Efficiency and Transmission in European Electricity Markets

A SemiNonParametric Approach

Abstract

This paper describes mean and volatility transmissions between the Phelix and Nordpool energy markets and suggests some market and policy implications. A multivariate semi-parametric GARCH model (*SNP*) is optimally and sequentially evolved and used to identify sources and magnitudes of mean and volatility in these two interconnected electricity markets. The mean equations show strong negative serial correlation and positive mutual cross correlation. The cross-mean correlations are both in size and significance dominated by Nordpool. The bi-dimensional *SNP*-polynoms report non-gaussian features and interactions. The volatility for both markets report means reversion and strong serial correlation. The cross volatility correlation is mainly found in the leverage and level *BEKK* coefficients. The results induce mean and volatility effects not accompanying an efficient market. Policy implications for integration and efficient market pricing are to increase transparency and credibility especially in the Phelix market, extend the size and number of market interconnectors, and due to high public sector control, scale down to secure a larger number of market participants and privatise for increased competition.

Classification: C32; C51; L94; Q40

Keywords: electricity markets, transmission, efficiency, competition

1 Introduction

This paper examines the transmission of price changes and volatility between the two major spot electricity markets in Europe; the Phelix and the Nordpool markets. The European Energy Exchange (Phelix) is Germany's energy exchange and is located in Leipzig. Preceding companies were LPX Leipzig Power Exchange, located in Leipzig and European Energy Exchange, located in Frankfurt. Both exchanges and their supporting associations merged within the year 2002. The objective of European Energy Exchange is to become the leading energy exchange in Central Europe. In future, nuclear power, gas and other energy sources are to be tradable at EEX. This range is to be completed by services related to the exchange, such as Clearing of transactions outside the exchange (OTC Clearing). There are about 48 participants for EUA Spot listed at the Phelix web-site (February 2006). The Phelix market is dominated by large nuclear producers showing low transparency and credibility regarding their production and maintenance decisions. Many power producers are reluctant to release data on actual production, available production capacity and planned maintenance, as they consider this kind of information confidential or market sensitive. Moreover, Phelix coal plants may have two-regime behaviour. Below a threshold price the decision is low-end production for grid maintenance; above the threshold price, the decision is maximum production. The Nordic Power Exchange (Nordpool) is a multinational exchange for trading electric power. Nord Pool was established in 1993, and is owned by the two national grid companies, Statnett SF in Norway (50%) and Affärsverket Svenska Kraftnät in Sweden (50%). Norway was the first of the Nordic countries to deregulate its power markets. The Energy Act of 1990 formed the basis for deregulation in the other Nordic countries. There are about 283 participants listed at the Norpool Spot web-site (February 2006). Nordpool Spot offers a market in which it is voluntary to trade and thereby contributes to enhanced competition. The market schedules urgent market messages of transmission capacity. Phelix and Nordpool Spot are therefore market places where energy and capacity is combined in one simultaneous auction (Solibakke, 2002). From both number of participants and available market information, the Nordpool market relative to Phelix, shows higher transparency and credibility regarding production, maintenance and grid congestion information. Even market participants as for example Dick van der Klauw, CEO of Delta has said in 2006: *"the publication of unexpected non-available power plants was an issue, and that market players should follow the Nordic example of immediately publishing information on unexpected outages."* The need for change at Phelix was also stressed by Peter Styles chairman of EFET's electricity committee arguing in favour of mandatory transparency rules. Styles claimed: *"A voluntary scheme would only give an inadequate picture whereby it would be hard to establish the price-setting power plant."*

The ownership of Nordic producers is dominated by large public companies (Statkraft, Vattenfall) possibly exerting market power. However, relative to Phelix, the number of producers is large in Nordpool Spot market manly due to many hydro-electric producers (283 > 48). However, for example in Norway due to cross-ownership Statkraft controls about 70-75% for all the Norwegian power production. The Nordpool and Phelix markets are interconnected at several points. The hypotheses are therefore built on cross-correlations for both prices and volatilities. An interconnector snapshot (map) is shown in Figure 1. Transmissions are bi-directional, suggesting that at surplus times the Nordic area electric market exports electricity to the European market and vice versa. However, there are limitations of physical transfer capacity. Therefore congestions may not only occur inside the respective markets but it may also occur between the markets. For both markets appropriate regulatory and commercial mechanisms are established for creation of efficient markets. These mechanisms will of course have an impact on prices of electricity. The deregulation of the Norwegian electric-power market in 1992 for example, introduced a period for the Nordic electric-power market (Nordpool) showing an immediate reduction in spot prices and an evolution of a derivative market in1995 showing a strong growth in liquidity; lower trading costs and lower bid-asks spreads. The Phelix market started its derivative trading much later in 2002. Moreover, the fact that producers in the Phelix market are reluctant to release data on actual production, available production capacity, and planned maintenance, make this market less transparent and credible than the Nordpool market. The market microstructure therefore induces hypothesized structures of cross-markets effects.

The bi-dimensional series are analysed applying a model called the score generator or in more technical terms the SemiNonParametric[1] (SNP) model. Bayes Information Criterion[2] (BIC) values are used to approximate conditional densities from data series, applying serial correlation, volatility clustering as leading terms (parametric), and hermite polynomial series expansions for higher order data features. The SNP model is fitted using conventional maximum likelihood together with a statistical objective model selection strategy (BIC). Using the physical market characteristics and the model building blocks, the paper establishes the interesting relationships/ hypotheses.

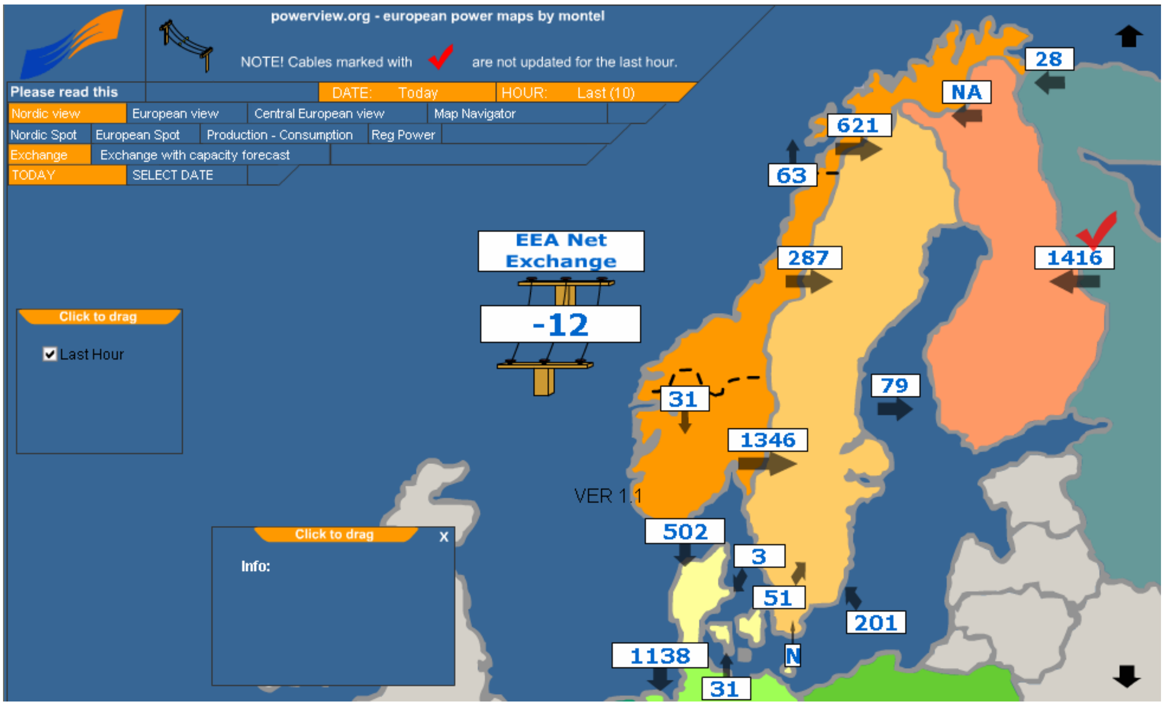

Figure 1. Snapshot of Interconnecters between Phelix and Nordpool and inside Nordpool.

