Prob.***	**t-Statistic**	**Prob.***
Augmented Dickey-Fuller test statistic			-19.32733	0.0000	-18.71780	0.000
Test critical values:	1% level		-3.437085		-3.437071	
	5% level		-2.864402		-2.864396	
	10% level		-2.568347		-2.568343	

Figure 14 : Ljiung Box test: EEX Spot Return

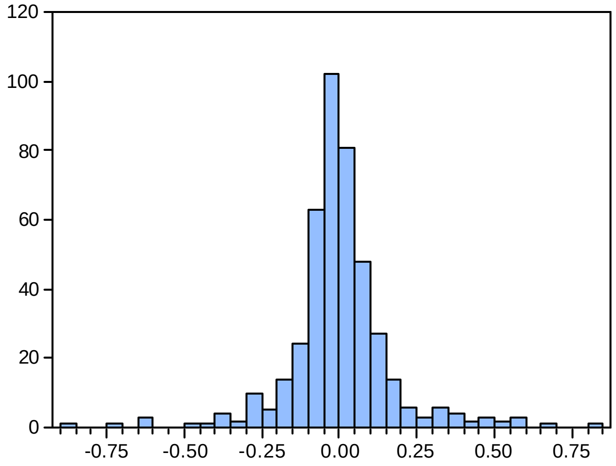
```
Date: 02/08/08   Time: 19:05
Sample: 7/02/2002 2/14/2006
Included observations: 946
==========================================================================
   Autocorrelation      Partial Correlation      AC     PAC    Q-Stat  Prob
==========================================================================
   ***|     |             ***|     |       1  -0.392  -0.392  145.92  0.000
     *|     |              **|     |       2  -0.094  -0.293  154.38  0.000
      |     |               *|     |       3   0.037  -0.162  155.71  0.000
      |     |               *|     |       4   0.007  -0.095  155.75  0.000
      |     |               *|     |       5  -0.052  -0.121  158.34  0.000
      |     |               *|     |       6  -0.018  -0.134  158.66  0.000
      |     |                |     |       7   0.050  -0.063  161.07  0.000
      |     |                |     |       8   0.005  -0.027  161.10  0.000
     *|     |               *|     |       9  -0.078  -0.110  166.93  0.000
      |*    |                |     |      10   0.087  -0.008  174.10  0.000
     *|     |               *|     |      11  -0.066  -0.086  178.28  0.000
      |     |                |     |      12   0.044  -0.015  180.10  0.000
      |     |                |     |      13  -0.032  -0.053  181.10  0.000
      |     |               *|     |      14  -0.025  -0.094  181.71  0.000
```

```
   |*    |            |    |        15   0.081   0.012   188.06   0.000
   |     |            |    |        16  -0.005   0.034   188.09   0.000
  *|     |           *|    |        17  -0.125  -0.127   203.22   0.000
   |*    |            |    |        18   0.127   0.010   218.89   0.000
   |     |            |    |        19  -0.045  -0.037   220.87   0.000
   |     |            |    |        20  -0.004  -0.029   220.89   0.000
   |     |            |    |        21   0.018   0.011   221.21   0.000
   |     |            |    |        22   0.026   0.018   221.85   0.000
   |     |            |    |        23  -0.064  -0.051   225.85   0.000
   |     |           *|    |        24  -0.046  -0.107   227.88   0.000
   |*    |            |    |        25   0.101  -0.013   237.88   0.000
   |     |            |    |        26  -0.032  -0.037   238.90   0.000
   |     |           *|    |        27  -0.051  -0.068   241.43   0.000
   |*    |            |    |        28   0.076  -0.020   247.04   0.000
   |     |            |    |        29  -0.016  -0.007   247.28   0.000
   |     |            |    |        30  -0.040  -0.065   248.82   0.000
   |     |            |    |        31   0.051   0.007   251.41   0.000
   |     |            |    |        32   0.036   0.073   252.70   0.000
  *|     |            |    |        33  -0.083  -0.036   259.53   0.000
   |     |           *|    |        34  -0.014  -0.071   259.72   0.000
   |     |            |    |        35   0.074   0.019   265.05   0.000
   |     |            |    |        36  -0.005   0.021   265.07   0.000
```

Figure 15 : Ljiung Box test: EEX Futures Return

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.| |	.| |	1	0.054	0.054	2.7874	0.095
.| |	.| |	2	0.000	-0.003	2.7874	0.248
*| |	*| |	3	-0.074	-0.074	7.9382	0.047
.| |	.| |	4	-0.039	-0.032	9.4106	0.052
.| |	.| |	5	0.013	0.017	9.5829	0.088
.| |	.| |	6	-0.020	-0.027	9.9622	0.126
.| |	*| |	7	-0.056	-0.060	12.978	0.073
*| |	.| |	8	-0.060	-0.054	16.418	0.037
.| |	.| |	9	-0.017	-0.014	16.703	0.054
.| |	.| |	10	-0.039	-0.048	18.147	0.053
.| |	.| |	11	-0.042	-0.051	19.812	0.048
.| |	.| |	12	-0.010	-0.012	19.913	0.069
.| |	.| |	13	-0.031	-0.039	20.807	0.077
.| |	.| |	14	0.016	0.002	21.040	0.101
.| |	.| |	15	-0.001	-0.015	21.041	0.136
.| |	.| |	16	0.006	-0.006	21.071	0.176
.| |	.| |	17	0.038	0.028	22.443	0.168
.| |	.| |	18	0.042	0.029	24.137	0.151

