

Appendices for “Counterfactual Analysis and Inference with Nonstationary Data”

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A Auxiliary Results

This appendix collects the building blocks to our main result (Theorem 1). The first one is well-known result since Phillips (1991) and it will be stated here without proof for completeness.

Proposition 1. *Let $\mathbf{S}_t = \sum_{j=1}^t \mathbf{z}_j$ be the partial sum of the sequence $\{\mathbf{z}_t\}_{t=1}^\infty$ of $(n \times 1)$ random vectors. Then, under Assumption 3, (a) $\Sigma = \lim_{T \rightarrow \infty} T^{-1} \mathbb{E}(\mathbf{S}_T \mathbf{S}_T')$ exists and is positive definite and (b) $\mathbf{Z}_T(r) \equiv T^{-1/2} \mathbf{S}_{[rT]} \Rightarrow \Sigma^{1/2} \mathbf{W}(r)$, where $[\cdot]$ denotes the integer part and $\mathbf{W}(\cdot)$ is a vector Wiener process on $[0, 1]^n$.*

The implied convergence in Proposition 1(a) is a direct consequence of the stationarity assumption together with the mixing condition as shown by Ibragimov and Linnik (1971). Finally, Proposition 1(b) is a multivariate generalization of the univariate invariance principle (Durlauf and Phillips 1985).

The next proposition state the relation between estimator applied to the pre-intervention period and the same estimator applied to the transformed variables. It also define the pseudo-true parameter β_0 in term of the DGP parameters. Specifically, the OLS estimator $\hat{\beta}$ of y_{1t} on \mathbf{y}_{0t} and a constant is related to the OLS estimator $\hat{\gamma}$ of z_{1t} on \mathbf{z}_{0t} and a constant by:

Proposition 2. *Let $\mathbf{H} := \mathbf{H}(r, \boldsymbol{\mu})$ to be the transformation defined in (3.4) for $0 \leq r \leq n$ and $\boldsymbol{\mu} \in \mathbb{R}^n$. Then, $\underset{2:n+1:2:n+1}{[\mathbf{D}]} (\hat{\beta} - \beta_0) = \hat{\gamma}$, where $\mathbf{D} := \mathbf{H}^{-1}$ and $\beta_0 := \left(\underset{2:n+1:2:n+1}{[\mathbf{D}]} \right)^{-1} \underset{2:n+1 \times 1}{[\mathbf{D}]}$ is given by*

$$\beta_0 := \beta_0(r, \boldsymbol{\mu}) := \begin{cases} \mathbf{0} & \text{if } r = 0 \text{ and } \boldsymbol{\mu} = \mathbf{0}, \\ \left(\mathbf{0}_{n-2}, \frac{\mu_1}{\mu_n}, 0 \right)' & \text{if } r = 0 \text{ and } \boldsymbol{\mu} \neq \mathbf{0}, \\ (-\boldsymbol{\Gamma}', \boldsymbol{\alpha})' & \text{if } r = 1, \\ [\boldsymbol{\pi}', (1, -\boldsymbol{\pi}') (-\boldsymbol{\Gamma}', \boldsymbol{\alpha})]' & \text{if } 2 \leq r \leq n - 1 \text{ and} \\ [\boldsymbol{\pi}', (1, -\boldsymbol{\pi}') \mathbf{h}(0), \delta]' & \text{if } r = n. \end{cases}$$

We can now state the asymptotic distribution of $\hat{\gamma}$, i.e., the OLS estimator in the transformed variables. For that, we first establish some more notation. For any zero mean vector

process covariance-stationary $\{\mathbf{v}_t\}$, we define the following $(n \times n)$ non-random matrices:

$$\begin{aligned}
\mathbf{\Omega}_0(\mathbf{v}) &:= \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \mathbb{E}(\mathbf{v}_t \mathbf{v}_t'), \\
\mathbf{\Omega}_j(\mathbf{v}) &:= \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \sum_{s=1}^{t-j} \mathbb{E}(\mathbf{v}_s \mathbf{v}_t'), \quad j = 1, 2, \dots \\
\mathbf{\Omega}(\mathbf{v}) &:= \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E} \left(\sum_{t=1}^T \mathbf{v}_t \sum_{t=1}^T \mathbf{v}_t' \right), \\
\mathbf{\Upsilon}(\mathbf{v}) &:= \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{V} \left(\sum_{t=1}^T [\mathbf{v}_t]_1 \mathbf{v}_t \right),
\end{aligned} \tag{A.1}$$

if the limits and expectations exist.

Some particular cases of the result below can be found elsewhere in the time-series literature. See, for instance, Durlauf and Phillips (1985) and Phillips (1986a,b).

Proposition 3. *Suppose that Assumption 1 holds and that $\{\mathbf{v}_t := \mathbf{H}'(\boldsymbol{\varepsilon}_t, 0)'\}_{t=1}^\infty$ fulfills Assumption 3, where $\mathbf{H} := \mathbf{H}(r, \boldsymbol{\mu})$ is the transformation defined in (3.4). Then, as $T \rightarrow \infty$,*

$$\mathbf{\Lambda}_{T_0} \widehat{\boldsymbol{\gamma}} \Rightarrow \mathbf{q}^*,$$

where $\mathbf{\Lambda}_{T_0} := \mathbf{\Lambda}_{T_0}(r, \boldsymbol{\mu}) := \text{diag}[\boldsymbol{\lambda}_{T_0}(r, \boldsymbol{\mu})]$ with

