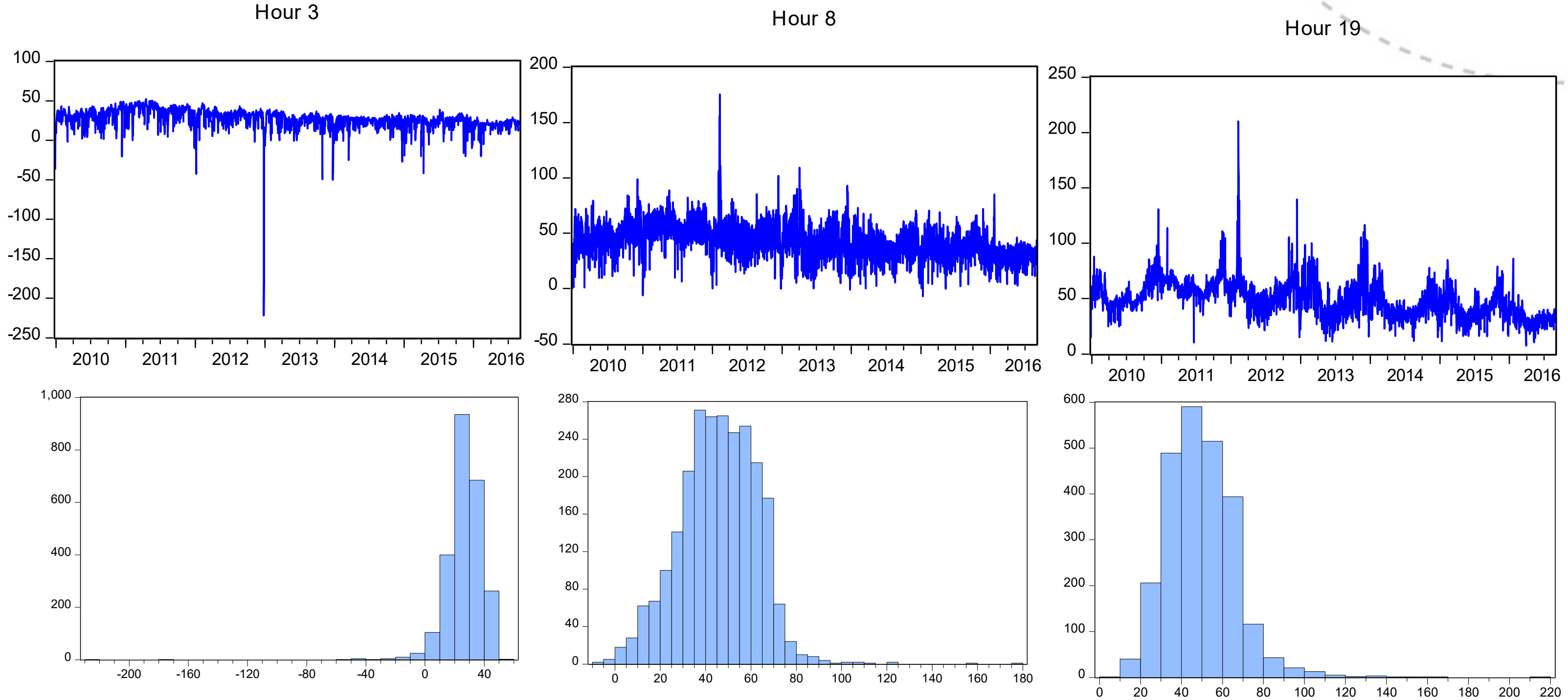
Forecasting Price Distribution in the German Electricity Market

Presentation Energy Finance Christmas Workshop (EFC17)
13-15 December 2017, Kraków, Poland



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Outline

- Introduction
- Literature review
- The German electricity market
- Data analysis
- Econometric methods and procedures
- Results
- Conclusions and further research

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The Economist 25Feb17

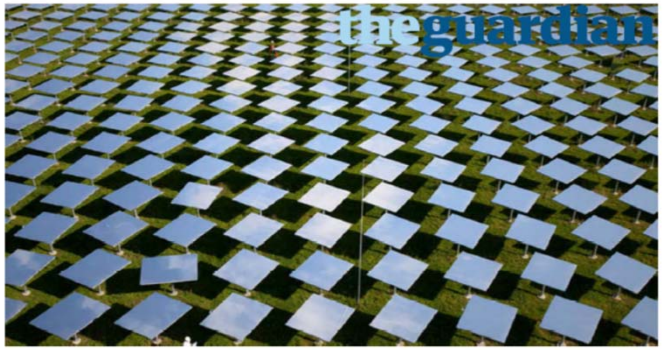
Renewable energy

A world turned upside down

Wind and solar energy are disrupting a century-old model of providing electricity. What will replace it?

Print edition | Briefing Feb 25th 2017 | WILDPOLDSRIED

The Guardian 17June17



Record levels of green energy in UK create strange new world for generators

As renewables play a greater role in the British market, they are making the price of power increasingly unstable

Adam Vaughan

Saturday 17 June 2017 16.43 BST

Why modelling and predicting electricity price distributions?

Bloomberg 30Oct17

There Was So Much Wind Power In Germany This Weekend, Consumers Got Free Energy

By Jesper Starn

30. oktober 2017 14:00

From

The Independent 27Oct17

Environment

Germany set to pay customers for elect usage as renewable energy generation creates huge power surplus

Output from wind turbines forecast to hit record on Sunday

Jesper Starn | Friday 27 October 2017 08:29 BST | 20 comments

Introduction

Electricity prices are challenging…..

- Electricity is <u>non-storable</u> by nature, and a stable power system requires a <u>constant demand & supply balance</u>
- This makes electricity a unique commodity with <u>complex price dynamics and non-linear relations to fundamentals</u>
- Prices are characterised by sudden (positive and negative) <u>spikes</u>, high <u>volatility</u> and volatility clustering, and <u>seasonality patters</u> over hours, days, weeks, months, and years
- The <u>input mix</u> to electricity generation might change over time, hence also the price dynamics at different seasons
- Thus, <u>forecasting prices and price distributions</u> in electricity markets is arguably more <u>challenging</u> than in traditional financial markets.

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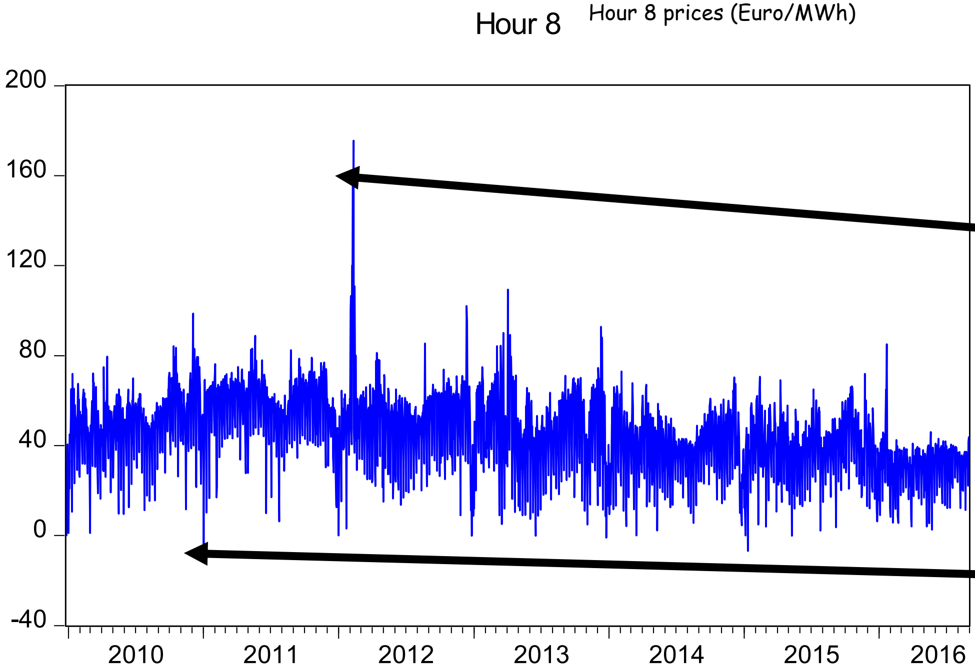
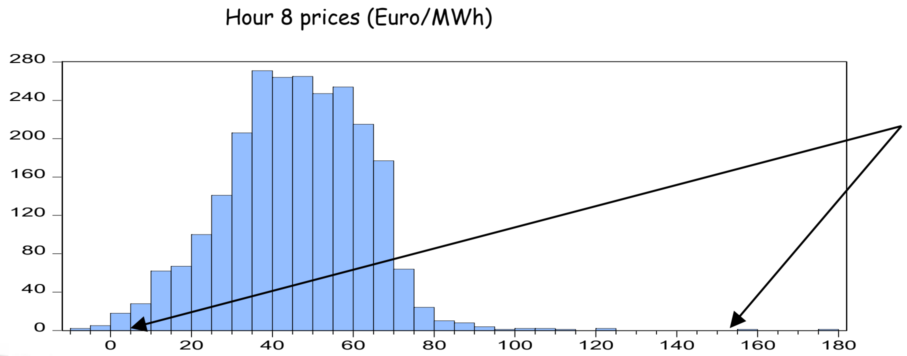
Introduction



Loss for a consumer or trader having a short electricity position.

