

Estimating the Volatility of Electricity Prices: The Case of the England and Wales Wholesale Electricity Market

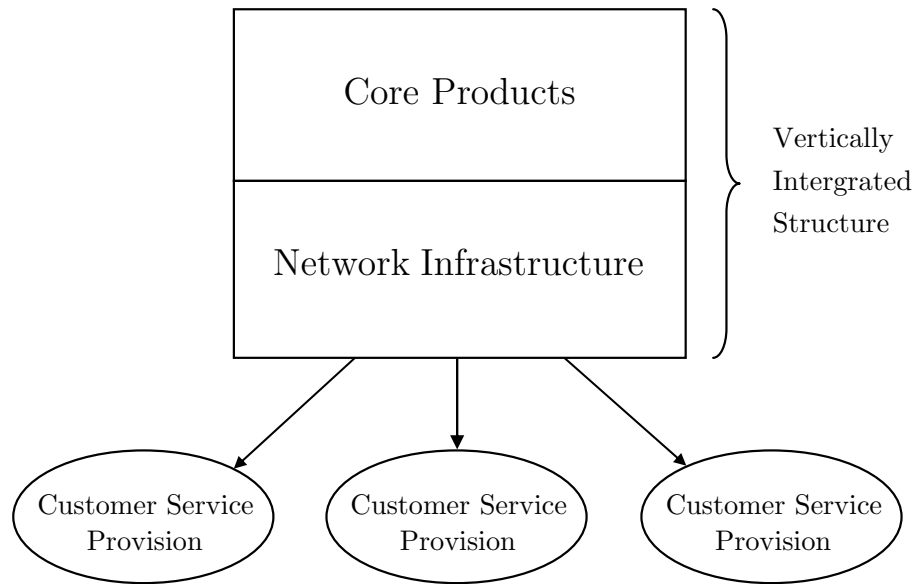
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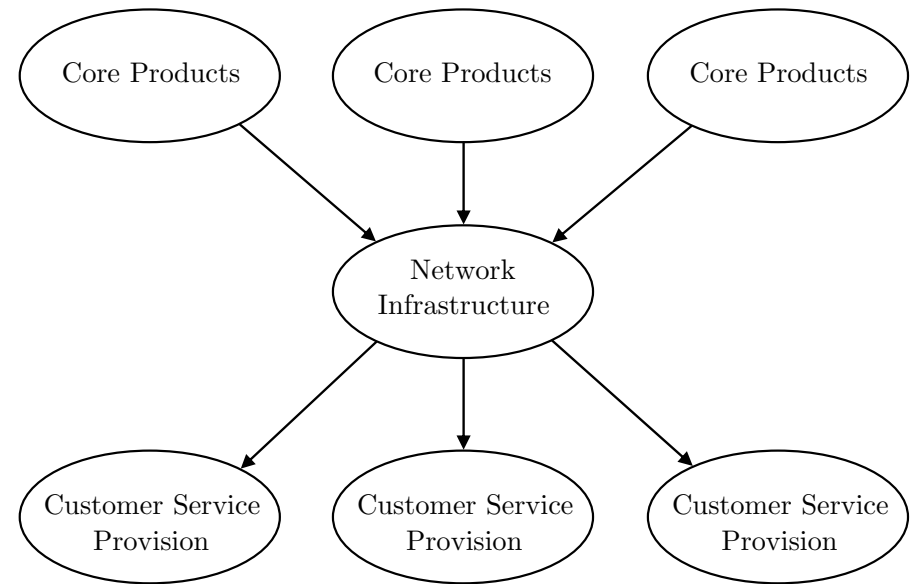
Prague, June 2014

