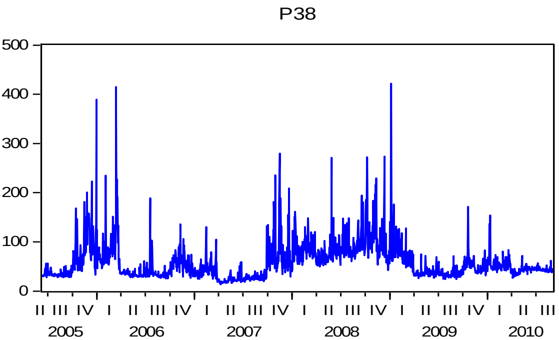
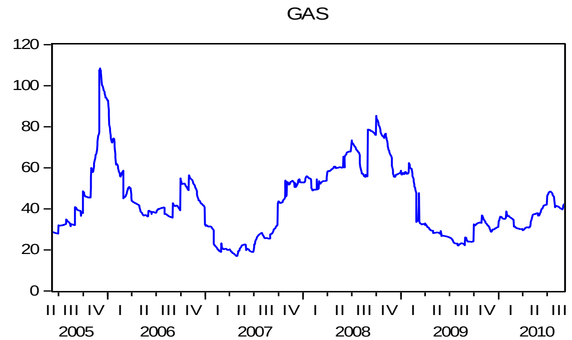
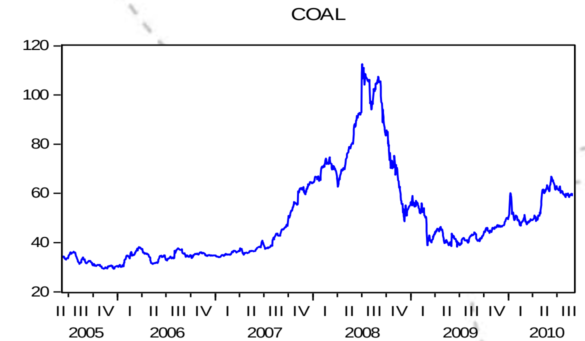
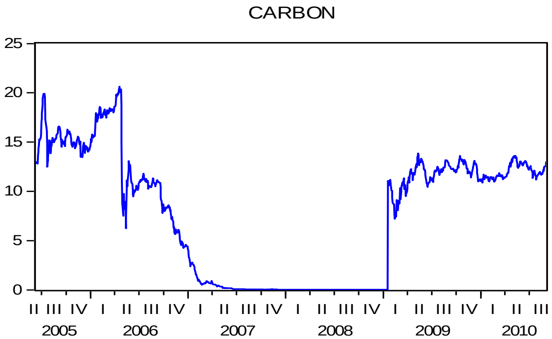
MODELLING AND FORECASTING ELECTRICITY PRICE RISK USING VOLATILITY ADJUSTED QUANTILE REGRESSION

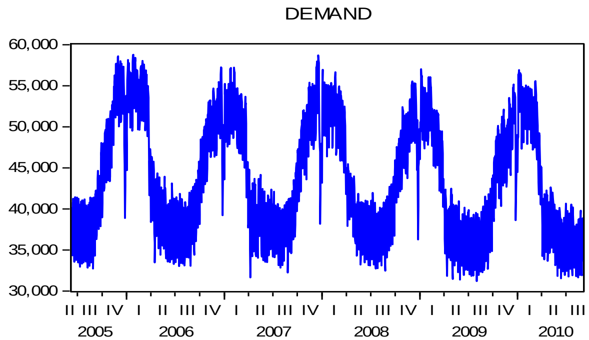
Wroclaw 20 December 2011

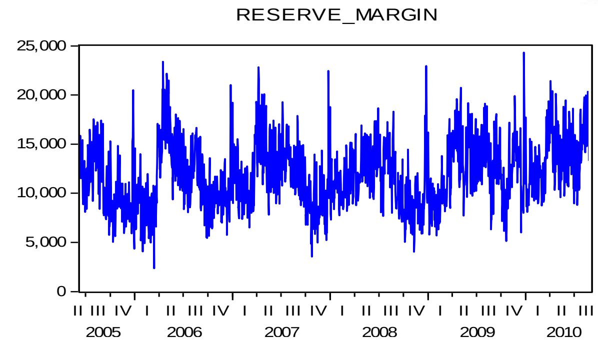












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Outline

- Introduction – Idea of the paper
- Literature
- Fundamental analysis of electricity spot price formation
- Quantile regression
- Data and descriptive statistics
- Price distribution modelling and forecasting
  - In sample analysis
  - Out of sample analysis - Forecasting Value at Risk
- Conclusions and further research
- References

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Introduction – Idea of the paper

- Correct modelling and forecasting of price distributions is important:
    - Forming trading and bidding strategies
    - Risk management

- This paper seeks to characterise the nonlinear effects of exogenous factors on peak hour wholesale electricity price formation as well as forecasting the price distribution.