Figure 9: Ljiung Box test: Power Next Spot Return

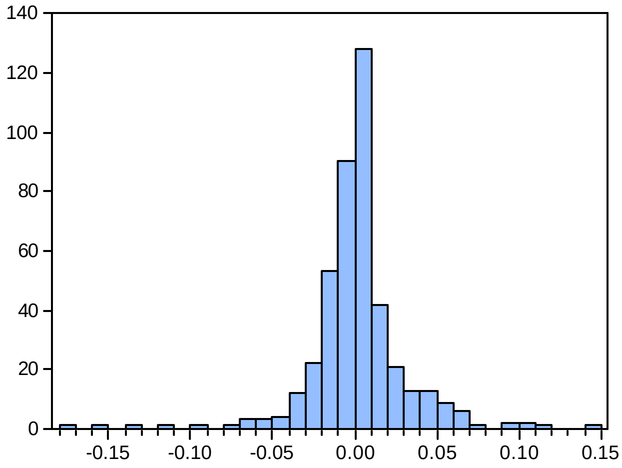


```
Series: SPOT
Sample 6/21/2004 2/14/2006
Observations 432

Mean          0.002234
Median       -0.004867
Maximum       0.838954
Minimum      -0.850259
Std. Dev.     0.168958
Skewness      0.143846
Kurtosis      8.819029

Jarque-Bera   610.9895
Probability   0.000000
```

Figure 10: Ljiung Box test: Power Next Futures Return (1100)



```
Series: FUTURE
Sample 6/21/2004 2/14/2006
Observations 432

Mean          0.001871
Median        0.000000
Maximum       0.148070
Minimum      -0.170697
Std. Dev.     0.029464
Skewness     -0.401778
Kurtosis      11.32722

Jarque-Bera   1259.788
Probability   0.000000
```

Figure 8: Unit Root Dickey Fuller Test, Spot and Futures Return Power Next

			Spot Returns		**Futures Returns**	
			t-Statistic	**Prob.***	**t-Statistic**	**Prob.***
Augmented Dickey-Fuller test statistic			**-15.94289**	**0.0000**	**-20.59333**	**0.0000**
Test critical values:	1% level		-3.436143		-3.445267	
	5% level		-2.863986		-2.868011	

	10% level		-2.568124		-2.570281	

Figure 9: Ljiung Box test: Power Next Spot Return

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>***|. |</td><td>***|. |</td><td>1</td><td>-0.326</td><td>-0.326</td><td>46.364</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>**|. |</td><td>2</td><td>-0.068</td><td>-0.195</td><td>48.352</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>3</td><td>0.014</td><td>-0.088</td><td>48.441</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>4</td><td>-0.026</td><td>-0.075</td><td>48.728</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>0.046</td><td>0.008</td><td>49.668</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|* |</td><td>6</td><td>0.045</td><td>0.068</td><td>50.567</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>-0.013</td><td>0.047</td><td>50.640</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.040</td><td>-0.013</td><td>51.362</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>-0.026</td><td>-0.047</td><td>51.650</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>0.008</td><td>-0.035</td><td>51.677</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>11</td><td>-0.021</td><td>-0.058</td><td>51.878</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>12</td><td>-0.012</td><td>-0.061</td><td>51.945</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>13</td><td>-0.029</td><td>-0.074</td><td>52.316</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>14</td><td>-0.074</td><td>-0.135</td><td>54.783</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>15</td><td>0.138</td><td>0.063</td><td>63.350</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>16</td><td>-0.089</td><td>-0.040</td><td>66.896</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>-0.018</td><td>-0.043</td><td>67.046</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>18</td><td>0.024</td><td>-0.012</td><td>67.299</td><td>0.000</td></tr>
</table>

Figure 10: Ljiung Box test: Power Next Futures Return (1100)

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.006</td><td>0.006</td><td>0.0145</td><td>0.904</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>2</td><td>-0.091</td><td>-0.091</td><td>3.6425</td><td>0.162</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>3</td><td>-0.080</td><td>-0.080</td><td>6.4684</td><td>0.091</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>-0.008</td><td>-0.016</td><td>6.4954</td><td>0.165</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>5</td><td>0.067</td><td>0.053</td><td>8.4504</td><td>0.133</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.043</td><td>0.035</td><td>9.2490</td><td>0.160</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>7</td><td>-0.067</td><td>-0.059</td><td>11.206</td><td>0.130</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.026</td><td>-0.010</td><td>11.502</td><td>0.175</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>0.049</td><td>0.047</td><td>12.582</td><td>0.182</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>10</td><td>-0.101</td><td>-0.118</td><td>17.075</td><td>0.073</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.019</td><td>0.020</td><td>17.239</td><td>0.101</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.023</td><td>-0.030</td><td>17.483</td><td>0.132</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>-0.026</td><td>-0.032</td><td>17.779</td><td>0.166</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>-0.039</td><td>-0.053</td><td>18.452</td><td>0.187</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.057</td><td>0.058</td><td>19.926</td><td>0.175</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>0.024</td><td>0.023</td><td>20.180</td><td>0.212</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>-0.041</td><td>-0.053</td><td>20.952</td><td>0.228</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>18</td><td>0.027</td><td>0.043</td><td>21.294</td><td>0.265</td></tr>
</table>