$$\boldsymbol{\lambda}_{T_0}(r, \boldsymbol{\mu}) := \begin{cases} (\mathbf{1}_n - 1, T_0^{-1/2})' & \text{if } r = 0 \text{ and } \boldsymbol{\mu} = \mathbf{0} \\ (\mathbf{1}_n - 2, T_0^{1/2}, T_0^{-1/2})' & \text{if } r = 0 \text{ and } \boldsymbol{\mu} \neq \mathbf{0} \\ (T_0 \mathbf{1}_n - 1, T_0^{1/2})' & \text{if } r = 1 \text{ and } \boldsymbol{\mu} = \mathbf{0} \\ (T_0 \mathbf{1}_n - 2, T_0^{3/2}, T_0^{1/2})' & \text{if } r = 1 \text{ and } \boldsymbol{\mu} \neq \mathbf{0} \\ (T_0^{1/2} \mathbf{1}_r - 1, T_0 \mathbf{1}_n - r, T_0^{1/2})' & \text{if } 2 \leq r \leq n - 2 \text{ and } \boldsymbol{\mu} = \mathbf{0} \\ (T_0^{1/2} \mathbf{1}_r - 1, T_0 \mathbf{1}_n - 1 - r, T_0^{3/2}, T_0^{1/2})' & \text{if } 2 \leq r \leq n - 2 \text{ and } \boldsymbol{\mu} \neq \mathbf{0} \\ (T_0^{1/2} \mathbf{1}_n - 1, T_0^{1/2})' & \text{if } r = n - 1 \text{ and } \boldsymbol{\mu} = \mathbf{0} \\ (T_0^{1/2} \mathbf{1}_n - 2, T_0^{3/2}, T_0^{1/2})' & \text{if } r = n - 1 \text{ and } \boldsymbol{\mu} \neq \mathbf{0} \\ (T_0^{1/2} \mathbf{1}_n - 2, F_{T_0}, T_0^{1/2})' & \text{if } r = n. \end{cases}$$

F_{T_0} is a positive increasing sequence such that $\lim_{T_0 \rightarrow \infty} \sum_{t=1}^{T_0} \left(\frac{f_t}{F_{T_0}} \right)^2 =: \phi^2 > 0$ is finite and the

random vector $\mathbf{q}^* := \mathbf{q}^*(r, \boldsymbol{\mu})$ is given by:

$$\mathbf{q}^*(0, \boldsymbol{\mu}) := \begin{cases} \left(\begin{array}{cc} \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] & \left[\int_0^1 \mathbf{B} ds \right] \\ 2:n \times 2:n & 2:n \\ & 1 \end{array} \right)^{-1} \left(\begin{array}{c} \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] \\ 2:n \times 1:1 \\ \left[\int_0^1 \mathbf{B} ds \right] \\ 1:1 \end{array} \right) & , \text{ if } \boldsymbol{\mu} = \mathbf{0} \\ \left(\begin{array}{ccc} \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] & \left[\mu_n \int_0^1 s \mathbf{B} ds \right] & \left[\int_0^1 \mathbf{B} ds \right] \\ 2:n-1 \times 2:n-1 & 2:n-1 & 2:n-1 \\ & \frac{\mu_n^2}{3} & \frac{\mu_n}{2} \\ & & 1 \end{array} \right)^{-1} \left(\begin{array}{c} \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] \\ 2:n-1 \times 1:1 \\ \left[\mu_n \int_0^1 s \mathbf{B} ds \right] \\ 1:1 \\ \left[\int_0^1 \mathbf{B} ds \right] \\ 1:1 \end{array} \right) & , \text{ if } \boldsymbol{\mu} \neq \mathbf{0} \end{cases}$$

$$\mathbf{q}^*(1, \boldsymbol{\mu}) := \begin{cases} \left(\begin{array}{cc} \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] & \left[\int_0^1 \mathbf{B} ds \right] \\ 2:n \times 2:n & 2:n \\ & 1 \end{array} \right)^{-1} \left(\begin{array}{c} \left[\int_0^1 \mathbf{B} d\mathbf{B}' + \boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1 \right] \\ 2:n \times 1:1 \\ \left[\int_0^1 d\mathbf{B} \right] \\ 1:1 \end{array} \right) & , \text{ if } \boldsymbol{\mu} = \mathbf{0} \\ \left(\begin{array}{ccc} \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] & \left[\mu_n \int_0^1 s \mathbf{B} ds \right] & \left[\int_0^1 \mathbf{B} ds \right] \\ 2:n-1 \times 2:n-1 & 2:n-1 & 2:n-1 \\ & \frac{\mu_n^2}{3} & \frac{\mu_n}{2} \\ & & 1 \end{array} \right)^{-1} \left(\begin{array}{c} \left[\int_0^1 \mathbf{B} d\mathbf{B}' + \boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1 \right] \\ 2:n-1 \times 1:1 \\ \left[\mu_n \int_0^1 s d\mathbf{B} \right] \\ 1:1 \\ \left[\int_0^1 d\mathbf{B} \right] \\ 1:1 \end{array} \right) & , \text{ if } \boldsymbol{\mu} \neq \mathbf{0} \end{cases}$$

$$\mathbf{q}^*(r, \boldsymbol{\mu}) := \begin{cases} \left(\begin{array}{ccc} \left[\boldsymbol{\Omega}_0 \right] & 0 & 0 \\ 2:r \times 2:r & & \\ \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] & \left[\int_0^1 \mathbf{B} ds \right] \\ r+1:n \times r+1:n & r+1:n \\ & 1 \end{array} \right)^{-1} \\ \times \left(\begin{array}{c} \left[\int_0^1 d\mathbf{B}^* \right] \\ 2:r \\ \left[\int_0^1 \mathbf{B} d\mathbf{B}' + 1(\boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1) \right] \\ r+1:n \times 1:1 \\ \left[\int_0^1 d\mathbf{B} \right] \\ 1:1 \end{array} \right) & , \text{ if } 2 \leq r \leq n-2 \text{ and } \boldsymbol{\mu} = \mathbf{0}, \\ \left(\begin{array}{ccc} \left[\boldsymbol{\Omega}_0 \right] & 0 & 0 & 0 \\ 2:r \times 2:r & & & \\ \left[\int_0^1 \mathbf{B}\mathbf{B}' ds \right] & \left[\mu_n \int_0^1 s \mathbf{B} ds \right] & \left[\int_0^1 \mathbf{B} ds \right] \\ r+1:n-1 \times r+1:n-1 & r+1:n-1 & r+1:n-1 \\ & \frac{\mu_n^2}{3} & \frac{\mu_n}{2} \\ & & 1 \end{array} \right)^{-1} \\ \times \left(\begin{array}{c} \left[\int_0^1 d\mathbf{B}^* \right] \\ 2:r \\ \left[\int_0^1 \mathbf{B} d\mathbf{B}' + 1(\boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1) \right] \\ r+1:n-1 \times 1:1 \\ \left[\mu_n \int_0^1 s d\mathbf{B} \right] \\ 1:1 \\ \left[\int_0^1 d\mathbf{B} \right] \\ 1:1 \end{array} \right) & , \text{ if } 2 \leq r \leq n-2 \text{ and } \boldsymbol{\mu} \neq \mathbf{0}, \end{cases}$$

