

# Multiscale Testing for Equality of Nonparametric Trend Curves

Marina Khismatullina<sup>1</sup>  
University of Bonn

Michael Vogt<sup>2</sup>  
University of Bonn

We develop multiscale methods to test qualitative hypotheses about nonparametric time trends. In many applications, practitioners are interested in whether the observed time series has a time trend at all, that is, whether the trend function is non-constant. Moreover, they would like to get further information about the shape of the trend function. Among other things, they would like to know in which time regions there is an upward/downward movement in the trend. When multiple time series are observed, another important question is whether the observed time series all have the same time trend. We design multiscale tests to formally approach these questions. We derive asymptotic theory for the proposed tests and investigate their finite sample performance by means of simulations. In addition, we illustrate the methods by two applications to temperature data.

**Key words:** Multiscale statistics; nonparametric regression; time series errors; shape constraints; strong approximations; anti-concentration bounds.

**AMS 2010 subject classifications:** 62E20; 62G10; 62G20; 62M10.

## 1 The model

Before we proceed any further, we need to introduce some notation used throughout the paper. For a vector  $\mathbf{v} = (v_1, \dots, v_m) \in \mathbb{R}^m$ , we write  $|\mathbf{v}| = (\sum_{i=1}^m v_i^2)^{1/2}$  and  $|\mathbf{v}|_q = (\sum_{i=1}^m v_i^q)^{1/q}$  respectively. For a random vector  $\mathbf{V}$ , we define its  $\mathcal{L}^q, q > 1$  norm as  $\|\mathbf{V}\|_q = (\mathbb{E}|\mathbf{V}|^q)^{1/q}$ . For a particular case  $q = 2$ , we write  $\|\mathbf{V}\| := \|\mathbf{V}\|_2$ .

Following Wu (2005), we define the *physical dependence measure* for the process  $\mathbf{L}(\mathcal{F}_t)$  as the following:

$$\delta_q(\mathbf{L}, t) = \|\mathbf{L}(\mathcal{F}_t) - \mathbf{L}(\mathcal{F}'_t)\|_q,$$

where  $\mathcal{F}_t = (\dots, \epsilon_{-1}, \epsilon_0, \epsilon_1, \dots, \epsilon_{t-1}, \epsilon_t)$  and  $\mathcal{F}'_t = (\dots, \epsilon_{-1}, \epsilon'_0, \epsilon_1, \dots, \epsilon_{t-1}, \epsilon_t)$  is a coupled process of  $\mathcal{F}_t$  with  $\epsilon'_0$  being an i.i.d. copy of  $\epsilon_0$ .

The model setting is as follows. We observe a panel of  $n$  time series  $\mathcal{Z}_i = \{(Y_{it}, \mathbf{X}_{it}) : 1 \leq t \leq T\}$  of length  $T$  for  $1 \leq i \leq n$ . Each time series  $\mathcal{Z}_i$  satisfies the model equation

$$Y_{it} = \beta_i^\top \mathbf{X}_{it} + m_i\left(\frac{t}{T}\right) + \alpha_i + \varepsilon_{it} \quad (1.1)$$

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<sup>1</sup>Address: Bonn Graduate School of Economics, University of Bonn, 53113 Bonn, Germany. Email: [marina.k@uni-bonn.de](mailto:marina.k@uni-bonn.de).

<sup>2</sup>Corresponding author. Address: Department of Economics and Hausdorff Center for Mathematics, University of Bonn, 53113 Bonn, Germany. Email: [michael.vogt@uni-bonn.de](mailto:michael.vogt@uni-bonn.de).

for  $1 \leq t \leq T$ , where  $\beta_i$  is a  $d \times 1$  vector of unknown parameters,  $\mathbf{X}_{it}$  is a  $d \times 1$  vector of individual covariates,  $m_i$  is an unknown nonparametric trend function defined on  $[0, 1]$ ,  $\alpha_i$  is a (deterministic or random) intercept term and  $\mathcal{E}_i = \{\varepsilon_{it} : 1 \leq t \leq T\}$  is a zero-mean stationary error process. As usual in nonparametric regression, the trend functions  $m_i$  in model (1.1) depend on rescaled time  $t/T$  rather than on real time  $t$ ; cp. Robinson (1989), Dahlhaus (1997) and Vogt and Linton (2014) for the use and some discussion of the rescaled time argument. The functions  $m_i$  are only identified up to an additive constant in model (1.1): One can reformulate the model as  $Y_{it} = [m_i(t/T) + c_i] + \beta_i^\top \mathbf{X}_{it} + [\alpha_i - c_i] + \varepsilon_{it}$ , that is, one can freely shift additive constants  $c_i$  between the trend  $m_i(t/T)$  and the error component  $\alpha_i$ . In order to obtain identification, one may impose different normalization constraints on the trends  $m_i$ . One possibility is to normalize them such that  $\int_0^1 m_i(u) du = 0$  for all  $i$ . In what follows, we take for granted that the trends  $m_i$  satisfy this constraint. The term  $\alpha_i$  can also be regarded as an additional error component. In the econometrics literature, it is commonly called a fixed effect error term. It can be interpreted as capturing unobserved characteristics of the time series  $\mathcal{Z}_i$  which remain constant over time. We allow the error terms  $\alpha_i$  to be dependent across  $i$  in an arbitrary way. Hence, by including them in model equation (1.1), we allow the  $n$  time series  $\mathcal{Z}_i$  in our panel to be correlated with each other. Whereas the terms  $\alpha_i$  may be correlated, the error processes  $\mathcal{E}_i$  are assumed to be independent across  $i$ . Technical conditions regarding the model are discussed further in this section.

Finally, note that throughout the paper, we restrict attention to the case where the number of time series  $n$  in model (1.1) is fixed. Extending our theoretical results to the case where  $n$  slowly grows with the sample size  $T$  is a possible topic for further research.

## 1.1 Assumptions

Each process  $\mathcal{E}_i$  is supposed to satisfy the following conditions:

(C1) For each  $i$  the variables  $\varepsilon_{it}$  allow for the representation  $\varepsilon_{it} = G_i(\dots, \eta_{it-1}, \eta_{it})$ , where  $\eta_{it}$  are i.i.d. random variables across  $t$  and  $G_i : \mathbb{R}^{\mathbb{Z}} \rightarrow \mathbb{R}$  is a measurable function. Denote  $\mathcal{J}_{it} = (\dots, \eta_{it-2}, \eta_{it-1}, \eta_{it})$ .

(C2) For all  $i$  it holds that  $\mathbb{E}[\varepsilon_{it}] = 0$  and  $\|\varepsilon_{it}\|_q < \infty$  for some  $q > 4$ .

Following Wu (2005), we impose conditions on the dependence structure of the error processes  $\mathcal{E}_i$  in terms of the physical dependence measure  $\delta_q(G_i, t)$ . In particular, we assume the following:

(C3) Define  $\Theta_{i,t,q} = \sum_{s \geq t} \delta_q(G_i, s)$  for  $t \geq 0$ . For each  $i$  it holds that  $\Theta_{i,t,q} = O(t^{-\tau_q}(\log t)^{-A})$ , where  $A > \frac{2}{3}(1/q + 1 + \tau_q)$  and  $\tau_q = \{q^2 - 4 + (q - 2)\sqrt{q^2 + 20q + 4}\}/8q$ .

The conditions (C1)–(C3) are fulfilled by a wide range of stationary processes  $\mathcal{E}_i$ . For a detailed discussion of these properties, see Khismatullina and Vogt (2019).

Regarding the independent variables  $\mathbf{X}_{it}$ , we need the following additional assumptions for each  $i$ :

- (C4) The covariates  $\mathbf{X}_{it}$  allow for the representation  $\mathbf{X}_{it} = \mathbf{H}_i(\dots, u_{it-1}, u_{it})$  with  $u_{it}$  being i.i.d. random variables and  $\mathbf{H}_i := (H_{i1}, H_{i2}, \dots, H_{id})^\top : \mathbb{R}^{\mathbb{Z}} \rightarrow \mathbb{R}^d$  is a measurable function such that  $\mathbf{H}_i(\mathcal{U}_{it})$  is well defined. Denote  $\mathcal{U}_{it} = (\dots, u_{it-1}, u_{it})$ .
- (C5) Let  $N_i$  be the  $d \times d$  matrix with  $kl$ -th entry  $n_{i,kl} = \mathbb{E}[H_{ik}(\mathcal{U}_{i0})H_{il}(\mathcal{U}_{i0})]$ . We assume that the smallest eigenvalue of  $N_i$  is strictly bigger than 0.
- (C6) Let  $\mathbb{E}[\mathbf{H}_i(\mathcal{U}_{i0})] = \mathbf{0}$  and  $\|\mathbf{H}_i(\mathcal{U}_{it})\|_{q'} < \infty$  for some  $q' > \max\{2\theta, 4\}$ , where  $\theta$  will be introduced further in Assumption (C12).
- (C7)  $\sum_{s=0}^{\infty} \delta_{q'}(\mathbf{H}_i, s) < \infty$  for  $q'$  from Assumption (C6).
- (C8) For each  $i$  it holds that  $\sum_{s=t}^{\infty} \delta_{q'}(\mathbf{H}_i, s) = O(t^{-\alpha})$  for  $q'$  from Assumption (C6) and for some  $\alpha > 1/2 - 1/q'$ .

To be able to prove the main theorems in Section 2, we need additional assumptions on the relationship between the covariates and the error process.

- (C9)  $\mathbf{X}_{it}$  (elementwise) and  $\varepsilon_{is}$  are uncorrelated for each  $t, s \in \{1, \dots, T\}$ .
- (C10) Let  $\zeta_{i,t} = (u_{it}, \eta_{it})^\top$ . Define  $\mathcal{I}_{i,t} = (\dots, \zeta_{i,t-1}, \zeta_{i,t})$  and  $\mathbf{U}_i(\mathcal{I}_{i,t}) = \mathbf{H}_i(\mathcal{U}_{it})G_i(\mathcal{J}_{it})$ . Then,  $\sum_{s=0}^{\infty} \delta_2(\mathbf{U}_i, s) < \infty$ .

## 2 Testing for equality of time trends

In this section, we adapt the multiscale method developed in Khismatullina and Vogt (2019) to the problem of comparison of the trend curves  $m_i$  in model (1.1). As we will see, the proposed multiscale method does not only allow to test whether the null hypothesis is violated. It also provides information on where violations occur. More specifically, it allows to identify, with a pre-specified confidence, (i) trend functions which are different from each other and (ii) time intervals where these trend functions differ.

### 2.1 Construction of the test statistic

In what follows, we describe the construction of the test statistic that addresses the question of comparing different trend curves. More specifically, we test the null hypothesis

$H_0 : m_1 = m_2 = \dots = m_n$  in model (1.1). We assume that all the trend functions  $m_i(\cdot)$  are continuously differentiable on  $[0, 1]$ .

It is obvious that if  $\alpha_i$  and  $\beta_i$  are known, the problem of testing for the common time trend would be greatly simplified. That is, we would test  $H_0 : m_1 = m_2 = \dots = m_n$  in the model

$$\begin{aligned} Y_{it} - \alpha_i - \beta_i^\top \mathbf{X}_{it} &=: Y_{it}^\circ \\ &= m_i\left(\frac{t}{T}\right) + \varepsilon_{it}, \end{aligned}$$

which is a standard nonparametric regression equation. The variables  $Y_{it}^\circ$  are not observed since the intercept  $\alpha_i$  and the coefficients  $\beta_i$  are not known. Given appropriate estimators  $\hat{\beta}_i$  and  $\hat{\alpha}_i$ , we can then consider

$$\hat{Y}_{it} := Y_{it} - \hat{\alpha}_i - \hat{\beta}_i^\top \mathbf{X}_{it} = (\beta_i - \hat{\beta}_i)^\top \mathbf{X}_{it} + m_i\left(\frac{t}{T}\right) + (\alpha_i - \hat{\alpha}_i) + \varepsilon_{it}.$$

Then our unobserved variables  $Y_{it}^\circ$  can be approximated by  $\hat{Y}_{it}$  and we compute our test statistic based on  $\hat{Y}_{it}$ . In what follows, we assume that an estimator with the property that  $\beta_i - \hat{\beta}_i = O_P(T^{-1/2})$  is given. Details on one of the possible ways to construct  $\hat{\beta}_i$  are deferred to Section 2.4.

