

Estimation of a Nonparametric model for Bond Prices from Cross-section and Time series Information

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Overview

- Develop estimation methodology for an **additive nonparametric panel** model suitable for capturing the **pricing of coupon-paying government bonds** over many periods.
- The novelty lies in the combination of (1) **cross-sectional nonparametric** methods and (2) kernel estimation for **time varying dynamics**.
- Estimate the yield curve and its dynamics and Predict **individual bond prices** given the full payment schedule.
- Asymptotic results** are provided and **simulations and US bonds application** show strong performance of the proposed method.

Bond pricing: Panel data framework

Discrete time semiparametric model:

$$p_{it} = \sum_{j=1}^{m_{it}} c_{it}(\tau_{ij})d(\tau_{ij}, X_t) + \varepsilon_{it}, \quad (1)$$

where $c_{it}(\tau_{ij})$ are the cash flows at future payment dates, $\{\tau_{ij}\}_{j=1}^{m_{it}}$ for each bond i .

- $X_t \in \mathbb{R}^L$, with $L \ll n (= \min_i n_i)$: (possibly stochastic) **observable covariates** or **factors**
- ε_{it} : a conditional (on X_t) mean zero **pricing error**
- $d(\cdot)$: **discount function** unspecified but smoothly varying over its arguments.

Modelling issues

- Discount (d), yield (y) and forward curves (f)

$$d(\tau, x) = e^{-\tau y(\tau, x)}, \quad f(\tau, x) = -\frac{d'(\tau, x)}{d(\tau, x)}$$

- Diebold and Li (2006):

$$d_{\theta_i}(\tau) = \exp(-\tau y_{\theta_i}(\tau)) \quad (2)$$

$$y_{\theta_i}(\tau) = \sum_{j=0}^2 \beta_{jt} \varphi_j(\tau; \tau_j),$$

where $\varphi_0(\tau; \tau_0) = 1$, for some τ_1 and τ_2 , $\varphi_1(\tau; \tau_1) = (1 - \exp(-\tau/\tau_1))(\tau/\tau_1)$, and $\varphi_2(\tau; \tau_2) = \varphi_1(\tau; \tau_2) - \exp(-\tau/\tau_2)$.

- Relevance of our model to Diebold and Li:

- If X_t are the unobserved dynamic parameters β_t , Diebold and Li is a special case of our model
- For the case of observable X_t ,

$$y(\tau, X_t) = \sum_{j=1}^L \beta_j(X_t) \varphi_j(\tau), \quad (3)$$

where $\beta_j(\cdot)$, $\varphi_j(\cdot)$ are smooth but unknown functions

- Static and Dynamic Arbitrage restrictions

- Under the modelling setting, no static arbitrage opportunities exist but without further restriction, there may be dynamic arbitrage opportunities.
- Gouriéroux et al. (2002) under dynamic no arbitrage restriction: $d_t(\tau) = \exp(a_\tau X_t + b_\tau)$, where a_τ and b_τ satisfy nonlinear first order difference equations, which is a special case of our model

Forecasting Future Bond Prices

Forecasting bond prices within the model

- Case where $X_t = t/T$, i.e. the deterministic evolution of the yield curve

$$d\left(\tau, \frac{T+k}{T}\right) = d(\tau, 1) + d_2(\tau, 1) \frac{k}{T} + o(kT^{-1}),$$

- Special case in relation to Diebold and Li

$$y(\tau, t/T) = \sum_{j=1}^L \beta_{jt} \varphi_j(\tau),$$

where the quantities $\beta_{jt} = \beta_j(t/T)$ are deterministically slowly time varying or have an AR structure.

