

Jackknife and Analytical Bias Reduction for Nonlinear Panel Models

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Abstract

Fixed effects estimator of panel models can be severely biased because of the well-known incidental parameter problems. It is shown that such bias can be reduced as T grows with n by using an analytical bias correction or by using a panel jackknife. We describe both of these approaches. We consider asymptotics where n and T grow at the same rate as an approximation that allows us to compare bias properties. Under these asymptotics the bias corrected estimators are centered at the truth, whereas the fixed effects estimator is not. This asymptotic theory shows the bias reduction given by the analytical or jackknife correction.

1 Introduction

Panel data, consisting of observations across time for different individual economic agents, allows the possibility of controlling for unobserved individual heterogeneity. Such heterogeneity can be an important phenomenon, and failure to control for it can result in misleading inferences. This problem is particularly severe when the unobserved heterogeneity is correlated with explanatory variables. Such situation arises naturally when some of the explanatory variables are decision variables.

Models and methods of controlling for unobserved heterogeneity in linear models are well established. A partial list of references is Amemiya and MaCurdy (1986), Anderson and Hsiao (1982), Bhargava and Sargan (1983), Chamberlain (1982), Hausman and Taylor (1981), and Mundlak (1978). Controlling for unobserved heterogeneity is much more difficult in nonlinear models. Conditional maximum likelihood can be used in the rare instance that there is a sufficient statistic for the individual effect. In a few cases the individual effects can be removed by transformations. However, such cases are the exception rather than the rule. Generally it is not possible to find a transformation or a sufficient statistic to remove the individual effect.

One way of attempting to control for individual effects in nonlinear models is to treat each effect as a separate parameter to be estimated. Unfortunately, such estimators are typically subject to the incidental parameters problem noted by Neyman and Scott (1948). The estimators of the parameters of interest will be inconsistent if the number of individuals n goes to infinity while the number of time periods T is held fixed. This inconsistency occurs because only a finite number of observations are available to estimate each individual effect, so that the estimate of the individual effects are random, even in the limit, and this randomness contaminates the estimates of the parameters of interest.

Even in static models the incidental parameters bias can be severe when there are few observations, e.g. see Chamberlain (1982) and Abrevaya (1997). With many time series observations the bias in static models may be small, as in the Monte Carlo studies of Heckman (1981), although the bias is more pronounced in dynamic models, e.g. Heckman (1981) and Nickell (1981). This bias is so severe that estimators are even asymptotically biased if T grows at the same rate as n . This problem is exemplified by the results of Hahn and Kuersteiner (2001), who find asymptotic bias in fixed effects estimators of linear dynamic models under such asymptotics. We find here an analogous fixed effects asymptotic bias for nonlinear models.

The purpose of this note is to consider two approaches to reducing the bias from fixed effects estimation in nonlinear models. One approach is an analytical bias correction using the the bias formula obtained from an asymptotic expansion as T grows, similarly to Hahn and Kuersteiner (2001). This correction is obtained by generalizing a bias formula from Waterman et. al. (2000), estimating the bias term, and using this to correct the estimator. The second approach is based on a jackknife in the time series dimension of the panel. The idea here is to use the variation in the fixed effects estimators as a time period is dropped to form a bias corrected estimator. We do this by applying the Quenouilles (1956) and Tukey (1958) jackknife formula to the fixed effects estimators that drop each time period. This produces an estimator with properties similar to the analytical approach without explicit computation of the bias term.

We analyze the properties of both of these estimators under asymptotics as n and T grow at the same

rate. We find that both approaches yield an estimator that is asymptotically normal and centered at the truth. This large n , large T asymptotics provides a way to formalize the idea that the bias corrected estimators should be closer to the truth. As usual, the asymptotic theory is primarily intended as an approximation to the finite sample distribution of the estimator, here especially to its bias. Under our asymptotic approximation, bias correction does not increase the asymptotic variance. This suggests that the benefit of bias reduction substantially dominates any potential increase of variance.

We conjecture that the bias corrected estimators have an even stronger property, being asymptotically normal and correctly centered as long as T grows faster than $n^{1/3}$. This property would provide further justification for the bias corrected estimators. It would mean they have little bias even when T is allowed to be much smaller than n , a situation that is often encountered in practice.

In Section 2 we use some comparatively simple calculations to describe how the bias corrections work. Section 3 gives the form of the analytical bias correction. Section 4 describes the jackknife bias correction. Asymptotic theory is given in Section 5.

2 The Effect of Bias Correction

Some expansions can be used to motivate the bias results. Let θ denote an R -dimensional parameter vector of interest with true value θ_0 , and let $\theta_{[T]}$ denote the limiting value, as $n \rightarrow \infty$ with T fixed, of a fixed effects estimator $\hat{\theta}$ of θ_0 . A consequence of the incidental parameters problem is that typically $\theta_{[T]} \neq \theta_0$. Note that the bias should be small for large enough T , i.e., $\lim_{T \rightarrow \infty} \theta_{[T]} = \theta_0$. Indeed, it can be shown that in some generality,

$$\theta_{[T]} = \theta_0 + \frac{\beta}{T} + O\left(\frac{1}{T^2}\right).$$

To see the resultant bias of the fixed effects estimator, suppose that as $n/T \rightarrow \rho$ it is the case that $\sqrt{nT}(\hat{\theta} - \theta_{[T]}) \xrightarrow{d} N(0, \Omega)$. Then

$$\sqrt{nT}(\hat{\theta} - \theta_0) = \sqrt{nT}(\hat{\theta} - \theta_{[T]}) + \sqrt{nT}\frac{\beta}{T} + O\left(\sqrt{\frac{n}{T^3}}\right) \xrightarrow{d} N(\beta\sqrt{\rho}, \Omega).$$

Thus we see that even when T grows as fast as n the fixed effects estimator has asymptotic bias, with its limit distribution not being centered at zero.

The first approach to bias correction consists of estimating β by some $\hat{\beta}$ and then forming a bias corrected estimator

$$\hat{\hat{\theta}} \equiv \hat{\theta} - \frac{\hat{\beta}}{T}, \tag{1}$$

This estimator should be less biased than the fixed effects estimator $\hat{\theta}$. Specifically, when n and T grow at the same rate as before and $\hat{\beta} \xrightarrow{p} \beta$,

$$\sqrt{nT}(\hat{\hat{\theta}} - \theta_0) = \sqrt{nT}(\hat{\theta} - \theta_{[T]}) - \sqrt{\frac{n}{T}}(\hat{\beta} - \beta) + O\left(\sqrt{\frac{n}{T^3}}\right) \xrightarrow{d} N(0, \Omega), \tag{2}$$

so that the use of $\hat{\hat{\theta}}$ eliminates that bias. Thus, all we need to do is find a consistent estimator of β . We do this by plugging in consistent estimators of components of the formula for β . We show that equation (2) holds for the $\hat{\beta}$ we use.

The panel jackknife provides an alternative approach that avoids estimation of β . To describe it, let $\widehat{\theta}_{(t)}$ be the fixed effects estimator based on the subsample excluding the observations of the t th period. The jackknife estimator is

$$\widetilde{\theta} \equiv T\widehat{\theta} - (T-1) \sum_{t=1}^T \widehat{\theta}_{(t)}/T \quad (3)$$

To explain the bias correction from this estimator it is helpful to consider a further expansion

$$\theta_{[T]} = \theta + \frac{\beta}{T} + \frac{\gamma}{T^2} + O\left(\frac{1}{T^3}\right). \quad (4)$$

To see how the jackknife affects the bias we can consider the limit of $\widetilde{\theta}$ for fixed T and see how it changes with T . The estimator $\widetilde{\theta}$ will converge in probability to

$$\begin{aligned} T\theta_{[T]} - (T-1)\theta_{[T-1]} &= \theta + \left(\frac{1}{T} - \frac{1}{T-1}\right)\gamma + O\left(\frac{1}{T^2}\right) \\ &= \theta - \frac{1}{T(T-1)}\gamma + O\left(\frac{1}{T^2}\right) = \theta + O\left(\frac{1}{T^2}\right). \end{aligned}$$

Thus we see that the bias of the jackknife corrected value is of order $1/T^2$. Furthermore, as shown below, the jackknife estimator $\widetilde{\theta}$ has the same property as $\widehat{\theta}$ under the large n and T approximation, namely $\sqrt{nT}(\widetilde{\theta} - \theta_0) \xrightarrow{d} N(0, \Omega)$.

Our conjecture, that the analytical bias correction works if T grows faster than $n^{1/3}$, can also be explained by an analogous expansion. Suppose now that $\widehat{\beta}$ is \sqrt{nT} consistent, so that $\widehat{\beta} = \beta + O(1/\sqrt{nT})$. Then expanding as in equation (2) gives

$$\sqrt{nT}(\widehat{\theta} - \theta_0) = \sqrt{nT}(\widehat{\theta} - \theta_{[T]}) - \sqrt{nT}(\widehat{\beta} - \beta)/T + O\left(\sqrt{\frac{n}{T^3}}\right) \xrightarrow{d} N(0, \Omega).$$

Although we do not verify this conjecture here, this expansion strongly suggests that the bias correction removes asymptotic bias under the condition that T grows at least as fast as $n^{1/3}$. This conjecture suggests that the bias corrected fixed effects estimator should be approximately unbiased when T is much smaller than n .

3 Analytical Bias Correction

We first describe the model we consider. Let the data observations be denoted by x_{it} , ($t = 1, \dots, T$; $i = 1, \dots, n$). We assume that these observations are mutually independent and that there is a density function $f(x; \theta, \alpha)$ such that

$$x_{it} \sim f(\cdot; \theta_0, \alpha_{i0}), \quad (t = 1, \dots, T; i = 1, \dots, n)$$

We assume that $\dim(\theta) = R \geq 1$ and that $\dim(\alpha) = 1$. Thus, here $X_{iT} \equiv (x_{i1}, \dots, x_{iT})$ is i.i.d. over t , while the distribution of observations across i differs only due to α_{i0} . The fixed effects estimator is given

by

$$\begin{aligned}\hat{\theta} &= \operatorname{argmax}_{\theta} \sum_{i=1}^n q(X_{iT}, \theta), \\ q(X_{iT}, \theta) &\equiv \sum_{t=1}^T \log f(x_{it}; \theta, \hat{\alpha}_i(\theta)), \\ \hat{\alpha}_i(\theta) &\equiv \operatorname{argmax}_{\alpha_i} \sum_{t=1}^T \log f(x_{it}; \theta, \alpha_i).\end{aligned}$$

By the usual results for extremum estimators, for fixed T the estimator $\hat{\theta}$ will be consistent for

$$\theta_{[T]} = \operatorname{argmax}_{\theta} E[q(X_{iT}, \theta)] = \operatorname{argmax}_{\theta} E[\log f(x_{it}; \theta, \hat{\alpha}_i(\theta))].$$

The incidental parameters problem, with $\theta_{[T]} \neq \theta_0$, arises because of randomness of $\hat{\alpha}_i(\theta)$. If $\hat{\alpha}_i(\theta)$ were replaced by $\alpha_i(\theta) \equiv \operatorname{argmax}_{\alpha_i} E[\log f(x_{it}; \theta, \alpha)]$, i.e. if the sum over T were replaced by the expectation, then it is straightforward to show that $\theta_{[T]} = \theta_0$.

To describe the analytical bias correction, we need to define some additional derivatives. Let

$$\begin{aligned}s_{\theta}(x_{it}; \theta, \alpha_i) &\equiv \frac{\partial}{\partial \theta} \log f(x_{it}; \theta, \alpha_i), & V(x_{it}; \theta, \alpha_i) &\equiv \frac{\partial}{\partial \alpha_i} \log f(x_{it}; \theta, \alpha_i), \\ V_2(x_{it}; \theta, \alpha_i) &\equiv f(x_{it}; \theta, \alpha_i)^{-1} \frac{\partial^2}{\partial \alpha_i^2} f(x_{it}; \theta, \alpha_i).\end{aligned}$$

Also, for the fixed effect estimator $\hat{\theta}$ and $\hat{\alpha}_1, \dots, \hat{\alpha}_n$, let

$$\begin{aligned}\hat{s}_{it} &\equiv s_{\theta}(x_{it}; \hat{\theta}, \hat{\alpha}_i), & \hat{V}_{it} &\equiv V(x_{it}; \hat{\theta}, \hat{\alpha}_i), & \hat{V}_{2it} &\equiv V_2(x_{it}; \hat{\theta}, \hat{\alpha}_i), \\ \hat{U}_{it} &\equiv \hat{s}_{it} - \hat{V}_{it} \left(\frac{\sum_{u=1}^T \hat{V}_{it} \hat{s}_{it}}{\sum_{u=1}^T \hat{V}_{it}^2} \right) \Big/ \left(\frac{\sum_{u=1}^T \hat{V}_{it}^2}{\sum_{u=1}^T \hat{V}_{it}^2} \right).\end{aligned}$$

Then the bias term estimator is

$$\hat{\beta} = -\frac{1}{2} \left(\frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T \hat{U}_{it} \hat{U}'_{it} \right)^{-1} \left(\frac{1}{n} \sum_{i=1}^n \left(\frac{\sum_{t=1}^T \hat{U}_{it} \hat{V}_{2it}}{\sum_{t=1}^T \hat{V}_{it}^2} \right) \right).$$

The bias corrected estimator can then be formed as in equation (1).

This object can be interpreted as local bias correction for random parameters. Note that $1/\sum_{t=1}^T \hat{V}_{it}^2$ is an information approximation to the variance of $\hat{\alpha}_i$. From Chesher (1984), we know that the score for a random α_i with variance $1/\sum_{t=1}^T \hat{V}_{it}^2$ would be

$$\hat{D}_{it} = \frac{1}{2} \left(\frac{1}{\sum_{t=1}^T \hat{V}_{it}^2} \right) \hat{V}_{2it}.$$

Applying the Kiefer and Skoog (1984) general formula for local bias of the MLE under misspecification to the special case of random parameters then gives $\hat{\beta}$. Thus we see that $\hat{\beta}$ is an estimator of the local bias that results from random parameters, and so bias correcting with it makes the bias go away faster.

4 Jackknife Bias Correction

The jackknife bias correction is constructed by re-estimating θ while dropping each time series observation in turn. To describe it, for a given θ let the fixed effect estimator of α_i from all observations but the t^{th} be given by

$$\hat{\alpha}_{i(t)}(\theta) \equiv \operatorname{argmax}_{\alpha} \sum_{s \neq t, s=1}^T \log f(x_{is}; \theta, \alpha).$$

The fixed effects estimator of θ excluding time period t is then given by

$$\hat{\theta}_{(t)} = \operatorname{argmax}_{\theta} \sum_{i=1}^n \sum_{s \neq t} \log f(x_{is}; \theta, \hat{\alpha}_{i(t)}(\theta))$$

The jackknife bias corrected estimator is then as given in equation (3).

The jackknife bias correction requires recomputing the estimator T times, but avoids the computation of higher-order derivatives needed for the analytic bias correction. The fixed effects estimator $\hat{\theta}, \hat{\alpha}_1, \dots, \hat{\alpha}_n$ provide a good starting value for these computations. Starting at the fixed effects and iterating towards $\hat{\theta}_{(t)}$ should be straightforward computationally, requiring no additional software. Thus, the jackknife provides a straightforward approach to bias correction.

A simple example may serve to illustrate this jackknife bias correction. Suppose

$$x_{it} \stackrel{i.i.d.}{\sim} N(\alpha_{i0}, \theta_0) \quad t = 1, \dots, T : i = 1, \dots, n$$

so that

$$\log f(x_{it}; \theta, \alpha_i) = C - \frac{1}{2} \log \theta - \frac{(x_{it} - \alpha_i)^2}{2\theta}$$

The fixed effects MLE is

$$\begin{aligned} \hat{\alpha}_i &= \frac{1}{T} \sum_{t=1}^T x_{it} \equiv \bar{x}_i, \\ \hat{\theta} &= \frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T (x_{it} - \hat{\alpha}_i)^2 = \frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T (x_{it} - \bar{x}_i)^2 \end{aligned}$$

As is well known, $E[\hat{\theta}] = \frac{T-1}{T} \theta_0$. It is straightforward to show that

$$\tilde{\theta} \equiv T\hat{\theta} - \frac{T-1}{T} \sum_{t=1}^T \hat{\theta}_{(t)} = \frac{1}{n(T-1)} \sum_{i=1}^n \sum_{t=1}^T (x_{it} - \bar{x}_i)^2 = \frac{T}{(T-1)} \hat{\theta}.$$

In this example, the jackknife bias corrected estimator is unbiased.

5 Asymptotic Theory

The first result we consider is the asymptotic distribution of the fixed effects MLE when $n, T \rightarrow \infty$ at the same rate. We impose the following conditions:

Condition 1 $n, T \rightarrow \infty$ such that $\frac{n}{T} \rightarrow \rho$, where $0 < \rho < \infty$.

