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Kristi Kuljus and Bo Ranneby

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Kristi Kuljus [1] and Bo Ranneby

Centre of Biostochastics
Swedish University of Agricultural Sciences, 901 83 Umeå, Sweden

Abstract

This work presents an empirical approach to modeling Swedish electricity prices, where the expected mean price will be independent of past prices. Linear regression is used for modeling the mean price and autoregressive time series models for describing the behavior of the regression residuals. The estimated model can be used for investigating what influence the explanatory variables in the regression model have on the Swedish area price.

1 Introduction

In this article we consider weekly electricity prices for Sweden for 2000–2009. The main purpose is to obtain a model for the electricity prices which enables to describe the behavior of the prices far in the future. Electricity in Nordic countries is traded at the Nordic electricity exchange Nord Pool Spot, which covers Norway, Sweden, Finland, Denmark, and from April 2010 also Estonia. At Nord Pool Spot electricity is traded for each hour of the following day. It is a day-ahead market. At first, a "system" price is calculated for every hour. This is determined by the cut point of the demand curve (all the purchase bids) and the supply curve (all the sale offers). System price is the common theoretical price for the whole Nordic area, if there were no transmission limitations or "bottlenecks". Due to physical limitations of trading capacities, the Nordic area is divided into bidding areas and an "area" trading price is calculated for each region. Norway and Denmark have been divided internally, but not Finland and Sweden (so far). The Nordic electricity market is very diversified, because electricity generation techniques vary across countries. In Norway, basically all electricity comes from hydropower. In Sweden, about 90% is generated by hydropower and nuclear power (in 2008, 47% and 42%, respectively). Finland has a mixture of hydro-, nuclear and thermal energy and Denmark has mainly thermal power. In 2008, 57% of electricity in the Nordic area was produced from hydropower and 21% from

[1] E-mail address to the corresponding author: kristi.kuljus@sekon.slu.se

nuclear power. Therefore, the amount of precipitation, and weather in general, is an influential factor for Nordic electricity prices. For a complete overview of Nord Pool Spot, see `http://www.nordpoolspot.com`. A good overview of the Nordic electricity market and influential factors to the Nordic electricity prices is given in a report by the Swedish Energy Markets Inspectorate (Energimarknadsinspektionen, 2006). In this report also the prices of natural gas, carbon and oil have been pointed out as factors that impact the Nordic electricity prices.

There are different approaches to modeling electricity products at Nord Pool. Both univariate and multivariate models exist. Lucia and Schwarz (2002) describe the behavior of the spot price in terms of two types of components: the first component is a totally predictable deterministic component that accounts for example for a deterministic trend and any periodic behavior, the second, the stochastic component, is assumed to follow a continuous time diffusion process. Weron et al. (2003) propose a mean reverting jump diffusion model for the spot price, since spot prices are in general regarded to be mean reverting. Deng (2006) studies in his doctoral thesis various financial aspects of the spot and futures/forward markets at the Nord Pool power exchange. In his Essay II he considers the relationship between futures/forward prices and water reservoir content given the storability of hydropower. A comparison of restructured electricity markets is provided in Wolak (2000). He considers a vector autoregressive model of order 8 for describing hourly prices at Nord Pool. Regression function with day of the week and month indicators as explanatory variables is used for modeling the time-varying mean of electricity prices. He estimates a regression for every hour and has a huge number of regression parameters (> 4600). Each of the 24 determination coefficients R^2 is at least 0.99, thus all the regressions have really high explanatory power. The main goal in Fell (2008) is to determine the dynamic relationship between the Nord Pool spot prices and EU-ETS (EU emission trading scheme) CO_2 allowance prices (EUAs). To account for interdependencies between different markets, the relationship between Nordic electricity prices, EUA prices and the prices of various generation fuels is estimated through a cointegrated vector autoregressive (CVAR) approach. Fell (2008) includes in his model also air temperature.

For a structured overview of the existing literature about various time series regression modeling approaches applied to electricity markets throughout the world we refer to Higgs and Worthington (2008). They discuss both univariate and multivariate models and analyze strengths and weaknesses of different approaches. This review article is a good summary of existing electricity price modeling studies.

A natural approach when modeling electricity prices is to model the returns or more generally, to describe the prices by an autoregressive process of order p. If the interest is in forecasting the prices far in the future or investigating how different scenarios affect the prices, it is less appropriate to use former prices for predicting future prices. Therefore, we have chosen to model the mean electricity price without using previous prices. The deterministic part is modeled by regression techniques and the residuals are described by time series models.

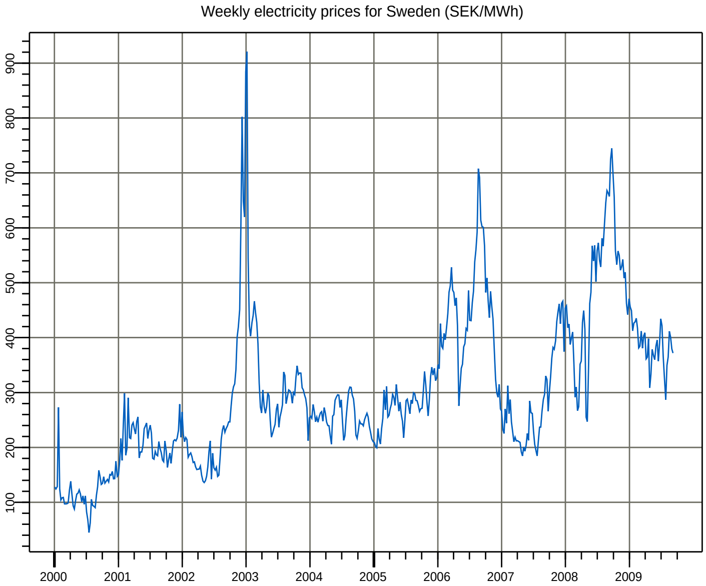

Figure 1: Electricity prices for Sweden in 2000–2009.