$$\mathbf{q}^*(n-1, \boldsymbol{\mu}) := \begin{cases} \begin{pmatrix} [\boldsymbol{\Omega}_0] & 0 \\ 2:n \times 2:n & 1 \end{pmatrix}^{-1} \begin{pmatrix} \int_0^1 d\mathbf{B}^* \\ 2:n \\ \int_0^1 d\mathbf{B} \\ 1:1 \end{pmatrix} & , \text{ if } \boldsymbol{\mu} = \mathbf{0} \\ \begin{pmatrix} [\boldsymbol{\Omega}_0] & 0 & 0 \\ 2:n-1 \times 2:n-1 & \frac{\mu_n^2}{3} & \frac{\mu_n}{2} \\ & & 1 \end{pmatrix}^{-1} \begin{pmatrix} \int_0^1 d\mathbf{B}^* \\ 2:n-1 \\ [\mu_n \int_0^1 s d\mathbf{B}] \\ 1:1 \\ \int_0^1 d\mathbf{B} \\ 1:1 \end{pmatrix} & , \text{ if } \boldsymbol{\mu} \neq \mathbf{0} \end{cases}$$

$$\mathbf{q}^*(n, \boldsymbol{\mu}) := \begin{cases} \begin{pmatrix} [\boldsymbol{\Omega}_0] & 0 \\ 2:n \times 2:n & 1 \end{pmatrix}^{-1} \begin{pmatrix} \int_0^1 d\mathbf{B}^* \\ 2:n \\ \int_0^1 d\mathbf{B} \\ 1:1 \end{pmatrix} & , \text{ for } \boldsymbol{\mu} = \mathbf{0} \\ \begin{pmatrix} [\boldsymbol{\Omega}_0] & 0 & 0 \\ 2:n-1 \times 2:n-1 & \mu_n^2 \phi^2 & \mu_n \tilde{\phi} \\ & & 1 \end{pmatrix}^{-1} \begin{pmatrix} \int_0^1 d\mathbf{B}^* \\ 2:n-1 \\ [\mu_n \phi \mathbf{B}] \\ 1:1 \\ \int_0^1 d\mathbf{B} \\ 1:1 \end{pmatrix} & , \text{ for } \boldsymbol{\mu} \neq \mathbf{0}, \end{cases}$$

with $\tilde{\phi} := \lim_{T_0 \rightarrow \infty} \sum_{t=1}^{T_0} \frac{f_t}{F_{T_0} \sqrt{T_0}} < \infty$, $\mathbf{B} := \boldsymbol{\Omega}^{1/2} \mathbf{W}$ and $\mathbf{B}^* := \boldsymbol{\Upsilon}^{1/2} \mathbf{W}$ where $\mathbf{W} := \{\mathbf{W}(s), s \in [0, 1]\}$, denotes a standard vector Wiener process on $[0, 1]^n$ and $\boldsymbol{\Omega} := \boldsymbol{\Omega}(\mathbf{v})$, $\boldsymbol{\Omega}_0 := \boldsymbol{\Omega}_0(\mathbf{v})$, $\boldsymbol{\Omega}_1 := \boldsymbol{\Omega}_1(\mathbf{v})$, $\boldsymbol{\Upsilon} := \boldsymbol{\Upsilon}(\mathbf{v})$ are defined in (A.1).

If the DGP has only deterministic trends ($r = n$), the trend is of the form $f_t = t^k, k > 0$. In this case, $F_{T_0} = T_0^{k+1/2}$ and $\phi^2 := \lim_{T_0 \rightarrow \infty} \frac{1}{T_0} \sum_{t=1}^{T_0} \left(\frac{t}{T_0}\right)^{2k} = \frac{1}{2k+1}$ and $\tilde{\phi} := \lim_{T \rightarrow \infty} \sum_{t=1}^{T_0} \frac{t^k}{T^{k+1}} = \frac{1}{k+1}$. For $k = 1$, the asymptotic distributions for the DGP when $r = n - 1$ and $r = n$ are identical.

B Unpacking Notation of Theorem 1

Set $V := V(r) := \begin{pmatrix} [\boldsymbol{\Omega}_0] \\ 1:1 \times 1:1 \end{pmatrix} I(r > 0)$, where $I(\cdot)$ is the indicator function. Define $\mathbf{G} := \mathbf{G}(r) := \lim_{T_0 \rightarrow \infty} \xi_{T_0} \begin{pmatrix} \boldsymbol{\Lambda}_T & [\mathbf{D}] \\ 2:n+1:2:n+1 \end{pmatrix}^{-1}$. The $n + 1$ -dimensional random vector $\mathbf{p} := \mathbf{p}(r, \boldsymbol{\mu})$, for the case where $\boldsymbol{\mu} = \mathbf{0}$ is given by

$$\mathbf{p}(0, \mathbf{0}) := \begin{bmatrix} \int_{\lambda_0}^1 \mathbf{B} ds \\ 1 - \lambda_0 \end{bmatrix}; \quad \mathbf{p}(1, \mathbf{0}) := \begin{bmatrix} \int_{\lambda_0}^1 d\mathbf{B} \\ 1:1 \\ \int_{\lambda_0}^1 \mathbf{B} ds \\ 2:n \\ 1 - \lambda_0 \end{bmatrix}; \quad \mathbf{p}(r, \mathbf{0}) := \begin{bmatrix} \int_{\lambda_0}^1 d\mathbf{B} \\ 1:1 \\ \int_{\lambda_0}^1 d\mathbf{B} \\ 2:r \\ \int_{\lambda_0}^1 \mathbf{B} ds \\ r+1:n \\ 1 - \lambda_0 \end{bmatrix} \quad \text{for } 2 \leq r \leq n - 2;$$

$$\mathbf{p}(n-1, \mathbf{0}) = \mathbf{p}(n, \mathbf{0}) := \begin{bmatrix} \int_{\lambda_0}^1 d\mathbf{B} \\ 1:1 \\ \int_{\lambda_0}^1 d\mathbf{B} \\ 2:n \\ 1 - \lambda_0 \end{bmatrix},$$

and for $\boldsymbol{\mu} \neq \mathbf{0}$:

