# Modeling and forecasting electricity forward prices: A DSFM approach

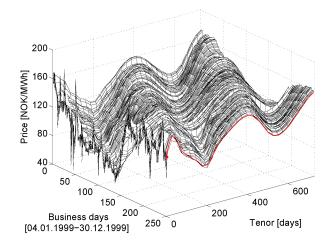
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#### How can we model the dynamics of the electricity forward curve?



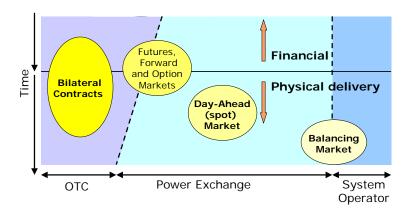
#### Motivation

- The electricity forward curve is a complex object with a non-trivial structure which exhibits seasonality and extreme volatility at the short end
- Our aim is to model and estimate forward curves for trading, hedging and risk management
- In this context the electricity forward curve acts as a very high-dimensional state variable
- Practice requires a low-dimensional representation of the curve

#### **Agenda**

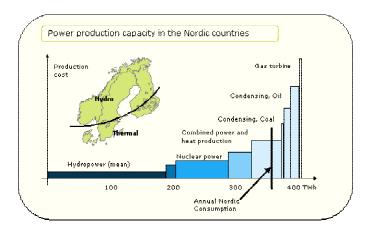
- 1. Motivation ✓
- 2. The Nordic power market and the forward curves
- 3. The Dynamic Semiparametric Factor Model
- 4. Modeling and forecasting
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## Wholesale power market structure

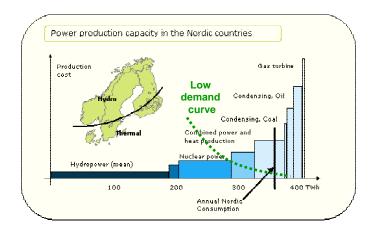




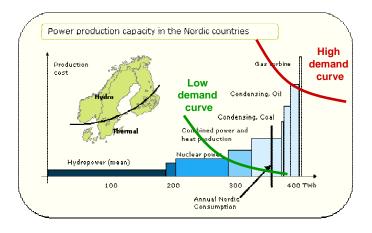
## Supply stack and the market cross



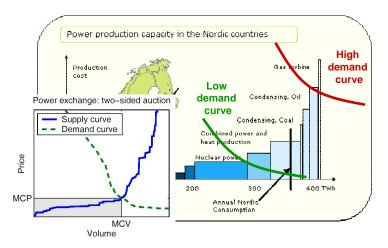
## Supply stack and the market cross cont.



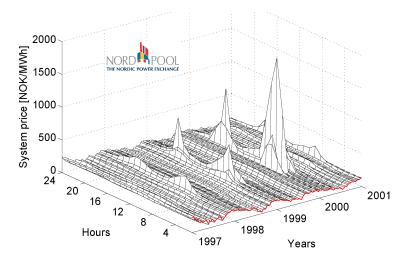
## Supply stack and the market cross cont.



## Supply stack and the market cross cont.

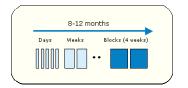


## Seasonality, extreme volatility and spikes



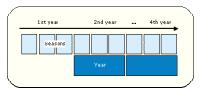


#### Futures and forwards at Nord Pool



#### Futures contracts

Day contracts (Dxx): 24 hours Week contracts (GUxx): 7 days Block contracts (GBxx): 4 weeks

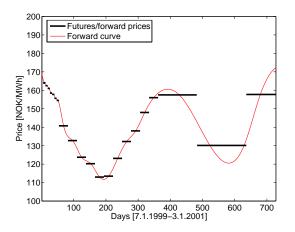


#### Forward contracts

Winter 1 (FWV1xx): January - April Summer (FWSOxx): May - September Winter 2 (FWV2xx): October - December Year (FWYRxx)



#### The forward curve ...



## ... and its dynamics



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## Background

- Primary application: Dimension reduction
- Originally introduced for modeling implied volatility surfaces [Fengler et al. (2007)]
- Can be seen as a combination of functional principal component analysis (fPCA) and nonparametric curve estimation

#### The model

$$\mathbf{Y}_t = m_0(\mathbf{X}_t) + \sum_{l=1}^{L} Z_{t,l} m_l(\mathbf{X}_t) + \varepsilon_t$$

where the data vector  $\mathbf{X}_t$  has J coordinates  $X_{t,j}$  (observations per day)

- oxdots  $\mathbf{Z}_t = (1, Z_{t,1}, \dots, Z_{t,L})^{ op}$  is a multivariate time series