Given  $\hat{\beta}_i$ , consider an appropriate estimator  $\hat{\alpha}_i$  for the intercept  $\alpha_i$  calculated by

$$\begin{aligned} \hat{\alpha}_i &= \frac{1}{T} \sum_{t=1}^T (Y_{it} - \hat{\beta}_i^\top \mathbf{X}_{it}) = \frac{1}{T} \sum_{t=1}^T (\beta_i^\top \mathbf{X}_{it} - \hat{\beta}_i^\top \mathbf{X}_{it} + \alpha_i + m_i(t/T) + \varepsilon_{it}) = \quad (2.1) \\ &= (\beta_i - \hat{\beta}_i)^\top \frac{1}{T} \sum_{t=1}^T \mathbf{X}_{it} + \alpha_i + \frac{1}{T} \sum_{i=1}^T m_i(t/T) + \frac{1}{T} \sum_{i=1}^T \varepsilon_{it}. \end{aligned}$$

Note that  $\frac{1}{T} \sum_{i=1}^T \varepsilon_{it} = O_P(T^{-1/2})$  and  $\frac{1}{T} \sum_{i=1}^T m_i(t/T) = O(T^{-1})$  due to Lipschitz continuity of  $m_i$  and normalization  $\int_0^1 m_i(u) du = 0$ . Furthermore,  $\frac{1}{T} \sum_{t=1}^T \mathbf{X}_{it} = O_P(1)$  by Chebyshev's inequality and  $\hat{\beta}_i - \beta_i = O_P(T^{-1/2})$ . Plugging all these results together in (2.1), we get that  $\hat{\alpha}_i - \alpha_i = O_P(T^{-1/2})$ . Thus, the unobserved variable  $Y_{it}^\circ := Y_{it} - \beta_i^\top \mathbf{X}_{it} - \alpha_i = m_i(t/T) + \varepsilon_{it}$  can be well approximated by  $\hat{Y}_{it} = Y_{it} - \hat{\alpha}_i - \hat{\beta}_i^\top \mathbf{X}_{it} = Y_{it}^\circ + O_P(T^{-1/2})$ .

We further let  $\hat{\sigma}_i^2$  be an estimator of the long-run error variance  $\sigma_i^2 = \sum_{\ell=-\infty}^{\infty} \text{Cov}(\varepsilon_{i0}, \varepsilon_{i\ell})$  which is computed from the constructed sample  $\{\hat{Y}_{it} : 1 \leq t \leq T\}$ . We thus regard  $\hat{\sigma}_i^2 = \hat{\sigma}_i^2(\hat{Y}_{i1}, \dots, \hat{Y}_{iT})$  as a function of the variables  $\hat{Y}_{it}$  for  $1 \leq t \leq T$ . Throughout the section, we assume that  $\hat{\sigma}_i^2 = \sigma_i^2 + o_p(\rho_T)$  with  $\rho_T = o(1/\log T)$ . Details on how to construct estimators of  $\sigma_i^2$  are deferred to Section ??.

We are now ready to introduce the multiscale statistic for testing the hypothesis  $H_0 : m_1 = m_2 = \dots = m_n$ . For any pair of time series  $i$  and  $j$ , we define the kernel averages

$$\hat{\psi}_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) (\hat{Y}_{it} - \hat{Y}_{jt}),$$

where  $w_{t,T}(u, h)$  are the local linear kernel weights calculated by the following formula.

$$w_{t,T}(u, h) = \frac{\Lambda_{t,T}(u, h)}{\{\sum_{t=1}^T \Lambda_{t,T}(u, h)^2\}^{1/2}}, \quad (2.2)$$

where

$$\Lambda_{t,T}(u, h) = K\left(\frac{\frac{t}{T} - u}{h}\right) \left[ S_{T,2}(u, h) - \left(\frac{\frac{t}{T} - u}{h}\right) S_{T,1}(u, h) \right],$$

$S_{T,\ell}(u, h) = (Th)^{-1} \sum_{t=1}^T K\left(\frac{\frac{t}{T} - u}{h}\right) \left(\frac{\frac{t}{T} - u}{h}\right)^\ell$  for  $\ell = 0, 1, 2$  and  $K$  is a kernel function with the following properties:

- (C11) The kernel  $K$  is non-negative, symmetric about zero and integrates to one. Moreover, it has compact support  $[-1, 1]$  and is Lipschitz continuous, that is,  $|K(v) - K(w)| \leq C|v - w|$  for any  $v, w \in \mathbb{R}$  and some constant  $C > 0$ .

The kernel average  $\hat{\psi}_{ij,T}(u, h)$  can be regarded as measuring the distance between the two trend curves  $m_i$  and  $m_j$  on the interval  $[u - h, u + h]$ .

We now combine the test statistics  $\hat{\psi}_{ij,T}(u, h)$  for a wide range of different locations  $u$  and bandwidths or scales  $h$  in a following way:

$$\hat{\Psi}_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\hat{\psi}_{ij,T}(u, h)}{(\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{1/2}} \right| - \lambda(h) \right\},$$

where  $\lambda(h) = \sqrt{2 \log\{1/(2h)\}}$  and the set  $\mathcal{G}_T$  is the set of points  $(u, h)$  that are taken into consideration. The statistic  $\hat{\Psi}_{ij,T}$  can be interpreted as a global distance measure between the two curves  $m_i$  and  $m_j$ . Thus, the multiscale statistic  $\hat{\Psi}_{ij,T}$  simultaneously takes into account all locations  $u$  and bandwidths  $h$  with  $(u, h) \in \mathcal{G}_T$ . Throughout the paper, we suppose that  $\mathcal{G}_T$  is some subset of  $\mathcal{G}_T^{\text{full}} = \{(u, h) : u = t/T \text{ for some } 1 \leq t \leq T \text{ and } h \in [h_{\min}, h_{\max}]\}$ , where  $h_{\min}$  and  $h_{\max}$  denote some minimal and maximal bandwidth value, respectively. For our theory to work, we require the following conditions to hold:

- (C12)  $|\mathcal{G}_T| = O(T^\theta)$  for some arbitrarily large but fixed constant  $\theta > 0$ , where  $|\mathcal{G}_T|$  denotes the cardinality of  $\mathcal{G}_T$ .
- (C13)  $h_{\min} \gg T^{-(1-\frac{2}{q})} \log T$ , that is,  $h_{\min}/\{T^{-(1-\frac{2}{q})} \log T\} \rightarrow \infty$  with  $q > 4$  defined in (C2) and  $h_{\max} < 1/2$ .

We finally define the multiscale statistic for testing the null hypothesis  $H_0 : m_1 = m_2 = \dots = m_n$  as

$$\hat{\Psi}_{n,T} = \max_{1 \leq i < j \leq n} \hat{\Psi}_{ij,T},$$

that is, we define it as the maximal distance  $\hat{\Psi}_{ij,T}$  between any pair of curves  $m_i$  and  $m_j$  with  $i \neq j$ .

## 2.2 The test procedure

Let  $Z_{it}$  for  $1 \leq t \leq T$  and  $1 \leq i \leq n$  be independent standard normal random variables which are independent of the error terms  $\varepsilon_{it}$  and the covariates  $\mathbf{X}_{it}$ . Denote the empirical average of the variables  $Z_{i1}, \dots, Z_{iT}$  by  $\bar{Z}_{i,T} = T^{-1} \sum_{t=1}^T Z_{it}$ . To simplify notation, we write  $\bar{Z}_i = \bar{Z}_{i,T}$  in what follows. For each  $i$  and  $j$ , we introduce the Gaussian statistic

$$\Phi_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\phi_{ij,T}(u,h)}{(\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{1/2}} \right| - \lambda(h) \right\},$$

where  $\phi_{ij,T}(u,h) = \sum_{t=1}^T w_{t,T}(u,h) \{ \hat{\sigma}_i(Z_{it} - \bar{Z}_i) - \hat{\sigma}_j(Z_{jt} - \bar{Z}_j) \}$ . Moreover, we define the statistic

$$\Phi_{n,T} = \max_{1 \leq i < j \leq n} \Phi_{ij,T} \quad (2.3)$$

and denote its  $(1 - \alpha)$ -quantile by  $q_{n,T}(\alpha)$ . Our multiscale test of the hypothesis  $H_0 : m_1 = m_2 = \dots = m_n$  is defined as follows: For a given significance level  $\alpha \in (0, 1)$ , we reject  $H_0$  if  $\hat{\Psi}_{n,T} > q_{n,T}(\alpha)$ .

## 2.3 The theoretical properties of the test

To start with, we introduce the auxiliary statistic

$$\hat{\Phi}_{n,T} = \max_{1 \leq i < j \leq n} \hat{\Phi}_{ij,T}, \quad (2.4)$$

where

$$\hat{\Phi}_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\hat{\phi}_{ij,T}(u,h)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2}} \right| - \lambda(h) \right\}$$

and  $\hat{\phi}_{ij,T}(u,h) = \sum_{t=1}^T w_{t,T}(u,h) \{ (\varepsilon_{it} - \bar{\varepsilon}_i) + (\beta_i - \hat{\beta}_i)^\top (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) - (\varepsilon_{jt} - \bar{\varepsilon}_j) - (\beta_j - \hat{\beta}_j)^\top (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j) \}$  with  $\bar{\varepsilon}_i = \bar{\varepsilon}_{i,T} = T^{-1} \sum_{t=1}^T \varepsilon_{it}$  and  $\bar{\mathbf{X}}_i = \bar{\mathbf{X}}_{i,T} = T^{-1} \sum_{t=1}^T \mathbf{X}_{it}$  respectively. Our first theoretical result characterizes the asymptotic behaviour of the statistic  $\hat{\Phi}_{n,T}$ .

**Theorem 2.1.** *Suppose that the error processes  $\mathcal{E}_i = \{\varepsilon_{it} : 1 \leq t \leq T\}$  are independent across  $i$  and satisfy (C1)–(C3) for each  $i$ . Moreover, let (C4)–(C13) be fulfilled and assume that  $\hat{\sigma}_i^2 = \sigma_i^2 + o_p(\rho_T)$  with  $\rho_T = o(1/\log T)$  for each  $i$ . Then*

$$\mathbb{P}(\hat{\Phi}_{n,T} \leq q_{n,T}(\alpha)) = (1 - \alpha) + o(1)$$

Theorem 2.1 is the main stepping stone to derive the theoretical properties of our multiscale test. The proof of the theorem is provided in the Section ??.

## 2.4 Estimation of the parameters $\beta_i$

We now focus on finding an appropriate estimator  $\hat{\beta}_i$  of  $\beta_i$ . For that purpose, for each  $i$  we consider the time series  $\{\Delta Y_{it} : 2 \leq t \leq T\}$  of the differences  $\Delta Y_{it} = Y_{it} - Y_{it-1}$ . We then have

$$\Delta Y_{it} = Y_{it} - Y_{it-1} = \beta_i^\top \Delta \mathbf{X}_{it} + \left( m_i\left(\frac{t}{T}\right) - m_i\left(\frac{t-1}{T}\right) \right) + \Delta \varepsilon_{it},$$

where  $\Delta \mathbf{X}_{it} = \mathbf{X}_{it} - \mathbf{X}_{it-1}$  and  $\Delta \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$ . Since  $m_i(\cdot)$  is Lipschitz, we can use the fact that  $|m_i(\frac{t}{T}) - m_i(\frac{t-1}{T})| = O(\frac{1}{T})$  and rewrite

$$\Delta Y_{it} = \beta_i^\top \Delta \mathbf{X}_{it} + \Delta \varepsilon_{it} + O\left(\frac{1}{T}\right). \quad (2.5)$$

In particular, for each  $i$  we employ the least squares estimation method to estimate  $\beta_i$  in (2.5), treating  $\Delta \mathbf{X}_{it}$  as the regressors and  $\Delta Y_{it}$  as the response variable. That is, we propose the following differencing estimator:

$$\hat{\beta}_i = \left( \sum_{t=2}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^\top \right)^{-1} \sum_{t=2}^T \Delta \mathbf{X}_{it} \Delta Y_{it} \quad (2.6)$$

Then the asymptotic consistency for this differencing estimator is given by the following theorem:

**Theorem 2.2.** *Under Assumptions (C1) - (C10), we have*

$$\beta_i - \hat{\beta}_i = O_P\left(\frac{1}{\sqrt{T}}\right),$$

where  $\hat{\beta}_i$  is the differencing estimator given by (2.6).

## 3 Appendix

In this section, we prove the theoretical results from Section 2. We use the following notation: The symbol  $C$  denotes a universal real constant which may take a different value on each occurrence. For  $a, b \in \mathbb{R}$ , we write  $a_+ = \max\{0, a\}$  and  $a \vee b = \max\{a, b\}$ . For any set  $A$ , the symbol  $|A|$  denotes the cardinality of  $A$ . The notation  $X \stackrel{\mathcal{D}}{=} Y$  means that the two random variables  $X$  and  $Y$  have the same distribution. Finally,  $f_0(\cdot)$  and  $F_0(\cdot)$  denote the density and the distribution function of the standard normal distribution, respectively.