General Introduction Liberalization of Electricity Industry

Fig. 1: *Structure of a Network Industry before and after Liberalization*



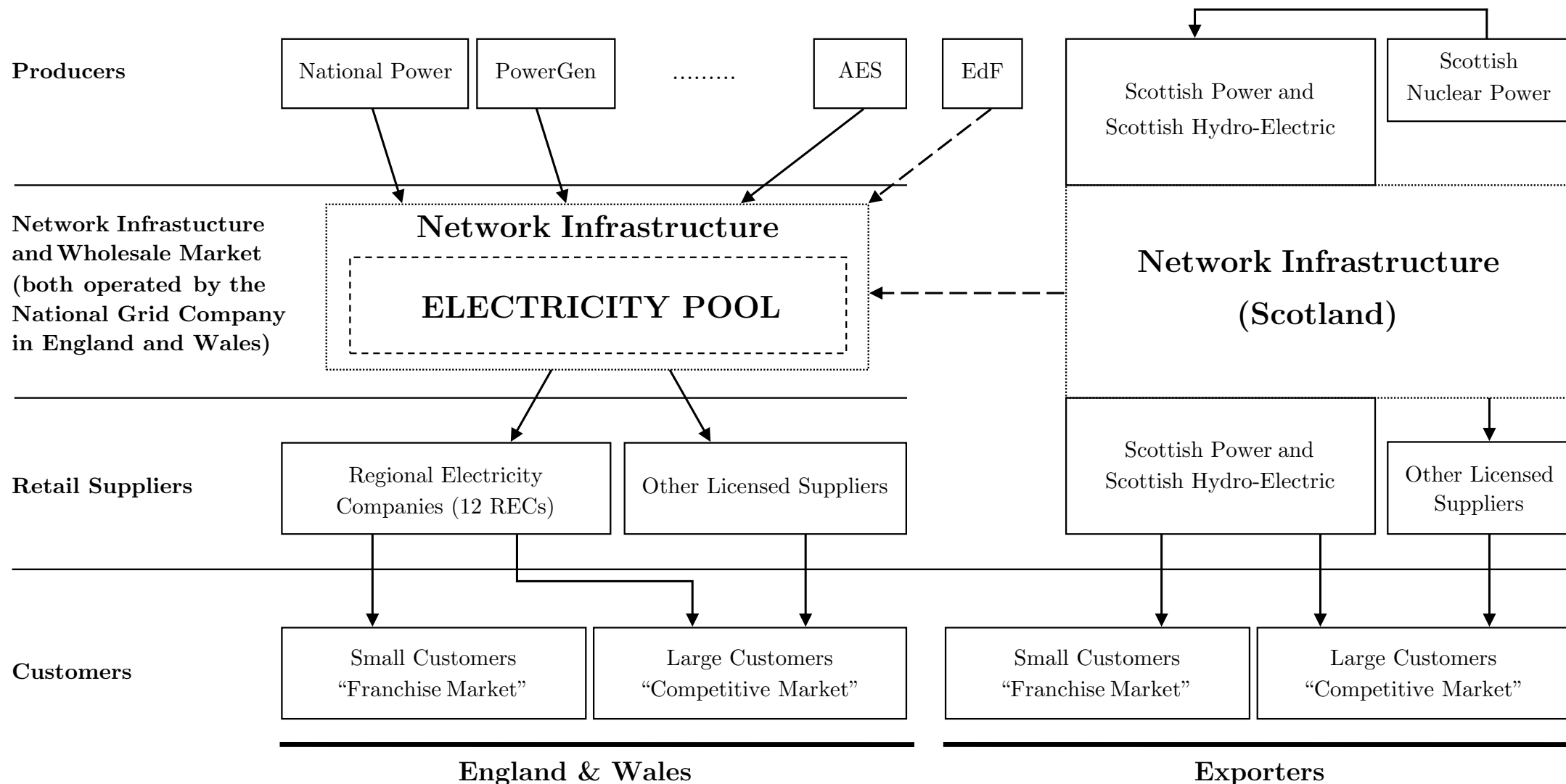
(a) Vertically Integrated Case



(b) Vertically Separated Case

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Fig. 2: *Description of the Electricity Industry in Great Britain*



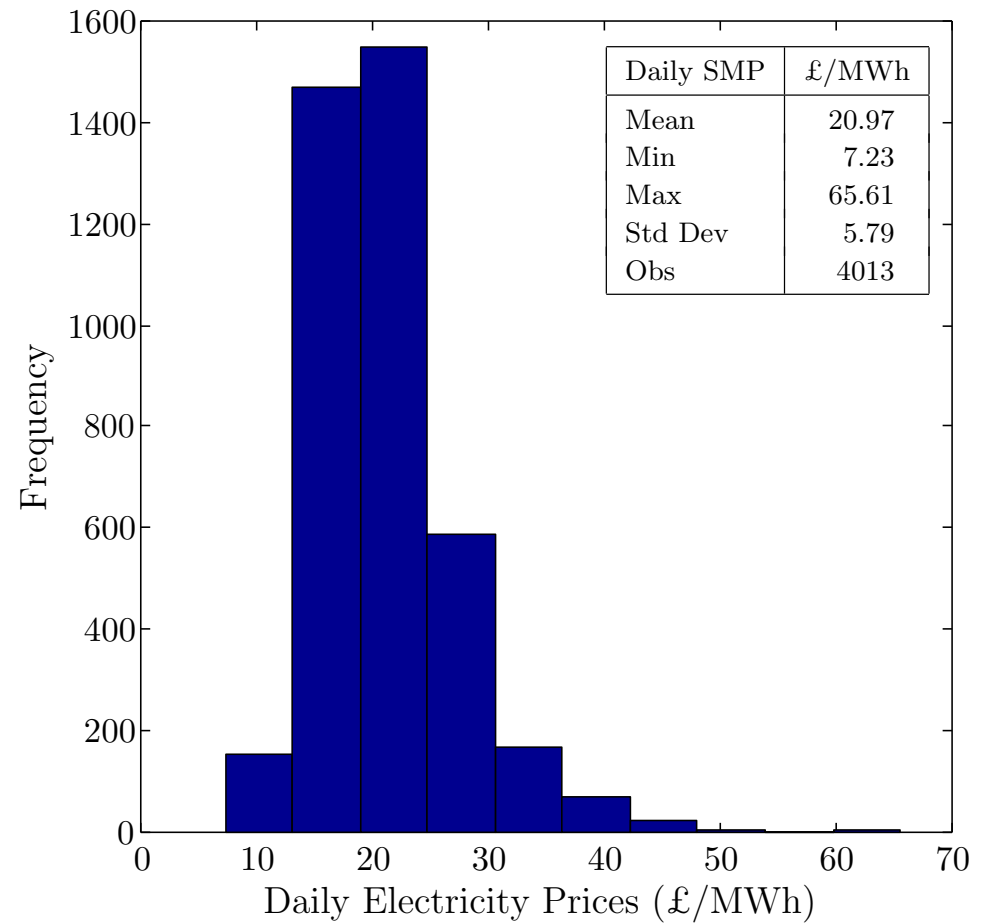
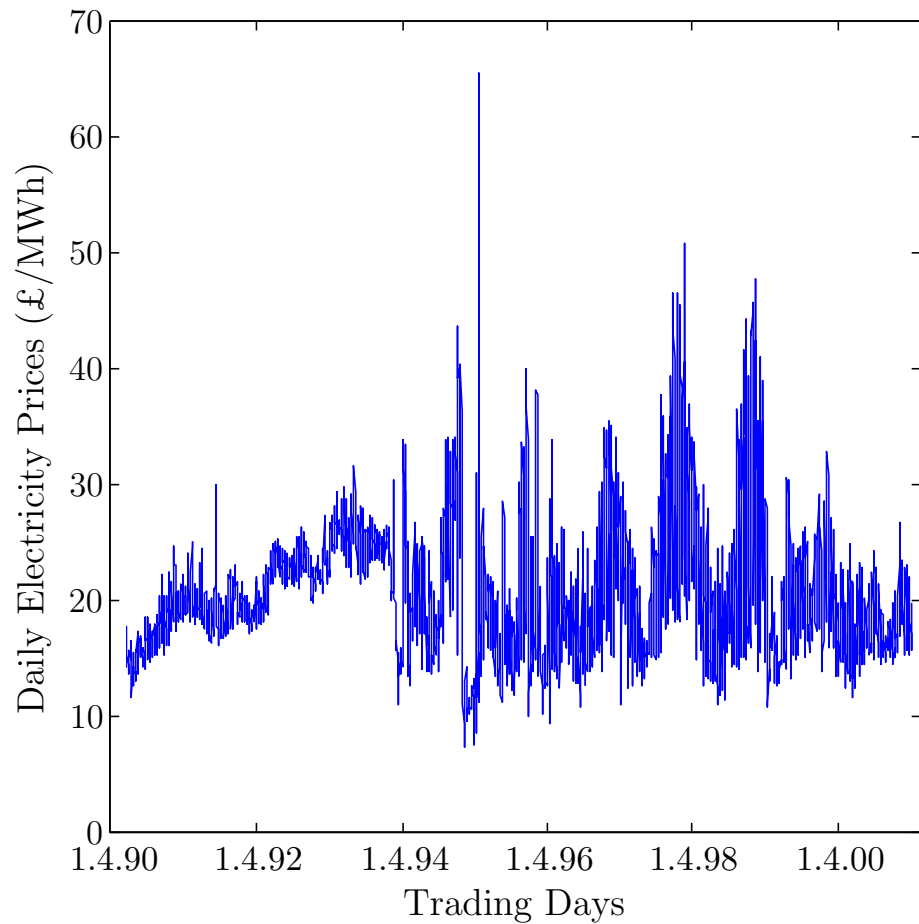
General Introduction **Liberalization of Electricity Industry**

