Robust estimation and forecasting of the long-term seasonal component (LTSC) of electricity spot prices

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Essen, 9 October 2013

Based on J. Nowotarski, J. Tomczyk, R. Weron (2013) Robust estimation and forecasting of the long-term seasonal component of electricity spot prices, Energy Economics 39, 13-27

Financed by NCN grant no. 2011/01/B/HS4/01077

Introduction

- When building electricity spot price models we should address two questions:
  - How to estimate the trend-seasonal component?
  - How to forecast it?

Why?

3 approaches to LTSC modeling

1. Piecewise constant functions or dummies
   - Non-smooth LTSC with jumps between months

   Bhanot (2000), Fanone et al. (2012), Fleten et al. (2011), Gianfreda and Grossi (2012), Haldrup et al. (2010), Haugom and Ullrich (2012), Higgs and Worthington (2008), Knittel and Roberts (2005), Lucia and Schwartz (2002)

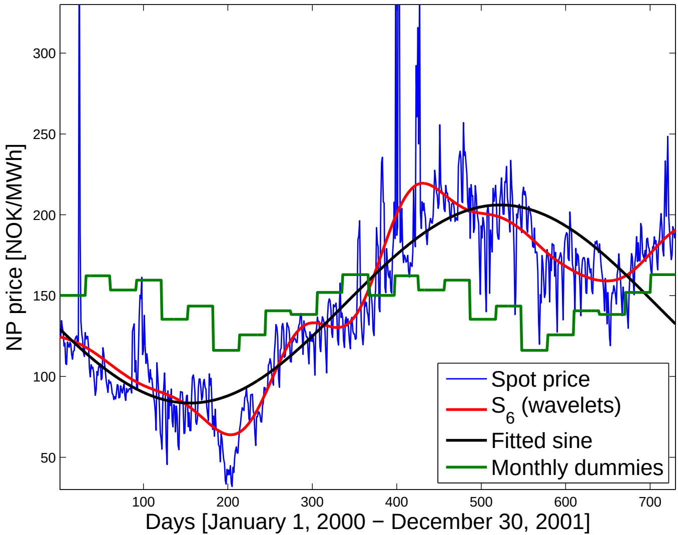
2. Sinusoidal functions (also coupled with EWMA)
   - Annual periodicity can hardly be observed in market data

   Benth et al. (2012), Bierbrauer et al. (2007), Cartea and Figueroa (2005), De Jong (2006), Geman and Roncoroni (2006), Janczura et al. (2013), Lucia and Schwartz (2002), Pilipovic (1998), Weron (2008)

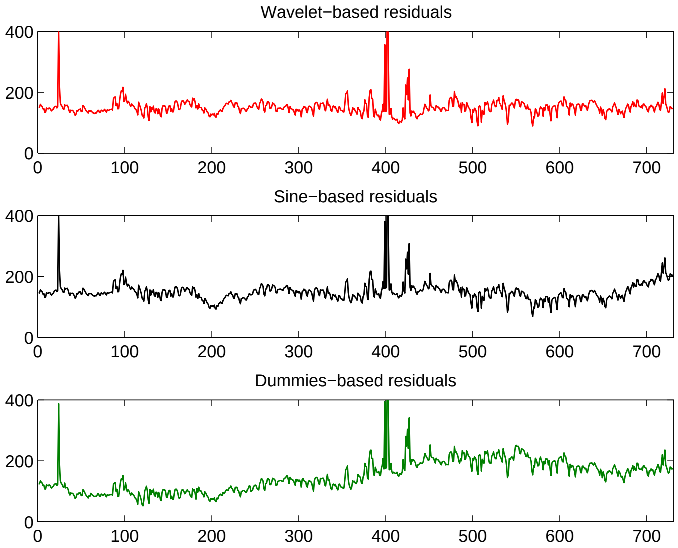
3. Wavelets or other nonparametric smoothers
   - More robust to outliers and less periodic
   - ... but forecasting of a nonparametric LTSC is not trivial

   Bordignon et al. (2013), Conejo et al. (2005), Janczura et al. (2013), Janczura and Weron (2010,2012), Stevenson (2001), Schlueter (2010), Stevenson et al. (2006), Weron (2006,2009), Weron et al. (2004)