The first set of hypotheses is serial correlation in the mean equation due to strong seasonal structures in the respective series (i.e. days of week effects). Any systematic pattern may spur

[1] See Gallant & Tauchen, 1989
[2] see Schwartz (1978)

short-run predictability not complying with the efficient market hypothesis. Secondly, due to the physical market interconnectors, mutual cross mean serial correlation is expected. The cross effects are hypothesised to be dominated by the most transparent and credible market due to a higher systematic information flow. Hence, due to higher transparency and credibility at Nordpool relative to Phelix, the cross-mean influence should be dominated by Nordpool. The third set of hypotheses is related to serial correlation in volatility. Mean-reversion and volatility clustering seem to be viable for many financial time series. This paper hypothesises the same properties for electricity markets. GARCH-coefficients suggest a non-Markov series and mean-reversion suggests sensitivity to shocks. Differences between market coefficients induce market characteristics comparable for market (in-)efficiency. The fourth set of hypotheses is cross-volatility effects. However, these effects are much more difficult to assess and explain due to the fact that volatility is latent and in most cases, has very low mean effects. As for the mean the lack of transparency and credibility in the Phelix market may cause higher immediate volatility effects (mean reversion) and an overall higher volatility at Phelix than at Nordpool. Fifthly, high ownership concentration and a low number of producers in both markets may reduce the competition, increases the possibility for exertion of market power and tendency of monopoly pricing. The level effects inducing volatility as a function of the price change levels can proxy for the degree of information flow in a market and information transfer between the markets. Competitive markets show the highest inducement for symmetric and synchronous information. Hence, due to a higher number of participants and therefore competition in Nordpool relative to Phelix, the level effect in the conditional volatility process, is hypothesised to be stronger at Nordpool. For the information transfer interpretation, high price change levels increase market information flow, increasing the level effect in both markets. Sixthly, negative asymmetry is a well-known fact from financial markets (the leverage effect). This property is expected to be found also in electricity markets. However, due to the short-run non-transparent shut-down option for the highly concentrated Phelix producers, making positive asymmetry, a significant negative asymmetry is more likely at Nordpool. In addition, the grid maintenance and threshold price coal-plant switching max-production fact at Phelix, may also contribute significantly to positive asymmetry. The paper therefore hypothesises a negative asymmetry for Nordpool and a positive coefficient for Phelix. Finally, using general market intuition and the fact that the markets are physically interconnected, the conditional correlation between the two markets should be positive, inducing a rather low effect of diversification. The Phelix market has grown in maturity since its derivatives start in 2002. The conditional correlation is therefore hypothesized to move higher for the most recent periods.

The rest of the paper is organised as follows. Section 2 defines the series and expands sequentially the score generator (SNP). Section 3 reports the score characteristics, evaluates hypotheses and discusses market and policy implications. Section 4 summarises and concludes.

2 The SNP Method, Data and Model Selection

2.1 Setup, Notation and Intuition

The SemiNonParametric method (SNP) suggests that it lies halfway between parametric and nonparametric procedures. The leading term of the series is an established parametric model known to give a reasonable approximation to the process; higher order terms capture departures from that model. Hence, the SNP approach does not suffer from the curse of dimensionality to the same extent as kernels and splines. Where data is sparse, the leading term (parametric model) helps to fill in smoothly between data points. Where data is plentiful, the higher order terms accommodate deviation from the leading terms and fits are comparable to kernel estimates.

The SNP methodology is based on the notion that a Hermite expansion can be used as a general purpose approximation to a density function.The Gaussian component of the Hermite expansion makes it easy to subsume into the leading term familiar time series models, including VAR, ARCH, and GARCH models (Engels, 1982, Bollerslev, 1986).

The basic approach is estimation of the conditional density of a bi-dimensional time series $\{y_t\}$. The process begins with a sequence of innovations $\{z_t\}$. In a case of homogeneous innovations, the density of $\{z_t\}$ can be approximated by $h(z) \propto [P(z)]^2 \phi(z)$ where $P(z)$ is a polynomial of degree K_z. The location scale transformation $y_t = R \cdot z_t + \mu_x$ where μ_x is a linear function that depends on L_μ lags $\mu_x = b_0 + B \cdot x_{t-1}$. The density becomes $f(y \mid x, \theta) \infty [P(z)]^2 n_M(y \mid \mu_x, \Sigma)$ where $z = R^{-1}(y - \mu_x)$. To approximate conditionally heterogeneous processes, let each coefficient of the polynomial $P(z)$ be a polynomial of degree K_x in *x*. Denote this polynomial $P(z, x)$. We denote the mapping from *x* to the coefficients *a* of $P(z)$ such that $P(z \mid a_x) = P(z, x)$ by a_x and the number of lags on which it depends by L_p. The density becomes $f(y \mid x, \theta) \infty [P(z, x)]^2 n_M(y \mid \mu_x, \Sigma)$ where $z = R^{-1}(y - \mu_x)$. When K_x is positive, the shape of the density will depend upon *x*. Thus, all moments can depend upon *x* and the density can, in principal, approximate any form of conditional heterogeneity. In some applications, the second moment can exhibit marked dependence on *x* (large K_x). In an attempt to keep K_x small when data are markedly conditional heteroscedastic, the leading term $n_M(y \mid \mu_x, \Sigma)$ of the expansion can be put to a Gaussian ARCH/GARCH rather than a Gaussian VAR. The *BEKK* form is:

$$
\begin{aligned}
\Sigma_{x_{t-1}} &= R_0 \cdot R_0' + \sum_{i=1}^{L_g} Q_i \cdot \Sigma_{x_{t-i-1}} Q_i' + \sum_{i=1}^{L_r} P(y_{t-i} - \mu_{\tau-\iota-1})(y_{t-i} - \mu_{\tau-\iota-1})' \cdot P_i' \\
&+ \sum_{i=1}^{L_v} \max[0, V_i(y_{t-i} - \mu_{\tau-\iota-1})] \cdot \max[0, V_i(y_{t-i} - \mu_{\tau-\iota-1})]' \\
&+ \sum_{i=1}^{L_w} W_i \cdot x_{(1),t-i} \cdot x_{(1),t-i}' \cdot W_i'
\end{aligned}
$$

R_0 is an upper triangular matrix. The matrices P_i, Q_i, V_i, and W_i can be scalar, diagonal, or full *M* by *M* matrices. With R_x specified as either an ARCH or a GARCH, the form of the conditional density becomes $f(y \mid x, \theta) \infty \left[P(z,x)\right]^2 n_M(y \mid \mu_x, \Sigma_x)$ where $z = R^{-1}\left(y - \mu_x\right)$. The parameters are estimated by minimizing the active elements of θ in $s_n(\theta) = -\left(1/n\right)\sum_{t=1}^{n} \log\left[f(y_t \mid x_{t-1}, \theta\right]$.

2.2 Data and Statistics

The electricity data to which we fit the SNP Method is a bi-dimensional time series comprised of 2028 daily observations, $\left\{\tilde{y}_{i,t}\right\}_{t=1}^{2028}$, $i = 1, 2$ on movements on the Nordpool Exchange Spot and Phelix Exchange Spot over the period 2000-06 to 2005-12[3]. The two mostly synchronic time series[4] show weekend, holiday and other seasonal effects over the whole period. The properties of the log first difference of the two price series are reported in Table 1. The Phelix (Nordpool) series shows a mean of 0.0632 (0.0638), standard deviation of 32.74 (9.23), maximum and minimum of 236.9 (118.9) and -196.3 (-77.3), respectively, and skewness and kurtosis of 4.4 (24.3) and 0.889 (1.427), respectively[5]. Both the quartile and K_S Z-tests for normal densities are rejected. There are strong serial correlation in the series and the squared series. The KPSS statistic induces stationary series, ARCH-test is significant, the DF and EG test statistics suggest no unit roots and cointegration and the BDS test show general data dependence. Finally the CHOW-test induces a structural break in March 2001 for both series (282 for Phelix and 262 for Nordpool). Subperiods are therefore defined based on these test results. The periods are defined as Sub1: 2000-06 to 2001-03 and Sub-2: 2001-04 – 2005-12. The sub-periods are used to evaluate and test any changes in model specifications and coefficients[6].

[3] The price series and log price series are not stationary. The KPSS statistic (see Table 1) indicates non-stationary price and log price series. Figure 2 shows the Spot settlement price mechanism.
[4] Released at approximately 01.00 pm every day. The Phelix Monday spot price is released at approximately 2.00 pm Fridays the week before. The Nordpool Monday spot price is released at approximately 01.00 pm Sundays.
[5] Dickey Fuller (1979) rejects the null of unit root. Engle & Granger (1987) rejects co-integration.
[6] Due to space considerations, the sub-period results are note extensively reported. However, the results are available from author upon request.

