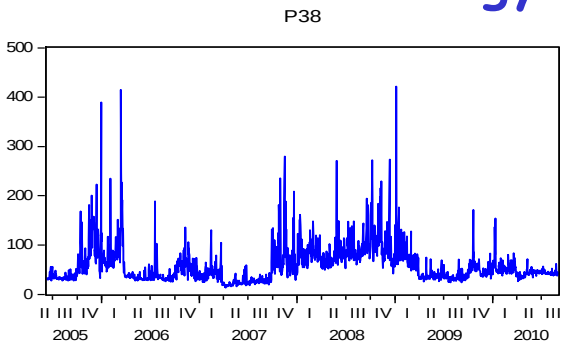
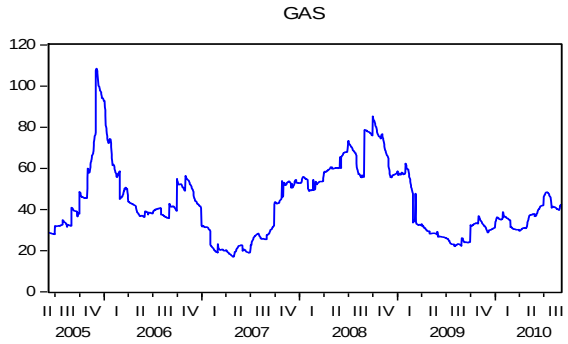
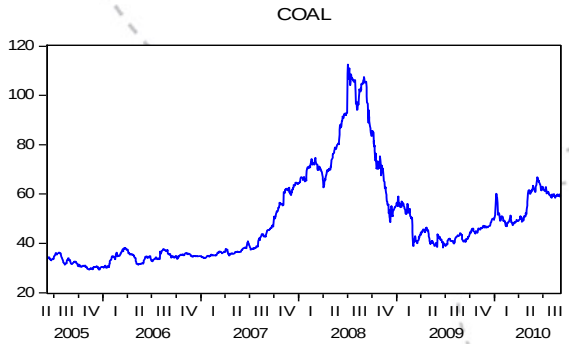
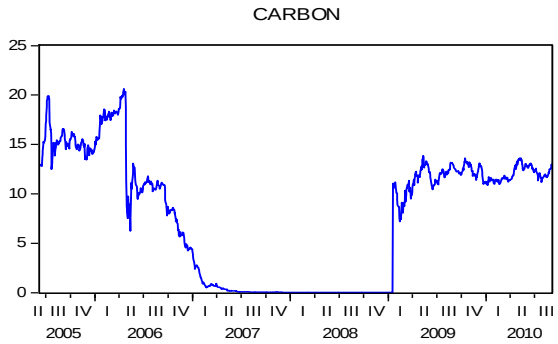
MODELLING AND FORECASTING ELECTRICITY PRICE RISK WITH QUANTILE FACTOR MODELS

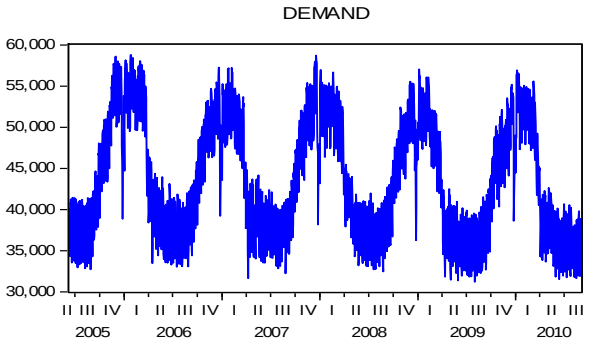
Energy Finance Seminar Essen 23 January 2013

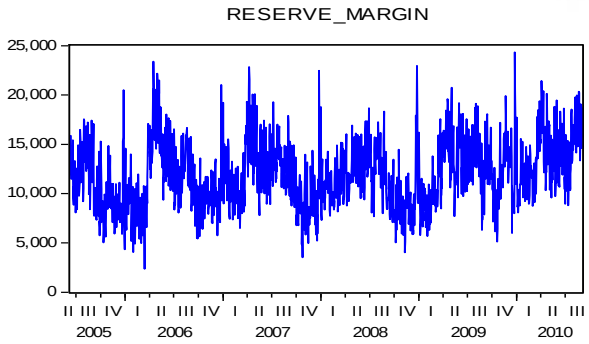












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Outline

- Why modelling electricity price distributions?
- Literature – Risk modelling of energy prices
- Fundamental analysis of electricity spot price formation
- Quantile regression
- Data and descriptive statistics – UK El. market
- Price distribution modelling and forecasting
  - In sample analysis – Non-linear sensitivities
  - Out of sample analysis - Forecasting Value at Risk
- Conclusions and further research
- References

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Introduction – Idea of the paper

- Correct short term modelling and forecasting of price distributions is useful for energy market participants (producers, retailers, and speculators):

  - Bidding into the market production/consumption at different prices at different hours next day

  - Trading long/short positions in spot market after the auction is closed

  - Risk management / Scenario analysis / Stress testing in general

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Introduction – Idea of the paper