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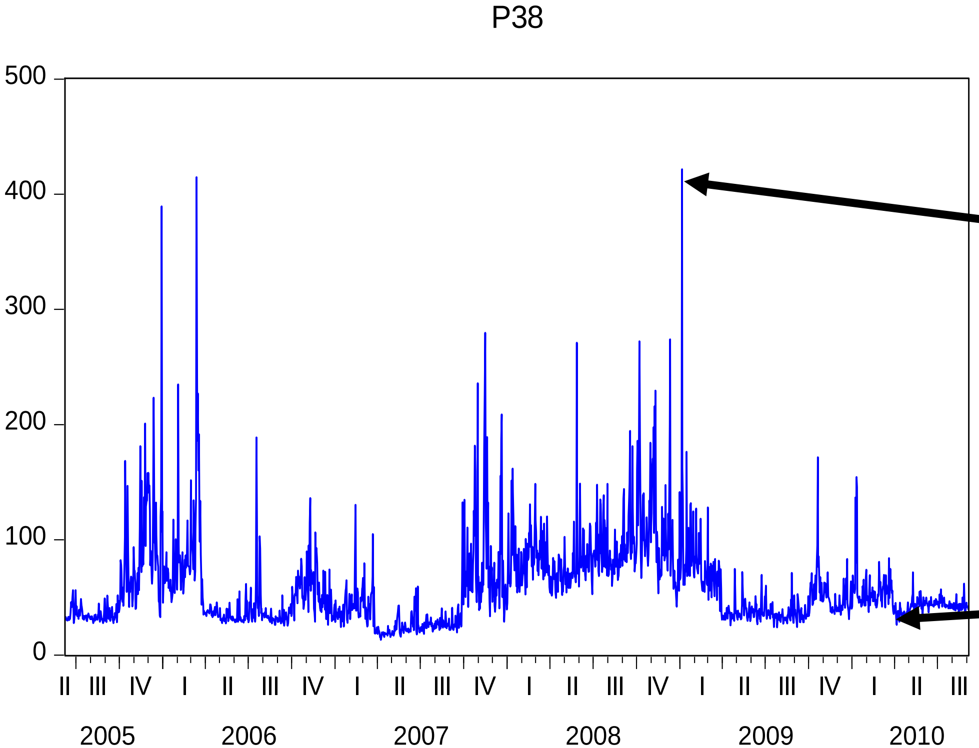
Introduction – Idea of the paper

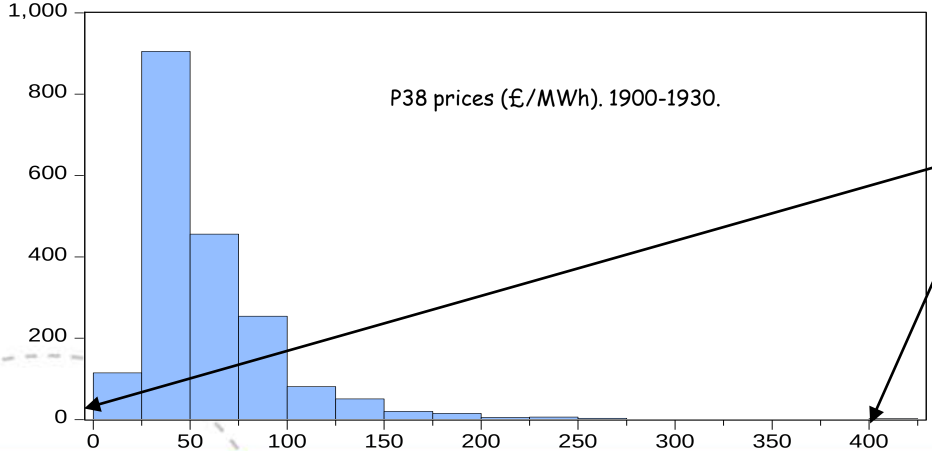
- Using a volatility corrected dynamic quantile regression model for el prices, we capture effects such as
    - Mean reversion
    - Spikes
    - Time varying volatility
    - At the same time, estimate the rather complex relationship to fundamentals (gas/coal/carbon prices, forecasts of demand and capacity).

Introduction - Idea of the paper



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 – Idea of the paper

- **We argue that quantile regression:**

1. Gives a better fundamental understanding of how different determinants affect various quantiles (and hence risk), than for example standard GARCH type of models.

2. Gives relatively satisfactory out of sample forecasts for Value at Risk for both short and long positions compared to GARCH/CaViaR type models at different quantiles.

3. Is easy to implement and understand. It also closely linked to the aim of the analysis, namely to model and predict quantiles.

4. Do not assume any specific form of the error distribution, in fact the distribution is what "comes out" of the model.

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Literature

- **Value at Risk analysis for energy commodities:**
  - Aloui (2008)
  - Chan and Gray (2006)
  - Giot and Laurent (2003)
  - Hung et al. (2008)
- **Stochastic modelling of electricity markets – selected studies:**
  - Bernhardt et al. (2008)
  - Bunn and Karakatsani (2003)
  - Bystrøm (2005)
  - Chang et al. (2008)
  - Escribano et al. (2002)
  - Goto and Karolyi (2004)
  - Hadsell et al. (2004)
  - Higgs (2009)
  - Higgs and Worthington (2005, 2008)
  - Huisman and Huurman (2003)
  - Knittel and Roberts (2001)
  - Koopman et al. (2007)
  - Lucia and Schwartz (2001)
  - Solibakke (2002, 2006)
  - Ullrich (2009)
  - Weron (2008)
  - Weron and Misiorek (2008)
- **Fundamental analysis of the UK electricity market:**
  - Chen (2009)
  - Chen and Bunn (2007)
  - Fezzi and Bunn (2006)
  - Karakatsani and Bunn (2008)
- **Quantile regression in general and applications in financial risk management:**
  - Alexander (2008)
  - Engle and Manganelli (2004)
  - Füss et al. (2009)
  - Hao and Naiman (2007)
  - Koenker and Hallock (2001)
  - Koenker (2005)
  - Taylor (2008)

We want to fill the gap in the literature by performing Value at Risk analysis for the electricity market using quantile regression models based on fundamental market information. According to our knowledge, no such study has been performed yet.