- Predictive regression whereby the stochastic X_t that enter d , and hence y , are taken to be lagged values

- Let

$$\hat{g}(\tau, x) = \frac{\sum_{t=1}^{T-1} \sum_{j=1}^{n_t} K_h(\tau - \tau_j) K_h(x - X_t) \hat{d}(\tau_j, X_{t+1})}{\sum_{t=1}^{T-1} \sum_{j=1}^{n_t} K_h(\tau - \tau_j) K_h(x - X_t)}$$

Then define the forecast of $p_{i, T+1}$

$$\hat{p}_{i, T+1|T} = \sum_{j=1}^{m_{i, T+1}} c_{ij, T+1} \hat{g}(\tau_{ij}, X_T),$$

Estimation: Local constant smoothing

- For s_i in the neighbourhood of τ_i ,

$$Q_{nT}(d) = \sum_{t=1}^T \sum_{i=1}^{n_t} \int \left\{ p_{it} - \sum_{j=1}^{m_{it}} c_{it}(\tau_{ij}) d(s_{ij}, x) \right\}^2 \prod_{k=1}^{m_{it}} \{ K_h(s_{ik} - \tau_{ik}) d s_{ik} \} \mathcal{K}_h(x - X_t) dx, \quad (4)$$

where $\mathcal{K}_h(s) = \prod_{i=1}^L K_{h_i}(s_i)$ with a bandwidth parameter h_i and $K_{h_i}(\cdot) = K(\cdot/h_i)$.

- The estimator of the discount function is the minimizer of $Q_{nT}(\cdot)$ such that

$$\hat{d}(\cdot) = \arg \min_{d(\cdot) \in \mathcal{D}} Q_{nT}(d) \quad (5)$$

where \mathcal{D} is the class of all functions for which $Q(\cdot)$ is well defined.

- Obtaining F.O.C

- Let $\delta_{(\tau, x)}(\cdot, \cdot)$ be the $(L+1)$ -dimensional Dirac delta function at (τ, x) such that $\int_{\mathbb{R}^L} \int_{\mathbb{R}^+} \delta_{(\tau, x)}(y, r) g(y, r) dy dr = g(\tau, x)$ for any generic function $g(\cdot, \cdot)$ continuous at the point (τ, x)
- Let $d(\cdot, \cdot) = \hat{d}(\cdot, \cdot) + \eta \delta_{(\tau, x)}(\cdot, \cdot)$, and differentiate $Q_{nT}(d)$ with respect to η at the point of $\eta = 0$.

$$\begin{aligned} & \sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} c_{it}(\tau_{ij})^2 K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t) \hat{d}(\tau, x) - \sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} p_{it} c_{it}(\tau_{ij}) K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t) \\ & = - \sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} \sum_{p=1, p \neq j}^{m_{it}} c_{it}(\tau_{ij}) c_{it}(\tau_{ip}) K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t) \int \hat{d}(\tau', x) K_h(\tau' - \tau_{ip}) d\tau'. \end{aligned} \quad (6)$$

$$\hat{d}(\tau, x) = \bar{d}(\tau, x) + \int \hat{H}(\tau, \tau', x) \hat{d}(\tau', x) d\tau', \quad (7)$$

where:

$$\bar{d}(\tau, x) = \frac{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} p_{it} c_{it}(\tau_{ij}) K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t)}{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} c_{it}(\tau_{ij})^2 K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t)}, \quad (8)$$

$$\hat{H}(\tau, \tau', x) = - \frac{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} \sum_{p=1, p \neq j}^{m_{it}} c_{it}(\tau_{ij}) c_{it}(\tau_{ip}) K_h(\tau - \tau_{ij}) K_h(\tau' - \tau_{ip}) \mathcal{K}_h(x - X_t)}{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} c_{it}(\tau_{ij})^2 K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t)}. \quad (9)$$

Alternatives and other variations

- Linking between bond yields and macro variables

$$\begin{aligned} \mathcal{Q}_{nT}(y) & = \sum_{t=1}^T \sum_{i=1}^{n_t} \int \left\{ p_{it} - \sum_{j=1}^{m_{it}} c_{it}(\tau_{ij}) \exp\{-s_{ij} y(s_{ij}, x)\} \right\}^2 \\ & \times \prod_{k=1}^{m_{it}} \{ K_h(s_{ik} - \tau_{ik}) d s_{ik} \} \mathcal{K}_h(x - X_t) dx. \end{aligned} \quad (10)$$

