

# Simultaneous Inference of a Partially Linear Model in Time Series

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# Contributions

- ▶ Simultaneous inference of the non-parametric part of a partially linear model in “time series” is conducted when the non-parametric component is a “multivariate” unknown function.
- ▶ The developed methodology is applied to two examples in time series: (1) the forward premium regression and (2) a factor asset pricing model.

# Model

- ▶ Partially linear time series model:

$$Y_i = \mathbf{Z}_i^\top \boldsymbol{\beta} + \mu(\mathbf{X}_i) + \epsilon_i, \quad i = 1, \dots, T,$$

where  $\epsilon_i$  is a random error with some general dependence structure. The goal of this study is to perform *specification test* for the null  $H_0 : \mu(\cdot) = \mu_\theta(\cdot)$  for some  $\theta \in \Theta$ . Here  $\mu_\theta(\cdot)$  is some parametric function with unknown  $\theta$ .

# Assumption 1

- ▶ Let the error process be:

$$\epsilon_j = \sum_{k=0}^{\infty} a_k \zeta_{j-k},$$

where  $\zeta_j$  is an IID process. We require an algebraic decay rate of temporal dependence: For  $\gamma > 0$  and  $c_s > 0$ , let

$$\sum_{k \geq i} |a_k| \leq c_s i^{-\gamma}, \quad i \geq 1, \quad \gamma > 0, \quad c_s > 0$$

## Assumption 2

- ▶ The kernel function  $K(\cdot)$  is defined on  $\mathbb{I} = [-1, 1]^d$  and is continuously differentiable up to order two.
- ▶ Assume  $\max_{x \in \mathbb{I}} |K(x)| < \infty$  and  $\int_{\mathbb{I}} K(x) dx = 1$ . Also, assume  $K(x)$  has its first-order derivative with  $\sup_{x \in \mathbb{I}} \max_{1 \leq i \leq d} |\partial_i K(x)| < \infty$ .
- ▶ Assume the bandwidth parameter  $h \rightarrow 0$  and  $h^d n \rightarrow \infty$ .

## Assumption 3

- ▶ Let  $g(x|\mathcal{F}_{i-1})$  and  $X_{ij}$  have a finite  $q$ -th moment, for  $q > 2$ . Define

$$\begin{aligned}\theta_{k,q} = & \max_{x \in \mathbb{R}^d} \|g(x|\mathcal{F}_i) - g(x|\mathcal{F}_{i,\{i-k\}})\|_q \\ & + \left\| \max_{1 \leq j \leq d} |X_{ij} - X_{ij,\{i-k\}}| \right\|_q.\end{aligned}$$

- ▶ Let  $\sup_{m \geq 0} m^{\alpha'} \sum_{k \geq m} \theta_{k,q} < \infty$  for some  $\alpha' > 0$ .

## Assumption 4

- ▶ Let  $\Omega$  be some compact region. For some constants  $c_g, c'_g > 0$ , assume

$$c_g \leq \inf_{x \in \Omega} g(x) \leq \sup_{x \in \Omega} g(x) \leq c'_g.$$

Additionally, assume  $\sup_{x \in \Omega} \max_{1 \leq j \leq d} |\partial g(x) / \partial x_j| < \infty$ .

- ▶ Assume, for any  $s, t \in \Omega$ ,  $\sup_{i_1, i_2} |g_{i_1, i_2}(s, t | \mathcal{F}_{i-1})| \leq c$  for some constant  $c$ . In addition, assume

$$\sup_{i_1, i_2} \left( \max_{1 \leq j \leq d} \left| \frac{\partial g_{i_1, i_2}(s, t | \mathcal{F}_{i-1})}{\partial s_j} \right| + \max_{1 \leq j \leq d} \left| \frac{\partial g_{i_1, i_2}(s, t | \mathcal{F}_{i-1})}{\partial t_j} \right| \right) \leq c',$$

for some constant  $c' > 0$ .