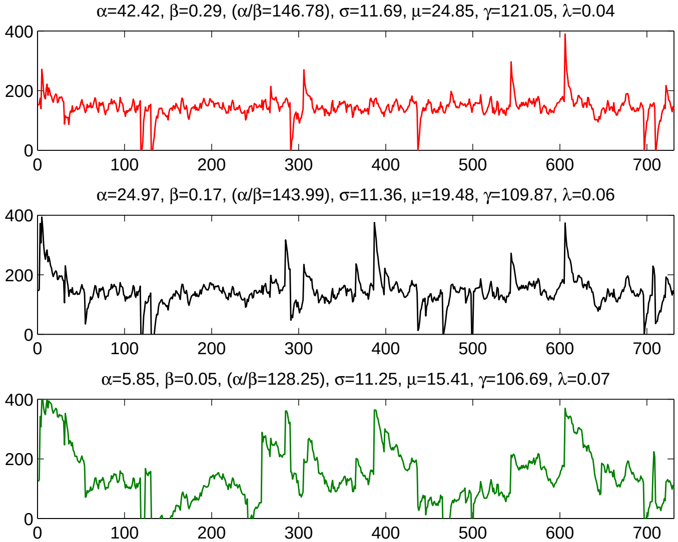
3 LTSC fits to Nord Pool spot prices



3 stochastic components (residuals)



3 MRJD fits: $dX = (\alpha - \beta X)dt + \sigma dB + \mathcal{N}(\mu, \gamma)dN(\lambda)$



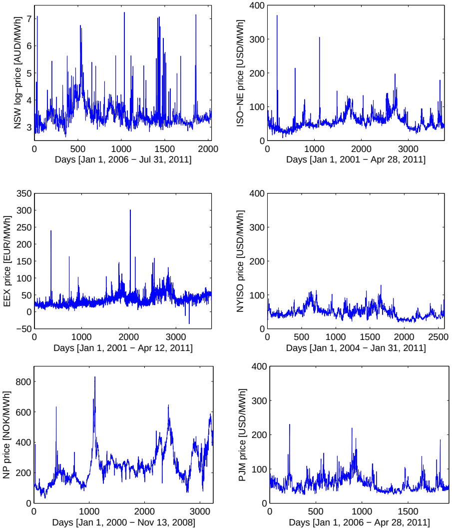
Agenda

- Introduction
- **Datasets and models**
- Estimating and forecasting the LTSC
- Results
- Conclusions

Daily electricity spot prices

6 markets:

- NSW, Australia (2038 obs.)
- EEX, Germany (3754 obs.)
- Nord Pool, Scandinavia (3240 obs.)
- ISO-NE, U.S. (3770 obs.)
- NYISO, U.S. (2588 obs.)
- PJM, U.S. (1944 obs.)



304 models: Simple and sine-based models

- Simple models (**1*000***) $\longrightarrow$ 16 models
  - mean, median, linear regression
  - linear/exponential decay from the current spot price to the median
  - dummies: mean-based, median-based
- Sines fitted to raw prices (**2***00**) $\longrightarrow$ 24 models
  - 1-4 sines used
  - periods estimated or set to 1y, $\frac{1}{2}$y, $\frac{1}{3}$y and $\frac{1}{4}$y
- Sines fitted to spike-filtered prices (**3****0**) $\longrightarrow$ 48 models
  - Spikes replaced by the mean or the upper/lower 2.5% quantiles of the deseasonalized prices
    - $\longrightarrow$ Janczura et al., Energy Economics 38 (2013) 96-110

304 models: Wavelet-based models

- Wavelets with an exponential decay to the median fitted to raw prices (**4***0***) $\longrightarrow$ 48 models
  - 4 types of wavelets (Daubechies, Coiflets)
  - 3 approximation levels (6, 7, 8)
  - 2 exponential decay constants
- Wavelets with a linear decay to the median fitted to raw prices (**5***00**) $\longrightarrow$ 24 models
- Wavelets with an exponential decay to the median fitted to spike-filtered prices (**6*******) $\longrightarrow$ 96 models
  - Spikes replaced by the mean or the upper/lower 2.5% quantiles of the deseasonalized prices
- Wavelets with an exponential decay to the median fitted to spike-filtered prices (**7****0**) $\longrightarrow$ 48 models