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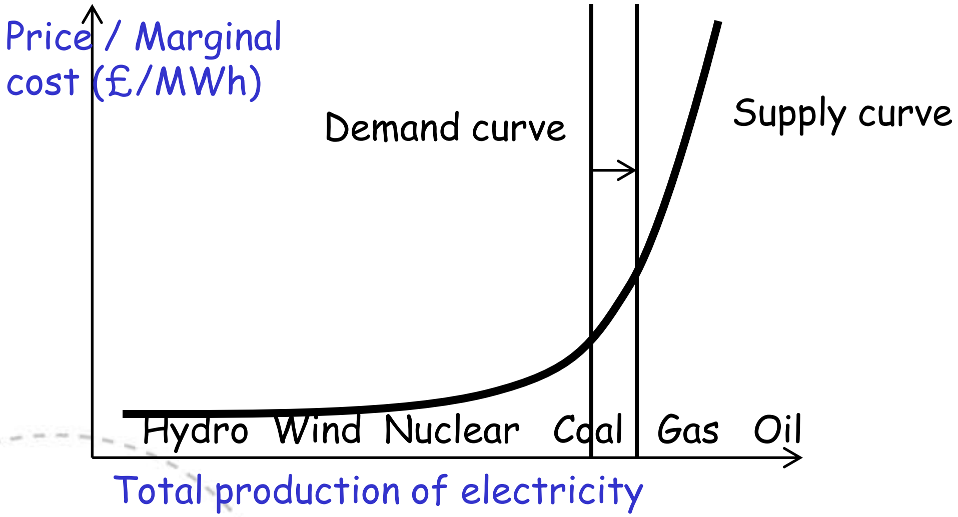
Fundamental analysis of electricity spot price formation

- Demand for electricity is rather in-elastic for "normal" sets of prices ranges

- The supply function is well-known to be convex, steeply increasing and discontinuous. One important reason for this functional form, is that the generator's supply function will tend, in an efficient market, to reflect the merit order of short-run marginal costs, which increase steeply as plant move from baseload to peaking segments of the market.



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Fundamental analysis of electricity spot price formation

The implication of this for the exogenous price drivers are:

- Elasticity's to demand is positive and increase nonlinearly with higher prices

- Elasticity's to reserve margin is negative and decrease nonlinearly with higher prices

- Elasticity's to fuel prices and carbon prices is positive and may be nonlinear with higher prices

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Fundamental analysis of electricity spot price formation

- Electricity prices also show properties of:
  - *Mean reversion*
  - *Volatility clustering*
  - *Seasonal effects (intra year, week, and day).*

- We will therefore include lagged price dynamics, volatility correction and demand seasonality in order to explain electricity price behaviour in addition to fundamental factors.

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Quantile regression

- Quantile regression was introduced by Koenker and Bassett (1978) and is fully described in Koenker (2005) and Hao and Naiman (2007).

- Applications in financial risk management (stocks / currency markets) can be found by Engle and Manganelli (2004), Alexander (2008), Taylor (2008).

Quantile regression

- If you think of OLS as simply modelling the mean of the electricity prices as the dependent variable, then quantile regression can model the median, the 1%, 5%, 10%, 90%, 95%, and 99% percentiles, etc., or a whole set of them to effectively describe the full distribution.

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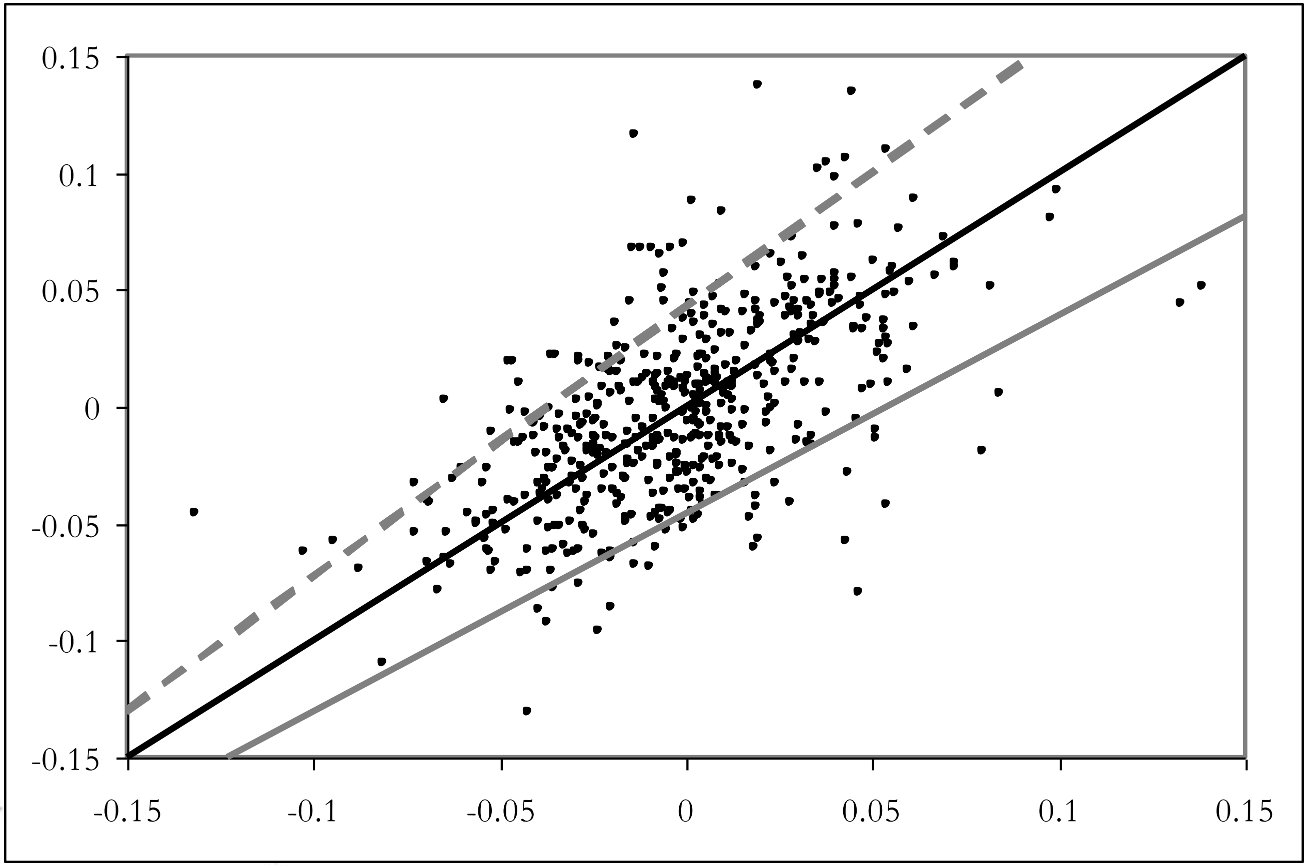
Quantile regression

$$F^{-1}(q \mid X) = \alpha + \beta X + F_{\varepsilon}^{-1}(q \mid X)$$



0.1, 0.5, and 0.9 quantile regression lines. Figure from Alexander (2008).