$$\mathbf{p}(0, \boldsymbol{\mu}) := \begin{bmatrix} \left[\int_{\lambda_0}^1 \mathbf{B} ds \right] \\ 1:n-1 \\ \frac{\mu_n(1-\lambda_0^2)}{2} \\ 1-\lambda_0 \end{bmatrix}; \quad \mathbf{p}(1, \boldsymbol{\mu}) := \begin{bmatrix} \left[\int_{\lambda_0}^1 d\mathbf{B} \right] \\ 1:1 \\ \left[\int_{\lambda_0}^1 \mathbf{B} ds \right] \\ 2:n-1 \\ \frac{\mu_n(1-\lambda_0^2)}{2} \\ 1-\lambda_0 \end{bmatrix}; \quad \mathbf{p}(r, \boldsymbol{\mu}) := \begin{bmatrix} \left[\int_{\lambda_0}^1 d\mathbf{B} \right] \\ 1:1 \\ \left[\int_{\lambda_0}^1 d\mathbf{B} \right] \\ 2:r \\ \left[\int_{\lambda_0}^1 \mathbf{B} ds \right] \\ r+1:n-1 \\ \frac{\mu_n(1-\lambda_0^2)}{2} \\ 1-\lambda_0 \end{bmatrix} \quad \text{for } 2 \leq r \leq n-2;$$

$$\mathbf{p}(n-1, \boldsymbol{\mu}) := \begin{bmatrix} \left[\int_{\lambda_0}^1 d\mathbf{B} \right] \\ 1:1 \\ \left[\int_{\lambda_0}^1 d\mathbf{B} \right] \\ 2:n-1 \\ \frac{\mu_n(1-\lambda_0^2)}{2} \\ 1-\lambda_0 \end{bmatrix}; \quad \mathbf{p}(n, \boldsymbol{\mu}) := \begin{bmatrix} \left[\int_{\lambda_0}^1 d\mathbf{B} \right] \\ 1:1 \\ \left[\int_{\lambda_0}^1 d\mathbf{B} \right] \\ 2:n-1 \\ \mu_n \check{\phi} \\ 1-\lambda_0 \end{bmatrix},$$

where $\check{\phi} := \lim_{T \rightarrow \infty} \sum_{t > T_0}^T \frac{f_t}{F_T \sqrt{T}} < \infty$ and the processes \mathbf{B} will be defined below.

The $n+1$ -dimensional random vector $\mathbf{q} := \mathbf{q}(r, \boldsymbol{\mu})$ is defined as

$$\mathbf{q}(0, \boldsymbol{\mu}) := \begin{cases} \begin{pmatrix} \left(\begin{bmatrix} \int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds \\ 2:n \times 2:n \\ \int_0^{\lambda_0} \mathbf{B} ds \\ 2:n \\ \lambda_0 \end{bmatrix} \right)^{-1} \begin{pmatrix} \int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds \\ 2:n \times 1:1 \\ \int_0^{\lambda_0} \mathbf{B} ds \\ 1:1 \end{pmatrix} \end{pmatrix}, & \text{if } \boldsymbol{\mu} = \mathbf{0} \\ \begin{pmatrix} \left(\begin{bmatrix} \int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds \\ 2:n-1 \times 2:n-1 \\ \mu_n \int_0^{\lambda_0} s \mathbf{B} ds \\ 2:n-1 \\ \frac{\mu_n^2 \lambda_0^3}{3} \\ \int_0^{\lambda_0} \mathbf{B} ds \\ 2:n-1 \\ \frac{\mu_n \lambda_0^2}{2} \\ \lambda_0 \end{bmatrix} \right)^{-1} \begin{pmatrix} \int_0^{\lambda_0} \mathbf{B} d\mathbf{B}' + \lambda_0(\boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1) \\ 2:n-1 \times 1:1 \\ \mu_n \int_0^{\lambda_0} s d\mathbf{B} \\ 1:1 \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{pmatrix} \end{pmatrix}, & \text{if } \boldsymbol{\mu} \neq \mathbf{0} \end{cases}$$

$$\mathbf{q}(1, \boldsymbol{\mu}) := \begin{cases} \begin{pmatrix} \left(\begin{bmatrix} \int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds \\ 2:n \times 2:n \\ \int_0^{\lambda_0} \mathbf{B} ds \\ 2:n \\ \lambda_0 \end{bmatrix} \right)^{-1} \begin{pmatrix} \int_0^{\lambda_0} \mathbf{B} d\mathbf{B}' + \boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1 \\ 2:n \times 1:1 \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{pmatrix} \end{pmatrix}, & \text{if } \boldsymbol{\mu} = \mathbf{0} \\ \begin{pmatrix} \left(\begin{bmatrix} \int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds \\ 2:n-1 \times 2:n-1 \\ \mu_n \int_0^{\lambda_0} s \mathbf{B} ds \\ 2:n-1 \\ \frac{\mu_n^2 \lambda_0^3}{3} \\ \int_0^{\lambda_0} \mathbf{B} ds \\ 2:n-1 \\ \frac{\mu_n \lambda_0^2}{2} \\ \lambda_0 \end{bmatrix} \right)^{-1} \begin{pmatrix} \int_0^{\lambda_0} \mathbf{B} d\mathbf{B}' + \lambda_0(\boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1) \\ 2:n-1 \times 1:1 \\ \mu_n \int_0^{\lambda_0} s d\mathbf{B} \\ 1:1 \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{pmatrix} \end{pmatrix}, & \text{if } \boldsymbol{\mu} \neq \mathbf{0} \end{cases}$$

$$\mathbf{q}(r, \boldsymbol{\mu}) := \left\{ \begin{array}{l} \left(\begin{array}{ccc} [\boldsymbol{\Omega}_0] & 0 & 0 \\ 2:r \times 2:r & & \\ \int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds & \int_0^{\lambda_0} \mathbf{B} ds & \\ r+1:n \times r+1:n & r+1:n & \\ & & \lambda_0 \end{array} \right)^{-1} \\ \times \left(\begin{array}{c} \int_0^{\lambda_0} d\mathbf{B}^* \\ 2:r \\ \int_0^{\lambda_0} \mathbf{B} d\mathbf{B}' + 1(\boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1) \\ r+1:n \times 1:1 \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{array} \right) \quad , \text{ if } 2 \leq r \leq n-2 \text{ and } \boldsymbol{\mu} = \mathbf{0}, \\ \left(\begin{array}{ccc} [\boldsymbol{\Omega}_0] & 0 & 0 \\ 2:r \times 2:r & & \\ \int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds & \left[\mu_n \int_0^{\lambda_0} s\mathbf{B} ds \right] & \int_0^{\lambda_0} \mathbf{B} ds \\ r+1:n-1 \times r+1:n-1 & r+1:n-1 & r+1:n-1 \\ & \frac{\mu_n^2 \lambda_0^3}{3} & \frac{\mu_n \lambda_0^2}{2} \\ & & \lambda_0 \end{array} \right)^{-1} \\ \times \left(\begin{array}{c} \int_0^{\lambda_0} d\mathbf{B}^* \\ 2:r \\ \int_0^{\lambda_0} \mathbf{B} d\mathbf{B}' + \lambda_0(\boldsymbol{\Omega}_0 + \boldsymbol{\Omega}_1) \\ r+1:n-1 \times 1:1 \\ \left[\mu_n \int_0^{\lambda_0} s d\mathbf{B} \right] \\ 1:1 \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{array} \right) \quad , \text{ if } 2 \leq r \leq n-2 \text{ and } \boldsymbol{\mu} \neq \mathbf{0}, \end{array} \right.$$