Loss for a producer or trader having a long electricity position.



We are hence trying to model and forecast the upper and lower tail of the price distribution using standard risk measures such as Value at Risk for different quantiles (1%, 5%, 10%, 90%, 95%, 99%).

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Introduction

- Price forecasts serve as aids for producers, consumers, retailers, and speculators who seek to determine their optimal short-term strategies for production, consumption, hedging and trading
- Uncontrolled exposure to market price risk can have devastating consequences for market participants (see Deng and Oren (2006) for a discussion)
- This has led to an increased focus on risk management in power markets the last years, hence the forecast of the distribution

Introduction

- Over the last 15 years, the bulk of research has been concerned with predicting the mean of electricity prices. As stakeholders require explicit control of the risk of both high and low extreme prices, point forecasts are inadequate in many cases (see Nowotarski and Weron (2017) for more details)

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Introduction

We have also chosen to look at the German market for several reasons;

1. It is probably the most important electricity market in Europe
2. Data quality, transparency, and access are excellent
3. The input mix of production towards renewables has changed a lot over the years, challenging us to build models that capture this dynamics

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Introduction – What do we do?

- In this paper we model and forecast Value at Risk (VaR) for the German EPEX spot price using variable selection with quantile regression (Koenker and Basset (1978), exponential weighted quantile regression (Taylor 2008a,b), exponential weighted double kernel quantile regression (Taylor 2008a,b), GARCH models with skewed t error distributions (Giot and Laurent (2003), and various CAViaR models (Engle and Manganelli (2004)).

- We form a set of fundamental factors (supply and demand variables) and perform a variable selection procedure for each trading period and quantile with the aim of (1) proper in- sample fit, and (2) optimal out-of-sample fit for a given hour and a given quantile.

- Hence, in additional to the dimension of model choice, we stress the fact variable selection should be carefully monitored as different fundamentals influence hours and quantile differently.

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Literature Review

We position ourselves between the following groups of literature;

- VaR forecasting of energy commodities
- Fundamental analysis of electricity price formation.

Kuester et al. (2006) and Serena et al. (2012) provide a comprehensive review of VaR prediction strategies that can solve the complex issue of high frequency asset price returns. They groups the model alternatives into 3 categories:

- ***Fully parametric models*** *assuming a given error distribution. (e.g. a GARCH-skew-t model, EVT, CaviaR models etc.)*

- ***Non parametric approaches*** *such as Historical simulation where one computes empirical quantiles based on past data. Historical simulation can be filtered taking into account time-varying volatility*

- ***Semi-parametric models*** *such as Quantile regression that directly models specific quantiles with no assumption regarding the error distribution.*

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Literature Review

Some relevant models examples of energy price and distribution modelling and forecasting:

- Giot and Laurent (2003). GARCH with different error distributions.
- Garcia et al. (2005). GARCH-ARIMA models.
- Bystrom (2005). GARCH-EVT models.
- Chan and Gray (2006). GARCH-EVT models.
- Karakatsani and Bunn (2008). State Space models with Kalman filter.
- Fuss et.al. (2010)). GARCH , Historical simulation, Cornish Fisher, and CaViaR models.
- Lundby and Uppheim (2011). Quantile Regression.
- Paraschiv et al. (2014). State Space models with Kalman Filter.
- Nowotarski and Weron (2014). Quantile regression averaging.

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Literature Review

Some relevant models examples of energy price and distribution modelling and forecasting:

- Huisman at al (2015a,b). Non-linear models.
- Huisman at al (2015c). State Space models with Kalman filter.
- Gurrola-Perez and Murphy (2015). Historical Simulation and Filtered Historical Simulation.
- Bunn et al. (2016). Quantile regression, GARCH, and CaViAR models.
- Hagfors et al. (2016a,b). Quantile regression.
- Hagfors et al. (2016c). Limited dependent variable models.
- Keles et al. (2016). Neural Networks.
- Maciejowska and Weron (2016). Factor quantile regression averaging
- Maciejowska et al., (2016). Factor quantile regression averaging
- Paraschiv and Hadzi-Mishev (2016). GARCH-EVT models.

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Literature Review

- Review papers on electricity spot price and distributional forecasting include Weron (2014) and Nowotarski and Weron (2017).
- "Academics and practitioners have come to understand that probabilistic electricity price forecasting is now more important for energy systems planning, risk management and operations than ever before" (Nowotarski and Weron (2017)).
- Despite the importance of measure value at risk in power markets, Weron (2014) and Nowotarski and Weron (2017) finds that distribution forecasting is "barely touched upon" in electricity price forecasting literature.
- Maciejowska et al. (2016) claim that the lack of such research is likely due to the embedded complexity of the research problem compared to point forecasting
- This statement is also supported by Bunn et al. (2016), who argue that for electricity markets, VaR forecasting remains a highly "under-researched" area.
- These observations forms the motivation for our research and we aim to contribute into this context

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The German Spot Electricity Market

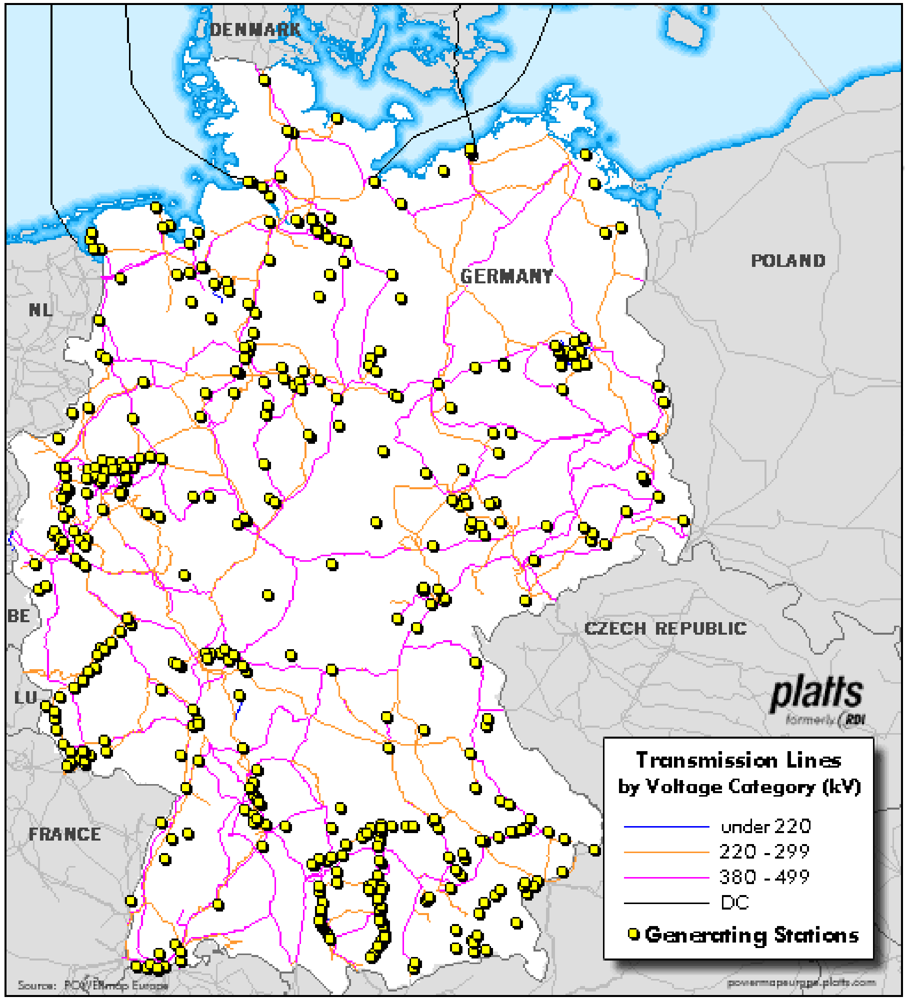
- One area price, 24 hourly prices each day