- The Key Question to Analyze Liberalization
 - Do liberalized markets drive price volatility?
- Case Study
 - Wholesale electricity market in England and Wales

General Introduction Liberalization of Electricity Industry

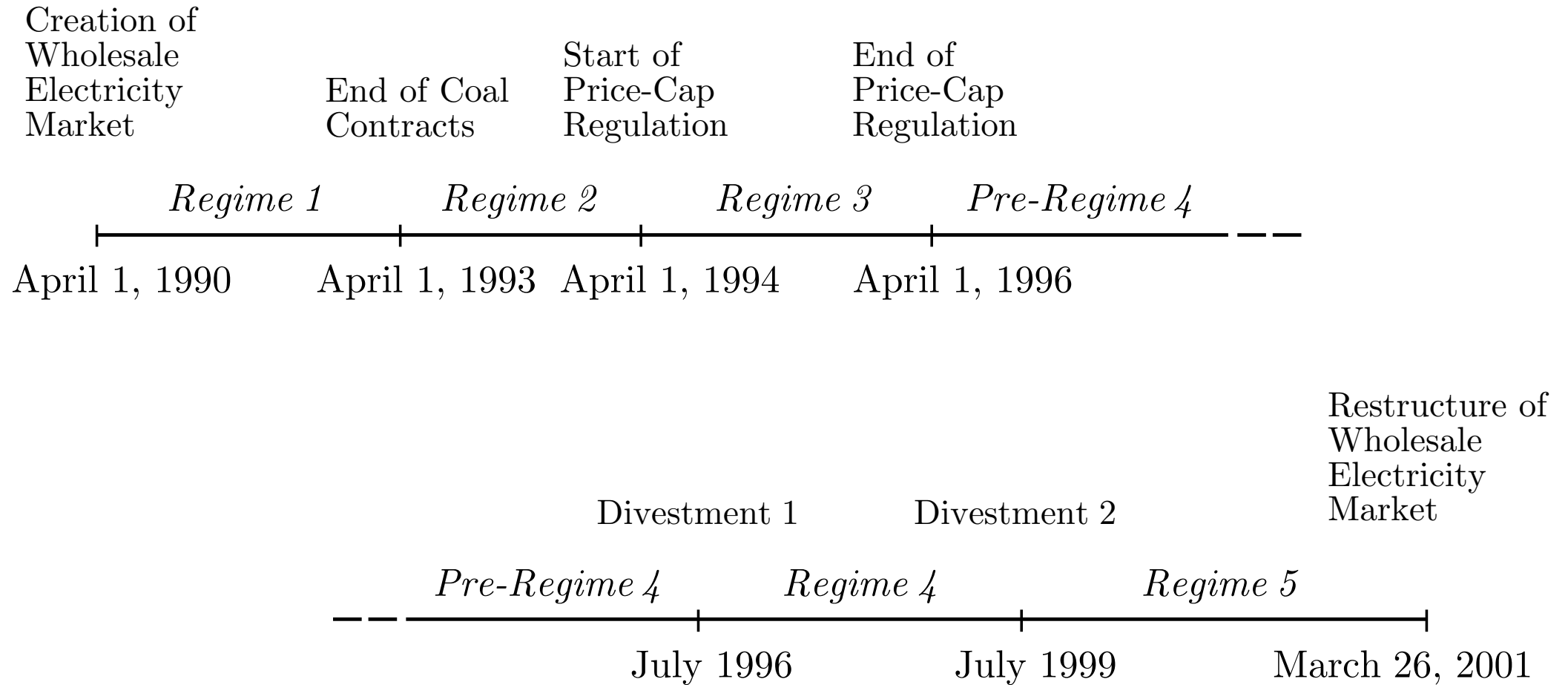
- Motivation

Fig. 3: *Daily Electricity Prices (April 1, 1990–March 26, 2001)*



General Introduction Liberalization of Electricity Industry

Institutional Changes and Regulatory Reforms



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Paper Estimating the Volatility of Electricity Prices

- Motivation

Policy Importance

- Price fluctuations:
 - uncertainty about revenues and costs
 - higher electricity prices for consumers

Research Question

- How did the institutional changes and regulatory reforms affect the dynamics of electricity prices during the liberalization process?