2 Data description

We will model weekly electricity prices for Sweden during 2000–2009 using data from week 1, 2000 to week 37, 2009 (506 weeks in total). The prices are plotted in Figure 1. The summary statistics for the prices are as follows:

Min	1st Quartile	Median	Mean	3rd Quartile	Max	St.dev.
45	212	273	303	382	921	138

As explanatory variables we consider: inflow to the Swedish and Norwegian hydropower reservoirs, water reservoir contents in Sweden and Norway, electricity consumption in Sweden, Swedish net price index, EU allowances prices, electricity import and export to and from Sweden, and nuclear power production in Sweden. Several explanatory variables are strongly affected by seasonal variation. One possibility is to model this by fitting some periodic function, but it has shown to be quite difficult to get satisfactory descriptions of the seasonal variation in this way. We have chosen an empirical approach instead: for every week we calculate a historical average value and use the deviation from that average as our variable. The value of the transformed variable for a particular week shows whether the variable is above or below its "normal" value. By using the arithmetic mean, the influence from extreme years may be too high, and by using the median, the average may be imprecise. Thus we have chosen a compromise and use a truncated mean, where the highest and lowest values of the variable are not used when calculating the mean. Next we will describe how the transformed variables are obtained, because these will be used later in the modeling.

I. Water variables (Swedenergy). We have weekly data for week 1, 1995–week 37, 2009 for the following variables:

   1) inflow to the Swedish and Norwegian hydropower reservoirs (GWh/week),
   2) water reservoir content for Sweden and Norway (GWh).

   To take into account seasonality in the water variables, we transform these variables as follows. A truncated mean for every week i, $i = 1, \ldots, 52$, is calculated by taking away the two smallest and largest values for every week. For weeks 1–37 we have data for 15 years, for weeks 38–52 we have data for 14 years. For week 53 we take the mean of the values in 1998 and 2004. Thereafter, the standardized variables $st.inflow.sweden$, $st.inflow.norway$, $st.res.sweden$ and $st.res.norway$ are formed in the following way:

$$st.water.country_t = water.country_t - trunc.mean(water.country)_t\,,$$

   $t = 1, \ldots, 506$. In the modeling process we consider for every transformed water variable separately the positive and negative part of it. For example:

$$inflow.pos.sweden = \begin{cases} st.inflow.sweden, & \text{if } st.inflow.sweden > 0, \\ 0, & \text{else;} \end{cases}$$

$$inflow.neg.sweden = \begin{cases} -st.inflow.sweden, & \text{if } st.inflow.sweden < 0, \\ 0, & \text{else.} \end{cases}$$

   As an illustration, we have plotted the original and standardized values of inflow to the Norwegian water reservoirs in Figure 2.

II. Consumption (Nord Pool Spot AB). We have data for daily consumption (MWh/day) in Sweden for 1/1/1996–25/11/2009. At first these are summarized as consumption per week (GWh/week). Since consumption has also seasonality effect, we compute again standardized weekly values:

$$st.cons_t = consumption_t - trunc.mean(consumption)_t\,,\ t = 1, \ldots, 506\,.$$

   The truncated mean is again calculated without the two smallest and two largest values for every week. For weeks 1–37 we have data for 14, for weeks 38–52 for 13 years. In the regression model we look separately at the positive and negative part of the transformed consumption: cons.pos and cons.neg.

III. Net price index (NPI) (at the homepage of Statistics Sweden). NPI measures the fluctuations of consumer prices with indirect taxes deducted and subsidies added. It is currently presented on an index reference base of 1980 = 100. The NPI is published every month. To obtain weekly values, we use interpolation and calculate an NPI value for each day, thereafter we take the average over every week.

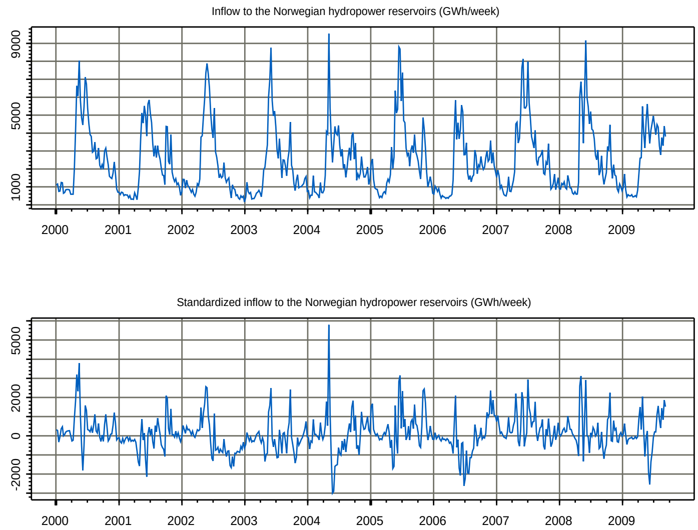

Figure 2: The original and transformed water inflow for Norway.