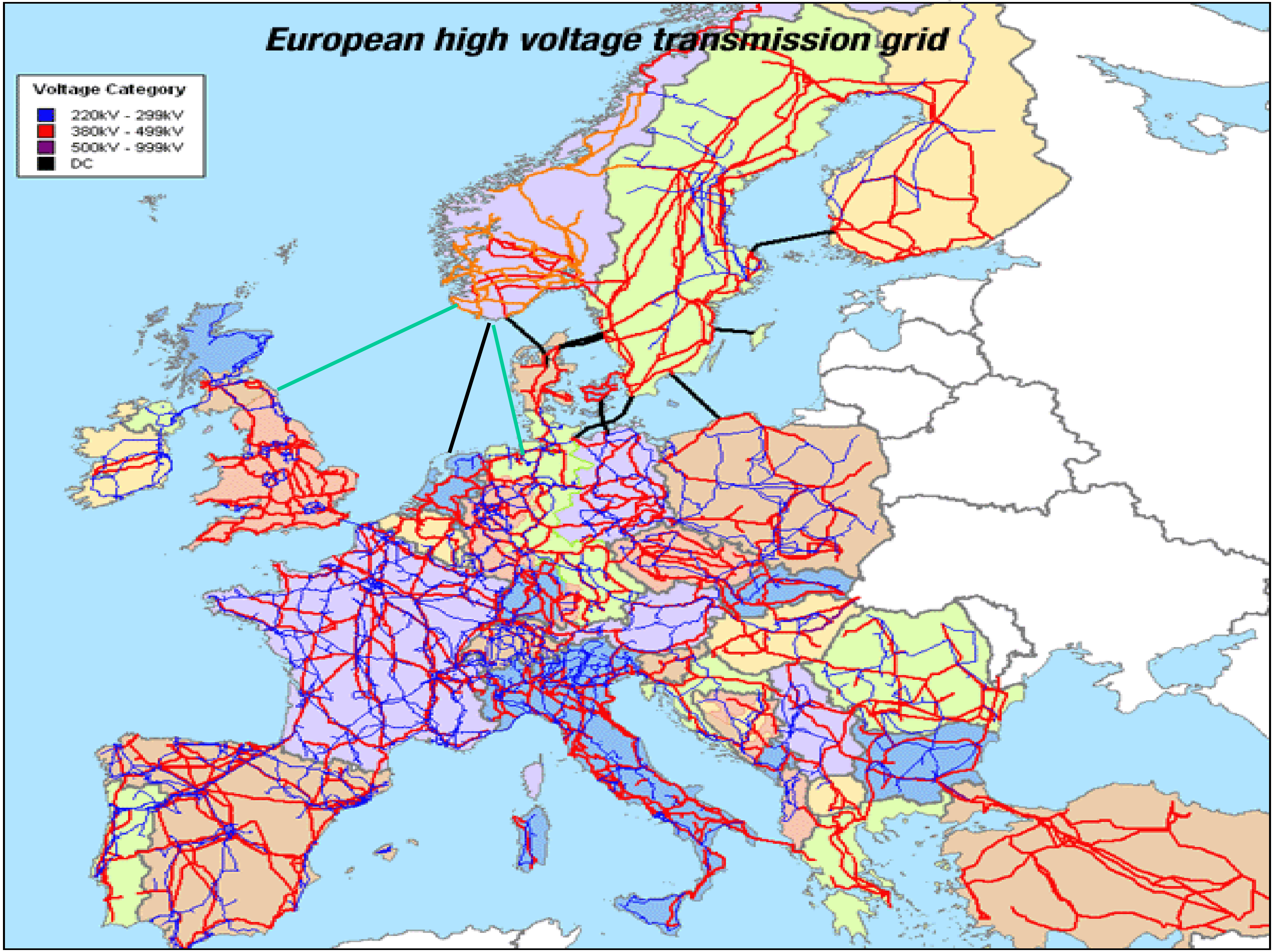
- Auction market where the physical delivery of power takes place on the next day

- The spot market for electricity is operated by **EPEX SPOT** in Germany (known as the Phelix market)

- On each day of the year, EPEX SPOT operates day ahead auctions (1200 o'clock) for three market areas: Germany/Austria, France and Switzerland (the day-ahead market)

- Participants in the market can buy up to 45 minutes before every hour electricity for the specific hour (the balancing market). This market operates 24/7 without exceptions. The electricity for the next day can be traded from 15:00 onwards.




European high voltage transmission grid
Voltage Category
220kV - 299kV
380kV - 499kV
500kV - 999kV
DC

The German Spot Electricity Market

Source	2010	2011	2012	2013	2014	2015	2016
Coal	41.6	42.9	44.1	45.2	43.8	42.1	40.3
Nuclear	22.2	17.6	15.8	15.3	15.5	14.2	13.1
Natural gas	14.1	14.1	12.2	10.6	9.7	9.6	12.4
Oil	1.4	1.2	1.2	1.1	0.9	1.0	0.9
Renewable energies:	16.5	20.1	22.6	23.7	25.8	29.0	29.0
Wind	6.0	8.0	8.1	8.1	9.1	12.3	11.9
Solar	1.9	3.2	4.2	4.9	5.7	6.0	5.9
Biomass	4.6	5.2	6.1	6.3	7.7	6.9	7.0
Hydro power	3.3	2.9	3.5	3.6	3.1	2.9	3.2
Waste to energy	0.7	0.8	0.8	0.8	1.0	0.9	0.9
Other	4.2	4.1	4.1	4.1	4.3	4.1	4.2

Table 3.1: Electricity production in Germany by source (%). Data from AG Energibalanzen e.V. (2017) anc
Clean Energy Wire (2017).

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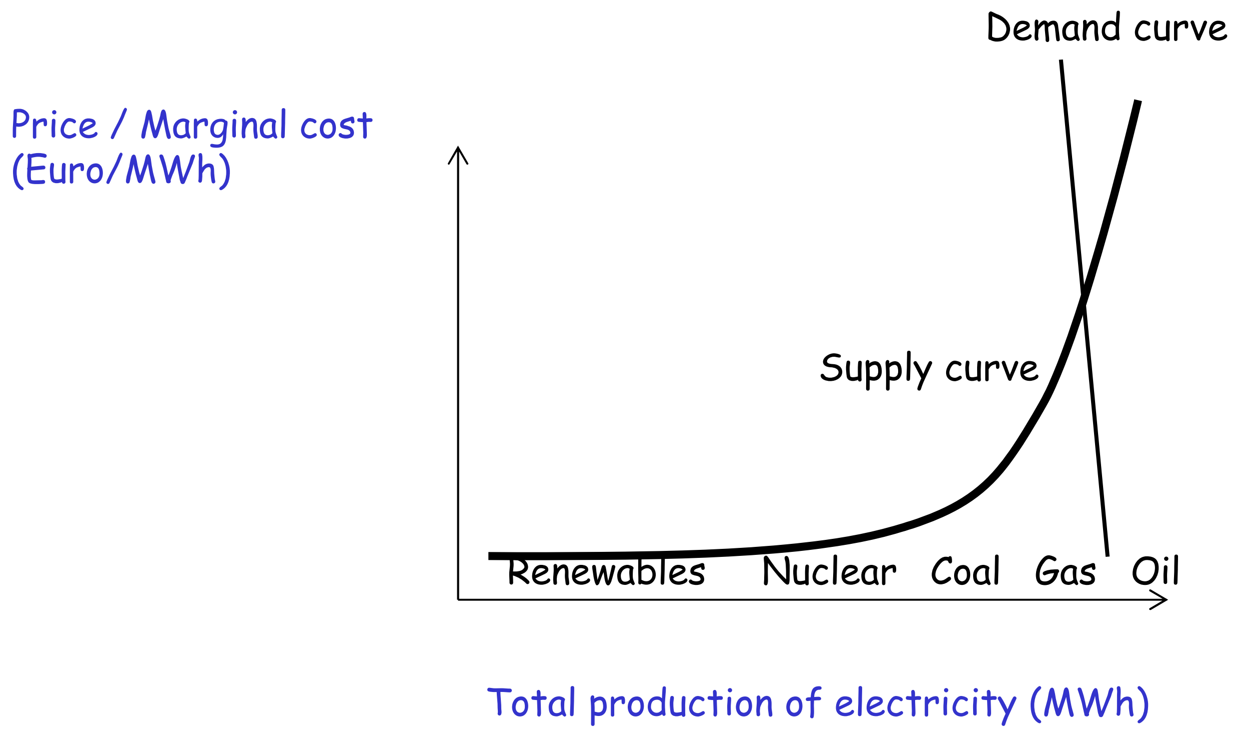
The German Spot Electricity Market



