

Multiscale Testing for Equality of Nonparametric Trend Curves

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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.

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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 the 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 ϵ'_0 being an i.i.d. copy of ϵ_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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for $1 \leq t \leq T$, where β_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 $[0, 1]$, α_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 α_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 α_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 α_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 α_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 ε_{it} allow for the representation $\varepsilon_{it} = G_i(\dots, \eta_{it-1}, \eta_{it})$, where η_{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 θ 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 ε_{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 $\mathbf{U}_i(\mathcal{I}_{i,t}) = \mathbf{H}_i(\mathcal{U}_{it})G_i(\mathcal{J}_{it})$. With this notation at hand, we assume that $\sum_{s=0}^{\infty} \delta_2(\mathbf{U}_i, s) < \infty$.

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 α_i and β_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}° are not observed since the intercept α_i and the coefficients β_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}° 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 α_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 now turn to the estimator of the long-run error variance $\sigma_i^2 = \sum_{\ell=-\infty}^{\infty} \text{Cov}(\varepsilon_{i0}, \varepsilon_{i\ell})$. For the moment, we assume that the long-run variance does not depend on i , that is $\sigma_i^2 = \sigma^2$ for all i . We further let $\hat{\sigma}_i^2$ be an estimator of $\sigma_i^2 = \sigma^2$ 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 $1 \leq t \leq T$. Hence, whereas the true long-run variance is the same for all time series, the estimators are different. Throughout the section, we assume that $\hat{\sigma}_i^2 = \sigma_i + o_p(\rho_T)$ with $\rho_T = o(\sqrt{h_{\min}}/\log T)$. Details on how to construct $\hat{\sigma}_i^2$ are deferred to Section ??.

Moreover, in the proof of our main theorem 2.1 we will need additional auxiliary statistics that do not include the covariates \mathbf{X}_{it} . Hence, we imagine that we know the parameters β_i and consider the unobserved variables

$$\begin{aligned}\widehat{\widehat{Y}}_{it} &:= Y_{it} - \beta_i^\top \mathbf{X}_{it} - \frac{1}{T} \sum_{t=1}^T (Y_{it} - \beta_i^\top \mathbf{X}_{it}) = \\ &= m_i\left(\frac{t}{T}\right) - \frac{1}{T} \sum_{t=1}^T m_i\left(\frac{t}{T}\right) + \varepsilon_{it} - \frac{1}{T} \sum_{t=1}^T \varepsilon_{it}.\end{aligned}$$

For this auxiliary statistics we will use the auxiliary estimator $\widehat{\widehat{\sigma}}_i^2$ of the long-run error variance σ_i which is computed from the augmented sample $\{\widehat{\widehat{Y}}_{it} : 1 \leq t \leq T\}$. We thus regard $\widehat{\widehat{\sigma}}_i^2 = \widehat{\widehat{\sigma}}_i^2(\widehat{\widehat{Y}}_{i1}, \dots, \widehat{\widehat{Y}}_{iT})$ as a function of the variables $\widehat{\widehat{Y}}_{it}$ for $1 \leq t \leq T$. As with $\widehat{\sigma}_i^2$, we assume that $\widehat{\widehat{\sigma}}_i^2 = \sigma^2 + o_p(\rho_T)$ with $\rho_T = o(\sqrt{h_{\min}}/\log T)$.

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

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

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 $\widehat{\psi}_{ij,T}(u, h)$ 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 $\widehat{\psi}_{ij,T}(u, h)$ for a wide range of different locations u and bandwidths or scales h in a following way:

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

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 $\widehat{\Psi}_{ij,T}$ can be interpreted as a global distance measure

between the two curves m_i and m_j . Thus, the multiscale statistic $\widehat{\Psi}_{ij,T}$ 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:

$$(C12) \quad |\mathcal{G}_T| = O(T^\theta) \text{ for some arbitrarily large but fixed constant } \theta > 0, \text{ where } |\mathcal{G}_T| \text{ denotes the cardinality of } \mathcal{G}_T.$$

$$(C13) \quad h_{\min} \gg T^{-(1-\frac{2}{q})} \log T, \text{ that is, } h_{\min}/\{T^{-(1-\frac{2}{q})} \log T\} \rightarrow \infty \text{ with } q > 4 \text{ defined in (C2) and } h_{\max} < 1/2.$$

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

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

that is, we define it as the maximal distance $\widehat{\Psi}_{ij,T}$ 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 ε_{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

$$\Phi_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\phi_{ij,T}(u, h)}{(\sigma_i^2 + \sigma_j^2)^{1/2}} \right| - \lambda(h) \right\}, \quad (2.4)$$

where $\phi_{ij,T}(u, h) = \sum_{t=1}^T w_{t,T}(u, h) \{ \sigma_i(Z_{it} - \bar{Z}_i) - \sigma_j(Z_{jt} - \bar{Z}_j) \}$. Since by our assumption $\sigma_i^2 = \sigma_j^2 = \sigma^2$, we can rewrite the Gaussian statistic as follows:

$$\Phi_{ij,T} = \max_{(u,h) \in \mathcal{G}_T} \left\{ \frac{1}{\sqrt{2}} \left| \sum_{t=1}^T w_{t,T}(u, h) \{ (Z_{it} - \bar{Z}_i) - (Z_{jt} - \bar{Z}_j) \} \right| - \lambda(h) \right\},$$

which means that $\Phi_{ij,T}$ does not depend on any unknown quantities such as σ^2 and the distribution of this random variable is fully known. However, we will stick to the notation in (2.4) for the sake of similarity to $\widehat{\Psi}_{ij,T}$.

Moreover, we define the statistic

$$\Phi_{n,T} = \max_{1 \leq i < j \leq n} \Phi_{ij,T} \quad (2.5)$$

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 $\widehat{\Psi}_{n,T} > q_{n,T}(\alpha)$.

2.3 Theoretical properties of the test

To start with, we introduce the auxiliary statistic

$$\widehat{\Phi}_{n,T} = \max_{1 \leq i < j \leq n} \widehat{\Phi}_{ij,T}, \quad (2.6)$$

where

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

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

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 for all $i \in \{1, \dots, n\}$ we have $\sigma_i^2 = \sigma^2$, $\widehat{\sigma}_i^2 = \sigma^2 + o_p(\rho_T)$ and $\widehat{\sigma}_i^2 = \sigma^2 + o_p(\rho_T)$ with $\rho_T = o(\sqrt{h_{\min}}/\log T)$. Then*

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

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 3.2.

2.4 Estimation of the parameters β_i

We now focus on finding an appropriate estimator $\widehat{\beta}_i$ of β_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

$$\Delta Y_{it} = \beta_i^\top \Delta \mathbf{X}_{it} + \Delta \varepsilon_{it} + O\left(\frac{1}{T}\right). \quad (2.7)$$

In particular, for each i we employ the least squares estimation method to estimate β_i in (2.7), treating $\Delta \mathbf{X}_{it}$ as the regressors and ΔY_{it} as the response variable. That is, we propose the following differencing estimator:

$$\widehat{\beta}_i = \left(\sum_{t=2}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^\top \right)^{-1} \sum_{t=2}^T \Delta \mathbf{X}_{it} \Delta Y_{it} \quad (2.8)$$

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 (2.8).

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.

3.1 Statistics used in the Appendix

Table 1: Relationship between statistics used in the proofs

	$\hat{\Phi}_{n,T}$	$\hat{\hat{\Phi}}_{n,T}$	$\tilde{\Phi}_{n,T}$	$\Phi_{n,T}$
$\hat{\Psi}_{n,T}$	Equal under H_0			
$\hat{\Phi}_{n,T}$		Close due to Prop. A.2		
$\hat{\hat{\Phi}}_{n,T}$			Same distribution (Prop. A.3)	
$\tilde{\Phi}_{n,T}$				Lemma A.6 with the help of Prop. A.3 and Prop. A.5

In the proof of Theorem 2.1, we use a number of different test statistics, either defined in Section 2 or the auxiliary statistics defined below. Each of these statistics plays an important role in one or more steps of the proof. In the following list, we present these test statistics, describe how they are constructed and explain in which parts of the proof they are used. Table 1 is a useful guide for connecting these statistics with their places in the proof strategy presented below.