## Assumption 5

- Assume that there exists some bounded function  $h(\cdot)$ :  $\mathbb{R}^d \rightarrow \mathbb{R}^\ell$ , such that

$$Z_i = h(X_i) + u_i,$$

where  $h(\cdot)$  is Lipschitz-continuous and  $u_i$  are vectors in  $\mathbb{R}^\ell$  satisfying

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n (u_i u_i^\top) = B,$$

where  $B$  is a positive definite matrix.

- In addition, let

$$\limsup_{n \rightarrow \infty} \frac{1}{\sqrt{n} \log n} \max_{1 \leq m \leq n} \left| \sum_{k=1}^m u_{j_k} \right|_2 < \infty,$$

for any permutation  $j_1, \dots, j_n$  of the integers  $1, 2, \dots, n$ .  
Moreover,

$$\max_{1 \leq i \leq n} |u_i|_2 \leq C.$$

# Simultaneous Confidence Region

- ▶ Estimation of  $\mu(\cdot)$  is achieved by:

$$\hat{\mu}_R(\mathbf{s}) = \underset{\theta}{\operatorname{argmin}} \frac{1}{nh^d} \sum_{i=1}^n K\left(\frac{\mathbf{s} - X_i}{h}\right) \left(Y_i - \mathbf{Z}_i^\top \hat{\beta}_R - \theta\right)^2,$$

where  $\hat{\beta}_R$  is the Robinson estimate (Robinson, 1988) of  $\beta$ . This leads to:

$$\hat{\mu}_R(\mathbf{s}) = \frac{1}{nh^d \hat{g}(\mathbf{s})} \sum_{i=1}^n K\left(\frac{\mathbf{s} - X_i}{h}\right) \left(Y_i - \mathbf{Z}_i^\top \hat{\beta}_R\right),$$

with

$$\hat{g}(\mathbf{s}) = \frac{1}{nh^d} \sum_{i=1}^n K\left(\frac{\mathbf{s} - X_i}{h}\right).$$

# Simultaneous Confidence Region

- ▶ Let  $S^2$  be the the long-run variance of  $\epsilon_j$  and  $w_j(x_j)$  be the kernel weight function defined by:

$$w_j(x_j) = \frac{K\left(\frac{x_i - X_j}{h}\right)}{\sum_{k=1}^n K\left(\frac{x_i - X_k}{h}\right)}$$

- ▶ Denote  $G_{i,\cdot} = (G_{i,1}, \dots, G_{i,n})$ , where  $G_{i,j}$  is defined by  $G_{i,j} = w_j(x_j) \cdot S$ .

## Asymptotic results

- ▶ Let  $\eta \in \mathbb{R}^n$  be a standard normal random vector. If we consider  $\delta = n^{-(d+1)/d}$ , then  $N = O(1/\delta^d) = O(n^{d+1})$ . Under Assumptions 1–4, if  $\log(n)^{1/2} h^{d+2} n \rightarrow 0$  and  $(d+1)/q - \gamma + \log_n \log(n)^{1/2} < 0$ , we have:

$$\sup_{u \in \mathbb{R}} \left| \mathbb{P} \left( \sup_{x \in \Omega} |\hat{\mu}(x) - \mu(x)| < u \right) - \mathbb{P} \left( \max_{1 \leq i \leq N} |G_{i, \eta}| < u \right) \right| \lesssim \Delta,$$

where  $\hat{\mu}(x)$  is an “infeasible” estimate based on the true  $\beta$  and

$$\begin{aligned} \Delta = & (h^d n)^{-1/6} (\log N n)^{7/6} + (n^{2/q} / (h^d n))^{1/3} \\ & + \log(N n)^q (h^d n)^{-q/2+1} + C_n \end{aligned}$$