Table 1: All the statistics used in the proofs

| Statistic  | Notation                 | Formula   |
|--|--------------------------|---|
| Multiscale statistics  | $\widehat{\Psi}_{n,T}$   | $\widehat{\Psi}_{n,T} = \max_{1 \leq i < j \leq n} \widehat{\Psi}_{ij,T}$<br>$\widehat{\Psi}_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left  \frac{\widehat{\psi}_{ij,T}(u,h)}{(\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2)^{1/2}} \right  - \lambda(h) \right\}$     |
| “Gaussian” statistic   | $\Phi_{n,T}$             | $\Phi_{n,T} = \max_{1 \leq i < j \leq n} \Phi_{ij,T}$ ,<br>$\Phi_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left  \frac{\phi_{ij,T}(u,h)}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2}} \right  - \lambda(h) \right\}$   |
| Auxiliary statistic  | $\widehat{\Phi}_{n,T}$   | $\widehat{\Phi}_{n,T} = \max_{1 \leq i < j \leq n} \widehat{\Phi}_{ij,T}$ ,<br>$\widehat{\Phi}_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left  \frac{\widehat{\phi}_{ij,T}(u,h)}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2}} \right  - \lambda(h) \right\}$ |
| Statistics that is identically distributed as $\widehat{\Phi}_{n,T}$ | $\widetilde{\Phi}_{n,T}$ |   |
| 3  | 23.113231                | c   |

### 3.1 Statistics used in the Appendix

The kernel averages are defined as follows:

$$\widehat{\psi}_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) (\widehat{Y}_{it} - \widehat{Y}_{jt}),$$

$$\phi_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) \{ \widehat{\sigma}_i(Z_{it} - \bar{Z}_i) - \widehat{\sigma}_j(Z_{jt} - \bar{Z}_j) \},$$

$$\widehat{\phi}_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) \{ (\varepsilon_{it} - \bar{\varepsilon}_i) + (\beta_i - \widehat{\beta}_i)^\top (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) - (\varepsilon_{jt} - \bar{\varepsilon}_j) - (\beta_j - \widehat{\beta}_j)^\top (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j) \}.$$

| Notation                         | Exact formula   |
|----------------------------------|---|
| $\Phi_{n,T}$                     | $\widehat{\Phi}_{n,T} = \max_{1 \leq i < j \leq n} \widehat{\Phi}_{ij,T}, \quad \widehat{\Phi}_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left  \frac{\widehat{\phi}_{ij,T}(u,h)}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2}} \right  - \lambda(h) \right\}$ |
| $\widehat{\widehat{\Phi}}_{n,T}$ | $x - y$   |
| $\widetilde{\Phi}_{n,T}$         |   |

### 3.2 Proof of Theorem 2.1

We will build the proof of Theorem 2.1 on the auxiliary results derived below. The steps of the proof are as follows.

- First, by Proposition A.1, there exist statistics  $\widetilde{\Phi}_{n,T}$  for  $T = 1, 2, \dots$  which are distributed as  $\widehat{\Phi}_{n,T}$  for any  $T \geq 1$  and which have the property that

$$|\widetilde{\Phi}_{n,T} - \Phi_{n,T}| = o_p\left(\frac{T^{1/q}}{\sqrt{Th_{\min}}} + \frac{\rho_T}{\sqrt{h_{\min}}} \sqrt{\log T}\right), \quad (3.1)$$



where  $\Phi_{n,T}$  is a Gaussian statistic as defined in (2.3). The approximation result (3.1) allows us to replace the multiscale statistic  $\widehat{\widehat{\Phi}}_{n,T}$  by an identically distributed version  $\widetilde{\Phi}_{n,T}$  which is close to the Gaussian statistic  $\Phi_{n,T}$ .

- Second, by Proposition A.3 we show that  $\Phi_{n,T}$  does not concentrate too strongly in small regions of the form  $[x - \delta_T, x + \delta_T]$  with  $\delta_T$  converging to zero. Or, in other words, it holds that

$$\sup_{x \in \mathbb{R}} \mathbb{P}(|\Phi_{n,T} - x| \leq \delta_T) = o(1), \quad (3.2)$$

where  $\delta_T = T^{1/q} / \sqrt{Th_{\min}} + \rho_T \sqrt{\log T} / \sqrt{h_{\min}}$ .

- In the third step we make use of Lemma A.4 to show that

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\widehat{\widehat{\Phi}}_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x)| = o(1). \quad (3.3)$$

This statement directly follows from the previous two steps and the fact that  $\widetilde{\Phi}_{n,T}$  is distributed as  $\widehat{\widehat{\Phi}}_{n,T}$  for any  $n \geq 2, T \geq 1$ .

- And finally, in Proposition A.9 we prove that

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x)| = o(1), \quad (3.4)$$

which immediately implies the statement of Theorem 2.1.

## Introducing additional intermediate statistic

The auxiliary statistic  $\widehat{\Phi}_{n,T}$  defined in Section 2.3 (which is basically the version of the main statistic  $\widehat{\Psi}_{n,T}$  under the null hypothesis) heavily depends on the known covariates  $\mathbf{X}_{it}$ , whereas the Gaussian version  $\Phi_{n,T}$  does not. This is the reason why we need to introduce additional intermediate test statistic that connects  $\widehat{\Phi}_{n,T}$  and  $\Phi_{n,T}$ . Thus, for each  $i$  and  $j$ , consider the following kernel averages:

$$\widehat{\phi}_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) \{(\varepsilon_{it} - \bar{\varepsilon}_i) - (\varepsilon_{jt} - \bar{\varepsilon}_j)\}.$$

The intermediate statistic is then defined as

$$\begin{aligned} \widehat{\widehat{\Phi}}_{n,T} &= \max_{1 \leq i < j \leq n} \widehat{\Phi}_{ij,T} \quad \text{with} \\ \widehat{\Phi}_{ij,T} &= \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\widehat{\phi}_{ij,T}(u, h)}{(\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2)^{1/2}} \right| - \lambda(h) \right\}. \end{aligned} \quad (3.5)$$

This statistic can thus be regarded as an approximation of the statistic  $\widehat{\Phi}_{n,T}$ . Heuristically, the kernel averages  $\widehat{\phi}_{ij,T}(u, h)$  are close to the kernel averages  $\widehat{\phi}_{ij,T}(u, h)$  because of the properties of our estimators  $\widehat{\beta}_i$  and assumptions on  $\mathbf{X}_{it}$  but we will prove it later in this Section.

## Auxiliary results using strong approximation theory

The main purpose of this section is to prove that there is a version of the multiscale statistic  $\widehat{\widehat{\Phi}}_{n,T}$  defined in (3.5) which is close to a Gaussian statistic whose distribution is known. More specifically, we prove the following result.

**Proposition A.1.** *Under the conditions of Theorem 2.1, there exist statistics  $\widetilde{\Phi}_{n,T}$  for  $T = 1, 2, \dots$  with the following two properties: (i)  $\widetilde{\Phi}_{n,T}$  has the same distribution as  $\widehat{\widehat{\Phi}}_{n,T}$  for any  $T$ , and (ii)*

$$|\widetilde{\Phi}_{n,T} - \Phi_{n,T}| = o_p\left(\frac{T^{1/q}}{\sqrt{T}h_{\min}} + \frac{\rho_T}{\sqrt{h_{\min}}} \sqrt{\log T}\right),$$

where  $\Phi_{n,T}$  is a Gaussian statistic as defined in (2.3).

**Proof of Proposition A.1.** For the proof, we draw on strong approximation theory for each stationary process  $\mathcal{E}_i = \{\varepsilon_{it} : 1 \leq t \leq T\}$  that fulfill the conditions (C1)–(C3). By Theorem 2.1 and Corollary 2.1 in Berkes et al. (2014), the following strong approximation result holds true: On a richer probability space, there exists a standard Brownian motion  $\mathbb{B}$  and a sequence  $\{\widetilde{\varepsilon}_t : t \in \mathbb{N}\}$  such that  $[\widetilde{\varepsilon}_1, \dots, \widetilde{\varepsilon}_T] \stackrel{D}{=} [\varepsilon_1, \dots, \varepsilon_T]$  for each  $T$  and

$$\max_{1 \leq t \leq T} \left| \sum_{s=1}^t \widetilde{\varepsilon}_s - \sigma \mathbb{B}(t) \right| = o(T^{1/q}) \quad \text{a.s.}, \quad (3.6)$$

where  $\sigma^2 = \sum_{k \in \mathbb{Z}} \text{Cov}(\varepsilon_0, \varepsilon_k)$  denotes the long-run error variance.

We apply this result for each stationary process  $\mathcal{E}_i = \{\varepsilon_{it} : 1 \leq t \leq T\}$  separately. In order to do this, we define

$$\widetilde{\Phi}_{n,T} = \max_{1 \leq i < j \leq n} \widetilde{\Phi}_{ij,T}, \quad (3.7)$$

where

$$\widetilde{\Phi}_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\widetilde{\phi}_{ij,T}(u,h)}{\{\widetilde{\sigma}_i^2 + \widetilde{\sigma}_j^2\}^{1/2}} \right| - \lambda(h) \right\},$$

where  $\widetilde{\phi}_{ij,T}(u,h) = \sum_{t=1}^T w_{t,T}(u,h) \{(\widetilde{\varepsilon}_{it} - \widetilde{\varepsilon}_i) - (\widetilde{\varepsilon}_{jt} - \widetilde{\varepsilon}_j)\}$  and  $\widetilde{\sigma}_i^2$  are the same estimators as  $\widehat{\sigma}_i^2$  with  $\widehat{Y}_{it} = (\beta_i - \widehat{\beta}_i)^\top \mathbf{X}_{it} + m_i(t/T) + (\alpha_i - \widehat{\alpha}_i) + \varepsilon_{it}$  replaced by  $\widetilde{Y}_{it} = (\beta_i - \widehat{\beta}_i)^\top \mathbf{X}_{it} + m_i(t/T) + (\alpha_i - \widehat{\alpha}_i) + \widetilde{\varepsilon}_{it}$  for  $1 \leq t \leq T$ . In addition, we let

$$\Phi_{n,T} = \max_{1 \leq i < j \leq n} \Phi_{ij,T} = \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\phi_{ij,T}(u,h)}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2}} \right| - \lambda(h) \right\} \text{ as in (2.3),}$$

$$\text{and } \Phi_{n,T}^\diamond = \max_{1 \leq i < j \leq n} \Phi_{ij,T}^\diamond = \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\phi_{ij,T}(u,h)}{\{\widetilde{\sigma}_i^2 + \widetilde{\sigma}_j^2\}^{1/2}} \right| - \lambda(h) \right\}$$

with

$$\phi_{ij,T}(u,h) = \sum_{t=1}^T w_{t,T}(u,h) \{\widehat{\sigma}_i(Z_{it} - \bar{Z}_i) - \widehat{\sigma}_j(Z_{jt} - \bar{Z}_j)\}$$

and  $Z_{it} = \mathbb{B}_i(t) - \mathbb{B}_i(t-1)$ . With this notation, we can write

$$|\tilde{\Phi}_{n,T} - \Phi_{n,T}| \leq |\tilde{\Phi}_{n,T} - \Phi_{n,T}^\diamond| + |\Phi_{n,T}^\diamond - \Phi_{n,T}|. \quad (3.8)$$

First consider  $|\tilde{\Phi}_{n,T} - \Phi_{n,T}^\diamond|$ . Straightforward calculations yield that

$$|\tilde{\Phi}_{n,T} - \Phi_{n,T}^\diamond| \leq \max_{1 \leq i < j \leq n} \left( \{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2\}^{-1/2} \max_{(u,h) \in \mathcal{G}_T} |\tilde{\phi}_{ij,T}(u, h) - \phi_{ij,T}(u, h)| \right). \quad (3.9)$$

Using summation by parts,  $(\sum_{i=1}^n a_i b_i = \sum_{i=1}^{n-1} A_i(b_i - b_{i+1}) + A_n b_n$  with  $A_j = \sum_{j=1}^i a_j$ ) we further obtain that

$$\begin{aligned} |\tilde{\phi}_{ij,T}(u, h) - \phi_{ij,T}(u, h)| &= \\ &= \left| \sum_{t=1}^T w_{t,T}(u, h) \{(\tilde{\varepsilon}_{it} - \tilde{\varepsilon}_i) - (\tilde{\varepsilon}_{jt} - \tilde{\varepsilon}_j) - \hat{\sigma}_i(Z_{it} - \bar{Z}_i) + \hat{\sigma}_j(Z_{jt} - \bar{Z}_j)\} \right| = \\ &= \left| \sum_{t=1}^{T-1} A_{ij,t} (w_{t,T}(u, h) - w_{t+1,T}(u, h)) + A_{ij,T} w_{T,T}(u, h) \right|, \end{aligned}$$

where

$$A_{ij,t} = \sum_{s=1}^t \{(\tilde{\varepsilon}_{is} - \tilde{\varepsilon}_i) - (\tilde{\varepsilon}_{js} - \tilde{\varepsilon}_j) - \hat{\sigma}_i(Z_{is} - \bar{Z}_i) + \hat{\sigma}_j(Z_{js} - \bar{Z}_j)\}.$$