#### The model cont.

- $\Box$  The functions  $m_l$  reflect the time invariant structure of  $\mathbf{Y}_t$
- $\widehat{m}_l$  is a nonparametric estimator of  $m_l$  obtained **directly** from the data points  $X_{t,j}$ , i.e. not from some estimated functions of  $X_{t,j}$  as in PCA (piecewise constant, smoothed forward curves)
- $oxed{oxed}$  The coefficients  $Z_{t,l}$  describe the dynamic behavior of the forward curves
- The whole complex system can be modeled through a typical time series analysis of the estimates  $\widehat{Z}_{t,l}$

#### **Estimation**

$$\mathbf{Z}_t^{\top} \mathbf{m}(\mathbf{X}_t) = \sum_{l=0}^{L} Z_{t,l} \sum_{k=1}^{K} a_{l,k} \psi_k(\mathbf{X}_t) = \mathbf{Z}_t^{\top} \mathbf{A} \psi(\mathbf{X}_t)$$

- $\ \ \ \ \psi(\cdot) = (\psi_1, \dots, \psi_K)^{\top}$  is a vector of known expansion functions (e.g. B-splines)
- oxdot  $\mathbf{A} \in \mathbb{R}^{(L+1) \times K}$  is a matrix of coefficients
- the smoothing parameters L (dimension of the time series; we use L = 3,...,6) and K (number of series expansion functions; K = 19 functions on 16 knots) have to be specified in advance

#### Estimation cont.

The least squares estimators  $\widehat{\mathbf{Z}}_t = (\widehat{Z}_{t,0},...,\widehat{Z}_{t,L})^{\top}$  and  $\widehat{\mathbf{A}} = (\widehat{a}_{l,k})_{l=0,...,L;k=1,...,K}$  are obtained from

$$\sum_{t=1}^{T} \sum_{j=1}^{J} \left\{ Y_{t,j} - \widehat{\mathbf{Z}}_{t}^{\top} \widehat{\mathbf{A}} \psi(X_{t,j}) \right\}^{2} = \min_{\widehat{\mathbf{Z}}_{t}, \widehat{\mathbf{A}}}$$

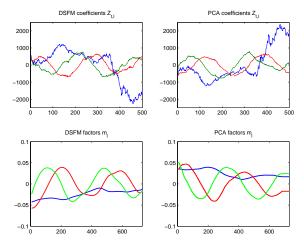
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#### The data

- □ Database of Nord Pool futures and forward prices from the period Jan. 4, 1999 May 23, 2002, i.e. 843 (business) days
- □ A 500 day window is used for calibration
- For each day, 1, 5, 10, 25 and 125 day-ahead forward curve forecasts is computed
- $oxed{oxed}$  Both DSFM and PCA models for various  $L \ (=3,\ldots,6)$  are evaluated

## Sample DSMF and PCA fits ...



# ... and their dynamics





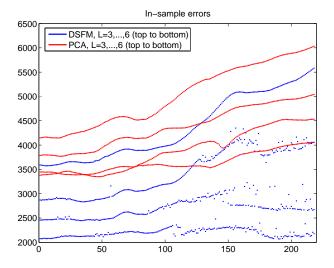
#### In-sample error measure

 We compute an absolute in-sample error weighted by the length of the delivery period for each contract

$$\epsilon_t = \sum_j |\mathsf{Model}(X_{t,j}) - Y_{t,j}| \cdot ||I_{t,j}||$$

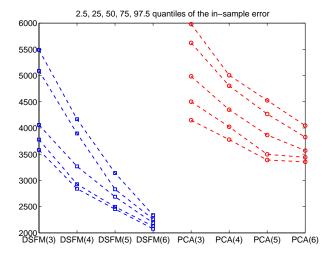
- $\odot$  where  $X_{t,j}$  are the observed maturities (mid-points of the delivery periods)  $j=1,2,\ldots$  for day t
- o  $Y_{t,j}$  are the respective prices
- $□ I_{t,j}$  are the respective time intervals with a constant price  $Y_{t,j}$ , such that  $\bigcup_i I_{t,j} = (0,2]$  years

#### In-sample errors





#### In-sample error statistics





## Forecasting setup

- $\Box$  For a 500 day window the DSFM and PCA models (with  $L=3,\ldots,6$  factors) are calibrated
- $oxed{oxed}$  A sinusoidal function  $g_I(t) = A_I \sin(B_I t + C_I)$  is fitted and removed yielding  $\widetilde{Z}_{t,2}, \ldots, \widetilde{Z}_{t,L}$

$$Y_{t,j} = m_0(X_{t,j}) + \sum_{l=1}^{L} \widehat{Z}_{t,l} m(X_{t,j}) + \varepsilon_{t,j}$$

$$= m_0(X_{t,j}) + \sum_{l=2}^{L} g_l(t) m(X_{t,j}) + \sum_{l=1}^{L} \widetilde{Z}_{t,l} m(X_{t,j}) + \varepsilon_{t,j}$$