# Asymptotic results

- ▶ Under the assumptions of Assumptions 1–5, if  $\log(n)^{1/2}h^{d+2}n \rightarrow 0$  and  $(d+1)/q - \gamma + \log_n \log(n)^{1/2} < 0$ , we have:

$$\sup_{u \in \mathbb{R}} \left| \mathbb{P} \left( \sup_{x \in \Omega} |\hat{\mu}_R(x) - \mu(x)| < u \right) - \mathbb{P} \left( \max_{1 \leq i \leq N} |\mathbf{G}_{i,\cdot} \eta| < u \right) \right| \lesssim \Delta,$$

where  $\hat{\mu}_R(x)$  is  $\hat{\mu}(x)$  with the Robinson estimate (1988) in it.

# Simultaneous Confidence Region

- ▶ Then, the  $p$ -th percentile *simultaneous confidence interval* for  $\mu(\cdot)$  can be shown by:

$$\hat{\mu}_R(\mathbf{x}) - z_p \leq \mu(\mathbf{x}) \leq \hat{\mu}_R(\mathbf{x}) + z_p,$$

where  $z_p$  is the  $p$ -th quantile for the  $\max_j |G_{j,\cdot}\eta|$  and  $\eta$  is a standard Gaussian random vector.

# Forward Premium Regression

- ▶ Consider the monetary model in Mark (1995):

$$s_{t+1} - s_t = \alpha + \beta(x_t - s_t) + u_{t+1}$$

where  $s_t$  is log of monthly *spot* exchange rate at time  $t$  and  $x_t$  is the equilibrium level of the spot exchange rate

$x_t := m_t - m_t^* - \lambda(y_t - y_t^*)$  with  $m_t$  and  $y_t$  being log of domestic money stock and log of monthly production, respectively.

- ▶ We let  $\lambda = 1$ . One can rewrite the model as:

$$s_{t+1} - s_t = \alpha + \beta(x_t - f_{1,t}) + \beta(f_{1,t} - s_t) + u_{t+1}$$

where  $f_{1,t}$  is log of monthly *forward* exchange rate with one-month maturity at time  $t$ .

# Forward Premium Regression

- ▶ A flexible way to model the risk premium is:

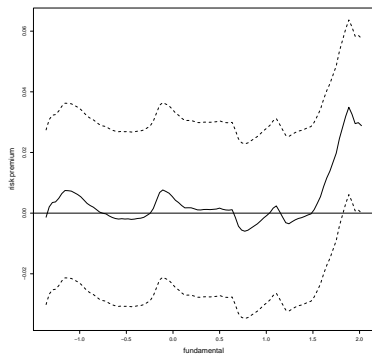
$$s_{t+1} - s_t = \mu(x_t - f_{1,t}) + \beta(f_{1,t} - s_t) + u_{t+1} \quad (1)$$

where  $\mu(\cdot)$  is some unknown function.

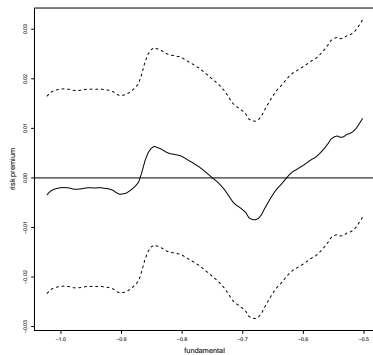
- ▶ The theory of Uncovered Interest Parity (*UIP*) implies  $\mu(\cdot) = 0$ , while numerous empirical studies actually show  $\mu(\cdot) \neq 0$ . Interestingly, (1) is a special case of the partially linear model framework. Hence the methodology developed here can be readily applied to decide whether or not the *UIP* condition holds.



# Forward Premium Regression



(a) *GBP/USD*



(b) *EUR/USD*

## Conditional factor model

- ▶ Consider the single-factor asset pricing model:

$$R_{it} = \alpha(X_t) + \beta R_t^m + \zeta_{it} \quad (2)$$

where  $R_{it}$  is the excess return of momentum portfolio and  $R_t^m$  is the excess return on the value-weighted market index portfolio at  $t$ , respectively.