Note that by construction  $A_{ij,T} = 0$  for all pairs  $(i, j)$ . Denoting

$$W_T(u, h) = \sum_{t=1}^{T-1} |w_{t+1,T}(u, h) - w_{t,T}(u, h)|,$$

we have

$$|\tilde{\phi}_{ij,T}(u, h) - \phi_{ij,T}(u, h)| = \left| \sum_{t=1}^{T-1} A_{ij,t} (w_{t,T}(u, h) - w_{t+1,T}(u, h)) \right| \leq W_T(u, h) \max_{1 \leq t \leq T} |A_{ij,t}|. \quad (3.10)$$

Now consider  $\max_{1 \leq t \leq T} |A_{ij,t}|$ :

$$\begin{aligned} \max_{1 \leq t \leq T} |A_{ij,t}| &\leq \max_{1 \leq t \leq T} \left| \sum_{s=1}^t (\tilde{\varepsilon}_{is} - \tilde{\varepsilon}_i) - \hat{\sigma}_i \sum_{s=1}^t \{Z_{is} - \bar{Z}_i\} \right| + \\ &\quad + \max_{1 \leq t \leq T} \left| \sum_{s=1}^t (\tilde{\varepsilon}_{js} - \tilde{\varepsilon}_j) - \hat{\sigma}_j \sum_{s=1}^t \{Z_{js} - \bar{Z}_j\} \right| \leq \\ &\leq \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \hat{\sigma}_i \sum_{s=1}^t Z_{is} \right| + \max_{1 \leq t \leq T} |t(\tilde{\varepsilon}_i - \hat{\sigma}_i \bar{Z}_i)| + \\ &\quad + \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \hat{\sigma}_j \sum_{s=1}^t Z_{js} \right| + \max_{1 \leq t \leq T} |t(\tilde{\varepsilon}_j - \hat{\sigma}_j \bar{Z}_j)| = \end{aligned}$$

$$\begin{aligned}
&= \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \hat{\sigma}_i \sum_{s=1}^t Z_{is} \right| + T \left| \frac{1}{T} \left( \sum_{s=1}^T \tilde{\varepsilon}_{is} - \hat{\sigma}_i \sum_{s=1}^T Z_{is} \right) \right| + \\
&\quad + \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \hat{\sigma}_j \sum_{s=1}^t Z_{js} \right| + T \left| \frac{1}{T} \left( \sum_{s=1}^T \tilde{\varepsilon}_{js} - \hat{\sigma}_j \sum_{s=1}^T Z_{js} \right) \right| \leq \\
&\leq 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \hat{\sigma}_i \sum_{s=1}^t Z_{is} \right| + 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \hat{\sigma}_j \sum_{s=1}^t Z_{js} \right| = \\
&= 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \hat{\sigma}_i \sum_{s=1}^t (\mathbb{B}_i(s) - \mathbb{B}_i(s-1)) \right| + \\
&\quad + 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \hat{\sigma}_j \sum_{s=1}^t (\mathbb{B}_j(s) - \mathbb{B}_j(s-1)) \right| = \\
&= 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \hat{\sigma}_i \mathbb{B}_i(t) \right| + 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \hat{\sigma}_j \mathbb{B}_j(t) \right| \leq \\
&\leq 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \sigma_i \mathbb{B}_i(t) \right| + 2 \max_{1 \leq t \leq T} \left| \sigma_i \mathbb{B}_i(t) - \hat{\sigma}_i \mathbb{B}_i(t) \right| + \\
&\quad + 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \sigma_j \mathbb{B}_j(t) \right| + 2 \max_{1 \leq t \leq T} \left| \sigma_j \mathbb{B}_j(t) - \hat{\sigma}_j \mathbb{B}_j(t) \right|
\end{aligned}$$

Note that for all  $1 \leq i \leq n$  we have  $\hat{\sigma}_i^2 - \sigma_i^2 = o_P(\rho_T)$  which leads to  $\hat{\sigma}_i - \sigma_i = o_P(\rho_T)$ . Furthermore, regarding the standard Brownian motion  $\mathbb{B}_i(t)$  as a sum of standard normal random variables, we get the following result:

$$\begin{aligned}
\max_{1 \leq t \leq T} |\mathbb{B}_i(t)| &= \max_{1 \leq t \leq T} \left| \sum_{s=1}^t Z_{is} \right| = \max_{1 \leq t \leq T} \left| \sqrt{t} \frac{1}{\sqrt{t}} \sum_{s=1}^t Z_{is} \right| \leq \\
&\leq \max_{1 \leq t \leq T} \sqrt{t} \max_{1 \leq t \leq T} \left| \frac{1}{\sqrt{t}} \sum_{s=1}^t Z_{is} \right| = \sqrt{T} \max_{1 \leq t \leq T} \left| \frac{1}{\sqrt{t}} \sum_{s=1}^t Z_{is} \right| = O_P(\sqrt{T \log T}),
\end{aligned}$$

where we used the bound for the maximum of  $T$  standard normal random variables and the fact that for each  $t$ ,  $1 \leq t \leq T$ ,  $\frac{1}{\sqrt{t}} \sum_{s=1}^t Z_{is}$  is a standard normal random variable. Therefore, applying the strong approximation result (3.6), we can infer that

$$\begin{aligned}
\max_{1 \leq t \leq T} |A_{ij,t}| &\leq 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \sigma_i \mathbb{B}_i(t) \right| + 2 |\sigma_i - \hat{\sigma}_i| \max_{1 \leq t \leq T} |\mathbb{B}_i(t)| + \\
&\quad + 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \sigma_j \mathbb{B}_j(t) \right| + 2 |\sigma_j - \hat{\sigma}_j| \max_{1 \leq t \leq T} |\mathbb{B}_j(t)| = \\
&= o_P(T^{1/q} + \rho_T \sqrt{T \log T}). \tag{3.11}
\end{aligned}$$

Standard arguments show that  $\max_{(u,h) \in \mathcal{G}_T} W_T(u,h) = O(1/\sqrt{Th_{\min}})$ . Plugging (3.11)

in (3.10) and then in (3.9), we can thus infer that

$$\begin{aligned} |\tilde{\Phi}_{n,T} - \Phi_{n,T}^\diamond| &\leq \{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2\}^{-1/2} \max_{(u,h) \in \mathcal{G}_T} W_T(u,h) \max_{1 \leq i < j \leq n} \max_{1 \leq t \leq T} |A_{ij,t}| = \\ &= o_P\left(\frac{T^{1/q}}{\sqrt{Th_{\min}}} + \frac{\rho_T}{\sqrt{h_{\min}}} \sqrt{\log T}\right). \end{aligned} \quad (3.12)$$

Now consider  $|\Phi_{n,T}^\diamond - \Phi_{n,T}|$ . Since  $\phi_{ij,T}(u,h)$  is distributed as  $N(0, \hat{\sigma}_i^2 + \hat{\sigma}_j^2)$  for all  $(u,h) \in \mathcal{G}_T$  and all  $1 \leq i < j \leq n$ ,  $|\mathcal{G}_T| = O(T^\theta)$  for some large but fixed constant  $\theta$  by Assumption (C12),  $n$  is fixed and  $\hat{\sigma}_i^2 = \sigma_i^2 + o_p(\rho_T)$  as well as  $\tilde{\sigma}_i^2 = \sigma_i^2 + o_p(\rho_T)$ , we can establish that

$$|\Phi_{n,T}^\diamond - \Phi_{n,T}| \leq \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left| \frac{\phi_{ij,T}(u,h)}{\{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2\}^{1/2}} - \frac{\phi_{ij,T}(u,h)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2}} \right| = o_P(\rho_T \sqrt{\log T}). \quad (3.13)$$

Plugging (3.12) and (3.13) in (3.8) completes the proof.  $\square$

## Auxiliary results using anti-concentration bounds

In this section, we establish some properties of the Gaussian statistic  $\Phi_{n,T}$  defined in (2.3). We in particular show that  $\Phi_{n,T}$  does not concentrate too strongly in small regions of the form  $[x - \delta_T, x + \delta_T]$  with  $\delta_T$  converging to zero.

The main technical tool for proving Proposition A.3 are anti-concentration bounds for Gaussian random vectors. The following proposition slightly generalizes anti-concentration results derived in Chernozhukov et al. (2015), in particular Theorem 3 therein.

**Proposition A.2.** *Let  $(X_1, \dots, X_p)^\top$  be a Gaussian random vector in  $\mathbb{R}^p$  with  $\mathbb{E}[X_j] = \mu_j$  and  $\text{Var}(X_j) = \sigma_j^2 > 0$  for  $1 \leq j \leq p$ . Define  $\bar{\mu} = \max_{1 \leq j \leq p} |\mu_j|$  together with  $\underline{\sigma} = \min_{1 \leq j \leq p} \sigma_j$  and  $\bar{\sigma} = \max_{1 \leq j \leq p} \sigma_j$ . Moreover, set  $a_p = \mathbb{E}[\max_{1 \leq j \leq p} (X_j - \mu_j)/\sigma_j]$  and  $b_p = \mathbb{E}[\max_{1 \leq j \leq p} (X_j - \mu_j)]$ . For every  $\delta > 0$ , it holds that*

$$\sup_{x \in \mathbb{R}} \mathbb{P}\left(\left| \max_{1 \leq j \leq p} X_j - x \right| \leq \delta\right) \leq C\delta\{\bar{\mu} + a_p + b_p + \sqrt{1 \vee \log(\underline{\sigma}/\delta)}\},$$

where  $C > 0$  depends only on  $\underline{\sigma}$  and  $\bar{\sigma}$ .

The proof of Proposition A.2 is provided in Khismatullina and Vogt (2019).

**Proposition A.3.** *Under the conditions of Theorem 2.1, it holds that*

$$\sup_{x \in \mathbb{R}} \mathbb{P}(|\Phi_{n,T} - x| \leq \delta_T) = o(1),$$

where  $\delta_T = T^{1/q}/\sqrt{Th_{\min}} + \rho_T \sqrt{\log T}/\sqrt{h_{\min}}$ .

**Proof of Proposition A.3.** We write  $x = (u, h)$  along with  $\mathcal{G}_T = \{x : x \in \mathcal{G}_T\} = \{x_1, \dots, x_p\}$ , where  $p := |\mathcal{G}_T| \leq O(T^\theta)$  for some large but fixed  $\theta > 0$  by our assumptions. Moreover, for  $k = 1, \dots, p$ , we set

$$U_{ij,2k-1} = \frac{\phi_{ij,T}(x_{k1}, x_{k2})}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2}} - \lambda(x_{k2})$$

$$U_{ij,2k} = -\frac{\phi_{ij,T}(x_{k1}, x_{k2})}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2}} - \lambda(x_{k2})$$

with  $x_k = (x_{k1}, x_{k2})$ . This notation allows us to write

$$\Phi_{n,T} = \max_{1 \leq i < j \leq n} \max_{1 \leq k \leq 2p} U_{ij,k}, = \max_{1 \leq l \leq (n-1)np} U'_l$$

where  $(U'_1, \dots, U'_{(n-1)np})^\top \in \mathbb{R}^{n(n-1)p}$  is a Gaussian random vector with the following properties: (i)  $\mu_l := \mathbb{E}[U'_l] = \{\mathbb{E}[U_{ij,2k}] \text{ or } \mathbb{E}[U_{ij,2k-1}]\} = -\lambda(x_{k2})$  and thus

$$\bar{\mu} = \max_{1 \leq l \leq (n-1)np} |\mu_l| \leq C\sqrt{\log T},$$

and (ii)  $\sigma_l^2 := \text{Var}(U'_l) = 1$  for all  $1 \leq l \leq (n-1)np$ . Hence,  $a_{(n-1)np} = b_{(n-1)np}$ . Moreover, as the variables  $(U'_l - \mu_l)/\sigma_l$  are standard normal, we have that  $a_{(n-1)np} = b_{(n-1)np} \leq C\sqrt{\log((n-1)np)} \leq C\sqrt{\log T}$ . With this notation at hand, we can apply Proposition A.2 to obtain that

$$\sup_{x \in \mathbb{R}} \mathbb{P}(|\Phi_{n,T} - x| \leq \delta_T) \leq C\delta_T \left[ \sqrt{\log T} + \sqrt{\log(1/\delta_T)} \right] = o(1)$$

with  $\delta_T = T^{1/q}/\sqrt{Th_{\min}} + \rho_T\sqrt{\log T}/\sqrt{h_{\min}}$ , which is the statement of Proposition A.3. This part does not go through! For this part to go through we need stricter assumption on  $\rho_T$ :

$$\rho_T = O\left(\frac{1}{T^{1/2-1/q}\sqrt{\log T}}\right)!$$

□

## Other auxiliary results

**Lemma A.4.** *Let  $V_T$  and  $W_T$  be real-valued random variables for  $T = 1, 2, \dots$  such that  $V_T - W_T = o_p(\delta_T)$  with some  $\delta_T = o(1)$ . If*

$$\sup_{x \in \mathbb{R}} \mathbb{P}(|V_T - x| \leq \delta_T) = o(1), \tag{3.14}$$

*then*

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(V_T \leq x) - \mathbb{P}(W_T \leq x)| = o(1). \tag{3.15}$$

Proof of this lemma is provided in Khismatullina and Vogt (2019).