The lines are found by the following min. problem:

$$\underset{\alpha,\beta}{Min} \sum_{t=1}^{T} (q - \mathbf{1}_{Y_t \le \alpha + \beta X_t})(Y_t - (\alpha + \beta X_t))$$

where

$$\mathbf{1}_{Y_t \le \alpha + \beta X_t} = \begin{cases} 1 & \text{if } Y_t \le \alpha + \beta X_t \\ 0 & \text{otherwise} \end{cases}$$

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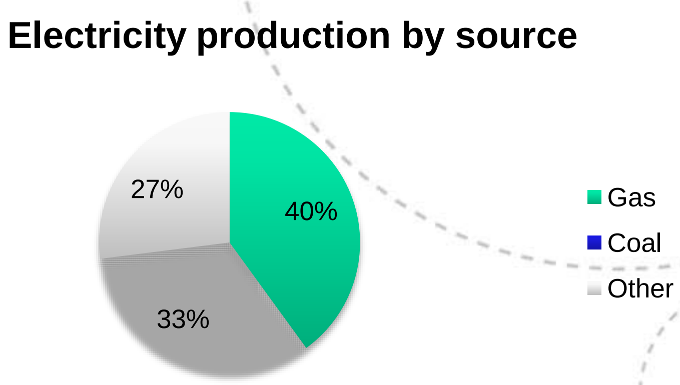
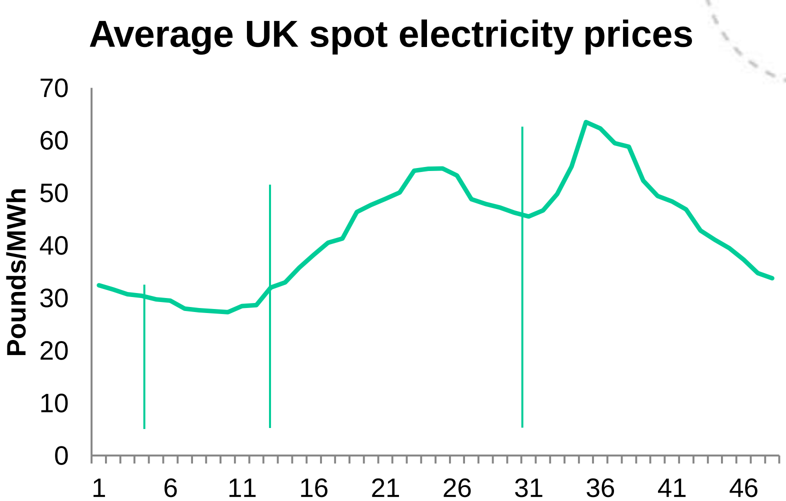
Data and descriptive statistics

- **The UK electricity market**
  - In March 2001 the New Electricity Trading Arrangement (NETA) got implemented and introduced fully liberalised bilateral contracting and voluntary spot trading in most of UK to replace the compulsory, day-ahead uniform auction Pool that had existed since 1990
  - In April 2005 the British Electricity Trading and Transmission Arrangement (BETTA) was formed and the whole of UK was included
  - Gas, Coal. Nuclear main input
  - No location prices
  - 48 half-hour prices (48 periods intra-day)
  - Spot market trades up to 1 hour prior to delivery both OTC and at the exchange UKPX/APX
  - Each day, demand forecast and reserve forecast for all the 48 periods for the next day are released
  - Period analysed: 8th June 2005 to 4th September 2010 (1915 observations altogether)
  - Peak price period 38 are examined (19:00-19:30)





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Data and descriptive statistics