IV. EUA - European Union Allowances (NASDAQ OMX). We have daily spot prices (EUR/ton) for 25/10/2005–15/12/2009. The prices exist only for weekdays, therefore we have calculated weekly prices by taking the mean of the weekday prices and converting these into Swedish krona. We used the exchange rates from Sveriges Riksbank. Trading with the EUAs was introduced in 2005. The first, "pilot" phase, ran from 2005–2007. Phase II lasts from 2008 to 2012. In Figure 3 it can be seen how the EUA prices decreased basically to zero at the end of Phase I, because there was a surplus of allowances. When Phase II started, the prices jumped up again.

V. Electricity export and import from and to Sweden in GWh/week (Swedenergy). In the model we consider net exports,

$$netexports = export - import\,.$$

VI. Nuclear power production in Sweden (Swedenergy), weekly data in GWh/week for 1995–2009. Because nuclear power production depends also on season, we use in modeling the variables *nuclear.pos* and *nuclear.neg* which are obtained in the same way as the positive and negative water and consumption variables.

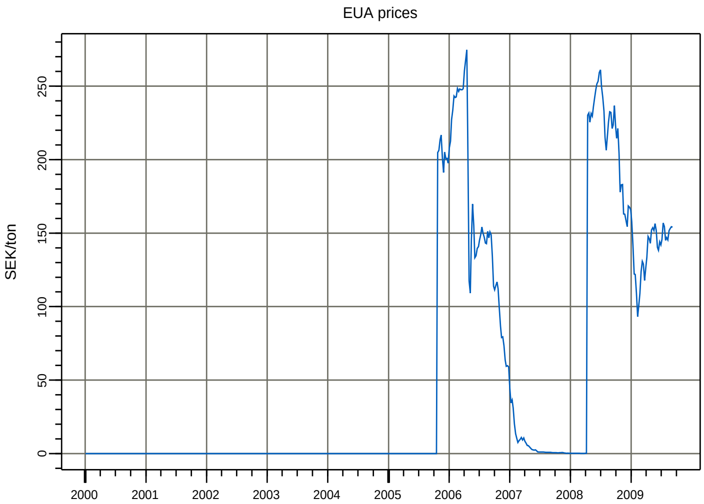

Figure 3: The prices of European Union Allowances.

In the following table all the explanatory variables used in regression analysis are given with their measurement units:

$res.norway.pos$, $res.norway.neg$	GWh
$res.sweden.pos$, $res.sweden.neg$	GWh
$inflow.norway.pos$, $inflow.norway.neg$	GWh/week
$inflow.sweden.pos$, $inflow.sweden.neg$	GWh/week
$cons.pos$, $cons.neg$	GWh/week
$nuclear.pos$, $nuclear.neg$	GWh/week
npi	
$netexports$	GWh/week
eua	SEK/ton

3 Methods for modeling electricity prices

As already mentioned in Introduction, we are interested in studying the behavior of the electricity price under different scenarios and forecasting the price far in the future. Thus, we do not want to include the lagged prices in the model. We will use the following approach: the mean price is modeled by linear regression techniques and the residuals are described by a time series model. Let $\mathbf{x}_t = (1, x_{1t}, \ldots, x_{kt})'$ denote the values of the studied k explanatory variables (where 1 corresponds to the intercept) at time point t and let $\mathbf{X} : n \times (k+1)$ be the matrix with rows given by $\mathbf{x}_t'$,

$t = 1, \ldots, n$. Let $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_k)'$ denote the vector of regression coefficients. The price at time t will be expressed as

$$y_t = f(\mathbf{x}_t) + z_t\,, \quad t = 1, \ldots, n,$$

where the regression function

$$f(\mathbf{x}_t) = \beta_0 + \beta_1 x_{1t} + \ldots + \beta_k x_{kt} = \boldsymbol{\beta}'\mathbf{x}_t$$

describes the mean electricity price and z_t is the residual.

3.1 Modeling $f(\mathbf{x}_t)$

The ordinary least squares method was used for estimating the regression coefficients $\beta_0, \beta_1, \ldots, \beta_k$. To take into account that the residuals z_t are heteroscedastic and serially correlated, we used the Newey-West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard error estimates for $\hat{\beta}_i$, $i = 0, \ldots, k$. The standard error estimate $\widehat{se}_{HAC}(\hat{\beta}_i)$ is given by the square root of the respective diagonal element of

$$\widehat{Cov}_{HAC}(\hat{\boldsymbol{\beta}}) = (\mathbf{X}'\mathbf{X})^{-1}\hat{S}_{HAC}(\mathbf{X}'\mathbf{X})^{-1}\,, \tag{1}$$

where

$$\hat{S}_{HAC} = \sum_{t=1}^{n} \hat{z}_t^2 \mathbf{x}_t\mathbf{x}_t' + \sum_{l=1}^{q} w_l \sum_{t=l+1}^{n} (\mathbf{x}_t\hat{z}_t\hat{z}_{t-l}\mathbf{x}_{t-l}' + \mathbf{x}_{t-l}\hat{z}_{t-l}\hat{z}_t\mathbf{x}_t')\,.$$

Here $w_l = 1 - l/(q+1)$ is the Bartlett weight function, $\hat{z}_t$ is the sample residual, and q is a truncation parameter which represents the number of autocorrelations used to approximate the dynamics for z_t. Observe that q must grow with the sample size in order for the estimate to be consistent. The Newey-West standard error estimates were used when testing the significance of the regression coefficients with t-statistics. By taking the serial correlation into account the standard errors of the coefficients increase, which may reduce the number of variables that are significant.