**Definition A.1.** *Dependence adjusted norm:*  $\|X.\|_{q,\alpha}^q = \sup_{m \geq 0} (m+1)^\alpha \sum_{t=m}^\infty \delta_q(X, t)$ .

**Theorem A.1.** *Wu et al. (2016) Assume that  $\|X.\|_{q,\alpha}^q < \infty$ , where  $q > 2$  and  $\alpha > 0$ , and  $\sum_{t=1}^T a_t^2 = T$ . Moreover, assume that  $\alpha > 1/2 - 1/q$ . Denote  $S_T = a_1 X_1 + \dots + a_T X_T$ . Then for all  $x > 0$ ,*

$$\mathbb{P}(|S_T| \geq x) \leq C_1 \frac{|a|_q^q \|X.\|_{q,\alpha}^q}{x^q} + C_2 \exp\left(-\frac{C_3 x^2}{T \|X.\|_{2,\alpha}^2}\right),$$

where  $C_1, C_2, C_3$  are constants that only depend on  $q$  and  $\alpha$ .

**Theorem A.2.** *Wu (2007) Let  $(\xi_i)_{i \in \mathbb{Z}}$  be a stationary and ergodic Markov chain and  $g(\cdot)$  be a measurable function. Let  $g(\xi_1) \in \mathcal{L}^q, q > 2, \mathbb{E}[g(\xi_0)] = 0$  and  $l$  be a positive, nondecreasing slowly varying function. Assume that*

$$\sum_{i=n}^\infty \|\mathbb{E}[g(\xi_i)|\xi_0] - \mathbb{E}[g(\xi_i)|\xi_{-1}]\|_q = O([\log n]^{-\beta}),$$

where  $0 \leq \beta < 1/q$  and

$$\sum_{k=1}^\infty \frac{k^{-\beta q}}{[l(2^k)]^q} < \infty.$$

Then  $S_n = g(\xi_1) + \dots + g(\xi_n) = o_{a.s.}[\sqrt{n}l(n)]$ .

**Proposition A.5.** *Wu (2007) Let  $(\epsilon_n)_{n \in \mathbb{Z}}$  be i.i.d. random variables,  $\xi_n = (\dots, \epsilon_{n-1}, \epsilon_n)$  and  $g(\cdot)$  be a measurable function such that  $g(\xi_n)$  is a proper random variable for each  $n \geq 0$ . For  $k \geq 0$  let  $\tilde{\xi}_k = (\dots, \epsilon_{-1}, \epsilon'_0, \epsilon_1, \dots, \epsilon_{k-1}, \epsilon_k)$ , where  $\epsilon'_0$  is an i.i.d. copy of  $\epsilon_0$ . Let  $g(\xi_0) \in \mathcal{L}^q, q > 1$  and  $\mathbb{E}[g(\xi_0)] = 0$ . For  $n \geq 1$  we have*

$$\|\mathbb{E}[g(\xi_n)|\xi_0] - \mathbb{E}[g(\xi_n)|\xi_{-1}]\|_q \leq 2 \|g(\xi_n) - g(\tilde{\xi}_n)\|_q.$$

**Proposition A.6.** *Under the conditions of Theorem 2.1, it holds that*

$$\bar{\mathbf{X}}_i = \frac{1}{T} \sum_{t=1}^T \mathbf{H}_i(\mathcal{U}_{it}) = o_P(1).$$

**Proof of Proposition A.6.** To prove this fact, we will use two results from Wu (2007) stated above. First, fix  $j \in \{1, \dots, d\}$ . Denote  $\xi_t = \mathcal{U}_{it}, \tilde{\xi}_t = \mathcal{U}'_{it}$  and  $g(\cdot) = H_{i,j}(\cdot)$ . Then by Assumption (C6),  $g(\xi_0) = H_{i,j}(\mathcal{U}_{i0}) \in \mathcal{L}^{q'}$  for  $q' > 4$  and  $\mathbb{E}[g(\xi_0)] = \mathbb{E}[H_{i,j}(\mathcal{U}_{i0})] = 0$  and we can apply Proposition A.5 that says that for all  $s \geq 1$  we have:

$$\|\mathbb{E}[g(\xi_s)|\xi_0] - \mathbb{E}[g(\xi_s)|\xi_{-1}]\|_{q'} \leq 2 \|g(\xi_s) - g(\tilde{\xi}_s)\|_{q'},$$

or, equivalently,

$$\|\mathbb{E}[H_{i,j}(\mathcal{U}_{is})|\mathcal{U}_{i0}] - \mathbb{E}[H_{i,j}(\mathcal{U}_{is})|\mathcal{U}_{i(-1)}]\|_{q'} \leq 2 \|H_{i,j}(\mathcal{U}_{is}) - H_{i,j}(\mathcal{U}'_{is})\|_{q'}.$$

Since this holds simultaneously for all  $j \in \{1, \dots, d\}$ , we can use the obvious bound  $\|H_{i,j}(\mathcal{U}_{is}) - H_{i,j}(\mathcal{U}'_{is})\|_{q'} \leq \|\mathbf{H}_i(\mathcal{U}_{is}) - \mathbf{H}_i(\mathcal{U}'_{is})\|_{q'} = \delta_{q'}(\mathbf{H}_i, s)$  and Assumption (C8) to write

$$0 \leq \sum_{s=t}^{\infty} \|\mathbb{E}[g(\xi_s)|\xi_0] - \mathbb{E}[g(\xi_s)|\xi_{-1}]\|_{q'} \leq \sum_{s=t}^{\infty} \delta_{q'}(\mathbf{H}_i, s) = O(t^{-\alpha}),$$

where  $\alpha > 1/2 - 1/q'$ .

Now we want to apply Theorem A.2. As a parameter  $\beta$  in the theorem we can take any value satisfying assumption  $0 \leq \beta 1/q'$  because for every  $\beta \geq 0$  we have

$$\sum_{s=t}^{\infty} \|\mathbb{E}[g(\xi_s)|\xi_0] - \mathbb{E}[g(\xi_s)|\xi_{-1}]\|_{q'} \leq \sum_{s=t}^{\infty} \delta_{q'}(\mathbf{H}_i, s) = O(t^{-\alpha}) = O([\log t]^{-\beta}).$$

Furthermore, as a positive, nondecreasing slowly varying function  $l$  we can take  $l(x) = \log^{2/q' - \beta}(x)$ . Then,

$$\begin{aligned} \sum_{k=1}^{\infty} \frac{k^{-\beta q'}}{[l(2^k)]^{q'}} &= \sum_{k=1}^{\infty} \frac{k^{-\beta q'}}{[\log^{2/q' - \beta}(2^k)]^{q'}} = \\ &= \sum_{k=1}^{\infty} \frac{k^{-\beta q'}}{[k \log 2]^{(2/q' - \beta)q'}} = \\ &= \sum_{k=1}^{\infty} \frac{k^{-\beta q'}}{k^{2 - \beta q'} (\log 2)^{(2/q' - \beta)q'}} = \\ &= \frac{1}{(\log 2)^{2 - \beta q'}} \sum_{k=1}^{\infty} \frac{1}{k^2} < \infty. \end{aligned}$$

Hence,  $S_T = g(\xi_1) + \dots + g(\xi_T) = o_{a.s.}[\sqrt{T} \log^{2/q' - \beta}(T)]$ , or, equivalently,  $\bar{X}_{i,j} = S_T/T = o_{a.s.}[\log^{2/q' - \beta}(T)/\sqrt{T}] = o_P(1)$  for each  $j \in \{1, \dots, d\}$ . Obviously, this means that  $\bar{\mathbf{X}}_i = o_P(1)$ .  $\square$

## Auxiliary results concerning the intermediate statistic

In this section, we establish some properties of the intermediate test statistic  $\widehat{\Phi}_{n,T}$  defined in (3.5) and its relationship with  $\widehat{\Phi}_{n,T}$ . First of all, we prove the proposition that relates the distribution of these two statistics.

**Proposition A.7.** *For any  $x \in \mathbb{R}$  and any  $\gamma_{n,T} > 0$ , we have*

$$\begin{aligned} \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(|\widehat{\Phi}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}) &\leq \mathbb{P}(\widehat{\Phi}_{n,T} \leq x) \leq \\ &\leq \mathbb{P}(\widehat{\Phi}_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(|\widehat{\Phi}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}). \end{aligned}$$



**Proof of Proposition A.7.** From the law of total probability and the monotonic property of the probability function, we have

$$\begin{aligned}\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) &= \mathbb{P}\left(\widehat{\Phi}_{n,T} \leq x, |\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| \leq \gamma_{n,T}\right) + \mathbb{P}\left(\widehat{\Phi}_{n,T} \leq x, |\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}\right) \leq \\ &\leq \mathbb{P}\left(\widehat{\Phi}_{n,T} \leq x, \widehat{\Phi}_{n,T} - \gamma_{n,T} \leq \widehat{\widehat{\Phi}}_{n,T} \leq \widehat{\Phi}_{n,T} + \gamma_{n,T}\right) + \mathbb{P}\left(|\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}\right) \leq \\ &\leq \mathbb{P}\left(\widehat{\widehat{\Phi}}_{n,T} \leq x + \gamma_{n,T}\right) + \mathbb{P}\left(|\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}\right).\end{aligned}$$

Analogously,

$$\begin{aligned}\mathbb{P}(\widehat{\widehat{\Phi}}_{n,T} \leq x - \gamma_{n,T}) &= \mathbb{P}\left(\widehat{\widehat{\Phi}}_{n,T} \leq x - \gamma_{n,T}, |\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| \leq \gamma_{n,T}\right) + \\ &\quad + \mathbb{P}\left(\widehat{\widehat{\Phi}}_{n,T} \leq x - \gamma_{n,T}, |\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}\right) \leq \\ &\leq \mathbb{P}\left(\widehat{\widehat{\Phi}}_{n,T} \leq x - \gamma_{n,T}, \widehat{\widehat{\Phi}}_{n,T} - \gamma_{n,T} \leq \widehat{\Phi}_{n,T} \leq \widehat{\widehat{\Phi}}_{n,T} + \gamma_{n,T}\right) + \\ &\quad + \mathbb{P}\left(|\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}\right) \leq \\ &\leq \mathbb{P}\left(\widehat{\Phi}_{n,T} \leq x\right) + \mathbb{P}\left(|\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}\right),\end{aligned}$$

which completes the proof.  $\square$

The aim of the next proposition is to determine the value of  $\gamma_{n,T}$  such that the difference between the distributions of  $\widehat{\Phi}_{n,T}$  and  $\widehat{\widehat{\Phi}}_{n,T}$  is not too big. In other words,

**Proposition A.8.** *There exists a sequence of random numbers  $\{\gamma_{n,T}\}_T$ , that converges to 0 as  $T \rightarrow \infty$ , such that*

$$\mathbb{P}\left(|\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}\right) = o(1).$$

**Proof of Proposition A.8.** Consider  $|\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}|$ . Analogously as in the proof of Proposition A.1, we can establish that

$$|\widehat{\widehat{\Phi}}_{n,T} - \widehat{\Phi}_{n,T}| \leq \max_{1 \leq i < j \leq n} \left( \{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{-1/2} \max_{(u,h) \in \mathcal{G}_T} \left| \widehat{\phi}_{ij,T}(u, h) - \widehat{\phi}_{ij,T}(u, h) \right| \right),$$

where

$$\widehat{\phi}_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) \{(\varepsilon_{it} - \bar{\varepsilon}_i) - (\varepsilon_{jt} - \bar{\varepsilon}_j)\}$$

and

$$\widehat{\phi}_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) \{(\varepsilon_{it} - \bar{\varepsilon}_i) + (\boldsymbol{\beta}_i - \widehat{\boldsymbol{\beta}}_i)^\top (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) - (\varepsilon_{jt} - \bar{\varepsilon}_j) - (\boldsymbol{\beta}_j - \widehat{\boldsymbol{\beta}}_j)^\top (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j)\}.$$