Large sample properties

$$\mathcal{B}_d^*(\tau, x) = \tilde{\mathcal{B}}_d^*(\tau, x) + \mathcal{B}_d^{**}(\tau, x),$$

$$\tilde{\mathcal{B}}_d^*(\tau, x) = \frac{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} c_{it}^2(\tau_{ij}) [d(\tau_{ij}, X_t) - d(\tau, x)] K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t)}{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} c_{it}^2(\tau_{ij}) K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t)},$$

$$\mathcal{B}_d^{**}(\tau, x) = \frac{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} \sum_{p=1, p \neq j}^{m_{it}} c_{it}(\tau_{ij}) c_{it}(\tau_{ip}) K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t) \int K_h(\tau' - \tau_{ip}) [d(\tau_{ip}, x) - d(\tau', x)] d\tau'}{\sum_{t=1}^T \sum_{i=1}^{n_t} \sum_{j=1}^{m_{it}} c_{it}^2(\tau_{ij}) K_h(\tau - \tau_{ij}) \mathcal{K}_h(x - X_t)},$$

$$\gamma_d^*(\tau, x) = (nTh^{L+1}) \text{var} \left[\sum_{t=1}^T \sum_{i=1}^{n_t} \omega_{it}(\tau, x) \varepsilon_{it} \right], \quad (11)$$

Theorem

Suppose that assumptions (A1)-(A4) and (B1)-(B2) hold. Then,

$$\sqrt{nTh^{L+1}} \gamma_d^*(\tau, x)^{-1/2} \left(\hat{d}(\tau, x) - d(\tau, x) - \mathcal{B}_d^*(\tau, x) \right) \xrightarrow{d} \mathcal{N}(0, 1). \quad (12)$$

Corollary

Suppose that all assumptions for Theorem 1 hold. Then,

$$\sqrt{nTh^{L+1}} \gamma_y^*(\tau, x)^{-1/2} \left(\hat{y}(\tau, x) - y(\tau, x) - \mathcal{B}_y^*(\tau, x) \right) \xrightarrow{d} \mathcal{N}(0, 1),$$

where $\mathcal{B}_y^*(\tau, x) = (\tau d(\tau, x))^{-1} \mathcal{B}_d^*(\tau, x)$ and $\gamma_y^* = (\tau d(\tau, x))^{-2} \gamma_d^*(\tau, x)$ with $\gamma_d^*(\tau, x)$ specified in (11).

$$\Sigma_d^*(\tau, x) = \lim_{n, T \rightarrow \infty} \text{var} \left[\frac{1}{\sqrt{nTh^{L+1}}} \sum_{t=1}^T \sum_{i=1}^{n_t} \omega_{it}(\tau, x) \varepsilon_{it} \right]. \quad (13)$$

$$\hat{V}_d^*(\tau, x) = \frac{1}{nTh^{L+1}} \sum_{t=1}^T \sum_{s=1}^T \sum_{j=1}^{n_t} \sum_{i=1}^{n_s} \omega_{it}(\tau, x) \omega_{js}(\tau, x) \hat{\varepsilon}_{it} \hat{\varepsilon}_{js}.$$

Theorem

Suppose that assumptions (A1)-(A4), (B1)-(B2) and (C1)-(C2) hold. Then, as $n, T \rightarrow \infty$