Research Approach

- stationarity and seasonality
- *AR-ARCH* model with a smoothly time-varying intercept term

Paper Estimating the Volatility of Electricity Prices

- Literature Review

- **Crespo *et al.* (2004)**

Hourly prices from the Leipzig Power Exchange (Jun. 16, 2000–Oct. 15, 2001)
AR, *ARMA* models: separate studies of each hour yielded better forecasts

- **Guthrie and Videbeck (2007)**

30-min prices from the New Zealand Electricity Market (Nov. 1, 1996–Apr. 30, 2005)
Half-hourly trading periods naturally fall into 5 groups, which can be studied separately using a periodic *AR* model

- **Huisman *et al.* (2007)**

The Amsterdam Power Exchange (APX), the European Energy Exchange (EEX; Germany), and the Paris Power Exchange (PPX) for the year 2004
Hourly electricity prices are treated as a panel in which hours represent cross-sectional units and days represent the time dimension. SUR is applied

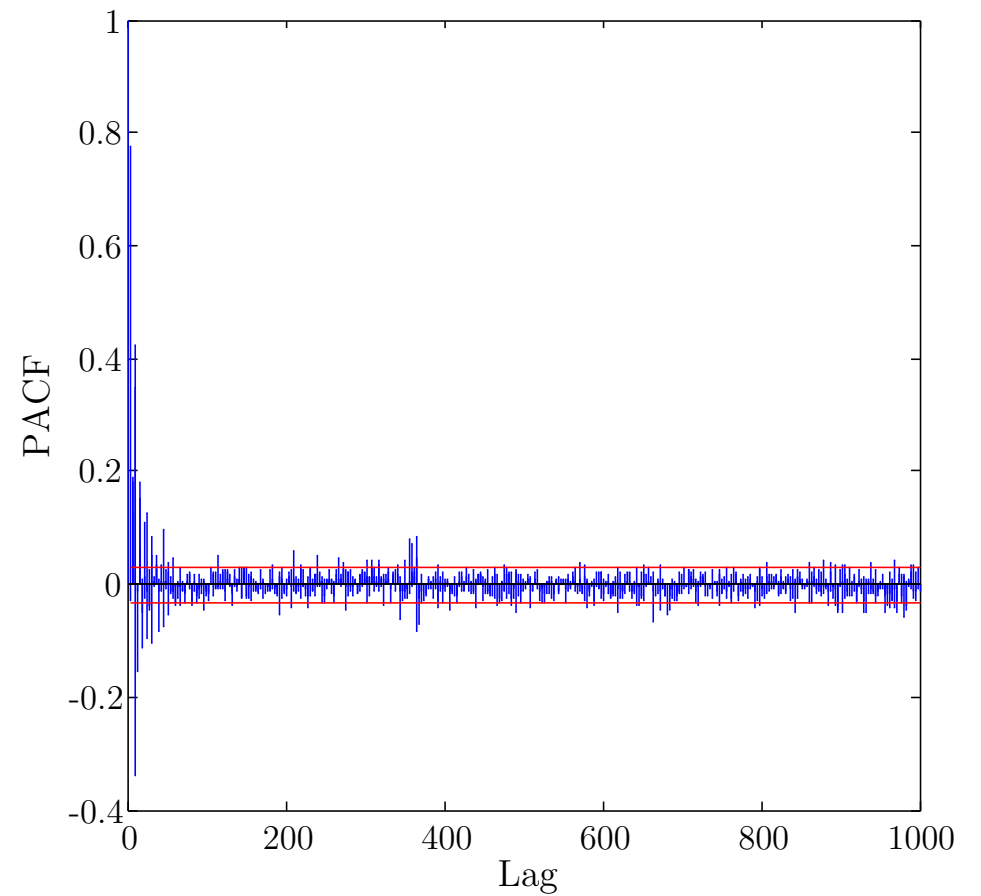
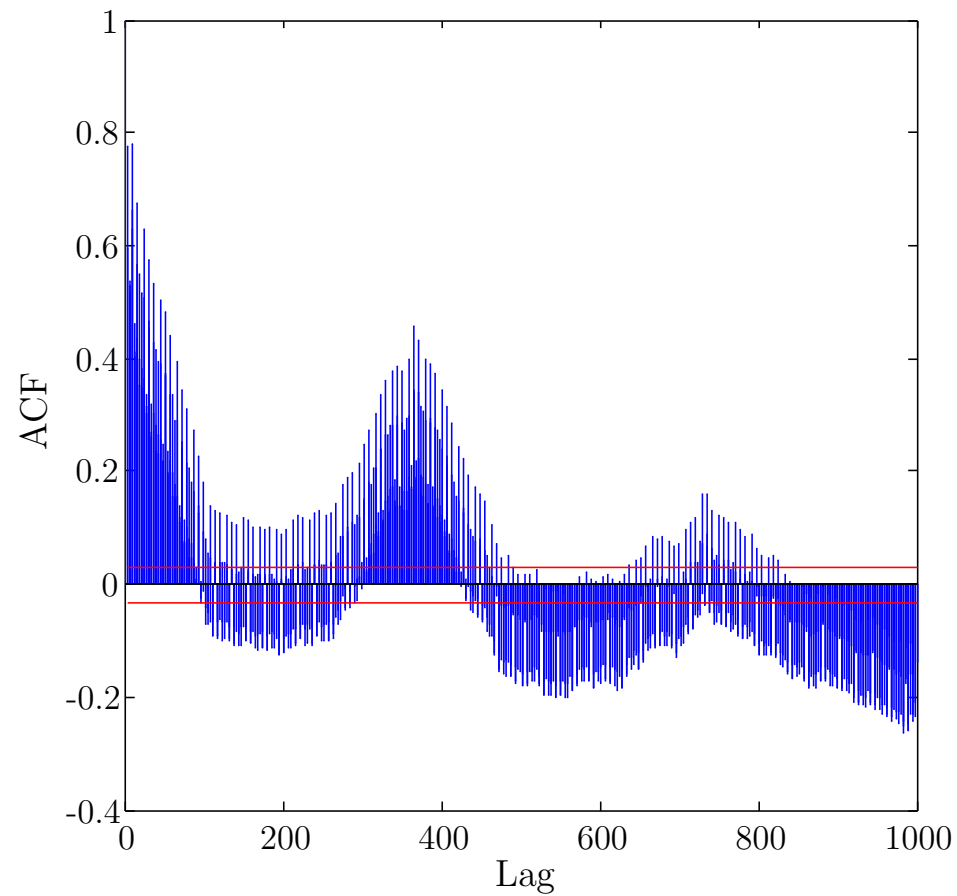
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- Literature Review (*cont.*)
 - **Conejo *et al.* (2005)**
PJM interconnection data for the year 2002
Dynamic modeling is preferred to seasonal differencing
 - **Garcia *et al.* (2005)**
Spanish and California electricity markets (Sept. 1, 1999–Nov. 30, 2000; Jan. 1, 2000–Dec. 31, 2000)
GARCH model outperforms a general *ARIMA* model when volatility and price spikes are present
 - **Bosco *et al.* (2007)**
Daily prices from the Italian wholesale electricity market
Periodic *AR-GARCH* methodology