Thus,

$$\begin{aligned}
\left| \widehat{\phi}_{ij,T}(u, h) - \widehat{\phi}_{ij,T}(u, h) \right| &= \left| \sum_{t=1}^T w_{t,T}(u, h) \{ (\beta_i - \widehat{\beta}_i)^\top (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) - (\beta_j - \widehat{\beta}_j)^\top (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j) \} \right| \leq \\
&\leq \left| \sum_{t=1}^T w_{t,T}(u, h) (\beta_i - \widehat{\beta}_i)^\top (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) \right| + \left| \sum_{t=1}^T w_{t,T}(u, h) (\beta_j - \widehat{\beta}_j)^\top (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j) \right| = \\
&= |\beta_i - \widehat{\beta}_i|^\top \left| \sum_{t=1}^T w_{t,T}(u, h) (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) \right| + |\beta_j - \widehat{\beta}_j|^\top \left| \sum_{t=1}^T w_{t,T}(u, h) (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j) \right| = \\
&= |\beta_i - \widehat{\beta}_i|^\top \left| \sum_{t=1}^T w_{t,T}(u, h) (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) \right| + |\beta_j - \widehat{\beta}_j|^\top \left| \sum_{t=1}^T w_{t,T}(u, h) (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j) \right| \leq \\
&\leq |\beta_i - \widehat{\beta}_i|^\top \left| \sum_{t=1}^T w_{t,T}(u, h) \mathbf{X}_{it} \right| + |(\beta_i - \widehat{\beta}_i)^\top \bar{\mathbf{X}}_i| \left| \sum_{t=1}^T w_{t,T}(u, h) \right| + \\
&\quad + |\beta_j - \widehat{\beta}_j|^\top \left| \sum_{t=1}^T w_{t,T}(u, h) \mathbf{X}_{jt} \right| + |(\beta_j - \widehat{\beta}_j)^\top \bar{\mathbf{X}}_j| \left| \sum_{t=1}^T w_{t,T}(u, h) \right|
\end{aligned}$$

Hence,

$$\begin{aligned}
\left| \widehat{\Phi}_{n,T} - \widehat{\Phi}_{n,T} \right| &\leq 2 \max_{1 \leq i < j \leq n} \left( \{ \widehat{\sigma}_i^2 + \widehat{\sigma}_j^2 \}^{-1/2} |\beta_i - \widehat{\beta}_i|^\top \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u, h) \mathbf{X}_{it} \right| \right) + \\
&\quad + 2 \max_{1 \leq i < j \leq n} \left( \{ \widehat{\sigma}_i^2 + \widehat{\sigma}_j^2 \}^{-1/2} |(\beta_i - \widehat{\beta}_i)^\top \bar{\mathbf{X}}_i| \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u, h) \right| \right)
\end{aligned} \tag{3.16}$$

To begin with, we consider the first summand in (3.16).

First, by our assumptions  $\widehat{\sigma}_i^2 = \sigma_i^2 + o_P(\rho_T)$ . Moreover, for all  $i \in \{1, \dots, n\}$  we know  $\sigma_i^2 \neq 0$ . Hence,  $\max_{1 \leq i < j \leq n} \{ \widehat{\sigma}_i^2 + \widehat{\sigma}_j^2 \}^{-1/2} = O_P(1)$ .

Then, by Theorem 2.2, we know that  $|\beta_i - \widehat{\beta}_i| = O_P(1/\sqrt{T})$ .

Now consider the term  $\left| \sum_{t=1}^T w_{t,T}(u, h) \mathbf{X}_{it} \right|$ . Without loss of generality, we can regard the covariates  $\mathbf{X}_{it}$  to be scalars  $X_{it}$ , not vectors. The proof in case of vectors proceeds analogously.

By construction the weights  $w_{t,T}(u, h)$  are not equal to 0 if and only if  $T(u - h) \leq t \leq T(u + h)$ . We can use this fact to rewrite

$$\left| \sum_{t=1}^T w_{t,T}(u, h) X_{it} \right| = \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right|.$$

We want to show that

$$\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u, h) X_{it} \right| = \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right| = o_P(\sqrt{T}). \tag{3.17}$$

Note that

$$\begin{aligned}
\sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}^2(u, h) &= \sum_{t=1}^T w_{t,T}^2(u, h) = \\
&= \sum_{t=1}^T \frac{K^2 \left( \frac{t-u}{h} \right) \left[ S_{T,2}(u, h) - \left( \frac{t-u}{h} \right) S_{T,1}(u, h) \right]^2}{\left\{ \sum_{s=1}^T K^2 \left( \frac{s-u}{h} \right) \left[ S_{T,2}(u, h) - \left( \frac{s-u}{h} \right) S_{T,1}(u, h) \right]^2 \right\}} = \\
&= 1.
\end{aligned}$$

Denoting by  $D_{T,u,h}$  the number of integers between  $\lfloor T(u-h) \rfloor$  and  $\lceil T(u+h) \rceil$  incl. (with obvious bounds  $2Th \leq D_{T,u,h} \leq 2Th + 2$ ), we can normalize the weights as follows:

$$\sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} \left( \sqrt{D_{T,u,h}} \cdot w_{t,T}(u, h) \right)^2 = D_{T,u,h}.$$

According to Theorem A.1 (Theorem 2(ii) in Wu et al. (2016)), denoting the weights from the theorem as  $a_t = \sqrt{D_{T,u,h}} \cdot w_{t,T}(u, h)$  we can bound the following probability:

$$\begin{aligned}
&\mathbb{P} \left( \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} \sqrt{D_{T,u,h}} \cdot w_{t,T}(u, h) X_{it} \right| \geq x \right) \leq \\
&\leq C_1 \frac{\left( \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} |\sqrt{D_{T,u,h}} \cdot w_{t,T}(u, h)|^{q'} \right) \|X_{i \cdot}\|_{q', \alpha}^{q'}}{x^{q'}} + C_2 \exp \left( -\frac{C_3 x^2}{D_{T,u,h} \|X_{i \cdot}\|_{2, \alpha}^2} \right) = \\
&= C_1 \frac{(\sqrt{D_{T,u,h}})^{q'} \left( \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} |w_{t,T}(u, h)|^{q'} \right) \|X_{i \cdot}\|_{q', \alpha}^{q'}}{x^{q'}} + C_2 \exp \left( -\frac{C_3 x^2}{D_{T,u,h} \|X_{i \cdot}\|_{2, \alpha}^2} \right)
\end{aligned}$$

We want to prove (3.17). For that, take any  $\delta > 0$ :

$$\begin{aligned}
&\mathbb{P} \left( \frac{\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right|}{\sqrt{T}} \geq \delta \right) = \\
&= \mathbb{P} \left( \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right| \geq \delta \sqrt{T} \right) \leq \\
&\stackrel{\text{Boole's inequality}}{\leq} \sum_{(u,h) \in \mathcal{G}_T} \mathbb{P} \left( \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right| \geq \delta \sqrt{T} \right) = \\
&\stackrel{\text{"normalisation"}}{=} \sum_{(u,h) \in \mathcal{G}_T} \mathbb{P} \left( \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} \sqrt{D_{T,u,h}} \cdot w_{t,T}(u, h) X_{it} \right| \geq \delta \sqrt{D_{T,u,h} T} \right) \leq \\
&\stackrel{\text{Wu's Theorem}}{\leq} \sum_{(u,h) \in \mathcal{G}_T} \left[ C_1 \frac{(\sqrt{D_{T,u,h}})^{q'} \left( \sum |w_{t,T}(u, h)|^{q'} \right) \|X_{i \cdot}\|_{q', \alpha}^{q'}}{(\delta \sqrt{D_{T,u,h} T})^{q'}} + C_2 \exp \left( -\frac{C_3 (\delta \sqrt{D_{T,u,h} T})^2}{D_{T,u,h} \|X_{i \cdot}\|_{2, \alpha}^2} \right) \right] =
\end{aligned}$$

$$\begin{aligned}
& \stackrel{\text{simplification}}{=} \sum_{(u,h) \in \mathcal{G}_T} \left[ C_1 \frac{(\sum |w_{t,T}(u,h)|^{q'}) \|X_{i\cdot}\|_{q',\alpha}^{q'}}{(\delta\sqrt{T})^{q'}} + C_2 \exp\left(-\frac{C_3\delta^2 T}{\|X_{i\cdot}\|_{2,\alpha}^2}\right) \right] \leq \\
& \leq C_1 \frac{T^\theta \|X_{i\cdot}\|_{q',\alpha}^{q'}}{T^{q'/2} \cdot \delta^{q'}} \max_{(u,h) \in \mathcal{G}_T} \left( \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} |w_{t,T}(u,h)|^{q'} \right) + C_2 T^\theta \exp\left(-\frac{C_3\delta^2 T}{\|X_{i\cdot}\|_{2,\alpha}^2}\right) = \\
& \leq C \frac{T^{\theta-q'/2}}{\delta^{q'}} + CT^\theta \exp(-CT\delta^2).
\end{aligned}$$

where the symbol  $C$  denotes a universal real constant that does not depend neither on  $T$  nor on  $\delta$  and that takes a different value on each occurrence. Here in the last equality we used the following facts:

1.  $\|X_{i\cdot}\|_{q',\alpha}^{q'} = \sup_{t \geq 0} (t+1)^\alpha \sum_{s=t}^\infty \delta_{q'}(H_i, s) < \infty$  holds true since  $\sum_{s=t}^\infty \delta_{q'}(H_i, s) = O(t^{-\alpha})$  by Assumption (C8);
2.  $\max_{(u,h) \in \mathcal{G}_T} \left( \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} |w_{t,T}(u,h)|^{q'} \right) < \infty$  because for every  $x \in [0, 1]$  we have  $0 \leq |x|^{q'/2} \leq x \leq 1$ . Thus, since  $\sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}^2(u,h) = 1$ , we have  $0 \leq w_{t,T}^2(u,h) \leq 1$  for all  $t$  and

$$0 \leq |w_{t,T}(u,h)|^{q'} = |w_{t,T}^2(u,h)|^{q'/2} \leq w_{t,T}^2(u,h) \leq 1.$$

This leads us to a bound:

$$\max_{(u,h) \in \mathcal{G}_T} \left( \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} |w_{t,T}(u,h)|^{q'} \right) \leq \max_{(u,h) \in \mathcal{G}_T} \left( \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} |w_{t,T}(u,h)|^2 \right) = 1 < \infty.$$

3.  $\|X_{i\cdot}\|_{2,\alpha}^2 < \infty$  (follows from 1).

By Assumption (C6),  $\theta - q'/2 < 0$  and the term on the RHS of the above inequality is converging to 0 as  $T \rightarrow \infty$  for any fixed  $\delta > 0$ . Hence,

$$\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u,h) X_{it} \right| = o_P(\sqrt{T}).$$

Combining all of the above results, we get the following:

$$\begin{aligned}
& 2 \max_{1 \leq i < j \leq n} \left( \{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{-1/2} |\beta_i - \hat{\beta}_i|^\top \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u,h) \mathbf{X}_{it} \right| \right) = \\
& = O_P(1) \cdot O_P(1/\sqrt{T}) \cdot o_P(\sqrt{T}) = o_P(1).
\end{aligned} \tag{3.18}$$

Now, consider the second summand in (3.16).

Similarly as before,  $\max_{1 \leq i < j \leq n} \{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{-1/2} = O_P(1)$  and  $|\beta_i - \hat{\beta}_i| = O_P(1/\sqrt{T})$ .

Then, by Proposition A.6  $\bar{\mathbf{X}}_i = o_P(1)$ .

Finally, consider the local linear kernel weights  $w_{t,T}(u, h)$  defined in (2.2). Again, by construction the weights  $w_{t,T}(u, h)$  are not equal to 0 if and only if  $T(u - h) \leq t \leq T(u + h)$ . We can use this fact to bound  $\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u, h) \right|$  using the Cauchy-Schwarz inequality:

$$\begin{aligned} \left| \sum_{t=1}^T w_{t,T}(u, h) \right| &= \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) \right| = \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) \cdot 1 \right| \leq \\ &\leq \sqrt{\sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}^2(u, h)} \sqrt{\sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} 1^2} = \\ &= \sqrt{1} \cdot \sqrt{D_{T,u,h}} \leq \sqrt{2Th + 2} \leq \sqrt{2Th_{\max} + 2} \leq \sqrt{T + 2}. \end{aligned}$$

Hence,  $\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u, h) \right| = O(\sqrt{T})$ .

