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Modeling Prices of Electricity Futures at EEX

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***Abstract*—**The main aim of this paper is to develop and calibrate an econometric model for modeling prices of long term electricity futures contracts. The calibration of our model is performed on data from EEX AG allowing us to capture the specific features of German electricity market. The data sample contains several structural breaks which have to be taken into account for modeling. We model the data with an ARIMAX model which reveals high correlation between the price of electricity futures contracts and prices of LT futures contracts of fuels (namely coal, natural gas and crude oil). Besides this, also a share price index of representative electricity companies traded on Xetra, spread between 10Y and 1Y German bonds and exchange rate between EUR and USD appeared to have significant explanatory power over these futures contracts on EEX.

***Keywords*—**electricity futures, EEX, ARIMAX, emission allowances

I. Introduction

THE electricity market in Germany was liberalized during the late 1990s. The main aim of the liberalization process was to establish a sufficient level of competition among agents participating in the market. However, the electricity market structure remained oligopolistic with high level of vertical integration. The four most important market players (namely E. ON, RWE, EnBW and Vattenfall Europe) represent approximately 85 % of the total net electricity generation capacity in Germany according to data provided by Bundesnetzagentur in 2007.

In year 2002 the Leipzig Power Exchange (LPX) and European Energy Exchange with the seat in Frankfurt am Main merged together and founded new energy exchange under the name European Energy Exchange (EEX) with seat in Leipzig. Nowadays EEX is the biggest market with energy in continental Europe with respect to both, turnover and number of agents. EEX enables trading in power, natural gas, coal as well as emission allowances. Besides the liquid daily spot market, electricity is also being traded in form of futures and option contracts.

The paper consists of six parts. The first chapter summarizes current theoretical and empirical literature concerning our topic. We focused mainly on papers which offer interesting methodology and which employ similar (or ideally the same) markets as in our case. Next chapter describes the specifics of the general model for futures pricing and its modifications that enable to use the model for our purposes. The third part is devoted to data analysis and methodology description. All variables are introduces and explained. The econometrical approaches we used are explained in the fourth part. The fifth chapter summarizes econometrical results obtained. At the end we provide a summary of the results, conclusive remarks and suggestions for future research.

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II. Literature Overview

This part contains the overview of recent theoretical and empirical literature discussing the topic of Long-term (LT) electricity contracts modeling. The attention paid to this topic by researchers is not as large as it is in case of Short-term (ST) contracts modeling and the numbers of studies is limited. We would like to underline the three most important papers.

The most influential paper from our point of view was written by *Povh and Fleten* [2]. In their paper authors focused on modeling LT electricity forward prices with the data from the Nord Pool Power Exchange Market. Besides the empirical analysis they provide also a general approach for analyzing electricity markets. They modeled the relationship between prices of LT forward contracts on fuels (such as oil, coal and natural gas), the price of emission allowances and imported electricity and the LT price of electricity forwards.

The second important study written by *Povh, Fleten and Golob* [3] is a valuable extension of the first paper. It models the LT electricity forwards with time to maturity between one and two years again at Nord Pool on weekly basis during the period of 2005 to 2007. Besides the above mentioned variables authors included also price of aluminum and in addition to this electricity price from the neighboring EEX market as explanatory variables. They used vector autoregressive model for LT modeling and concluded that the gas prices were insignificant in this model.

The third interesting contribution was made by *Redl* [4] who described a model for forecasting futures electricity prices directly on the EEX. As a representative contract he chose year-ahead base load forward contracts traded on this market. He found out that the forward prices are mostly influenced by futures prices of fuels (namely natural gas and coal) and CO_2 emission allowances. He also pointed out that if forward contracts are priced correctly, then both futures and spot prices should follow the same trend corrected by a risk premium (market value of risk affiliated with time). In his paper, he concludes that there is no persistent trend neither in the amount of the risk premium nor in the sign of this risk premium.