$$\mathbf{q}(n-1, \boldsymbol{\mu}) := \left\{ \begin{array}{l} \left(\begin{array}{cc} [\boldsymbol{\Omega}_0] & 0 \\ 2:n \times 2:n & \\ & \lambda_0 \end{array} \right)^{-1} \left(\begin{array}{c} \int_0^{\lambda_0} d\mathbf{B}^* \\ 2:n \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{array} \right) \quad , \text{ if } \boldsymbol{\mu} = \mathbf{0} \\ \left(\begin{array}{ccc} [\boldsymbol{\Omega}_0] & 0 & 0 \\ 2:n-1 \times 2:n-1 & & \\ \frac{\mu_n^2 \lambda_0^3}{3} & \frac{\mu_n \lambda_0^2}{2} & \\ & & \lambda_0 \end{array} \right)^{-1} \left(\begin{array}{c} \int_0^{\lambda_0} d\mathbf{B}^* \\ 2:n-1 \\ \left[\mu_n \int_0^{\lambda_0} s d\mathbf{B} \right] \\ 1:1 \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{array} \right) \quad , \text{ if } \boldsymbol{\mu} \neq \mathbf{0} \end{array} \right.$$

$$\mathbf{q}(n, \boldsymbol{\mu}) := \left\{ \begin{array}{l} \left(\begin{array}{cc} [\boldsymbol{\Omega}_0] & 0 \\ 2:n \times 2:n & \\ & \lambda_0 \end{array} \right)^{-1} \left(\begin{array}{c} \int_0^{\lambda_0} d\mathbf{B}^* \\ 2:n \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{array} \right) \quad , \text{ for } \boldsymbol{\mu} = \mathbf{0} \\ \left(\begin{array}{ccc} [\boldsymbol{\Omega}_0] & 0 & 0 \\ 2:n-1 \times 2:n-1 & & \\ \mu_n^2 \phi^2 & \mu_n \tilde{\phi} & \\ & & \lambda_0 \end{array} \right)^{-1} \left(\begin{array}{c} \int_0^{\lambda_0} d\mathbf{B}^* \\ 2:n-1 \\ \left[\mu_n \phi \mathbf{B} \right] \\ 1:1 \\ \int_0^{\lambda_0} d\mathbf{B} \\ 1:1 \end{array} \right) \quad , \text{ for } \boldsymbol{\mu} \neq \mathbf{0}, \end{array} \right.$$

Finally, the random variable $a := a(r, \boldsymbol{\mu})$, for the case when $\boldsymbol{\mu} = \mathbf{0}$, is given by

$$a(r, \mathbf{0}) := \begin{cases} \frac{1}{1-\lambda_0} \begin{pmatrix} \left[\int_{\lambda_0}^1 \mathbf{B}\mathbf{B}' ds \right]_{1:1 \times 1:1} - 2\mathbf{q}(0, \mathbf{0})' & \begin{bmatrix} \left[\int_{\lambda_0}^1 \mathbf{B}\mathbf{B}' ds \right]_{2:n \times 1:1} \\ \left[\int_{\lambda_0}^1 \mathbf{B} ds \right]_{1:1} \end{bmatrix} \\ \mathbf{q}(0, \mathbf{0})' & \begin{bmatrix} \left[\int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds \right]_{2:n \times 2:n} & \left[\int_0^{\lambda_0} \mathbf{B} ds \right]_{2:n} \\ \lambda_0 \end{bmatrix} \end{pmatrix} \mathbf{q}(0, \mathbf{0}) \end{cases}, \text{ if } r = 0 \\ \frac{1}{1-\lambda_0} \left[\int_{\lambda_0}^1 d\mathbf{B}^* \right]_{1:1}, \text{ for } r \geq 1 \end{cases}$$

and for the case $\boldsymbol{\mu} \neq \mathbf{0}$:

$$a(r, \boldsymbol{\mu}) := \begin{cases} \frac{1}{1-\lambda_0} \begin{pmatrix} \left[\int_{\lambda_0}^1 \mathbf{B}\mathbf{B}' ds \right]_{1:1 \times 1:1} - 2\mathbf{q}(0, \boldsymbol{\mu})' & \begin{bmatrix} \left[\int_{\lambda_0}^1 \mathbf{B}\mathbf{B}' ds \right]_{2:n-1 \times 1:1} \\ \mu_n \left[\int_{\lambda_0}^1 s \mathbf{B} ds \right]_{1:1} \\ \left[\int_{\lambda_0}^1 \mathbf{B} ds \right]_{1:1} \end{bmatrix} \\ \mathbf{q}(0, \boldsymbol{\mu})' & \begin{bmatrix} \left[\int_0^{\lambda_0} \mathbf{B}\mathbf{B}' ds \right]_{2:n-1 \times 2:n-1} & \begin{bmatrix} \left[\mu_n \int_0^{\lambda_0} s \mathbf{B} ds \right]_{2:n-1} \\ \frac{\mu_n^2 \lambda_0^3}{3} \end{bmatrix} & \left[\int_0^{\lambda_0} \mathbf{B} ds \right]_{2:n-1} \\ \lambda_0 \end{bmatrix} \end{pmatrix} \mathbf{q}(0, \boldsymbol{\mu}) \end{cases}, \text{ if } r = 0 \\ \frac{1}{1-\lambda_0} \left[\int_{\lambda_0}^1 d\mathbf{B}^* \right]_{1:1}, \text{ for } r \geq 1, \end{cases}$$

with $\tilde{\phi} := \lim_{T \rightarrow \infty} \sum_{t=1}^{T_0} \frac{f_t}{F_T \sqrt{T}} < \infty$, $\mathbf{B} := \boldsymbol{\Omega}^{1/2} \mathbf{W}$ and $\mathbf{B}^* := \boldsymbol{\Upsilon}^{1/2} \mathbf{W}$ where $\mathbf{W} := \{\mathbf{W}(s), s \in [0, 1]\}$, denotes a standard vector Wiener process on $[0, 1]^n$ and $\boldsymbol{\Omega} := \boldsymbol{\Omega}(v)$, $\boldsymbol{\Omega}_0 := \boldsymbol{\Omega}_0(v)$, $\boldsymbol{\Omega}_1 := \boldsymbol{\Omega}_1(v)$, $\boldsymbol{\Upsilon} := \boldsymbol{\Upsilon}(v)$ are defined in (A.1).