- Multiscale statistics that is calculated based on data (defined in (2.3)):

$$\begin{aligned}
\widehat{\Psi}_{n,T} &= \max_{1 \leq i < j \leq n} \widehat{\Psi}_{ij,T} \\
\widehat{\Psi}_{ij,T} &= \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\widehat{\psi}_{ij,T}(u,h)}{(\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2)^{1/2}} \right| - \lambda(h) \right\}, \\
\widehat{\psi}_{ij,T}(u,h) &= \sum_{t=1}^T w_{t,T}(u,h) (\widehat{Y}_{it} - \widehat{Y}_{jt}).
\end{aligned} \tag{3.1}$$

- Auxiliary statistics that can be regarded as the version of our multiscale statistic $\widehat{\Psi}_{n,T}$ under H_0 (defined in (2.6)):

$$\begin{aligned}
\widehat{\Phi}_{n,T} &= \max_{1 \leq i < j \leq n} \widehat{\Phi}_{ij,T}, \\
\widehat{\Phi}_{ij,T} &= \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\widehat{\phi}_{ij,T}(u,h)}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2}} \right| - \lambda(h) \right\}, \\
\widehat{\phi}_{ij,T}(u,h) &= \sum_{t=1}^T w_{t,T}(u,h) \{ (\varepsilon_{it} - \bar{\varepsilon}_i) + (\beta_i - \widehat{\beta}_i)^\top (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) - \\
&\quad - (\varepsilon_{jt} - \bar{\varepsilon}_j) - (\beta_j - \widehat{\beta}_j)^\top (\mathbf{X}_{jt} - \bar{\mathbf{X}}_j) \}.
\end{aligned} \tag{3.2}$$

- Intermediate statistics that is close to $\widehat{\Phi}_{n,T}$ but is based on the kernel averages that do not include the covariates:

$$\begin{aligned}
\widehat{\widehat{\Phi}}_{n,T} &= \max_{1 \leq i < j \leq n} \widehat{\widehat{\Phi}}_{ij,T}, \\
\widehat{\widehat{\Phi}}_{ij,T} &= \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\widehat{\widehat{\phi}}_{ij,T}(u,h)}{\{\widehat{\widehat{\sigma}}_i^2 + \widehat{\widehat{\sigma}}_j^2\}^{1/2}} \right| - \lambda(h) \right\}, \\
\widehat{\widehat{\phi}}_{ij,T}(u,h) &= \sum_{t=1}^T w_{t,T}(u,h) \{ (\varepsilon_{it} - \bar{\varepsilon}_i) - (\varepsilon_{jt} - \bar{\varepsilon}_j) \}.
\end{aligned} \tag{3.3}$$

- Auxiliary statistic that has the same distribution as $\widehat{\widehat{\Phi}}_{n,T}$ for each $T = 1, 2, \dots$

$$\begin{aligned}
\widetilde{\Phi}_{n,T} &= \max_{1 \leq i < j \leq n} \widetilde{\Phi}_{ij,T}, \\
\widetilde{\Phi}_{ij,T} &= \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\widetilde{\phi}_{ij,T}(u,h)}{\{\widetilde{\sigma}_i^2 + \widetilde{\sigma}_j^2\}^{1/2}} \right| - \lambda(h) \right\}, \\
\widetilde{\phi}_{ij,T}(u,h) &= \sum_{t=1}^T w_{t,T}(u,h) \{ (\widetilde{\varepsilon}_{it} - \widetilde{\varepsilon}_i) - (\widetilde{\varepsilon}_{jt} - \widetilde{\varepsilon}_j) \}
\end{aligned} \tag{3.4}$$

with $[\widetilde{\varepsilon}_{i1}, \dots, \widetilde{\varepsilon}_{iT}] \stackrel{\mathcal{D}}{=} [\varepsilon_{i1}, \dots, \varepsilon_{iT}]$ for each i and T .

- The Gaussian statistics that is used to calculate the critical values (defined in

(2.5)):

$$\begin{aligned}
\Phi'_{n,T} &= \max_{1 \leq i < j \leq n} \Phi'_{ij,T}, \\
\Phi'_{ij,T} &= \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\phi'_{ij,T}(u,h)}{(\sigma_i^2 + \sigma_j^2)^{1/2}} \right| - \lambda(h) \right\}, \\
\phi'_{ij,T}(u,h) &= \sum_{t=1}^T w_{t,T}(u,h) \{ \sigma_i(Z_{it} - \bar{Z}_i) - \sigma_j(Z_{jt} - \bar{Z}_j) \}.
\end{aligned} \tag{3.5}$$

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.

1. First, we introduce the intermediate statistic $\widehat{\widehat{\Phi}}_{n,T}$ that can be regarded as the version of the statistics $\widehat{\Phi}_{n,T}$ but without the regressors and in Propositions A.1 and A.2 we show that this intermediate statistic is close to $\widehat{\Phi}_{n,T}$, i.e. there exists a sequence $\gamma_{n,T}$ that converges to 0 as $T \rightarrow \infty$ such that for all $x \in \mathbb{R}$

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

and

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

2. Second, by Proposition A.3, there exist statistics $\widetilde{\Phi}_{n,T}$ for $T = 1, 2, \dots$ which are distributed as $\widehat{\widehat{\Phi}}_{n,T}$ for any $T \geq 1$ and which have the property that

$$|\widetilde{\Phi}_{n,T} - \Phi'_{n,T}| = o_p\left(\frac{T^{1/q}}{\sqrt{Th_{\min}}} + \rho_T \sqrt{\log T}\right),$$

where $\Phi'_{n,T}$ is a true Gaussian statistic that is very similar to the pseudo-Gaussian statistic $\Phi_{n,T}$ defined in (2.5). This approximation result 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 true Gaussian statistic $\Phi'_{n,T}$.

3. Then, by Proposition A.5 we show that $\Phi'_{n,T}$ does not concentrate too strongly in small regions of the form $[x - \delta_T, x + \delta_T]$ with δ_T converging to zero. Or, in other words, it holds that

$$\sup_{x \in \mathbb{R}} \mathbb{P}(|\Phi'_{n,T} - x| \leq \delta_T) = o(1),$$

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

4. In the fourth step we make use of Lemma A.6 to show that

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = o(1).$$

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

5. In the fifth step, by the means of Proposition A.7 we prove that

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = o(1).$$

6. And finally, in Proposition A.8 we connect the quantiles of the true Gaussian statistics $\Phi'_{n,T}$ (that can not be simulated because they include the unknown parameters σ_i^2) to the quantiles of the “Gaussian” statistic $\Phi_{n,T}$ (that can be simulated and used for testing):

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\Phi'_{n,T} \leq x) - \mathbb{P}(\Phi_{n,T} \leq x)| = o(1),$$

which immediately implies the statement of Theorem 2.1.

Here we need conditional distribution for the “Gaussian” statistics! NOT DONE YET

Step 1

The auxiliary statistic $\widehat{\Phi}_{n,T}$ defined in Section 2.3 (which is equal to our multiscale statistics $\widehat{\Psi}_{n,T}$ 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 without the covariates that connects $\widehat{\Phi}_{n,T}$ and $\Phi_{n,T}$.

We do it in the following way. For each i and j , consider the 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

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

with $\widehat{\sigma}_i^2$ being 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 unobserved sample $\{\widehat{Y}_{it} : 1 \leq t \leq T\}$. We thus regard

$\widehat{\sigma}_i^2 = \widehat{\sigma}_i^2(\widehat{Y}_{i1}, \dots, \widehat{Y}_{iT})$ as a function of the variables \widehat{Y}_{it} for $1 \leq t \leq T$. As with the estimator $\widehat{\sigma}_i^2$, we assume that $\widehat{\sigma}_i^2 = \sigma_i^2 + o_p(\rho_T)$ with $\rho_T = o(\sqrt{h_{\min}}/\log T)$.

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 $\widehat{\beta}_i$, $\widehat{\sigma}_i^2$ and assumptions on \mathbf{X}_{it} . In the following two propositions we prove it formally.

Proposition A.1. *For any $x \in \mathbb{R}$ and any $\gamma_{n,T} > 0$, we have*

$$\begin{aligned} \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(|\widehat{\Phi}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}) &\leq \mathbb{P}(\widehat{\Phi}_{n,T} \leq x) \leq \\ &\leq \mathbb{P}(\widehat{\Phi}_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(|\widehat{\Phi}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}). \end{aligned} \quad (3.6)$$

Proof of Proposition A.1. From the law of total probability and the monotonic property of the probability function, we have

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

Analogously,

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

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 $\widehat{\Phi}_{n,T}$ is not too big. In other words,

Proposition A.2. *There exists a sequence of random numbers $\{\gamma_{n,T}\}_T$, that converges to 0 as $T \rightarrow \infty$, such that*

$$\mathbb{P}(|\widehat{\Phi}_{n,T} - \widehat{\Phi}_{n,T}| > \gamma_{n,T}) = o(1). \quad (3.7)$$

Proof of Proposition A.2. Straightforward calculations yield that

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

Then, consider the difference of the kernel averages:

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

Hence,

$$\begin{aligned}
|\widehat{\Phi}_{n,T} - \widehat{\Phi}_{n,T}| &\leq \max_{1 \leq i < j \leq n} |\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{-1/2} - \{\sigma_i^2 + \sigma_j^2\}^{-1/2}| \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} |\widehat{\phi}_{ij,T}(u,h)| + \\
&\quad + 2 \max_{1 \leq i < j \leq n} \{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{-1/2} \max_{1 \leq i \leq n} \left(|\beta_i - \widehat{\beta}_i|^\top \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u,h) \mathbf{X}_{it} \right| \right) + \\
&\quad + 2 \max_{1 \leq i < j \leq n} \{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{-1/2} \max_{1 \leq i \leq n} |(\beta_i - \widehat{\beta}_i)^\top \bar{\mathbf{X}}_i| \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u,h) \right|
\end{aligned} \tag{3.8}$$

We start by evaluating the second summand in (3.8).