Condition 2 (i) The function $\ln f(\cdot; \theta, \alpha)$ is continuous in $(\theta, \alpha) \in \Upsilon$; (ii) The parameter space Υ is compact; (iii) There exists a function $M(x_{it})$ such that $|\log f(x_{it}; \theta, \alpha_i)| \leq M(x_{it})$, $\left| \frac{\partial \log f(x_{it}; \theta, \alpha_i)}{\partial(\theta, \alpha_i)} \right| \leq M(x_{it})$, and $\sup_i E \left[M(x_{it})^{33} \right] < \infty$.

Condition 3 For each $\eta > 0$, $\inf_i \left[G_{(i)}(\theta_0, \alpha_{i0}) - \sup_{\{(\theta, \alpha): |(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta\}} G_{(i)}(\theta, \alpha) \right] > 0$, where

$$\widehat{G}_{(i)}(\theta, \alpha_i) \equiv T^{-1} \sum_{t=1}^T \log f(x_{it}; \theta, \alpha_i) \equiv T^{-1} \sum_{t=1}^T g(x_{it}; \theta, \alpha_i), \quad G_{(i)}(\theta, \alpha_i) \equiv E[\log f(x_{it}; \theta, \alpha_i)]$$

Let

$$\begin{aligned} U_{it} &\equiv s_\theta(x_{it}; \theta_0, \alpha_{i0}) - \rho_{i0} \cdot V_{it}, & V_{it} &\equiv V(x_{it}; \theta_0, \alpha_{i0}), \\ \rho_{i0} &\equiv E[s_\theta(x_{it}; \theta_0, \alpha_{i0})V_{it}] / E[V_{it}^2], & V_{2it} &\equiv V_2(x_{it}; \theta_0, \alpha_{i0}), \\ \mathcal{I}_i &\equiv E[U_{it}U'_{it}]. \end{aligned}$$

Condition 4 (i) There exists some $M(x_{it})$ such that

$$\left| \frac{\partial^{m_1+m_2} \log f(x_{it}; \theta, \alpha_i)}{\partial \theta^{m_1} \partial \alpha_i^{m_2}} \right| \leq M(x_{it}) \quad 0 \leq m_1 + m_2 \leq 1, \dots, 6$$

and $\sup_i E \left[M(x_{it})^Q \right] < \infty$ for some $Q > 64$; (ii) $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n E[U_{it}U'_{it}] > 0$; (iii) $\min_i E[V_i^2] > 0$.

Under these conditions we can obtain the asymptotic distribution of the fixed effects MLE as n and T grow at the same rate.

Theorem 1 Under Conditions 1, 2, 3, and 4, we have

$$\sqrt{nT}(\widehat{\theta} - \theta_0) \rightarrow N \left(\beta \sqrt{\rho}, \left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right)^{-1} \right)$$

where

$$\beta \equiv -\frac{1}{2} \left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right)^{-1} \left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \frac{E[V_{2it}U_{it}]}{E[V_{it}^2]} \right)$$

Proof. See Appendix B. ■

Waterman et al (2000) establish the asymptotic distribution of $\sqrt{nT}(\widehat{\theta} - \theta_0)$ assuming that $\widehat{\theta}$ and $\widehat{\alpha}_i(\widehat{\theta})$ are consistent for θ_0 and α_{i0} , and $\dim(\theta) = 1$. We show that $\widehat{\theta}$ and $\widehat{\alpha}_i$ are consistent for θ_0 and α_{i0} : Theorems 4 and 5 in Appendix A establish such consistency under Conditions 1, 2, and 3. We also allow for $\dim(\theta)$ to be bigger than 1.

Next, we show that the analytic bias correction eliminates the asymptotic bias term.

Theorem 2 Under Conditions 1, 2, 3, and 4, we have $\widehat{\beta} = \beta + o_p(1)$

Proof. See Appendix E. ■

Corollary 1 *Suppose that Conditions 1, 2, 3, and 4 hold. Let*

$$\widehat{\theta} \equiv \widehat{\theta} - \frac{1}{T}\widehat{\beta}$$

We then have

$$\sqrt{nT} \left(\widehat{\theta} - \theta_0 \right) \rightarrow N \left(0, \left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right)^{-1} \right).$$

Proof. The conclusion easily follows from

$$\sqrt{nT} \cdot \frac{1}{T}\widehat{\beta} = \sqrt{\frac{n}{T}}\widehat{\beta} = \beta\sqrt{\rho} + o_p(1)$$

■

Remark 1 *By equation (22) in Appendix E, we can see that $\left(\frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T \widehat{U}_{it}\widehat{U}'_{it} \right)^{-1}$ is a consistent estimator of the asymptotic variance $\left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right)^{-1}$ of $\sqrt{nT} \left(\widehat{\theta} - \theta_0 \right)$.*

To compare our result with Waterman et. al. (2000), let $\widetilde{V}_{it} \equiv (V_{it}, V_{2it})'$ and

$$\begin{aligned} \widetilde{\rho}_i &\equiv \left(E \left[\widetilde{V}_{it}\widetilde{V}'_{it} \right] \right)^{-1} E \left[\widetilde{V}_{it}U_{it} \right], \\ U^*(x_{it}; \theta, \alpha) &= s_\theta(x_{it}; \theta, \alpha_i) - (V(x_{it}; \theta, \alpha_i), V_2(x_{it}; \theta, \alpha_i)) \widetilde{\rho}_i. \end{aligned}$$

They showed the same conclusion as above with scalar θ for a nonfeasible estimator obtained by solving

$$\sum_{i=1}^n \sum_{t=1}^T U_i^*(x_{it}; \theta, \alpha) = 0, \quad \sum_{t=1}^T V_i(x_{it}; \theta, \alpha_i) = 0.$$

This estimator is not feasible because $\widetilde{\rho}_i$ is unknown. In contrast, our result shows that a feasible bias corrected estimator satisfies the conclusion.

The jackknife bias corrected estimator has the same limiting distribution as the analytic bias corrected estimator. In order to simplify the proof we only show this for scalar θ .

Theorem 3 *Suppose that $\dim(\theta) = 1$. Also suppose that Conditions 1, 2, 3, and 4, hold. We then have*

$$\sqrt{nT} \left(\widetilde{\theta} - \theta_0 \right) \rightarrow N \left(0, \frac{1}{\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n E[U_i^2]} \right).$$

Proof. See Appendix I. ■

6 Summary

We developed two methods of reducing bias of the fixed effects maximum likelihood estimator for nonlinear panel models with fixed effects, an analytic method and an automatic method based on a time series jackknife. It might be of interest consider the extra term γ in the expansion of equation (4), and seek to remove this term by analytical and/or jackknife methods. We expect that such could be done under yet another alternative approximation where n and T grow to infinity at a different rate. Such analysis is expected to be substantially complicated, and we leave it to future research.

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Appendix

A Consistency

Throughout this section, we assume that Conditions 1, 2, and 3 hold.

Lemma 1 *Assume that W_t are iid with $E[W_t] = 0$ and $E[W_t^{2k}] < \infty$. Then,*

$$E \left[\left(\sum_{t=1}^T W_t \right)^{2k} \right] = C(k)T^k + o(T^k)$$

for some constant $C(k)$.

Proof. By adopting an argument in the proof of Lemma 5.1 in Lahiri (1992), we have

$$E \left[\left(\sum_{t=1}^T W_t \right)^{2k} \right] = \sum_{j=1}^{2k} \sum_{\alpha} C(\alpha_1, \dots, \alpha_j) \sum_I E \left[\prod_{s=1}^j W_{t_s}^{\alpha_s} \right], \quad (5)$$

where for each fixed $j \in \{1, \dots, 2k\}$, \sum_{α} extends over all j -tuples of positive integers $(\alpha_1, \dots, \alpha_j)$ such that $\alpha_1 + \dots + \alpha_j = 2k$ and \sum_I extends over all ordered j -tuples (t_1, \dots, t_j) of integers such that $1 \leq t_j \leq T$. Also, $C(\alpha_1, \dots, \alpha_j)$ stands for a bounded constant. Note, that if $j > k$ then at least one of the indices $\alpha_j = 1$. By independence and the fact that $E[W_t] = 0$ it follows that $E \left[\prod_{s=1}^j W_{t_s}^{\alpha_s} \right] = 0$ whenever $j > k$. This shows that $\left| E \left[\left(\sum_{t=1}^T W_t \right)^{2k} \right] \right| \leq C(k)T^k \cdot E[W_t^{2k}]$ for some constant $C(k)$. ■

Lemma 2 *Suppose that, for each i , $\{\xi_{it}, t = 1, 2, \dots\}$ is a sequence of zero mean i.i.d. random variables. We assume that $\{\xi_{it}, t = 1, 2, 3\}$ are independent across i . We also assume that $\max_i E[|\xi_{it}|^{16}] < \infty$. Finally, we assume that $n = O(T)$. We then have*

$$\max_i \Pr \left[\left| \frac{1}{T} \sum_{t=1}^T \xi_{it} \right| > \eta \right] = o(T^{-2})$$

for every $\eta > 0$.

Proof. Using Lemma 1, we obtain

$$E \left[\left| \sum_{t=1}^T \xi_{it} \right|^{16} \right] \leq CT^8 \cdot E[\xi_{it}^{16}],$$

where $C > 0$ is a constant. Therefore, we have

$$T^2 \Pr \left[\left| \frac{1}{T} \sum_{t=1}^T \xi_{it} \right| > \eta \right] \leq T^2 \frac{CT^8}{T^{16}\eta^{16}} E[\xi_{it}^{16}]$$

or

$$\max_i T^2 \Pr \left[\left| \frac{1}{T} \sum_{t=1}^T \xi_{it} \right| > \eta \right] \leq \frac{C}{T^6\eta^{16}} \max_i E[\xi_{it}^{16}] = o(1).$$

■

Lemma 3 Suppose that Conditions 1 and 2 hold. We then have for all $\eta > 0$ that

$$\Pr \left[\max_{1 \leq i \leq n} \sup_{(\theta, \alpha)} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| \geq \eta \right] = o(T^{-1})$$

Proof. Let $\eta > 0$ be given. We note that

$$\Pr \left[\max_{1 \leq i \leq n} \sup_{(\theta, \alpha)} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| \geq \eta \right] \leq \sum_{i=1}^n \Pr \left[\sup_{(\theta, \alpha)} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| \geq \eta \right]. \quad (6)$$

Let $\varepsilon > 0$ be chosen such that $2\varepsilon \max_i E[M(x_{it})] < \frac{\eta}{3}$. Divide Υ into subsets $\Upsilon_1, \Upsilon_2, \dots, \Upsilon_{M(\varepsilon)}$ such that $|(\theta, \alpha) - (\theta', \alpha')| < \varepsilon$ whenever (θ, α) and (θ', α') are in the same subset. Let (θ_j, α_j) denote *some* point in Υ_j for each j . Then,

$$\sup_{(\theta, \alpha)} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| = \max_j \sup_{\Upsilon_j} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right|,$$

and therefore

$$\Pr \left[\sup_{(\theta, \alpha)} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| > \eta \right] \leq \sum_{j=1}^{M(\varepsilon)} \Pr \left[\sup_{\Upsilon_j} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| > \eta \right] \quad (7)$$

For $(\theta, \alpha) \in \Upsilon_j$, we have

$$\left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| \leq \left| \widehat{G}_{(i)}(\theta_j, \alpha_j) - G_{(i)}(\theta_j, \alpha_j) \right| + \frac{\varepsilon}{T} \left| \sum_{t=1}^T (M(x_{it}) - E[M(x_{it})]) \right| + 2\varepsilon E[M(x_{it})]$$

Then,

$$\begin{aligned} \Pr \left[\sup_{\Upsilon_j} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| > \eta \right] &\leq \Pr \left[\left| \widehat{G}_{(i)}(\theta_j, \alpha_j) - G_{(i)}(\theta_j, \alpha_j) \right| > \frac{\eta}{3} \right] \\ &\quad + \Pr \left[\frac{1}{T} \left| \sum_{t=1}^T (M(x_{it}) - E[M(x_{it})]) \right| > \frac{\eta}{3\varepsilon} \right] \\ &= o(T^{-2}) \end{aligned} \quad (8)$$

by Lemma 2. Combining (6), (7), (8), and $n = O(T)$, we obtain the desired conclusion. ■

Theorem 4 Under Conditions 1, 2, and 3, $\Pr \left[\left| \widehat{\theta} - \theta_0 \right| \geq \eta \right] = o(T^{-1})$ for every $\eta > 0$.

Proof. Let η be given, and let $\varepsilon \equiv \inf_i \left[G_{(i)}(\theta_0, \alpha_{i0}) - \sup_{\{(\theta, \alpha): |(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta\}} G_{(i)}(\theta, \alpha) \right] > 0$. With probability equal to $1 - o\left(\frac{1}{T}\right)$, we have

$$\begin{aligned} \max_{|\theta - \theta_0| > \eta, \alpha_1, \dots, \alpha_n} n^{-1} \sum_{i=1}^n \widehat{G}_{(i)}(\theta, \alpha_i) &\leq \max_{|(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta} n^{-1} \sum_{i=1}^n \widehat{G}_{(i)}(\theta, \alpha_i) \\ &< \max_{|(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta} n^{-1} \sum_{i=1}^n G_{(i)}(\theta, \alpha_i) + \frac{1}{3}\varepsilon \\ &< n^{-1} \sum_{i=1}^n G_{(i)}(\theta_0, \alpha_{i0}) - \frac{2}{3}\varepsilon \\ &< n^{-1} \sum_{i=1}^n \widehat{G}_{(i)}(\theta_0, \alpha_{i0}) - \frac{1}{3}\varepsilon, \end{aligned}$$

where the second and fourth inequalities are based on Lemma 3. Because

$$\max_{\theta, \alpha_1, \dots, \alpha_n} n^{-1} \sum_{i=1}^n \widehat{G}_{(i)}(\theta, \alpha_i) \geq n^{-1} \sum_{i=1}^n \widehat{G}_{(i)}(\theta_0, \alpha_{i0})$$

by definition, we can conclude that $\Pr \left[\left| \widehat{\theta} - \theta_0 \right| \geq \eta \right] = o\left(\frac{1}{T}\right)$. ■

Theorem 5 *Under Conditions 1, 2, and 3,*

$$T \Pr \left[\max_{1 \leq i \leq n} |\widehat{\alpha}_i - \alpha_{i0}| \geq \eta \right] = o(1)$$

Proof. We first prove that

$$T \Pr \left[\max_{1 \leq i \leq n} \sup_{\alpha} \left| \widehat{G}_{(i)}(\widehat{\theta}, \alpha) - G_{(i)}(\theta_0, \alpha) \right| \geq \eta \right] = o(1) \quad (9)$$

for every $\eta > 0$. Note that

$$\begin{aligned} & \max_{1 \leq i \leq n} \sup_{\alpha} \left| \widehat{G}_{(i)}(\widehat{\theta}, \alpha) - G_{(i)}(\widehat{\theta}, \alpha) \right| \\ & \leq \max_{1 \leq i \leq n} \sup_{\alpha} \left| \widehat{G}_{(i)}(\widehat{\theta}, \alpha) - G_{(i)}(\widehat{\theta}, \alpha) \right| + \max_{1 \leq i \leq n} \sup_{\alpha} \left| G_{(i)}(\widehat{\theta}, \alpha) - G_{(i)}(\theta_0, \alpha) \right| \\ & \leq \max_{1 \leq i \leq n} \sup_{(\theta, \alpha)} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| + \max_{1 \leq i \leq n} E[M(x_{it})] \cdot \left| \widehat{\theta} - \theta_0 \right|. \end{aligned}$$

Therefore,

$$\begin{aligned} T \Pr \left[\max_{1 \leq i \leq n} \sup_{\alpha} \left| \widehat{G}_{(i)}(\widehat{\theta}, \alpha) - G_{(i)}(\theta_0, \alpha) \right| \geq \eta \right] & \leq T \Pr \left[\max_{1 \leq i \leq n} \sup_{(\theta, \alpha)} \left| \widehat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| \geq \frac{\eta}{2} \right] \\ & \quad + T \Pr \left[\left| \widehat{\theta} - \theta_0 \right| \geq \frac{\eta}{2(1 + \max_{1 \leq i \leq n} E[M(x_{it})])} \right] \\ & = o(1) \end{aligned}$$

by Lemma 3 and Theorem 4.