C Proof of the Main Results

Proof of Proposition 2

Let $\tilde{\mathbf{y}}_t := (\mathbf{y}_t^{(0)'}, 1)'$ and recall that $\mathbf{z}_t := \mathbf{H}' \tilde{\mathbf{y}}_t$. Let $\tilde{\mathbf{Y}}$ be the $(T_0 \times n + 1)$ matrix constructed by stacking $\tilde{\mathbf{y}}_t'$ for $t = 1, \dots, T_0$. Define \mathbf{Z} by stacking \mathbf{z}_t' . Hence, $\mathbf{Z} = \tilde{\mathbf{Y}} \mathbf{H}$. Define the $(n + 1 \times n + 1)$ matrices $\boldsymbol{\Sigma} := \tilde{\mathbf{Y}}' \tilde{\mathbf{Y}}$ and $\boldsymbol{\Omega} := \mathbf{Z}' \mathbf{Z}$, such that

$$\hat{\boldsymbol{\beta}} := \begin{pmatrix} & [\boldsymbol{\Sigma}] \\ \begin{bmatrix} 2:n+1 \times 2:n+1 \end{bmatrix} & \end{pmatrix}^{-1} [\boldsymbol{\Sigma}]_{2:n+1 \times 1:1} \quad \text{and} \quad \hat{\boldsymbol{\gamma}} := \begin{pmatrix} & [\boldsymbol{\Omega}] \\ \begin{bmatrix} 2:n+1 \times 2:n+1 \end{bmatrix} & \end{pmatrix}^{-1} [\boldsymbol{\Omega}]_{2:n+1 \times 1:1},$$

provided that $\begin{bmatrix} \boldsymbol{\Sigma} \\ 2:n+1 \times 2:n+1 \end{bmatrix}$ and $\begin{bmatrix} \boldsymbol{\Omega} \\ 2:n+1 \times 2:n+1 \end{bmatrix}$ are non-singular. To show the relation between $\widehat{\boldsymbol{\beta}}$ and $\widehat{\boldsymbol{\gamma}}$ recall that $\boldsymbol{D} = \boldsymbol{H}^{-1}$. Therefore, we may write $\boldsymbol{\Sigma} = \boldsymbol{D}'\boldsymbol{\Omega}\boldsymbol{D}$. Notice that

$$\begin{aligned} \begin{bmatrix} \boldsymbol{\Sigma} \\ 2:n+1 \times 2:n+1 \end{bmatrix} &= \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 1:1 \times 2:n+1 \end{bmatrix}' & \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 2:n+1 \end{bmatrix}' \end{pmatrix} \boldsymbol{\Omega} \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 1:1 \times 2:n+1 \end{bmatrix} \\ \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 2:n+1 \end{bmatrix} \end{pmatrix} \\ \begin{bmatrix} \boldsymbol{\Sigma} \\ 2:n+1 \times 1:1 \end{bmatrix} &= \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 1:1 \times 2:n+1 \end{bmatrix}' & \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 2:n+1 \end{bmatrix}' \end{pmatrix} \boldsymbol{\Omega} \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 1:1 \times 1:1 \end{bmatrix} \\ \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 1:1 \end{bmatrix} \end{pmatrix} \end{aligned}$$

In all cases considered we have that $\begin{bmatrix} \boldsymbol{D} \\ 1:1 \times 2:n+1 \end{bmatrix} = \mathbf{0}$, which implies that we can rewrite $\widehat{\boldsymbol{\beta}}$ as

$$\widehat{\boldsymbol{\beta}} = \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 2:n+1 \end{bmatrix} \end{pmatrix}^{-1} \left(\widehat{\boldsymbol{\gamma}} + \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 1:1 \end{bmatrix} \right)$$

Rearranging the terms and setting $\boldsymbol{\beta}_0 = \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 2:n+1 \end{bmatrix} \end{pmatrix}^{-1} \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 1:1 \end{bmatrix}$ yield the result.

Proof of Proposition 3

Let $z_{1t} := \begin{bmatrix} \boldsymbol{z}_t \\ 1:1 \end{bmatrix}$ and $z_{0t} := \begin{bmatrix} \boldsymbol{z}_t \\ 2:n+1 \end{bmatrix}$. Then,

$$\boldsymbol{\Lambda}_T \widehat{\boldsymbol{\gamma}} = \left(\boldsymbol{\Lambda}_T^{-1} \sum_{t=1}^{T_0} z_{0t} z_{0t}' \boldsymbol{\Lambda}_T^{-1} \right)^{-1} \boldsymbol{\Lambda}_T^{-1} \sum_{t=1}^{T_0} z_{0t} z_{1t} =: \boldsymbol{M}_T^{-1} \boldsymbol{m}_T.$$

Applying the convergence results of Lemma 1 and the continuous mapping theorem, we have $\boldsymbol{M}_T^{-1} \boldsymbol{m}_T \Rightarrow \boldsymbol{M}^{-1} \boldsymbol{m} =: \boldsymbol{q}^*$, where the non-singular random matrix $\boldsymbol{M} := \boldsymbol{M}(r, \boldsymbol{\mu})$ and the random vector $\boldsymbol{m} := \boldsymbol{m}(r, \boldsymbol{\mu})$ are defined in the Proposition 3.