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,

$$\max_{1 \leq i < j \leq n} \{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{-1/2} = O_P(1). \tag{3.9}$$

Then, by Theorem 2.2, we know that

$$|\beta_i - \widehat{\beta}_i| = O_P(1/\sqrt{T}). \tag{3.10}$$

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

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

Note that

$$\sum_{t=\lceil T(u-h) \rceil}^{\lceil T(u+h) \rceil} w_{t,T}^2(u, h) = \sum_{t=1}^T w_{t,T}^2(u, h) = \sum_{t=1}^T \frac{\Lambda_{t,T}^2(u, h)}{\sum_{s=1}^T \Lambda_{s,T}^2(u, h)} = 1. \quad (3.11)$$

Denoting by $D_{T,u,h}$ the number of integers between $\lceil T(u-h) \rceil$ 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:

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

According to Theorem A.1 (Theorem 2(ii) in Wu et al. (2016)), if we denote 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:

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

Now take any $\delta > 0$:

$$\begin{aligned} \mathbb{P} \left(\frac{\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=\lceil T(u-h) \rceil}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right|}{\sqrt{T}} \geq \delta \right) &= \\ &= \mathbb{P} \left(\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=\lceil T(u-h) \rceil}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right| \geq \delta \sqrt{T} \right) \leq \\ &\stackrel{\text{Boole's inequality}}{\leq} \sum_{(u,h) \in \mathcal{G}_T} \mathbb{P} \left(\left| \sum_{t=\lceil T(u-h) \rceil}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) X_{it} \right| \geq \delta \sqrt{T} \right) = \\ &\stackrel{\text{"normalisation"}}{=} \sum_{(u,h) \in \mathcal{G}_T} \mathbb{P} \left(\left| \sum_{t=\lceil T(u-h) \rceil}^{\lceil T(u+h) \rceil} \sqrt{D_{T,u,h}} \cdot w_{t,T}(u, h) X_{it} \right| \geq \delta \sqrt{D_{T,u,h} T} \right) \leq \end{aligned}$$

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

where the symbol C denotes a universal real constant that does not depend neither on T nor on δ 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 $\sum_{t=1}^T w_{t,T}^2(u,h) = 1$, we have $0 \leq w_{t,T}^2(u,h) \leq 1$ for all $t \in \{1, \dots, T\}$ and all $(u,h) \in \mathcal{G}_T$ 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,

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

and similarly

$$\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u,h) \mathbf{X}_{it} \right| = o_P(\sqrt{T}). \quad (3.12)$$

Combining (3.9), (3.10) and (3.12), we get the following:

$$\begin{aligned}
& 2 \max_{1 \leq i < j \leq n} \{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{-1/2} \max_{1 \leq i \leq n} \left(|\beta_i - \hat{\beta}_i|^\top \max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u,h) \mathbf{X}_{it} \right| \right) = \\
& = O_P(1) \cdot O_P(1/\sqrt{T}) \cdot o_P(\sqrt{T}) = o_P(1).
\end{aligned} \quad (3.13)$$

Now, consider the third summand in (3.8).

Similarly as before,

$$\max_{1 \leq i < j \leq n} \{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{-1/2} = O_P(1) \quad (3.14)$$

and

$$|\beta_i - \widehat{\beta}_i| = O_P(1/\sqrt{T}). \quad (3.15)$$

Then, by Proposition A.12 $\bar{\mathbf{X}}_i = o_P(1)$.

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 $\left| \sum_{t=1}^T w_{t,T}(u, h) \right|$ for all $(u, h) \in \mathcal{G}_T$ using the Cauchy-Schwarz inequality:

$$\begin{aligned} \left| \sum_{t=1}^T w_{t,T}(u, h) \right| &= \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) \right| = \left| \sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}(u, h) \cdot 1 \right| \leq \\ &\leq \sqrt{\sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} w_{t,T}^2(u, h)} \sqrt{\sum_{t=\lfloor T(u-h) \rfloor}^{\lceil T(u+h) \rceil} 1^2} = \\ &= \sqrt{1} \cdot \sqrt{D_{T,u,h}} \leq \sqrt{2Th + 2} \leq \sqrt{2Th_{\max} + 2} \leq \sqrt{T + 2}. \end{aligned} \quad (3.16)$$

Hence,

$$\max_{(u,h) \in \mathcal{G}_T} \left| \sum_{t=1}^T w_{t,T}(u, h) \right| = O(\sqrt{T}). \quad (3.17)$$

Combining (3.14), (3.15), Proposition A.12 and (3.17), we get the following:

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

Lastly, we look at the first summand in (3.8). Since $\widehat{\sigma}_i^2 = \sigma_i^2 + o_P(\rho_T)$ and $\widehat{\sigma}_i^2 = \sigma_i^2 + o_P(\rho_T)$ by our assumptions, we have that

$$\max_{1 \leq i < j \leq n} |\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{-1/2} - \{\sigma_i^2 + \sigma_j^2\}^{-1/2}| = o_P(\rho_T). \quad (3.19)$$

Then since $\widehat{\phi}_{ij,T}(u, h)$ has the same distribution as $\widetilde{\phi}_{ij,T}(u, h)$ for each $1 \leq i < j \leq n$

and each $(u, h) \in \mathcal{G}_T$, we can look at $\max_{(u,h) \in \mathcal{G}_T} |\tilde{\phi}_{ij,T}(u, h)|$ instead:

$$\begin{aligned}
\mathbb{P} \left(\left| \max_{(u,h) \in \mathcal{G}_T} \left| \hat{\phi}_{ij,T}(u, h) \right| \right| \geq c_T \right) &= \mathbb{P} \left(\left| \max_{(u,h) \in \mathcal{G}_T} \left| \tilde{\phi}_{ij,T}(u, h) \right| \right| \geq c_T \right) = \\
&= \mathbb{P} \left(\left| \max_{(u,h) \in \mathcal{G}_T} \left| \tilde{\phi}_{ij,T}(u, h) \right| - \max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h)| + \max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h)| \right| \geq c_T \right) \leq \\
&\leq \mathbb{P} \left(\left| \max_{(u,h) \in \mathcal{G}_T} \left| \tilde{\phi}_{ij,T}(u, h) \right| - \max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h)| \right| \geq c_T/2 \right) + \mathbb{P} \left(\left| \max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h)| \right| \geq c_T/2 \right) \leq \\
&\leq \mathbb{P} \left(\max_{(u,h) \in \mathcal{G}_T} \left| \tilde{\phi}_{ij,T}(u, h) - \phi'_{ij,T}(u, h) \right| \geq c_T/2 \right) + \mathbb{P} \left(\max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h)| \geq c_T/2 \right).
\end{aligned} \tag{3.20}$$

Here we will need one result that we will prove further: by (3.30) we have

$$\max_{(u,h) \in \mathcal{G}_T} \left| \tilde{\phi}_{ij,T}(u, h) - \phi'_{ij,T}(u, h) \right| = o_P \left(\frac{T^{1/q}}{\sqrt{T h_{\min}}} \right).$$

Furthermore, $\phi'_{ij,T}(u, h)$ is distributed as $N(0, \sigma_i^2 + \sigma_j^2)$ for all $(u, h) \in \mathcal{G}_T$ and all $1 \leq i < j \leq n$ and $|\mathcal{G}_T| = O(T^\theta)$ for some large but fixed constant θ by Assumption (C12). By the standard results from the probability theory, we know that

$$\max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h)| = O_P(\sqrt{\log T}).$$

Hence, if we take $c_T = o(\sqrt{\log T})$ in (3.20), we will get the following:

$$\begin{aligned}
\mathbb{P} \left(\left| \max_{(u,h) \in \mathcal{G}_T} \left| \hat{\phi}_{ij,T}(u, h) \right| \right| \geq c_T \right) &\leq \\
&\leq \mathbb{P} \left(\max_{(u,h) \in \mathcal{G}_T} \left| \tilde{\phi}_{ij,T}(u, h) - \phi'_{ij,T}(u, h) \right| \geq c_T/2 \right) + \mathbb{P} \left(\max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h)| \geq c_T/2 \right) = \\
&= o(1) + o(1) = o(1),
\end{aligned}$$

which means that

$$\max_{(u,h) \in \mathcal{G}_T} \left| \hat{\phi}_{ij,T}(u, h) \right| = o_P(\sqrt{\log T}) \tag{3.21}$$

Combining (3.19) and (3.21), we get the following:

$$\begin{aligned}
&\max_{1 \leq i < j \leq n} \left| \{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{-1/2} - \{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{-1/2} \right| \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left| \hat{\phi}_{ij,T}(u, h) \right| = \\
&= o_P(\rho_T) \cdot o_P(\sqrt{\log T}) = \\
&= o_P(1)
\end{aligned} \tag{3.22}$$

since by our assumption $\rho_T = O(\sqrt{h_{\min}}/\log T)$. Plugging (3.13), (3.18) and (3.22) in (3.8), we get that $|\hat{\Phi}_{n,T} - \hat{\Phi}_{n,T}| = o_P(1)$ and the statement of the theorem follows. \square

Step 2

The main purpose of this section is to prove that there is a version of the multiscale statistic $\widehat{\Phi}_{n,T}$ which is close to a true Gaussian statistic $\Phi'_{n,T}$ (defined in (??)) whose distribution is known (given that we know σ_i^2). More specifically, we prove the following result.