We started modeling with all the explanatory variables given in the table on p.6 in the model. We chose deliberately to consider the positive and negative parts of the standardized variables as separate explanatory variables in the model. This enables to model a possible different effect of the positive and negative part of a variable on the electricity price. There is for example no reason to assume that positive and negative values of the water reservoir level affect the electricity price in the same way. We used stepwise modeling and removed insignificant explanatory variables from the model one by one. The main criteria in the model building process for choosing a suitable regression model were the significance of the explanatory variables and the signs of the estimated coefficients $\hat{\beta}_i$, $i = 1, \ldots, k$.

One has to be careful with the water variables, because they depend on the amount of precipitation in two neighboring countries. The correlation coefficients for these pairs are as follows:

$$r(st.inflow.norway, st.inflow.sweden) = 0.62\,,$$

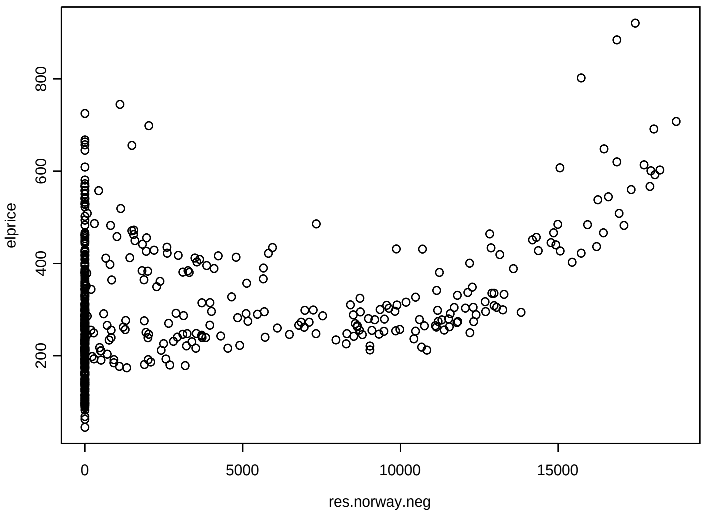

Figure 4: Relationship between the negative reservoir values in Norway and Swedish electricity prices.

$$r(st.res.norway, st.res.sweden) = 0.84\,.$$

The water variables for Sweden were removed in the modeling process, because they turned out to be insignificant. The water variables for Norway appear to describe the variability in Swedish area prices better than the respective variables for Sweden. Since there is a quadratic relationship between the electricity prices and the negative reservoir content levels, see Figure 4, we decided to include the quadratic term $res.norway.neg^2$ in the model. The selected regression function is:

$$elprice \sim npi + res.norway.pos + res.norway.neg + res.norway.neg^2 + inflow.norway.pos + netexports + eua\,. \quad (2)$$

The estimated regression coefficients of the variables in the model above are given in Subsection 4.1.

3.2 Modeling z_t

There are three steps in time series model building: identification, estimation and diagnostic checking. In our case the model can be easily identified by examining the sample autocorrelation and partial autocorrelation functions (ACF and PACF), because these follow the theoretical ACF and PACF of autoregressive (AR) models. The autoregressive model of order p, or the AR(p) model, is given by

$$z_t = \phi_1 z_{t-1} + \ldots + \phi_p z_{t-p} + \varepsilon_t\,,$$

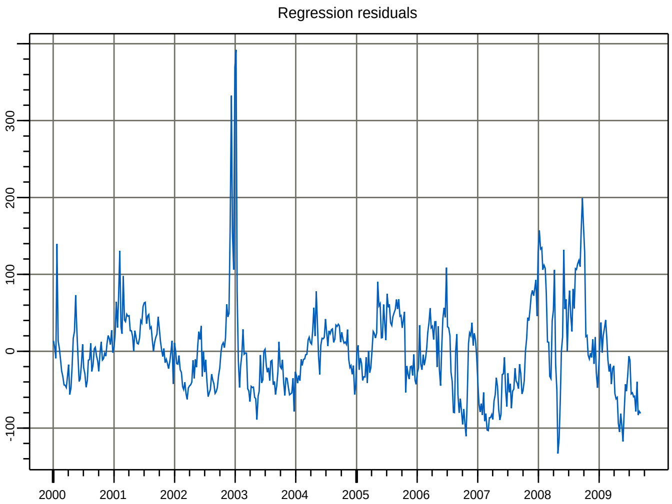

Figure 5: Regression residuals z_t.

where ε_t are called random shocks or innovations. If a stationary time series follows an AR(p) model, then the ACF is dominated by exponential decay, while the PACF truncates at lag p, i.e. the partial autocorrelation coefficients of order higher than p are equal to zero.