Combining the results above, we get the following:

$$\begin{aligned} 2 \max_{1 \leq i < j \leq n} \left( \{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{-1/2} |(\beta_i - \hat{\beta}_i)^\top \bar{\mathbf{X}}_i| \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u, h) \right| \right) = \\ = O_P(1) \cdot O_P(1/\sqrt{T}) \cdot o_P(1) \cdot O(\sqrt{T}) = o_P(1). \end{aligned} \quad (3.19)$$

Plugging (3.18) and (3.19) in (3.17), we get that  $|\hat{\Phi}_{n,T} - \hat{\Phi}_{n,T}| = o_P(1)$  and the statement of the theorem follows.  $\square$

**Proposition A.9.** *Under the conditions of Theorem 2.1, it holds that*

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\hat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x)| = o(1).$$

**Proof of Proposition A.9.** First, we consider those  $x \in \mathbb{R}$  such that  $\mathbb{P}(\hat{\Phi}_{n,T} \leq x) \geq \mathbb{P}(\Phi_{n,T} \leq x)$ . Then by Proposition A.7 and taking  $\gamma_{n,T}$  from the Proposition A.8 we have

$$\begin{aligned} 0 &\leq |\mathbb{P}(\hat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x)| = \mathbb{P}(\hat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x) \leq \\ &\leq \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(|\hat{\Phi}_{n,T} - \hat{\Phi}_{n,T}| > \gamma_{n,T}) - \mathbb{P}(\Phi_{n,T} \leq x) = \\ &= \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi_{n,T} \leq x) + o(1) = \\ &= \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(\Phi_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi_{n,T} \leq x) + o(1) = \\ &= \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(x \leq \Phi_{n,T} \leq x + \gamma_{n,T}) + o(1) \leq \\ &\leq \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(|\Phi_{n,T} - x| \leq \gamma_{n,T}) + o(1). \end{aligned}$$

Now consider such  $x \in \mathbb{R}$  that  $\mathbb{P}(\hat{\Phi}_{n,T} \leq x) < \mathbb{P}(\Phi_{n,T} \leq x)$ . Then again by Proposition

A.7 for  $\gamma_{n,T}$  from Proposition A.8 we have

$$\begin{aligned}
0 &\leq |\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x)| = \mathbb{P}(\Phi_{n,T} \leq x) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x) \leq \\
&\leq \mathbb{P}(\Phi_{n,T} \leq x) + \mathbb{P}(|\widehat{\Phi}_{n,T} - \Phi_{n,T}| > \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) = \\
&= \mathbb{P}(\Phi_{n,T} \leq x) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) + o(1) = \\
&= \mathbb{P}(\Phi_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x - \gamma_{n,T}) + \mathbb{P}(\Phi_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) + o(1) = \\
&= \mathbb{P}(x - \gamma_{n,T} \leq \Phi_{n,T} \leq x) + \mathbb{P}(\Phi_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) + o(1) \leq \\
&\leq \mathbb{P}(|\Phi_{n,T} - x| \leq \gamma_{n,T}) + \mathbb{P}(\Phi_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) + o(1).
\end{aligned}$$

Now note that since  $\gamma_{n,T} \rightarrow 0$ , we can use the anticoncentration results for the Gaussian statistic  $\Phi_{n,T}$  to get  $\mathbb{P}(|\Phi_{n,T} - x| \leq \gamma_{n,T}) = o(1)$ . Thus,

$$\begin{aligned}
\sup_{x \in \mathbb{R}} |\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x)| &\leq \\
&\leq \max \left\{ \sup_{x \in \mathbb{R}} \left| \mathbb{P}(\Phi_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) \right|, \right. \\
&\quad \left. \sup_{x \in \mathbb{R}} \left| \mathbb{P}(\Phi_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x + \gamma_{n,T}) \right| \right\} + o(1) = \\
&= \sup_{y \in \mathbb{R}} \left| \mathbb{P}(\Phi_{n,T} \leq y) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq y) \right| + o(1) = o(1).
\end{aligned}$$

□

### 3.3 Proof of Theorem 2.2

We define the first-differenced regressors as follows.

$$\Delta \mathbf{X}_{it} = \mathbf{H}_i(\mathcal{U}_{it}) - \mathbf{H}_i(\mathcal{U}_{it-1}) := \Delta \mathbf{H}_i(\mathcal{U}_{it}).$$

Similarly,

$$\Delta \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1} = G_i(\mathcal{J}_{it}) - G_i(\mathcal{J}_{it-1}) = \Delta G_i(\mathcal{J}_{it}).$$

With these assumptions we can prove the following propositions.

**Proposition A.10.** *Under Assumptions (C4) and (C6),  $\|\Delta \mathbf{H}_i(\mathcal{U}_{it})\|_4 < \infty$ .*

**Proof of Proposition A.10.** By Assumption (C6),

$$\|\Delta \mathbf{H}_i(\mathcal{U}_{it})\|_4 \leq \|\mathbf{H}_i(\mathcal{U}_{it})\|_4 + \|\mathbf{H}_i(\mathcal{U}_{it-1})\|_4 < \infty.$$

□

**Proposition A.11.** Under Assumption (C7),  $\Delta \mathbf{X}_{it}$  (elementwise) and  $\Delta \varepsilon_{it}$  are uncorrelated for each  $t \in \{1, \dots, T\}$ .

**Proof of Proposition A.11.** By Assumption (C7),

$$\begin{aligned} \mathbb{E}[\Delta \mathbf{X}_{it} \Delta \varepsilon_{it}] &= \mathbb{E}[(\mathbf{X}_{it} - \mathbf{X}_{it-1})(\varepsilon_{it} - \varepsilon_{it-1})] = \\ &= \mathbb{E}[\mathbf{X}_{it} \varepsilon_{it}] - \mathbb{E}[\mathbf{X}_{it-1} \varepsilon_{it}] - \mathbb{E}[\mathbf{X}_{it} \varepsilon_{it-1}] + \mathbb{E}[\mathbf{X}_{it-1} \varepsilon_{it-1}] = \\ &= \mathbb{E}[\mathbf{X}_{it}] \mathbb{E}[\varepsilon_{it}] - \mathbb{E}[\mathbf{X}_{it-1}] \mathbb{E}[\varepsilon_{it}] - \mathbb{E}[\mathbf{X}_{it}] \mathbb{E}[\varepsilon_{it-1}] + \mathbb{E}[\mathbf{X}_{it-1}] \mathbb{E}[\varepsilon_{it-1}] = \\ &= (\mathbb{E}[\mathbf{X}_{it}] - \mathbb{E}[\mathbf{X}_{it-1}]) (\mathbb{E}[\varepsilon_{it}] - \mathbb{E}[\varepsilon_{it-1}]) = \mathbb{E}[\Delta \mathbf{X}_{it}] \mathbb{E}[\Delta \varepsilon_{it}] \end{aligned}$$

□

**Proposition A.12.** Define

$$\Delta \mathbf{U}_i(\mathcal{I}_{i,t}) := \Delta \mathbf{H}_i(\mathcal{U}_{it}) \Delta G_i(\mathcal{J}_{it}).$$

Under Assumptions (C2) - (C3), (C8) - ??, we have that  $\sum_{s=0}^{\infty} \delta_2(\Delta \mathbf{U}_i, s) < \infty$ .

**Proof of Proposition A.12.** Note the following

$$\begin{aligned} \delta_2(\Delta \mathbf{U}_i, t) &= \|\Delta \mathbf{U}_i(\mathcal{I}_{i,t}) - \Delta \mathbf{U}_i(\mathcal{I}'_{i,t})\|_2 = \\ &= \|\Delta \mathbf{H}_i(\mathcal{U}_{it}) \Delta G_i(\mathcal{J}_{it}) - \Delta \mathbf{H}_i(\mathcal{U}'_{it}) \Delta G_i(\mathcal{J}'_{it})\|_2 = \\ &= \|(\mathbf{H}_i(\mathcal{U}_{it}) - \mathbf{H}_i(\mathcal{U}_{it-1})) (G_i(\mathcal{J}_{it}) - G_i(\mathcal{J}_{it-1})) - (\mathbf{H}_i(\mathcal{U}'_{it}) - \mathbf{H}_i(\mathcal{U}'_{it-1})) (G_i(\mathcal{J}'_{it}) - G_i(\mathcal{J}'_{it-1}))\|_2 = \\ &= \|\mathbf{H}_i(\mathcal{U}_{it}) G_i(\mathcal{J}_{it}) - \mathbf{H}_i(\mathcal{U}_{it-1}) G_i(\mathcal{J}_{it}) - \mathbf{H}_i(\mathcal{U}_{it}) G_i(\mathcal{J}_{it-1}) + \mathbf{H}_i(\mathcal{U}_{it-1}) G_i(\mathcal{J}_{it-1}) - \\ &\quad - \mathbf{H}_i(\mathcal{U}'_{it}) G_i(\mathcal{J}'_{it}) + \mathbf{H}_i(\mathcal{U}'_{it-1}) G_i(\mathcal{J}'_{it}) + \mathbf{H}_i(\mathcal{U}'_{it}) G_i(\mathcal{J}'_{it-1}) - \mathbf{H}_i(\mathcal{U}'_{it-1}) G_i(\mathcal{J}'_{it-1})\|_2 \leq \\ &\leq \|\mathbf{H}_i(\mathcal{U}_{it}) G_i(\mathcal{J}_{it}) - \mathbf{H}_i(\mathcal{U}'_{it}) G_i(\mathcal{J}'_{it})\|_2 + \|\mathbf{H}_i(\mathcal{U}_{it-1}) G_i(\mathcal{J}_{it-1}) - \mathbf{H}_i(\mathcal{U}'_{it-1}) G_i(\mathcal{J}'_{it-1})\|_2 + \\ &\quad + \|\mathbf{H}_i(\mathcal{U}_{it-1}) G_i(\mathcal{J}_{it}) - \mathbf{H}_i(\mathcal{U}'_{it-1}) G_i(\mathcal{J}'_{it})\|_2 + \|\mathbf{H}_i(\mathcal{U}_{it}) G_i(\mathcal{J}_{it-1}) - \mathbf{H}_i(\mathcal{U}'_{it}) G_i(\mathcal{J}'_{it-1})\|_2 = \\ &= \delta_2(\mathbf{U}_i, t) + \delta_2(\mathbf{U}_i, t-1) + \\ &\quad + \|\mathbf{H}_i(\mathcal{U}_{it-1}) G_i(\mathcal{J}_{it}) - \mathbf{H}_i(\mathcal{U}'_{it-1}) G_i(\mathcal{J}_{it}) + \mathbf{H}_i(\mathcal{U}'_{it-1}) G_i(\mathcal{J}_{it}) - \mathbf{H}_i(\mathcal{U}'_{it-1}) G_i(\mathcal{J}'_{it})\|_2 + \\ &\quad + \|\mathbf{H}_i(\mathcal{U}_{it}) G_i(\mathcal{J}_{it-1}) - \mathbf{H}_i(\mathcal{U}'_{it}) G_i(\mathcal{J}_{it-1}) + \mathbf{H}_i(\mathcal{U}'_{it}) G_i(\mathcal{J}_{it-1}) - \mathbf{H}_i(\mathcal{U}'_{it}) G_i(\mathcal{J}'_{it-1})\|_2 \leq \\ &\leq \delta_2(\mathbf{U}_i, t) + \delta_2(\mathbf{U}_i, t-1) + \\ &\quad + \|(\mathbf{H}_i(\mathcal{U}_{it-1}) - \mathbf{H}_i(\mathcal{U}'_{it-1})) G_i(\mathcal{J}_{it})\|_2 + \|\mathbf{H}_i(\mathcal{U}'_{it-1}) (G_i(\mathcal{J}_{it}) - G_i(\mathcal{J}'_{it}))\|_2 + \\ &\quad + \|(\mathbf{H}_i(\mathcal{U}_{it}) - \mathbf{H}_i(\mathcal{U}'_{it})) G_i(\mathcal{J}_{it-1})\|_2 + \|\mathbf{H}_i(\mathcal{U}'_{it}) (G_i(\mathcal{J}_{it-1}) - G_i(\mathcal{J}'_{it-1}))\|_2 \leq \\ &\leq \delta_2(\mathbf{U}_i, t) + \delta_2(\mathbf{U}_i, t-1) + (\delta_2(\mathbf{H}_i, t-1) + \delta_2(\mathbf{H}_i, t)) \|G_i\|_2 + (\delta_2(G_i, t-1) + \delta_2(G_i, t)) \|\mathbf{H}_i\|_2 \end{aligned}$$

Here  $\mathcal{U}'_{it} = (\dots, u_{i(-1)}, u'_{i0}, u_{i1}, \dots, u_{it-1}, u_{it})$ ,  $\mathcal{U}'_{it-1} = (\dots, u_{i(-1)}, u'_{i0}, u_{i1}, \dots, u_{it-1})$ ,  $\mathcal{J}'_{it} = (\dots, \eta_{i(-1)}, \eta'_{i0}, \eta_{i1}, \dots, \eta_{it-1}, \eta_{it})$ ,  $\mathcal{J}'_{it-1} = (\dots, \eta_{i(-1)}, \eta'_{i0}, \eta_{i1}, \dots, \eta_{it-1})$  are coupled processes with  $u'_{i0}$  being an i.i.d. copy of  $u_{i0}$  and  $\eta'_{i0}$  being an i.i.d. copy of  $\eta_{i0}$ .