Proposition A.3. *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 $\widehat{\Phi}_{n,T}$ for any T , and (ii)*

$$|\widetilde{\Phi}_{n,T} - \Phi'_{n,T}| = o_p\left(\frac{T^{1/q}}{\sqrt{T}h_{\min}} + \rho_T\sqrt{\log T}\right), \quad (3.23)$$

where $\Phi'_{n,T}$ is a Gaussian statistic as defined in (??).

Proof of Proposition A.3. 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}_i and a sequence $\{\widetilde{\varepsilon}_{it} : t \in \mathbb{N}\}$ such that $[\widetilde{\varepsilon}_{i1}, \dots, \widetilde{\varepsilon}_{iT}] \stackrel{\mathcal{D}}{=} [\varepsilon_{i1}, \dots, \varepsilon_{iT}]$ for each T and

$$\max_{1 \leq t \leq T} \left| \sum_{s=1}^t \widetilde{\varepsilon}_{is} - \sigma_i \mathbb{B}_i(t) \right| = o(T^{1/q}) \quad \text{a.s.}, \quad (3.24)$$

where $\sigma_i^2 = \sum_{k \in \mathbb{Z}} \text{Cov}(\varepsilon_{i0}, \varepsilon_{ik})$ denotes the long-run error variance.

We apply this result for each stationary process $\mathcal{E}_i = \{\varepsilon_{it} : 1 \leq t \leq T\}$ so that each process $\widetilde{\mathcal{E}}_i = \{\widetilde{\varepsilon}_{it} : t \in \mathbb{N}\}$ is independent of $\widetilde{\mathcal{E}}_j = \{\widetilde{\varepsilon}_{jt} : t \in \mathbb{N}\}$ for $i \neq j$.

Furthermore, we define

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

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 $1 \leq t \leq T$. Since $[\widetilde{\varepsilon}_{i1}, \dots, \widetilde{\varepsilon}_{iT}] \stackrel{\mathcal{D}}{=} [\varepsilon_{i1}, \dots, \varepsilon_{iT}]$, we have $\sum_{\ell=-\infty}^{\infty} \text{Cov}(\widetilde{\varepsilon}_{i0}, \widetilde{\varepsilon}_{i\ell}) = \sum_{\ell=-\infty}^{\infty} \text{Cov}(\varepsilon_{i0}, \varepsilon_{i\ell}) = \sigma_i^2$, hence by construction $\widetilde{\sigma}_i^2 = \sigma_i^2 + o_P(\rho_T)$.

In addition, we let

$$\Phi_{n,T}^\diamond = \max_{1 \leq i < j \leq n} \Phi_{ij,T}^\diamond = \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left\{ \left| \frac{\phi'_{ij,T}(u,h)}{\{\sigma_i^2 + \sigma_j^2\}^{1/2}} \right| - \lambda(h) \right\}$$

with $\phi'_{ij,T}(u, h)$ defined in (??) and $Z_{it} = \mathbb{B}_i(t) - \mathbb{B}_i(t-1)$. With this notation, we can write

$$|\tilde{\Phi}_{n,T} - \Phi'_{n,T}| \leq |\tilde{\Phi}_{n,T} - \Phi_{n,T}^\diamond| + |\Phi_{n,T}^\diamond - \Phi'_{n,T}|. \quad (3.25)$$

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

$$|\tilde{\Phi}_{n,T} - \Phi_{n,T}^\diamond| \leq \max_{1 \leq i < j \leq n} \left(\{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2\}^{-1/2} \max_{(u,h) \in \mathcal{G}_T} |\tilde{\phi}_{ij,T}(u, h) - \phi'_{ij,T}(u, h)| \right). \quad (3.26)$$

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

$$\begin{aligned} |\tilde{\phi}_{ij,T}(u, h) - \phi'_{ij,T}(u, h)| &= \\ &= \left| \sum_{t=1}^T w_{t,T}(u, h) \{(\tilde{\varepsilon}_{it} - \tilde{\varepsilon}_i) - (\tilde{\varepsilon}_{jt} - \tilde{\varepsilon}_j) - \sigma_i(Z_{it} - \bar{Z}_i) + \sigma_j(Z_{jt} - \bar{Z}_j)\} \right| = \\ &= \left| \sum_{t=1}^{T-1} A_{ij,t} (w_{t,T}(u, h) - w_{t+1,T}(u, h)) + A_{ij,T} w_{T,T}(u, h) \right|, \end{aligned}$$

where

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

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

$$|\tilde{\phi}_{ij,T}(u, h) - \phi'_{ij,T}(u, h)| = \left| \sum_{t=1}^{T-1} A_{ij,t} (w_{t,T}(u, h) - w_{t+1,T}(u, h)) \right| \leq W_T(u, h) \max_{1 \leq t \leq T} |A_{ij,t}|. \quad (3.27)$$

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

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

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

Applying the strong approximation result (3.24), we can infer that

$$\begin{aligned}
\max_{1 \leq t \leq T} |A_{ij,t}| &\leq 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{is} - \sigma_i \mathbb{B}_i(t) \right| + 2 \max_{1 \leq t \leq T} \left| \sum_{s=1}^t \tilde{\varepsilon}_{js} - \sigma_j \mathbb{B}_j(t) \right| = \\
&= o_P(T^{1/q}).
\end{aligned} \tag{3.28}$$

Standard arguments show that $\max_{(u,h) \in \mathcal{G}_T} W_T(u,h) = O(1/\sqrt{Th_{\min}})$. Plugging (3.28) in (3.27) and then in (3.26), we can thus infer that

$$\begin{aligned}
|\tilde{\Phi}_{n,T} - \Phi_{n,T}^\diamond| &\leq \{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2\}^{-1/2} \max_{(u,h) \in \mathcal{G}_T} W_T(u,h) \max_{1 \leq i < j \leq n} \max_{1 \leq t \leq T} |A_{ij,t}| = \\
&= o_P\left(\frac{T^{1/q}}{\sqrt{Th_{\min}}}\right).
\end{aligned} \tag{3.29}$$

Now consider $|\Phi_{n,T}^\diamond - \Phi'_{n,T}|$. Since $\phi'_{ij,T}(u,h)$ is distributed as $N(0, \sigma_i^2 + \sigma_j^2)$ 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 θ by Assumption (C12), n is fixed and $\tilde{\sigma}_i^2 = \sigma_i^2 + o_p(\rho_T)$, we can establish that

$$|\Phi_{n,T}^\diamond - \Phi'_{n,T}| \leq \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left| \frac{\phi'_{ij,T}(u,h)}{\{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2\}^{1/2}} - \frac{\phi'_{ij,T}(u,h)}{\{\sigma_i^2 + \sigma_j^2\}^{1/2}} \right| = o_P(\rho_T \sqrt{\log T}). \tag{3.30}$$

Plugging (3.29) and (3.30) in (3.25) completes the proof. \square

Step 3

In this section, we establish some properties of the Gaussian statistic $\Phi'_{n,T}$ defined in (??). 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 δ_T converging to zero.

The main technical tool for proving Proposition A.5 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.4. *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*

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

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

The proof of Proposition A.4 is provided in Khismatullina and Vogt (2019).