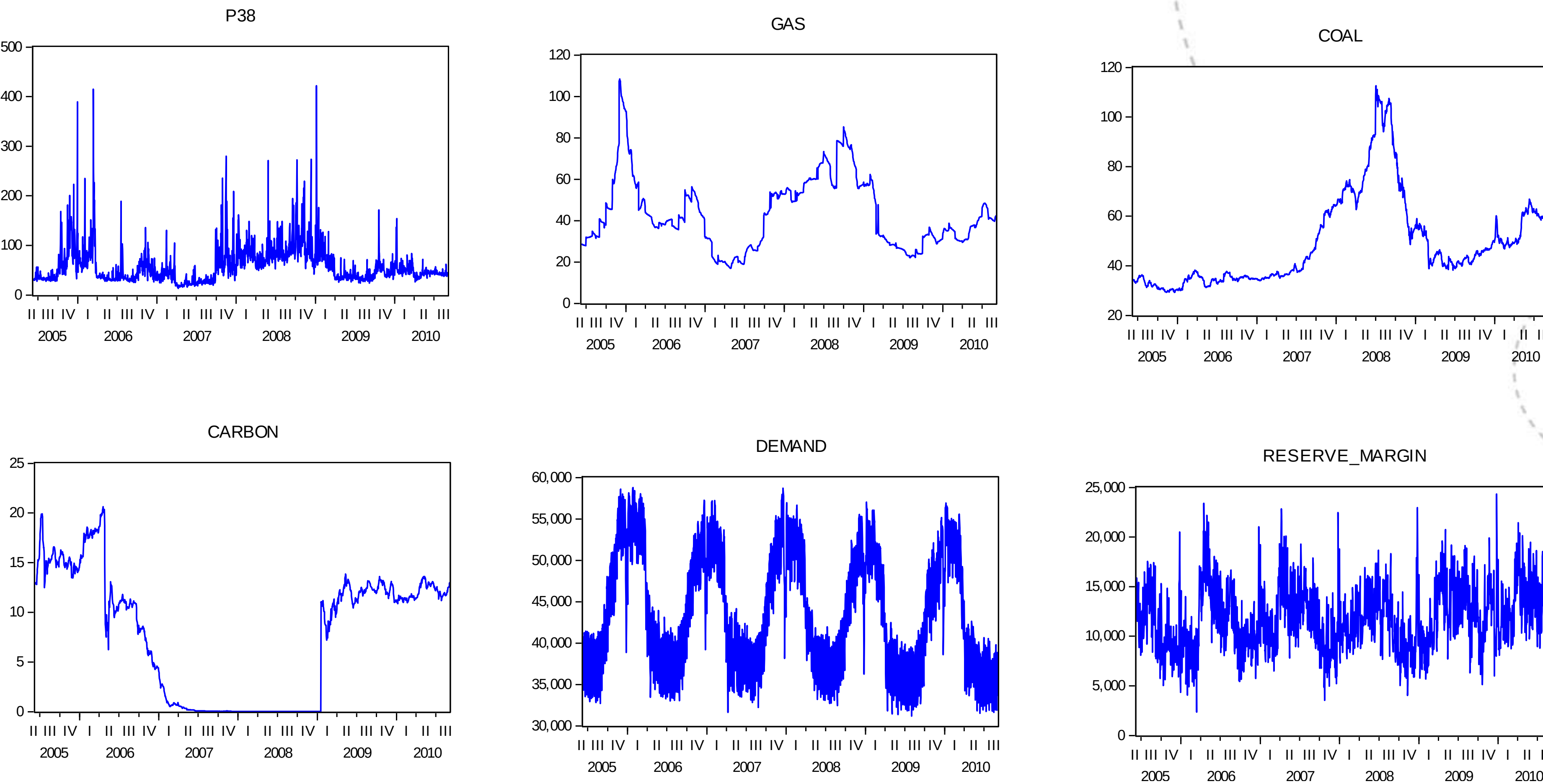

Figure 1. Price of UKPX period 38 (19:00-19:30) in £/MWh, UK day ahead forward gas price (£/BTU) from the National Balancing Point, Daily Steam Coal Europe-ARA index (translated into £/ton), EEX-EU Carbon emission price daily spot price (translated into £/ton), The UK national demand forecast for period 38 from the system operator (MWh), the UK national forecast of reserve margin for period 38 from the system operator (MWh). The data spans from 8th June 2005 to 4th September 2010 (1915 observations altogether).

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Data and descriptive statistics