- ▶ Here  $\alpha(\cdot)$  is the *pricing error* of the factor model that depends on  $X_t$ , a vector of random variables. The pricing error in (2) is likely to be time-varying and its variation is related to  $X_t$ . We let  $X_t$  contain the size factor or the book-to-market ratio, etc.

## Conditional factor model

- ▶ To that end, we consider a *bivariate* pricing error:

$$R_{it} = \alpha(SMB_t, HML_t) + \beta R_t^m + \zeta_{it} \quad (3)$$

where  $SMB_t$  and  $HML_t$  represent the size and book-to-market factors, respectively.

- ▶ Given that (3) is a special case of the partially linear model, our methodology readily applies here. By constructing a *SCR* for the unknown  $\alpha(\cdot, \cdot)$ , one can conduct simultaneous inference for the zero-pricing-error hypothesis for the factor model in (3).

# Conditional factor model

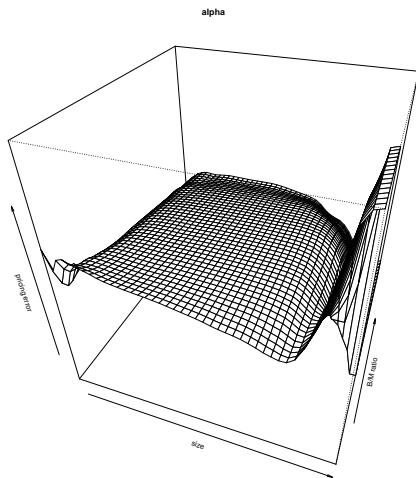
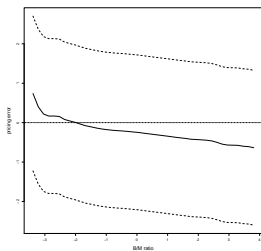
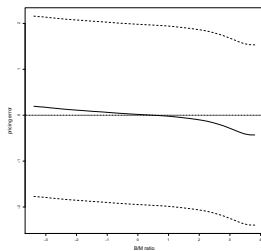


Figure:

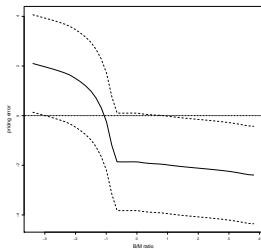
# Conditional factor model



(a) 5th-percentile of size

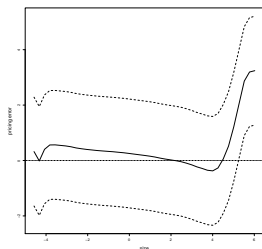


(b) 50th-percentile of size

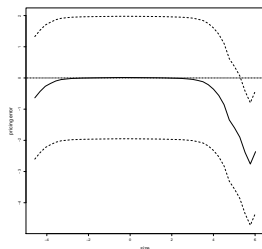


(c) 95th-percentile of size

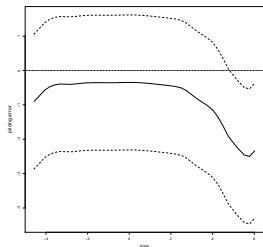
# Conditional factor model



(a) 5th-percentile of B/M ratio



(b) 50th-percentile of B/M ratio



(c) 95th-percentile of B/M ratio

# Summary

- ▶ We illustrate how to construct the simultaneous confidence region (*SCR*) for the multivariate unknown function in time series.
- ▶ The inference of the model is conducted through the construction of *SCR*, which is a multi-dimensional extension of the two-dimensional uniform confidence band.
- ▶ The zero-risk-premium hypothesis for *GBP/USD* is narrowly rejected at a 5 percent level, mainly due to the surge in the risk premium estimate when the fundamental takes on a large value.
- ▶ The hypothesis of zero-pricing-error is also rejected for the factor model, due to the underlying non-linear nature.