$$\hat{V}_d^*(\tau, x) \xrightarrow{p} \Sigma_d^*(\tau, x).$$

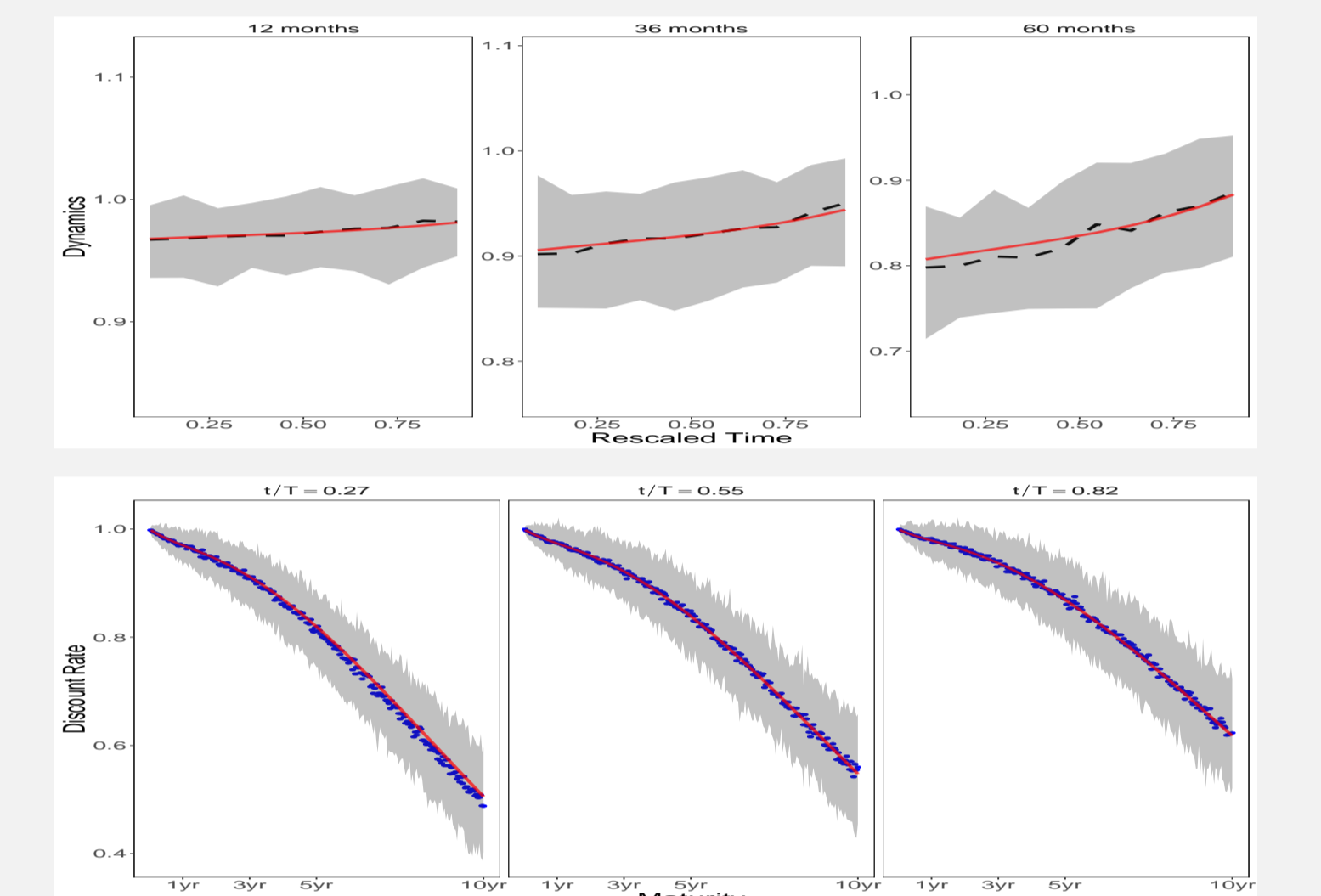
Monte Carlo Study

Simulation design

- Time horizon of 10 years of bi-weekly data
- Number of bonds to $n = 24$ daily on average
- Face value: 100
- Zero coupon bonds (1-12 months), Coupon bonds (1-10 years, biannual payment)
- Replace each expired bond with a new one in the same data structure but with a different identification number
- Bond prices are generated by (1) and for a given i , ε_t has a ARMA(1,1) structure with AR coefficient (-0.1) and MA coefficient (0.2) to allow for temporal dependence
- Variance is set to increase over duration across bond types
- Discount function is generated from (2) with the parameter vector $\beta_0 = 0$, $\beta_1 = 0.05$, $\beta_2 = 2$, $\tau_1 = 0.75$ and $\tau_2 = 125$.