We now get back to the proof of Theorem 5. It suffices to prove that

$$T \Pr \left[\max_{1 \leq i \leq n} |\widehat{\alpha}_i - \alpha_{i0}| \geq \eta \right] = o(1)$$

for every $\eta > 0$. Let η be given, and let $\varepsilon \equiv \inf_i \left[G_{(i)}(\theta_0, \alpha_{i0}) - \sup_{\{\alpha_i: |\alpha_i - \alpha_{i0}| > \eta\}} G_{(i)}(\theta_0, \alpha_i) \right] > 0$. Condition on the event $\left\{ \max_{1 \leq i \leq n} \sup_{\alpha} \left| \widehat{G}_{(i)}(\widehat{\theta}, \alpha) - G_{(i)}(\theta_0, \alpha) \right| \leq \frac{1}{3}\varepsilon \right\}$, which has a probability equal to $1 - o\left(\frac{1}{T}\right)$ by (9). We then have

$$\max_{|\alpha_i - \alpha_{i0}| > \eta} \widehat{G}_{(i)}(\widehat{\theta}, \alpha_i) < \max_{|\alpha_i - \alpha_{i0}| > \eta} G_{(i)}(\theta_0, \alpha_i) + \frac{1}{3}\varepsilon < G_{(i)}(\theta_0, \alpha_{i0}) - \frac{2}{3}\varepsilon < \widehat{G}_{(i)}(\widehat{\theta}, \alpha_{i0}) - \frac{1}{3}\varepsilon$$

This is inconsistent with $\widehat{G}_{(i)}(\widehat{\theta}, \widehat{\alpha}_i) \geq \widehat{G}_{(i)}(\widehat{\theta}, \alpha_{i0})$, and therefore, $|\widehat{\alpha}_i - \alpha_{i0}| \leq \eta$ for every i . ■

B Proof of Theorem 1

We can see that the MLE $\hat{\theta}$ also solves

$$0 = \sum_{i=1}^n \sum_{t=1}^T U(x_{it}; \hat{\theta}, \hat{\alpha}_i(\hat{\theta})).$$

Let $F \equiv (F_1, \dots, F_n)$ denote the collection of distribution functions. Let $\hat{F} \equiv (\hat{F}_1, \dots, \hat{F}_n)$, where \hat{F}_i denotes the empirical distribution function for the stratum i . Define $F(\epsilon) \equiv F + \epsilon\sqrt{T}(\hat{F} - F)$ for $\epsilon \in [0, T^{-1/2}]$. For each fixed θ and ϵ , let $\alpha_i(\theta, F_i(\epsilon))$ be the solution to the estimating equation

$$0 = \int V_i[\theta, \alpha_i(\theta, F_i(\epsilon))] dF_i(\epsilon),$$

and let $\theta(F(\epsilon))$ be the solution to the estimating equation

$$0 = \sum_{i=1}^n \int U_i(x_{it}; \theta(F(\epsilon)), \alpha_i(\theta(F(\epsilon)), F_i(\epsilon))) dF_i(\epsilon).$$

By Taylor series expansion, we have

$$\theta(\hat{F}) - \theta(F) = \frac{1}{\sqrt{T}}\theta^\epsilon(0) + \frac{1}{2}\left(\frac{1}{\sqrt{T}}\right)^2\theta^{\epsilon\epsilon}(0) + \frac{1}{6}\left(\frac{1}{\sqrt{T}}\right)^3\theta^{\epsilon\epsilon\epsilon}(\tilde{\epsilon}),$$

where $\theta^\epsilon(\epsilon) \equiv d\theta(F(\epsilon))/d\epsilon$, $\theta^{\epsilon\epsilon}(\epsilon) \equiv d^2\theta(F(\epsilon))/d\epsilon^2, \dots$, and $\tilde{\epsilon}$ is somewhere in between 0 and $T^{-1/2}$. We therefore have

$$\sqrt{nT}\left(\theta(\hat{F}) - \theta(F)\right) = \sqrt{nT}\frac{1}{\sqrt{T}}\theta^\epsilon(0) + \sqrt{nT}\frac{1}{2}\left(\frac{1}{\sqrt{T}}\right)^2\theta^{\epsilon\epsilon}(0) + \frac{1}{6}\sqrt{\frac{n}{T}}\frac{1}{\sqrt{T}}\theta^{\epsilon\epsilon\epsilon}(\tilde{\epsilon}). \quad (10)$$

Theorem 6 in Appendix D establishes that last term in (10) is $o_p(1)$ under Condition 4. It is shown later in Appendix C that

$$\begin{aligned} \sqrt{nT}\frac{1}{\sqrt{T}}\theta^\epsilon(0) &\rightarrow N\left(0, \left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i\right)^{-1}\right), \\ \sqrt{nT}\frac{1}{2}\left(\frac{1}{\sqrt{T}}\right)^2\theta^{\epsilon\epsilon}(0) &= -\frac{1}{2}\sqrt{\frac{n}{T}}\left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i\right)^{-1} \left(\frac{1}{n} \sum_{i=1}^n \frac{E[V_{2it}U_i]}{E[V_i^2]}\right) + o_p(1), \end{aligned}$$

from which Theorem 1 follows.

C Derivatives of θ

Let

$$h_i(\cdot, \epsilon) \equiv U_i(\cdot; \theta(F(\epsilon)), \alpha_i(\theta(F(\epsilon)), F_i(\epsilon))) \quad (11)$$

The first order condition may be written as

$$0 = \frac{1}{n} \sum_{i=1}^n \int h_i(\cdot, \epsilon) dF_i(\epsilon) \quad (12)$$

Differentiating repeatedly with respect to ϵ , we obtain

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{dh_i(\cdot, \epsilon)}{d\epsilon} dF_i(\epsilon) + \frac{1}{n} \sum_{i=1}^n \int h_i(\cdot, \epsilon) d\Delta_{iT} \quad (13)$$

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} dF_i(\epsilon) + 2 \frac{1}{n} \sum_{i=1}^n \int \frac{dh_i(\cdot, \epsilon)}{d\epsilon} d\Delta_{iT} \quad (14)$$

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{d^3 h_i(\cdot, \epsilon)}{d\epsilon^3} dF_i(\epsilon) + 3 \frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} d\Delta_{iT} \quad (15)$$

where $\Delta_{iT} \equiv \sqrt{T} (\hat{F}_i - F_i)$.

C.1 $\theta^\epsilon(0)$

Because

$$\frac{dh_i(\cdot, \epsilon)}{d\epsilon} = \frac{\partial h_i(\cdot, \epsilon)}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \epsilon}$$

we may rewrite (13) as

$$0 = \frac{1}{n} \sum_{i=1}^n \int \left(\frac{\partial h_i(\cdot, \epsilon)}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \epsilon} \right) dF_i(\epsilon) + \frac{1}{n} \sum_{i=1}^n \int h_i(\cdot, \epsilon) d\Delta_{iT} \quad (16)$$

Evaluating at $\epsilon = 0$, and noting that $E[U_i^{\alpha_i}] = 0$, we obtain

$$\theta^\epsilon(0) = \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right)^{-1} \left(\frac{1}{n} \sum_{i=1}^n \int U_i d\Delta_{iT} \right) \quad (17)$$

We therefore have

$$\sqrt{nT} \frac{1}{\sqrt{T}} \theta^\epsilon(0) = \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right)^{-1} \left(\frac{1}{\sqrt{n}\sqrt{T}} \sum_{i=1}^n \sum_{t=1}^T U_i \right) \rightarrow N \left(0, \left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right)^{-1} \right)$$

C.2 α_i^θ and α_i^ϵ

In the i th stratum, $\alpha_i(\theta, F_i(\epsilon))$ solves the estimating equation

$$\int V_i(\cdot; \theta, \alpha_i(\theta, F_i(\epsilon))) dF_i(\epsilon) = 0 \quad (18)$$

Differentiating the LHS with respect to θ and ϵ , we obtain

$$\begin{aligned} 0 &= \int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \theta} dF_i(\epsilon) + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta}, \\ 0 &= \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} + \int V_i(\cdot, \theta, \epsilon) d\Delta_{iT}. \end{aligned}$$

Observe that

$$\begin{aligned} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta} &= - \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right)^{-1} \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \theta} dF_i(\epsilon) \right), \\ \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} &= - \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right)^{-1} \left(\int V_i(\cdot, \theta, \epsilon) d\Delta_{iT} \right). \end{aligned}$$

Equating these equations to zero and solving for derivatives of α_i evaluated at $\epsilon = 0$ gives

$$\alpha_i^\theta = -\frac{E\left[\frac{\partial V_i}{\partial \theta}\right]}{E\left[\frac{\partial V_i}{\partial \alpha_i}\right]} = \frac{E\left[\frac{\partial V_i}{\partial \theta}\right]}{E[V_i^2]} = O(1), \quad (19)$$

$$\alpha_i^\epsilon = -\frac{\sum_{t=1}^T V_{it}}{\sqrt{T}E\left[\frac{\partial V_i}{\partial \alpha_i}\right]} = \frac{T^{-1/2}\sum_{t=1}^T V_{it}}{E[V_i^2]} = O_p(1), \quad (20)$$

where

$$\alpha_i^\theta \equiv \frac{\partial \alpha_i(\theta, F_i(0))}{\partial \theta}, \quad \alpha_i^\epsilon \equiv \frac{\partial \alpha_i(\theta, F_i(0))}{\partial \epsilon}.$$

C.3 $\theta^{\epsilon\epsilon}(0)$

Note that

$$\begin{aligned} \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} &= \mathcal{G}_i(\cdot, \epsilon) + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right) \frac{\partial \theta}{\partial \epsilon} + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \frac{\partial \alpha_i}{\partial \epsilon} \frac{\partial \theta}{\partial \epsilon} \\ &\quad + \frac{\partial h_i(\cdot, \epsilon)}{\partial \theta'} \frac{\partial^2 \theta}{\partial \epsilon^2} \\ &\quad + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \frac{\partial \theta}{\partial \epsilon} \frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right)^2 + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right) \frac{\partial \alpha_i}{\partial \epsilon} \\ &\quad + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \left(\frac{\partial \theta'}{\partial \epsilon} \frac{\partial^2 \alpha_i}{\partial \theta \partial \theta'} \right) \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial^2 \alpha_i}{\partial \theta' \partial \epsilon} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \theta'} \frac{\partial^2 \theta}{\partial \epsilon^2} \\ &\quad + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \frac{\partial \theta}{\partial \epsilon} \frac{\partial \alpha_i}{\partial \epsilon} + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right) \frac{\partial \alpha_i}{\partial \epsilon} + \frac{\partial^2 h_i(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \epsilon} \right)^2 \\ &\quad + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial^2 \alpha_i}{\partial \epsilon \partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial^2 \alpha_i}{\partial \epsilon^2}, \end{aligned}$$

where $\mathcal{G}_i(\cdot, \epsilon)$ is a R -dimensional column vector such that its r -th element $\mathcal{G}_i^{(r)}(\cdot, \epsilon)$ is equal to

$$\mathcal{G}_i^{(r)}(\cdot, \epsilon) = \frac{\partial \theta(\cdot, \epsilon)'}{\partial \epsilon} \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \theta \partial \theta'} \frac{\partial \theta(\cdot, \epsilon)}{\partial \epsilon},$$

and $h_i^{(r)}(\cdot, \epsilon)$ denotes the r -th element of h_i .

Evaluating each term of (14) at $\epsilon = 0$, and noting that $E[U_i^{\alpha_i}] = 0$, we obtain

$$\begin{aligned} 0 &= \frac{1}{n} \sum_{i=1}^n E \left[\frac{\partial U_i}{\partial \theta'} \right] \theta^{\epsilon\epsilon}(0) \\ &\quad + \frac{2}{n} \sum_{i=1}^n \alpha_i^\epsilon \cdot E \left[\frac{\partial^2 U_i}{\partial \theta' \partial \alpha_i} \right] \theta^\epsilon(0) + \frac{2}{n} \sum_{i=1}^n \alpha_i^\epsilon (\theta^\epsilon(0)') \alpha_i^\theta \cdot E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] \\ &\quad + \mathcal{G} + \frac{2}{n} \sum_{i=1}^n \theta^\epsilon(0)') \alpha_i^\theta \cdot E \left[\frac{\partial^2 U_i}{\partial \theta' \partial \alpha_i} \right] \theta^\epsilon(0) + \frac{1}{n} \sum_{i=1}^n (\theta^\epsilon(0)') \alpha_i^\theta)^2 \cdot E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] \\ &\quad + \frac{1}{n} \sum_{i=1}^n (\alpha_i^\epsilon)^2 \cdot E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] \\ &\quad + \frac{2}{n} \sum_{i=1}^n \left(\int \frac{\partial U_i}{\partial \theta'} d\Delta_{iT} \right) \theta^\epsilon(0) + \frac{2}{n} \sum_{i=1}^n (\theta^\epsilon(0)') \alpha_i^\theta \cdot \int \frac{\partial U_i}{\partial \alpha_i} d\Delta_{iT} + \frac{2}{n} \sum_{i=1}^n \alpha_i^\epsilon \cdot \int \frac{\partial U_i}{\partial \alpha_i} d\Delta_{iT} \end{aligned}$$

where

$$\mathcal{G} = \begin{bmatrix} \theta^\epsilon(0)' \left(\frac{1}{n} \sum_{i=1}^n E \left[\frac{\partial^2 U_i^{(L)}}{\partial \theta \partial \theta'} \right] \right) \theta^\epsilon(0) \\ \vdots \\ \theta^\epsilon(0)' \left(\frac{1}{n} \sum_{i=1}^n E \left[\frac{\partial^2 U_i^{(R)}}{\partial \theta \partial \theta'} \right] \right) \theta^\epsilon(0) \end{bmatrix}$$

from which we obtain

$$\begin{aligned} \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right) \theta^{\epsilon\epsilon}(0) &= \frac{1}{n} \sum_{i=1}^n (\alpha_i^\epsilon)^2 \cdot E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] + \frac{2}{n} \sum_{i=1}^n \alpha_i^\epsilon \cdot \int \frac{\partial U_i}{\partial \alpha_i} d\Delta_{iT} \\ &+ 2 \left(\frac{1}{n} \sum_{i=1}^n \alpha_i^\epsilon \cdot E \left[\frac{\partial^2 U_i}{\partial \theta' \partial \alpha_i} \right] \right) \theta^\epsilon(0) + \left(\frac{1}{n} \sum_{i=1}^n \alpha_i^\epsilon E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] (\alpha_i^\theta)' \right) \theta^\epsilon(0) \\ &+ 2 \left(\frac{1}{n} \sum_{i=1}^n \int \frac{\partial U_i}{\partial \theta'} d\Delta_{iT} \right) \theta^\epsilon(0) + \left(\frac{1}{n} \sum_{i=1}^n \int \frac{\partial U_i}{\partial \alpha_i} d\Delta_{iT} \cdot (\alpha_i^\theta)' \right) \theta^\epsilon(0) \\ &+ \mathcal{G} + \frac{2}{n} \sum_{i=1}^n \theta^\epsilon(0)' \alpha_i^\theta \cdot E \left[\frac{\partial^2 U_i}{\partial \theta' \partial \alpha_i} \right] \theta^\epsilon(0) + \frac{1}{n} \sum_{i=1}^n (\theta^\epsilon(0)' \alpha_i^\theta)^2 \cdot E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] \end{aligned}$$

Because

$$\begin{aligned} \frac{1}{n} \sum_{i=1}^n (\alpha_i^\epsilon)^2 \cdot E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] &= \frac{1}{n} \sum_{i=1}^n E [U_i^{\alpha_i; \alpha_i}] \left(\frac{\sum_{t=1}^T V_{it}}{\sqrt{T} E[V_i^2]} \right)^2 \\ \sum_{i=1}^n \alpha_i^\epsilon \cdot \int \frac{\partial U_i}{\partial \alpha_i} d\Delta_{iT} &= \frac{1}{n} \sum_{i=1}^n \frac{\sum_{t=1}^T V_{it}}{\sqrt{T} E[V_i^2]} \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T (U_i^{\alpha_i} - E[U_i^{\alpha_i}]) \right) \\ \left(\frac{1}{n} \sum_{i=1}^n \alpha_i^\epsilon \cdot E \left[\frac{\partial^2 U_i}{\partial \theta' \partial \alpha_i} \right] \right) \theta^\epsilon(0) &= O_p \left(\frac{1}{\sqrt{n}} \right) O_p \left(\frac{1}{\sqrt{n}} \right) = O_p \left(\frac{1}{n} \right) \\ \left(\frac{1}{n} \sum_{i=1}^n \alpha_i^\epsilon E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] (\alpha_i^\theta)' \right) \theta^\epsilon(0) &= O_p \left(\frac{1}{\sqrt{n}} \right) O_p \left(\frac{1}{\sqrt{n}} \right) = O_p \left(\frac{1}{n} \right) \\ \left(\frac{1}{n} \sum_{i=1}^n \int \frac{\partial U_i}{\partial \theta'} d\Delta_{iT} \right) \theta^\epsilon(0) &= O_p \left(\frac{1}{\sqrt{n}} \right) O_p \left(\frac{1}{\sqrt{n}} \right) = O_p \left(\frac{1}{n} \right) \\ \left(\frac{1}{n} \sum_{i=1}^n \int \frac{\partial U_i}{\partial \alpha_i} d\Delta_{iT} \cdot (\alpha_i^\theta)' \right) \theta^\epsilon(0) &= O_p \left(\frac{1}{\sqrt{n}} \right) O_p \left(\frac{1}{\sqrt{n}} \right) = O_p \left(\frac{1}{n} \right) \end{aligned}$$

and

$$\begin{aligned} \theta^\epsilon(0)' \left(\frac{1}{n} \sum_{i=1}^n E \left[\frac{\partial^2 U_i^{(r)}}{\partial \theta \partial \theta'} \right] \right) \theta^\epsilon(0) &= O_p \left(\frac{1}{\sqrt{n}} \right) O(1) O_p \left(\frac{1}{\sqrt{n}} \right) = O_p \left(\frac{1}{n} \right) \\ \frac{1}{n} \sum_{i=1}^n \theta^\epsilon(0)' \alpha_i^\theta \cdot E \left[\frac{\partial^2 U_i}{\partial \theta' \partial \alpha_i} \right] \theta^\epsilon(0) &= O_p \left(\frac{1}{\sqrt{n}} \right) O(1) O_p \left(\frac{1}{\sqrt{n}} \right) = O_p \left(\frac{1}{n} \right) \\ \frac{1}{n} \sum_{i=1}^n (\theta^\epsilon(0)' \alpha_i^\theta)^2 \cdot E \left[\frac{\partial^2 U_i}{\partial \alpha_i^2} \right] &= O_p \left(\frac{1}{\sqrt{n}} \right)^2 O(1) = O_p \left(\frac{1}{n} \right) \end{aligned}$$

we may write

$$\begin{aligned}
\theta^{\epsilon\epsilon}(0) &= \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i\right)^{-1} \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i \alpha_i}] \left(\frac{\sum_{t=1}^T V_{it}}{\sqrt{T} E[V_i^2]}\right)^2 \\
&\quad + 2 \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i\right)^{-1} \frac{1}{n} \sum_{i=1}^n \frac{\sum_{t=1}^T V_{it}}{\sqrt{T} E[V_i^2]} \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T (U_i^{\alpha_i} - E[U_i^{\alpha_i}])\right) \\
&\quad + O_p\left(\frac{1}{n}\right) \\
&= 2 \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i\right)^{-1} \frac{1}{n} \sum_{i=1}^n \left[\frac{\sum_{t=1}^T V_{it}}{\sqrt{T} E[V_i^2]}\right] \left[\frac{1}{\sqrt{T}} \sum_{t=1}^T \left(U_i^{\alpha_i} + \frac{E[U_i^{\alpha_i \alpha_i}]}{2E[V_i^2]} V_{it}\right)\right] + o_p(1)
\end{aligned}$$