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

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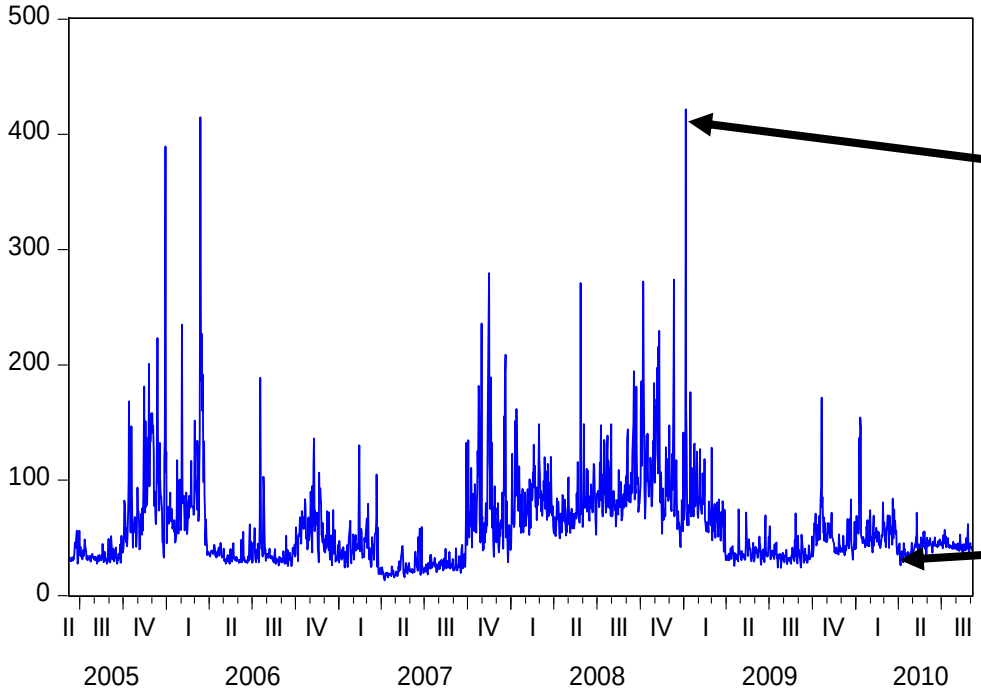
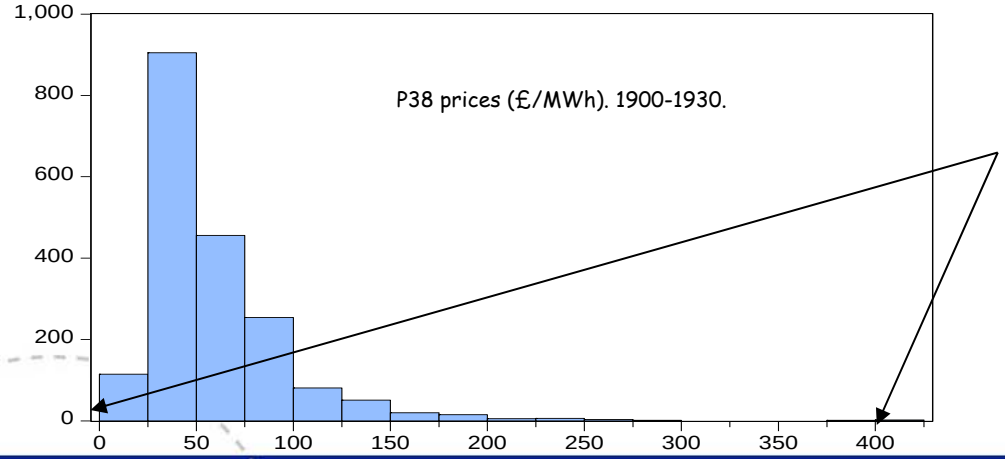
Introduction – Idea of the paper

P38



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), compare to e.g. standard GARCH/CaViaR type of models

2. Is **easy** to implement and understand. It also closely linked to the aim of the analysis, namely to model and predict quantiles. We do not assume any specific form of the error distribution, in fact the **distribution** is what "comes out" of the model

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

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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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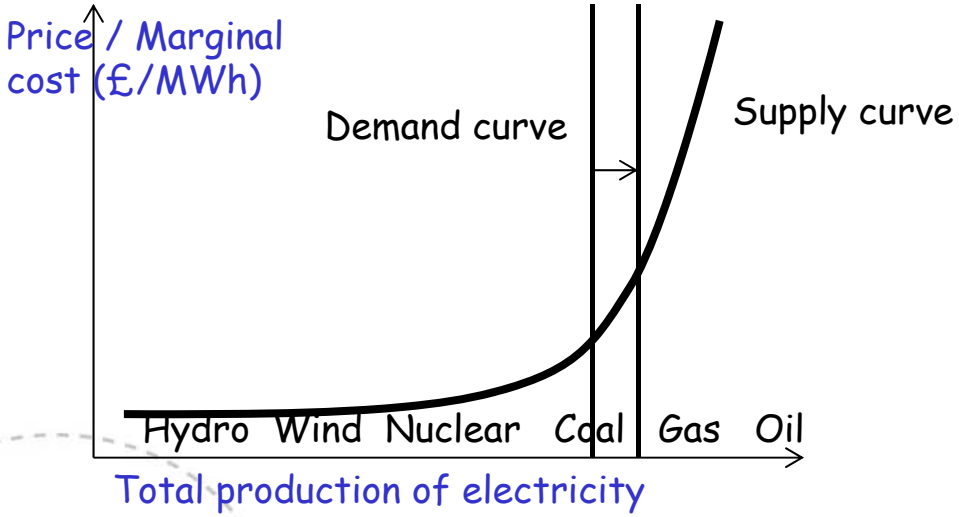
Fundamental analysis of electricity spot price formation

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

- 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:

- Demand elasticity is positive and increases nonlinearly with higher quantiles

- Reserve margin elasticity is negative and decreases nonlineary with higher quantiles

- Fuel (gas,coal,carbon price) elasticities will be positive but may have nonlinear, non-monotonic functional relations across quantiles (because of changes of relative marginal cost)

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Fundamental analysis of electricity spot price formation

The implication of this for the exogenous price drivers are:

- Adaptive behavior (manifest as a lagged price) elasticity will be positive and non-linear across quantiles. This effect is expected to be stronger at higher prices as some generators will get increased market power.

- Inverse leverage effects (volatility will affect high prices than low prices) is an effect found in many energy markets as is expected to be found here as well (the opposite effect is seen in stock markets)

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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).