Table 1. Statistics for Rawdata from Phelix and Nordpool Energy Spot Markets

Panel A.		Standard	Max.	Moment	Quantile*	Quantile*	K-S	Q(12)
Pawdata	Mean	deviation	Min.	Kurt/Skew	Kurt/Skew	Normal	Z-test	$Q^2(12)$
Phelix	0.06318	32.7389	236.9369	4.3871	0.6080	31.2527	5.3818	1046.533
			-196.2710	0.8892	-0.0069	{0.0000}	{0.0000}	184.0076
Nordpool	0.06382	9.23257	118.8913	24.2711	0.6371	34.5659	{6.6195}	557.3252
			-77.3170	1.4270	0.0279	{0.0000}	{0.0000}	738.4642
Panel B.	BDS-statistic (ε = 1)			Stationary	ARCH	Contegration		Struct. Break
Pawdata	m=2	m=3	m=4	KPSS	(12)	DF	EG	Chow Test
Phelix	11.7571	13.4527	12.4132	0.0063	49.6434	-52.9953	-57.0565	(2- 282):
	{0.0000}	{0.0000}	{0.0000}	{1.0000}	{0.0000}	{0.0000}	{0.0000}	(283-2028)
Nordpool	2.0029	4.6315	5.3330	0.0278	145.2821	-51.6147	-55.5508	(2- 262):
	{0.0537}	{0.0000}	{0.0000}	{0.9869}	{0.0000}	{0.0000}	{0.0000}	(263-2028)

Footnotes: Quantile Kurt/Skew (Moors, 1988, Hogg, 1972) is alternative kurt/skew measures. Quantile Normal is based on Jarque Bera formula (Jarque & Bera, 1989) from quantile measures of the Kurt/Skew measures. The K-S Z goodness-of-fit test (Chakravart et al., 1967) tests whether the observations could reasonably have come from a normal distribution. The Q and Q^2 test statistics are test statistics (Ljung & Box, 1979) for autocorrelation for ordinary and squared return series, respectively. The KPSS statistic (Kwiatowski et al.), 1992) is a one sided Lagrange Multiplier statistic to test variance. DF (Dickey & Fuller, 1979) is a unit root test ($I(1)$) and EG (Engle & Granger, 1987) is a test of co-integration between series hypothesising a linear combination is $I(0)$. Chow (1960) checks the stability of regression coefficients in the model. The BDS test statistic (Brock et al., 1996) is a non-parametric method of testing for nonlinear patterns in time series.

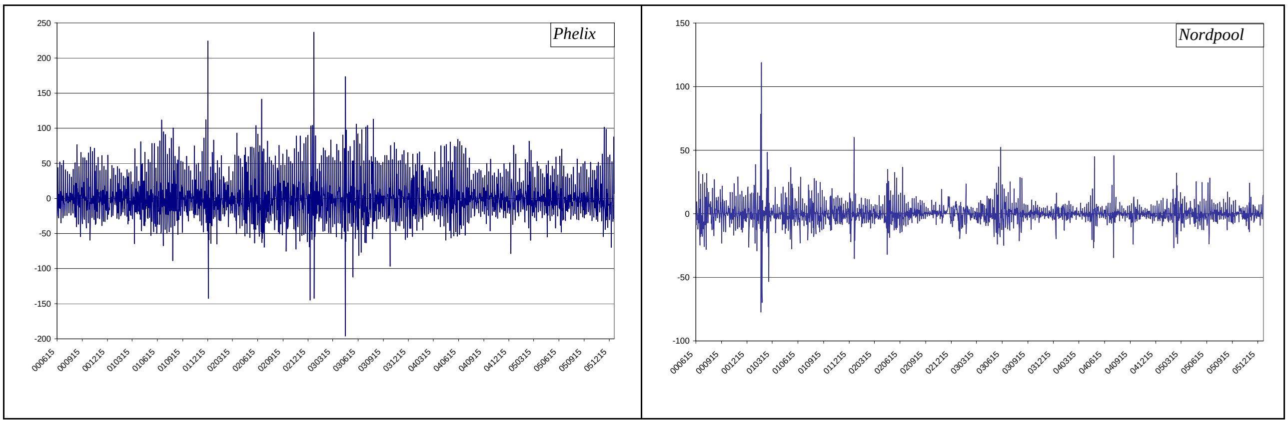

Figure 2. Phelix and Nordpool first difference daily spot prices from 2000-06 to 2005-12

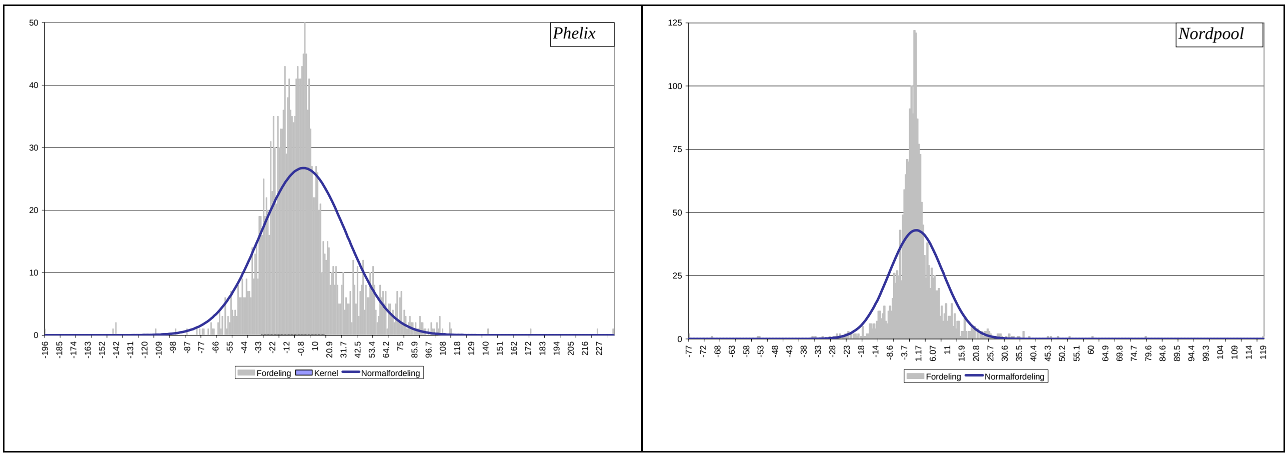

Figure 3. Phelix and Nordpool frequency distributions

A classical sequence plot in Figure 3 shows no apparent trend and regime switches for the Phelix and Nordpool data series. Figure 4 shows frequency distributions of the whole series together with the normal distribution. From the frequency characteristics, the two series deviate from a normal distribution showing too many observations around the mean, too few observations at one standard deviation (both positive and negative) and heavy tails (leptokurtosis).

2.3 Model selection strategy

The tuning parameters L_μ, L_g, L_r, L_p, K_z, and K_x follow the protocol that is described in detail in Bansal, Gallant, Hussey, and Tauchen (1995). The BIC (Schwarz, 1978) model selection criterion expands the model[7]. The protocol for the two spot series reports computed BIC, AIC and HQC values in Table 2[8]. The first block of Table 2 (cases 1-8) increases L_μ to determine the preferred *VAR* fit. The second block of the table (cases 9) increases L_r to determine the Schwarz preferred ARCH fit. Introducing GARCH by increasing L_g and adjusting L_r accordingly, determine the Schwarz preferred GARCH fit (case 10). Hence, this Gaussian GARCH Score model specifies seven lags in the mean equation and one moving average (ARCH) and one autoregressive (GARCH) lag for the variance equation. The Schwarz preferred Semi-parametric GARCH score (K_z>0) is shown in Table 2 case 11-13. Finally, a fully non-linear model specification is evaluated in Case 14. The results in Table 2 suggest that the preferred linear model is (L_μ, L_g, L_r, L_p, K_z, I_z, K_x, I_x) = (7,1f,1f,1f,1f,1,6,4,0,0). Moreover, the model incorporates full leverage and level effects. To check for a local optimum, several alternative specifications were tested using the BIC criterion. All alternatives have been rejected giving a strong indication of a global optimum (likelihood) for the two synchronous series. Specification tests of the model residuals are shown in Table 3 for the preferred linear SNP model.

---

[7] BIC is the Bayes Information Criterion of Schwarz (1978): $s_n(\hat{\theta}) + \frac{1}{2}\left[\frac{p_\rho}{n}\right]\log(n)$ with small values preferred.

[8] AIC is the Akaike Information criterion (Akaike, 1969) and HQC is the Hannan Quality Criterion (Hannan, 1987).