The Merit order curve

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Data Analysis

Variable	Daily	Hourly
Phelix spot price		X
Coal price	X	
Gas price	X	
Oil price	X	
CO_2 allowance price	X	
EU Expected wind		X
Expected solar (PV) infeed		X
Expected power plant availability (PPA)	X	
Expected demand		X

Table 4.1: Data granularity for our dependent and independent variables used in the analysis. We apply hour 3,8, and 19 with the associated forecasts in our analysis. The data period is from 1Jan2010 to 31Aug2016.

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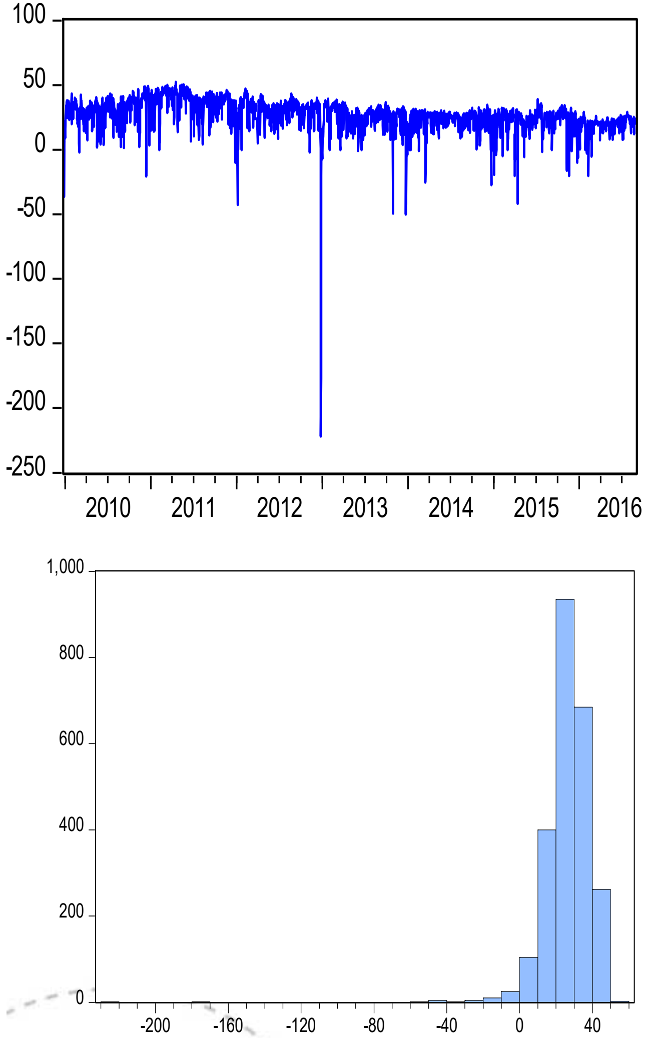
Variable	Units	Description	Data Source
Spot price	EUR/MWh	Market clearing price	European Energy Exchange: http://www.eex.com
Coal price	EUR/12,000 t	Latest available price (daily auctioned) of the front-month ARA futures contract before the electricity price auction takes place	European Energy Exchange: http://www.eex.com
Gas price	EUR/MWh	Latest price of the NCG Day Ahead Natural Gas Spot Price on the day before the electricity price auction takes place	Bloomberg, ticker: EGTHDAHD Index
Oil price	EUR/bbl	Latest price of the active ICE Brent Crude futures contract on the day before the electricity price auction takes place	Bloomberg, ticker: CO1 Comdty
CO2 price	EUR 0.01/EUA 1,000 t CO2	Latest available price of the EEX Carbon Index (Carbix), daily auctioned at 10.30 am	European Energy Exchange: http://www.eex.com
Expected wind and PV infeed	MWh	Sum of expected infeed of wind electricity into the grid, published by German transmission systems operators in the late afternoon following the electricity price auction	Transmission system operators: http://www.50Hertz.com, http://www.amprion.de, http://www.transnetbw.de, http://www.tennettso.de
Expected PPA	MWh	Forecast of expected power plant availability production (voluntary publication) on the delivery day (daily granularity), published at 10:00 am	European Energy Exchange & transmission energy operators: ftp://infoproducts.eex.com
Expected demand	MWh	Sum of the total vertical system load and actual wind infeed for the same hour on the last relevant delivery day	Transmission system operators: http://www.50Hertz.com, http://www.amprion.de, http://www.transnetbw.de, http://www.tennettso.de

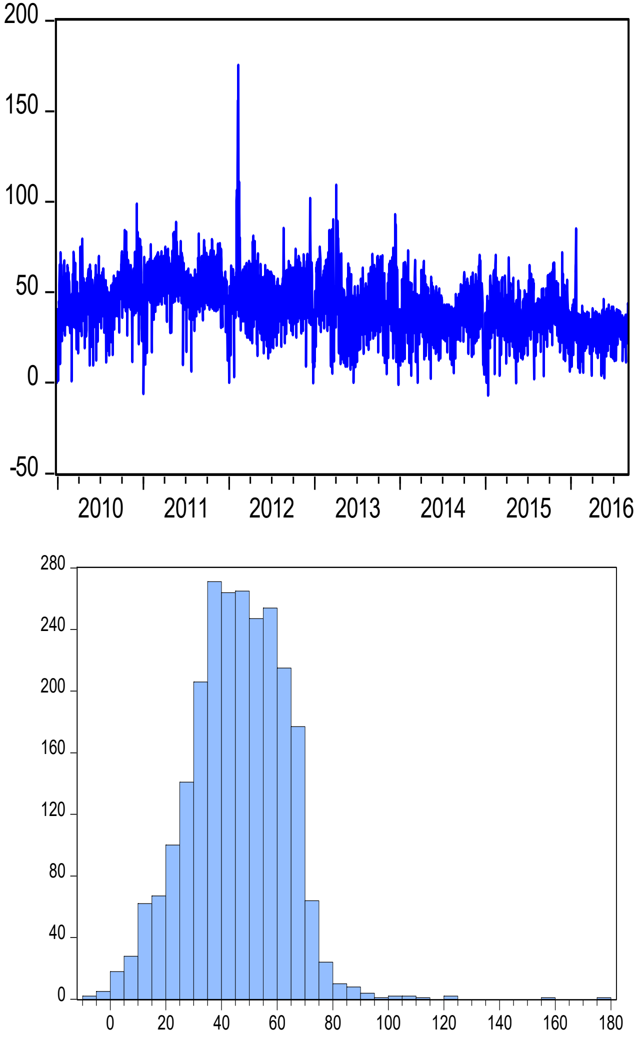
Table 4.2: Description of dependent and independent variables used in our analysis. We apply hour 3,8, and 19 with the associated forecasts in our analysis. The data period is from 1Jan2010 to 31Aug2016.