Paper Estimating the Volatility of Electricity Prices

- Seasonality: Time Domain Analysis

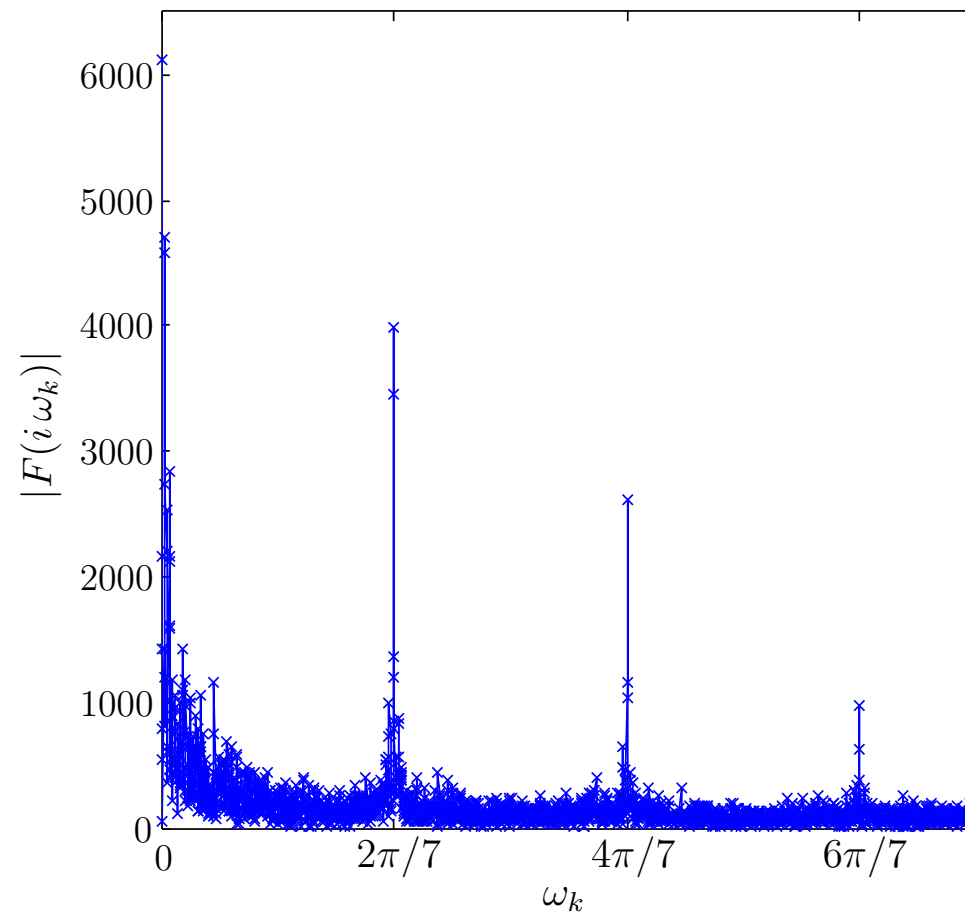
Fig. 4: *Correlogram for Daily Electricity Prices*



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- Seasonality: Frequency Domain Analysis

Fig. 5: *Periodogram for Daily Electricity Prices*



Paper Estimating the Volatility of Electricity Prices

- Regression Model

$$price_t = a_0 + \sum_{i=1}^P a_i price_{t-i} + z'_t \cdot \gamma + \varepsilon_t \quad (1)$$

$$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + z'_t \cdot \delta \quad (2)$$

$$\nu_t = \frac{\varepsilon_t}{\sqrt{h_t}} \sim \text{Generalized Normal Distribution}, \quad (3)$$

where z_t is a vector of additional explanatory variables including the sine/cosine periodic functions and regime dummy variables.