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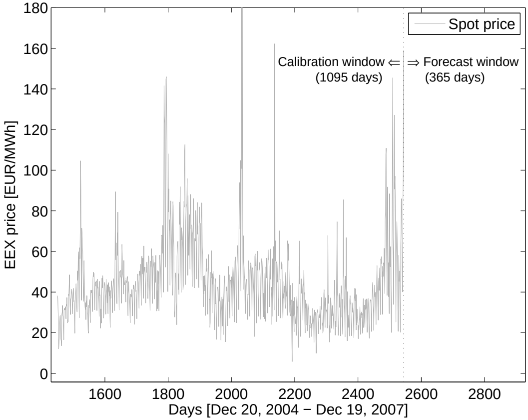
Estimation and forecasting scheme

2 calibration windows (rolling windows):

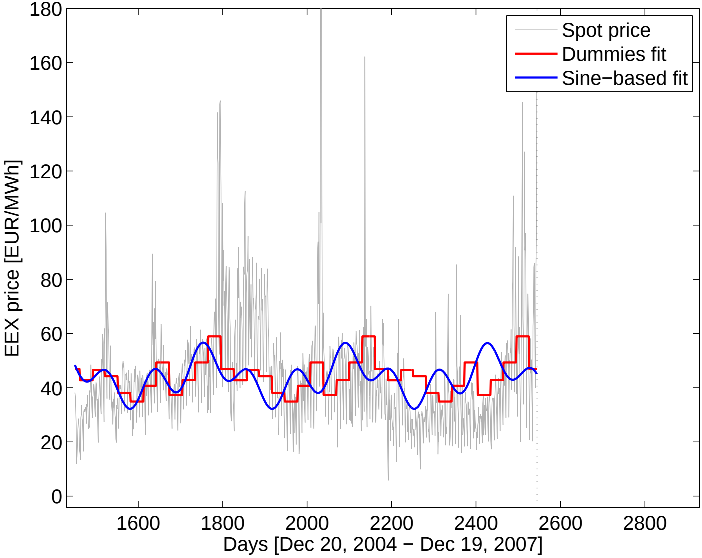
- 2-year (730 days)
- 3-year (1095 days)

6 forecast horizons:

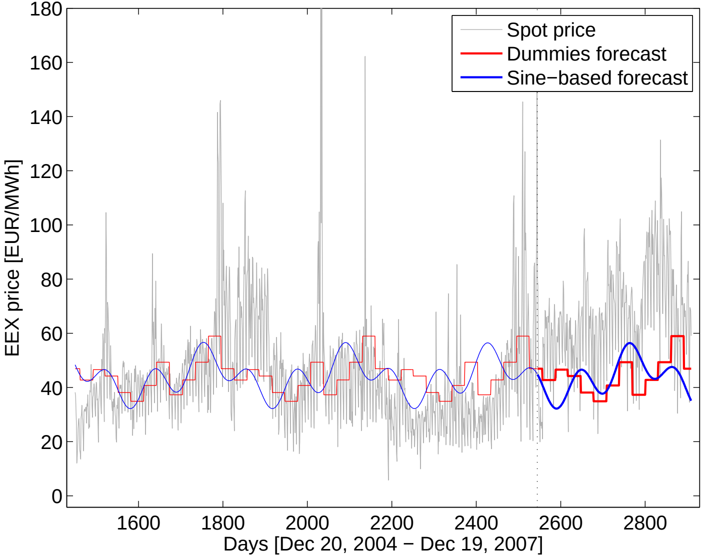
- 1-7 day, 8-30, 31-90
- 91-182 (2nd Qtr)
- 183-274 (3rd Qtr)
- 275-365 (4th Qtr)