The dependent variables

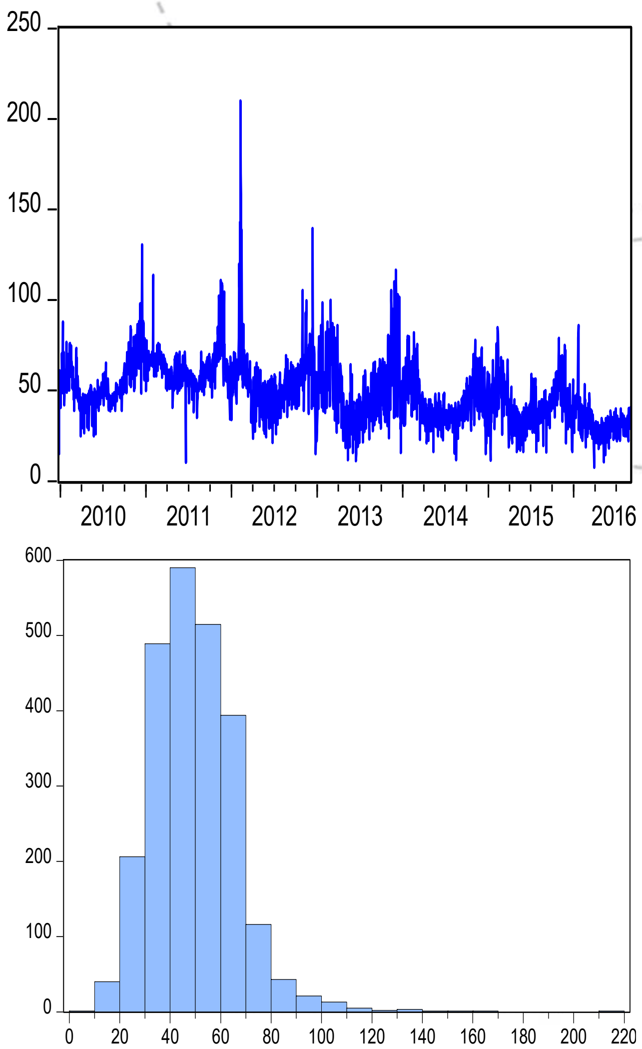
Hour 3



Hour 8



Hour 19



Hour 3	Median	Mean	Min	Max	Std.div.	Skewness	Kurtosis
2010	29.83	27.63	-18.10	50.15	10.60	-0.77	3.47
2011	38.58	34.85	-0.10	51.08	10.71	-1.10	3.47
2012	30.08	26.21	-221.94	45.20	20.99	-8.11	86.69
2013	25.90	23.29	-62.03	39.67	10.78	-2.03	13.98
2014	23.98	21.14	-60.26	34.46	9.00	-3.09	23.16
2015	24.02	21.29	-31.41	34.92	9.21	-1.82	7.73
2016	20.10	18.48	-19.30	30.01	6.27	-1.99	8.95
Total	25.67	25.00	-221.90	51.08	13.10	-5.37	84.24

Hour 8	Median	Mean	Min	Max	Std.div.	Skewness	Kurtosis
2010	51.55	50.07	1.06	98.71	14.66	-0.50	3.83
2011	60.63	57.44	-5.95	88.78	13.83	-1.18	5.10
2012	53.24	51.38	-0.09	175.55	19.35	1.15	10.20
2013	46.61	46.71	-0.98	109.36	18.14	-0.10	3.02
2014	41.03	39.65	0.05	72.94	13.81	-0.35	2.82
2015	40.46	38.85	-6.86	71.92	13.88	-0.43	3.05
2016	34.10	31.17	2.59	85.05	10.53	0.03	5.86
Total	46.37	45.76	-6.86	175.60	17.21	0.19	2.02

Hour 19	Median	Mean	Min	Max	Std.div.	Skewness	Kurtosis
2010	50.85	53.52	24.76	95.00	10.78	0.92	4.15
2011	62.53	62.37	21.49	117.49	9.79	0.20	6.20
2012	55.00	56.39	13.70	169.90	15.85	1.87	12.79
2013	49.55	51.29	9.28	120.16	15.67	0.85	4.45
2014	42.44	44.20	14.34	81.51	11.56	0.67	3.73
2015	42.11	42.53	10.55	98.05	11.39	0.44	4.40
2016	33.15	33.04	11.79	70.03	6.99	0.75	6.74
Total	48.95	49.85	9.28	169.90	14.99	0.74	2.65

Table 4.3: Descriptive statistics of EPEX spot prices hour 3,8, and 19 measured in Euros. The tables show the characteristics based on daily data each year from 1Jan2010 to 31Aug2016 (that is summary statistics are only given for part of 2016).

The in-dependent variables

Hour 3	Median	Mean	Min	Max	Std.div.	Skewness	Kurtosis
Wind	4491	6067	286	37322	5265	1.9	7.4
Solar	0.0	0.1	0.0	255.0	5.2	49.3	2433
Demand	31078	31219	19127	45071	3821	0.2	3.1
Coal	60.4	64.2	37.6	99.0	14.1	0.3	2.2
Gas	22.1	21.4	11.0	39.5	4.7	-0.3	2.7
Oil	45.3	40.4	15.0	56.7	10.1	-0.6	2.1
Co2	7.2	8.5	2.7	16.8	3.8	0.8	2.3
PPA	55531	55323	40016	64169	4863	-0.2	2.1

Hour 8	Median	Mean	Min	Max	Std.div.	Skewness	Kurtosis
Wind	4075	5875	229	35663	5399	1.8	6.9
Solar	2087	3011	0.0	11665	2849	0.8	2.6
Demand	48673	45193	22783	62594	7800	-0.8	2.3
Coal	60.4	64.2	37.6	99.0	14.1	0.3	2.2
Gas	22.1	21.4	11.0	39.5	4.7	-0.3	2.7
Oil	45.3	40.4	15.0	56.7	10.1	-0.6	2.1
Co2	7.2	8.5	2.7	16.8	3.8	0.8	2.3
PPA	55531	55323	40016	64169	4863	-0.2	2.1

Hour 19	Median	Mean	Min	Max	Std.div.	Skewness	Kurtosis
Wind	4473	6101	270	33522	5225	1.7	6.3
Solar	74.0	736	0.0	4730	1047	1.3	3.5
Demand	45947	45496	30768	60966	5840	-0.3	2.4
Coal	60.4	64.2	37.6	99.0	14.1	0.3	2.2
Gas	22.1	21.4	11.0	39.5	4.7	-0.3	2.7
Oil	45.3	40.4	15.0	56.7	10.1	-0.6	2.1
Co2	7.2	8.5	2.7	16.8	3.8	0.8	2.3
PPA	55531	55323	40016	64169	4863	-0.2	2.1

Table 4.4: Descriptive statistics of fundamental variables used in the analysis. Note that coal, gas, oil, $CO2$ and PPA has a daily data granularity, and therefore show the same numbers for all hours. The calculations are based on daily data from EPEX from 1Jan2010 to 31Aug2016.

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Correlations between dependent and in-dependent variables at different hours

Hour	Wind	Solar	Demand	Coal	Gas	Oil	Co2	PPA
3	-0,571	-0,003	0,264	0,370	0,151	0,222	0,316	-0,074
8	-0,378	-0,224	0,699	0,441	0,300	0,321	0,308	0,132
19	-0,394	-0,368	0,538	0,553	0,425	0,427	0,336	0,182

Table 4.5: Correlation between spot prices and fundamental variables. The calculations are based on daily data from EPEX from 1Jan2010 to 31Aug2016.

Econometric Methods and Procedures

- **We implement (using R and Matlab) three different quantile regression models, one GARCH model, and two CaViaR models;**

    - Traditional quantile regression (QR)
    - Exponential weighted quantile regression (EWQR)
    - Exponential weighted double kernel quantile regression (EWDKQR)
    - GARCH(1,1) with skewed student-t distribution (GARCH-T)
    - Symmetric absolute value CAViaR (SAV CAViaR)
    - Asymmetric slope CAViaR. (AS CaViaR)

Econometric Methods and Procedures

- We model and predict the 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95%, 99% quantiles

- Each model might have a different set of independent variables (among the described variables) according to given selection criteria (see later discussion). The general model has all in-dependent variables plus lagged values of prices

- The specific set of independent variables varies according to the specific model chosen, hour of the day and quantile that is modelled

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Econometric Methods and Procedures

- **Evaluation of models out of sample:**
  - Unconditional coverage test (Kupiec (1995))
  - Conditional coverage test (Christoffersen (1998))
  - Dynamic conditional quantile tests (Engle and Manganelli (2004))