Proof of Theorem 1

First notice that $\widehat{\delta}_t - \delta_t = \nu_t - (\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0)' \boldsymbol{x}_t = z_{1t} - \widehat{\boldsymbol{\gamma}}' z_{0t}$. Therefore, for (a) we have

$$\begin{aligned} \xi_{T_0}(\widehat{\delta}_t - \delta_t - \nu_t) &= -\xi_{T_0} \boldsymbol{x}_t' (\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0) = -\xi_{T_0} \boldsymbol{x}_t' \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 2:n+1 \end{bmatrix} \end{pmatrix}^{-1} \widehat{\boldsymbol{\gamma}} \\ &= -\boldsymbol{x}_t' \left[\xi_{T_0} \begin{pmatrix} \begin{bmatrix} \boldsymbol{D} \\ 2:n+1 \times 2:n+1 \end{bmatrix} \end{pmatrix}^{-1} \boldsymbol{\Lambda}_T^{-1} \right] (\boldsymbol{\Lambda}_T \widehat{\boldsymbol{\gamma}}) \Rightarrow -(\boldsymbol{G}\boldsymbol{q})' \boldsymbol{x}_t, \end{aligned}$$

where the convergence in distribution follows from the definition of \boldsymbol{G} , Proposition 3 and the Continuous Mapping Theorem (CMT). For (b), Lemma 1 and the CMT yield

$$\xi_T(\widehat{\Delta}_T - \Delta_T) = \frac{T}{T_2} \left[\left(\frac{\xi_T}{T} \sum_{t>T_0}^T z_{1t} \right) - (\boldsymbol{\Lambda}_T \widehat{\boldsymbol{\gamma}})' \left(\frac{\xi_T}{T} \boldsymbol{\Lambda}_T^{-1} \sum_{t>T_0}^T z_{0t} \right) \right] \Rightarrow \frac{1}{1 - \lambda_0} (1, \boldsymbol{q}') \boldsymbol{p},$$

where the random vectors \mathbf{q} and \mathbf{p} are defined as in the Theorem 1 for each case of r and $\boldsymbol{\mu}$. Similarly, for (c) we have that $(\widehat{\delta}_t - \delta_t)^2 = z_{1t}^2 - 2\widehat{\boldsymbol{\gamma}}' \mathbf{z}_{0t} z_{1t} + \widehat{\boldsymbol{\gamma}}' \mathbf{z}_{0t} \mathbf{z}'_{0t} \widehat{\boldsymbol{\gamma}}$. Hence,

$$\begin{aligned} \zeta_T \widehat{V}_T = \frac{T}{T_2} & \left[\left(\frac{\zeta_T}{T} \sum_{t>T_0}^T z_{1t}^2 \right) - 2(\boldsymbol{\Lambda}_T \widehat{\boldsymbol{\gamma}})' \left(\frac{\zeta_T}{T} \boldsymbol{\Lambda}_T^{-1} \sum_{t>T_0}^T \mathbf{z}_{0t} z_{1t} \right) \right. \\ & \left. + (\boldsymbol{\Lambda}_T \widehat{\boldsymbol{\gamma}})' \left(\frac{\zeta_T}{T} \boldsymbol{\Lambda}_T^{-1} \sum_{t>T_0}^T \mathbf{z}_{0t} \mathbf{z}'_{0t} \boldsymbol{\Lambda}_T^{-1} \right) (\boldsymbol{\Lambda}_T \widehat{\boldsymbol{\gamma}}) \right]. \end{aligned}$$

For $r = 0$ and $\zeta_T = 1/T$ we have the following result

$$\frac{1}{T} \widehat{V}_T \Rightarrow \frac{1}{1 - \lambda_0} [\mathbf{j}_1 - 2\mathbf{q}(0)' \mathbf{j}_2 + \mathbf{q}(0)' \mathbf{N} \mathbf{q}(0)] =: a,$$

where the random vectors \mathbf{j}_1 , \mathbf{j}_2 and matrix \mathbf{N} are defined in Appendix B. For $r \geq 1$, $\zeta_T = \sqrt{T}$ and the last two terms in parenthesis vanish in probability such that

$$\sqrt{T} \left(\widehat{V}_T - [\boldsymbol{\Omega}_0]_{1:1 \times 1:1} \right) \Rightarrow \frac{1}{1 - \lambda_0} \left[\int_{\lambda_0}^1 d\mathbf{B}^* \right]_{1:1}.$$

Proof of Theorem 2

Part (a) follows directly from of Theorem 1(a) combined with the Continuous Mapping Theorem. For (b), let $\widetilde{G}_T(\mathbf{x}) := \frac{1}{\tau} \sum_{j=1}^{\tau} I(\boldsymbol{\psi}_j \leq \mathbf{x})$ be the unfeasible counterpart of \widehat{G}_T , where $\tau := T_0 - T_2 + 1$. We now show that both $\widetilde{G}_T(\mathbf{x}) - G_T(\mathbf{x})$ and $\widehat{G}_T(\mathbf{x}) - \widetilde{G}_T(\mathbf{x})$ vanish in probability as $T_0 \rightarrow \infty$. The result then follows by the triangle inequality.

Due to the strictly stationarity assumption $\mathbb{E} \widetilde{G}_T(x) = \frac{1}{\tau} \sum_{j=1}^{\tau} \mathbb{P}(\boldsymbol{\psi}_j \leq x) = \mathbb{P}(\boldsymbol{\psi}_0 \leq x) =: G_T(x)$. Hence, $\widetilde{G}_T(x)$ is unbiased for $G_T(x)$. So, it is enough to show that $\mathbb{V} \widetilde{G}_T(x)$ converges to zero. The sequence $\{W_j := I(\boldsymbol{\psi}_j \leq x)\}_j$ is stationary and, as a consequence,

$$\mathbb{V} \widetilde{G}_T(x) = \frac{1}{\tau} \sum_{|k| < \tau} \left(1 - \frac{|k|}{\tau}\right) \gamma_k, \quad \gamma_k := \mathbb{C}(W_1, W_{1+k}).$$

Also, $0 \leq W_j \leq 1$. We can bound the first $T_2 - 1$ covariances by 1 and the remanning ones using a mixing inequality due to [?]. For $|k| \geq T_2$, we have $\gamma_k \leq 4\alpha(k - T_2 + 1)$, where $\alpha(j)$ is the mixing coefficient of $\{\epsilon_t\}_t$.⁶ Then,

$$\mathbb{V} \widetilde{G}_T(x) \leq \frac{2T_2 + 1}{\tau} + \frac{8}{\tau} \sum_{k=T_2}^{\tau} \alpha(k - T_2 + 1).$$

Finally, since $T_0 \rightarrow \infty$ implies $\tau \rightarrow \infty$, we have the first term converging to zero and the second converges to zero due to the strong mixing assumption.