Table 2. Optimized Likelihood and Model Selection Criteria

Case	L_μ	L_g	L_r	L_p	K_z	I_z	K_x	I_x	p_ρ	s_n	BIC	HQ	AIC	
1	1	0	0	1	0	0	0	0	8	2.7486	2.7617	2.7556	2.7520	
2	2	0	0	1	0	0	0	0	12	2.6967	2.7173	2.7077	2.7021	
3	3	0	0	1	0	0	0	0	16	2.6785	2.7066	2.6935	2.6859	
4	4	0	0	1	0	0	0	0	20	2.6484	2.6840	2.6674	2.6577	
5	5	0	0	1	0	0	0	0	24	2.5563	2.5995	2.5794	2.5677	
6	6	0	0	1	0	0	0	0	28	2.4680	2.5187	2.4951	2.4813	
7	7	0	0	1	0	0	0	0	32	2.4052	2.4634	2.4362	2.4205	*
8	8	0	0	1	0	0	0	0	36	2.3988	2.4645	2.4339	2.4161	
9	7	0	1	1	0	0	0	0	33	2.2183	2.2784	2.2504	2.2341	
10	7	1	1	1	0	0	0	0	48	1.9217	2.0100	1.9688	1.9449	*
11	7	1	1	1	4	0	0	0	56	1.8337	1.9369	1.8887	1.8608	
12	7	1	1	1	6	0	0	0	60	1.8261	1.9368	1.8851	1.8552	
13	7	1	1	1	6	4	0	0	66	1.8147	1.9367	1.8797	1.8467	**
14	7	1	1	1	6	0	1	0	86	1.8101	1.9696	1.8952	1.8520	

L_μ is the number of lags in the linear part of the SNP model; L_g is the number of lags in the GARCH part; L_r is the number of lags in the ARCH part; L_p is the number of lags in the polynomial part, $P(z,x)$. The polynomial $P(z,x)$ is the degree K_z in z and K_x in x; by convention, $L_p = 1$ if $K_x = 0$. p is the number of parameters. The values of I_z and I_x are polynom interactions.

Table 3. Statistics for Residuals of Phelix and Nordpool Semiparametric GARCH model

Panel A.		Standard	Max.	Moment	Quantile	Quantile	K-S	Q(12)
Residual	Mean	deviation	Min.	Kurt/Skew	Kurt/Skew	Normal	Z-test	$Q^2(12)$
Phelix	-0.0269	1.0115	6.7676	6.2496	0.2129	3.7767	2.2491	12.5527
			-8.0237	-0.3926	-0.0001	{0.1513}	{0.0001}	10.7570
Nordpool	0.0227336	0.98822307	5.5219	3.1278	0.1134	2.0453	{2.4113}	20.1041
			-7.0226	0.0719	0.0541	{0.3596}	{0.0000}	3.8291
Panel B.	BDS-statistic (ε=1)					ARCH	Reset	Joint
Residual	m=2	m=3	m=4	m=5	m=6	(12)	(12;6)	BIAS
Phelix	0.7331	1.6438	2.2654	1.9276	2.3514	0.1399	20.2023	0.8839
	{0.3049}	{0.1033}	{0.0307}	{0.0622}	{0.0251}	{0.7084}	{0.0634}	{0.8293}
Nordpool	1.8794	1.7290	1.2816	0.8996	0.9743	0.7353	16.8430	2.5508
	{0.0682}	{0.0895}	{0.1755}	{0.2662}	{0.2482}	{0.3912}	{0.1556}	{0.4662}

See Table 1 for statistics. RESET (12;6) (Ramsey,1969): A sensitivity test for mainly linearity in the mean equation. 12 is number of lags and 6 is the number of moments that is chosen in our implementation of the test statistic. $T{\cdot}R^2$ is χ^2 distributed with 12 degrees of freedom.

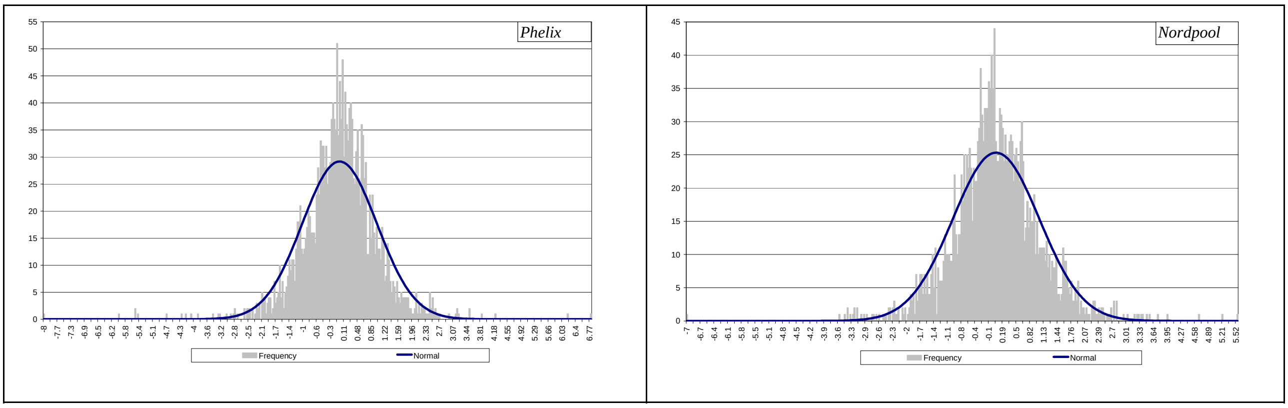

Figure 4. Phelix and Nordpool model residuals; frequency distributions

Both series show very little dependence in the residuals suggesting no need for a non-linear extension, as the non-linear BIC values show non-preferable values (see case 14 Table 2). Frequency distributions of the residuals are shown in Figure 4. The residuals are much closer to a normal frequency distribution than the original raw series.

3 Multivariate Results

3.1 Characteristic details

Some characteristics of the time series are reported in Figures 5-10. The daily conditional volatility series are plotted in Figure 5. The daily conditional co variances and correlations are reported in Figure 6. The one-step-ahead density $f_K(\tilde{y}_t \mid x_{t-1}.\hat{\theta})$, conditional on the values for $x_{t-1} = (\tilde{y}'_{t-L},\cdots,\tilde{y}'_{t-2},\tilde{y}'_{t-1})'$, is plotted in Figure 7. All lags are set at the unconditional mean of the data. The conditional expectations are clearly at a narrower range at Nordpool than at Phelix. The conditional variance functions are plotted in Figure 8. Figure 8 shows the average over all $x_{t-1} = (y_{t-L},\cdots,y_{t-2},y_{t-1})$ in the data of the conditional variance $VAR(y_t|y_{t-L},\cdots,y_{t-1}+\delta)$ plotted against δ, the percentage growth for Phelix and Nordpool, respectively. Figure 9 reports the conditional covariance function and the calculated correlation function. Finally, Figure 10 assesses persistence for Phelix and Nordpool. The persistence comes from over plots of $\hat{V}_j(x) = E\left[Var(y_{t+j} \mid x_{t+j-1}) \mid x_t = x\right]$, with x put successively to the values of the data.