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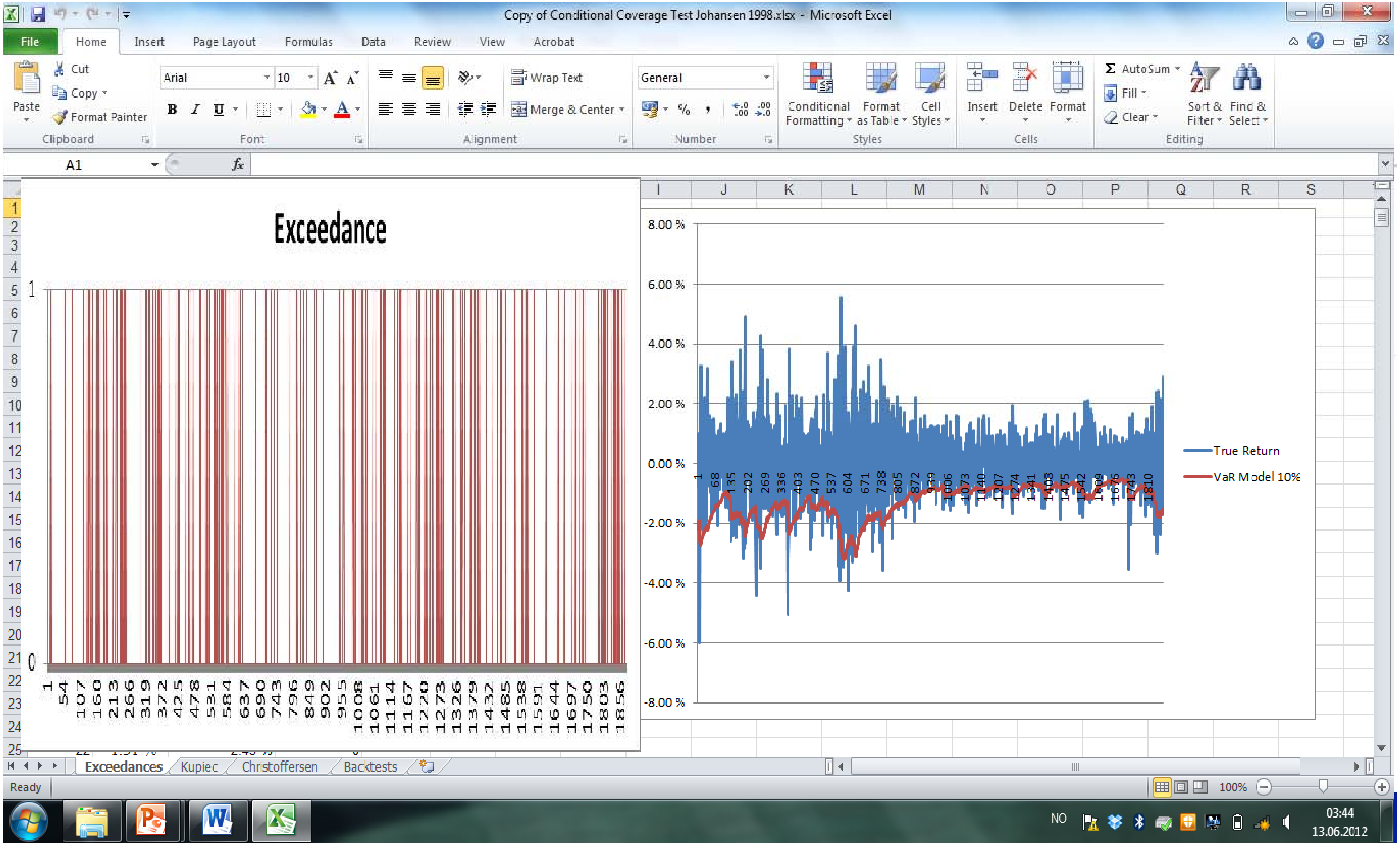
Econometric Methods and Procedures



Econometric Methods and Procedures

- Variable selection (models for each model, hours, and quantile)
- We choose models with a minimal rejections according to the out of sample criteria and, at the same time, have the lowest SIC score in sample (following the recommendations from Diebold (2017))
- We use a rolling window size of 2 years starting at the beginning of the data

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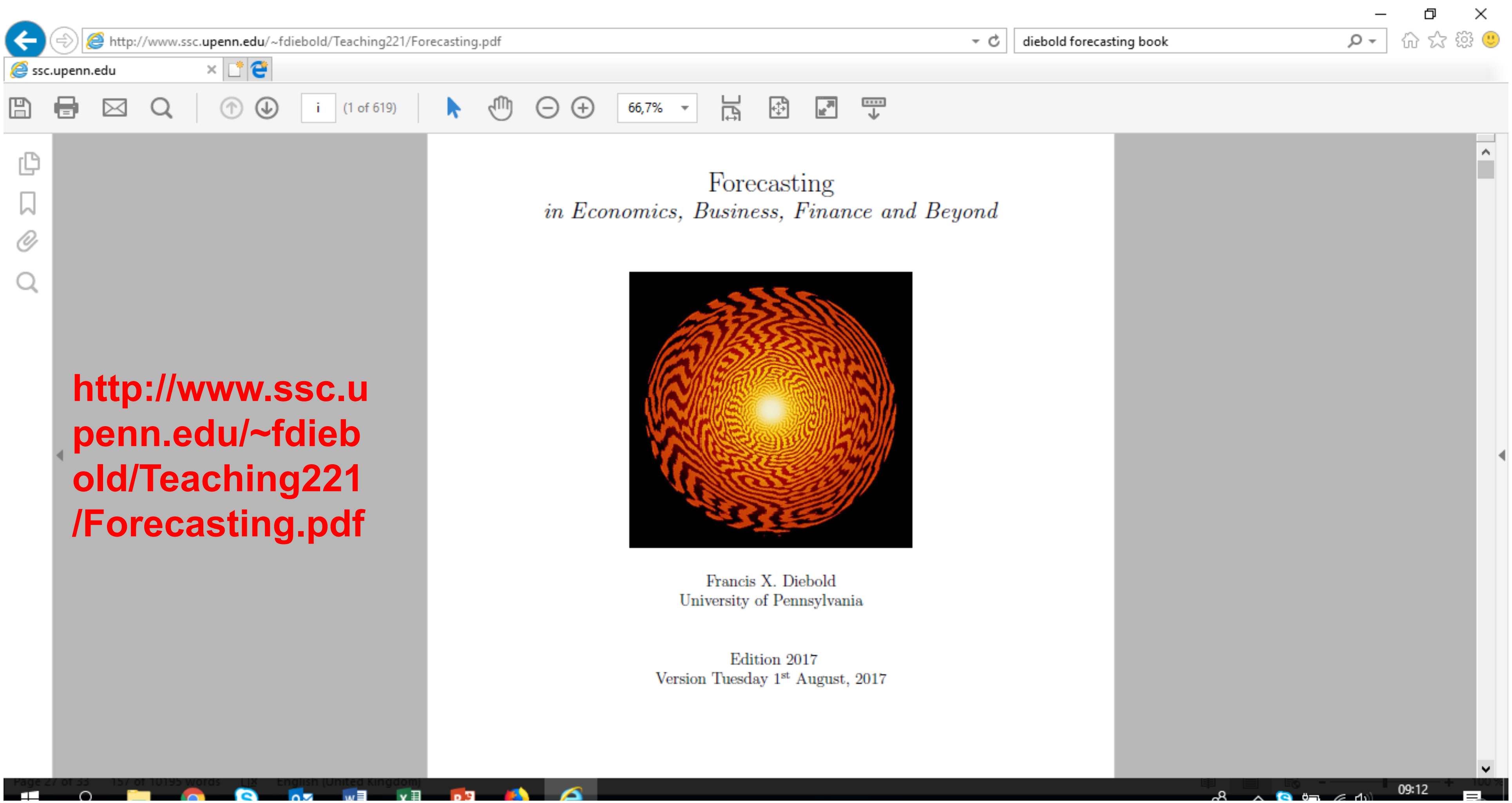
Econometric Methods and Procedures

- Free draft of new boom from Diebold:



Results

- Variable selection differs w.r.t different hours and quantiles (general results):
  - Wind is the best predictor for hour 3
  - Demand is the best predictor for hour 8 and 19
  - Coal and lagged prices improves forecast for all hours
  - More variables and lagged price dynamics are needed to improve conditional coverage

Results

	UC (27)	CC (27)	DQ1 (27)	DQ2 (27)	Total (108)
EWQR	2	14	16	9	41
QR	5	17	18	8	48
SAV CAViaR	5	15	16	13	49
EWDKQR	2	19	19	10	50
GARCH-T	9	17	12	19	57
AS CAViaR	8	21	18	12	59

Table 6.4: Total number of test rejections per model over all quantiles and periods. The table displays the total number of test rejections per model at the 5% significance level. The numbers in parentheses give the maximum number of rejections. A high number of rejections indicates poor calibration. UC is the unconditional coverage test, CC is the conditional coverage test, and DQ1 and DQ2 are the two dynamic conditional quantile tests, as described in Section 5. The models are also described in section 5.