III. Valuation of Futures Contracts

The standard approach used to calculate the price a futures contract is to meet so called no-arbitrage condition. This condition ensures that the futures contract is priced fairly and there is no possibility for risk-free arbitrage. Even thought this concept can be used for almost all commodities, it is not suitable for electricity futures since the electricity cannot be stored for an extended time period. Moreover, this model implies that there is no direct link between the spot and futures price. Thus the formula used for pricing a standard futures contract as it is described by (1) cannot be applied in our case:

$$F_{t,T} = S_{t,T} * (1 + r - \lambda)^{T-t}, \tag{1}$$

where $F_{t,T}$ represents the price of futures contract, $S_{t,T}$ stands for the spot price of a given commodity, the term $(1+ r - \lambda)$ denotes risk premium and $T - t$ reflects time to maturity.

The risk premium term, that explains the compensation for unexpected changes in the future spot price, consisting of risk free rate and the forward premium, can be affected in several ways. The first one is the fact that this risk premium is positively correlated to the risk premium of particular fuel prices (e.g. gas and oil) since an increase in the fuels' risk premium is transferred also to the risk premium of the electricity futures contracts. Moreover, it is obvious that the risk premium is also directly affected by the evolution of the reserve margin and this relationship is negative as this relation accounts for the scarcity of electricity. The particular risk premium components are discussed in [5].

Because we want to find out the pricing formula for the case of electricity, we have to modify (1) in order to employ expected spot price $E(S_{t,T})$ instead of the spot one. This is done in (2) which provides the basic formula suitable for pricing electricity futures:

$$F_{t,T} = E(S_{t,T}) * (1 + r - \lambda)^{T-t}. \tag{2}$$

In order to obtain a linear model, we transformed (2) into a logarithmic form:

$$\log F_{t,T} = \log E(S_{t,T}) + (T - t) * \log(1 + r - \lambda). \tag{3}$$

As [2] argue that the term $log(1 + r - \lambda)$ is relatively stable with *far maturity* (see [1] for explanation of far maturity) so the expected future spot price comprises most of the variability that explains futures price. Factors that determine future spot price are future supply and demand (unfortunately hardly predictable). Thus instead of them, variables directly influencing supply and demand are to be employed. The following variables can be considered to have significant impact on either demand or supply [2]:

1) fuel prices – gas, oil, coal
2) emission allowances
3) weather conditions
4) time factor
5) economic activity
6) other – historical or forecasted loads, electricity prices in neighboring markets, market structure, regulation and future demographical development

Nevertheless, not all of these factors can be observed with sufficient frequency or they are not liquid in some markets.

IV. Data Analysis and Methodology

The electricity market in Germany is by far represented by EEX. As a reference time series we consider a yearly Phelix Base Futures with next year´s delivery. Our data sample contains data from September 2006 to April 2009. Data in this period are observed on a daily basis which allows us for short-term modeling. Our dataset was trimmed from extreme observations and in addition to this, the EEX time series were transformed by linear interpolation.

As we mentioned above, we have to identify possible determinants of future spot price. Here at we divide variables with possible explanatory power into several groups.

In the first group we include the futures on fuel prices as they obviously influence the costs of electricity production. This group covers time series on oil, natural gas and coal. Oil prices are represented by a monthly futures contract of *BRENT* crude oil and a yearly futures contract of *NYMEX WTI* light sweet crude oil. Natural gas is represented by yearly futures of *TTF* gas from Zeebrugge hub. As coal is mostly OTC traded we consider *TFS API4* price index (coal delivered in Amsterdam, Rotterdam and Antwerp harbor).

The second group of variables impacting the production costs of electricity is the emission allowances. The system of emission allowances within the European Union was firstly introduced in January 2005 and nowadays it is to be considered as an important factor influencing the price of electricity futures contract. Because of the LT nature of our modeling, we incorporate prices of one year-ahead futures contracts of emission allowances *EU ETS*.

The last group of variables is the ones reflecting financial market conditions and economic development – those variables might have an indirect impact on the electricity prices. The first of those variables is the *EUR/USD* exchange rate. Then we consider variables that measures the risk premium associated with time factor of futures contracts. This risk premium can be indirectly observed from a shape of yield curve. For this purpose we used variable *SPREAD* which is defined as a difference between 10Y and 1Y government bonds in Germany. This variable models the right part of the yield curve shape. The higher the value of the *SPREAD* variable the steeper the yield curve is, which means the higher risk premium for the later maturity is expected by the market.