Therefore, we have

$$\sqrt{nT} \frac{1}{2} \left(\frac{1}{\sqrt{T}}\right)^2 \theta^{\epsilon\epsilon}(0) = \sqrt{\frac{n}{T}} \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i\right)^{-1} \frac{1}{n} \sum_{i=1}^n \left[\frac{1}{\sqrt{T}} \sum_{t=1}^T \frac{V_{it}}{E[V_i^2]}\right] \left[\frac{1}{\sqrt{T}} \sum_{t=1}^T \left(U_i^{\alpha_i} + \frac{E[U_i^{\alpha_i \alpha_i}]}{2E[V_i^2]} V_{it}\right)\right] + o_p(1)$$

The terms in square parentheses have joint limiting normal distributions by CLT. Their product is a quadratic form with mean

$$\frac{E[V_{it}U_i^{\alpha_i}]}{E[V_i^2]} + \frac{E[U_i^{\alpha_i \alpha_i}]}{2E[V_i^2]} = \frac{E[V_{it}U_i^{\alpha_i}]}{E[V_i^2]} - \frac{E[V_{it}U_i^{\alpha_i}]}{2E[V_i^2]} = \frac{E[V_{it}U_i^{\alpha_i}]}{2E[V_i^2]} = -\frac{E[V_{2it}U_i]}{2E[V_i^2]}.$$

Therefore, we have

$$\sqrt{nT} \frac{1}{2} \left(\frac{1}{\sqrt{T}}\right)^2 \theta^{\epsilon\epsilon}(0) = \frac{1}{2} \sqrt{\frac{n}{T}} \left(\frac{1}{n} \sum_{i=1}^n \mathcal{I}_i\right)^{-1} \left(-\frac{1}{n} \sum_{i=1}^n \frac{E[V_{2it}U_i]}{E[V_i^2]}\right) + o_p(1)$$

D Remainder in (10)

D.1 $\alpha_i^{\theta\theta}$, $\alpha_i^{\theta\epsilon}$, and $\alpha_i^{\epsilon\epsilon}$

Second order differentiation $\left(\frac{\partial^2}{\partial\theta^2}, \frac{\partial^2}{\partial\theta\partial\epsilon}, \frac{\partial^2}{\partial\epsilon^2}\right)$ of (18) yields

$$\begin{aligned}
0 &= \int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial\theta\partial\theta'} dF_i(\epsilon) + \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\theta} \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i\partial\theta'} dF_i(\epsilon)\right) + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i\partial\theta} dF_i(\epsilon)\right) \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\theta'} \\
&\quad + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i} dF_i(\epsilon)\right) \frac{\partial^2\alpha_i(\theta, F_i(\epsilon))}{\partial\theta\partial\theta'} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i^2} dF_i(\epsilon)\right) \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\theta} \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\theta'},
\end{aligned}$$

$$\begin{aligned}
0 &= \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial\theta\partial\alpha_i} dF_i(\epsilon)\right) \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\epsilon} \\
&\quad + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i} dF_i(\epsilon)\right) \frac{\partial^2\alpha_i(\theta, F_i(\epsilon))}{\partial\theta\partial\epsilon} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i^2} dF_i(\epsilon)\right) \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\theta} \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\epsilon} \\
&\quad + \int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial\theta} d\Delta_{iT} + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i} d\Delta_{iT}\right) \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\theta},
\end{aligned}$$

and

$$\begin{aligned}
0 &= \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i} dF_i(\epsilon)\right) \frac{\partial^2\alpha_i(\theta, F_i(\epsilon))}{\partial\epsilon^2} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i^2} dF_i(\epsilon)\right) \left(\frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\epsilon}\right)^2 \\
&\quad + 2 \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial\alpha_i} d\Delta_{iT}\right) \frac{\partial\alpha_i(\theta, F_i(\epsilon))}{\partial\epsilon}.
\end{aligned}$$

These three equalities characterizes $\frac{\partial^2\alpha_i(\theta, F_i(\epsilon))}{\partial\theta\partial\theta'}$, $\frac{\partial^2\alpha_i(\theta, F_i(\epsilon))}{\partial\theta\partial\epsilon}$, and $\frac{\partial^2\alpha_i(\theta, F_i(\epsilon))}{\partial\epsilon^2}$.

D.2 Some Lemmas

Lemma 4 Suppose that, for each i , $\{\xi_{it}, t = 1, 2, \dots\}$ is a sequence of zero mean i.i.d. random variables. We assume that $\{\xi_{it}, t = 1, 2, 3\}$ are independent across i . We also assume that $\max_i E \left[|\xi_{it}|^{16} \right] < \infty$. Finally, assume that $n = O(T)$. We then have

$$\Pr \left[\max_i \left| \frac{1}{T} \sum_{t=1}^T \xi_{it} \right| > \eta \right] = o \left(\frac{1}{T} \right)$$

for every $\eta > 0$.

Proof. The conclusion follows from combining Lemma 2 with the observation that

$$T \Pr \left[\max_i \left| \frac{1}{T} \sum_{t=1}^T \xi_{it} \right| > \eta \right] \leq T \sum_{i=1}^n \Pr \left[\left| \frac{1}{T} \sum_{t=1}^T \xi_{it} \right| > \eta \right] \leq \max_i T^2 \Pr \left[\left| \frac{1}{T} \sum_{t=1}^T \xi_{it} \right| > \eta \right].$$

■

Lemma 5 Suppose that, for each i , $\{\xi_{it}(\phi), t = 1, 2, \dots\}$ is a sequence of zero mean i.i.d. random variables indexed by some parameter $\phi \in \Phi$. We assume that $\{\xi_{it}(\phi), t = 1, 2, 3\}$ are independent across i . We also assume that $\sup_{\phi \in \Phi} |\xi_{it}(\phi)| \leq B_{it}$ for some sequence of random variables B_{it} that is i.i.d. across t and independent across i . Finally, we assume that $\max_i E \left[|B_{it}|^{64} \right] < \infty$, and $n = O(T)$. We then have

$$\Pr \left[\max_i \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \xi_{it}(\phi_i) \right| > T^{\frac{1}{10}-v} \right] = o \left(\frac{1}{T} \right)$$

for every v such that $0 \leq v < \frac{1}{160}$. Here, $\{\phi_i\}$ is an arbitrary sequence in Φ .

Proof. This proof is a modification of Hall and Horowitz (1996, Lemma 1). Note that

$$\begin{aligned} T^2 \Pr \left[\max_{1 \leq t \leq T} |B_{it}| > T^{1/16} \right] &\leq T^2 \sum_{t=1}^T \Pr \left[|B_{it}| > T^{1/16} \right] = T^3 \Pr \left[|B_{it}| > T^{1/16} \right] \\ &\leq T^3 \frac{E \left[|B_{it}|^{64} \right]}{(T^{1/16})^{64}} \leq \frac{\max_i E \left[|B_{it}|^{64} \right]}{T} = o(1). \end{aligned}$$

Condition on $\max_{1 \leq t \leq T} |B_{it}| \leq T^{1/16}$. By Markov's inequality,

$$\begin{aligned} \Pr \left[\sup_{\phi \in \Phi} \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \xi_{it}(\phi_i) \right| > T^{\frac{1}{10}-v} \right] &= \Pr \left[\sup_{\phi \in \Phi} \left| \sum_{t=1}^T \xi_{it}(\phi_i) \right| > T^{\frac{3}{5}-v} \right] \\ &\leq \frac{E \left[\sup_{\phi \in \Phi} \left| \sum_{t=1}^T \xi_{it}(\phi_i) \right|^{64} \right]}{T^{\frac{3}{5} \times 64 - 64v} \eta^{64}} = \frac{\sup_{\phi \in \Phi} E \left[\left| \sum_{t=1}^T \xi_{it}(\phi_i) \right|^{64} \right]}{T^{\frac{192}{5} - 64v} \eta^{64}} \leq \frac{E \left[\left| \sum_{t=1}^T B_{it} \right|^{64} \right]}{T^{\frac{192}{5} - 64v} \eta^{64}}, \end{aligned}$$

where the last equality is based on dominated convergence. By Lahiri (1992, Lemma 5.1), we have

$$E \left[\left| \sum_{t=1}^T B_{it} \right|^{64} \right] \leq CT^{36},$$

where $C > 0$ is a constant. Therefore, we have

$$T^2 \Pr \left[\left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \xi_{it}(\phi_i) \right| > T^{\frac{1}{10}-v} \right] \leq T^2 \frac{CT^{36}}{T^{\frac{192}{5}-64v}\eta^{64}} = O\left(T^{-\frac{2}{5}+64v}\right),$$

and

$$T \Pr \left[\max_i \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \xi_{it}(\phi_i) \right| > T^{\frac{1}{10}-v} \right] \leq T \sum_{i=1}^n \Pr \left[\left| \frac{1}{\sqrt{T}} \sum_{t=1}^T \xi_{it}(\phi_i) \right| > T^{\frac{1}{10}-v} \right] = nT \cdot \frac{CT^{36}}{T^{\frac{192}{5}-64v}\eta^{64}} = o(1).$$

■

Lemma 6 *Under Conditions 1, 2, and 3,*

$$T \Pr \left[\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \hat{\theta}(\epsilon) - \theta_0 \right| \geq \eta \right] = o(1)$$

and

$$T \Pr \left[\max_{1 \leq i \leq n} \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} |\hat{\alpha}_i(\epsilon) - \alpha_{i0}| \geq \eta \right] = o(1)$$

for every $\eta > 0$.

Proof. Only the first assertion is proved. The second assertion can be proved similarly. Let η be given, and let $\varepsilon \equiv \inf_i \left[G_{(i)}(\theta_0, \alpha_{i0}) - \sup_{\{(\theta, \alpha) : |(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta\}} G_{(i)}(\theta, \alpha) \right] > 0$. Recall that

$$F(\epsilon) \equiv F + \epsilon\sqrt{T}(\hat{F} - F), \quad \epsilon \in \left[0, \frac{1}{\sqrt{T}}\right]$$

We have

$$\int g(\cdot; \theta, \alpha_i(\theta)) dF_i(\epsilon) = (1 - \epsilon\sqrt{T}) G_{(i)}(\theta, \alpha_i) + \epsilon\sqrt{T} \hat{G}_{(i)}(\theta, \alpha_i)$$

and

$$\left| \int g(\cdot; \theta, \alpha_i(\theta)) dF_i(\epsilon) - G_{(i)}(\theta, \alpha_i) \right| \leq (1 - \epsilon\sqrt{T}) \left| \hat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right| \leq \left| \hat{G}_{(i)}(\theta, \alpha) - G_{(i)}(\theta, \alpha) \right|.$$

By Lemma 3, we have

$$\Pr \left[\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \max_{1 \leq i \leq n} \sup_{(\theta, \alpha)} \left| \int g(\cdot; \theta, \alpha_i(\theta)) dF_i(\epsilon) - G_{(i)}(\theta, \alpha) \right| \geq \eta \right] = o(T^{-1})$$

Therefore, for every $0 \leq \epsilon \leq \frac{1}{\sqrt{T}}$ with probability equal to $1 - o\left(\frac{1}{T}\right)$, we have

$$\begin{aligned} \max_{|\theta - \theta_0| > \eta, \alpha_1, \dots, \alpha_n} n^{-1} \sum_{i=1}^n \int g(\cdot; \theta, \alpha_i(\theta)) dF_i(\epsilon) &\leq \max_{|(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta} n^{-1} \sum_{i=1}^n \int g(\cdot; \theta, \alpha_i(\theta)) dF_i(\epsilon) \\ &< \max_{|(\theta, \alpha) - (\theta_0, \alpha_{i0})| > \eta} n^{-1} \sum_{i=1}^n G_{(i)}(\theta, \alpha_i) + \frac{1}{3}\varepsilon \\ &< n^{-1} \sum_{i=1}^n G_{(i)}(\theta_0, \alpha_{i0}) - \frac{2}{3}\varepsilon \\ &< n^{-1} \sum_{i=1}^n \int g(\cdot; \theta_0, \alpha_{i0}) dF_i(\epsilon) - \frac{1}{3}\varepsilon. \end{aligned}$$

We also have

$$\max_{\theta, \alpha_1, \dots, \alpha_n} n^{-1} \sum_{i=1}^n \int g(\cdot; \theta, \alpha_i) dF_i(\epsilon) \geq n^{-1} \sum_{i=1}^n \int g(\cdot; \theta_0, \alpha_{i0}) dF_i(\epsilon)$$

by definition. It follows that

$$\max_{|\theta - \theta_0| > \eta, \alpha_1, \dots, \alpha_n} n^{-1} \sum_{i=1}^n \int g(\cdot; \theta, \alpha_i(\theta)) dF_i(\epsilon) < \max_{\theta, \alpha_1, \dots, \alpha_n} n^{-1} \sum_{i=1}^n \int g(\cdot; \theta, \alpha_i) dF_i(\epsilon) - \frac{1}{3}\epsilon$$

for every $0 \leq \epsilon \leq \frac{1}{\sqrt{T}}$. We therefore obtain that $\Pr \left[\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \widehat{\theta}(\epsilon) - \theta_0 \right| \geq \eta \right] = o\left(\frac{1}{T}\right)$. ■

Lemma 7 *Assume that Condition 4 holds. Suppose that $K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon))$ is equal to*

$$\frac{\partial^{m_1+m_2} \log f(x_{it}; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon))}{\partial \theta^{m_1} \partial \alpha_i^{m_2}}$$

for some $m_1 + m_2 \leq 1, \dots, 5$. Then, for any $\eta > 0$, we have

$$\Pr \left[\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \frac{1}{n} \sum_{i=1}^n \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - \frac{1}{n} \sum_{i=1}^n E[K_i(x_{it}; \theta_0, \alpha_{i0})] \right| > \eta \right] = o\left(\frac{1}{T}\right)$$

and

$$\Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - E[K_i(x_{it}; \theta_0, \alpha_{i0})] \right| > \eta \right] = o\left(\frac{1}{T}\right).$$

Also,

$$\Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) d\Delta_{iT} \right| > CT^{\frac{1}{10}-v} \right] = o\left(\frac{1}{T}\right)$$

for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$.