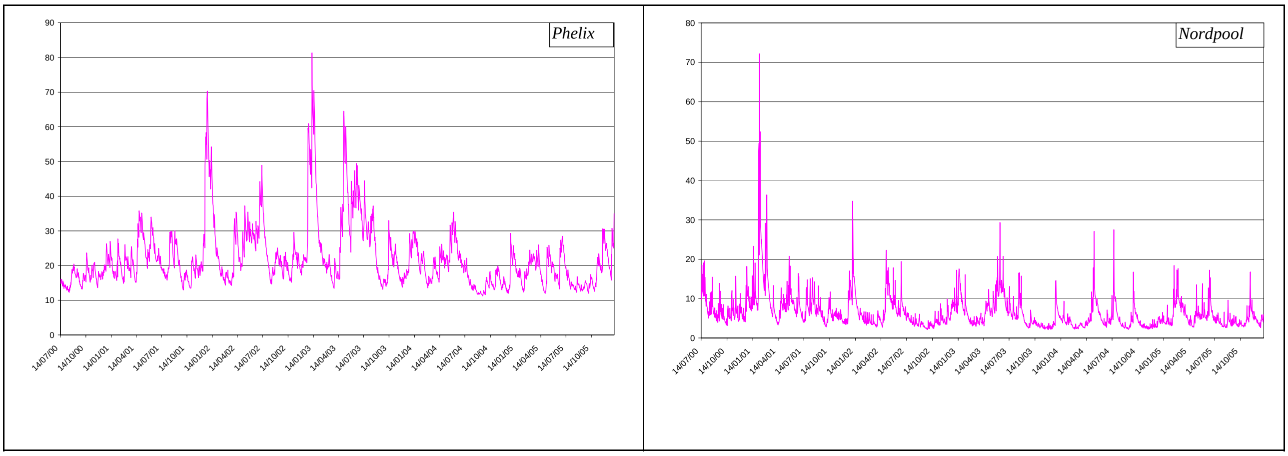

Figure 5. Phelix and Nordpool conditional standard deviation series

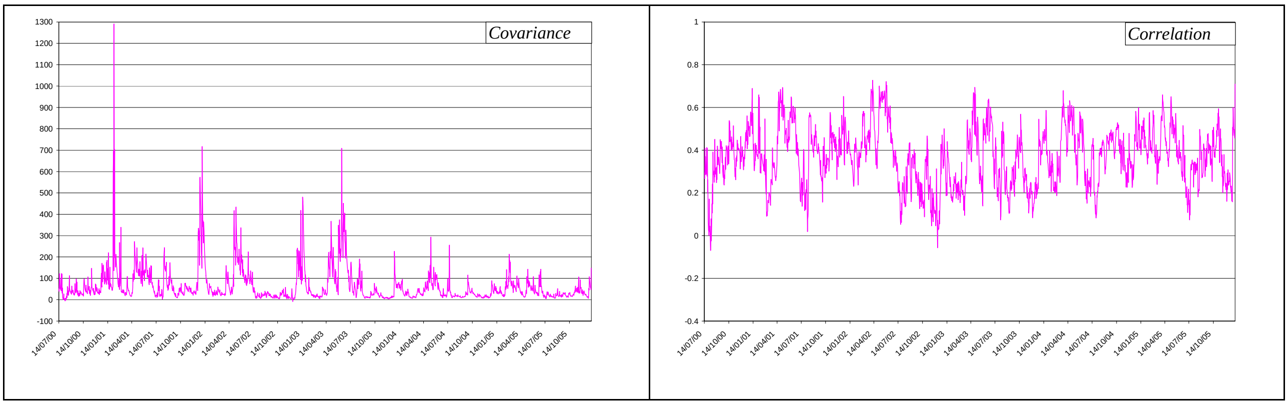

Figure 6. Phelix and Nordpool conditional covariance and correlation series

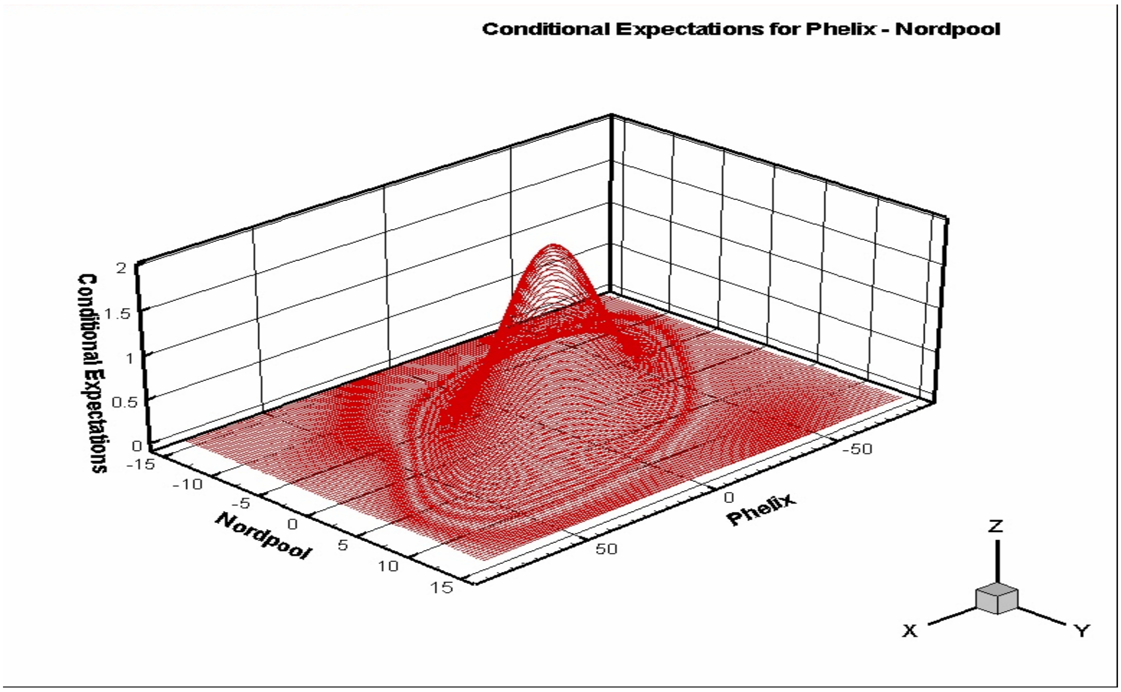

Figure 7. Phelix and Nordpool conditional one-step ahead forecast

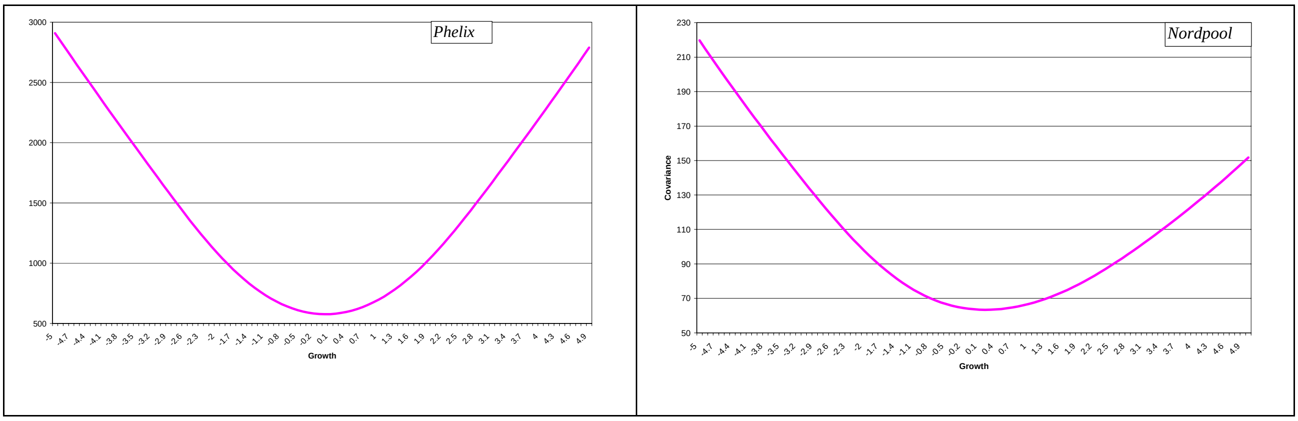

Figure 8. Phelix and Nordpool conditional variance functions

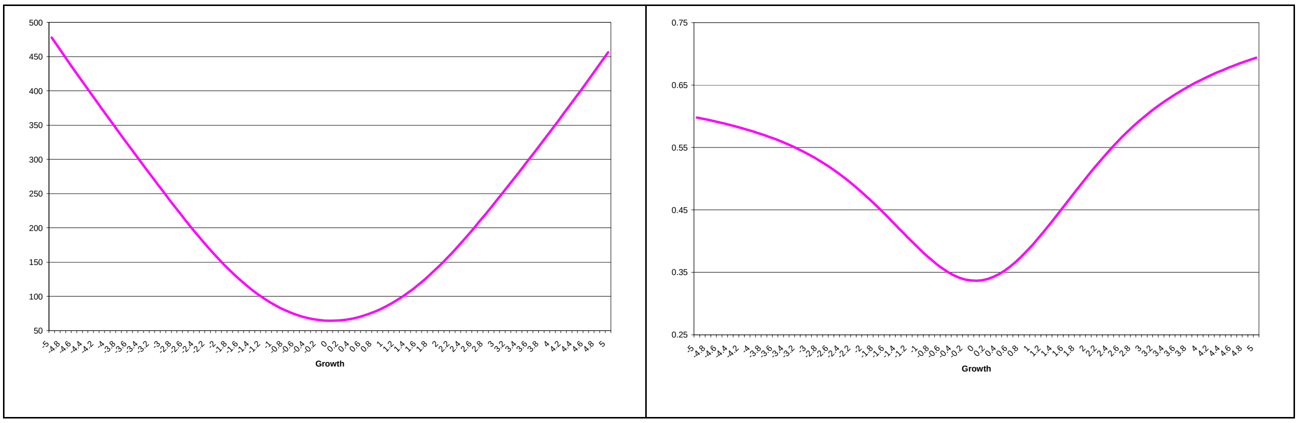

Figure 9. Phelix and Nordpool conditional Co-variance and Correlation functions

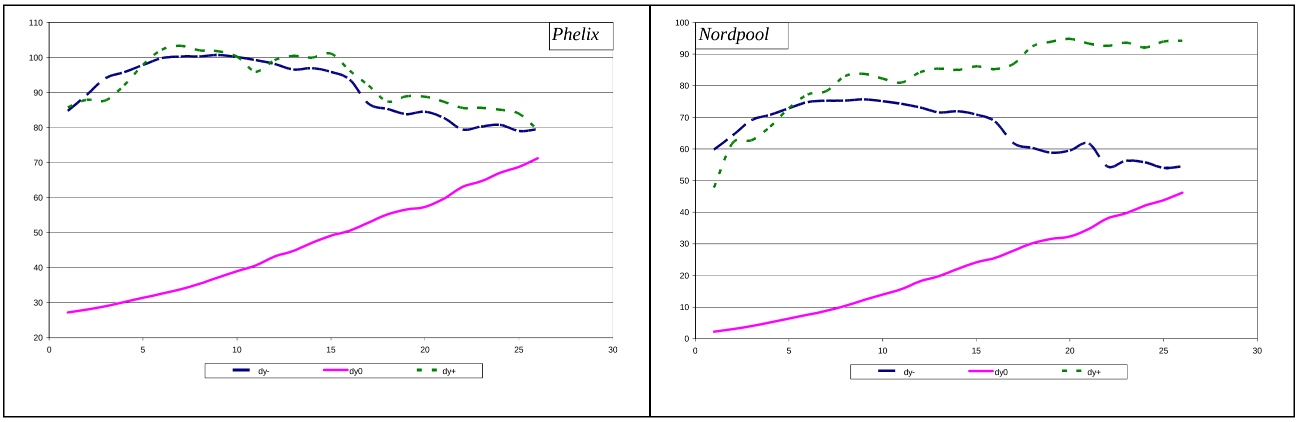

Figure 10. Phelix and Nordpool profile bundles to assess persistence

3.2 Empirical Findings

The full period model coefficients, standard errors and associated *t*-statistics are reported in Table 4. The empirical results suggest serial correlation and cross correlation. The serial correlation is mostly negative (mean reversion), except for a positive lag 7. Using the intuitive consumption numbers (volume) for both markets, Mondays should always report higher prices and Saturdays and Sundays lower prices, suggesting a similar correlation structure. The remaining consistent and significant negative correlation from day 1 to day 4 can also be originated for these weekend effects. Alternatively, using market insight induces Mondays show positive price changes, while Tuesday to Sunday shows negative price changes. Hence, the first set of hypotheses cannot be rejected. Short-run predictability may be available in both markets. Moreover, the negative serial correlation coefficients at Phelix are about 3 to 4 times higher than at Nordpool, except for the positive coefficients for Mondays, which is only about 2 times higher. Importantly, for financial traders, to exploit profitable positions the forward markets must be employed (short/long positions), which most likely have incorporated this information in the short-run forward price quotes. In contrast, producers having a long spot position in both markets may apply this information in their production decision strategies with the objective to maximise profits. Hence, in a transparent and credible market containing strong predictable mean correlation, producers can optimize production/profit based on price predictions. In a non transparent market when a small number of producers also have short-run shut-down options, a long production position can be highly profitable.

Table 4. Model Coefficients and Standard errors with associated t-values

Mean	Phelix Est Coefficient	Standard Error	t-value	Nordpool Est Coefficient	Standard Error	t-value	Cross-Mean effects Cross	Coefficients	Error	t-value
Lag 1	-0.40658	0.02047	-19.86224	-0.11675	0.02601	-4.48866	1,2(lag1)	0.08299	0.01493	5.55861
							2,1(lag1)	0.08967	0.01917	4.67762
Lag 2	-0.42644	0.02053	-20.77155	-0.09947	0.02048	-4.85693	1,2(lag2)	0.04620	0.01562	2.95775
							2,1(lag2)	0.09577	0.01984	4.82712
Lag 3	-0.37931	0.02172	-17.46363	-0.11052	0.02197	-5.03050	1,2(lag3)	0.05822	0.01472	3.95516
							2,1(lag3)	0.08696	0.01962	4.43221
Lag 4	-0.36477	0.02196	-16.61066	-0.04450	0.02180	-2.04128	1,2(lag4)	0.01046	0.01460	0.71644
							2,1(lag4)	0.06201	0.01942	3.19310
Lag 5	-0.36847	0.02177	-16.92559	-0.05651	0.02074	-2.72469	1,2(lag5)	0.02130	0.01471	1.44799
							2,1(lag5)	0.07589	0.01941	3.90984
Lag 6	-0.29628	0.02062	-14.36857	0.02675	0.02020	1.32426	1,2(lag6)	-0.02265	0.01454	-1.55777
							2,1(lag6)	0.11897	0.01950	6.10103
Lag 7	0.35410	0.02040	17.35784	0.20043	0.02031	9.86854	1,2(lag7)	0.05087	0.01467	3.46762
							2,1(lag7)	0.08128	0.01898	4.28240