To test for serial correlation in ε_t, we used the Durbin-Watson statistic:

$$DW = \frac{\sum_{t=2}^{n}(\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=1}^{n}\hat{\varepsilon}_t^2} .$$

The Durbin-Watson statistic was also calculated for the estimated regression residuals $\hat{z}_t$. It holds that $DW \approx 2(1-\hat{\rho})$, where $\hat{\rho}$ is the estimated correlation between $\hat{\varepsilon}_t$ and $\hat{\varepsilon}_{t-1}$. Therefore, the values of DW around two indicate no serial correlation in the innovations.

To check whether the random shocks from an estimated AR(p) model behave as a white noise process, we used the Ljung-Box modified Q-statistic defined as:

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{\hat{\rho}_j^2}{n-j} ,$$

where $\hat{\rho}_j$ is the j-th order sample autocorrelation coefficient and m is the number of lags being tested. In our case, $\hat{\rho}_j = \sum_{t=j+1}^{n}\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}/\sum_{t=1}^{n}\hat{\varepsilon}_t^2$. Under the null hypothesis that ε_t follows a white noise process, $Q(m)$ is asymptotically distributed as $\mathcal{X}^2(m-p)$. If $Q(m)$ exceeds the critical value of $\mathcal{X}^2(m-p)$, then at least one value of $\hat{\rho}_j$, $j = 1, \ldots, m$, is different from zero at the specified significance level.

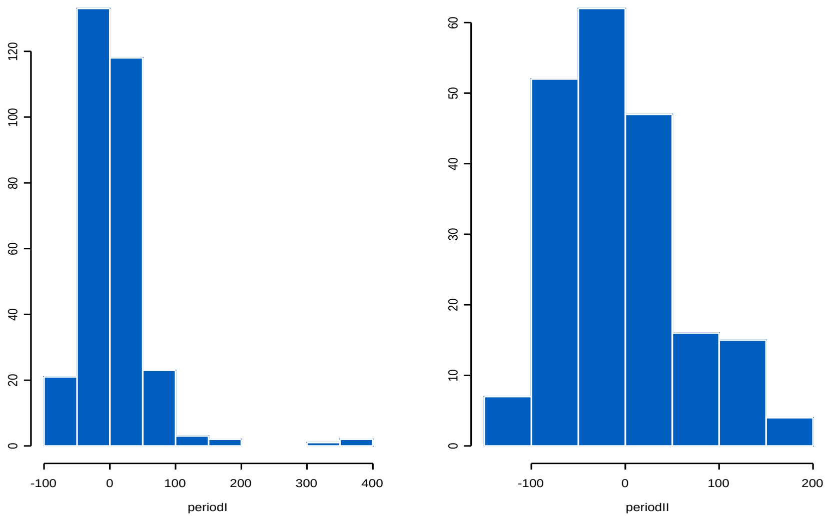

Figure 6: Regression residual distributions for 2000–2005 and 2006–2009.

4 Empirical contributions

4.1 Estimated regression model

The summary statistics of the selected regression model (2) are presented below:

	Estimate	s.e.	t-value	p-value
Intercept	-1384.1537	170.3112	-8.1272	0.0000
npi	7.0283	0.7303	9.6238	0.0000
$res.norway.pos$	-0.0070	0.0017	-4.2094	0.0000
$res.norway.neg$	-0.0180	0.0049	-3.7000	0.0002
$res.norway.neg^2$	$1.70 \cdot 10^{-6}$	$3.93 \cdot 10^{-7}$	4.3164	0.0000
$inflow.norway.pos$	-0.0176	0.0053	-3.3394	0.0009
$netexports$	-0.1072	0.0209	-5.1332	0.0000
eua	0.5692	0.0841	6.7673	0.0000

The model has a high determination coefficient: $R^2 = 0.82$. The residual standard error is 58.67 and the residuals are serially correlated: $DW = 0.3964$. The negative coefficient of $res.norway.pos$ shows that when the water reservoir content level in Norway is above its mean value, the electricity price will decrease. The variable $netexports$ has also negative coefficient meaning that when the electricity import to Sweden is higher than export from Sweden, the price will increase.

4.2 Estimated time series models

The residuals z_t from the regression analysis are serially correlated, $DW = 0.3964$. It can be seen in Figure 5 that the time series of the estimated regression residuals appears to have a somewhat different behaviour from around the beginning of 2006, e.g. the standard deviation seems to be larger for the last years. This could be explained by the EUA prices entering the regression model at the end of 2005. Figure 6 demonstrates that the residuals have different distributions for 2000–2005 and 2006–2009. The standard deviation of the regression residuals for the first period is 53, while it is 64 for the second period. For these reasons, we have performed separate analyses of z_t for the two periods.

Period I: 2000–2005. The sample ACF and PACF in Figure 7 indicate that an AR(3) model is suitable for describing the regression residuals for the first period, because the ACF exhibits a decaying pattern similar to an AR model and the PACF is truncated at $p = 3$, the partial autocorrelations of higher order are not significantly different from zero. A summary of the fitted AR(3) model is given below:

	Estimate	s.e.	t-value
$\hat{\phi}_1$	0.7811	0.05475	14.270
$\hat{\phi}_2$	−0.2758	0.06913	−3.989
$\hat{\phi}_3$	0.3172	0.05475	5.792

The Durbin-Watson statistic for the innovation process for period I takes the value 1.93, which indicates no serial correlation in the random shocks. In Figure 8, the sample ACF and PACF for the innovations are plotted together with their 95% confidence intervals about zero. We can see that none of the estimated autocorrelations and partial autocorrelations are significantly different from zero, indicating a white noise process. The p-values for the Ljung-Box statistic (see Figure 8) are all larger than 0.1, thus the null hypothesis that the innovation process for the first period is a white noise process can not be rejected.