⁶In fact the sequence $\{W_j(\nu_j, \dots, \nu_{j+T_2-1})\}_j$ is also strong mixing.

For the second part, fix \mathbf{x} as a continuity point of G and write

$$\widehat{G}(\mathbf{x}) := \frac{1}{\tau} \sum_{j=1}^{\tau} I(\boldsymbol{\psi}_0 + (\widehat{\boldsymbol{\psi}} - \boldsymbol{\psi}_0) \leq \mathbf{x}).$$

For any $\epsilon > 0$ define the events $\mathcal{A}_T(\epsilon) = \{\|\widehat{\boldsymbol{\psi}} - \boldsymbol{\psi}_0\|_{\infty} < \epsilon\}$ and $\mathcal{B}_T(\epsilon, x) = \{|\widetilde{G}(x) - G(x)| < \epsilon\}$. On \mathcal{A}_T we have $\widetilde{G}(\mathbf{x} - \epsilon \boldsymbol{\iota}) \leq \widehat{G}(\mathbf{x}) \leq \widetilde{G}(\mathbf{x} + \epsilon \boldsymbol{\iota})$, where $\boldsymbol{\iota}$ is a conformable vector of ones. If we condition on \mathcal{B}_T , we have for the continuity points of $G(x)$ $G(\mathbf{x} - \epsilon \boldsymbol{\iota}) - \epsilon \leq \widehat{G}(\mathbf{x}) \leq G(\mathbf{x} + \epsilon \boldsymbol{\iota}) + \epsilon$. Set $\epsilon \rightarrow 0$ to conclude since $\mathcal{A}_T \cap \mathcal{B}_T$ occurs with probability approaching 1.

For (c) we use the fact that (b) is equivalent (refer to Theorem 6.3.1 of ?]) to say that for any subsequence $\{T_j\}$, we can extract a subsequence $\{T_{j_k}\}$ such that $\widehat{G}_{T_{j_k}}(\omega, x) \rightarrow G(x)$ for all $\omega \in \Omega_3$ and x a continuity point of G with $\mathbb{P}(\Omega_3) = 1$. Since G is assumed continuous and for each fixed ω , $\widehat{G}_{T_{j_k}}(\omega, x)$ is a CDF, the last convergence can be made uniform by Polya's theorem, i.e., $\sup_{x \in \mathbb{R}^b} |\widehat{G}_{T_{j_k}}(\omega, x) - G_{T_{j_k}}(x)| \rightarrow 0$ for all $\omega \in \Omega_3$. The result then follows by using the equivalence (in the other direction) of Theorem 6.3.1 of ?].

Proof of Theorem 3

Let F denote the CDF of p , i.e. $F(x) := \mathbb{P}(p \leq x)$. Since $\sqrt{b}L_j$ and $\sqrt{T}(\widehat{\Delta}_T - \Delta_T)$ has the same limiting distribution p according to Theorem 1(b) and p is a continuous random variable, we have that $\widehat{F}_{t,b}$ is asymptotically mean unbiased for F_T for every $x \in \mathbb{R}$ since

$$\mathbb{E}(\widehat{F}_{T,b}(x) - F_T(x)) = \frac{1}{\#\mathcal{J}} \sum_{j \in \mathcal{J}} \mathbb{P}(\sqrt{b}L_j \leq x) - \mathbb{P}(\sqrt{T}(\widehat{\Delta}_T - \Delta_T) \leq x) = o(1).$$

To show that $\widehat{F}_{T,b}(x)$ converges to $F_T(x)$ in probability, it is enough to show that the variance of $\widehat{F}_{T,b}(x)$ vanishes. Let $H_j := I(\sqrt{b}L_j \leq x)$ and $\gamma_{i,j} := \mathbb{C}(H_i, H_j)$. Since H_j is binary, we have that $|\gamma_{ij}| \leq 1$. Therefore, $\mathbb{V}(\widehat{F}_{T,b}(x)) \leq \frac{(2b+1)}{T-b+1} + \frac{1}{(T-b+1)^2} \sum_{|i-j|>b} \gamma_{i,j}$. The first term is $o(1)$ under the theorem's assumptions. For the second term, notice that for any pair $(i, j) \in \mathcal{J}^2$ we have that H_i and H_j are functions of the subsamples indexed by \mathcal{S}_i and \mathcal{S}_j , respectively. For $|i - j| > b$ we have $\mathcal{S}_i \cap \mathcal{S}_j = \emptyset$. Hence, we can bound the covariance as $|\gamma_{i,j}| \leq 4\alpha(|i - j| - b)$, where $\alpha(\cdot)$ is the mixing coefficient of the process $\{\boldsymbol{\epsilon}_t\}_t$ and the mixing inequality is due to Ibragimov (1962). Thus,

$$\frac{1}{(T - b + 1)^2} \sum_{|i-j|>b} \gamma_{i,j} \leq \frac{4}{(T - b + 1)^2} \sum_{|i-j|>b} \alpha(|i - j| - b) \leq \frac{8}{(T - b + 1)} \sum_{k=1}^{T-b+1} \alpha(k) = o(1),$$

which proves the pointwise convergence, namely $|\widehat{F}_{T,b}(x) - F_T(x)| \xrightarrow{p} 0$ for every $x \in \mathbb{R}$.

For the uniform result we once again use the equivalence given in Theorem 6.3.1 of Resnick (1999) to say that for any subsequence $\{T_j\}$, we can extract a subsequence $\{T_{j_k}\}$ such that $\widehat{F}_{T_{j_k}}(\omega, x) \rightarrow F(x)$ for all $\omega \in \Omega_4$ and $x \in \mathbb{R}$ with $\mathbb{P}(\Omega_4) = 1$. Since F is continuous and for each fixed ω , $\widehat{F}_{T_{j_k}}(\omega, x)$ is a CDF, the last convergence can be made uniform by Polya's theorem

such that $\sup_{x \in \mathbb{R}^b} |\widehat{F}_{T_{j_k}}(\omega, x) - F_{T_{j_k}}(x)| \rightarrow 0$ for all $\omega \in \Omega_4$. The result then follows by using the equivalence (in the other direction) of Theorem 6.3.1 of Resnick (1999).