Proof. Note that we may write

$$\begin{aligned} & \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - \int K_i(\cdot; \theta_0, \alpha_i(\theta_0, 0)) dF_i(\epsilon) \\ &= \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - \int K_i(\cdot; \theta_0, \alpha_i(\theta_0, 0)) dF_i(\epsilon) \\ & \quad + \int K_i(\cdot; \theta_0, \alpha_i(\theta_0, 0)) dF_i(\epsilon) - \int K_i(\cdot; \theta_0, \alpha_i(\theta_0, 0)) dF_i(\epsilon) \\ &= \int \frac{\partial K_i(\cdot; \theta^*, \alpha_i^*)}{\partial \theta'} \cdot (\theta(\epsilon) - \theta_0) dF_i(\epsilon) \\ & \quad + \int \frac{\partial K_i(\cdot; \theta^*, \alpha_i^*)}{\partial \alpha_i} \cdot (\alpha_i(\theta(\epsilon), \epsilon) - \alpha_i(\theta_0, 0)) dF_i(\epsilon) \\ & \quad + \epsilon \sqrt{T} \int K_i(\cdot; \theta_0, \alpha_i(\theta_0, 0)) d(\widehat{F}_i - F_i) \end{aligned}$$

where (θ^*, α_i^*) are between (θ, α_i) and $(\theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon))$. Therefore, we have

$$\begin{aligned} & \left| \frac{1}{n} \sum_{i=1}^n \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - \frac{1}{n} \sum_{i=1}^n E[K_i(x_{it}; \theta_0, \alpha_{i0})] \right| \\ & \leq |\theta(\epsilon) - \theta| \cdot \frac{1}{n} \sum_{i=1}^n \left(E[M(x_{it})] + \frac{1}{T} \sum_{t=1}^T M(x_{it}) \right) \\ & \quad + \left(\frac{1}{n} \sum_{i=1}^n (\alpha_i(\theta(\epsilon), \epsilon) - \alpha_i)^2 \right)^{1/2} \left(\frac{1}{n} \sum_{i=1}^n \left(E[M(x_{it})] + \frac{1}{T} \sum_{t=1}^T M(x_{it}) \right)^2 \right)^{1/2} \\ & \quad + \left| \frac{1}{n} \sum_{i=1}^n \left(\frac{1}{T} \sum_{t=1}^T M(x_{it}) - E[M(x_{it})] \right) \right| \end{aligned}$$

where $M(\cdot)$ is defined in Condition 4. Using Lemmas 4 and 6, we can bound

$$\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \frac{1}{n} \sum_{i=1}^n \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - \frac{1}{n} \sum_{i=1}^n E[K_i(x_{it}; \theta_0, \alpha_{i0})] \right|$$

in absolute value by some $\eta > 0$ with probability $1 - o(\frac{1}{T})$. Because

$$\begin{aligned} & \left| \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - E[K_i(x_{it}; \theta_0, \alpha_{i0})] \right| \\ & \leq |\theta(\epsilon) - \theta| \cdot \left(E[M(x_{it})] + \frac{1}{T} \sum_{t=1}^T M(x_{it}) \right) \\ & \quad + |\alpha_i(\theta(\epsilon), \epsilon) - \alpha_i| \cdot \left(E[M(x_{it})] + \frac{1}{T} \sum_{t=1}^T M(x_{it}) \right) \\ & \quad + \left| \frac{1}{T} \sum_{t=1}^T M(x_{it}) - E[M(x_{it})] \right|, \end{aligned}$$

we can bound

$$\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) dF_i(\epsilon) - E[K_i(x_{it}; \theta_0, \alpha_{i0})] \right|$$

in absolute value by some $\eta > 0$ with probability $1 - o(\frac{1}{T})$.

Using Condition 4 and Lemmas 5, we can also show that

$$\max_i \left| \int K_i(\cdot; \theta(\epsilon), \alpha_i(\theta(\epsilon), \epsilon)) d\Delta_{iT} \right|$$

can be bounded by in absolute value by $CT^{\frac{1}{10}-v}$ for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$ with probability $1 - o(\frac{1}{T})$. ■

D.3 Bounds

Lemma 8 *Suppose that Condition 4 holds. Then, we have*

$$\begin{aligned} \Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} |\alpha_i^\theta(\epsilon)| > C \right] &= o(T^{-1}) \\ \Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} |\alpha_i^\epsilon(\epsilon)| > CT^{\frac{1}{10}-v} \right] &= o(T^{-1}) \end{aligned}$$

for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$.

Proof. From Appendix C.2, we obtain

$$\begin{aligned}\frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta} &= - \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right)^{-1} \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \theta} dF_i(\epsilon) \right), \\ \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} &= - \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right)^{-1} \left(\int V_i(\cdot, \theta, \epsilon) d\Delta_{iT} \right).\end{aligned}$$

Using Lemma 7 and Condition 4, we can see that

$$\left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right)^{-1}$$

is uniformly bounded away from zero. We can also see that

$$\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \theta} dF_i(\epsilon)$$

is uniformly bounded by some constant C , and

$$\int V_i(\cdot, \theta, \epsilon) d\Delta_{iT}$$

is uniformly bounded by $CT^{\frac{1}{10}-v}$ for some constant C and v such that $0 \leq v < \frac{1}{160}$. ■

Lemma 9 Suppose that Condition 4 holds. Then, we have

$$\Pr \left[\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} |\theta^\epsilon(\epsilon)| > CT^{\frac{1}{10}-v} \right] = o(T^{-1})$$

for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$.

Proof. From (16), we have

$$\begin{aligned}\theta^\epsilon(\epsilon) &= - \left[\frac{1}{n} \sum_{i=1}^n \int \left(\frac{\partial h_i(\cdot, \epsilon)}{\partial \theta'} + \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \theta'} \right) dF_i(\epsilon) \right]^{-1} \\ &\quad \left[\frac{1}{n} \sum_{i=1}^n \frac{\partial \alpha_i}{\partial \epsilon} \left(\int \frac{\partial h_i(\cdot, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) + \frac{1}{n} \sum_{i=1}^n \int h_i(\cdot, \epsilon) d\Delta_{iT} \right]\end{aligned}$$

Using Lemmas 7, 8, and Condition 4, we can bound the denominator of $\theta^\epsilon(\epsilon)$ by some $C > 0$, and the numerator by some $CT^{\frac{1}{10}-v}$ with probability $1 - o(T^{-1})$. ■

Lemma 10 Suppose that Condition 4 holds. Then, we have

$$\begin{aligned}\Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \alpha_i^{\theta_r \theta_{r'}}(\epsilon) \right| > C \right] &= o(T^{-1}) \\ \Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \alpha_i^{\theta_r \epsilon}(\epsilon) \right| > CT^{\frac{1}{10}-v} \right] &= o(T^{-1}) \\ \Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \alpha_i^{\epsilon \epsilon}(\epsilon) \right| > C \left(T^{\frac{1}{10}-v} \right)^2 \right] &= o(T^{-1})\end{aligned}$$

for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$. Here, $\alpha_i^{\theta_r \theta_{r'}} \equiv \frac{\partial^2 \alpha_i}{\partial \theta_r \partial \theta_{r'}}$. We similarly define $\alpha_i^{\theta_r \epsilon}$.

Proof. From Appendix D.1, we have

$$\begin{aligned}
0 &= \int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \theta \partial \theta'} dF_i(\epsilon) + \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta} \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta'} dF_i(\epsilon) \right) + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta'} \\
&\quad + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta \partial \theta'} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta'}, \\
0 &= \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \theta \partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \\
&\quad + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta \partial \epsilon} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \\
&\quad + \int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \theta} d\Delta_{iT} + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} d\Delta_{iT} \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta},
\end{aligned}$$

and

$$\begin{aligned}
0 &= \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^2} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \left(\frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \right)^2 \\
&\quad + 2 \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} d\Delta_{iT} \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon}.
\end{aligned}$$

The result then follows by applying the same argument as in the proof of Lemma 8. ■

Lemma 11 *Suppose that Condition 4 holds. Then, we have*

$$\Pr \left[\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} |\theta^{\epsilon\epsilon}(\epsilon)| > C \left(T^{\frac{1}{10}-v} \right)^2 \right] = o(T^{-1})$$

for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$.

Proof. The conclusion follows by using the characterization of $\theta^{\epsilon\epsilon}(\epsilon)$ in Appendix C.3, and Lemmas 7, 8, 9, and 10. ■

Lemma 12 *Suppose that Condition 4 holds. Then, we have*

$$\begin{aligned}
\Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \alpha_i^{\theta_r \theta_{r'} \theta_{r''}}(\epsilon) \right| > C \right] &= o(T^{-1}) \\
\Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \alpha_i^{\theta_r \theta_{r'} \epsilon}(\epsilon) \right| > CT^{\frac{1}{10}-v} \right] &= o(T^{-1}) \\
\Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \alpha_i^{\theta_r \epsilon \epsilon}(\epsilon) \right| > C \left(T^{\frac{1}{10}-v} \right)^2 \right] &= o(T^{-1}) \\
\Pr \left[\max_i \max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} \left| \alpha_i^{\epsilon \epsilon \epsilon}(\epsilon) \right| > C \left(T^{\frac{1}{10}-v} \right)^3 \right] &= o(T^{-1})
\end{aligned}$$

for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$.

Proof. It was seen in Appendix D.1 that

$$\begin{aligned}
0 &= \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \theta_r \partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \\
&\quad + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r \partial \epsilon} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \\
&\quad + \int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \theta_r} d\Delta_{iT} + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} d\Delta_{iT} \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r},
\end{aligned}$$

and

$$0 = \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^2} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \left(\frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \right)^2 + 2 \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} d\Delta_{iT} \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon}.$$

We therefore obtain

$$\begin{aligned} 0 = & \int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \theta_r \partial \theta_{r'} \partial \theta_{r''}} dF_i(\epsilon) + \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta_r \partial \theta_{r'}} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r''}} \\ & + \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r \partial \theta_{r''}} \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta_{r'}} dF_i(\epsilon) \right) + \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r} \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta_{r'} \partial \theta_{r''}} dF_i(\epsilon) \right) \\ & + \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r''}} \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2 \partial \theta_{r'}} dF_i(\epsilon) \right) \\ & + \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta_r \partial \theta_{r''}} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r'}} + \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2 \partial \theta_r} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r'}} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r''}} \\ & + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta_r} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r'} \partial \theta_{r''}} \\ & + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i \partial \theta_{r''}} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r \partial \theta_{r'}} + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r''}} \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r \partial \theta_{r'}} \\ & + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial^3 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r \partial \theta_{r'} \partial \theta_{r''}} \\ & + \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2 \partial \theta_{r''}} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r'}} \\ & + \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^3} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r'}} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r''}} \\ & + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r \partial \theta_{r''}} \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r'}} \\ & + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r} \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_{r'} \partial \theta_{r''}}, \end{aligned}$$

which characterizes $\frac{\partial^3 \alpha_i(\theta, F_i(\epsilon))}{\partial \theta_r \partial \epsilon^2}$, and

$$\begin{aligned}
0 &= \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^2} + \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} d\Delta_{iT} \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^2} \\
&+ \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} dF_i(\epsilon) \right) \frac{\partial^3 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^3} \\
&+ \left(\int \frac{\partial^3 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^3} dF_i(\epsilon) \right) \left(\frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \right)^3 + \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} d\Delta_{iT} \right) \left(\frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \right)^2 \\
&+ 2 \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} dF_i(\epsilon) \right) \frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^2} \\
&+ 2 \left(\int \frac{\partial^2 V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i^2} d\Delta_{iT} \right) \left(\frac{\partial \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon} \right)^2 + 2 \left(\int \frac{\partial V_i(\cdot, \theta, \epsilon)}{\partial \alpha_i} d\Delta_{iT} \right) \frac{\partial^2 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^2},
\end{aligned}$$

which characterizes $\frac{\partial^3 \alpha_i(\theta, F_i(\epsilon))}{\partial \epsilon^3}$. Inspecting these derivatives and applying Lemmas 7, 8, and 10, we obtain the desired result. ■

Theorem 6 *Suppose that Condition 4 holds. Then, we have*

$$\Pr \left[\max_{0 \leq \epsilon \leq \frac{1}{\sqrt{T}}} |\theta^{\epsilon \epsilon}(\epsilon)| > C \left(T^{\frac{1}{10} - v} \right)^3 \right] = o(T^{-1})$$

for some constant $C > 0$ and v such that $0 \leq v < \frac{1}{160}$.

Proof. From (15), we have

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{d^3 h_i(\cdot, \epsilon)}{d\epsilon^3} dF_i(\epsilon) + 3 \frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} d\Delta_{iT}$$

Combining Lemmas 7, 8, 9, 10, and 11, we can bound $\frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} d\Delta_{iT}$ by $C \left(T^{\frac{1}{10} - v} \right)^3$ with probability $1 - o(T^{-1})$. It was seen in Appendix C.3 that the r -th component $\frac{d^2 h_i^{(r)}(\cdot, \epsilon)}{d\epsilon^2}$ of $\frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2}$ is equal to

$$\begin{aligned}
\frac{d^2 h_i^{(r)}(\cdot, \epsilon)}{d\epsilon^2} &= \frac{\partial \theta(\cdot, \epsilon)'}{\partial \epsilon} \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \theta \partial \theta'} \frac{\partial \theta(\cdot, \epsilon)}{\partial \epsilon} + \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right) \frac{\partial \theta}{\partial \epsilon} + \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \frac{\partial \alpha_i}{\partial \epsilon} \frac{\partial \theta}{\partial \epsilon} \\
&+ \frac{\partial h_i^{(r)}(\cdot, \epsilon)}{\partial \theta'} \frac{\partial^2 \theta}{\partial \epsilon^2} \\
&+ \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \frac{\partial \theta}{\partial \epsilon} \frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right)^2 + \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right) \frac{\partial \alpha_i}{\partial \epsilon} \\
&+ \frac{\partial h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i} \left(\frac{\partial \theta'}{\partial \epsilon} \frac{\partial^2 \alpha_i}{\partial \theta \partial \theta'} \right) \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial^2 \alpha_i}{\partial \theta' \partial \epsilon} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \theta'} \frac{\partial^2 \theta}{\partial \epsilon^2} \\
&+ \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \theta' \partial \alpha_i} \frac{\partial \theta}{\partial \epsilon} \frac{\partial \alpha_i}{\partial \epsilon} + \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \theta'} \frac{\partial \theta}{\partial \epsilon} \right) \frac{\partial \alpha_i}{\partial \epsilon} + \frac{\partial^2 h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i^2} \left(\frac{\partial \alpha_i}{\partial \epsilon} \right)^2 \\
&+ \frac{\partial h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial^2 \alpha_i}{\partial \epsilon \partial \theta'} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial h_i^{(r)}(\cdot, \epsilon)}{\partial \alpha_i} \frac{\partial^2 \alpha_i}{\partial \epsilon^2}.
\end{aligned}$$

Using Lemmas 7, 8, 9, 10, and 11 again, we can conclude that $\frac{1}{n} \sum_{i=1}^n \int \frac{d^3 h_i(\cdot, \epsilon)}{d\epsilon^3} dF_i(\epsilon)$ is equal to $\left(\frac{1}{n} \sum_{i=1}^n \int \frac{\partial h_i(\cdot, \epsilon)}{\partial \theta'} dF_i(\epsilon) \right) \frac{\partial^3 \theta}{\partial \epsilon^3}$ plus terms that can all be bounded by $\frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} d\Delta_{iT}$ by $C \left(T^{\frac{1}{10} - v} \right)^3$

with probability $1 - o(T^{-1})$. Because $\left(\frac{1}{n} \sum_{i=1}^n \int \frac{\partial h_i(\cdot, \epsilon)}{\partial \theta'} dF_i(\epsilon)\right)^{-1}$ is bounded away from 0 by Lemma 7 and Condition 4, we obtain the desired conclusion. ■

E Proof of Theorem 2

Note that

$$\begin{aligned}
& \left| \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) s_{\theta} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) - E \left[V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right] \right| \\
& \leq \left| \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) s_{\theta} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) - \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right| \\
& \quad + \left| \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) - E \left[V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right] \right| \\
& \leq \left(\max_i E \left[M_{it} \left(x_{it} \right)^2 \right] + \left| \frac{1}{T} \sum_{t=1}^T \left(M_{it} \left(x_{it} \right)^2 - E \left[M_{it} \left(x_{it} \right)^2 \right] \right) \right| \right) \left(\left| \hat{\theta} - \theta_0 \right| + \max_i \left| \hat{\alpha}_i - \alpha_{i0} \right| \right) \\
& \quad + \left| \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) - E \left[V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right] \right|
\end{aligned}$$

By Lemma 2, we obtain

$$\max_i \left| \frac{1}{T} \sum_{t=1}^T \left(M_{it} \left(x_{it} \right)^2 - E \left[M_{it} \left(x_{it} \right)^2 \right] \right) \right| = o_p(1)$$

and

$$\max_i \left| \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) - E \left[V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right] \right| = o_p(1)$$

Combined with Lemmas 4 and 5, we obtain

$$\max_i \left| \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) s_{\theta} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) - E \left[V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right] \right| = o_p(1)$$