Period II: 2006–2009. Again, since the sample ACF of the regression residuals in Figure 9 follows a decaying pattern characteristic to an AR process and the sample PACF is cut at lag $p = 1$, an AR(1) model seems to be suitable for describing the regression residuals for the second period. The estimated coefficient $\hat{\phi}_1$, its standard error and the t-statistic value are as follows:

	Estimate	s.e.	t-value
$\hat{\phi}_1$	0.8662	0.03516	24.64

The Durbin-Watson statistic value 2.04 indicates no serial correlation in the innovations. The innovations diagnostics in Figure 10 confirm that the estimated AR(1) model is a suitable time series model for period II: all the sample autocorrelations and partial autocorrelations lie within the 95% confidence limits and the p-values of the Ljung-Box Q-statistic for the lags $2, \ldots, 15$ exceed 0.15. Therefore, the null hypothesis about the innovations following a white noise process can not be rejected.

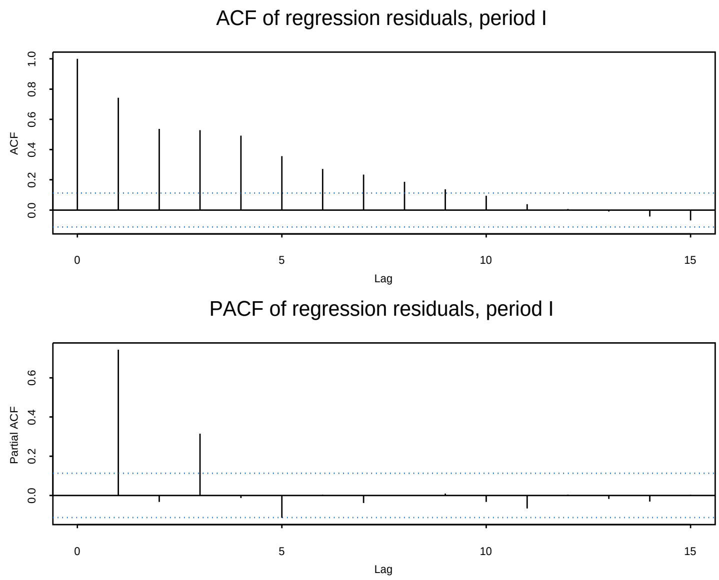

Figure 7: ACF and PACF of the regression residuals for 2000–2005.

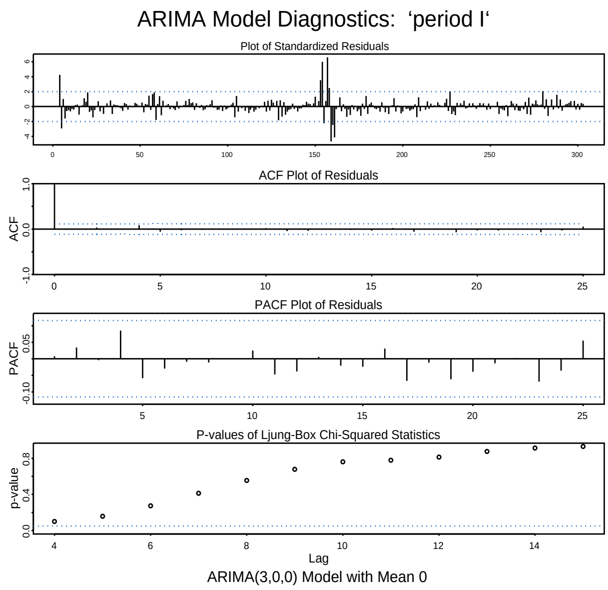

Figure 8: Innovation diagnostics for the period 2000–2005.

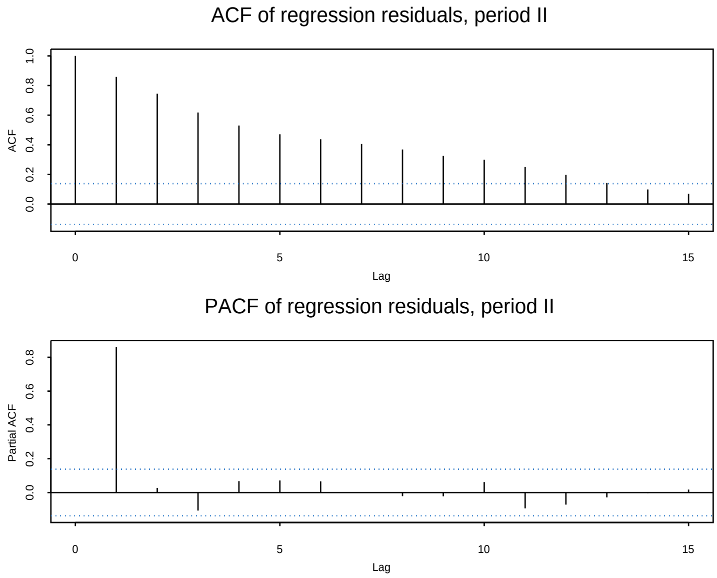

Figure 9: ACF and PACF of the regression residuals for 2006–2009.