Volatility	**Phelix Est Coefficient**	**Standard Error**	**t-value**	**Nordpool Est Coefficient**	**Standard Error**	**t-value**	**Phelix - Nordpool Covariance Estimated Cross**	**Coefficient**	**St. Error**	**t-value**
Constant	0.11439	0.01454	7.86726	0.07697	0.02379	3.23539		-0.01148	0.02020	-0.56832
ARCH(.,1)	0.38437	0.02315	16.60346	0.30814	0.03861	7.98083	(1,2)	-0.01619	0.03357	-0.48228
							(2,1)	-0.05116	0.02026	-2.52517
GARCH(.,1)	0.93406	0.00769	121.46424	0.92666	0.00815	113.70061	(1,2)	-0.02835	0.01105	-2.56561
							(2,1)	-0.00146	0.00688	-0.21221
Leverage	0.00155	0.07295	0.02125	-0.33567	0.05832	-5.75566	(1,2)	-0.30434	0.03191	-9.53745
							(2,1)	-0.06492	0.03212	-2.02117
Level effect	0.04132	0.04822	0.85691	0.73188	0.04764	15.36272	(1,2)	0.15921	0.03734	4.26379
							(2,1)	0.07075	0.03317	2.13295
Hermite Polynom	**Phelix Est Coefficient**	**Standard Error**	**t-value**	**Nordpool Est Coefficient**	**Standard Error**	**t-value**	**Interactions between the Polynoms**	**Coefficient**	**St. Error**	**t-value**
Polynom 1(a_0)	-0.01580	0.01249	-1.26501	-0.00331	0.01228	-0.26954	(1,2)	0.06207	0.01735	3.57752
Polynom 2(a_1)	-0.20883	0.01920	-10.87656	-0.08104	0.02937	-2.75928	(1,3)	0.01664	0.01507	1.10418
Polynom 3(a_3)	-0.01383	0.01504	-0.91955	0.00219	0.01761	0.12436	(1,4)	0.02193	0.01802	1.21698
Polynom 4(a_4)	0.13193	0.01456	9.06113	0.10366	0.01863	5.56414	(2,3)	-0.00359	0.01276	-0.28135
Polynom 5(a_5)	-0.00562	0.01527	-0.36804	-0.04530	0.02227	-2.03413	(2,4)	0.09284	0.01641	5.65753
Polynom 6(a_6)	-0.09411	0.01577	-5.96766	-0.02025	0.03019	-0.67075	(3,4)	-0.02947	0.01415	-2.08269

The size of the Phelix serial correlation coefficients relative to Nordpool's seems to clearly verify this proposition. From observations and theory, atomistic markets cannot maintain such a position for a long period of time. Unfortunately, observed energy market imperfections, such as large and few producers of a homogeneous electricity-product to numerous end-consumers, can effectively stop new competitors maintaining the dominated market position. The lagged cross mean coefficients are mostly positive and significant. The hypothesized mutual influence from the physical interconnections can therefore not be rejected. In addition, it seems that the lagged Nordpool information influences the Phelix market stronger in both size and significance. This observation indicates that Phelix market participants react more systematically to price information from Nordpool. Hence, transparent markets relative to non-transparent markets seems to influence markets more systematically. Importantly, these findings seem to contradict general believes in the market indicating that even though Nordpool market participants actually see Phelix reactions, the reaction patterns show lower systematic behaviour.

The Hermite-polynoms report deviations from Gaussian densities. These polynoms are higher and more significant in the Phelix market than in Nordpool, suggesting as expected due to non-transparency, that the non-gaussian features are more severe in the Phelix market. Moreover, the polynoms report significant interactions in both directions, suggesting that both series influence each others distributions (*t*-like tails, densities with tails that are thinner than Gaussian, and skewed densities). In fact, the coefficients are mostly positive indicating that the stronger non-gaussian features at Phelix influences the more normal Nordpool. Hence, an average Phelix shock will affect Phelix itself and Nordpool more profoundly than an average shock at Nordpool.