Simulation outputs

Figure: Cubic time-dynamics of the discount curve



US yield curve evolution

Data description

- Daily US treasury data from CRSP
- Seven-year-period from Jan. 2001 to Dec. 2007
- Deterministic time ($u = t/T$) and three-month treasury bill rates (r) as factors

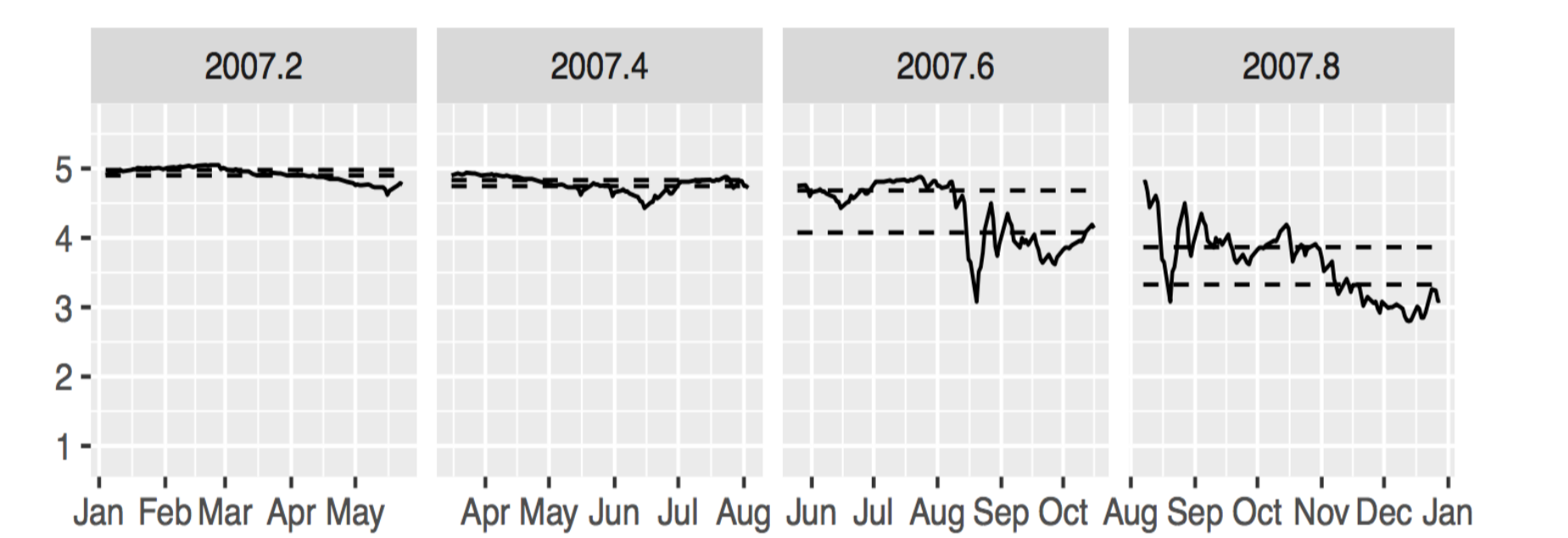


Figure: Three-month Treasury Bill Rates

Estimation results

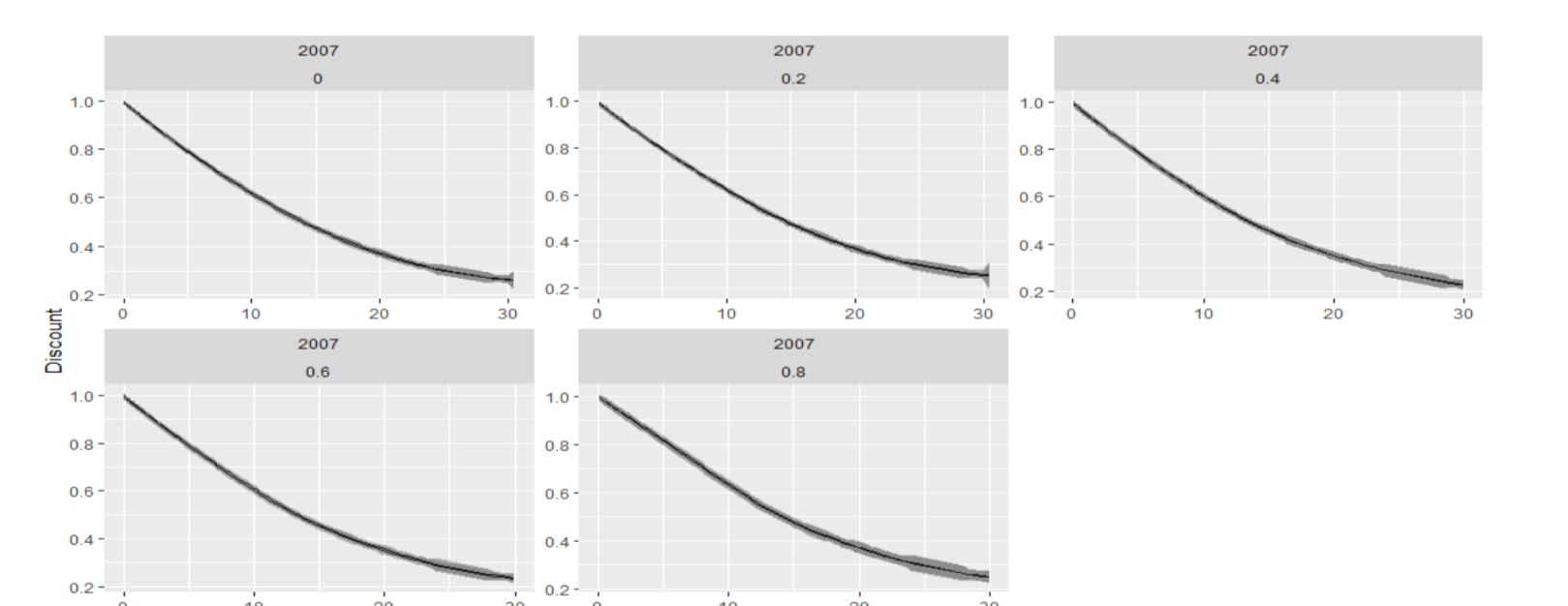


Figure: Estimates for the discount function $\hat{d}(\tau, x)$ with pointwise confidence intervals