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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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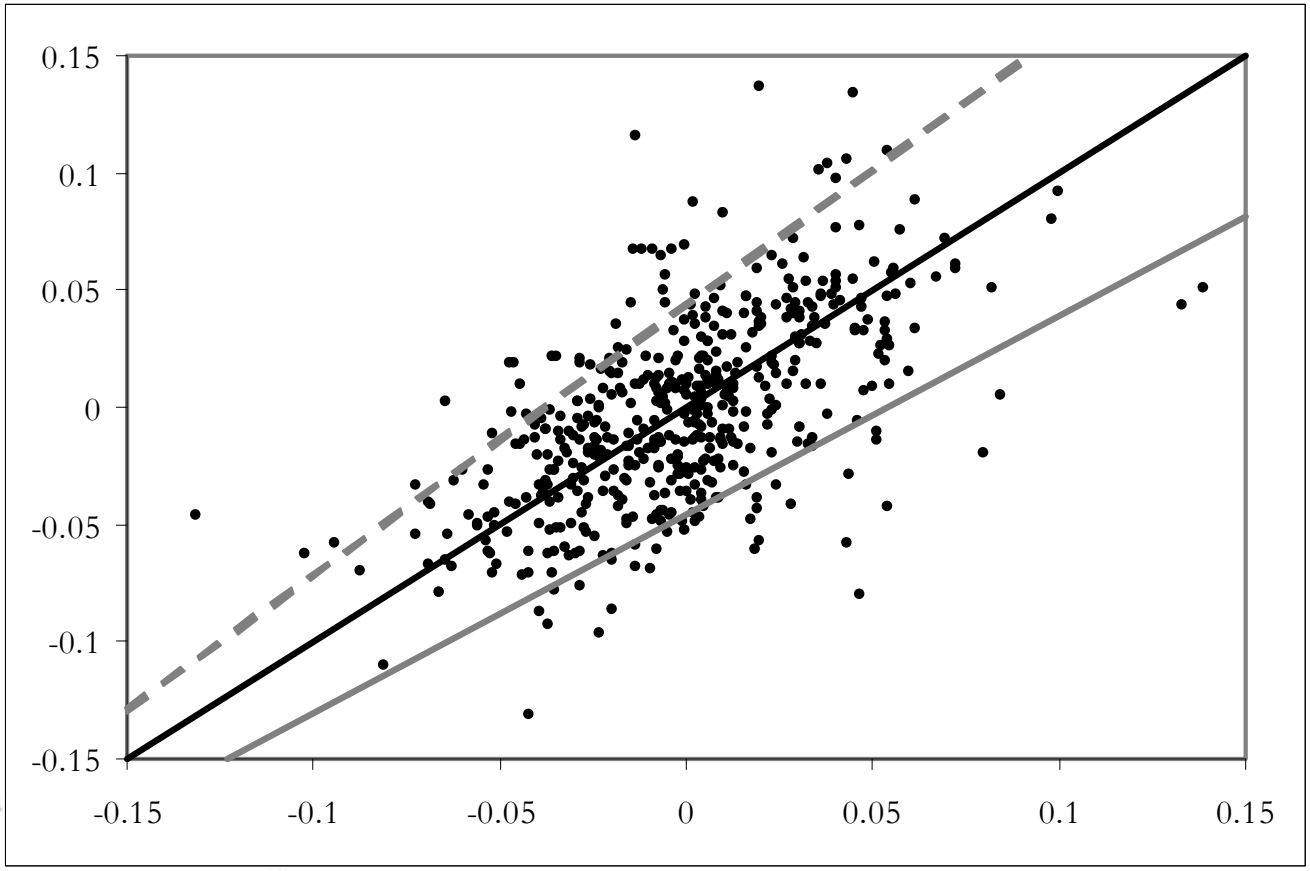
Quantile regression

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



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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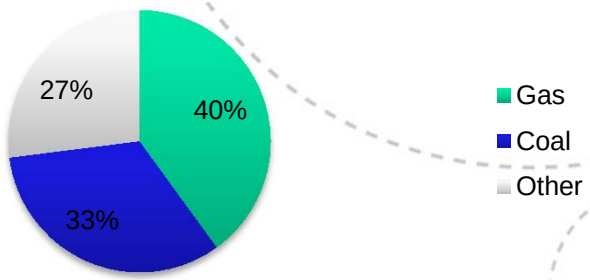
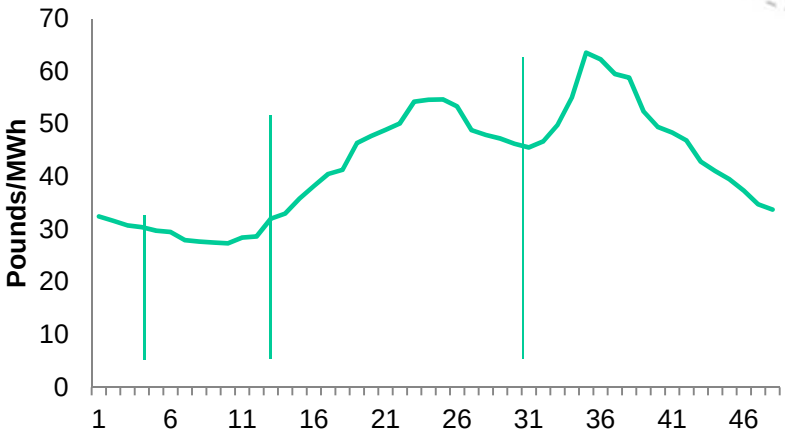
Data and descriptive statistics

- **The UK electricity market**
  - One of the earliest el. markets formed in 1990
  - Combined auction and spot market trading
  - In April 2005 the British Electricity Trading and Transmission Arrangement (BETTA) was formed and all parts of of UK was included in the market
  - Gas, Coal. Nuclear main input
  - No location prices
  - 48 half-hour prices (48 periods intra-day)
  - Auction market and 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 (19:00-1930)