Proposition A.5. *Under the conditions of Theorem 2.1, it holds that*

$$\sup_{x \in \mathbb{R}} \mathbb{P}(|\Phi'_{n,T} - x| \leq \delta_T) = o(1), \quad (3.31)$$

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

Proof of Proposition A.5. 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

$$U_{ij,2k-1} = \frac{\phi'_{ij,T}(x_{k1}, x_{k2})}{\{\sigma_i^2 + \sigma_j^2\}^{1/2}} - \lambda(x_{k2})$$

$$U_{ij,2k} = -\frac{\phi'_{ij,T}(x_{k1}, x_{k2})}{\{\sigma_i^2 + \sigma_j^2\}^{1/2}} - \lambda(x_{k2})$$

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.4 to obtain that

$$\sup_{x \in \mathbb{R}} \mathbb{P}\left(|\Phi'_{n,T} - x| \leq \delta_T\right) \leq C\delta_T \left[\sqrt{\log T} + \sqrt{\log(1/\delta_T)}\right] = o(1)$$

with $\delta_T = T^{1/q}/\sqrt{Th_{\min}} + \rho_T\sqrt{\log T}$, which is the statement of Proposition A.5. \square

Step 4

Lemma A.6. *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*

$$\sup_{x \in \mathbb{R}} \mathbb{P}(|V_T - x| \leq \delta_T) = o(1), \quad (3.32)$$

then

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(V_T \leq x) - \mathbb{P}(W_T \leq x)| = o(1). \quad (3.33)$$

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

Applying Lemma A.6 to $\tilde{\Phi}_{n,T}$ and $\Phi'_{n,T}$ together with the results (3.23) and (3.31) and noting the fact that $\tilde{\Phi}_{n,T}$ is distributed as $\hat{\Phi}_{n,T}$ for any $n \geq 2$, $T \geq 1$ leads us to

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\hat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = o(1).$$

Step 5

Proposition A.7. *Under the conditions of Theorem 2.1, it holds that*

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\hat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = o(1). \quad (3.34)$$

Proof of Proposition A.7. 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.1 and taking $\gamma_{n,T}$ from the Proposition A.2 we have

$$\begin{aligned} 0 &\leq |\mathbb{P}(\hat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = \mathbb{P}(\hat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x) \leq \\ &\leq \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(|\hat{\Phi}_{n,T} - \hat{\Phi}_{n,T}| > \gamma_{n,T}) - \mathbb{P}(\Phi'_{n,T} \leq x) = \\ &= \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi'_{n,T} \leq x + \gamma_{n,T}) + \\ &\quad + \mathbb{P}(\Phi'_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi'_{n,T} \leq x) + \mathbb{P}(|\hat{\Phi}_{n,T} - \hat{\Phi}_{n,T}| > \gamma_{n,T}) = \\ &= \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi'_{n,T} \leq x + \gamma_{n,T}) + \\ &\quad + \mathbb{P}(x < \Phi'_{n,T} \leq x + \gamma_{n,T}) + \mathbb{P}(|\hat{\Phi}_{n,T} - \hat{\Phi}_{n,T}| > \gamma_{n,T}) \leq \\ &\leq \mathbb{P}(\hat{\Phi}_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\Phi'_{n,T} \leq x + \gamma_{n,T}) + \\ &\quad + \mathbb{P}(|\Phi'_{n,T} - x| \leq \gamma_{n,T}) + \mathbb{P}(|\hat{\Phi}_{n,T} - \hat{\Phi}_{n,T}| > \gamma_{n,T}). \end{aligned}$$

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.1 for $\gamma_{n,T}$ from Proposition A.2 we have

$$\begin{aligned}
0 &\leq |\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = \mathbb{P}(\Phi'_{n,T} \leq x) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x) \leq \\
&\leq \mathbb{P}(\Phi'_{n,T} \leq x) + \mathbb{P}(|\widehat{\Phi}_{n,T} - \Phi_{n,T}| > \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) = \\
&= \mathbb{P}(\Phi'_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x - \gamma_{n,T}) + \\
&\quad + \mathbb{P}(\Phi'_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) + \mathbb{P}(|\widehat{\Phi}_{n,T} - \Phi_{n,T}| > \gamma_{n,T}) = \\
&= \mathbb{P}(x - \gamma_{n,T} < \Phi'_{n,T} \leq x) + \mathbb{P}(\Phi'_{n,T} \leq x - \gamma_{n,T}) - \\
&\quad - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) + \mathbb{P}(|\widehat{\Phi}_{n,T} - \Phi_{n,T}| > \gamma_{n,T}) \leq \\
&\leq \mathbb{P}(|\Phi'_{n,T} - x| \leq \gamma_{n,T}) + \mathbb{P}(\Phi'_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) + \mathbb{P}(|\widehat{\Phi}_{n,T} - \Phi_{n,T}| > \gamma_{n,T}).
\end{aligned}$$

Now note that since $\gamma_{n,T} \rightarrow 0$, we can use the anticoncentration results (3.31) for the Gaussian statistic $\Phi'_{n,T}$ to get $\sup_{x \in \mathbb{R}} \mathbb{P}(|\Phi'_{n,T} - x| \leq \gamma_{n,T}) = o(1)$. Moreover,

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

by Proposition A.2 and does not depend on x .

Thus,

$$\begin{aligned}
&\sup_{x \in \mathbb{R}} |\mathbb{P}(\widehat{\Phi}_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| \leq \\
&\leq \max \left\{ \sup_{x \in \mathbb{R}} \left| \mathbb{P}(\Phi'_{n,T} \leq x - \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x - \gamma_{n,T}) \right|, \right. \\
&\quad \left. \sup_{x \in \mathbb{R}} \left| \mathbb{P}(\Phi'_{n,T} \leq x + \gamma_{n,T}) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq x + \gamma_{n,T}) \right| \right\} + \\
&\quad + \sup_{x \in \mathbb{R}} \mathbb{P}(|\Phi'_{n,T} - x| \leq \gamma_{n,T}) + \sup_{x \in \mathbb{R}} \mathbb{P}(|\widehat{\Phi}_{n,T} - \Phi_{n,T}| > \gamma_{n,T}) = \\
&= \sup_{y \in \mathbb{R}} \left| \mathbb{P}(\Phi'_{n,T} \leq y) - \mathbb{P}(\widehat{\Phi}_{n,T} \leq y) \right| + o(1) + o(1) = o(1).
\end{aligned}$$

□

Step 6

Proposition A.8. *Under the conditions of Theorem 2.1, it holds that*

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\Phi_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = o(1). \quad (3.35)$$

Proof of Proposition A.8. It is clear that we can bound $|\Phi_{n,T} - \Phi'_{n,T}|$ as follows

$$\begin{aligned}
|\Phi_{n,T} - \Phi'_{n,T}| &\leq \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left| \frac{\phi'_{ij,T}(u,h)}{(\sigma_i^2 + \sigma_j^2)^{1/2}} - \frac{\phi'_{ij,T}(u,h)}{(\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2)^{1/2}} \right| + \\
&\quad + \max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left| \frac{\phi'_{ij,T}(u,h)}{(\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2)^{1/2}} - \frac{\phi_{ij,T}(u,h)}{(\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2)^{1/2}} \right|
\end{aligned} \quad (3.36)$$

To begin with, consider the first part in (3.36). We can proceed analogously to the proof of Proposition A.3. Since $\phi'_{ij,T}(u, h)$ is distributed as $N(0, \sigma_i^2 + \sigma_j^2)$ 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 θ by Assumption (C12), n is fixed and $\hat{\sigma}_i^2 = \sigma_i^2 + o_p(\rho_T)$, we can establish that

$$\max_{1 \leq i < j \leq n} \max_{(u, h) \in \mathcal{G}_T} \left| \frac{\phi'_{ij,T}(u, h)}{(\sigma_i^2 + \sigma_j^2)^{1/2}} - \frac{\phi'_{ij,T}(u, h)}{(\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{1/2}} \right| = o_P(\rho_T \sqrt{\log T}). \quad (3.37)$$

Now let us evaluate the second part in (3.36):

$$\begin{aligned} & \max_{1 \leq i < j \leq n} \max_{(u, h) \in \mathcal{G}_T} \left| \frac{\phi'_{ij,T}(u, h)}{(\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{1/2}} - \frac{\phi_{ij,T}(u, h)}{(\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{1/2}} \right| = \\ & = \max_{1 \leq i < j \leq n} \left((\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{-1/2} \max_{(u, h) \in \mathcal{G}_T} |\phi'_{ij,T}(u, h) - \phi_{ij,T}(u, h)| \right). \end{aligned} \quad (3.38)$$

We proceed in much the same way as in the proof of Proposition A.3. 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

$$\begin{aligned} & |\phi'_{ij,T}(u, h) - \phi_{ij,T}(u, h)| = \\ & = \left| \sum_{t=1}^T w_{t,T}(u, h) \{ \hat{\sigma}_i(Z_{it} - \bar{Z}_i) - \hat{\sigma}_j(Z_{jt} - \bar{Z}_j) - \sigma_i(Z_{it} - \bar{Z}_i) + \sigma_j(Z_{jt} - \bar{Z}_j) \} \right| = \\ & = \left| \sum_{t=1}^{T-1} B_{ij,t} (w_{t,T}(u, h) - w_{t+1,T}(u, h)) + B_{ij,T} w_{T,T}(u, h) \right|, \end{aligned}$$

where

$$B_{ij,t} = \sum_{s=1}^t \{ \hat{\sigma}_i(Z_{is} - \bar{Z}_i) - \hat{\sigma}_j(Z_{js} - \bar{Z}_j) - \sigma_i(Z_{is} - \bar{Z}_i) + \sigma_j(Z_{js} - \bar{Z}_j) \}.$$