We can similarly show that

$$\begin{aligned}
& \max_i \left| \frac{1}{T} \sum_{t=1}^T V_{it} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right)^2 - E \left[V_{it} \left(x_{it}; \theta_0, \alpha_{i0} \right)^2 \right] \right| = o_p(1) \\
& \max_i \left| \frac{1}{T} \sum_{t=1}^T V_{2it} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) V_{it} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) - E \left[V_{2it} \left(x_{it}; \theta_0, \alpha_{i0} \right) V_{it} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right] \right| = o_p(1) \\
& \max_i \left| \frac{1}{T} \sum_{t=1}^T s_{\theta} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right)^2 - E \left[s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right)^2 \right] \right| = o_p(1) \\
& \max_i \left| \frac{1}{T} \sum_{t=1}^T s_{\theta} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) V_{it} \left(x_{it}; \hat{\theta}, \hat{\alpha}_i \right) - s_{\theta} \left(x_{it}; \theta_0, \alpha_{i0} \right) V_{it} \left(x_{it}; \theta_0, \alpha_{i0} \right) \right| = o_p(1)
\end{aligned}$$

It follows that

$$\begin{aligned} \left| \frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T \widehat{U}_{it} \widehat{U}'_{it} - \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i \right| &= o_p(1) \\ \left| \frac{1}{n} \sum_{i=1}^n \frac{\frac{1}{T} \sum_{t=1}^T \widehat{U}_{it} \widehat{V}_{2it}}{\frac{1}{T} \sum_{t=1}^T \widehat{V}_{it}^2} - \frac{1}{n} \sum_{i=1}^n \frac{E[V_{2it} U_{it}]}{E[V_{it}^2]} \right| &= o_p(1) \end{aligned}$$

from which we obtain

$$\frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T \widehat{U}_{it} \widehat{U}'_{it} = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathcal{I}_i + o_p(1) \quad (22)$$

$$\frac{1}{n} \sum_{i=1}^n \frac{\frac{1}{T} \sum_{t=1}^T \widehat{U}_{it} \widehat{V}_{2it}}{\frac{1}{T} \sum_{t=1}^T \widehat{V}_{it}^2} = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \frac{E[V_{2it} U_{it}]}{E[V_{it}^2]} + o_p(1) \quad (23)$$

F V-Statistics

F.1 Properties of Normalized V-Statistics

Consider a statistic of the form

$$\begin{aligned} W_{i,T} &\equiv \frac{1}{T^{m/2}} \sum_{t_1=1}^T \sum_{t_2=1}^T \cdots \sum_{t_m=1}^T k_1(x_{i,t_1}) k_2(x_{i,t_2}) \cdots k_m(x_{i,t_m}) \\ &\equiv T^{m/2} \bar{k}_{i,1} \bar{k}_{i,2} \cdots \bar{k}_{i,m} \\ &\equiv T^{m/2} K_{i,T} \end{aligned}$$

where $E[k_j(x_{i,t})] = 0$. We will call the average

$$\frac{1}{n} \sum_{i=1}^n W_{i,T}$$

of such $W_{i,T}$ the normalized V-statistic of order m . We will focus on normalized V-statistic up to order 4.

Condition 5 (i) $n = O(T)$; (ii) $E[k_j(x_{i,t})] = 0$; (iii) $|k_j(x_{i,t})| \leq CM(x_{i,t})$ such that $\sup_i E[M(x_{i,t})^8] < \infty$, where C denotes a generic constant.

Lemma 13 Suppose that Condition 5 holds. When $m = 1, 2, 3, 4$, then $\frac{1}{n} \sum_{i=1}^n W_{i,T} = O_p(1)$.

Proof. Suppose that $m = 1$. By Chebyshev's inequality, we have

$$\begin{aligned} \Pr \left[\left| \frac{1}{\sqrt{n}} \sum_{i=1}^n W_{i,T} \right| \geq \mathcal{M} \right] &= \Pr \left[\left| \frac{1}{\sqrt{n}} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right) \right| \geq \mathcal{M} \right] \\ &\leq \frac{E \left[\left| \frac{1}{\sqrt{n}} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right) \right|^2 \right]}{(\mathcal{M})^2} \\ &= \frac{\frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T E[k_1(x_{i,t})^2]}{(\mathcal{M})^2} \\ &\leq \frac{C^2 \sup_i E[M(x_{i,t})^2]}{(\mathcal{M})^2} \end{aligned}$$

It therefore follows that $\frac{1}{\sqrt{n}} \sum_{i=1}^n W_{i,T} = O_p(1)$, from which we obtain the desired conclusion.

Now suppose that $m = 2$. By Markov's inequality, we have

$$\begin{aligned} \Pr \left[\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^2 \geq \mathcal{M} \right] &\leq \frac{E \left[\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^2 \right]}{\mathcal{M}} \\ &= \frac{\frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T E \left[k_1(x_{i,t})^2 \right]}{\mathcal{M}} \\ &= \frac{C^2 \sup_i E \left[M(x_{i,t})^2 \right]}{\mathcal{M}} \end{aligned}$$

It therefore follows that $\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^2 = O_p(1)$. Likewise, we have $\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_2(x_{i,t}) \right)^2 = O_p(1)$. Because

$$\left| \frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right) \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_2(x_{i,t}) \right) \right| \leq \left(\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^2 \right)^{1/2} \left(\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_2(x_{i,t}) \right)^2 \right)^{1/2},$$

we obtain the desired conclusion.

Now, suppose that $m = 3$. By Markov's inequality, we have

$$\Pr \left[\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^4 \geq \mathcal{M} \right] \leq \frac{E \left[\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^4 \right]}{\mathcal{M}}$$

Because

$$\begin{aligned} E \left[\left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^4 \right] &= \frac{TE \left[k_1(x_{i,t})^4 \right] + 6 \frac{T(T-1)}{2} E \left[k_1(x_{i,t})^2 \right]^2}{T^2} \\ &= \frac{E \left[k_1(x_{i,t})^4 \right]}{T} + 3 \frac{(T-1) E \left[k_1(x_{i,t})^2 \right]^2}{T} \\ &\leq \frac{E \left[M(x_{i,t})^4 \right]}{T} + 3 \frac{(T-1) E \left[M(x_{i,t})^4 \right]}{T} \\ &< \infty \end{aligned}$$

we have $\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right)^4 = O_p(1)$. Likewise, we have $\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_2(x_{i,t}) \right)^4 = O_p(1)$, and $\frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_3(x_{i,t}) \right)^4 = O_p(1)$. This implies that

$$\frac{1}{n} \sum_{i=1}^n \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right|^3 = O_p(1), \quad \frac{1}{n} \sum_{i=1}^n \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T k_2(x_{i,t}) \right|^3 = O_p(1), \quad \frac{1}{n} \sum_{i=1}^n \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T k_3(x_{i,t}) \right|^3 = O_p(1)$$

by Jensen's inequality. Because

$$\begin{aligned} &\left| \frac{1}{n} \sum_{i=1}^n \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right) \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_2(x_{i,t}) \right) \left(\frac{1}{\sqrt{T}} \sum_{t=1}^T k_3(x_{i,t}) \right) \right| \\ &\leq \left(\frac{1}{n} \sum_{i=1}^n \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T k_1(x_{i,t}) \right|^3 \right)^{1/3} \left(\frac{1}{n} \sum_{i=1}^n \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T k_2(x_{i,t}) \right|^3 \right)^{1/3} \left(\frac{1}{n} \sum_{i=1}^n \left| \frac{1}{\sqrt{T}} \sum_{t=1}^T k_3(x_{i,t}) \right|^3 \right)^{1/3} \end{aligned}$$

by repeated application of Holder's inequality, we obtain the desired conclusion for $m = 3$. We obtain the same conclusion for $m = 4$ by the same method. ■

F.2 “Jackknifing” Normalized V-Statistics

We consider the average of delete- t estimators

$$\begin{aligned} \frac{1}{T} \sum_{t=1}^T W_{i,T,(-t)} &= \frac{1}{T} \sum_{t=1}^T (T-1)^{m/2} K_{i,T,(-t)} \\ &= (T-1)^{m/2} \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{T-1} \sum_{t_1 \neq t}^T k_1(x_{i,t_1}) \right) \left(\frac{1}{T-1} \sum_{t_2 \neq t}^T k_2(x_{i,t_2}) \right) \cdots \left(\frac{1}{T-1} \sum_{t_m \neq t}^T k_m(x_{i,t_m}) \right) \\ &= (T-1)^{m/2} \frac{1}{T} \sum_{t=1}^T \frac{T\bar{k}_{i,1} - k_1(x_{i,t})}{T-1} \frac{T\bar{k}_{i,2} - k_2(x_{i,t})}{T-1} \cdots \frac{T\bar{k}_{i,m} - k_m(x_{i,t})}{T-1} \end{aligned}$$

Lemma 14 *Suppose that Condition 5 holds. When $m = 1$, then $\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i=1}^n W_{i,T,(-t)} \right) = \frac{(T-1)^{1/2}}{T^{1/2}} \frac{1}{n} \sum_{i=1}^n W_{i,T}$. When $m = 2$, then $\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i=1}^n W_{i,T,(-t)} \right) = \frac{T-2}{T-1} \frac{1}{n} \sum_{i=1}^n W_{i,T} + \frac{1}{T(T-1)} \frac{1}{n} \sum_{i=1}^n \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t})$. When $m = 3$ or 4, then $\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i=1}^n W_{i,T,(-t)} \right) = \frac{1}{n} \sum_{i=1}^n W_{i,T} + o_p\left(\frac{1}{\sqrt{T}}\right)$.*

Proof. Lemma 14 would follow if (i) when $m = 1$,

$$\frac{1}{T} \sum_{t=1}^T W_{i,T,(-t)} = \frac{1}{T} \sum_{t=1}^T (T-1)^{1/2} K_{i,T,(-t)} = (T-1)^{1/2} K_{i,T} = \frac{(T-1)^{1/2}}{T^{1/2}} W_{i,T}$$

(ii) when $m = 2$,

$$\frac{1}{T} \sum_{t=1}^T W_{i,T,(-t)} = \frac{T-2}{T-1} W_{i,T} + \frac{1}{T(T-1)} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t})$$

(iii) when $m = 3$, we have

$$\begin{aligned} \frac{1}{T} \sum_{t=1}^T W_{i,T,(-t)} &= \frac{T^3 - 3T^2}{T^{3/2} (T-1)^{3/2}} W_{i,T} \\ &\quad + \frac{T^{1/2}}{(T-1)^{3/2}} \left(T^{1/2} \bar{k}_{i,1} \right) \left(\frac{1}{T} \sum_{t=1}^T k_2(x_{i,t}) k_3(x_{i,t}) \right) \\ &\quad + \frac{T^{1/2}}{(T-1)^{3/2}} \left(T^{1/2} \bar{k}_{i,2} \right) \left(\frac{1}{T} \sum_{t=1}^T k_3(x_{i,t}) k_1(x_{i,t}) \right) \\ &\quad + \frac{T^{1/2}}{(T-1)^{3/2}} \left(T^{1/2} \bar{k}_{i,3} \right) \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) \right) \\ &\quad - \frac{1}{(T-1)^{3/2}} \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_3(x_{i,t}) \right) \end{aligned}$$

(iv) when $m = 4$, we have

$$\begin{aligned}
\frac{1}{T} \sum_{t=1}^T W_{i,T,(-t)} &= \frac{T^2 - 4T}{(T-1)^2} W_{i,T} \\
&+ \frac{T}{(T-1)^2} (T^{1/2} \bar{k}_{i,1}) (T^{1/2} \bar{k}_{i,2}) \left(\frac{1}{T} \sum_{t=1}^T k_3(x_{i,t}) k_4(x_{i,t}) \right) \\
&+ \frac{T}{(T-1)^2} (T^{1/2} \bar{k}_{i,1}) (T^{1/2} \bar{k}_{i,3}) \left(\frac{1}{T} \sum_{t=1}^T k_2(x_{i,t}) k_4(x_{i,t}) \right) \\
&+ \frac{T}{(T-1)^2} (T^{1/2} \bar{k}_{i,1}) (T^{1/2} \bar{k}_{i,4}) \left(\frac{1}{T} \sum_{t=1}^T k_2(x_{i,t}) k_3(x_{i,t}) \right) \\
&+ \frac{T}{(T-1)^2} (T^{1/2} \bar{k}_{i,2}) (T^{1/2} \bar{k}_{i,3}) \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_4(x_{i,t}) \right) \\
&+ \frac{T}{(T-1)^2} (T^{1/2} \bar{k}_{i,2}) (T^{1/2} \bar{k}_{i,4}) \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_3(x_{i,t}) \right) \\
&+ \frac{T}{(T-1)^2} (T^{1/2} \bar{k}_{i,3}) (T^{1/2} \bar{k}_{i,4}) \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) \right) \\
&- \frac{T^{1/2}}{(T-1)^2} (T^{1/2} \bar{k}_{i,1}) \left(\frac{1}{T} \sum_{t=1}^T k_2(x_{i,t}) k_3(x_{i,t}) k_4(x_{i,t}) \right) \\
&- \frac{T^{1/2}}{(T-1)^2} (T^{1/2} \bar{k}_{i,2}) \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_3(x_{i,t}) k_4(x_{i,t}) \right) \\
&- \frac{T^{1/2}}{(T-1)^2} (T^{1/2} \bar{k}_{i,3}) \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_4(x_{i,t}) \right) \\
&- \frac{T^{1/2}}{(T-1)^2} (T^{1/2} \bar{k}_{i,4}) \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_3(x_{i,t}) \right) \\
&+ \frac{1}{(T-1)^2} \left(\frac{1}{T} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_3(x_{i,t}) k_4(x_{i,t}) \right)
\end{aligned}$$

In order to prove the preceding assertions, we note the following. For $m = 1$, it suffices to note that

$$\frac{1}{T} \sum_{t=1}^T K_{i,T,(-t)} = \bar{k}_{i,1} = K_{i,T}$$

For $m = 2$, it suffices to note that

$$\frac{1}{T} \sum_{t=1}^T K_{i,T,(-t)} = \frac{T^2 - 2T}{(T-1)^2} \bar{k}_{i,1} \bar{k}_{i,2} + \frac{1}{T(T-1)^2} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t})$$

For $m = 3$, it suffices to note that

$$\begin{aligned} \frac{1}{T} \sum_{t=1}^T K_{i,T,(-t)} &= \frac{T^3 - 3T^2}{(T-1)^3} \bar{k}_{i,1} \bar{k}_{i,2} \bar{k}_{i,3} \\ &+ \frac{1}{(T-1)^3} \bar{k}_{i,1} \sum_{t=1}^T k_2(x_{i,t}) k_3(x_{i,t}) + \frac{1}{(T-1)^3} \bar{k}_{i,2} \sum_{t=1}^T k_3(x_{i,t}) k_1(x_{i,t}) \\ &+ \frac{1}{(T-1)^3} \bar{k}_{i,3} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) - \frac{1}{T(T-1)^3} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_3(x_{i,t}) \end{aligned}$$

For $m = 4$, it suffices to note that

$$\begin{aligned} \frac{1}{T} \sum_{t=1}^T K_{i,T,(-t)} &= \frac{T^4 - 4T^3}{(T-1)^4} \bar{k}_{i,1} \bar{k}_{i,2} \bar{k}_{i,3} \bar{k}_{i,4} \\ &+ \bar{k}_{i,1} \bar{k}_{i,2} \frac{T}{(T-1)^4} \sum_{t=1}^T k_3(x_{i,t}) k_4(x_{i,t}) + \bar{k}_{i,1} \bar{k}_{i,3} \frac{T}{(T-1)^4} \sum_{t=1}^T k_2(x_{i,t}) k_4(x_{i,t}) \\ &+ \bar{k}_{i,1} \bar{k}_{i,4} \frac{T}{(T-1)^4} \sum_{t=1}^T k_2(x_{i,t}) k_3(x_{i,t}) + \bar{k}_{i,2} \bar{k}_{i,3} \frac{T}{(T-1)^4} \sum_{t=1}^T k_1(x_{i,t}) k_4(x_{i,t}) \\ &+ \bar{k}_{i,2} \bar{k}_{i,4} \frac{T}{(T-1)^4} \sum_{t=1}^T k_1(x_{i,t}) k_3(x_{i,t}) + \bar{k}_{i,3} \bar{k}_{i,4} \frac{T}{(T-1)^4} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) \\ &- \frac{1}{(T-1)^4} \bar{k}_{i,1} \sum_{t=1}^T k_2(x_{i,t}) k_3(x_{i,t}) k_4(x_{i,t}) - \frac{1}{(T-1)^4} \bar{k}_{i,2} \sum_{t=1}^T k_1(x_{i,t}) k_3(x_{i,t}) k_4(x_{i,t}) \\ &- \frac{1}{(T-1)^4} \bar{k}_{i,3} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_4(x_{i,t}) - \frac{1}{(T-1)^4} \bar{k}_{i,4} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_3(x_{i,t}) \\ &+ \frac{1}{T(T-1)^4} \sum_{t=1}^T k_1(x_{i,t}) k_2(x_{i,t}) k_3(x_{i,t}) k_4(x_{i,t}) \end{aligned}$$

■

F.3 “Jackknifing” Functions of Normalized V-Statistic

Now, consider a statistic of the form

$$W_T = W_{[1],T} W_{[2],T} \cdots W_{[L],T}$$

where

$$\begin{aligned} W_{[\ell],T} &\equiv \frac{1}{n} \sum_{i=1}^n \frac{1}{T^{m_\ell/2}} \sum_{t_1=1}^T \sum_{t_2=1}^T \cdots \sum_{t_{m_\ell}=1}^T k_{[\ell,1]}(x_{i,t_1}) k_{[\ell,2]}(x_{i,t_2}) \cdots k_{[\ell,m_\ell]}(x_{i,t_{m_\ell}}) \\ &\equiv T^{m_\ell/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[\ell,1]} \bar{k}_{i,[\ell,2]} \cdots \bar{k}_{i,[\ell,m_\ell]} \\ &\equiv T^{m_\ell/2} \frac{1}{n} \sum_{i=1}^n K_{i,[\ell],T} \\ &\equiv T^{m_\ell/2} K_{[\ell],T}. \end{aligned}$$

Therefore, W_T is the product of m_1, \dots, m_L normalized V-statistics. We will also call them normalized V-statistic of order $\sum_{\ell=1}^L m_\ell$.