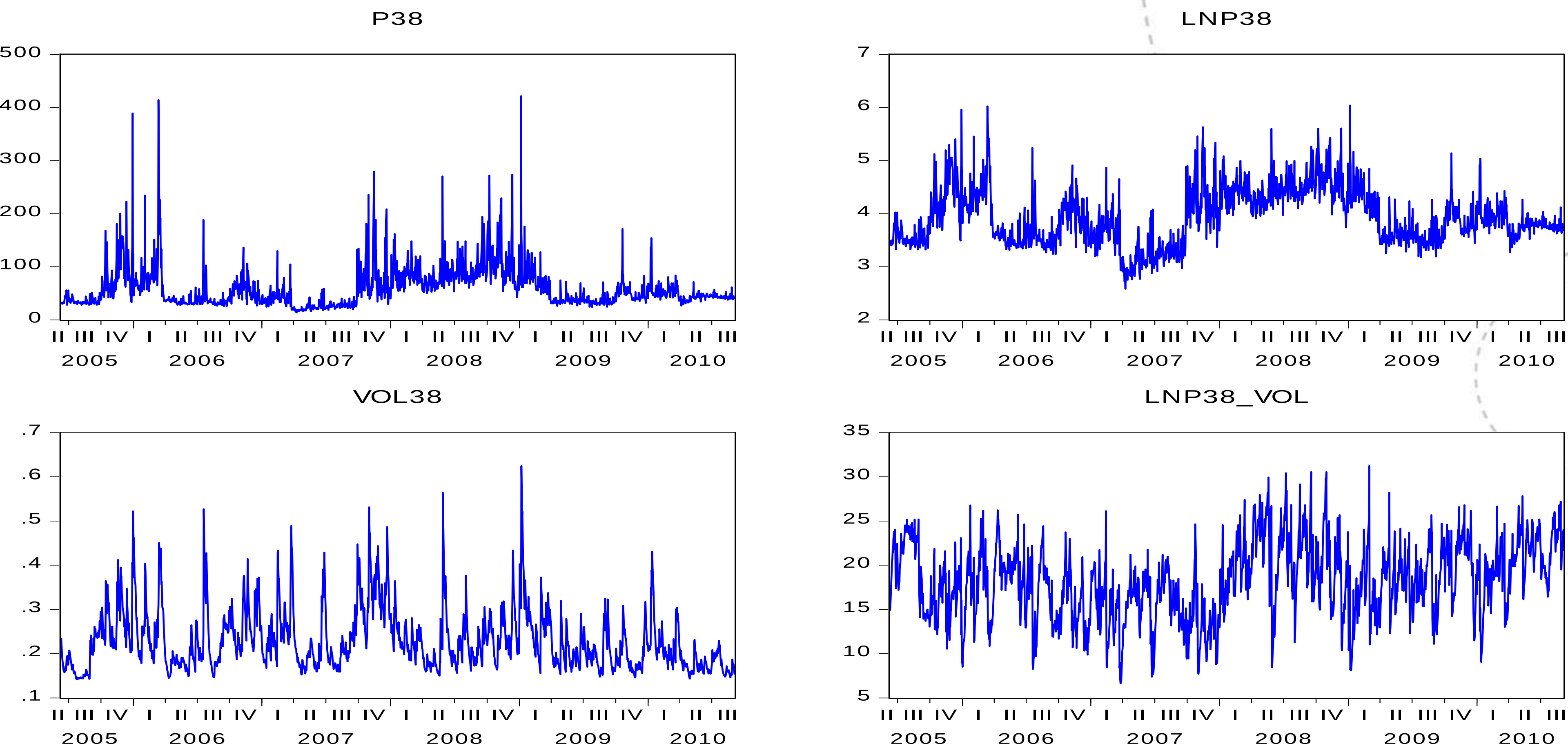

Figure 2. Upper left: Price of UKPX period 38 (19:00-19:30) in £/MWh,. Upper right: The natural logarithm of the UKPX period 38 prices. Lower left: The conditional volatility estimated from a GARCH(1,1) model on UKPX period 38 log price residuals from the fundamental model. Lower right: The natural logarithm of UKPX period 38 prices divided by the conditional volatility. The data spans from 8th June 2005 to 4th September 2010 (1915 observations altogether).

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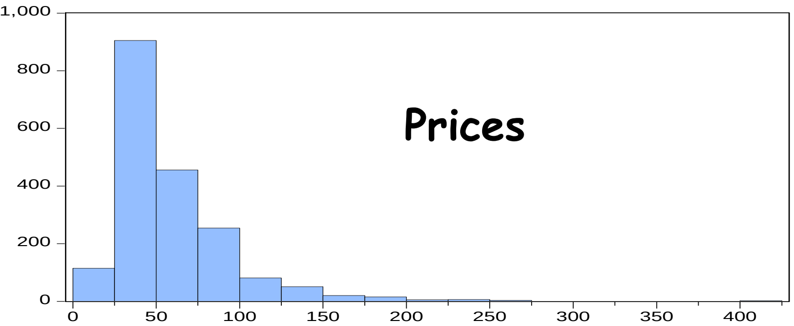
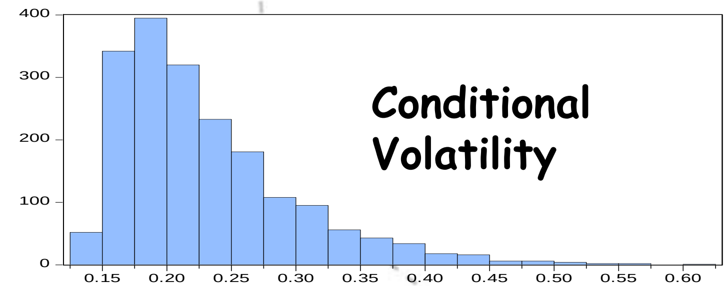
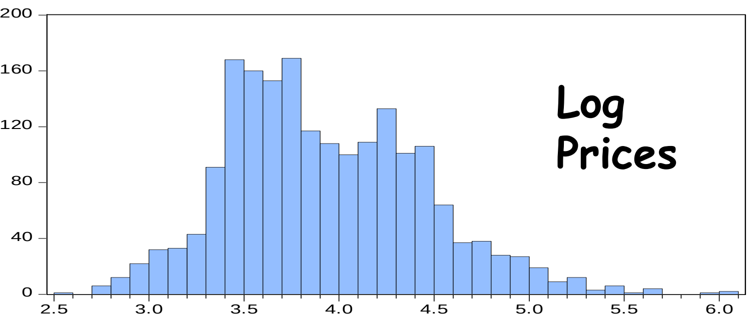
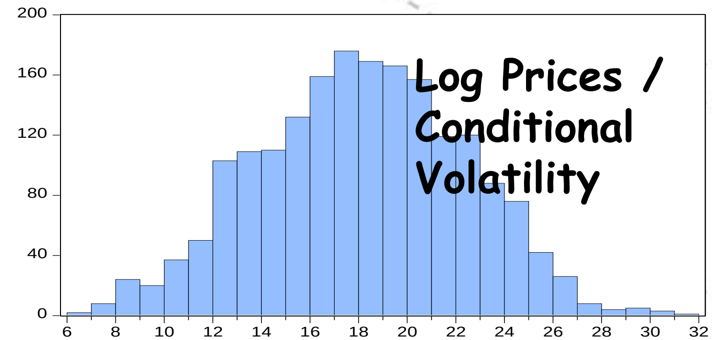
Data and descriptive statistics









Descriptive statistics of price, log prices, conditional volatility, and log prices divided by conditional volatility. Period 38.

Statistics	Mean	Med	Min	Max	Std	Skew	Kurt	JB	ADF	ρ_1	ρ_{10}	Q(10)
P_t	58.79	46.93	13.22	421.72	37.54	2.92	18.92	23040	-6.93	0.71	0.52	3268
$\ln P_t$	3.93	3.85	2.58	6.04	0.52	0.49	3.19	79	-4.55	0.84	0.72	5586
Vol_t	0.23	0.21	0.14	0.62	0.07	1.46	5.65	1241	-9.46	0.91	0.36	7599
$\ln P_t/Vol_t$	18.11	18.23	31.26	6.63	4.25	-0.03	2.64	11	-10.41	0.85	0.38	6823

Quantiles	1%	5%	10%	90%	95%	99%
P_t	18.18	24.12	28.89	98.38	130.07	194.06
$\ln P_t$	2.90	3.18	3.36	4.59	4.87	5.27
Vol_t	0.15	0.15	0.16	0.32	0.37	0.45
$\ln P_t/Vol_t$	8.44	11.09	12.54	23.71	24.73	27.20

Table 1. The table gives descriptive statistics the UKPX period 38 prices, the natural logarithm of prices, the conditional GARCH(1,1) volatility, and the logarithm of price divided by the conditional volatility. Daily data are collected from the period from 8th June 2005 to 4th September 2010 (1915 observations). The table shows the mean, median, min, max, standard deviation, skewness, excess kurtosis, Jarque-Bera, Augmented Dickey Fuller with constant and control lags according to the SIC criteria, autocorrelation at lag 1 and 10 and Ljung-Box statistics with 10 lags. We also show the empirical 1%,5%,10%,90%,95%, and 99% quantiles. Critical values at 1% level for JB is 9.21, for ADF-test -3.43, and for LB(10) 23.21.