Electricity production by source



Average UK spot electricity prices



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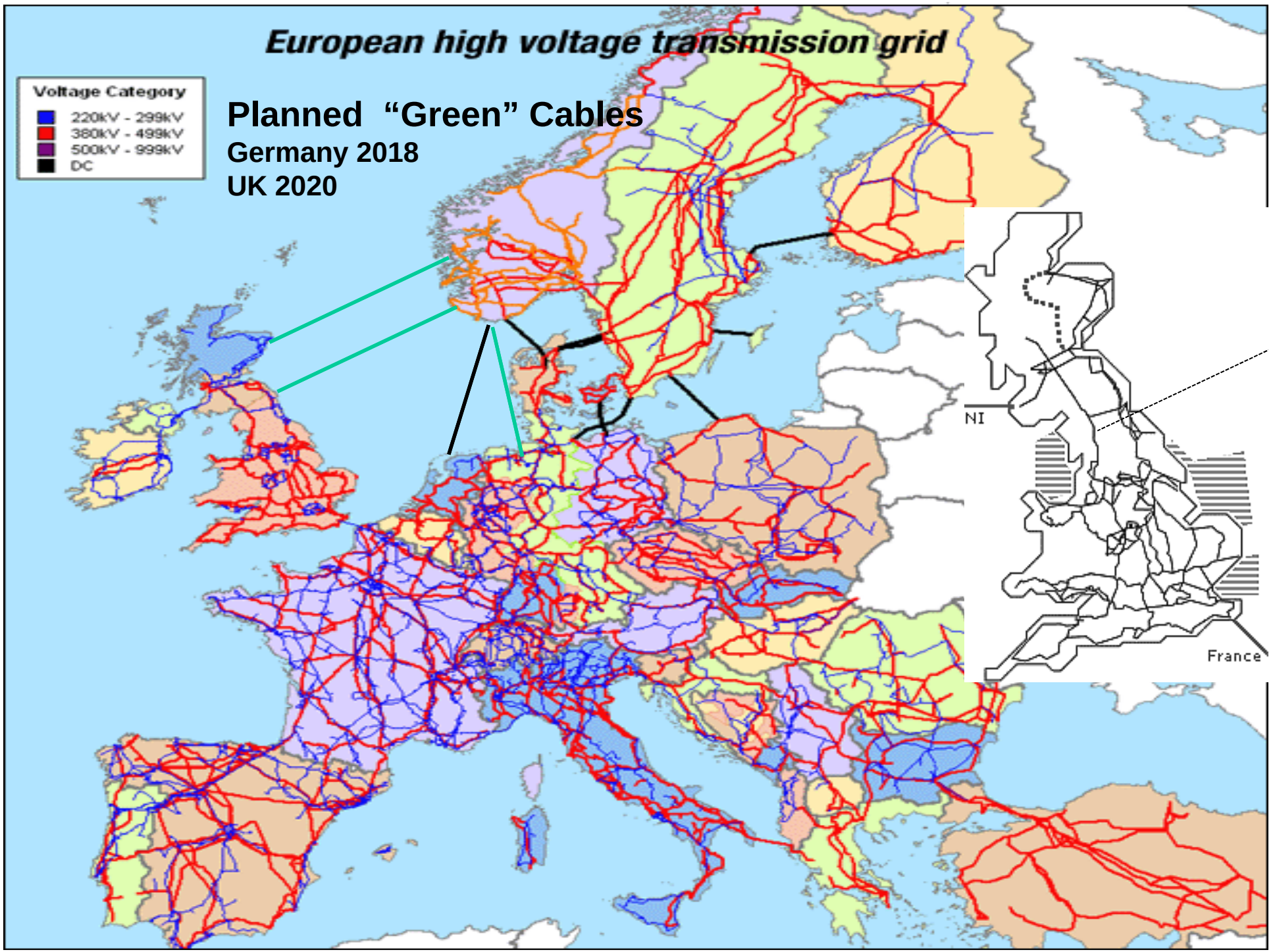
European high voltage transmission grid
Voltage Category
220kV - 299kV
380kV - 499kV
500kV - 999kV
DC
Planned "Green" Cables
Germany 2018
UK 2020
NI
France

http://www.iea.org/gtf/server/exportJPG.php

iea.org

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IEA - Gas Trade Flows in Europe, in Mcm