The last explanatory variable type is the Prime Utilities Index *(UTIL)* traded on Xetra. This index contains weighted results of share price evolution of the following companies: E.ON AG, MVV Energie AG, RWE AG St and RWE AG Vz.

We believe this variable might be used as proxy through which financial markets reveals the market expectations on the price of electricity futures (these are then reflected in the share price).

V. ECONOMETRIC ANALYSIS

As all the variables are defined, we continue with description of the econometrical model for electricity futures. We apply ARIMAX – autoregressive integrated moving average model with exogenous input that is derived from simple ARIMA – autoregressive moving average model. The general form of the model we use is described by equation (4):

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{b} \gamma_k X_{t-k}, \qquad (4)$$

where α is a drift, the first sum denotes an autoregressive term, ε_t is an error term, the second sum represents a moving average process of past error terms and the last sum denotes the exogenous variables. All the data are going to be transformed into natural logarithms and then differenced in order to avoid spurious regression that could be caused by using possibly non-stationary series. The model estimated by using OLS method. The dependant variable is the price of LT electricity futures contract.

For the purpose of econometric analysis we used the above mentioned data series. The observation period is 11th Sep 2006 to 5th April 2009.

TABLE I
UNIT ROOT TEST

Group unit root test: Summary
Series: EEX, BRENT, TTF, EMISSION, EURUSD, LIBOR3, SPREAD, TFSE, UTIL
Date: 11/16/09 Time: 20:07
Sample: 1/02/2006 6/03/2009
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic selection of lags based on SIC: 0 to 4
Newey-West bandwidth selection using Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-91.9486	0.0000	9	7355
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-83.4376	0.0000	9	7355
ADF - Fisher Chi-square	1389.00	0.0000	9	7355
PP - Fisher Chi-square	1440.14	0.0000	9	7363

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

At first we have to check whether the data series are stationary using unit root test[1]. The results are summarized in Table I. It shows that both commonly used tests (namely Augmented Dickey-Fuller test and Phillips-Perron test) reject the null hypothesis at very high levels of significance. Based on this finding we can treat the data series as being stationary.

Application of the standard OLS regression on the data sample revealed several problems. One of the most severe was the presence of structural breaks in the dataset. In order to identify them, we used Quandt-Andrews unknown breakpoint test and Chow Breakpoint test. These two tests indentified the presence of two structural breaks in our dataset with relatively high significance levels. This is shown in tables II and III:

TABLE II
STRUCTURAL BREAKS ANALYSIS - 8/08/2007

Chow Breakpoint Test: 8/08/2007
Null Hypothesis: No breaks at specified breakpoints

Equation Sample: 11/09/2006 5/04/2009

F-statistic	1.519317	Prob. F(29,269)	0.0474
Log likelihood ratio	49.60069	Prob. Chi-Square(29)	0.0100
Wald Statistic	45.87286	Prob. Chi-Square(29)	0.0242

TABLE III
STRUCTURAL BREAKS ANALYSIS - 10/11/2007

Chow Breakpoint Test: 10/11/2007
Null Hypothesis: No breaks at specified breakpoints

Equation Sample: 11/09/2006 5/04/2009

F-statistic	1.487737	Prob. F(29,269)	0.0564
Log likelihood ratio	48.64269	Prob. Chi-Square(29)	0.0126
Wald Statistic	46.93959	Prob. Chi-Square(29)	0.0189

Another problem was related to the heteroscedasticity of residuals. Moreover, it was not clear which form of heteroscedasticity the dataset exhibits. In order to solve these two issues (namely presence of structural breaks and heteroscedasticity of residuals) we decided to use Newey-West heteroscedasticity and autocorrelation consistent covariance estimates. These estimates provide more general covariance estimator than White estimate and it also returns results with high explanatory power even in the presence of both, heteroscedasticity and autocorrelation of unknown form. This enables us to use OLS method even when there are autocorrelated residuals and heteroscedasticity in the dataset. For this reason we decided to use the Newey-West estimator.