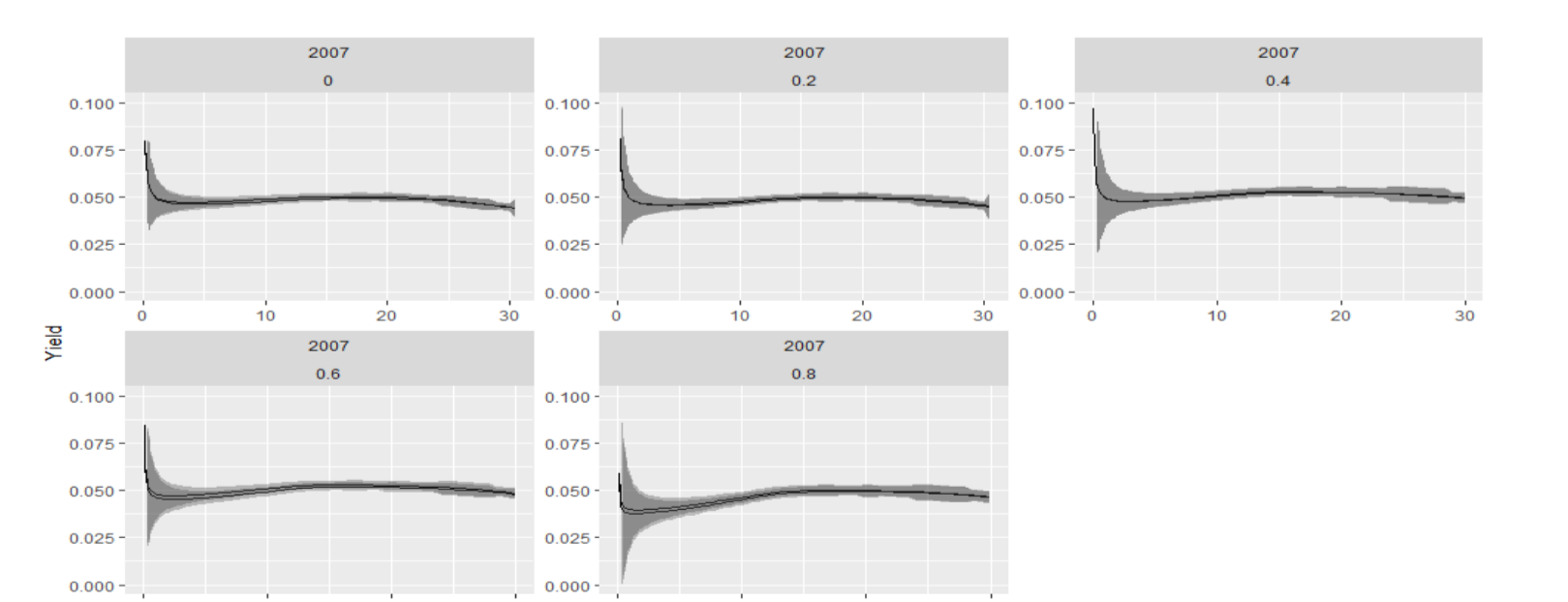


Figure: Estimates for the yield curve $\hat{y}(\tau, x)$ with pointwise confidence intervals

