

## 1 Appendix F: Estimation Errors of Fourier Coefficients for Random Balance Design

### 2 Sampling

3 Based on the definition of Fourier coefficients  $C_{00 \dots r_i \dots 00}^{(\theta)}$  in eq. (13) and eq. (14), we  
 4 have

$$\begin{aligned}
 C_{00 \dots r_i \dots 00}^{(\theta)} &= E_{\theta}(g(G(\theta_1), \dots, G(\theta_n))e^{-i(r_i \theta_i)}) \\
 &= \left(\frac{1}{2\pi}\right)^n \int_0^{2\pi} \cdots \int_0^{2\pi} g(G(\theta_1), \dots, G(\theta_n))e^{-i(r_i \theta_i)} d\theta_1 \cdots d\theta_n \\
 &= \frac{1}{2\pi} \int_0^{2\pi} E_{\theta}(g(G(\theta_1), \dots, G(\theta_n)) | \theta_i) e^{-i(r_i \theta_i)} d\theta_i \quad (\text{F1}) \\
 &= \frac{1}{2\pi} \int_0^{2\pi} u(\theta_i) e^{-i(r_i \theta_i)} d\theta_i \\
 &= E_{\theta_i}(u(\theta_i) e^{-i(r_i \theta_i)})
 \end{aligned}$$

6 where

$$u(\theta_i) = E_{\theta}(g(G(\theta_1), \dots, G(\theta_n)) | \theta_i). \quad (\text{F2})$$

8 Eq. (D2) suggests that, if we know  $u(\theta_i)$ , then the estimation of  $C_{00 \dots r_i \dots 00}^{(\theta)}$  can be  
 9 reduced to a one-dimension estimation. For a sample with size  $N$ ,  $C_{00 \dots r_i \dots 00}^{(\theta)}$  can  
 10 be estimated by

$$\hat{C}_{00 \dots r_i \dots 00}^{(\theta, u)} = \frac{1}{N} \sum_{j=1}^N [(u(\theta_i^{(j)}))e^{-i(r_i \theta_i^{(j)})}]. \quad (\text{F3})$$

12 For a grid sample with the same size  $N$  in eq. (39), the estimation of  $C_{00 \dots r_i \dots 00}^{(\theta)}$  based  
 13 on eq. (F3) is essentially a numerical integral using the rectangle rule, which has a  
 14 relatively high accuracy since the estimate error will decay at a rate of squared  
 15 sample size (see Appendix C for details). However, we are not able to know  $u(\theta_i)$   
 16 exactly. Using eq. (F2), the model  $y = g(G(\theta_1), \dots, G(\theta_n))$  can be decomposed as  
 17 follows,

$$g(G(\theta_1), \dots, G(\theta_n)) = u(\theta_i) + \xi_{-x_i} \quad (\text{F4})$$

1 where  $\xi_{-x_i}$  is the random noise independent from  $u(\theta_i)$ , which is resulted from the  
 2 uncertainty in other parameters. In view that

$$\begin{aligned} E(u(\theta_i)) &= E(E_\theta(g(G(\theta_1), \dots, G(\theta_n)) | \theta_i)) \\ &= E(g(G(\theta_1), \dots, G(\theta_n))) \end{aligned}$$

3 based on eq. (F4), we get

$$E(\xi_{-x_i}) = 0. \quad (F5)$$

4 Using the well known fact about the variance decomposition (Bickel and Doksum  
 5 2001)

$$V(g(G(\theta_1), \dots, G(\theta_n))) = V(E_\theta(g(G(\theta_1), \dots, G(\theta_n)) | \theta_i)) + E(V(g(G(\theta_1), \dots, G(\theta_n)) | \theta_i)),$$

6 we have

$$\begin{aligned} V(\xi_i) &= E(V(g(G(\theta_1), \dots, G(\theta_n)) | \theta_i)) \\ &= V(g(G(\theta_1), \dots, G(\theta_n))) - V(E_\theta(g(G(\theta_1), \dots, G(\theta_n)) | \theta_i)). \end{aligned}$$

7 Using the relationship of the variances between parameter space and  $\theta$ -space [see  
 8 eq. (6)], we get

$$V(\xi_{-x_i}) = V^{(x_1, \dots, x_n)} - V^{(x_i)}. \quad (F6)$$

9 For the estimation of Fourier coefficient  $C_{00 \dots r_i \dots 00}^{(\theta)}$  in eq. (15), we have

$$\begin{aligned} \hat{C}_{00 \dots r_i \dots 00}^{(\theta)} &= \frac{1}{N} \sum_{j=1}^N (g(G(\theta_1^{(j)}), \dots, G(\theta_n^{(j)})) e^{-i(r_i \theta_i^{(j)})}) \\ &= \frac{1}{N} \sum_{j=1}^N [(u(\theta_i^{(j)}) + \xi_i^{(j)}) e^{-i(r_i \theta_i^{(j)})}] \\ &= \frac{1}{N} \sum_{j=1}^N [u(\theta_i^{(j)}) e^{-i(r_i \theta_i^{(j)})}] + \frac{1}{N} \sum_{j=1}^N \xi_i^{(j)} e^{-i(r_i \theta_i^{(j)})} \\ &= \hat{C}_{00 \dots r_i \dots 00}^{(\theta, u)} + \hat{C}_{00 \dots r_i \dots 00}^{(\theta, \xi)}, \end{aligned} \quad (F7)$$