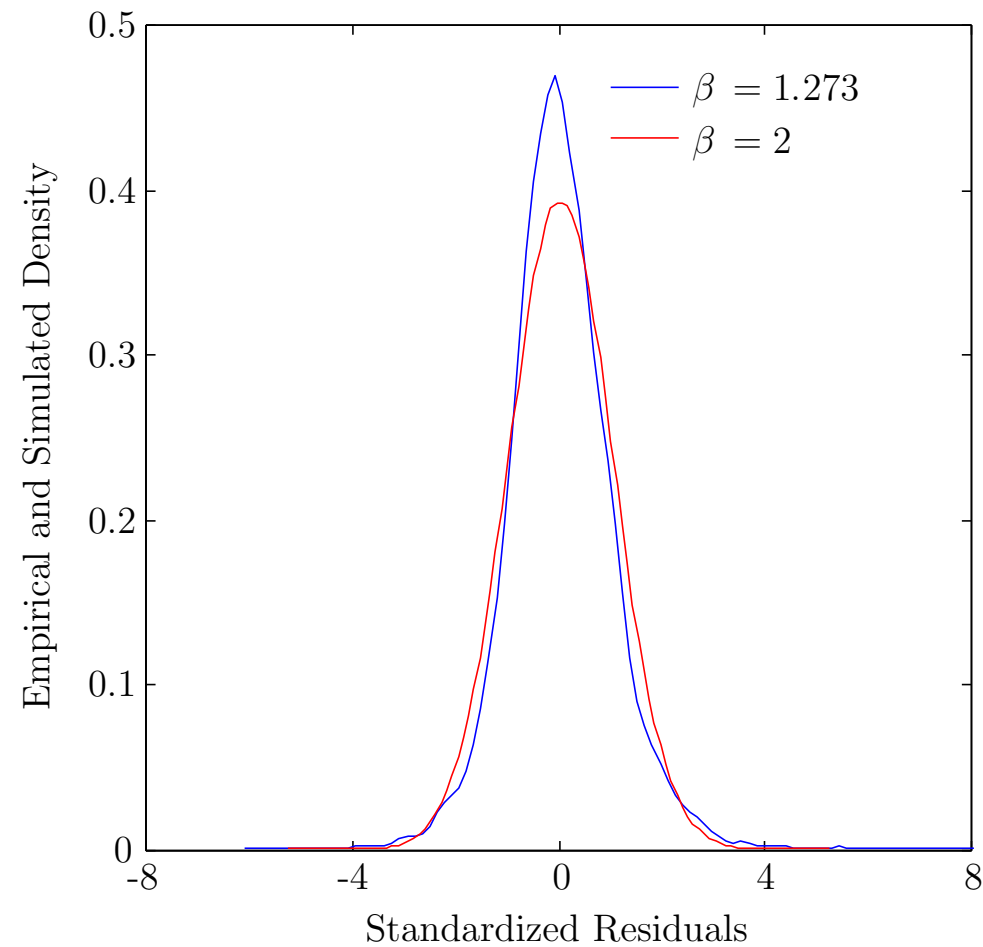
- Methodological findings:

- The sine/cosine periodic functions allow better modeling weekly seasonality
- + and – shocks from the previous week are found to asymmetrically affect volatility

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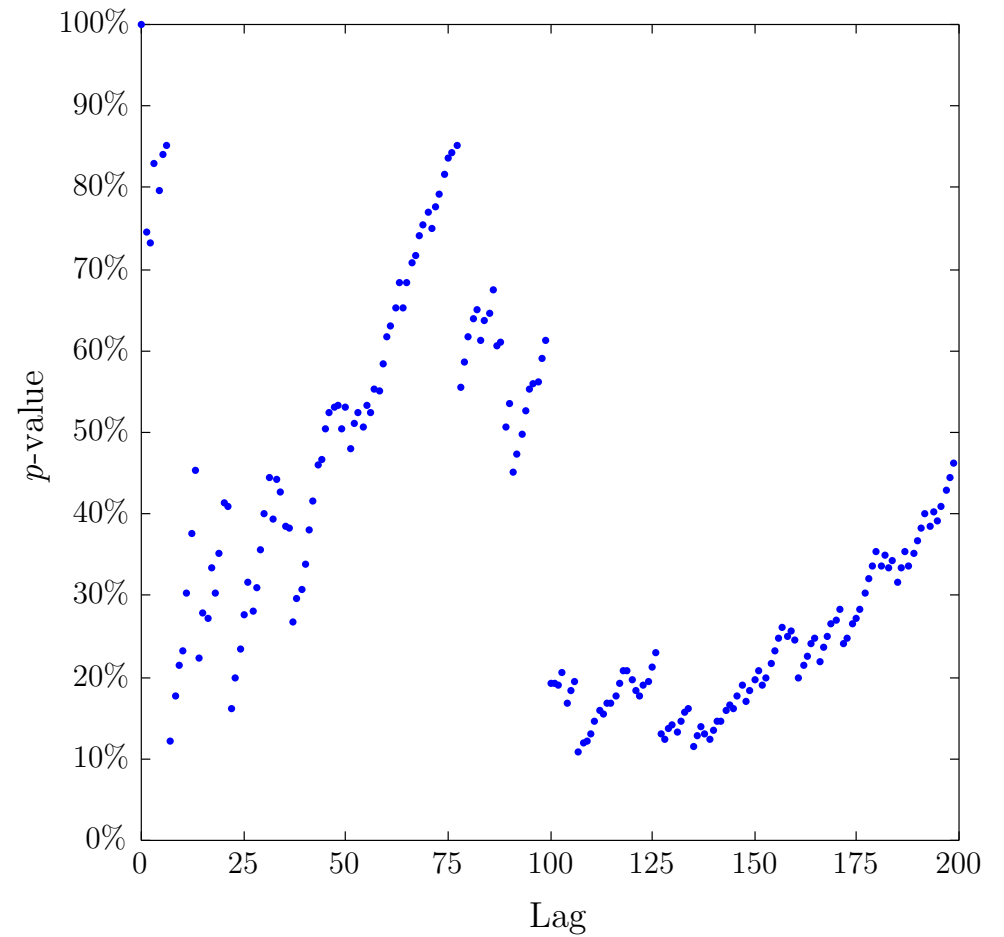
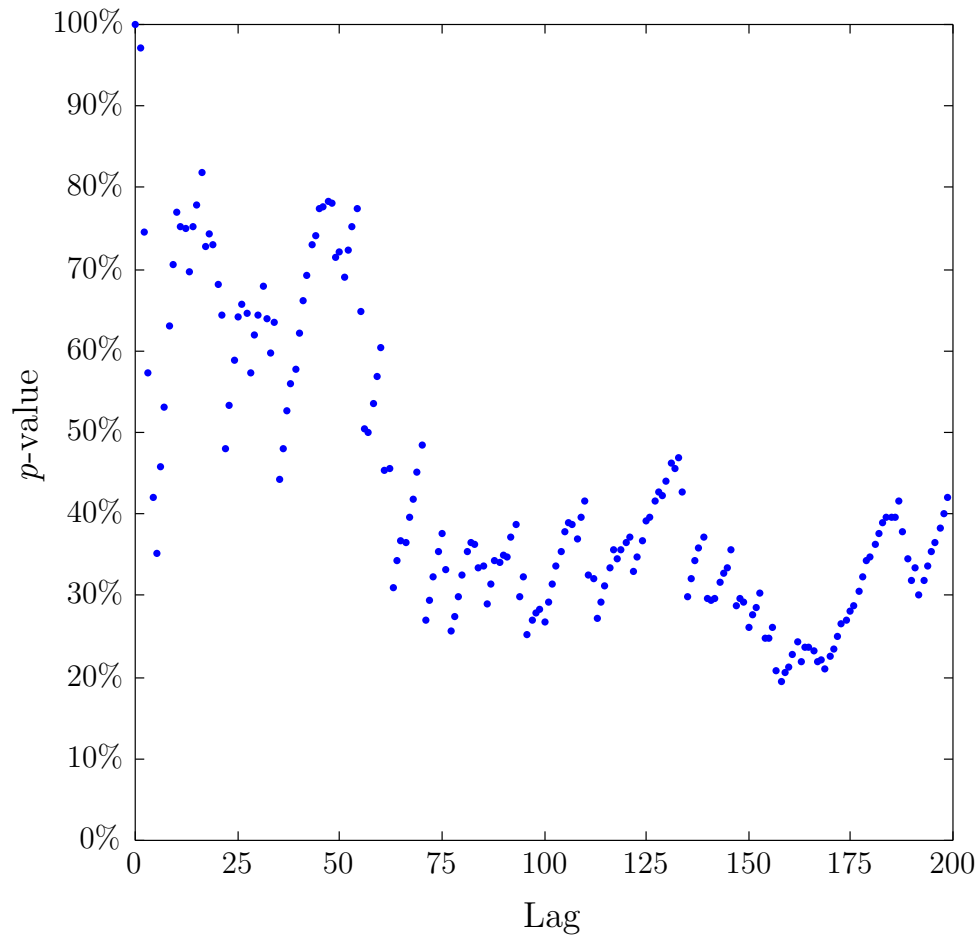
- Empirical Distribution