This leads us to

$$\begin{aligned} \sum_{s=0}^{\infty} \delta_2(\Delta \mathbf{U}_i, s) &\leq \sum_{s=0}^{\infty} \delta_2(\mathbf{U}_i, s) + \sum_{s=1}^{\infty} \delta_2(\mathbf{U}_i, s-1) + \\ &\quad + \sum_{s=1}^{\infty} (\delta_2(\mathbf{H}_i, s-1) + \delta_2(\mathbf{H}_i, s)) \|G_i\|_2 + \sum_{s=1}^{\infty} (\delta_2(G_i, s-1) + \delta_2(G_i, s)) \|\mathbf{H}_i\|_2 < \infty \end{aligned}$$

□

**Proposition A.13.** *Under Assumptions (C1) - ??,*

$$\left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \varepsilon_{it} \right| = O_P(1).$$

**Proof of Proposition A.13.** We need the following notation:

$$\begin{aligned} \mathcal{P}_{i,t}(\cdot) &:= \mathbb{E}[\cdot | \mathcal{I}_{i,t}] - \mathbb{E}[\cdot | \mathcal{I}_{i,t-1}], \\ \kappa_i &:= \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \varepsilon_{it}, \\ \kappa_{i,s}^{\mathcal{P}} &:= \frac{1}{T} \sum_{t=1}^T \mathcal{P}_{i,t-s}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it}). \end{aligned}$$

Then,

$$\begin{aligned} \|\kappa_{i,s}^{\mathcal{P}}\|^2 &= \left\| \frac{1}{T} \sum_{t=1}^T \mathcal{P}_{i,t-s}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it}) \right\|^2 \leq \\ &\leq \frac{1}{T^2} \sum_{t=1}^T \left\| \mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t-s}) - \mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t-s-1}) \right\|^2 = \\ &= \frac{1}{T^2} \sum_{t=1}^T \left\| \mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t-s}) - \mathbb{E}(\Delta \mathbf{X}'_{it,s} \Delta \varepsilon'_{it,s} | \mathcal{I}_{i,t-s}) \right\|^2, \end{aligned}$$

where  $\Delta \mathbf{X}'_{it,s} \Delta \varepsilon'_{it,s}$  denotes  $\Delta \mathbf{X}_{it} \Delta \varepsilon_{it}$  with  $\{\zeta_{i,t-s}\}$  replaced by its i.i.d. copy  $\{\zeta'_{i,t-s}\}$ . In this case  $\mathbb{E}(\Delta \mathbf{X}'_{it,s} \Delta \varepsilon'_{it,s} | \mathcal{I}_{i,t-s-1}) = \mathbb{E}(\Delta \mathbf{X}'_{it,s} \Delta \varepsilon'_{it,s} | \mathcal{I}_{i,t-s})$ . Furthermore, by linearity of the expectation and Jensen's inequality, we have

$$\begin{aligned} \|\kappa_{i,s}^{\mathcal{P}}\|^2 &\leq \frac{1}{T^2} \sum_{t=1}^T \left\| \mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t-s}) - \mathbb{E}(\Delta \mathbf{X}'_{it,s} \Delta \varepsilon'_{it,s} | \mathcal{I}_{i,t-s}) \right\|^2 \leq \\ &\leq \frac{1}{T^2} \sum_{t=1}^T \left\| \Delta \mathbf{X}_{it} \Delta \varepsilon_{it} - \Delta \mathbf{X}'_{it,s} \Delta \varepsilon'_{it,s} \right\|^2 = \\ &= \frac{1}{T^2} \sum_{t=1}^T \left\| \Delta \mathbf{H}_i(\mathcal{U}_{it}) \Delta G_i(\mathcal{J}_{it}) - \Delta \mathbf{H}_i(\mathcal{U}'_{it,s}) \Delta G_i(\mathcal{J}'_{it,s}) \right\|^2 = \\ &= \frac{1}{T^2} \sum_{t=1}^T \left\| \Delta \mathbf{U}_i(\mathcal{I}_{i,t}) - \Delta \mathbf{U}_i(\mathcal{I}'_{i,t,s}) \right\|^2 \leq \frac{1}{T^2} \sum_{t=1}^T \delta_2^2(\Delta \mathbf{U}_i, s) = \frac{1}{T} \delta_2^2(\Delta \mathbf{U}_i, s) \end{aligned}$$

with  $\mathcal{U}'_{it,s} = (\dots, u_{it-s-1}, u'_{it-s}, u_{it-s+1}, \dots, u_{it})$ ,  $\mathcal{J}'_{it,s} = (\dots, \eta_{it-s-1}, \eta'_{it-s}, \eta_{it-s+1}, \dots, \eta_{it})$ ,  $\zeta'_{it} = (u'_{it}, \eta'_{it})^\top$  and  $\mathcal{I}'_{i,t,s} = (\dots, \zeta_{it-s-1}, \zeta'_{it-s}, \zeta_{it-s+1}, \dots, \zeta_{it})$ .



Moreover,

$$\begin{aligned}
\kappa_i - \mathbb{E}\kappa_i &= \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \varepsilon_{it} - \mathbb{E}\kappa_i = \frac{1}{T} \sum_{t=1}^T \mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t}) - \mathbb{E}\kappa_i = \\
&= \frac{1}{T} \sum_{t=1}^T (\mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t}) - \mathbb{E}(\mathbf{X}_{it} \Delta \varepsilon_{it})) = \\
&= \frac{1}{T} \sum_{t=1}^T \sum_{s=0}^{\infty} (\mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t-s}) - \mathbb{E}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it} | \mathcal{I}_{i,t-s-1})) = \\
&= \frac{1}{T} \sum_{t=1}^T \sum_{s=0}^{\infty} \mathcal{P}_{i,t-s}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it}) = \sum_{s=0}^{\infty} \kappa_{i,s}^{\mathcal{P}}.
\end{aligned}$$

Thus, by Proposition A.12,

$$\|\kappa_i - \mathbb{E}\kappa_i\| \leq \sum_{s=0}^{\infty} \|\kappa_{i,s}^{\mathcal{P}}\| \leq \frac{1}{\sqrt{T}} \sum_{s=0}^{\infty} \delta_2(\Delta \mathbf{U}_i, s) = O\left(\frac{1}{\sqrt{T}}\right)$$

Since  $\mathbb{E}\kappa_i = 0$  by Proposition A.11, we conclude that

$$\left\| \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \varepsilon_{it} \right\| = O\left(\frac{1}{\sqrt{T}}\right).$$

Therefore, the proposition follows.  $\square$

**Proof of Theorem 2.2.** Define  $\Delta m_{it} = m_i\left(\frac{t}{T}\right) - m_i\left(\frac{t-1}{T}\right)$ .

Recall the differencing estimator  $\hat{\beta}_i$ :

$$\begin{aligned}
\hat{\beta}_i &= \left( \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta Y_{it} = \\
&= \left( \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \sum_{t=1}^T \Delta \mathbf{X}_{it} \left( \Delta \mathbf{X}_{it}^{\top} \beta_i + \Delta \varepsilon_{it} + \Delta m_{it} \right) = \\
&= \beta_i + \left( \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \varepsilon_{it} + \left( \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta m_{it}.
\end{aligned}$$

This leads to

$$\begin{aligned}
|\sqrt{T}(\hat{\beta}_i - \beta_i)| &\leq \left| \left( \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \varepsilon_{it} \right| + \\
&\quad + \left| \left( \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta m_{it} \right|.
\end{aligned} \tag{3.20}$$

First, we take a closer look at the second summand in (3.20). By the assumption in Theorem 2.2,  $m_i(\cdot)$  is Lipschitz continuous, that is,  $|\Delta m_{it}| = \left| m_i\left(\frac{t}{T}\right) - m_i\left(\frac{t-1}{T}\right) \right| \leq C \frac{1}{T}$

for all  $t \in \{1, \dots, T\}$  and some constant  $C > 0$ . Hence,

$$\begin{aligned}
\left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta m_{it} \right| &= \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{H}_i(\mathcal{U}_{it}) \Delta m_{it} \right| \leq \\
&\leq \frac{1}{\sqrt{T}} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})| \cdot |\Delta m_{it}| \leq \\
&\leq \frac{1}{\sqrt{T}} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})| \cdot |\Delta m_{it}| \leq \frac{C}{\sqrt{T}} \cdot \frac{1}{T} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})|.
\end{aligned} \tag{3.21}$$

Now, in order to show that the whole vector  $\frac{1}{T} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})|$  is  $O_P(1)$ , we will do that for every element  $\frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})|$  of this vector separately.

Fix  $j \in 1, \dots, d$ . By Chebyshev's inequality we have

$$\mathbb{P} \left( \frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| > a \right) \leq \frac{\mathbb{E} \left[ \left( \frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| \right)^2 \right]}{a^2} \tag{3.22}$$

and

$$\begin{aligned}
\mathbb{E} \left[ \left( \frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| \right)^2 \right] &= \frac{1}{T^2} \mathbb{E} \left[ \left( \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| \right)^2 \right] = \\
&= \frac{1}{T^2} \sum_{t=1}^T \mathbb{E} [\Delta H_{ij}^2(\mathcal{U}_{it})] + \frac{1}{T^2} \sum_{t=1, s=1, t \neq s}^T \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is})|].
\end{aligned} \tag{3.23}$$

Note that by the Cauchy-Schwarz inequality for all  $t$  and  $s$  we have

$$0 \leq \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is})|] \leq \sqrt{\mathbb{E} [\Delta H_{ij}^2(\mathcal{U}_{it})]} \sqrt{\mathbb{E} [\Delta H_{ij}^2(\mathcal{U}_{is})]} = \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})]$$

and

$$0 \leq |\mathbb{E} [H_{ij}(\mathcal{U}_{it}) H_{ij}(\mathcal{U}_{is})]| \leq \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is})|] \leq \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})]. \tag{3.24}$$

Hence,

$$\begin{aligned}
0 \leq \mathbb{E} [\Delta H_{ij}^2(\mathcal{U}_{it})] &= \mathbb{E} [(H_{ij}(\mathcal{U}_{it}) - H_{ij}(\mathcal{U}_{it-1}))^2] = \\
&= \mathbb{E} [H_{ij}^2(\mathcal{U}_{it})] - 2\mathbb{E} [H_{ij}(\mathcal{U}_{it}) H_{ij}(\mathcal{U}_{it-1})] + \mathbb{E} [H_{ij}^2(\mathcal{U}_{it-1})] \leq \\
&\leq \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})] + 2\mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})] + \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})] = \\
&= 4\mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})]
\end{aligned}$$

and the first summand in (3.23) can be bounded by  $\frac{4}{T} \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})]$ .

Now to the second summand in (3.23):

$$\begin{aligned}
0 \leq \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is})|] &= \mathbb{E} [|(H_{ij}(\mathcal{U}_{it}) - H_{ij}(\mathcal{U}_{it-1})) (H_{ij}(\mathcal{U}_{is}) - H_{ij}(\mathcal{U}_{is-1}))|] \leq \\
&\leq \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is})|] + \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it-1}) \Delta H_{ij}(\mathcal{U}_{is})|] + \\
&\quad + \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is-1})|] + \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it-1}) \Delta H_{ij}(\mathcal{U}_{is-1})|] \leq \\
&\leq 4\mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})],
\end{aligned}$$

where in the last inequality we used (3.24). This means that the second summand in (3.23) can be bounded by  $\frac{4T(T-1)}{T^2} \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})] = \frac{4(T-1)}{T} \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})]$ .

Plugging these bounds in (3.23), we get

$$\mathbb{E} \left[ \left( \frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| \right)^2 \right] \leq \frac{4}{T} \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})] + \frac{4(T-1)}{T} \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})] = 4 \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})],$$

which together with (3.22) leads to  $\frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| = O_P(1)$ . Since it holds for each  $j \in \{1, \dots, d\}$ , we can establish that

$$\frac{1}{T} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})| = \frac{1}{T} \sum_{t=1}^T |\Delta \mathbf{X}_{it}| = O_P(1). \quad (3.25)$$

Similarly, by Proposition A.10 and Chebyshev's inequality, we have that for each  $j, k \in \{1, \dots, d\}$

$$\left| \frac{1}{T} \sum_{t=1}^T \Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ik}(\mathcal{U}_{it}) \right| = O_P(1),$$

which leads to

$$\left| \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{H}_i(\mathcal{U}_{it}) \Delta \mathbf{H}_i(\mathcal{U}_{it})^\top \right| = \left| \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^\top \right| = O_P(1),$$

where  $|A|$  with  $A$  being a matrix is any matrix norm.

By Assumption (C5), we know that  $\mathbb{E}[\Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^\top] = \mathbb{E}[\Delta \mathbf{X}_{i0} \Delta \mathbf{X}_{i0}^\top]$  is invertible, thus,

$$\left| \left( \frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^\top \right)^{-1} \right| = O_P(1). \quad (3.26)$$

Plugging (3.25) into (3.21) and combining it with (3.26), we get that the second summand in (3.20) is  $O_P(1/\sqrt{T})$ .

Furthermore, we can apply the Proposition A.13 together with (3.26) to get that the first summand in (3.20) is  $O_P(1)$ . The statement of the theorem follows.  $\square$