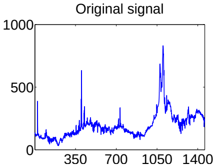
Estimation: Dummies and sines



Forecasting: Dummies and sines



Decomposition of a signal



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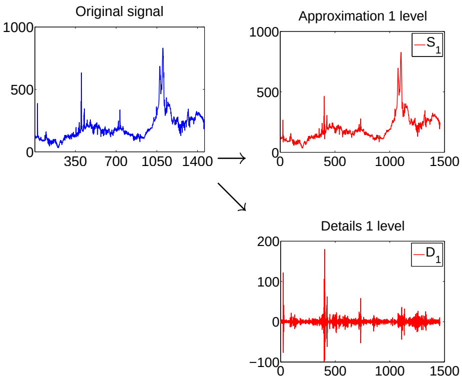

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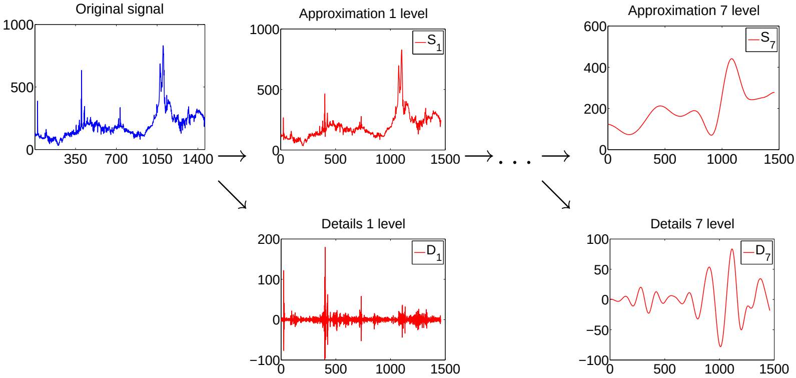
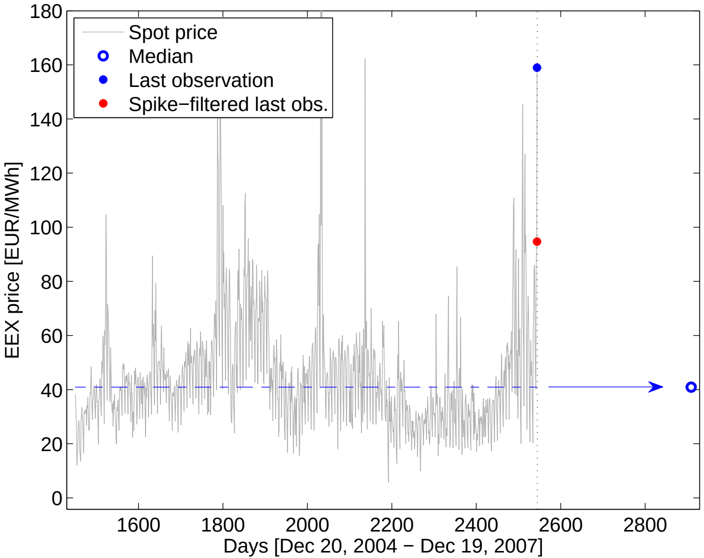
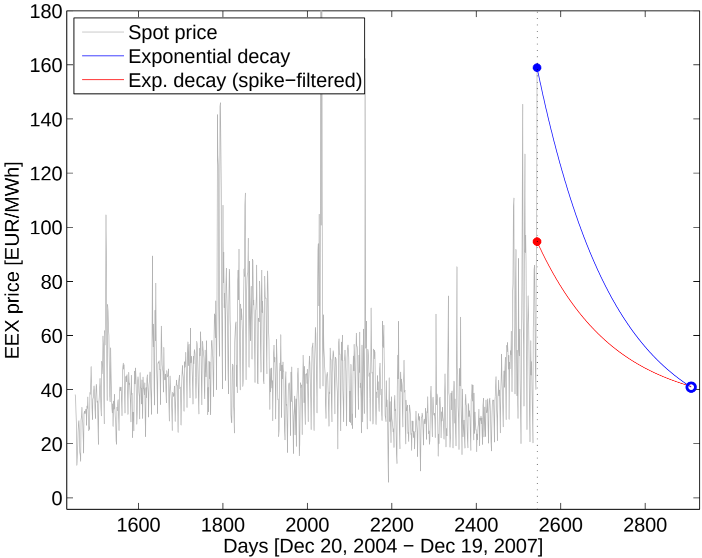


Estimation and forecasting: Wavelets



Estimation and forecasting: Wavelets cont.