Data and descriptive statistics

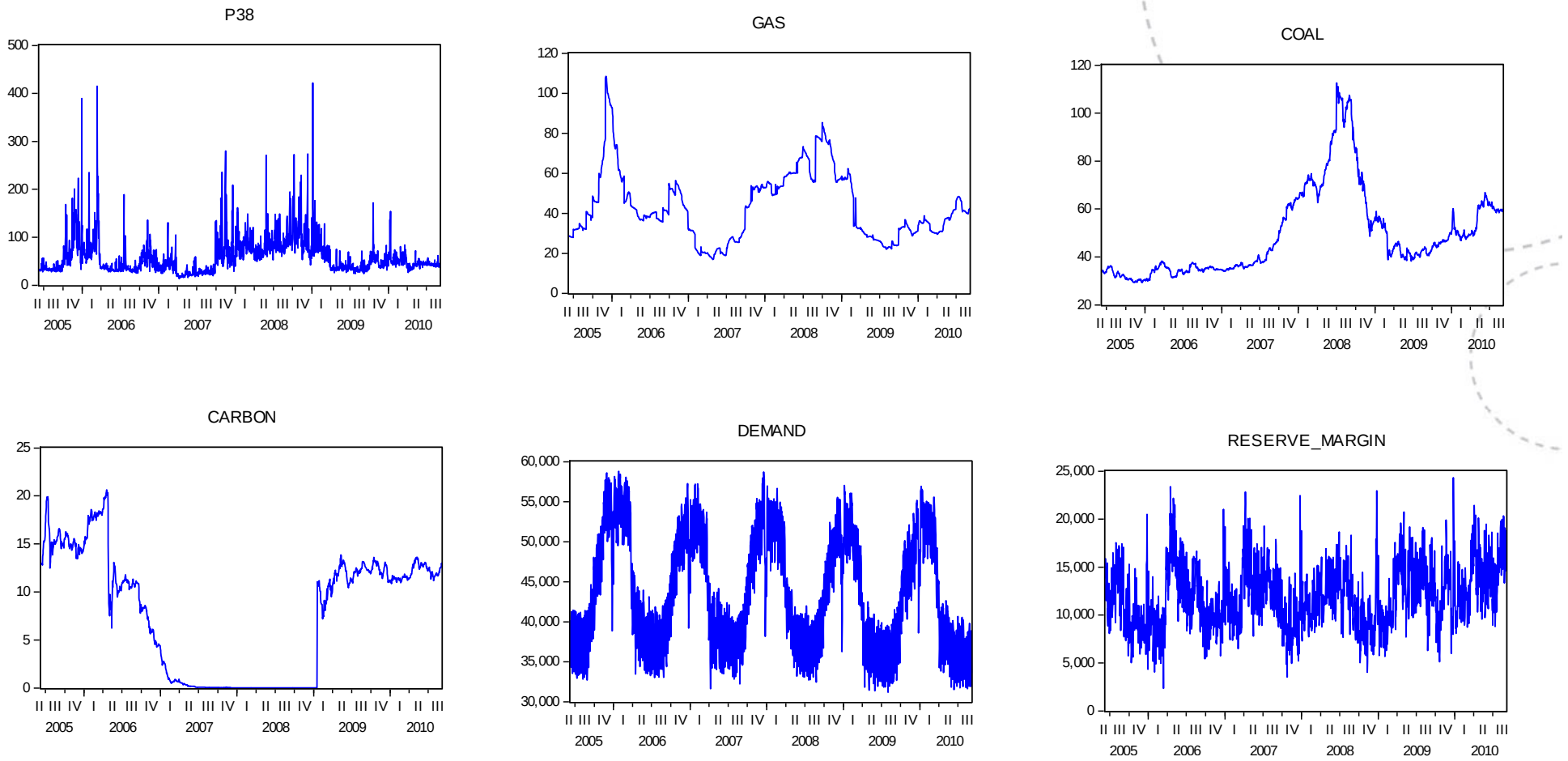

Figure 1. Price of UKPX period 38 (19:00-19:30) in £/MWh, UK day ahead forward gas price (£/BTU) from the National Balancing Point, Daily Steam Coal Europe-ARA index (translated into £/ton), EEX-EU Carbon emission price daily spot price (translated into £/ton), The UK national demand forecast for period 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

Statistics	Mean	Med	Min	Max	Std	Skew	Kurt
P_t	58.79	46.93	13.22	421.72	37.54	2.92	18.92
ln P_t	3.93	3.85	2.85	6.04	0.52	0.49	3.19
Statistics	**JB**	**ADF**	ρ_1	ρ_{10}	**Q(10)**		
P_t	23040	-6.93	0.71	0.52	3268		
ln P_t	79	-4.55	0.84	0.72	5586		
Quantiles	**1 %**	**5 %**	**10 %**	**90 %**	**95 %**	**99 %**	
P_t	18.18	24.12	28.89	98.38	130.07	194.06	
ln P_t	2.9	3.18	3.36	4.59	4.87	5.27	

Table 1. UKPX period 38 prices. 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.

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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 lagged prices, gas/coal/carbon prices, forecast of demand and reserve margin, and price volatility are investigated at different quantiles i (1%, 5%, 10%, 50%, 90%, 95%, and 99%). We run 7 quantile regressions altogether.

$$LnP38^{i}_{t} = \beta^{i}_{0}i + \beta^{i}_{1}LnP38_{t-1} + \beta^{i}_{2}LnGas_{t-1} + \beta^{i}_{3}LnCoal_{t-1} + \beta^{i}_{4}LnCarbon_{t-1} + \beta^{i}_{5}LnDemand_{t} + \beta^{i}_{6}LnReserve_{t} + \beta^{i}_{7}\sigma_{t} + e^{i}_{t}$$

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Price distribution modelling and forecasting

In sample analysis

Software applied:

- EViews (The QREG procedure)
- R (The quantreg module)

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Price distribution modelling and forecasting

In sample analysis

Quantile	lag P38	Gas	Coal	Carbon	Demand	Reserve Margin	Volatility	R^2-adjusted
1 %	0.22***	0.31***	0.31***	0.07***	0.08	-0.37***	-0.22***	49.0
5 %	0.28***	0.27***	0.33***	0.06***	0.23***	-0.28***	-0.11***	53.6
10 %	0.31***	0.27***	0.31***	0.05***	0.24***	-0.27***	-0.02	55.2
25 %	0.38***	0.23***	0.30***	0.04***	0.30***	-0.27***	-0.02	57.5
50 %	0.47***	0.19***	0.27***	0.03***	0.25***	-0.35***	0.06**	58.9
75 %	0.55***	0.20***	0.22***	0.02***	0.26***	-0.46***	0.02	58.2
90 %	0.59***	0.20***	0.16***	0.01	0.29***	-0.54***	0.04	58.9
95 %	0.50***	0.20***	0.22***	0.02***	0.34**	-0.63***	0.21***	59.8
99 %	0.35**	0.26*	0.30	0.02	0.42	-0.86***	0.16	58.3

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Quantile regression results. The *, ** and *** indicates significance at the 10%, 5% or 1% level, respectively.

Price distribution modelling and forecasting

In sample analysis

- Lagged prices
  - Significant positive effect. Generally increasing with quantiles
- Gas prices
  - Significant positive effect. No clear pattern
- Coal
  - Significant positive effect. No clear pattern
- Carbon
  - Significant (but small) positiv effect declining with quantiles
- Demand forecast
  - Significant positive effect, Generally increasing with quantiles.
- Reserve margin
  - Significant negative effect, Generally increasing effect with quantiles.
- Volatility
  - Negative for low prices and positive for high prices, same magnitude.