Note that by construction $B_{ij,T} = 0$ 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

$$|\phi'_{ij,T}(u, h) - \phi_{ij,T}(u, h)| = \left| \sum_{t=1}^{T-1} A_{ij,t} (w_{t,T}(u, h) - w_{t+1,T}(u, h)) \right| \leq W_T(u, h) \max_{1 \leq t \leq T} |B_{ij,t}|.$$

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

$$\begin{aligned}
\max_{1 \leq t \leq T} |B_{ij,t}| &\leq \max_{1 \leq t \leq T} \left| (\hat{\sigma}_i - \sigma_i) \sum_{s=1}^t \{Z_{is} - \bar{Z}_i\} \right| + \max_{1 \leq t \leq T} \left| (\hat{\sigma}_j - \sigma_j) \sum_{s=1}^t \{Z_{js} - \bar{Z}_j\} \right| \leq \\
&\leq \max_{1 \leq t \leq T} \left| (\hat{\sigma}_i - \sigma_i) \sum_{s=1}^t Z_{is} \right| + \max_{1 \leq t \leq T} \left| t(\hat{\sigma}_i - \sigma_i) \bar{Z}_i \right| + \\
&\quad + \max_{1 \leq t \leq T} \left| (\hat{\sigma}_j - \sigma_j) \sum_{s=1}^t Z_{js} \right| + \max_{1 \leq t \leq T} \left| t(\hat{\sigma}_j - \sigma_j) \bar{Z}_j \right| = \\
&= \max_{1 \leq t \leq T} \left| (\hat{\sigma}_i - \sigma_i) \sum_{s=1}^t Z_{is} \right| + T \left| \frac{1}{T} (\hat{\sigma}_i - \sigma_i) \sum_{s=1}^T Z_{is} \right| + \\
&\quad + \max_{1 \leq t \leq T} \left| (\hat{\sigma}_j - \sigma_j) \sum_{s=1}^t Z_{js} \right| + T \left| \frac{1}{T} (\hat{\sigma}_j - \sigma_j) \sum_{s=1}^T Z_{js} \right| \leq \\
&\leq 2 \max_{1 \leq t \leq T} \left| (\hat{\sigma}_i - \sigma_i) \sum_{s=1}^t Z_{is} \right| + 2 \max_{1 \leq t \leq T} \left| (\hat{\sigma}_j - \sigma_j) \sum_{s=1}^t Z_{js} \right|.
\end{aligned}$$

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, we get the following result:

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

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. Hence,

$$\max_{1 \leq t \leq T} |B_{ij,t}| = o_P(\rho_T \sqrt{T \log T})$$

and since as before, $\max_{(u,h) \in \mathcal{G}_T} W_T(u,h) = O(1/\sqrt{Th_{\min}})$, we have

$$\max_{(u,h) \in \mathcal{G}_T} |\phi'_{ij,T}(u,h) - \phi_{ij,T}(u,h)| = O(1/\sqrt{Th_{\min}}) \cdot o_P(\rho_T \sqrt{T \log T}) = o_P\left(\frac{\rho_T \log T}{\sqrt{h_{\min}}}\right). \quad (3.39)$$

Since by our assumption we have $\rho_T = O(\sqrt{h_{\min}}/\log T)$, by plugging (3.39) in (3.38) we can bound the second part in (3.36):

$$\max_{1 \leq i < j \leq n} \max_{(u,h) \in \mathcal{G}_T} \left| \frac{\phi'_{ij,T}(u,h)}{(\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{1/2}} - \frac{\phi_{ij,T}(u,h)}{(\hat{\sigma}_i^2 + \hat{\sigma}_j^2)^{1/2}} \right| = O_P(1) \cdot o_P\left(\frac{\rho_T \log T}{\sqrt{h_{\min}}}\right) = o_P\left(\frac{\rho_T \log T}{\sqrt{h_{\min}}}\right),$$

which together with (3.37) yields the following

$$|\Phi_{n,T} - \Phi'_{n,T}| = o_P(\rho_T \sqrt{\log T}) + o_P\left(\frac{\rho_T \log T}{\sqrt{h_{\min}}}\right) = o_P\left(\frac{\rho_T \log T}{\sqrt{h_{\min}}}\right). \quad (3.40)$$

Now we can apply Lemma A.6 to $\Phi_{n,T}$ and $\Phi'_{n,T}$ together with the results (3.40) derived above and (3.31) (anticoncentration result for the true Gaussian statistics $\Phi'_{n,T}$), which leads us to the desired conclusion

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\Phi_{n,T} \leq x) - \mathbb{P}(\Phi'_{n,T} \leq x)| = o(1).$$

□

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

$$\sup_{x \in \mathbb{R}} |\mathbb{P}(\Phi_{n,T} \leq x | \mathbf{X}_{it}) - \mathbb{P}(\Phi_{n,T} \leq x)| = ?? \quad (3.41)$$

Proof of Proposition A.9. This proof will be based on Lemma A.11 (Lemma 3.1 in Chernozhukov et al. (2013)).

We proceed in the same way as in the proof of Proposition A.5. 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 Assumption (C12). Moreover, for $k = 1, \dots, p$, we set

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

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

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

$$\Phi_{n,T} = \max_{1 \leq i < j \leq n} \max_{1 \leq k \leq p} \{Y'_{ij,2k-1} - \lambda(x_{k2}), Y'_{ij,2k} - \lambda(x_{k2})\}$$

where $(Y_{12,1}, \dots, Y_{(n-1)n,2p})^\top \in \mathbb{R}^{n(n-1)p}$ is a centered Gaussian random vector conditional on $\{\mathbf{X}_{it}\}_{i,t}$ with the following properties:

$$\mathbb{E}[Y_{ij,2k-1} | \mathbf{X}_{it}] = \mathbb{E}[Y_{ij,2k} | \mathbf{X}_{it}] = 0$$

and by the LIE

$$\mathbb{E}[Y_{ij,2k-1}] = \mathbb{E}[Y_{ij,2k}] = 0.$$

Now consider the following random value which we will need further to calculate the

entries of the covariance matrix:

$$\begin{aligned}
& \frac{\phi_{ij,T}(x_{k1}, x_{k2})}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2}} \frac{\phi_{i'j',T}(x_{k'1}, x_{k'2})}{\{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} = \\
&= \frac{\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) \{\hat{\sigma}_i(Z_{it} - \bar{Z}_i) - \hat{\sigma}_j(Z_{jt} - \bar{Z}_j)\} \sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) \{\hat{\sigma}_{i'}(Z_{i't} - \bar{Z}_{i'}) - \hat{\sigma}_{j'}(Z_{j't} - \bar{Z}_{j'})\}}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \\
&= \frac{\hat{\sigma}_i \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} - \\
&- \frac{\hat{\sigma}_j \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{jt} - \bar{Z}_j) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} - \\
&- \frac{\hat{\sigma}_i \hat{\sigma}_{j'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{j't} - \bar{Z}_{j'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} + \\
&+ \frac{\hat{\sigma}_j \hat{\sigma}_{j'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{jt} - \bar{Z}_j) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{j't} - \bar{Z}_{j'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}}.
\end{aligned}$$

Now remember that Z_{it} are independent of \mathbf{X}_{js} for all possible combinations of i, j, s and t . Hence, we write the unconditional and conditional expectations as

$$\begin{aligned}
& \mathbb{E} \left[\frac{\hat{\sigma}_i \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \right] = \\
&= \mathbb{E} \left[\frac{\hat{\sigma}_i \hat{\sigma}_{i'}}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \right] \mathbb{E} \left[\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right]
\end{aligned}$$

and

$$\begin{aligned}
& \mathbb{E} \left[\frac{\hat{\sigma}_i \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(u, h) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(u, h) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] = \\
&= \frac{\hat{\sigma}_i \hat{\sigma}_{i'}}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \mathbb{E} \left[\left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right) \right]
\end{aligned}$$

respectively. Consider two cases:

1. $i \neq i'$. Then

$$\begin{aligned}
& \mathbb{E} \left[\left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right) \right] = \\
&= \mathbb{E} \left[\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right] \mathbb{E} \left[\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right] = \\
&= 0
\end{aligned}$$

and

$$\begin{aligned}
& \mathbb{E} \left[\frac{\widehat{\sigma}_i \widehat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2} \{\widehat{\sigma}_{i'}^2 + \widehat{\sigma}_{j'}^2\}^{1/2}} \right] = \\
& = \mathbb{E} \left[\frac{\widehat{\sigma}_i \widehat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\widehat{\sigma}_i^2 + \widehat{\sigma}_j^2\}^{1/2} \{\widehat{\sigma}_{i'}^2 + \widehat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] = \\
& = 0.
\end{aligned}$$

2. $i = i'$. Then

$$\begin{aligned}
& \mathbb{E} \left[\left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{it} - \bar{Z}_i) \right) \right] = \\
& = \mathbb{E} \left[\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) (Z_{it} - \bar{Z}_i)^2 \right] + \\
& + \mathbb{E} \left[\sum_{t,s=1, t \neq s}^T w_{t,T}(x_{k1}, x_{k2}) w_{s,T}(x_{k'1}, x_{k'2}) (Z_{it} - \bar{Z}_i)(Z_{is} - \bar{Z}_i) \right] = \\
& = \sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) \mathbb{E} [Z_{it}^2] - \\
& - 2 \sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) \mathbb{E} [Z_{it} \bar{Z}_i] + \\
& + \sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) \mathbb{E} [\bar{Z}_i^2] + \\
& + \sum_{t,s=1, t \neq s}^T w_{t,T}(x_{k1}, x_{k2}) w_{s,T}(x_{k'1}, x_{k'2}) \mathbb{E} [Z_{it} Z_{is}] - \\
& - \sum_{t,s=1, t \neq s}^T w_{t,T}(x_{k1}, x_{k2}) w_{s,T}(x_{k'1}, x_{k'2}) \mathbb{E} [\bar{Z}_i Z_{is}] - \\
& - \sum_{t,s=1, t \neq s}^T w_{t,T}(x_{k1}, x_{k2}) w_{s,T}(x_{k'1}, x_{k'2}) \mathbb{E} [Z_{it} \bar{Z}_i] + \\
& + \sum_{t,s=1, t \neq s}^T w_{t,T}(x_{k1}, x_{k2}) w_{s,T}(x_{k'1}, x_{k'2}) \mathbb{E} [\bar{Z}_i^2].
\end{aligned}$$

Since $\{Z_{it}\}_t$ are i.i.d. standard normal random variables, we have obvious equalities: $\mathbb{E} [Z_{it}^2] = 1$, $\mathbb{E} [\bar{Z}_i^2] = 1/T$, $\mathbb{E} [Z_{it} Z_{is}] = \mathbb{E} [Z_{it}] \mathbb{E} [Z_{is}] = 0$ for $t \neq s$ and $\mathbb{E} [Z_{it} \bar{Z}_i] = 1/T$. Then,

$$\begin{aligned}
& \mathbb{E} \left[\left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{it} - \bar{Z}_i) \right) \right] = \\
& = \sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) - \frac{2}{T} \sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) + \\
& + \frac{1}{T} \sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) -
\end{aligned}$$

$$\begin{aligned}
& -\frac{2}{T} \sum_{t,s=1, t \neq s}^T w_{t,T}(x_{k1}, x_{k2}) w_{s,T}(x_{k'1}, x_{k'2}) + \\
& + \frac{1}{T} \sum_{t,s=1, t \neq s}^T w_{t,T}(x_{k1}, x_{k2}) w_{s,T}(x_{k'1}, x_{k'2}) = \\
& = \sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) w_{t,T}(x_{k'1}, x_{k'2}) - \frac{1}{T} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) \right).
\end{aligned}$$

For ease of notation, we denote the above value by $\mathcal{W}_{k,k',T}$. Then,

$$\begin{aligned}
& \mathbb{E} \left[\frac{\hat{\sigma}_i \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \right] = \\
& = \mathbb{E} \left[\frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_i^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \right] \cdot \mathcal{W}_{k,k',T}.
\end{aligned}$$

and

$$\begin{aligned}
& \mathbb{E} \left[\frac{\hat{\sigma}_i \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] = \\
& = \frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_i^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \cdot \mathcal{W}_{k,k',T}.
\end{aligned}$$

Now we are ready to calculate the elements of the unconditional and conditional covariance matrices. In what follows, we consider the case of $Y_{i,j,2k-1}$. The case $Y_{i,j,2k}$ is calculated analogously, the only difference being the sign.

$$\begin{aligned}
& \Sigma_{(ij,2k-1),(i'j',2k'-1)}^Y | \mathbf{X}_{it} := \mathbb{E}[Y_{ij,2k-1} Y_{i'j',2k'-1} | \mathbf{X}_{it}] - \mathbb{E}[Y_{ij,2k-1} | \mathbf{X}_{it}] \mathbb{E}[Y_{i'j',2k'-1} | \mathbf{X}_{it}] = \\
& = \mathbb{E} \left[\frac{\phi_{ij,T}(x_{k1}, x_{k2})}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2}} \frac{\phi_{i'j',T}(x_{k'1}, x_{k'2})}{\{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] = \\
& = \mathbb{E} \left[\frac{\hat{\sigma}_i \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] - \\
& - \mathbb{E} \left[\frac{\hat{\sigma}_j \hat{\sigma}_{i'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{jt} - \bar{Z}_j) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{i't} - \bar{Z}_{i'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] - \\
& - \mathbb{E} \left[\frac{\hat{\sigma}_i \hat{\sigma}_{j'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{it} - \bar{Z}_i) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{j't} - \bar{Z}_{j'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] + \\
& + \mathbb{E} \left[\frac{\hat{\sigma}_j \hat{\sigma}_{j'} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) (Z_{jt} - \bar{Z}_j) \right) \left(\sum_{t=1}^T w_{t,T}(x_{k'1}, x_{k'2}) (Z_{j't} - \bar{Z}_{j'}) \right)}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \middle| \mathbf{X}_{it} \right] =
\end{aligned}$$

$$= \begin{cases} 0, & \text{if } i \neq i', j' \text{ and } j \neq i', j'; \\ \mathcal{W}_{k,k',T}, & \text{if } i = i' \text{ and } j = j'; \\ \frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_i^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \mathcal{W}_{k,k',T}, & \text{if } i = i' \text{ but } j \neq j'; \\ \frac{\hat{\sigma}_j^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_j^2\}^{1/2}} \mathcal{W}_{k,k',T}, & \text{if } j = j' \text{ but } i \neq i'; \\ -\frac{\hat{\sigma}_j^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_j^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \mathcal{W}_{k,k',T}, & \text{if } j = i' \text{ but } i \neq j'; \\ -\frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_i^2\}^{1/2}} \mathcal{W}_{k,k',T}, & \text{if } i = j' \text{ but } j \neq i' \end{cases}$$

since $i < j$ and $i' < j'$. Similarly,

$$\begin{aligned} \Sigma_{(ij,2k-1),(i'j',2k'-1)}^Y &:= \mathbb{E}[Y_{ij,2k-1}Y_{i'j',2k'-1}] - \mathbb{E}[Y_{ij,2k-1}]\mathbb{E}[Y_{i'j',2k'-1}] = \\ &= \begin{cases} 0, & \text{if } i \neq i', j' \text{ and } j \neq i', j'; \\ \mathcal{W}_{k,k',T}, & \text{if } i = i' \text{ and } j = j'; \\ \mathbb{E} \left[\frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_i^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \right] \cdot \mathcal{W}_{k,k',T}, & \text{if } i = i' \text{ but } j \neq j'; \\ \mathbb{E} \left[\frac{\hat{\sigma}_j^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_j^2\}^{1/2}} \right] \cdot \mathcal{W}_{k,k',T}, & \text{if } j = j' \text{ but } i \neq i'; \\ -\mathbb{E} \left[\frac{\hat{\sigma}_j^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_j^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \right] \cdot \mathcal{W}_{k,k',T}, & \text{if } j = i' \text{ but } i \neq j'; \\ -\mathbb{E} \left[\frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_{i'}^2 + \hat{\sigma}_i^2\}^{1/2}} \right] \cdot \mathcal{W}_{k,k',T}, & \text{if } i = j' \text{ but } j \neq i'. \end{cases} \end{aligned}$$

In order to apply Lemma A.11, we need to check that there exist two constants such that the elements on the diagonal of the unconditional covariance matrix are bounded from below and above by these constants. Specifically,

$$\begin{aligned} \Sigma_{(ij,2k-1),(ij,2k-1)} &= \mathcal{W}_{k,k,T} = \\ &= \sum_{t=1}^T w_{t,T}^2(x_{k1}, x_{k2}) - \frac{1}{T} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) \right)^2 = \\ &= 1 - \frac{1}{T} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) \right)^2. \end{aligned}$$