10 where

$$\hat{C}_{00 \dots r_i \dots 00}^{(\theta, \xi)} = \frac{1}{N} \sum_{j=1}^N \xi_i^{(j)} e^{-i(r_i \theta_i^{(j)})}. \quad (F8)$$

1 For  $\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)} = \hat{a}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)} - i \hat{b}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)}$ , with

$$2 \quad \hat{a}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)} = \frac{1}{N} \sum_{j=1}^N (\xi^{(j)}) \cos(r_i \theta_i^{(j)}),$$

$$\hat{b}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)} = \frac{1}{N} \sum_{j=1}^N (\xi^{(j)}) \sin(r_i \theta_i^{(j)}),$$

3 based on the Central Limit theorem, the coefficient  $\hat{a}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)}$  and  $\hat{b}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)}$   
 4 will approximately follow a normal distribution. Specifically,

$$5 \quad \begin{aligned} \hat{a}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)} &\sim \ddot{N}\left(0, \frac{V(\xi_{-x_i})}{2N}\right), \\ \hat{b}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)} &\sim \ddot{N}\left(0, \frac{V(\xi_{-x_i})}{2N}\right), \end{aligned} \quad (\text{F9})$$

6 where  $\ddot{N}(u, v)$  represents a normal distribution with mean  $u$  and variance  $v$ . Eq. (F9)

7 indicates that the estimation error decays at a rate of  $\frac{1}{\sqrt{N}}$  with an increasing

8 sample size  $N$ . Therefore, the estimation error  $\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)}$  is much higher than the

9 estimation error for  $\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, u)}$ , which decays at a rate of  $\frac{1}{N^2}$ . For a relatively

10 large sample size  $N$ , if we assume that the estimation error for  $\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, u)}$  is

11 negligible compared to  $\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)}$  so that

$$12 \quad \hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, u)} \approx C_{00 \cdot r_i \cdot 00}^{(\theta)}, \quad (\text{F10})$$

13 then

$$14 \quad \begin{aligned} E\left(\left|\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta)}\right|^2\right) &\approx E\left(\left|C_{00 \cdot r_i \cdot 00}^{(\theta)}\right|^2\right) + E\left(\left|\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, \xi)}\right|^2\right) \\ &= \left|C_{00 \cdot r_i \cdot 00}^{(\theta)}\right|^2 + \frac{1}{N^2} \sum_{j=1}^N E\left[\xi_{-x_i}^{(j)} e^{-i(r_i \theta_i^{(j)})} \xi_{-x_i}^{(j)} e^{i(r_i \theta_i^{(j)})}\right] \\ &= \left|C_{00 \cdot r_i \cdot 00}^{(\theta)}\right|^2 + \frac{1}{N^2} \sum_{j=1}^N E\left[\xi_{-x_i}^{(j)}\right]^2 \\ &= \left|C_{00 \cdot r_i \cdot 00}^{(\theta)}\right|^2 + \frac{V(\xi_{-x_i})}{N}. \end{aligned} \quad (\text{F11})$$

15 For  $\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta)} = \hat{a}_{00 \cdot r_i \cdot 00}^{(\theta)} - i \hat{b}_{00 \cdot r_i \cdot 00}^{(\theta)}$ , if we assume that the estimation error for  $\hat{C}_{00 \cdot r_i \cdot 00}^{(\theta, u)}$

1 is negligible compared to  $\hat{C}_{00 \dots r_i \dots 00}^{(\theta, \xi)}$ , based on eq. (F9), eq. (F7) and eq. (F1), we have

$$\begin{aligned}
 \hat{a}_{00 \dots r_i \dots 00}^{(\theta)} &\sim \ddot{N}(a_{00 \dots r_i \dots 00}^{(\theta)}, \frac{V(\xi_{-x_i})}{2N}), \\
 \hat{b}_{00 \dots r_i \dots 00}^{(\theta)} &\sim \ddot{N}(b_{00 \dots r_i \dots 00}^{(\theta)}, \frac{V(\xi_{-x_i})}{2N}),
 \end{aligned}
 \tag{F12}$$

3 where

$$\begin{aligned}
 a_{00 \dots r_i \dots 00}^{(\theta)} &= E[g(G(\theta_1), \dots, G(\theta_n)) \cos(r_i \theta_i)], \\
 b_{00 \dots r_i \dots 00}^{(\theta)} &= E[g(G(\theta_1), \dots, G(\theta_n)) \sin(r_i \theta_i)].
 \end{aligned}$$

5 This also suggests that the estimation error for Fourier coefficient  
 6  $C_{00 \dots r_i \dots 00}^{(\theta)}$  obtained with random balance design sampling is much smaller than that  
 7 with simple random sampling, in view that estimation error for  $\hat{C}_{00 \dots r_i \dots 00}^{(\theta, u)}$  is negligible  
 8 compared to  $\hat{C}_{00 \dots r_i \dots 00}^{(\theta, \xi)}$  for random balance design sampling but not for simple random  
 9 sampling.

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### 11 **Reference**

12 Bickel, P. J., and K. A. Doksum. 2001. Mathematical statistics : basic ideas and  
 13 selected topics, 2nd edition. Prentice Hall, Upper Saddle River, N.J.