Table IV summarizes results of our model which was calibrated on 332 observations as they were collected during the period starting from 11/2006 until 5/2009. The adjusted R^2 of the model is higher than 0.20 which allows us to consider the model explanatory power as sufficient even in presence of higher volatility of almost all variables from the data sample after 09/2008 as a consequence of financial crises as mentioned in previous chapter.

[1] Unit root test is a test (e.g. Augmented Dickey-Fuller (ADF) test or Phillips-Perron test (PP)) which is able to detect the possible non-stationarity within the time series.

TABLE IV
ECONOMETRICAL RESULTS OLS

Dependent Variable: EEX
Method: Least Squares
Date: 11/16/09 Time: 20:01
Sample (adjusted): 11/09/2006 5/04/2009
Included observations: 332 after adjustments
Convergence achieved after 10 iterations
Newey-West HAC Standard Errors & Covariance (lag truncation=5)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001357	0.001983	-0.683933	0.4945
BRENT(-1)	0.100555	0.047241	2.128542	0.0341
BRENT(-2)	-0.128952	0.059156	-2.179845	0.0300
BRENT(-9)	0.159440	0.061131	2.608152	0.0095
EURUSD(-6)	-0.276049	0.122576	-2.252061	0.0250
SPREAD(-5)	-0.000474	0.000205	-2.310081	0.0215
SPREAD(-6)	0.001041	0.000433	2.405685	0.0167
SPREAD(-7)	-0.000826	0.000205	-4.035002	0.0001
TFSE(-3)	0.129734	0.055339	2.344328	0.0197
TFSE(-5)	0.109232	0.034734	3.144811	0.0018
TFSE(-10)	0.119621	0.042429	2.819338	0.0051
TTF(-1)	-0.106410	0.041586	-2.558777	0.0110
TTF(-2)	0.108323	0.038185	2.836804	0.0049
TTF(-4)	-0.067489	0.034933	-1.931986	0.0543
TTF(-8)	-0.095351	0.040396	-2.360421	0.0189
TTF(-9)	-0.107609	0.040242	-2.674066	0.0079
UTIL(-3)	-0.065560	0.028985	-2.261823	0.0244
UTIL(-7)	-0.090091	0.037860	-2.379544	0.0179
UTIL(-9)	-0.105776	0.032462	-3.258439	0.0012
UTIL(-10)	0.075008	0.032222	2.327832	0.0206
AR(7)	0.151188	0.075536	2.001537	0.0462
AR(9)	0.216110	0.065414	3.303724	0.0011
AR(10)	0.254300	0.064664	3.932664	0.0001

R-squared	0.269114	Mean dependent var	0.000260
Adjusted R-squared	0.217077	S.D. dependent var	0.013066
S.E. of regression	0.011561	Akaike info criterion	-6.015593
Sum squared resid	0.041300	Schwarz criterion	-5.751985
Log likelihood	1021.589	Hannan-Quinn criter.	-5.910466
F-statistic	5.171569	Durbin-Watson stat	1.818373
Prob(F-statistic)	0.000000		

Inverted AR Roots	.95	.71-.58i	.71+.58i	.23+.84i
	.23-.84i	-.31+.83i	-.31-.83i	-.72
	-.74-.42i	-.74+.42i		

If we plot the residuals retrieved from the model with respect to time (as shown in Fig 1), we can see significant increase in the variance of residuals starting from second quarter of 2008. Even though, the results obtained points to relatively good performance of our model.

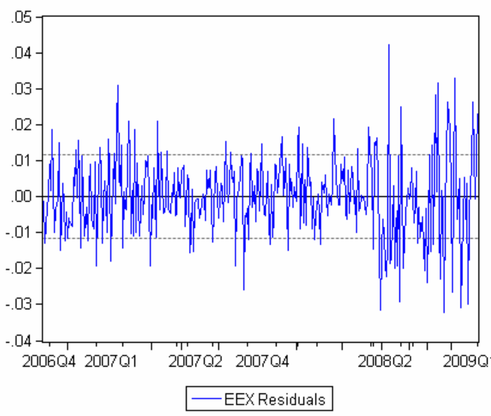

Fig. 1 Plot of residuals with respect to time

VI. INTERPRETATION OF RESULTS

This chapter contains economic interpretation of the results obtained in the previous section. The stationary of the data sample that was verified in the fourth part of our paper allows us interpret the obtained results. Table IV provides clear insights that, except for intercept and futures contracts on natural gas lagged by four periods (i.e. four months in our case), all variables are estimated as significant at least at 5 % level of significance.

