

Temperature models for pricing weather derivatives

Quantitative Finance, forthcoming

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Agenda

1 Literature review

- 2 Spline model
- 3 Results

4 Conclusion

Literature review

Whole zoo of models:

- ▶ Jewson and Penzer (2004): Index Modeling
- ▶ Dischel (1998): First daily simulation model
- Cao and Wei (2000): AR type process
- ► Alaton et al. (2002): Sine-shaped seasonality
- ▶ Brody et al. (2002): Long autocorrelation in temperature residues
- Campbell and Diebold (2005): Seasonal ARCH
- ▶ Benth and Šaltytė-Benth (2007): Standard OU-process with seasonal volatility

Only two contributions compare these models:

- ► Oetomo and Stevenson (2005)
- ► Papaziana and Skiadopoulos (2009)

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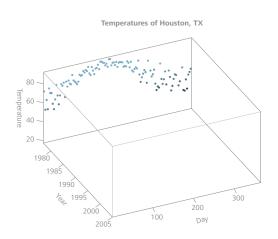
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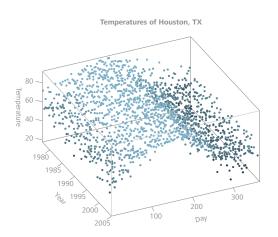
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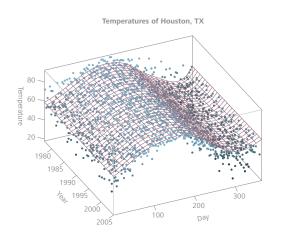
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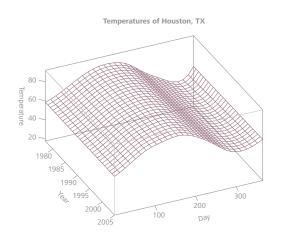
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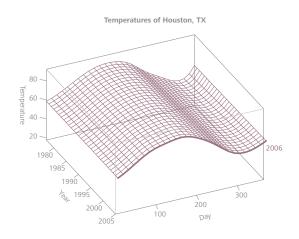












Spline model – Definition

- Consider the historical temperatures of each year from shortly before the measurement period till the end of the measurement period
- Split the temperatures into a trend and seasonality component in the mean and into a trend and seasonality component in the variance:

$$T_t = \mu_t + \sigma_t R_t$$

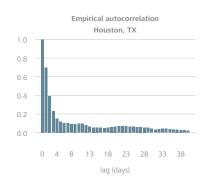
where

$$\mu, \sigma \in \mathbb{S}_{4,K_{\mathsf{Dav}}} \otimes \mathbb{S}_{2,K_{\mathsf{Year}}},$$

 $\mathbb{S}_{n,K}$ = Space of splines of degree n with knot sequence K



Spline model – Autocorrelation of the residues



- Fast decline of the autocorrelation at the beginning
- But: Positive autocorrelations for a long time period



Spline model – AROMA process

Main idea: Evolution of temperatures is caused by the interaction of different processes with different time scales:

> short-term Changes in the atmosphere mid-term Changes of the surface temperature long-term Changes of the water temperature

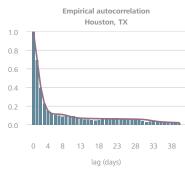
► Modeling the residues with an AROMA process (Jewson and Caballero, 2003)

$$\begin{split} R_t &= \phi_1 \bar{R}_{m_1,t} + \phi_2 \bar{R}_{m_2,t} + \phi_3 \bar{R}_{m_3,t} + \phi_4 \bar{R}_{m_4,t} + Z_t \\ \bar{R}_{m,t} &= \frac{1}{m} \sum_{i=1}^m R_{t-i}, \quad Z_t \sim \textit{N}(0, \sigma_{\phi}^2) \end{split}$$



Spline model – Fitting the AROMA process

- ► For a fixed length the parameters of a AROMA process can be estimated
- Choosing the length so that the empirical autocorrelation is fitted best



$$m_1 = 1, m_2 = 2, m_3 = 8, m_4 = 31$$

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Results - Backtesting

- ▶ Valuation of fictive contracts of the years 1983–2005 using
 - temperature data up to 180 days ahead of the measurement period
 - temperature data up to the middle of the measurement period.
- ▶ All models include linear detrending and use temperature data for the last 30 years
- ▶ Valuation of 12 typical contracts (6 HDD, 6 CDD) at 35 US locations
- Compare the predicted index values with realized index values
- Measure: (mean) relative error and (mean) squared relative error

$$\delta \hat{x} = \frac{\hat{x} - x}{x}, \quad (\delta \hat{x})^2 = \left(\frac{\hat{x} - x}{x}\right)^2$$

Results – MSRE by geographical regions, 180 days ahead of measurement period



HDD error

CDD error

Results – MSRE by geographical regions, 180 days ahead of measurement period



HDD error

CDD error

Results - MSRE by geographical regions, middle of measurement period



HDD error

CDD error



Results - Ranking of the models

Mann-Whitney U test

► Compare the MSRE of each pair of models

 \vdash $H_0: (\delta \hat{Y})_x^2 \ge (\delta \hat{Y})_y^2$ vs. $H_1: (\delta \hat{Y})_x^2 < (\delta \hat{Y})_y^2$

Significance at 5% level

Evaluated 180 days ahead of the measurement period:

Spline model \prec Index Modeling \prec Benth model \prec Alaton model

Evaluated in the middle of the measurement period:

Spline model \prec Alaton model \prec Index Modeling \prec Benth model



Results – Uncertainty

Table: Slope parameters for the relation between the realised standard deviation and the predicted standard deviation.

	Slope	95% Confidence Interval
Index Modeling	0.9976	(0.9821, 1.0131)
Alaton model	1.2259	(1.1971, 1.2546)
Benth model	1.0793	(1.0498, 1.1089)
Spline model	1.1556	(1.1387, 1.1726)

All daily simulation models underestimate the uncertainty of the prediction

Conclusion

- Models for temperature indices perform better when HDD indices than predicting CDD indices.
- ▶ Performance of the models depends on the geographic location of the weather station
- Main advantage of daily simulation models when evaluating contracts during the measurement period
 - Is this still the case when embedding meteorological temperature forecasts into the models?
- ▶ Daily simulation models underestimate the uncertainty of the prediction



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