Data and descriptive statistics

Stylised facts UK el. spot prices

- Price distribution P38 far from normally distributed
  - Positive skewness
  - Fat tails / high kurtosis

- Large price risk
  - Min/max: 13 to 421 £/MWh
  - 1% / 99% empirical VaR: 18 to 194 £/MWh

- Mean reversion in prices / stationarity

- Time varying volatility

- High degree of positive serial correlation and seasonal effects

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Price distribution modelling and forecasting

In sample analysis

We first perform in-sample analysis using all data from 9th June 2005 to 4th September 2010 which consist of 1948 observations. We use various quantile regression methods to model the distribution of the period 38 UK electricity prices. The price elasticity's of gas/coal/carbon prices, forecast of demand and reserve margin are investigated at different quantiles (1%, 5%, 10%, 50%, 90%, 95%, and 99%). We run 7 quantile regressions altogether.

$$lnP38\_vol_t^i = \beta_0^i + \beta_1^i lnP38\_vol_{t-1} + \beta_2^i lngas_{t-1} + \beta_3^i lncoal_{t-1} + \beta_4^i lncarbon_{t-1} + \beta_5^i lndemand_t + \beta_6^i lnreserve_t + e_t^i$$

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Price distribution modelling and forecasting

In sample analysis

Software applied:

- EViews (The QREG procedure)
- R (The quantreg module)
- Ox (G@RCH module)

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Price distribution modelling and forecasting

In sample analysis

Elasticities (ln and vol transformed prices)							
Quantile	**p38(t-1)**	**Gas**	**Coal**	**Carbon**	**Demand**	**Reserve**	**R2 adjusted**
1 %	**0.25**	**0.35**	**0.55**	**0.05**	**0.10**	**-0.25**	56.11 %
5 %	**0.27**	**0.36**	**0.51**	**0.03**	**0.29**	**-0.21**	57.09 %
10 %	**0.32**	**0.34**	**0.46**	**0.02**	**0.34**	**-0.18**	56.78 %
50 %	**0.50**	**0.27**	**0.30**	**0.01**	**0.27**	**-0.30**	58.65 %
90 %	**0.61**	**0.20**	**0.22**	0.01	**0.44**	**-0.49**	54.74 %
95 %	**0.64**	**0.15**	**0.18**	0.01	**0.42**	**-0.59**	53.31 %
99 %	**0.67**	**0.31**	**0.36**	0.00	**0.51**	**-0.78**	48.35 %

Table 2. Quantile regression results for the 1%,5%,10%,50%,90%,95%, and 99% quantiles. The parameter values and significance (bold indicate significance at 5% or lower) are displayed for the model using the natural logarithm of prices and the natural logarithm of all independent variables. Prices are corrected for time varying volatility. We also report the Koenker and Machado (1999) pseudo R-squared adjusted. Daily from 8th June 2005 to 4th September 2010 (1915 observations).

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Price distribution modelling and forecasting

In sample analysis

- Lagged prices
  - Significant positive effect. Generally increasing with quantiles
- Gas prices
  - Significant positive effect
- Coal
  - Significant positive effect, decreasing with quantiles
- Carbon
  - Significant (but small) positiv effect for lower quantiles. No effect for higher quantiles
- Demand forecast
  - Significant positive effect, Generally increasing with quantiles.
- Reserve margin
  - Significant negative effect, Increasing effect with quantiles.

Non-linear and significant elasticities (in line with the hypothesis) and excellent in sample performance for the QREG models!

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Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

- Value at Risk (VaR) modelling requires accuracy in the forecasting of the tails of the return density rather than in the main body of the return distribution.
- We will here focus on the ability to forecast the returns in the lower and upper tail, i.e. the extreme losses in a long respective short position.
- We apply unconditional and conditional coverage tests according to Kupiec (1995) and Christoffersen (1998). These tests and applications to financial risk management are described in Alexander (2008).

Models for comparison:

1. Fundamental Volatility Adjusted Quantile Regression Model including all variables
2. Reduced Form Volatility Adjusted Quantile Regression Model including only past price information
3. AR(7)-GARCH(1,1) with skewed-T error distribution
4. CaViAR model (Indirect GARCH(1,1))

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Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

- We use two approaches dividing in-sample and out-of-sample:
  - Expanding window in sample
    - Run models with the first 730 observations. Forecast quantiles of observation 731. Then run models with the first 731 observations. Forecast quantiles observation 732……… At the end, run models with the first 1914 observations. Forecast quantiles of the last observation 1915. Verify tail forecasting performance with 1915-730 = 1185 observations.
  - Rolling window in sample
    - Run models with the first 730 observations. Forecast quantiles of observation 731. Then run models with observations 2 to 731. Forecast quantiles of observation 732……… At the end, run models with observations 1184 to 1914. Forecast quantiles the last observation 1915. Verify tail forecasting performance with 1915-730 = 1185 observations.