We consider the average of delete- t estimators

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = \frac{1}{T} \sum_{t=1}^T W_{[1],T,(-t)} W_{[2],T,(-t)} \cdots W_{[L],T,(-t)}$$

where

$$\begin{aligned} W_{[\ell],T,(-t)} &\equiv \frac{1}{n} \sum_{i=1}^n \frac{1}{(T-1)^{m_\ell/2}} \sum_{t_1 \neq t}^T \sum_{t_2 \neq t}^T \cdots \sum_{t_{m_\ell} \neq t}^T k_{[\ell,1]}(x_{i,t_1}) k_{[\ell,2]}(x_{i,t_2}) \cdots k_{[\ell,m_\ell]}(x_{i,t_{m_\ell}}) \\ &= (T-1)^{m_\ell/2} \frac{1}{n} \sum_{i=1}^n \frac{T\bar{k}_{i,[\ell,1]} - k_{[\ell,1]}(x_{i,t})}{T-1} \frac{T\bar{k}_{i,[\ell,2]} - k_{[\ell,2]}(x_{i,t})}{T-1} \cdots \frac{T\bar{k}_{i,[\ell,m_\ell]} - k_{[\ell,m_\ell]}(x_{i,t})}{T-1} \\ &= \frac{1}{(T-1)^{m_\ell/2}} \frac{1}{n} \sum_{i=1}^n (T\bar{k}_{i,[\ell,1]} - k_{[\ell,1]}(x_{i,t})) (T\bar{k}_{i,[\ell,2]} - k_{[\ell,2]}(x_{i,t})) \cdots (T\bar{k}_{i,[\ell,m_\ell]} - k_{[\ell,m_\ell]}(x_{i,t})) \end{aligned}$$

Below, we characterize properties of “jackknifed” normalized V-statistic of order up to 4.

Lemma 15 *Suppose that Condition 5 holds. When $\sum_{\ell} m_\ell = 2, \sum_{\ell} m_\ell = 2, L = 2, m_1 = m_2 = 1$, we have*

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = \frac{T-2}{T-1} W_T + O_p\left(\frac{1}{nT}\right).$$

Proof. We have

$$W_{[1],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[1,1]}, \quad W_{[2],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[2,1]}$$

and therefore,

$$W_T = T \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \bar{k}_{i_1,[1,1]} \bar{k}_{i_2,[2,1]}$$

and

$$\begin{aligned} \frac{1}{T} \sum_{t=1}^T W_{T,(-t)} &= \frac{1}{T(T-1)} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T (T\bar{k}_{i_1,[1,1]} - k_{[1,1]}(x_{i_1,t})) (T\bar{k}_{i_2,[2,1]} - k_{[2,1]}(x_{i_2,t})) \\ &= \frac{T^2 - 2T}{T-1} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \bar{k}_{i_1,[1,1]} \bar{k}_{i_2,[2,1]} \\ &\quad + \frac{1}{T(T-1)} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \\ &= \frac{T-2}{T-1} W_T + \frac{1}{T(T-1)} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \end{aligned}$$

Note that

$$W_T = \frac{1}{n} \left(\frac{1}{\sqrt{n}} \sum_{i_1=1}^n (\sqrt{T} \bar{k}_{i_1,[1,1]}) \right) \left(\frac{1}{\sqrt{n}} \sum_{i_2=1}^n (\sqrt{T} \bar{k}_{i_2,[2,1]}) \right) = O_p\left(\frac{1}{n}\right)$$

and

$$\begin{aligned} & \frac{1}{T(T-1)} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \\ &= \frac{1}{n(T-1)} \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{\sqrt{n}} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{\sqrt{n}} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \end{aligned}$$

Because

$$\begin{aligned} & E \left[\left| \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{\sqrt{n}} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{\sqrt{n}} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \right|^2 \right] \\ & \leq \frac{1}{T} \sum_{t=1}^T E \left[\left(\frac{1}{\sqrt{n}} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right)^2 \left(\frac{1}{\sqrt{n}} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right)^2 \right] \\ & \leq E \left[\left(\frac{1}{\sqrt{n}} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right)^4 \right]^{1/2} E \left[\left(\frac{1}{\sqrt{n}} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right)^4 \right]^{1/2} \\ & \leq \frac{n \max_i E \left[k_1(x_{i,t})^4 \right] + 6 \frac{n(n-1)}{2} \max_i E \left[k_1(x_{i,t})^2 \right]^2}{n^2} \\ & < \infty \end{aligned}$$

we have

$$\frac{1}{T(T-1)} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) = O_p \left(\frac{1}{nT} \right)$$

Therefore, we have

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = \frac{T-2}{T-1} W_T + O_p \left(\frac{1}{nT} \right)$$

■

Lemma 16 Suppose that Condition 5 holds. When $\sum_{\ell} m_{\ell} = 3, L = 2, m_1 = 1, m_2 = 2$, we have

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right).$$

Proof. We have

$$W_{[1],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[1,1]}, \quad W_{[2],T} = T \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[2,1]} \bar{k}_{i,[2,2]}$$

and therefore,

$$W_T = T^{3/2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \bar{k}_{i_1,[1,1]} \bar{k}_{i_2,[2,1]} \bar{k}_{i_2,[2,2]}$$

and

$$\begin{aligned}
& \frac{1}{T} \sum_{t=1}^T W_{T,(-t)} \\
&= \frac{1}{T(T-1)^{3/2}} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T (T\bar{k}_{i_1,[1,1]} - k_{[1,1]}(x_{i_1,t})) (T\bar{k}_{i_2,[2,1]} - k_{[2,1]}(x_{i_2,t})) (T\bar{k}_{i_2,[2,2]} - k_{[2,2]}(x_{i_2,t})) \\
&= \frac{T^3 - 3T^2}{T^{3/2}(T-1)^{3/2}} W_T \\
&+ \frac{T^{1/2}}{(T-1)^{3/2}} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \\
&+ \frac{T^{1/2}}{(T-1)^{3/2}} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,2]}(x_{i_2,t}) \right) \\
&+ \frac{T^{1/2}}{(T-1)^{3/2}} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \right) \\
&- \frac{1}{(T-1)^{3/2}} \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \tag{24}
\end{aligned}$$

We now show that

$$\frac{T^{1/2}}{(T-1)^{3/2}} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \tag{25}$$

For this purpose, it suffices to note that

$$\begin{aligned}
& \left| \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right| \\
&\leq \left| \frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1,[1,1]} \right) \right| \left| \frac{1}{n} \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right| \\
&= O_p(1)
\end{aligned}$$

by Lemma 13.

We now show that

$$\begin{aligned}
& \frac{T^{1/2}}{(T-1)^{3/2}} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,2]}(x_{i_2,t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right), \\
& \frac{T^{1/2}}{(T-1)^{3/2}} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right). \tag{26}
\end{aligned}$$

For this purpose, we observe that

$$\begin{aligned}
& \left| \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1, t}) k_{[2,2]}(x_{i_2, t}) \right) \right|^2 \\
&= \left| \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) k_{[2,2]}(x_{i_2, t}) \right) \right|^2 \\
&\leq \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right)^2 \cdot \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) k_{[2,2]}(x_{i_2, t}) \right)^2 \\
&\leq \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right)^2 \cdot \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right)^2 k_{[2,2]}(x_{i_2, t})^2 \right) \\
&\leq \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t})^2 \right) \cdot \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right)^2 \left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t})^2 \right) \\
&\leq \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n M(x_{i_1, t})^2 \right) \cdot \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right)^2 \left(\frac{1}{T} \sum_{t=1}^T M(x_{i_2, t})^2 \right),
\end{aligned}$$

where the far RHS has an expectation equal to

$$\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n E \left[M(x_{i_1, t})^2 \right] \cdot \frac{1}{n} \sum_{i_2=1}^n E \left[k_{[2,1]}(x_{i_2, t})^2 \right] \left(\frac{1}{T} \sum_{t=1}^T E \left[M(x_{i_2, t})^2 \right] \right) = O(1)$$

Therefore, we have

$$\frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1, t}) k_{[2,2]}(x_{i_2, t}) \right) = O_p(1)$$

Likewise, we have

$$\frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1, t}) k_{[2,1]}(x_{i_2, t}) \right) = O_p(1)$$

We now show that

$$-\frac{1}{(T-1)^{3/2}} \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \quad (27)$$

For this purpose, it suffices to note that

$$\frac{1}{T^{3/2}} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) \right) = O_p(1)$$

Using equations (24) and (25), (26), (27), we conclude that

$$\frac{1}{T} \sum_{t=1}^T W_{T, (-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right)$$

■

Lemma 17 Suppose that Condition 5 holds. When $\sum_{\ell} m_{\ell} = 3, L = 3, m_1 = 1, m_2 = 1, m_3 = 1$, we have

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p\left(\frac{1}{\sqrt{T}}\right).$$

Proof. We have

$$W_{[1],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[1,1]}, \quad W_{[2],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[2,1]}, \quad W_{[3],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[3,1]}$$

and therefore,

$$W_T = T^{3/2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \bar{k}_{i_1,[1,1]} \bar{k}_{i_2,[2,1]}$$

and

$$\begin{aligned} & \frac{1}{T} \sum_{t=1}^T W_{T,(-t)} \\ &= \frac{1}{T(T-1)^{3/2}} \frac{1}{n^3} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{i_3=1}^n \sum_{t=1}^T (T\bar{k}_{i_1,[1,1]} - k_{[1,1]}(x_{i_1,t})) (T\bar{k}_{i_2,[2,1]} - k_{[2,1]}(x_{i_2,t})) (T\bar{k}_{i_3,[3,1]} - k_{[3,1]}(x_{i_3,t})) \\ &= \frac{T^3 - 3T^2}{T^{3/2}(T-1)^{3/2}} W_T \\ & \quad + \frac{T^{1/2}}{(T-1)^{3/2}} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\ & \quad + \frac{T^{1/2}}{(T-1)^{3/2}} \left(\frac{1}{n} \sum_{i_2=1}^n T^{1/2} \bar{k}_{i_2,[2,1]} \right) \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\ & \quad + \frac{T^{1/2}}{(T-1)^{3/2}} \left(\frac{1}{n} \sum_{i_3=1}^n T^{1/2} \bar{k}_{i_3,[3,1]} \right) \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \right) \\ & \quad - \frac{1}{(T-1)^{3/2}} \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \end{aligned} \quad (28)$$

We now show that

$$\begin{aligned} & \frac{T^{1/2}}{(T-1)^{3/2}} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = o_p\left(\frac{1}{\sqrt{T}}\right) \\ & \frac{T^{1/2}}{(T-1)^{3/2}} \left(\frac{1}{n} \sum_{i_2=1}^n T^{1/2} \bar{k}_{i_2,[2,1]} \right) \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = o_p\left(\frac{1}{\sqrt{T}}\right) \\ & \frac{T^{1/2}}{(T-1)^{3/2}} \left(\frac{1}{n} \sum_{i_3=1}^n T^{1/2} \bar{k}_{i_3,[3,1]} \right) \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \right) = o_p\left(\frac{1}{\sqrt{T}}\right) \\ & \frac{1}{(T-1)^{3/2}} \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = o_p\left(\frac{1}{\sqrt{T}}\right) \end{aligned} \quad (29)$$

Only the first assertion is proved. Others are proved similarly. It suffices to prove that $\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} =$

$O_p(1)$ and $\frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = O_p(1)$. Because

$$\begin{aligned} E \left[\left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right)^2 \right] &= \frac{1}{n^2} \sum_{i_1=1}^n E \left[\left(T^{1/2} \bar{k}_{i_1,[1,1]} \right)^2 \right] = \frac{1}{n^2 T} \sum_{i_1=1}^n E \left[\left(k_{[1,1]}(x_{i_1,t}) \right)^2 \right] \\ &\leq \frac{1}{nT} \max_i E \left[M(x_{i,t})^2 \right] \end{aligned}$$

we have

$$\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} = O_p \left(\frac{1}{\sqrt{nT}} \right)$$

and the first part is proved. We also have

$$\begin{aligned} E \left[\left| \frac{1}{T} \sum_{t=1}^T \left(\left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \right| \right] &\leq \frac{1}{n^2 T} \sum_{t=1}^T \sum_{i_2=1}^n \sum_{i_3=1}^n E \left[|k_{[2,1]}(x_{i_2,t})| |k_{[3,1]}(x_{i_3,t})| \right] \\ &\leq \frac{1}{n^2 T} \sum_{t=1}^T \sum_{i_2=1}^n \sum_{i_3=1}^n E \left[M(x_{i_2,t}) M(x_{i_3,t}) \right] \\ &= O(1) \end{aligned}$$

from which the second part follows.

We now get back to the proof of Lemma 17. Using equations (28) and (29), we conclude that

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right)$$

■

Lemma 18 *Suppose that Condition 5 holds. When $\sum_{\ell} m_{\ell} = 4, L = 2, m_1 = 1, m_2 = 3$, we have*

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right).$$

Proof. We have

$$W_{[1],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[1,1]}, \quad W_{[2],T} = T^{3/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[2,1]} \bar{k}_{i,[2,2]} \bar{k}_{i,[2,3]}$$

and therefore,

$$W_T = T^2 \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \bar{k}_{i_1,[1,1]} \bar{k}_{i_2,[2,1]} \bar{k}_{i_2,[2,3]}$$

and

$$\begin{aligned}
& \frac{1}{T} \sum_{t=1}^T W_{T,(-t)} \\
&= \frac{1}{T(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T (T\bar{k}_{i_1,[1,1]} - k_{[1,1]}(x_{i_1,t})) (T\bar{k}_{i_2,[2,1]} - k_{[2,1]}(x_{i_2,t})) \\
&\quad \times (T\bar{k}_{i_2,[2,2]} - k_{[2,2]}(x_{i_2,t})) (T\bar{k}_{i_2,[2,3]} - k_{[2,3]}(x_{i_2,t})) \\
&= \frac{T^2 - 4T}{(T-1)^2} W_T \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2,[2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2,[2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(T^{1/2} \bar{k}_{i_2,[2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,3]}(x_{i_2,t}) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(T^{1/2} \bar{k}_{i_2,[2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,2]} \right) \left(T^{1/2} \bar{k}_{i_2,[2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1,[1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2,[2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \\
&\quad + \frac{1}{(T-1)^2} \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right) \quad (30)
\end{aligned}$$

We now show that

$$\begin{aligned} \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right) \right) &= o_p \left(\frac{1}{\sqrt{T}} \right) \\ \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right) \right) &= o_p \left(\frac{1}{\sqrt{T}} \right) \\ \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) \right) \right) &= o_p \left(\frac{1}{\sqrt{T}} \right) \end{aligned}$$

Only the first claim is proved. Others can be proved similarly. For this purpose, it suffices to prove that

$$\left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right) \right) = O_p(1)$$

Because $\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} = O_p(1)$, we need only to prove that

$$\frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right) \right) = O_p(1)$$

Because

$$\left| \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right) \right) \right| \leq \frac{1}{n} \sum_{i_2=1}^n \left| T^{1/2} \bar{k}_{i_2, [2,1]} \right| \left| \frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right|,$$

we have

$$\begin{aligned} & E \left[\left| \frac{1}{n} \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right) \right) \right|^2 \right] \\ & \leq \frac{1}{n} \sum_{i_2=1}^n \left(E \left[\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right)^2 \right] \right)^{1/2} \left(E \left[\left(\frac{1}{T} \sum_{t=1}^T k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right)^2 \right] \right)^{1/2} \\ & \leq \frac{1}{n} \sum_{i_2=1}^n \left(E \left[k_{[2,1]}^2(x_{i_2, t}) \right] \right)^{1/2} E \left[\left(\frac{1}{T} \sum_{t=1}^T M(x_{i_2, t})^2 \right)^2 \right] \\ & = O(1). \end{aligned}$$

The conclusion follows by Markov inequality.