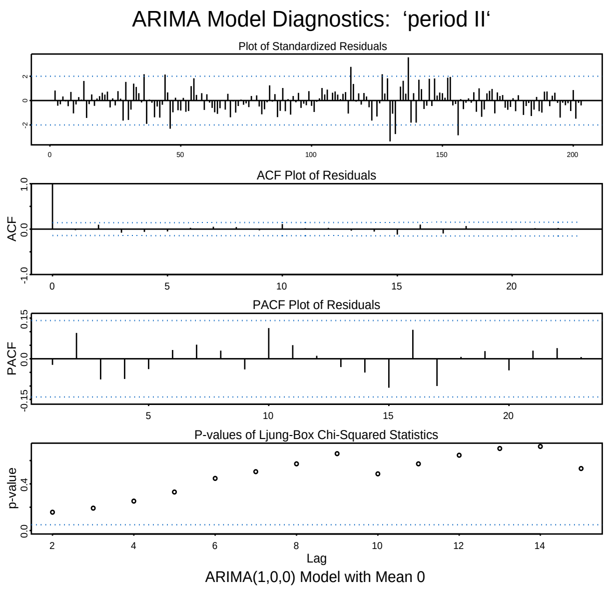

Figure 10: Innovation diagnostics for the period 2006–2009.

Scenarios	1	2	3	4	5	6	7	8	9
NPI	250	250	250	250	250	250	250	250	250
$res.norway.pos$	0	0	0	0	0	0	0	6000	6000
$res.norway.neg$	0	0	0	0	0	13000	13000	0	0
$inflow.norway.pos$	0	0	0	0	0	0	0	1000	1000
$Netexports$	0	0	0	-400	400	0	-400	0	400
EUA	150	300	600	150	150	150	150	150	150
$\hat{f}$	458	544	714	501	415	510	553	398	356
$\widehat{std}(\hat{f})$	13.9	20.4	42.7	16.6	15.8	17.0	18.4	12.6	16.1
95% CI	[431, 485]	[504, 594]	[631, 798]	[469, 534]	[384, 446]	[477, 544]	[517, 589]	[374, 423]	[324, 387]

The scenarios in the table:

1 – "standard period" according to our model;

2, 3 – EUA price increases;

4 – electricity import to Sweden is higher than export from Sweden during a number of weeks;

5 – export is higher than import;

6, 7 – correspond to a period when the value of the water reservoir content is lower than its mean value meaning water scarcity. In our data set there is a period of 31 weeks at the end of 2002 and at the beginning of 2003 when the water reservoir content in Norway was more than 10000 GWh/week below its mean value. Another such a long period occurred in the second half of 2006. The difference between 6 and 7 is that for scenario 6 import-export is in balance, whereas in the case of 7 the water scarcity causes lack of electricity, and thus a need to import.

8, 9 – correspond to a period when the inflow to the Norwegian hydropower reservoirs is above its mean value for several weeks. In our data set for example the inflow was more than 1000 GWh/week above its mean value during weeks 17–21 in 2000. The water reservoir content level in Norway during these weeks was more than 6000 GWh above its mean value. In the case of scenario 9 we assume an overflow of electricity in Sweden, thus the export from Sweden exceeds the import to Sweden.

4.3 Scenarios

The estimated regression function $\hat{f}(\mathbf{x}_t)$ can be used to estimate the effect of the explanatory variables in the model to the mean electricity price over a number of weeks. Since

$$E(y_t|\mathbf{x}_t) = f(\mathbf{x}_t) + Ez_t\,, \quad \text{where} \quad Ez_t = 0\,,$$

$\hat{f}(\mathbf{x}_t)$ gives an estimate of the expected electricity price for given $\mathbf{x}_t$. Suppose we want to know the mean electricity price over l weeks when the awaited values for the explanatory variables are $\mathbf{x}_1, \ldots, \mathbf{x}_l$ for these weeks. Then

$$\frac{1}{l}\sum_{i=1}^{l} \hat{E}(y_i|\mathbf{x}_i) = \frac{1}{l}\sum_{i=1}^{l} \hat{f}(\mathbf{x}_i) = \hat{\beta}_0 + \hat{\beta}_1\bar{x}_1 + \ldots + \hat{\beta}_k\bar{x}_k = \hat{\boldsymbol{\beta}}'\bar{\mathbf{x}} = \hat{f}(\bar{\mathbf{x}})$$

gives an estimate of the mean electricity price for these l weeks. Here $\bar{x}_j$, $j = 1, \ldots, k$, is the mean of the variable x_j over the l weeks. The estimate of the standard deviation of $\hat{f}$ is given by

$$\widehat{std}(\hat{f}(\bar{\mathbf{x}})) = [\bar{\mathbf{x}}'\widehat{Cov}_{HAC}(\hat{\boldsymbol{\beta}})\bar{\mathbf{x}}]^{1/2}\,,$$

where $\widehat{Cov}_{HAC}(\hat{\boldsymbol{\beta}})$ is the Newey-West estimate given in (1).