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Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

P38 QREG-Full-Expanding 730	1%	5%	10%	90%	95%	99%
Sum hits	15	62	115	1068	1118	1165
Share of sample	1.27%	5.23%	9.70%	90.13%	94.35%	98.31%
P-value unconditional coverage test	**0.38**	**0.72**	**0.73**	**0.88**	**0.31**	0.03
P-value conditional coverage test	**1.00**	**0.69**	**0.79**	**0.10**	**0.10**	**1.00**
P38 QREG-Full-Rolling 730	1%	5%	10%	90%	95%	99%
Sum hits	16	60	120	1070	1123	1165
Share of sample	1.35%	5.06%	10.13%	90.30%	94.77%	98.31%
P-value unconditional coverage test	**0.25**	**0.92**	**0.88**	**0.73**	**0.72**	0.03
P-value conditional coverage test	**0.23**	**0.99**	**0.95**	**0.38**	**0.25**	1.00
P38 QREG-Reduced-Expanding 730	1%	5%	10%	90%	95%	99%
Sum hits	8	52	112	1072	1128	1173
Share of sample	0.68%	4.39%	9.45%	90.46%	95.19%	98.99%
P-value unconditional coverage test	**0.25**	**0.92**	**0.88**	**0.73**	**0.72**	**0.03**
P-value conditional coverage test	**1.00**	**0.38**	**0.80**	**0.14**	**0.73**	**1.00**
P38 QREG-Reduced-Rolling 730	1%	5%	10%	90%	95%	99%
Sum hits	8	53	103	1071	1129	1174
Share of sample	0.68%	4.47%	8.69%	90.38%	95.27%	99.07%
P-value unconditional coverage test	**0.23**	**0.40**	**0.13**	**0.66**	**0.66**	**0.80**
P-value conditional coverage test	**0.23**	**0.99**	**0.95**	**0.38**	**0.25**	**1.00**

P38 GARCH-ST Expanding 730	1%	5%	10%	90%	95%	99%
Sum hits	3	52	116	1056	1106	1175
Share of sample	0.25%	4.39%	9.79%	89.11%	93.33%	99.16%
P-value unconditional coverage test	0.00	**0.32**	**0.81**	**0.32**	0.01	**0.58**
P-value conditional coverage test	**1.00**	**0.38**	**0.68**	0.06	0.02	**1.00**
P38 GARCH-ST Rolling 730	1%	5%	10%	90%	95%	99%
Sum hits	0	55	116	1058	1119	1175
Share of sample	0.00%	4.64%	9.79%	89.28%	94.43%	99.16%
P-value unconditional coverage test	0.00	**0.57**	**0.81**	**0.42**	**0.38**	**0.58**
P-value conditional coverage test	**1.00**	**0.57**	**0.50**	**0.36**	**0.34**	**1.00**
P38 CaViaR Expanding 730	1%	5%	10%	90%	95%	99%
Sum hits	12	53	114	1074	1122	1175
Share of sample	1.01%	4.47%	9.62%	90.63%	94.68%	99.16%
P-value unconditional coverage test	**0.97**	**0.40**	**0.66**	**0.46**	**0.62**	**0.58**
P-value conditional coverage test	**1.00**	**1.00**	**1.00**	0.07	**0.53**	**1.00**
P38 CaViaR Rolling 730	1%	5%	10%	90%	95%	99%
Sum hits	12	57	111	1041	1126	1174
Share of sample	1.01%	4.81%	9.37%	87.85%	95.02%	99.07%
P-value unconditional coverage test	**0.97**	**0.76**	**0.46**	0.02	**0.97**	**0.80**
P-value conditional coverage test	**1.00**	**1.00**	**1.00**	0.00	**0.71**	**1.00**

Table 3. Forecasting results out of sample for the quantile regression model using all independent variables, for the quantile regression model using only past price history, for a AR(7)-GARCH(1,1) with skewed-t error distribution, and for a CaViaR model (indirect GARCH). Both an expanding window and rolling window are using adding one day based on the first 730 observations out of 1915. Each panel show the pre-specified quantiles, the number of hits (number of observed prices below the predicted price), the percentage of observed prices below the predicted price, p-values for the unconditional coverage test by Kupiec (1995), and p-values for the conditional coverage test by Christoffersen (1998). P-values above 0.10 indicate that we will keep the null-hypothesis that the model predict quantiles equal to the pre-specified ones.

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Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

- **Quantile regression including all variables:**
  - All quantiles are forecasted properly apart from the 99% quantile. No clustering of exceedances.
- **Quantile regression including just price history:**
  - All quantiles are forecasted properly. No clustering of exceedances.
- **AR(7)-GARCH model with a skewed-T distribution:**
  - The 1% and 95% quantiles are not predicted satisfactory. There are also sign of clustering of exceedances.
- **CaViaR (indirect GARCH(1,1):**
  - All quantiles are forecasted properly apart from the 90% quantile. There are also some sign of clustering of exceedances for the 90% quantile.

⇨ **Excellent out of sample performance for the QREG models!**

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Conclusion

- By using Quantile regression analysis, we have shown how fundamental factors (gas/coal/carbon prices, forecast of demand and reserve margin affects the price distribution for the period 38 el. Price in UK. In sample models yield non-linear and significant effects with high explanatory power.

- The Quantile regression models gives excellent out-of-sample forecast (Value at Risk forecast) compare to GARCH and CaViAR models.

⇨ **The fundamental quantile regression model can be used to analyse effects of changes in risk factors as well as predicting the price distribution of peak electricity prices.**

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Further research

- **Similar fundamental risk analysis using quantile regression for other energy markets**
  - Other electricity markets (NordPool, EEX, APX, US and Australian markets. .....)
  - Other energy commodities (Oil, Gas, GasOil, Fuels, Coal, Carbon) in Europe, US, Asia

- **Extending the research setting for UKPX elprices:**
  - Non-linear quantile regression with copulas (e.g. Spark spread, Dark Spreads)
  - VAR/VECM models and quantile regression (Joint modelling of several el prices)
  - Regime switching models and quantile regression

→ **I need an army of phd students!!!!!!!!!**

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Thanks to:

- Participants ELCARBONRISK Project
  - Stein Erik Fleten, Norwegian University of Science and Technology
  - Gudbrand Lien, Lillehammer University College
  - Per Bjarte Soliebakke, Molde University College
  - Martin Emblem & Erik Helset, Tafjord Kraft
  - Torstein Thinn, Ståle Størdal, Jørn Gunnar Kleiven, Eidsiva Energi
  - The Research Council of Norway

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