Results

Rating	Model	Rejections
1	EWQR	12
2	QR	15
3	GARCH-T	16
4	EWDKQR	18
5	AS CAViaR	18
6	SA CAViaR	19

Hour 3 (36)

Rating	Model	Rejections
1	EWQR	17
2	EWDKQR	18
3	QR	20
4	SA CAViaR	21
5	GARCH-T	25
6	AS CAViaR	30

Hour 8 (36)

Rating	Model	Rejections
1	SA CAViaR	9
2	AS CAViaR	11
3	EWQR	12
4	QR	13
5	EWDKQR	14
6	GARCH-T	16

Hour 19 (36)

Table 6.5: Total number of test rejections per hour. The table displays the total number of test rejections per model at the 5% significance level. The numbers in parentheses give the maximum number of rejections. A high number of rejections indicates poor calibration.

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Results

Rating	Model	Rejections
1	EWDKQR	8
2	EWQR	9
3	SA CAViaR	9
4	GARCH-T	11
5	QR	12
6	AS CAViaR	17

Lower tail (36)

Rating	Model	Rejections
1	QR	17
2	EWQR	19
3	AS CAViaR	20
4	EWDKQR	22
5	SA CAViaR	25
6	GARCH-T	31

Mid-region (36)

Rating	Model	Rejections
1	EWQR	13
2	GARCH-T	15
3	SA CAViaR	15
4	QR	19
5	EWDKQR	20
6	AS CAViaR	22

Upper tail (36)

Table 6.6: Total number of test rejections in sections of the distribution. The table displays the total number of test rejections per model at the 5% significance level. The numbers in parentheses give the maximum number of rejections. A high number of rejections indicates poor calibration.

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Conclusion

No model is "perfect", clustering of exceedances seems to a remaining issue….

- Exponential weighted quantile regression gives the overall best results compare to GARCH-T and CaViaR models

- Hour 8 is most difficult to model, Hour 19 is the easiest to model

- Lower tail is most difficult to model.

Conclusion

- In this paper, our aim have been to forecast VaR for the German EPEX spot price using various set of fundamentals and econometric models such as quantile regression, exponential weighted quantile regression, exponential weighted double kernel quantile regression, GARCH models with skewed t error distributions, and various CAViaR models.

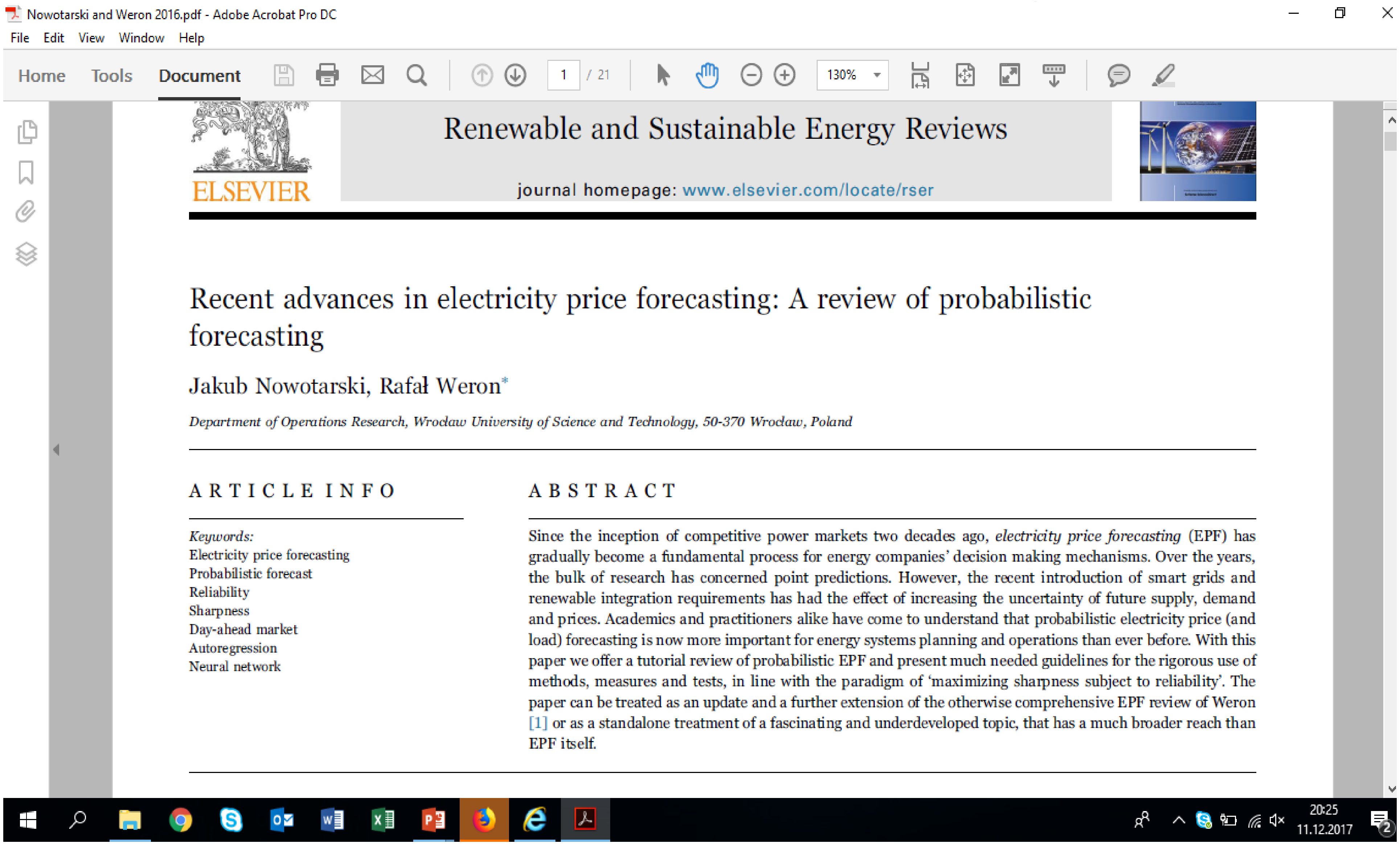
- We optimize the use of exogenous variables for prediction. This is motivated by evidence in literature that the impact of fundamentals differs across the distribution and between trading periods. Our findings highlight the importance of variable selection, and show that it in many cases is as important as the choice of model.

Conclusion

- In general we find that exponential weighted quantile regression is the best model overall based on the total number of test rejections
- Thus we recommend this model together with carefully selecting fundamentals for given hours and quantiles when the aim is to forcast VaR for German electricity prices
- Models should though be improved as there is a remaining issue of clustering of exceedances

Further research

Modelling Electricity Price Distributions



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Recent advances in electricity price forecasting: A review of probabilistic forecasting