Fig. 6: *Density of $\hat{\nu}_t$ and the Normal Distribution*



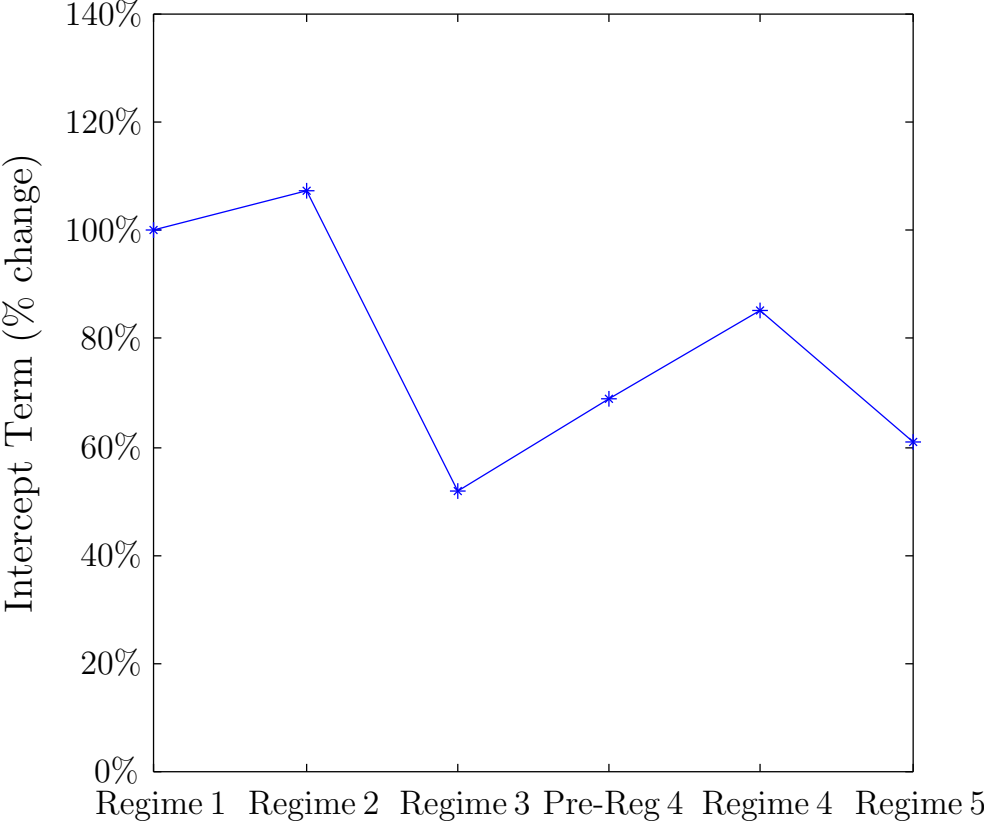
- Diagnostics of standardized residuals

Fig. 7: *Ljung–Box Q-Test for Standardized Residuals $\hat{\nu}_t$ and $\hat{\nu}_t^2$*