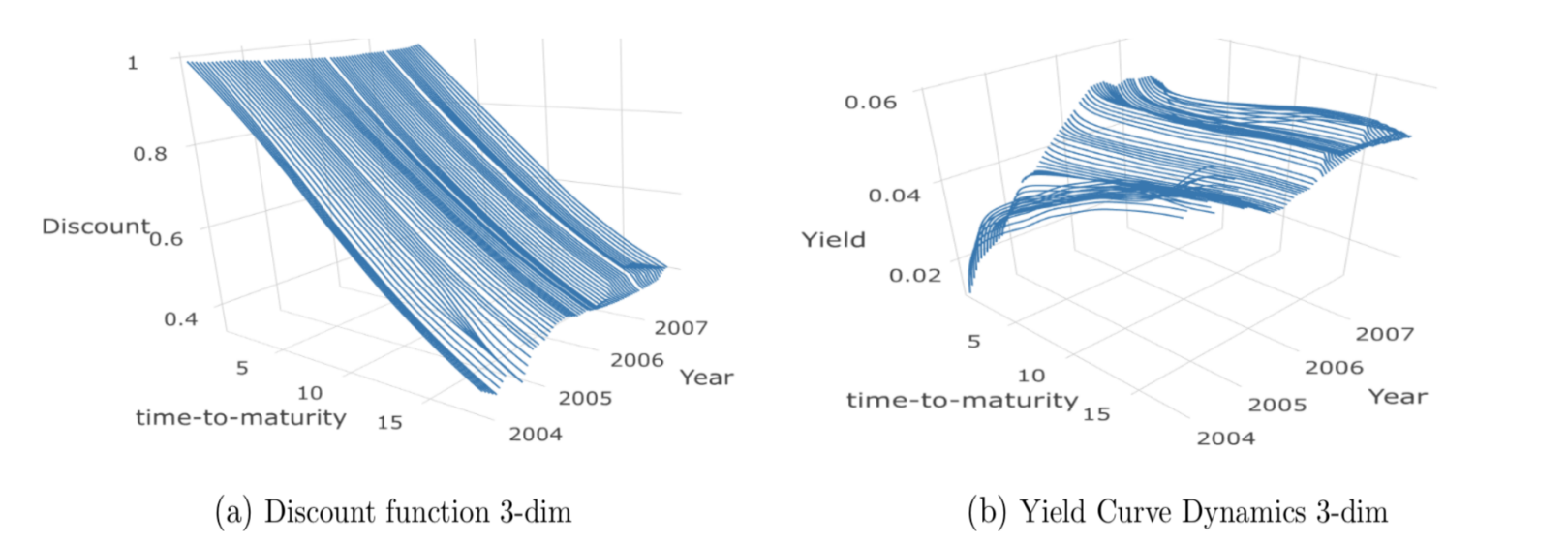


Figure: 3-dimensional shapes of $\hat{d}(\tau, x)$ and $\hat{y}(\tau, x)$

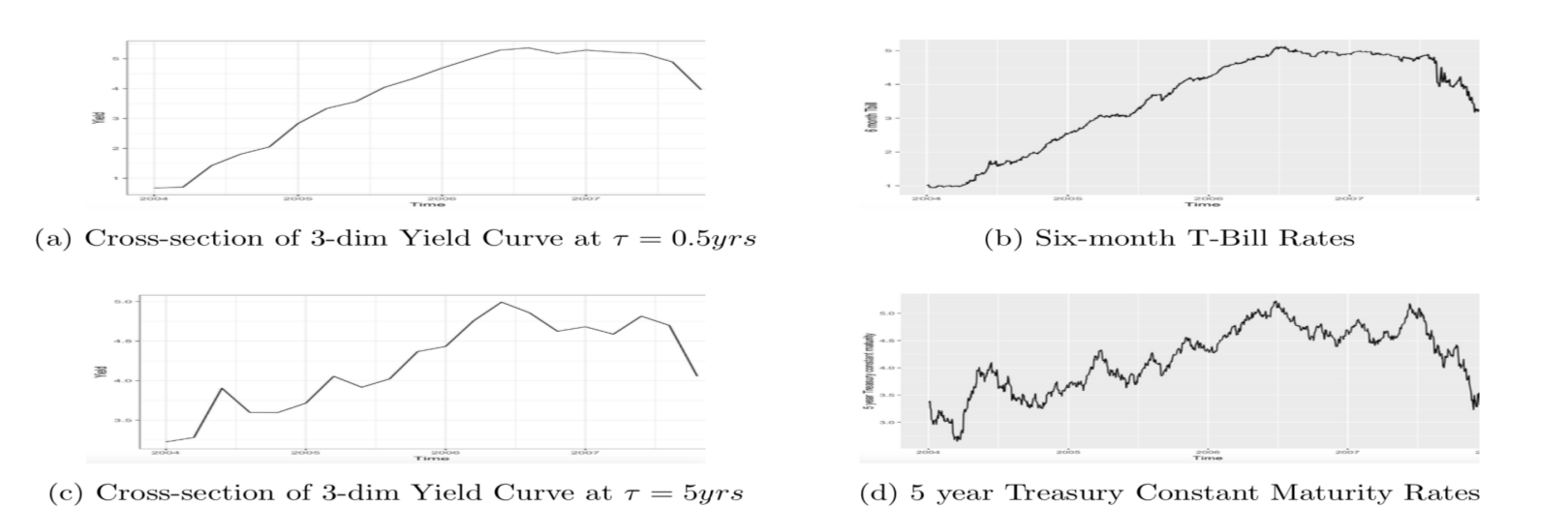


Figure: Cross-sections of $\hat{y}(\tau, x)$ at 6 month and 5 year time-to-maturities

Codes and Package

r-package ycevo has been developed in line with this paper and is available at <https://github.com/bonsook/ycevo>