Now remember that due to (3.16), for all $(u, h) \in \mathcal{G}_T$ we have

$$\left| \sum_{t=1}^T w_{t,T}(u, h) \right| \leq \sqrt{2Th + 2} \leq \sqrt{2Th_{\max} + 2}.$$

then we can bound the diagonal elements of the unconditional covariance matrix as follows:

$$1 - 2h_{\max} - 2/T \leq \Sigma_{(ij,2k-1),(ij,2k-1)} = 1 - \frac{1}{T} \left(\sum_{t=1}^T w_{t,T}(x_{k1}, x_{k2}) \right)^2 \leq 1.$$

Now we take $h_{\max} \leq 1/3$ (for example! anything smaller than $1/2$ will do), then for all $T \geq 7$ and for all $1 \leq i < j \leq n$ and $k \in \{1, \dots, p\}$ we have

$$0 < 1/21 \leq 1 - 2h_{\max} - 2/T \leq \Sigma_{(ij,2k-1),(ij,2k-1)} \leq 1.$$

Now we can calculate

$$\begin{aligned} \Delta_0 := & \max_{\substack{1 \leq i < j \leq n, \\ 1 \leq i' < j' < n, 1 \leq k \leq p}} \left\{ \left| \Sigma_{(ij, 2k-1), (i'j', 2k'-1)}^Y |\mathbf{X}_{it} - \Sigma_{(ij, 2k-1), (i'j', 2k'-1)}^Y| \right|, \right. \\ & \left| \Sigma_{(ij, 2k), (i'j', 2k'-1)}^Y |\mathbf{X}_{it} - \Sigma_{(ij, 2k), (i'j', 2k'-1)}^Y| \right|, \\ & \left| \Sigma_{(ij, 2k-1), (i'j', 2k')}^Y |\mathbf{X}_{it} - \Sigma_{(ij, 2k-1), (i'j', 2k')}^Y| \right|, \\ & \left. \left| \Sigma_{(ij, 2k-1), (i'j', 2k'-1)}^Y |\mathbf{X}_{it} - \Sigma_{(ij, 2k-1), (i'j', 2k'-1)}^Y| \right| \right\} = \\ & \max_{\substack{1 \leq i < j \leq n, \\ 1 \leq j' \leq n, j' \neq i, j' \neq j}} \left| \frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_i^2 + \hat{\sigma}_{j'}^2\}^{1/2}} - \mathbb{E} \left[\frac{\hat{\sigma}_i^2}{\{\hat{\sigma}_i^2 + \hat{\sigma}_j^2\}^{1/2} \{\hat{\sigma}_i^2 + \hat{\sigma}_{j'}^2\}^{1/2}} \right] \right| \cdot \max_{1 \leq k, k' \leq p} |\mathcal{W}_{k, k', T}| \end{aligned}$$

Here the first factor is $O_P(1)$ (since we are taking the maximum over the finite number of random values) and the second factor is $O(1)$ (definitely not converging to 0 as was shown in the calculations directly above). So the question: where am I going wrong? \square

Auxiliary results

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 α .

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*

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

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.10. *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 ϵ'_0 is an i.i.d. copy of ϵ_0 . Let $g(\xi_0) \in \mathcal{L}^q, q > 1$ and $\mathbb{E}[g(\xi_0)] = 0$. For $n \geq 1$ we have*

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

Lemma A.11. *Chernozhukov et al. (2013)* Let V and Y be centered Gaussian random vectors in \mathbb{R}^p with covariance matrices Σ^V and Σ^Y , respectively. Denote

$$\Delta_0 = \max_{1 \leq j, k \leq p} |\Sigma_{jk}^V - \Sigma_{jk}^Y|.$$

Suppose that there are some constants $0 < c_1 < C_1$ such that $c_1 \leq \Sigma_{jj}^Y \leq C_1$ for all $1 \leq j \leq p$. Then there exists a constant $C > 0$ depending only on c_1 and C_1 such that

$$\sup_{t \in \mathbb{R}} \left| \mathbb{P} \left(\max_{1 \leq j \leq p} V_j \leq t \right) - \mathbb{P} \left(\max_{1 \leq j \leq p} Y_j \leq t \right) \right| \leq C \Delta_0^{1/3} (1 \vee \log(p/\Delta_0))^{2/3}.$$

Proposition A.12. *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.12. 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.10 that says that for all $s \geq 1$ we have:

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

or, equivalently,

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

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

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

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

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

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

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

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

Proof of Proposition A.13. By Assumption (C6),

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

\square

Proposition A.14. *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.14. By Assumption (C7),

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

\square

Proposition A.15. *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) - (C10), we have that $\sum_{s=0}^{\infty} \delta_2(\Delta \mathbf{U}_i, s) < \infty$.

Proof of Proposition A.15. 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 η'_{i0} being an i.i.d. copy of η_{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.16. *Under Assumptions (C1) - (C10),*

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

Proof of Proposition A.16. 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,

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

$$= \frac{1}{T} \sum_{t=1}^T \sum_{s=0}^{\infty} \mathcal{P}_{i,t-s}(\Delta \mathbf{X}_{it} \Delta \varepsilon_{it}) = \sum_{s=0}^{\infty} \kappa_{i,s}^{\mathcal{P}}.$$

Thus, by Proposition A.15,

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

Since $\mathbb{E}\kappa_i = 0$ by Proposition A.14, 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

$$\begin{aligned} |\sqrt{T}(\hat{\beta}_i - \beta_i)| &\leq \left| \left(\frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \varepsilon_{it} \right| + \\ &\quad + \left| \left(\frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^{\top} \right)^{-1} \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta m_{it} \right|. \end{aligned} \tag{3.42}$$

First, we take a closer look at the second summand in (3.42). By the assumption in Theorem 2.2, $m_i(\cdot)$ is Lipschitz continuous, that is, $|\Delta m_{it}| = |m_i(\frac{t}{T}) - m_i(\frac{t-1}{T})| \leq C \frac{1}{T}$ for all $t \in \{1, \dots, T\}$ and some constant $C > 0$. Hence,

$$\begin{aligned} \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta m_{it} \right| &= \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \Delta \mathbf{H}_i(\mathcal{U}_{it}) \Delta m_{it} \right| \leq \\ &\leq \frac{1}{\sqrt{T}} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})| \cdot |\Delta m_{it}| \leq \\ &\leq \frac{1}{\sqrt{T}} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})| \cdot |\Delta m_{it}| \leq \frac{C}{\sqrt{T}} \cdot \frac{1}{T} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})|. \end{aligned} \tag{3.43}$$

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

$$\mathbb{P} \left(\frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| > a \right) \leq \frac{\mathbb{E} \left[\left(\frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| \right)^2 \right]}{a^2} \quad (3.44)$$

and

$$\begin{aligned} \mathbb{E} \left[\left(\frac{1}{T} \sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| \right)^2 \right] &= \frac{1}{T^2} \mathbb{E} \left[\left(\sum_{t=1}^T |\Delta H_{ij}(\mathcal{U}_{it})| \right)^2 \right] = \\ &= \frac{1}{T^2} \sum_{t=1}^T \mathbb{E} [\Delta H_{ij}^2(\mathcal{U}_{it})] + \frac{1}{T^2} \sum_{t=1, s=1, t \neq s}^T \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is})|]. \end{aligned} \quad (3.45)$$

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

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

and

$$0 \leq |\mathbb{E} [H_{ij}(\mathcal{U}_{it}) H_{ij}(\mathcal{U}_{is})]| \leq \mathbb{E} [|\Delta H_{ij}(\mathcal{U}_{it}) \Delta H_{ij}(\mathcal{U}_{is})|] \leq \mathbb{E} [\Delta H_{ij}^2(\mathcal{U}_{i0})]. \quad (3.46)$$

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 (3.45) can be bounded by $\frac{4}{T} \mathbb{E} [H_{ij}^2(\mathcal{U}_{i0})]$.

Now to the second summand in (3.45):

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

where in the last inequality we used (3.46). This means that the second summand in (3.45) 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 (3.45), 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 (3.44) 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

$$\frac{1}{T} \sum_{t=1}^T |\Delta \mathbf{H}_i(\mathcal{U}_{it})| = \frac{1}{T} \sum_{t=1}^T |\Delta \mathbf{X}_{it}| = O_P(1). \quad (3.47)$$

Similarly, by Proposition A.13 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,

$$\left| \left(\frac{1}{T} \sum_{t=1}^T \Delta \mathbf{X}_{it} \Delta \mathbf{X}_{it}^\top \right)^{-1} \right| = O_P(1). \quad (3.48)$$

Plugging (3.47) into (3.43) and combining it with (3.48), we get that the second summand in (3.42) is $O_P(1/\sqrt{T})$.

Furthermore, we can apply the Proposition A.16 together with (3.48) to get that the first summand in (3.42) is $O_P(1)$. The statement of the theorem follows. \square