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Price distribution modelling and forecasting

Out of sample analysis

Software applied:

- R (Developed code for forecasting application)
- Matlab (Available code for CaViaR models from Engle & Manganelli)

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Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

- Backtesting refers to testing the accuracy of VaR over a historical period when the true outcome is known
- The general approach to backtesting VaR for an asset is to record the number of occasions over a historical period when the actual loss exceeds the model predicted VaR and compare this number to the pre-specified VaR level

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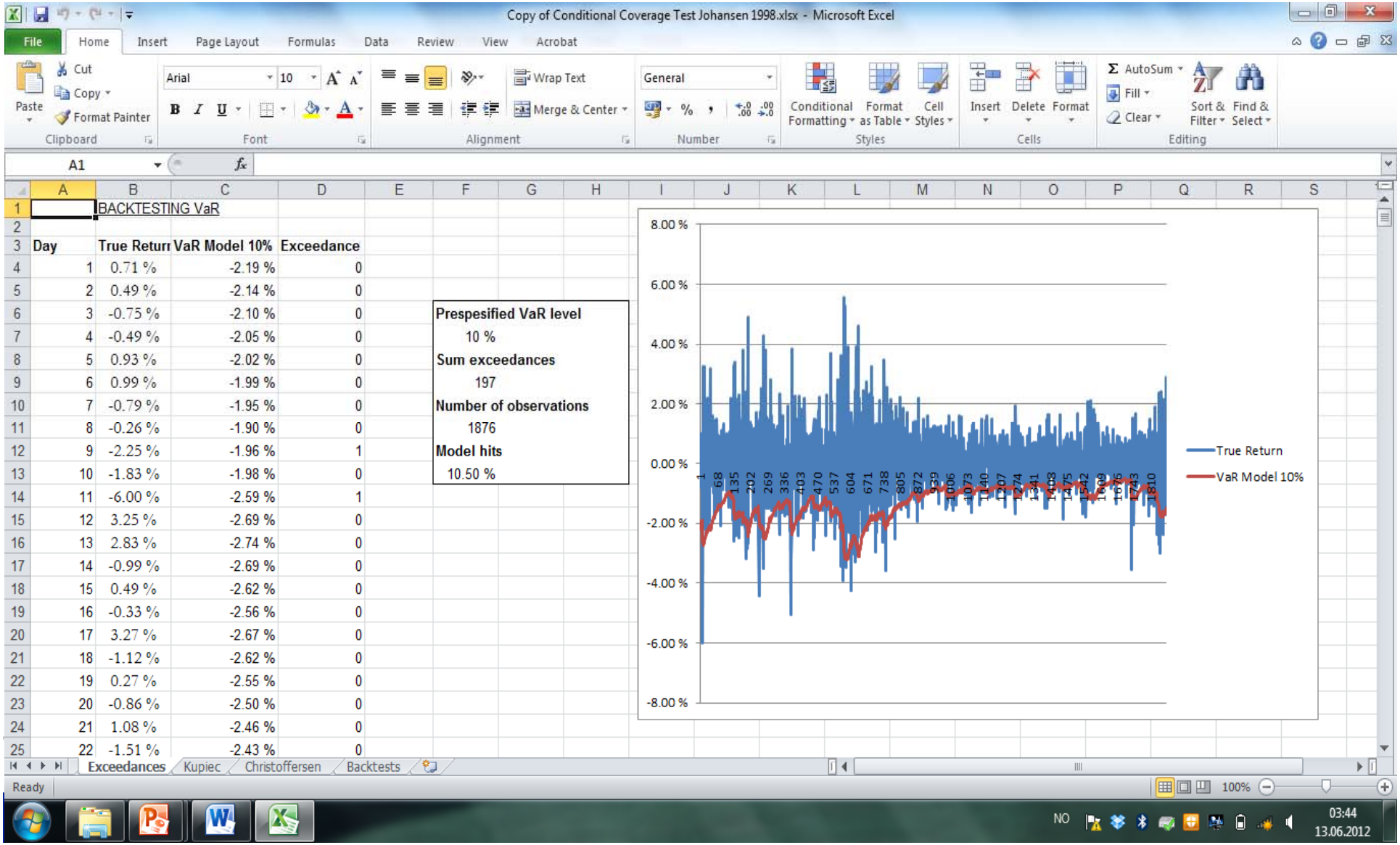
Price distribution modelling and forecasting