Figure 5 reports the conditional standard deviation showing that the volatility in Phelix is relatively higher than for Nordpool. Intuitively, from model insights, the non-transparent Phelix has higher model errors and consequently higher market turbulence. The conditional variance-covariance matrix for Phelix and Nordpool therefore shows high and significant (cross) volatility for both markets. The coefficients for volatility (ARCH/GARCH) are highly significant, suggesting that the hypothesised mean reversion and volatility clustering cannot be rejected. The lack of transparency and credibility of Phelix shows as hypothesised, a much higher ARCH-coefficient than Nordpool. Importantly, this result may contribute to a much higher understanding of energy market shocks/volatility. Firstly, a relatively higher level of volatility follows from lower market transparency. Secondly, the higher Phelix mean reversion coefficient relative to Nordpool, indicates higher shock absorption due to lower systematic market information interpretation. Thirdly, the higher absorption coefficient cannot alone explain the much higher Phelix volatility, indicating also a higher number of shocks in non-transparent markets. Cross volatility effects between both markets are small and barely significant. The cross conditional volatility coefficients suggest that Nordpool affect Phelix with a close to insignificant ARCH-coefficient (mean reversion), while Phelix affect Nordpool with a close to insignificant GARCH-coefficient (clustering). The fourth set of hypotheses is therefore close to rejection. Figure 6 reports the conditional covariance and correlation numbers from our multidimensional estimation[9]. The covariance level is usually between 0 and 100 units with several high spikes during the whole period. However, the correlation, defined as $\frac{Cov(R_P, R_N)}{\sigma_P \cdot \sigma_N}$, where the subscript P is Phelix and N is Nordpool, contains more information. The correlation seems to vary mostly between 0.2 and 0.7, indicating market dependence and therefore small and limited gains from diversification. Only two short-lived episodes show negative correlation between these two markets. However, from Figure 6, we *cannot* infer that the correlation between Phelix and Nordpool has increased in the last couple of years.

The *BEKK* formulation of the conditional volatility incorporates leverage (asymmetry) and level effects (*BEKK-LL*). The level effects are positive and significant for Nordpool but insignificant for Phelix. As hypothesised the level effect will be effective in competitive markets with a

[9] The conditional covariance in Figure 7 must not be mixed with the conditional covariance functions in Figure 9/10.

symmetric and synchronous information flow. The highly transparent and competitive Nordpool market showing positive coefficients induce a higher information flow and therefore higher volatility the higher the price changes. When the relation is insignificant, the information flow and volatility seem unaffected of level inducing that the competition is too low to alter the information flow. In addition for the insignificant Phelix coefficient, the shut-down production option creates higher shocks (unsystematic) and therefore (conditional) volatility, drowning the level effect. That is, only the more transparent and credible Nordpool market shows significant level effects inducing more information and volatility at high price change regimes. Therefore, the level effect hypothesis cannot be rejected. Negative and significant asymmetry is found in the Nordpool market. The hypothesised positive asymmetry of the Phelix market must be rejected as we find a positive but insignificant asymmetry coefficient. Negative asymmetry is found in majority of efficient financial market studies. Hence, Phelix market microstructure as nontransparent shut-down options and threshold-pricing seems therefore to cancel-out and making positive, a general negative market asymmetry. Finally, note that the leverage and level effects are not important in the Phelix market but they are both important as a cross effects to Nordpool. The effects from Nordpool to Phelix are much lower and barely significant. The results from the volatility equations therefore suggest that the volatility in Phelix seems to be generated internally. Applying the Nordpool information transfer and transparency interpretation, the market seems to be sensitive to level and leverage effects from Phelix as volatility factors at Nordpool. Hence, Nordpool seems more sensible to Phelix market shocks than the Phelix normal market behaviour. In contrast, the competitive and transparent Nordpool market does barely contribute to Phelix volatility. Figure 8 shows the conditional variance profiles. The Phelix plot confirms little asymmetry and Nordpool shows a negative asymmetric volatility. Figure 9 reports the covariance and correlation profiles between Phelix and Nordpool. The covariance is higher the higher the growth factor in absolute terms. The correlation profile, again defined as $\frac{Cov(R_P, R_N)}{\sigma_P \cdot \sigma_N}$, where the subscript P is Phelix and N is Nordpool, shows lowest correlation for small price changes (growth) and higher correlation at larger negative and positive price changes. Moreover, the correlation profile is lower at large negative growth than at large positive growth, suggesting asymmetric correlations. The higher correlation at larger absolute growth relative to lower growth may stem from different week-end price regimes in the two markets, the Phelix threshold-price production decision and the Phelix shut-down production options. These effects are lower/not applicable in the more transparent hydro-influenced Nordpool market.

Using the overall results from our empirical work, the physically interconnected markets seem therefore to interact for both mean and volatility. However, applying the overall model results the two markets show quite different features in the mean and volatility. The results suggest that due to higher transparency in Nordpool, the market seems to react systematically different relative to Phelix. Effects from lower transparency and credibility and threshold-pricing seems therefore to produce (1) increased serial correlation and non-gaussian features in association with lower cross mean effects, and (2) higher volatility and higher mean reversion volatility effects as well as (3) low level and asymmetry effects associated with higher level and asymmetry cross effects.

The spline transform is applied to the x_{t-1} that enter $P(z,x)$, μ_x and Σ_x. Moreover, the transformation is applied to the residuals $y_{t-i-1} - \mu_{x_{t-i-2}}$ that enters the ARCH terms and leverage effect terms in the expression for Σ_x. The dictum that ARCH and GARCH coefficients (squared) must be less than one, no longer holds (< 1). Persistence is therefore difficult to assess in full detail. However, GARCH-terms of 0.934^2 (0.927^2) for Phelix (Nordpool) does not indicate high persistence from previous shocks. Figure 10 shows the two plots to assess persistence for Phelix and Nordpool, respectively. The first line assesses negative price changes (δy^-) while the second line assesses positive price changes (δy^+) and the last line shows an average price change (δy^0). The two markets seem to suggest a rather low persistence to volatility shocks but the profiles are not completely similar. Nordpool's large negative price changes are followed with higher volatility than positive price changes. Moreover, the Nordpool's lower immediate volatility from positive price changes is associated with stronger persistence. Figure 10 confirms the Phelix no asymmetry result.

3.3 Subperiods Findings[10]

The CHOW test separate two optimal break periods for both Phelix and Nordpool. Both show an optimal break early in the time series. For both electricity markets the lag structure in the mean seems not to change between the sub-periods. In contrast, the GARCH coefficients are much higher in the late Sub-2 than in the early Sub-1, indicating higher volatility persistence in the last time period. Similarly, the cross volatility effects are higher in Sub-2 than in Sub-1, indicating a possibility for closer co-movements. All the higher order effects are close to zero and insignificant for the Sub-1 period. The Nordpool market shows for Sub-2 much higher leverage and level effects. Importantly, the Phelix market shows a positive coefficient in Sub-1 and a negative in Sub-2, inducing a change in the direction of asymmetry more similar to Nordpool. Moreover, the general picture is higher cross-mean correlation coefficients from Nordpool to Phelix. The mean reversion effects are higher from Phelix to Nordpool and higher order interactions are present for both markets.

The results from the sub-periods indicate that the serial correlation is prevailing. In fact, the serial correlation seems to increase from Sub-1 to Sub-2. This result confirms the evolution of the Phelix market from 2001, showing higher Phelix/Nordpool correlation. The cross-correlations are lower but the significance is at about the same level. The polynoms are only significant in the last period (Sub-2) and as shown above for the whole period, indicating that higher-order (cross-) effects seem to be a recent phenomenon in the electricity markets. Hence, even though the market has evolved and serial correlation is reduced the non-gaussian features seem to have increased.

[10] The characteristic details for the two sub-periods are available form author upon request.

The significant positive leverage coefficient in the first sub-period for the Phelix market, confirms the cancel-out negative asymmetry Phelix effect for the whole period. The result can be interpreted as a lower effect from the shut-down option and threshold- price microstructure features at Phelix. For the sub-periods, leverage and level effects are not present in the first sub-period for Nordpool. The second sub-period shows a strong increase in both leverage and level. For Phelix the level effect is not present for any period. The sub-period results also confirm strong increase in volatility persistence (GARCH-coefficient) for the second sub-period.