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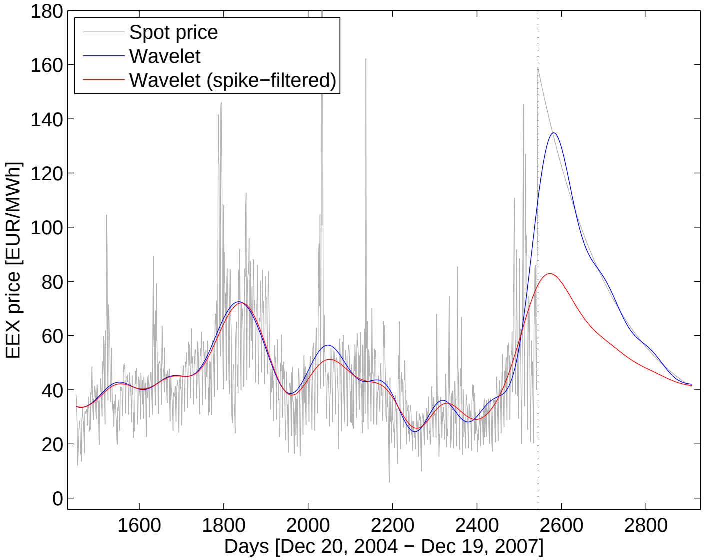
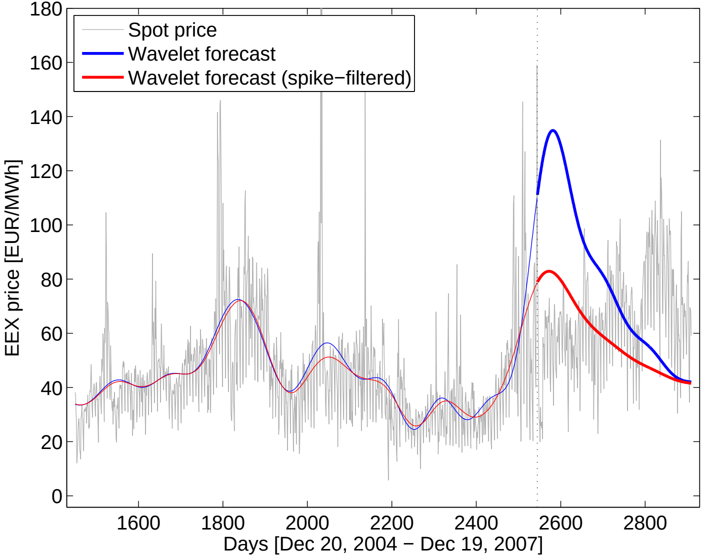


Estimation and forecasting: Wavelets cont.



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Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
d_1						
d_2						
d_3						
d_4						
d_5						
d_6						

- For every dataset d_i and every forecasting horizon h_j we **rank** the models according to MAE, MSE and MAPE

Evaluating forecasting performance

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- For every dataset d_i and every forecasting horizon h_j we **rank** the models according to MAE, MSE and MAPE
  - For each dataset we calculate the geometric means $GM(MAE_{*,d})$ and $GM(MSE_{*,d})$ of the ranks

Evaluating forecasting performance

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  - For each horizon we calculate the geometric means $GM(MAE_{h,*})$ and $GM(MSE_{h,*})$ of the ranks

Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
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  - For each horizon we calculate the geometric means $GM(MAE_{h,*})$ and $GM(MSE_{h,*})$ of the ranks
  - We also calculate the **global** geometric means $GM(MAE_{*,*})$ and $GM(MSE_{*,*})$ of the ranks

Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
d_1						
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- For every dataset d_i and every forecasting horizon h_j we **rank** the models according to MAE, MSE and MAPE
  - For each dataset we calculate the geometric means $GM(MAE_{*,d})$ and $GM(MSE_{*,d})$ of the ranks
  - For each horizon we calculate the geometric means $GM(MAE_{h,*})$ and $GM(MSE_{h,*})$ of the ranks
  - We also calculate the **global** geometric means $GM(MAE_{*,*})$ and $GM(MSE_{*,*})$ of the ranks
- Finally, we calculate $MAPE_{*,d}$, $MAPE_{h,*}$ and the **global** $MAPE_{*,*}$

Results

Top 15 models according to each of the three global forecast error measures

No.	GM(MAE$_{*,*}$)	Model	GM(MSE$_{*,*}$)	Model	MAPE$_{*,*}$	Model
1	17.13	731310	10.84	623322	30.04%	734110
2	23.37	723310	13.75	622322	30.04%	732110
3	23.93	631312	14.71	624322	30.06%	733110
4	24.86	623322	20.98	631322	30.06%	723310
5	24.86	722110	24.82	631312	30.08%	731110
6	25.16	723320	24.91	633122	30.09%	724310
7	25.58	721110	25.63	624122	30.14%	731310
8	25.91	724310	25.82	621322	30.15%	623322
9	26.44	623312	28.87	634122	30.16%	624322
10	26.97	724110	29.50	621122	30.18%	722310
11	29.49	623122	29.74	722320	30.20%	724320
12	29.82	722310	30.76	721120	30.20%	721110
13	29.94	624322	31.96	623122	30.20%	722110
14	30.97	624122	32.77	422302	30.21%	723320
15	31.25	723110	32.88	424302	30.26%	722320

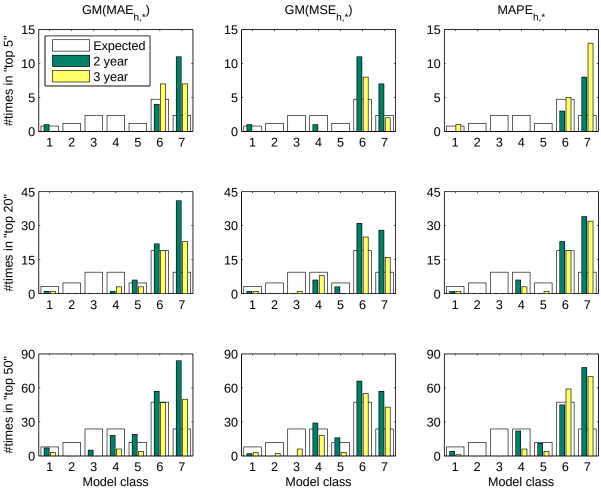
Results cont.

… models according to each of the three global forecast error measures

No.	GM(MAE$_{*,*}$)	Model	GM(MSE$_{*,*}$)	Model	MAPE$_{*,*}$	Model
51	.	.	.	.	30.51%	423302
55	53.42	523300	.	.	.	.
69	.	.	71.88	130001	.	.
70	62.27	423302	.	.	.	.
79	.	.	77.29	524200	.	.
82	70.87	120005	.	.	.	.
105	.	.	.	.	30.91%	524300
120	.	.	.	.	31.14%	130005
128	98.93	120008	.	.	.	.
173	.	.	143.57	231100	.	.
174	.	.	143.72	331110	.	.
182	.	.	148.64	130008	.	.
209	192.24	324320	.	.	.	.
225	.	.	.	.	34.47%	130008
226	206.55	232200	.	.	.	.
228	.	.	.	.	36.91%	331110
241	.	.	.	.	37.43%	231300

Results cont.

The number of times models from a given family are ranked in the top 5, 20 and 50 of all 304 models according to $GM(MAE_{h,*})$, $GM(MSE_{h,*})$ and $MAPE_{h,*}$ for each of the six forecast horizons h = 1,...,6



Conclusions

- A comprehensive study on the forecasting of the LTSC
- Over 300 models examined, including commonly used and new approaches
- Wavelet-based models outperform sine-based and monthly dummy models
  - Both in-sample (modeling) and out-of-sample (forecasting)
- Validity of stochastic models built on sines or monthly dummies is questionable