## Forecasting models

oxdot Random Walk (**RW**): forward (futures) prices from day t

$$Y_{t+h,j}^* = \widehat{m}_0(X_{t+h,j}) + \sum_{l=1}^L \widehat{Z}_{t,l} \widehat{m}_l(X_{t+h,j}) + \varepsilon_t$$

oxdot Trend update (STr for DSFM and PTr for PCA): the sinusoidal trend  $g_l$  is forecasted for  $l=2,\ldots,L$  and added to the forward price forecast

$$Y_{t+h,j}^* = \widehat{m}_0(X_{t+h,j}) + \sum_{l=2}^{L} g_l(t+h)\widehat{m}_l(X_{t+h,j}) + \sum_{l=1}^{L} \widetilde{Z}_{t,l}\widehat{m}_l(X_{t+h,j}) + \varepsilon_t$$

## Forecasting models cont.

Trend update from model (STr2, PTr2): Like 'Trend update', but without the error term

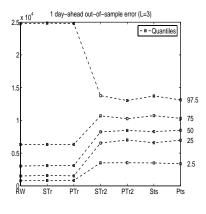
$$Y_{t+h,j}^* = \widehat{m}_0(X_{t+h,j}) + \sum_{l=2}^{L} g_l(t+h)\widehat{m}_l(X_{t+h,j}) + \sum_{l=1}^{L} \widetilde{Z}_{t,l}\widehat{m}_l(X_{t+h,j})$$

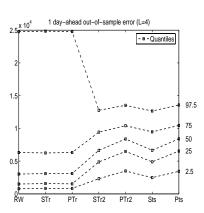
## Forecasting models cont.

**.** Full forecast with AR(2) time series (**Sts**, **Pts**): Additionally includes AR(2) forecasts of all coefficient time series  $\widehat{Z}_{t,1}$ ,  $\widetilde{Z}_{t,2}$ , . . . ,  $\widetilde{Z}_{t,L}$ 

$$Y_{t+h,j}^* = \widehat{m}_0(X_{t+h,j}) + \sum_{l=2}^{L} g_l(t+h)\widehat{m}_l(X_{t+h,j}) + \sum_{l=1}^{L} \widetilde{Z}_{t+h,l}^* \widehat{m}_l(X_{t+h,j})$$

#### One day-ahead forecasts: L = 3 vs. L = 4

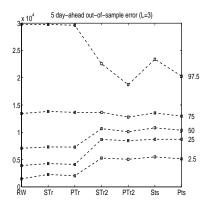


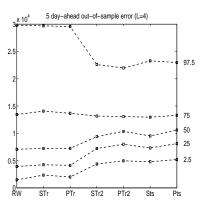






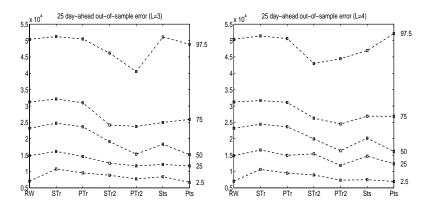
#### 5 day-ahead forecasts: L=3 vs. L=4





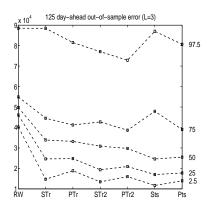


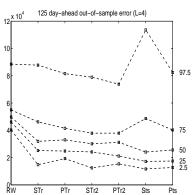
#### 25 day-ahead forecasts: L = 3 vs. L = 4





#### 125 day-ahead forecasts: L = 3 vs. L = 4

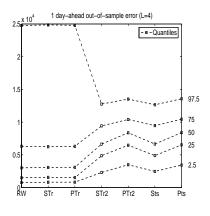


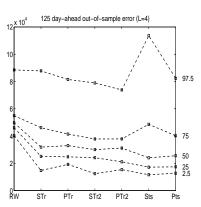


DSFM: Modeling and forecasting electricity forward prices



## Short vs. long term forecasts (L = 4)







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Conclusions — 5-2

#### **Conclusions**

- Like PCA, DSFM allows for dimension reduction
- It differs in that
  - the fits are obtained in the local neighborhood of forward price-maturity pairs for a given day
  - curve estimation and dimension reduction is achieved in one single step
- DSFM offers superior in-sample performance

#### Conclusions cont.

- DSFM-based models are slightly better than their PCA-based counterparts for short and long term forecasts and worse for medium term predictions
- The current forward curve (RW model) is on average the best predictor of the curve in the next few days, it is inferior for medium and long term forecasts
- Larger number of basis functions (larger L) improves short term forecasts but leads to increased variance of the longer term forecasts

Conclusions — 5-4

#### References

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Conclusions — 5-5

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