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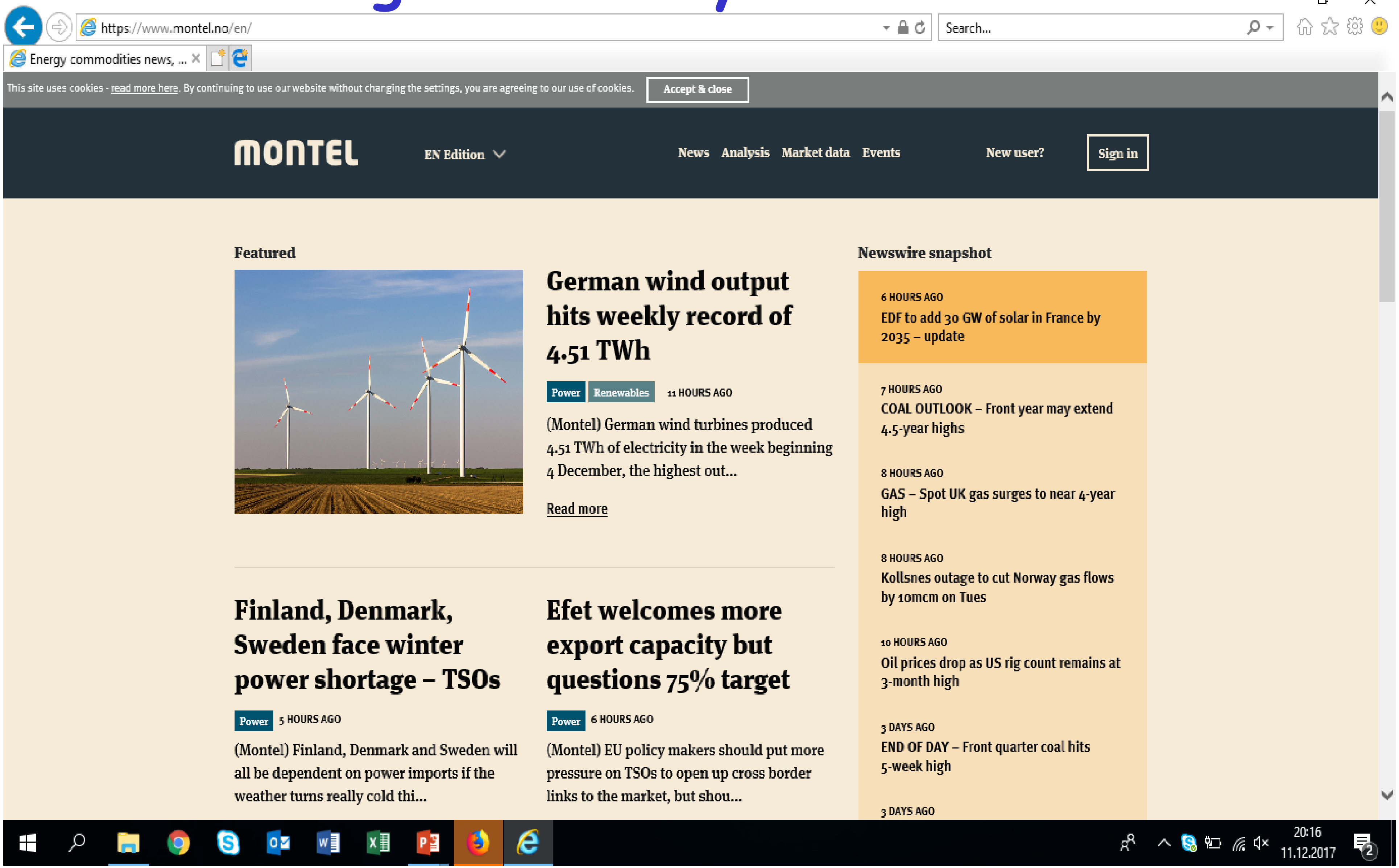
ABSTRACT

Since the inception of competitive power markets two decades ago, *electricity price forecasting* (EPF) has gradually become a fundamental process for energy companies' decision making mechanisms. Over the years, the bulk of research has concerned point predictions. However, the recent introduction of smart grids and renewable integration requirements has had the effect of increasing the uncertainty of future supply, demand and prices. Academics and practitioners alike have come to understand that probabilistic electricity price (and load) forecasting is now more important for energy systems planning and operations than ever before. With this paper we offer a tutorial review of probabilistic EPF and present much needed guidelines for the rigorous use of methods, measures and tests, in line with the paradigm of 'maximizing sharpness subject to reliability'. The paper can be treated as an update and a further extension of the otherwise comprehensive EPF review of Weron [1] or as a standalone treatment of a fascinating and underdeveloped topic, that has a much broader reach than EPF itself.

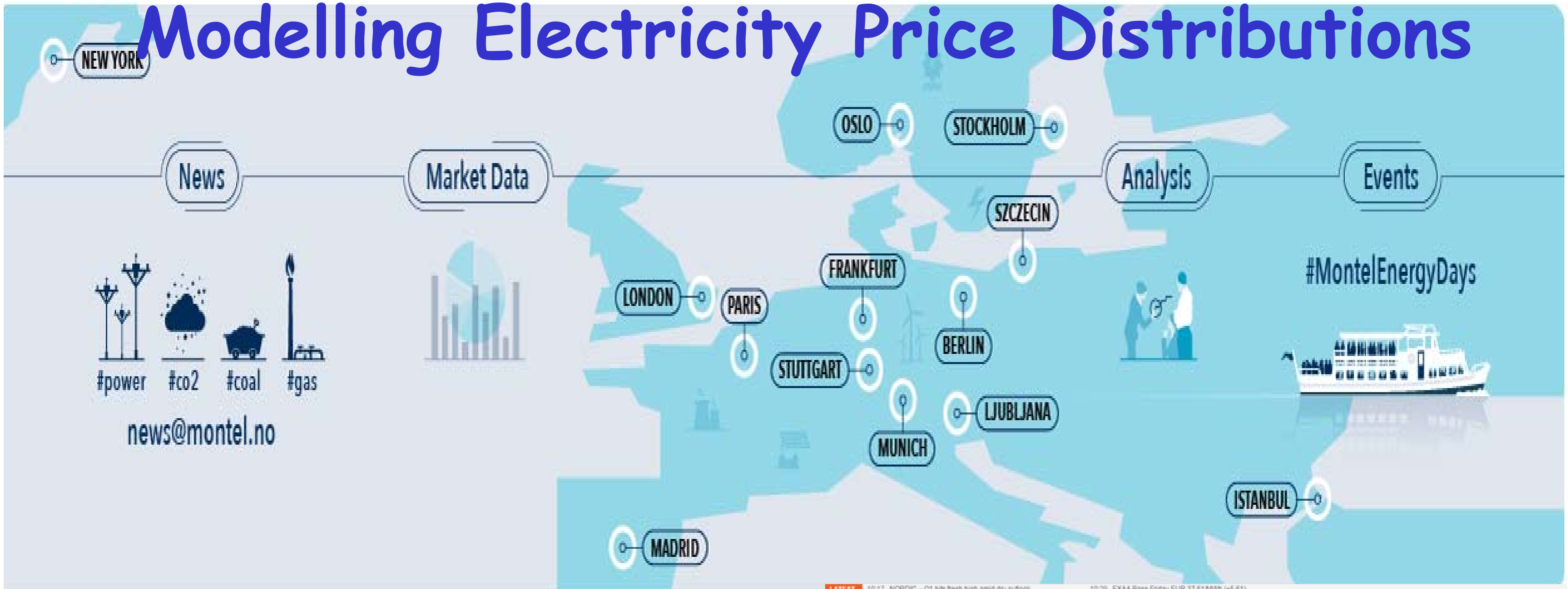
Further research

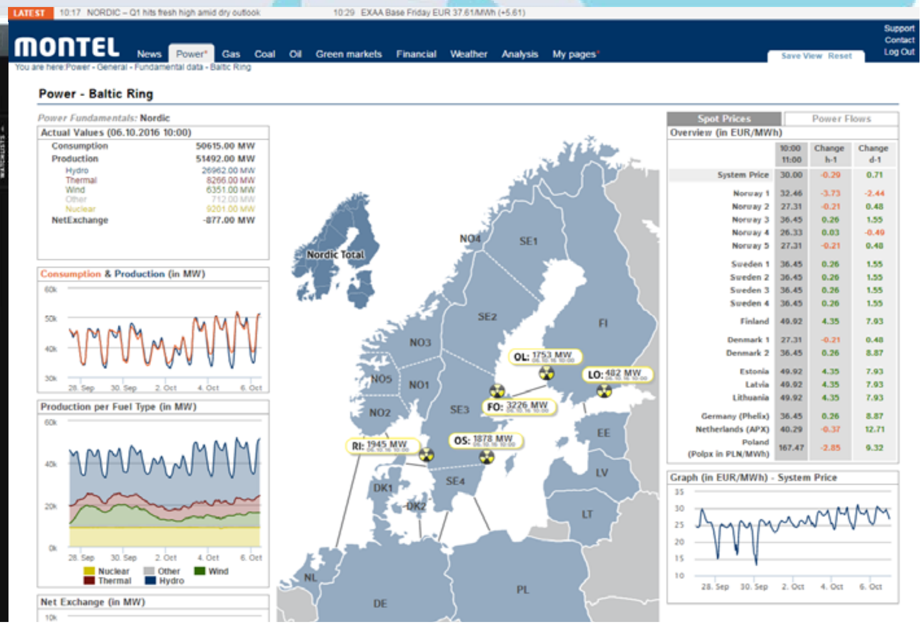
Modelling Electricity Price Distributions



Further research

Modelling Electricity Price Distributions





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