In the table on p.14 we consider nine different scenarios, i.e. nine conceivable combinations for the mean values of the explanatory variables. The number of weeks does not affect the estimated mean electricity price or its standard deviation directly. But the number of weeks and the period of the year has to be taken into account when we fix a mean value of an explanatory variable over these weeks — this value has to be reasonable.

Changing the value of only one variable at a time enables to estimate the effect of that particular variable to the mean electricity price. Consider for example scenarios 1 and 4 in the table. When the mean values of the explanatory variables are given by scenario 1 and we then change the value of netexports to -400, i.e. we obtain scenario 4 where the mean electricity import exceeds the export by 400 GWh/week meaning lack of electricity in Sweden, then the mean electricity price increases by 43 SEK/MWh (4.3 öre/kWh).

As a second example, compare scenario 1 corresponding to the "standard period" according to our model with scenario 6. Scenario 6 presents a period with water scarcity when the water reservoirs content level in Norway is much lower than normally. Such a situation is for example usual for years with small amount of precipitation. We can see that $res.norway.neg = 13000$ increases the mean electricity price by 5.2 öre. If we in addition to that assume that it is necessary to import electricity (scenario 7), the price will increase by 4.3 öre more.

On the contrary, when it rains and snows a lot so that the inflow to water reservoirs and the reservoir content level are above their mean values, then the mean electricity price falls, see scenarios 8 and 9.

From the scenarios we can also analyze the effect of an increase of the EUA price. An increase from 150 SEK to 300 SEK increases the electricity price by 8.6 öre/kWh. It is interesting to compare the results from our model to the estimates in Hill and

Kriström (2005). According to their estimates the electricity price will increase by 10 öre if the EUA price increases from 10 to 30 Euro. If we use our model with an exchange rate of 9.5 SEK/Euro, we also obtain an increase of 10 öre.

5 Discussion

Modeling electricity prices is a complicated task since electricity prices depend on many factors that form an intricate system with many interrelations. The model developed in this work is satisfactory because it has a high determination coefficient and the residuals for the last period can be described by an AR(1) process. But there is room for improvement if additional exogeneous variables, e.g. coal, natural gas and oil prices, are considered. Next, we will discuss some difficulties when modeling Nordic electricity prices.

The Nordic electricity market depends highly on weather: the supply is dependent on the amount of precipitation and the demand on temperature. Due to excessive heating, Sweden has for example the peak demand in winter. Besides, unexpected weather conditions such as extreme cold can cause sudden and huge price jumps. It is not obvious how or in which form to include air temperature in modeling. Therefore, we tried to catch the seasonal fluctuations in demand by the consumption variable, but this variable turned out to be insignificant. It is also interesting to point out the relationship between the electricity prices and water reservoir levels. On the one hand, electricity is a non-storable commodity, on the other hand, water and therefore hydropower is storable from a producer's perspective (Deng, 2006). Thus, "if hydroelectricity is generated strategically, reservoir levels will also be a function of electricity prices" (Fell, 2008).

As can be seen also from our model, the CO_2 emission prices have an influential effect on electricity prices. But it is not easy to measure and model this effect, because it is not obvious how the response of electricity prices to changes in EUA prices is affected by the mixture of Nordic electricity generation techniques. The system price is determined by the marginal generator fuel, which can be coal, natural gas or oil for the Nordic electricity market, since it includes a portion of fossil fuel energy. But coal, gas and oil have different CO_2 emission intensities. To estimate how EUA price changes affect electricity prices depending on the price-setting generator requires therefore information about the marginal generator. For a more detailed discussion, see Fell (2008).

For describing future electricity prices, it is crucial to explore interdependencies between electricity, EUA, carbon, natural gas and oil prices, because prices in one market impact prices in other markets. Thus, a multivariate approach is awaited to yield further improvements of the model.

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References

Deng, D. (2006). Three essays on electricity spot and financial derivative prices at the Nordic Power Exchange. Doctoral Thesis, *School of Business, Economics and Law, University of Gothenburg.*

Energimarknadsinspektionen (2006). Prisbildning och konkurrens på elmarknaden, *ER 2006:13.*

Fell, H. (2008). EU-ETS and Nordic electricity: a CVAR analysis, *Resources for the Future Discussion, Paper No. 08-31.*

Higgs, H. and Worthington, A.C. (2008). Modelling spot prices in deregulated wholesale electricity markets: a selected empirical review. Available at SSRN.

Hill, M. and Kriström, B. (2005). *Klimatmål, utsläppshandel och svensk ekonomi*, SNS Förlag.

Lucia, J.J. and Schwartz, E.S. (2002). Electricity prices and power derivatives: evidence from the Nordic Power Exchange, *Review of Derivatives Research*, **5**, 5–50.

Newey, W.K. and West, K.D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, **55**, 703–708.

Weron, R., Simonsen, I., Wilman, P. (2003). Modeling highly volatile and seasonal markets: evidence from the Nord Pool electricity market, *Econometrics series provided by EconWPA*, 0303007.

Wolak, F.A. (2000). Market design and price behavior in restructured electricity markets: an international comparison, in *Deregulation and Interdependence in the Asia-Pacific Region, NBER-EASE*, Volume **8**, 79–137.