The important point is to interpret the estimates of regression coefficients and their signs. If we recall Table IV presenting the results of regression analysis we find out that for the most of the variables (namely BRENT, SPREAD, TTF and UTIL) the sign of the regression coefficient depends on the time lag. Thus our model detected that the relationship between dependent variable and certain explanatory variables is not stable. The way how is the dependent variable influenced by these explanatory variables is sometimes positive and sometimes negative. This is rather counterintuitive for the first sight. However, there can be effects driving the value of the lagged variable below zero. One of the variables with constantly positive sign of regression coefficient for all time lags was TFSE. There is clearly a positive correlation between coal price and price of electricity futures contracts.

In order to evaluate whether the results are consistent even during the financial crises we took an exercise and tried to model two data samples before and after the crises. The results for both data sets were identical in terms of significance of particular variables, even though the size of residuals increased for the "crises" sample. Thus we can conclude that the model we used provides consistent results also during financial crises.

VII. CONCLUSION

In this paper we examined the possible determinants of the price of futures electricity contracts at EEX. We did it by empirical analysis based on ARIMAX model. As a dependent variable we chose Phelix Base Futures with next year´s delivery. We tried to explain this variable be incorporating contracts on fuels (namely natural gas, oil and coal), emission allowances and indicators from financial markets (index based on assets performance, Germany 1Y and 10Y bonds and EUR/USD exchange rate).

The results are summarized in Table IV that shows that all estimated variables have significant power in explaining electricity futures prices variability. The fact, whether a relationship between a certain variable and the electricity futures is positive or negative, depends on the time lag. The possible interpretation is that (especially in case of fuel contracts) it hinges on whether or not the "costs effects" dominates over "substitution effects". The exception to this trend is the coal with the persistent positive price effect for all time lags. The performance of the model measured as goodness of fit was relevant - our model is able to explain more than 25 percent of the variance observed in prices of electricity futures. In addition to this, even on these time series we can observe the impacts of recent financial crisis via substantial increase (with the exception of the price for emission allowances) in the variance in a corresponding period. This might lead to a decrease in the performance of our model.

If we would like to compare our results with other empirical literature considering the same topic, we can see that similarly to e.g. in [3] and [4] we found out the same conclusion – the significance of fuel costs or emission allowances.. Contrary to them, our analysis revealed that even natural gas has an explanatory power over prices of the electricity futures. Inclusion of other factors from the financial markets than the ones related to the evolution of interests rates seems to be rather innovative and thus it does not allow us to compare obtained results with previous empirical literature.

However, the comparison of results among particular papers is quite a difficult task since two out of three papers mentioned in the literature overview were devoted to modeling a different market with electricity futures, namely the Nord Pool and therefore the results (and models used) need not to be fully comparable due to the different characteristics of these markets. However, in general terms we can point out that we can see that similarly to e.g. similarly to [3] we found out the significance of fuel costs or emission allowances. Contrary to [3] our analysis revealed that even natural gas has an explanatory power over electricity futures.

The fact that we have included in our model the Prime Utilities Index traded on Xetra in order to account for the market sentiment seem to be rather innovative approach. Moreover, as the results of the model pointed out, this step caused an improvement in the explanatory power of it as all UTIL variables included in Table IV were significant.

Although the fact that our model is relatively up to date it could be somehow treated as outdated due to the rapid development of economic conditions caused by the ongoing financial crisis. Such crisis often changes the trends and relationships between particular variables. On the other hand, the "core" of revealed relationships is assumed to stay unchanged. This creates suitable position for further research - to verify, whether even in the after-crisis period, the results we mentioned in our paper still hold. Moreover, also modeling the same data with different methods (e.g. co-integration or neural networks) might shed more light on this topic and provide interesting answers.

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