4 Summaries, Conclusions and Policy Implications

Giles Chichester, chairman of the committee on industry, research and energy at the European parliament said in early 2006: *"The pace in developing a single European market has been slow and disappointing."* After listing a wide range of challenges for the European single market, the chairman also pinpointed: *"All member states need to fully implement the liberalisation directives. Look to the market for answers, not just administrators and legislators."*
In addition, the managing director of Triangel argued: *"Since not enough is currently being done to open up European energy markets, the liberalisation process requires a push from the EU. National governments are not strong enough.*

This paper takes a look at mean and volatility transmission between the Phelix and Nordpool spot markets from 2000 to 2006, emphasizing efficiency, integration and liberalisation. The first observation is that price series (including logs) are not stationary and the analysis is therefore performed using daily price change series (continuously compounded returns). The SNP methodology is used for the bi-dimensional Phelix-Nordpool time-series setup. The DF indicates *I*(0) (reject unit root) and the *EG* test statistic rejects co-integration. Importantly, the KPSS test statistic cannot reject neither level nor trend stationary series. The analysis reports highly significant serial correlation and cross-market mean effects from lagged information, indicating short-run forecasting abilities for both markets. For both markets, the polynoms suggest non-gaussian market features as well as inter-market non-gaussian mutual effects. The volatility coefficients are significant for both markets. In contrast to mean interactions the volatility market-interactions are lower. The pattern seems to be ARCH-effects from Nordpool to Phelix and GARCH from Phelix to Nordpool. Moreover, negative leverage and positive level effects are present at Nordpool but seem not to be present at Phelix. However, the subperiod results indicate a tendency for a positive leverage for Phelix. Finally, Phelix influences level and leverage at Nordpool. Extensive misspecification testing of model residuals suggests that the SNP specification captures return and volatility characteristics in and between the two European electricity-markets.

The more transparent and credible Nordpool market shows serial correlation clearly lower than Phelix. The Phelix electric-power producers, playing the spot market, seem therefore more able to exploit and extract the benefits relative to Nordpool producers, from their long production positions. The cross-market mean correlations are strong for three lags but size and significance are dominated by Nordpool. For the remaining lags, Phelix shows insignificant values except for lag 7 (one week). Nordpool show significant values for all cross-lags verifying cross-lag dominance for all lags. Seasonal influence is therefore mainly driven by the respective series' own lags, but Nordpool is the dominant cross-mean dominant factor, suggesting that Nordpool clearly contributes more to seasonal factors at Phelix than vice versa. The limited capacity of the interconnectors prevents full price integration, but Nordpool price changes and its Phelix influence seems to suggest a higher relative production export from Nordpool to Phelix. The relative market sizes in *kwh* fortifies this argument; same export figures would weight relative more to total production capacity in Nordpool than Phelix. The polynoms report deviation from a normal distribution of price returns. Our results indicate that these deviations are stronger for Phelix than Nordpool. Hence for derivative pricing and classical pricing methodology, the Nordpool market seems to produce more fairly prices relative to classical pricing schemes. However, there are significant cross-polynoms interactions, not easily interpreted with respect to market influence. The polynoms also show a higher impact at Phelix than Nordpool, inducing higher non-gaussian features at Phelix.

The results also indicate that shocks influence volatility immediately and persist for several days/weeks in both markets. For Nordpool positive price changes, show lower immediate volatility but much higher persistence[11]. Most of the shocks are generated internally in respective markets but cross-innovations from shocks do occur but these shocks show small persistence. The internal persistence captures the propensity of price changes of similar magnitude to cluster in time and partly explains some of the non-gaussian and non-stationary electricity spot prices. A GARCH process is non-Markovian, suggesting that neither Phelix nor Nordpool efficiently prices electricity.

These mean and volatility results suggest neither an integrated nor efficient market. The inability of the existing networks to create an integrated market for Phelix and Nordpool, suggests that differences in price regimes will in the short run prevail. The long run implications are of course dependent on the interconnectors between Phelix and Nordpool and the ability of Phelix to remove the non-transparent production dominance from the capacity decisions. Hence, a fully integrated market with one price is dependent on three factors; market evolvement/elaborateness, geographical proximity closely related to physical interconnectors between the markets, and finally transparent and symmetric information to be established in both markets. Inefficient pricing suggests that the market microstructure must be thoroughly evaluated.

In summary, the policy markers must decide on several important issues. They must decide on whether they want an integrated market or not. An integrated market requires a free float of electricity suggesting an increase in both size and number of interconnectors. Due to high

[11] Higher volatility from negative price changes and higher persistence from positive price changes are features often found in effective financial markets.

ownership concentration and large plants in the Phelix market, the dominance of the producers enforcing the use of shut-down/re-start options not transparent to market participants, suggest relatively higher profit potentials at Phelix than at Nordpool. Moreover, some of the available Phelix production plants (i.e. coal plants) operate within certain price ranges at full (threshold price) or only at minimum for grid maintenance. The implication is that spot prices may therefore not show the same degree of relationship to the observed forward prices in these two electricity markets. The suggestion is much higher relationship between forward and spot prices at Nordpool than at Phelix. In fact, due to many small producers of hydro-electric power, producers at Nordpool may actually operate their production plans in close relation to forward prices. At Phelix, part of the production decisions is based on the possibility of shut down/restart and threshold values from information in one-day/week forward prices. The markets dynamics for the Nordpool spot may therefore show quite different behaviour than Phelix spot prices. Relative to Nordpool producers, the Phelix producer’s long position together with the non-gaussian mean and serial correlation may induce stronger misuse of market power by Phelix producers adjusting production schemes. However, to reduce this implied market power in both markets, it is important for both markets to scale down to increase the number of participants. Using general market insight the plants should also be privatised to increase competition between the increased numbers of participants. These market features are essential to establish efficient energy markets.

References

Phelix market: www.eex.de
Nordpool Market: www.nordpool.no
Akaike, H., 1969, Fitting Autoregressive Models for Prediction, Annals of the Institute of Statistical Mathematics 21, 243-247.
Bollerslev, Tim, 1986, Generalised Autoregressive Conditional Heteroscedasticity, Journal of Econometrics, 31, pp. 307-327.
Brock, W. A., Dechert, W. D., Scheinkman, J. A. and LeBaron, B. (1996). A test for independence based on the correlation dimension, Econometric Reviews, 15,197-235.
Chakravarti, Laha, and Roy, 1967, *Handbook of Methods of Applied Statistics, Volume I*, John Wiley and Sons, pp. 392-394.
Chow, G.C., 1960, Tests of equality between sets of coeffcients in two linear regressions, Econometrica, Vol. 28, pp. 591-605.
Dickey, D., and W. Fuller, 1979, Distribution of the Estimators of Autoregressive Time Series with Unit Root, Journal of American Statistical Association, Vol. 74, pp. 427-431.
Engle, R., 1982, Autoregressive Conditional Heteroscedasticity with estimates of the Variance of United Kingdom Inflations, Econometrica, Vol. 50, pp. 987-1008.
Engle, R. and C.Granger, 1987, Co-integration and Error Correction: Representation, Estimation and Testing, Econometrica, Vol. 35, pp. 251-276.
Gallant, A. R., and G. Tauchen, 1989, Seminonparametric Estimation of Conditionally Constrained Heterogeneous Processes: Asset Pricing Applications," Econometrica 57, pp. 1091-1120.
Hannan, E.J., 1987, Rational Transfer Function Approximations, Statistical Science 2,1029-1054
Hogg. R.V., 1972, More light on the kurtosis and related statistics. Journal of the American Statistical Association 67, pp. 422-424.
Jarque, C.M. and A.K.Bera, 1989, "Efficient tests of normality, homoscedasticity and serial independence of regression residuals, Economic Letters, Vol. 6, pp. 255-259.
Kwiatowski, D., P.C.B. Phillips, P. Schmid and T. Shin, 1992, Testing the null hypothesis of stationary against the alternative of a unit root: How sure are we that economic series have a unit root, Journal of Econometrics, Vol. 54, pp 159-178.
Ljung, G. and G.Box, 1979, On a Measure of Lack of Fit in Time Series Models, Biometrika, Vol. 66, pp. 265-270.
Moors, J.J.A., 1988, A quantile alternative to kurtosis. The Statistician 37, pp. 25-32.
Ramsey,J. B., 1969, Tests for specification errors in classical least square regression analysis, Journal of Royal Statistical Society B, 31, pp. 350-371.
Schwarz, G., 1978, Estimating the Dimension of a Model, Annals of Statistics, 6, pp. 461-464.
Solibakke, Per Bjarte, 2002, Efficiently Estimated Mean and Volatility Characteristics for the Nordic Spot Electric Power Market, International Journal of Business, 7(2), pp. 17-35.