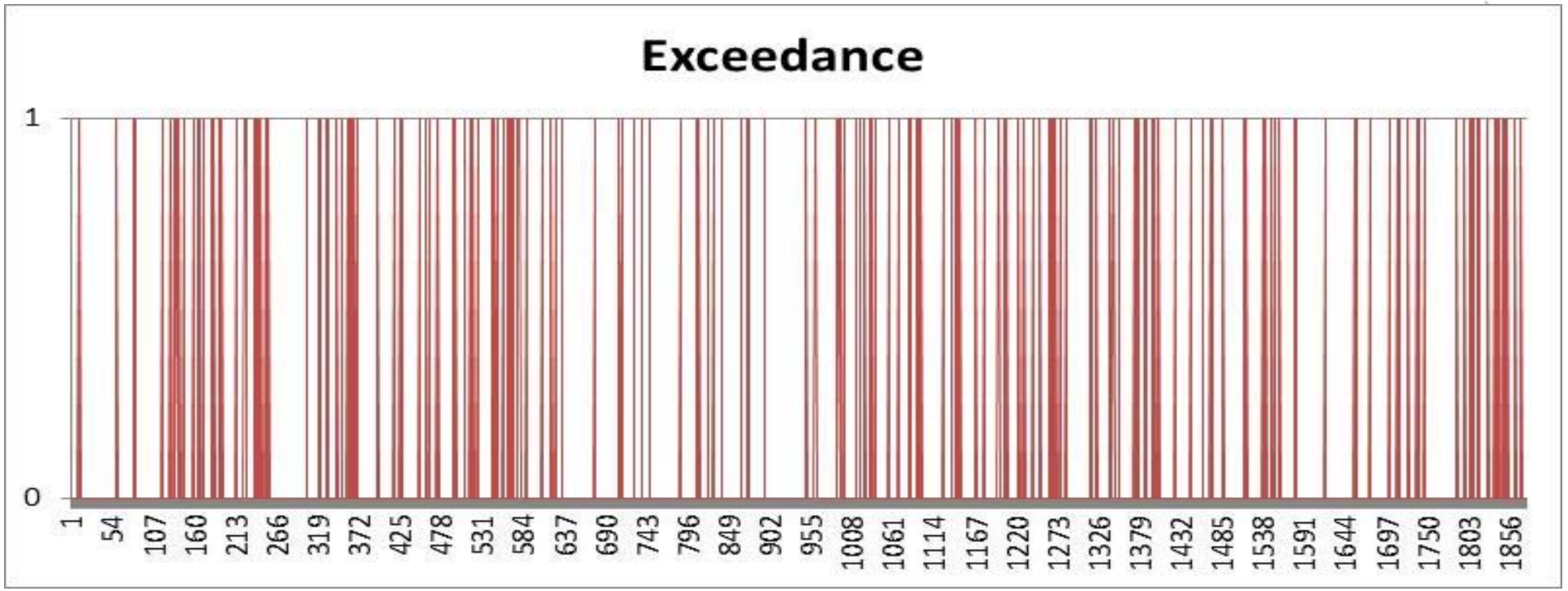
Out of sample analysis - Forecasting Value at Risk



Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

- **A proper VaR model has**
  - The number of exceedances as close as possible to the number implied by the VaR quantile we are trying to model
  - Exceedances that are randomly distributed over the sample (that is no "clustering" of exceedances). We do not want the model to over/under predict in certain periods



Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

- To validate the predictive performance of the models, we consider two types of test:
  - The unconditional test of Kupiec (1995)
  - The conditional coverage test of Christoffersen (1998)

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Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

Models for comparison (see paper for details):

- Different GARCH type of models with various error terms (normal, skew-t)
- Different CaViaR type of models
- Quantile regression model including only price history dynamics (7 lags)
- Quantile regression model including only price history dynamics (7 lags) and time-varying volatility (GARCH)
- Fundamental Quantile regression model including lagged price dynamics (1 lag), all structural variables and time-varying volatility (GARCH)

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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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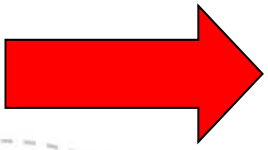
Price distribution modelling and forecasting

Out of sample analysis - Forecasting Value at Risk

- Main conclusions (details of the p-values for the VaR tests of the different models are found in the paper):
  1. GARCH type models perform rather well if errors are capture by a skew-t distribution
  2. The Indirect GARCH CaViaR model and Symmetric Absolute Value CaviaR performs rather well
  3. Linear quantile regression models:
     - The general findings is that introducing fundamental factors and volatility in the linear quantile regression model improves the results. This underpinning the importance of these risk factors in predicting tail probabilities



Excellent out of sample performance for the QREG model including the fundamentals

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Conclusion

- We have in this paper:
  - Characterised the nonlinear effects of exogenous factors on peak hour wholesale electricity price formation
  - Made forecast of the price distribution

- Using a dynamic quantile regression model with fundamental factors and volatility as explanatory variables, we capture the effects such as:
  - Mean reversion
  - Spikes
  - Time varying volatility
  - Seasonalities
  - Complex relations to fundamentals

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Conclusion

- We demonstrate how these factors influence the peak el. price distribution:
  - Lagged prices
  - Gas prices
  - Coal prices
  - Carbon prices
  - Forecast of demand
  - Forecast of reserve margin
  - Price volatility

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Conclusion

- In general, we find for the in-sample analysis:
  - Significant mean reversion effects
  - Positive elasticity's of gas, coal, carbon with no distinct pattern over the quantiles
  - Positive elasticity of demand with increased effect as prices gets higher
  - Negative elasticity of reserve margin with increased effect as prices gets higher
  - Volatility effect on prices for very low/high prices, no asymmetry effects

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Conclusion

- For the out-of-sample analysis we find:
  - We have used 11 different model alternatives testing the Value at Risk forecasting power using both expanding and rolling windows
  - The linear fundamental quantile regression model including all variables generally outperforms GARCH (autoregressive process for the volatility) and CAViaR (autoregressive process for the quantiles) type models

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Conclusion

- A linear fundamental quantile regression model is useful for energy market participants (with long/short positions in electricity) in:
  - Understanding the non-linear influence of risk factors at different el. price levels (low/medium/high)
  - Forecasting the electricity price distribution

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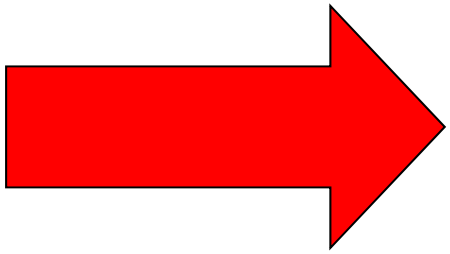
Further research

1. Extension of the analysis covering all 48 half hours (each half hour have very different price dynamics)
2. Similar analysis of other electricity markets (Nordic/EEX/ENDEX markets)
3. Non-linear quantile regression with copulas modelling
   - Between electricity prices in different areas resentation?)
   - Spark Spreads (Electricity – Gas)
   - Dark Spreads (Electricity – Coal)
   - Clean Spreads (Taken into account Carbon prices)

Further research



We need an army of phd students!!!!