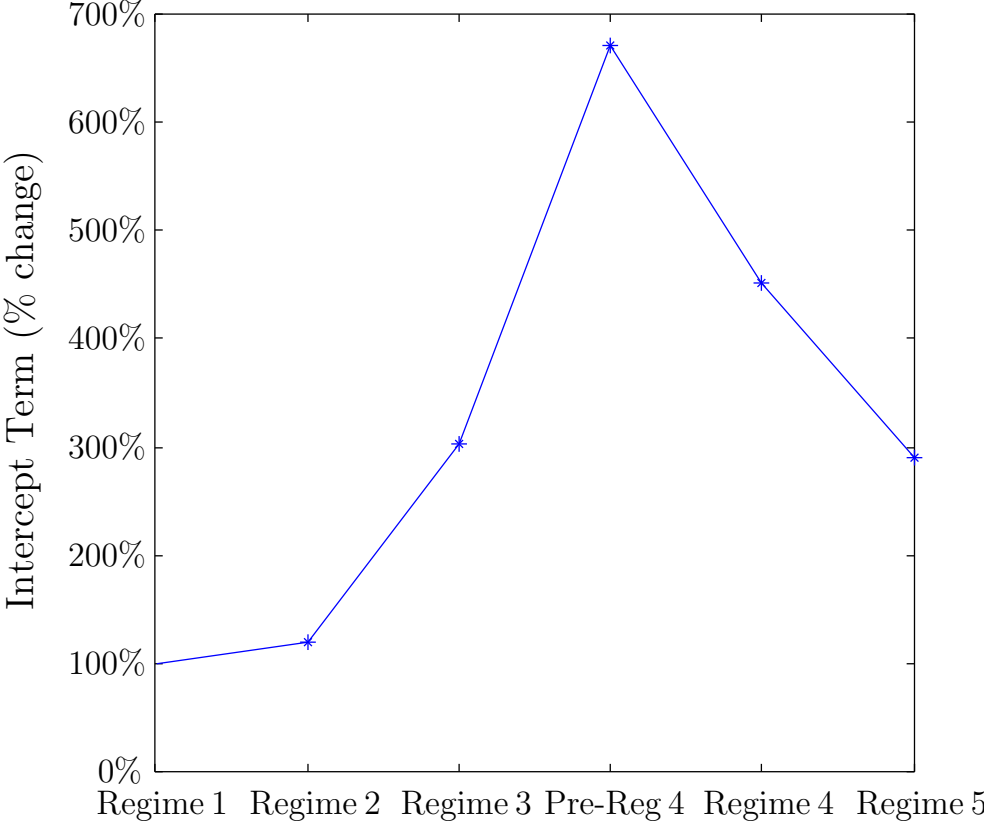


- Results

Fig. 8: *Impact on Price and Volatility Dynamics*



(a) Mean Equation



(b) Conditional Volatility Equation

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- Contributions
- Methodological contribution
 - Application of the sine and cosine periodic functions allow better modeling weekly seasonality
 - + and – shocks from the previous week are found to asymmetrically affect volatility
- Policy contribution
 - The price-cap regulation and first series of divestments are found to result in opposite directions for the movement in the price level and volatility
 - Higher price and lower volatility levels are interpreted as an indication of possible tacit collusion
 - During the last regime period it was possible to simultaneously decrease prices and volatility

Thank You

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- Seasonality: Frequency Domain Analysis

The Fourier transform of a real-valued function $p(t)$ on the domain $[0, T]$ is defined as

$$F(i\omega) = \mathcal{F}\{p(t)\} = \int_0^T p(t) \cdot e^{-i\omega t} dt$$

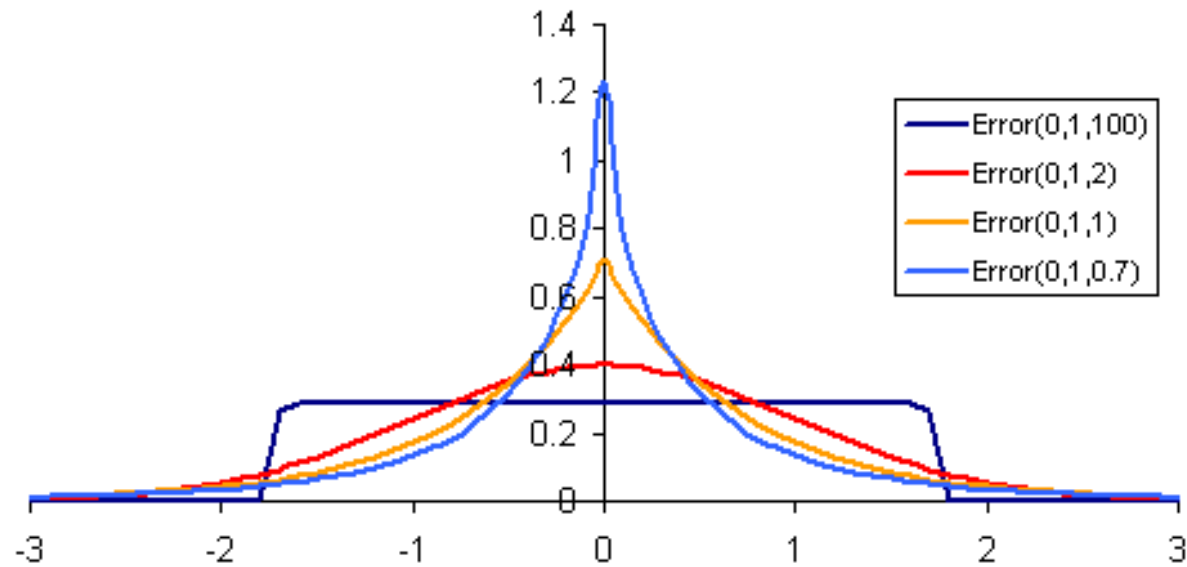
$$\begin{aligned} |F(i\omega_k)| &\approx \left| \sum_{t=0}^{T-1} p_t \cdot e^{-i\omega_k t} \right| = \left| \sum_{t=0}^{T-1} p_t \cdot (\cos \omega_k t - i \sin \omega_k t) \right| = \\ &= \left| \sum_{t=0}^{T-1} p_t \cdot \cos \omega_k t - i \sum_{t=0}^{T-1} p_t \cdot \sin \omega_k t \right| = \\ &= |(p_t, \cos \omega_k t) - i (p_t, \sin \omega_k t)| \longrightarrow \max_{\omega_k} \end{aligned}$$

where $\omega_k = \frac{k}{N-1} \cdot 2\pi$ and $k = 0, 1, 2, \dots, N-1$.

Paper Estimating the Volatility of Electricity Prices

- Generalized Normal Distribution

Fig. 9: *Generalized Normal Distribution for Different Values of the Shape Parameter β*



Notes:

Generalized Normal Distribution is also known as Generalized Error Distribution: $\text{Error}(\mu, \sigma, \beta)$.

In our case we have $\mu = 0$ and $\sigma^2 = 1$. For the special cases of the shape parameter $\beta = 1$, $\beta = 2$, and $\beta \rightarrow +\infty$ we obtain Laplace, Standard Normal, and Uniform distributions, respectively.