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Thanks to:

- Funding/involvement from the ELCARBONRISK Project
  - Tafjord Kraft and Eidsiva Energi
  - The Research Council of Norway
  - Norwegian University of Science and Technology
  - Lillehammer University College
  - Molde University College
  - London Business School
- Data
  - Enappsys (www.enappsys.com)

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References

- **Alexander C.**, 2008, Market Risk Analysis – Volume I,II,III, and IV, Wiley.
- **Aloui, C.**, 2008. Value-at-risk analysis for energy commodities: long-range dependencies at fat tails in return innovations. Journal of Energy Markets 1: 31-63.
- **Bernhardt C., Kluppelberg C., and Meyer-Brandis T.**, 2008, Estimating high quantiles for electricity prices by stable linear models, Journal of Energy Markets, Vol. 1, No. 1, Spring 2008, 3-19.
- **Bunn D.W., and Karakatsani N.**, 2003, Forecasting electricity prices, Working paper London Business School
- **Bystrøm H.N.E.**, 2005, Extreme value theory and extremely large electricity price changes, International Review of Economics and Finance, Vol. 14, 41-55.
- **Chang K.F., Gray P., and Campen B.V.**, 2008, A new approach to characterizing and forecasting electricity price volatility, International Journal of Forrecasting 24, 728-743.
- **Chan K. F., and Gray P.**, 2006, Using extreme value theory to measure value-at-risk for daily electricity spot prices., International Journal of Forecasting, Vol. 22, 283-300.
- **Chen D.**, 2009, Applications of discontinuous structural finite mixture and regime-switching time-series models to electricity price risk, Phd dissertation London Business School – Department of Management Science.
- **Chen D., and Bunn D.**, 2007, Analysis of the nonlinear response of electricity prices to fundamental and strategic factors, IEEE Transactions on Power Systems, 1-12.
- **Engle R.F., and Manganelli S.**, 2004, CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles, Journal of Business & Economic Statistics,Vol. 22, No. 4, 367-381.
- **Escribano A., Pena J.I., and Villaplana P.**, 2002, Modelling electricity prices: Intenational evidence, Working paper Universidad Carlos III De Madrid.
- **Füss R., Adams Z., and Kaiser D.G.**, 2009, The predictive power of Value-at-Risk Models in commodity futures markets, Working paper Department of Empirical Research and Econometrics – University of Freiburg.
- **Giot, P., Laurent, S.**, 2003. Market risk in commodity markets: a VaR approach. Energy Economics 25: 435–457
- **Fezzi C., and Bunn D.W.**, 2006, Structural analysis of high frequency electricity demand and supply interactions, Working Paper London Business School – Department of Management Science.
- **Goto M. and Karolyi**, 2004, Understanding electricity price volatility within and across markets, Working paper Fisher College of Business, Ohio USA.
- **Hadsell L., Marathe A., Shawky H.A.**, 2004, Estimating the volatility of wholesale electricity spot prices in US, The Energy Journal, 25, 4, 23-40
- **Hao L., and Naiman D.Q.**, 2007, Quantile Regression, Sage Publication

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References

- **Higgs H., Worthington A.**, 2005, Systematic features of high-frequency volatility in Australian electricity markets: Intraday patterns, Information arrival and calendar effects, Energy Journal, 26, 4, 23-41
- **Higgs H., Worthington A.**, 2008, Stochastic modelling of high volatility, mean-reverting, spike-prone commodities: The Austrialian wholesale spot electricity market, Energy Economics, 30, 3172-3185
- **Higgs H.**, 2009, Modelling spot prices in deregulated wholesale electricity markets: A selected empirical review, Working paper, Department of accounting, finance and economics, Griffith University
- **Huisman R., and Huurman C.**, 2007, Fat tail in power prices, Working paper Erasmus Series Research in Management, ERS-2003-059-F&A
- **Hung J., Lee M., Liu H.**, 2008, Estimation of value-at-risk for energy commodities via fat-tailed GARCH models, Energy Economics ,30, 1173-1191
- **Karakatsani N., and Bunn D.W.**, 2008, Forecasting electricity prices: The impact of fundamentals and time-varying coefficients, International Journal of Forecasting, Vol. 24, 764-785.
- **Knittel C.R., and Roberts M.R.**, 2005, An empirical examination of restructured electricity prices, Energy Economics 27, 791-817
- **Koenker R., and Hallock K.**, 2001, Quantile Regression, Journal of Economic Perspectives, Vol. 15., No. 4, 143-156.
- **Koenker R.**, 2005, Quantile Regression, Cambridge University Press
- **Koopman S.J., Ooms M., and Carnero M.A.**, 2007, Periodic Seasonal Reg-ARFIMA-GARCH Models for Daily Electricity Spot Prices, Journal of American Statistical Association, 102 (477), 16-27.
- **Lucia J.J., Schartz E.S.**, 2002, Electricity prices and power derivatives: Evidence from the Nordic power exchange, Review of derivatives research, Vol. 5, No. 1, 5-50.
- **Solibakke, P.B.**, 2002. Efficiently estimated mean and volatility characteristics for the Nordic spot electric power markets, International Journal of Business, 7,2, 17-35
- **Solibakke, P.B.**, 2006. Describing the Nordic forward electric power market: A stochastic model approach , International Journal of Business, 11, 4, 345-366
- **Ullrich C.J.**, 2009, Realized Volatility and Price Spikes in Electricity Markets: The Importance of Observation Frequency, Working paper (SSRN abstract no 1342586)
- **Taylor J.**, 2008, Using exponential weighted quantile regression to estimate value at risk and expected shortfall, Journal of Financial Econometrics, Vol. 6, 382-406.
- **Weron R.**, 2008, Forecasting wholesale electricity prices: A review of time series models, Working paper Hugo Steinhaus Center, Polen.
- **Weron R., and Misiorek A.**, 2008, Forecasting spot electricity prices: A comparison of parametric and semiparametric time series models, International Journal of Forecasting, 24, 744-763.