We now show that

$$\begin{aligned} \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,3]}(x_{i_2, t}) \right) &= o_p \left(\frac{1}{\sqrt{T}} \right) \\ \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,2]}(x_{i_2, t}) \right) &= o_p \left(\frac{1}{\sqrt{T}} \right) \\ \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,1]}(x_{i_2, t}) \right) &= o_p \left(\frac{1}{\sqrt{T}} \right) \end{aligned}$$

Only the first claim is proved. Others can be proved similarly. For this purpose, it suffices to prove that

$$\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,3]}(x_{i_2, t}) \right) = O_p(1)$$

Note that

$$\begin{aligned}
& \left| \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,3]}(x_{i_2, t}) \right) \right| \\
& \leq \frac{1}{n} \sum_{i_2=1}^n \left| T^{1/2} \bar{k}_{i_2, [2,1]} \right| \left| T^{1/2} \bar{k}_{i_2, [2,2]} \right| \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n |k_{[1,1]}(x_{i_1, t})| \right) |k_{[2,3]}(x_{i_2, t})| \right) \\
& \leq \frac{1}{n} \sum_{i_2=1}^n \left| T^{1/2} \bar{k}_{i_2, [2,1]} \right| \left| T^{1/2} \bar{k}_{i_2, [2,2]} \right| \left(\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n M(x_{i_1, t}) M(x_{i_2, t}) \right)
\end{aligned}$$

Therefore,

$$\begin{aligned}
& E \left[\left| \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,3]}(x_{i_2, t}) \right) \right|^2 \right] \\
& \leq \frac{1}{n} \sum_{i_2=1}^n \left(E \left[\left(\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n M(x_{i_1, t}) M(x_{i_2, t}) \right)^2 \right] \right)^{1/2} \\
& \quad \times \left(E \left[\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right)^4 \right] \right)^{1/4} \left(E \left[\left(T^{1/2} \bar{k}_{i_2, [2,2]} \right)^4 \right] \right)^{1/4}
\end{aligned}$$

But because

$$\begin{aligned}
E \left[\left(\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n M(x_{i_1, t}) M(x_{i_2, t}) \right)^2 \right] & \leq \frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n E \left[M(x_{i_1, t})^2 M(x_{i_2, t})^2 \right] \\
& \leq \frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n \max_i E \left[M(x_{i, t})^4 \right] \\
& = \max_i E \left[M(x_{i, t})^4 \right],
\end{aligned}$$

$$\begin{aligned}
E \left[\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right)^4 \right] & = \frac{TE \left[k_{[2,1]}(x_{i_2, t})^4 \right] + 3T(T-1) E \left[k_{[2,1]}(x_{i_2, t})^2 \right]^2}{T^2} \\
& \leq 3 \max_i E \left[M(x_{i, t})^4 \right],
\end{aligned}$$

and

$$E \left[\left(T^{1/2} \bar{k}_{i_2, [2,2]} \right)^4 \right] \leq 3 \max_i E \left[M(x_{i, t})^4 \right],$$

we should have

$$E \left[\left| \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,3]}(x_{i_2, t}) \right) \right|^2 \right] = O(1),$$

from which the conclusion follows.

We now show that

$$\frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) k_{[2,3]}(x_{i_2, t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \quad (33)$$

For this purpose, it suffices to prove that

$$\frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) = O_p(1)$$

This follows from

$$\frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) = O_p(1)$$

and

$$\frac{1}{n} \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) = O_p(1)$$

We now show that

$$\begin{aligned} \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) &= o_p\left(\frac{1}{\sqrt{T}}\right) \\ \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) &= o_p\left(\frac{1}{\sqrt{T}}\right) \\ \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,3]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) &= o_p\left(\frac{1}{\sqrt{T}}\right) \end{aligned}$$

Only the first claim is proved. Others can be proved similarly. For this purpose, it suffices to prove that

$$\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) = O_p(1)$$

Note that

$$\begin{aligned} &\left| \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right| \\ &\leq \frac{1}{n} \sum_{i_2=1}^n \left| T^{1/2} \bar{k}_{i_2, [2,1]} \right| \left(\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n M(x_{i_1,t}) M(x_{i_2,t})^2 \right) \end{aligned}$$

Therefore, we have

$$\begin{aligned} &E \left[\left| \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right| \right] \\ &\leq \frac{1}{n} \sum_{i_2=1}^n \left(E \left[\left| T^{1/2} \bar{k}_{i_2, [2,1]} \right|^2 \right] \right)^{1/2} \left(E \left[\left(\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n M(x_{i_1,t}) M(x_{i_2,t})^2 \right)^2 \right] \right)^{1/2} \\ &\leq \frac{1}{n} \sum_{i_2=1}^n \left(E \left[M(x_{i_2,t})^2 \right] \right)^{1/2} \left(E \left[\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n M(x_{i_1,t})^2 M(x_{i_2,t})^4 \right] \right)^{1/2} \\ &\leq \frac{1}{n} \sum_{i_2=1}^n \left(E \left[M(x_{i_2,t})^2 \right] \right)^{1/2} \left(\frac{1}{nT} \sum_{t=1}^T \sum_{i_1=1}^n \left(E \left[M(x_{i_1,t})^4 \right] \right)^{1/2} \left(E \left[M(x_{i_2,t})^8 \right] \right)^{1/2} \right)^{1/2} \\ &\leq \frac{1}{n} \sum_{i_2=1}^n \left(\max_i E \left[M(x_{i,t})^2 \right] \right)^{1/2} \left(\max_i E \left[M(x_{i,t})^4 \right] \right)^{1/4} \left(\max_i E \left[M(x_{i,t})^8 \right] \right)^{1/4} \\ &= O(1), \end{aligned}$$

from which the conclusion follows.

We now show that

$$\frac{1}{(T-1)^2} \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \quad (35)$$

For this purpose, it suffices to prove that

$$\left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right) = O_p(1)$$

Note that

$$\left| \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right| \leq \frac{1}{n^2 T} \sum_{t=1}^T \sum_{i_1=1}^n \sum_{i_2=1}^n M(x_{i_1,t}) M(x_{i_2,t})^3$$

Therefore, we have

$$E \left[\left| \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) k_{[2,3]}(x_{i_2,t}) \right) \right| \right] = O(1),$$

from which the conclusion follows.

We now get back to the proof of Lemma 18. Using equations (30) and (31), (32), (33), (34), (35), we conclude that

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right)$$

■

Lemma 19 *Suppose that Condition 5 holds. When $\sum_{\ell} m_{\ell} = 4, L = 3, m_1 = 1, m_2 = 2, m_3 = 1$, we have*

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right).$$

Proof. We have

$$W_{[1],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[1,1]}, \quad W_{[2],T} = T \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[2,1]} \bar{k}_{i,[2,2]}, \quad W_{[3],T} = T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[3,1]}$$

and therefore,

$$W_T = T^2 \frac{1}{n^3} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{i_3=1}^n \bar{k}_{i_1,[1,1]} \bar{k}_{i_2,[2,1]} \bar{k}_{i_3,[3,1]}$$

and

$$\begin{aligned}
& \frac{1}{T} \sum_{t=1}^T W_{T,(-t)} \\
&= \frac{1}{T(T-1)^2} \frac{1}{n^3} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{i_3=1}^n \sum_{t=1}^T (T\bar{k}_{i_1,[1,1]} - k_{[1,1]}(x_{i_1,t})) (T\bar{k}_{i_2,[2,1]} - k_{[2,1]}(x_{i_2,t})) \\
&\quad \times (T\bar{k}_{i_2,[2,2]} - k_{[2,2]}(x_{i_2,t})) (T\bar{k}_{i_3,[3,1]} - k_{[3,1]}(x_{i_3,t})) \\
&= \frac{T^2 - 4T}{(T-1)^2} W_T \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n (T^{1/2} \bar{k}_{i_2,[2,1]}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n (T^{1/2} \bar{k}_{i_2,[2,2]}) k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) \left(\frac{1}{n} \sum_{i_3=1}^n (T^{1/2} \bar{k}_{i_3,[3,1]}) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_2=1}^n (T^{1/2} \bar{k}_{i_2,[2,1]}) (T^{1/2} \bar{k}_{i_2,[2,2]}) \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n (T^{1/2} \bar{k}_{i_2,[2,1]}) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n (T^{1/2} \bar{k}_{i_3,[3,1]}) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n (T^{1/2} \bar{k}_{i_2,[2,2]}) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n (T^{1/2} \bar{k}_{i_3,[3,1]}) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n (T^{1/2} \bar{k}_{i_1,[1,1]}) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n (T^{1/2} \bar{k}_{i_2,[2,1]}) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n (T^{1/2} \bar{k}_{i_2,[2,2]}) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n (T^{1/2} \bar{k}_{i_3,[3,1]}) \right) \\
&\quad + \frac{1}{(T-1)^2} \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \quad (36)
\end{aligned}$$

We now show that

$$\begin{aligned}
& \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) k_{[2,2]}(x_{i_2, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3, t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) k_{[2,1]}(x_{i_2, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3, t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \frac{1}{n} \sum_{i_2=1}^n \left(\left(\frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) \right) \right) \left(\frac{1}{n} \sum_{i_3=1}^n \left(T^{1/2} \bar{k}_{i_3, [3,1]} \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3, t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,2]}(x_{i_2, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n \left(T^{1/2} \bar{k}_{i_3, [3,1]} \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1, t}) \right) k_{[2,1]}(x_{i_2, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n \left(T^{1/2} \bar{k}_{i_3, [3,1]} \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right)
\end{aligned}$$

Only the first assertion will be proved. Other can be proved similarly. For this purpose, it suffices to prove that

$$\left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) k_{[2,2]}(x_{i_2, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3, t}) \right) \right) = O_p(1)$$

Because

$$\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1, [1,1]} = O_p(1),$$

we only need to prove that

$$\left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) k_{[2,2]}(x_{i_2, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3, t}) \right) \right) = O_p(1)$$

Note that

$$\begin{aligned}
& E \left[\left| \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) k_{[2,2]}(x_{i_2, t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3, t}) \right) \right| \right] \\
& \leq \frac{1}{n^2 T} \sum_{i_2=1}^n \sum_{i_3=1}^n \sum_{t=1}^T E \left[\left| T^{1/2} \bar{k}_{i_2, [2,1]} \right| M(x_{i_2, t}) M(x_{i_3, t}) \right] \\
& \leq \frac{1}{n^2 T} \sum_{i_2=1}^n \sum_{i_3=1}^n \sum_{t=1}^T \left(E \left[\left| T^{1/2} \bar{k}_{i_2, [2,1]} \right|^2 \right] \right)^{1/2} \left(E \left[M(x_{i_2, t})^2 M(x_{i_3, t})^2 \right] \right)^{1/2} \\
& = O(1),
\end{aligned}$$

from which the conclusion follows.

We now show that

$$\begin{aligned}
\frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) & \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
\frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) & \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
\frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) & \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
\frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \right) & k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \left(\frac{1}{n} \sum_{i_3=1}^n \left(T^{1/2} \bar{k}_{i_3, [3,1]} \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right)
\end{aligned}$$

Only the first assertion will be proved. Other can be proved similarly. For this purpose, it suffices to prove that

$$\frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = O_p(1)$$

But it follows from

$$\frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) = O_p(1),$$

and

$$\begin{aligned}
& \left| \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right| \\
& \leq \frac{1}{n^2 T} \sum_{t=1}^T \sum_{i_2=1}^n \sum_{i_3=1}^n M(x_{i_2,t})^2 M(x_{i_3,t}) \\
& = O_p(1)
\end{aligned}$$

We now show that

$$\frac{1}{(T-1)^2} \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \tag{39}$$

For this purpose, it suffices to prove that

$$\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) = O_p(1)$$

This follows because

$$\begin{aligned}
& \left| \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right| \\
& \leq \frac{1}{n^2 T} \sum_{t=1}^T \sum_{i_2=1}^n \sum_{i_3=1}^n M(x_{i_1,t}) M(x_{i_2,t}) M(x_{i_3,t}) \\
& = O_p(1)
\end{aligned}$$

We now get back to the proof of Lemma 19. Using equations (36) and (37), (38), (39), we conclude

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p\left(\frac{1}{\sqrt{T}}\right)$$

■

Lemma 20 *Suppose that Condition 5 holds. When $\sum_{\ell} m_{\ell} = 4, L = 2, m_1 = 2, m_2 = 2$, we have*

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p\left(\frac{1}{\sqrt{T}}\right).$$

Proof. We have

$$W_{[1],T} = T \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[1,1]} \bar{k}_{i,[1,2]}, \quad W_{[2],T} = T \frac{1}{n} \sum_{i=1}^n \bar{k}_{i,[2,1]} \bar{k}_{i,[2,2]}$$

and therefore,

$$W_T = T^2 \frac{1}{n^3} \sum_{i_1=1}^n \sum_{i_2=1}^n \bar{k}_{i_1,[1,1]} \bar{k}_{i_1,[1,2]} \bar{k}_{i_2,[2,1]} \bar{k}_{i_3,[3,1]}$$

and

$$\begin{aligned}
& \frac{1}{T} \sum_{t=1}^T W_{T,(-t)} \\
&= \frac{1}{T(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T (T\bar{k}_{i_1,[1,1]} - k_{[1,1]}(x_{i_1,t})) (T\bar{k}_{i_1,[1,2]} - k_{[1,2]}(x_{i_1,t})) \\
&\quad \times (T\bar{k}_{i_2,[2,1]} - k_{[2,1]}(x_{i_2,t})) (T\bar{k}_{i_2,[2,2]} - k_{[2,2]}(x_{i_2,t})) \\
&= \frac{T^2 - 4T}{(T-1)^2} W_T \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n (T^{1/2}\bar{k}_{i_1,[1,1]}) (T^{1/2}\bar{k}_{i_1,[1,2]}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n \frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left((T^{1/2}\bar{k}_{i_1,[1,1]}) (T^{1/2}\bar{k}_{i_2,[2,1]}) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left((T^{1/2}\bar{k}_{i_1,[1,1]}) (T^{1/2}\bar{k}_{i_2,[2,2]}) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left((T^{1/2}\bar{k}_{i_1,[1,2]}) (T^{1/2}\bar{k}_{i_2,[2,1]}) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left((T^{1/2}\bar{k}_{i_1,[1,2]}) (T^{1/2}\bar{k}_{i_2,[2,2]}) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left((T^{1/2}\bar{k}_{i_2,[2,1]}) (T^{1/2}\bar{k}_{i_2,[2,2]}) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[1,2]}(x_{i_1,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n (T^{1/2}\bar{k}_{i_1,[1,1]}) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1,t}) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n (T^{1/2}\bar{k}_{i_1,[1,2]}) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n (T^{1/2}\bar{k}_{i_2,[2,1]}) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) k_{[1,2]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n (T^{1/2}\bar{k}_{i_2,[2,2]}) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) k_{[1,2]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) \right) \\
&\quad + \frac{1}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[1,2]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \tag{40}
\end{aligned}$$

We now show that

$$\begin{aligned}
& \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(T^{1/2} \bar{k}_{i_1, [1,2]} \right) \right) \left(\frac{1}{n} \sum_{i_2=1}^n \frac{1}{T} \sum_{t=1}^T k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_1, [1,2]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_1, [1,2]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[2,1]}(x_{i_2,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) k_{[1,2]}(x_{i_1,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right)
\end{aligned}$$

The first assertion follows from Lemma 13. For the remaining assertions, only the second will be established. Others can be proved similarly. In order to prove the first assertion, it suffices to note that

$$\begin{aligned}
& E \left[\left[\frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) \right] \right] \\
& \leq \frac{1}{n^2 T} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T E \left[\left| T^{1/2} \bar{k}_{i_1, [1,1]} \right| \left| T^{1/2} \bar{k}_{i_2, [2,1]} \right| M(x_{i_1,t}) M(x_{i_2,t}) \right] \\
& \leq \frac{1}{n^2 T} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T \left(E \left[\left(\left| T^{1/2} \bar{k}_{i_1, [1,1]} \right| \left| T^{1/2} \bar{k}_{i_2, [2,1]} \right| \right)^2 \right] \right)^{1/2} \left(E \left[M(x_{i_1,t})^2 M(x_{i_2,t})^2 \right] \right)^{1/2} \\
& \leq \frac{1}{n^2 T} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T \left(E \left| T^{1/2} \bar{k}_{i_1, [1,1]} \right|^4 \right)^{1/4} \left(E \left| T^{1/2} \bar{k}_{i_2, [2,1]} \right|^4 \right)^{1/4} \left(E \left[M(x_{i_1,t})^2 M(x_{i_2,t})^2 \right] \right)^{1/2} \\
& \leq \frac{1}{n^2 T} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T \left(3 \max_i E \left[M(x_{i,t})^4 \right] \right)^{1/4} \left(3 \max_i E \left[M(x_{i,t})^4 \right] \right)^{1/4} \left(\max_i E \left[M(x_{i,t})^4 \right] \right)^{1/2} \\
& = O(1)
\end{aligned}$$

We now show that

$$\begin{aligned}
& \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1,t}) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1,t}) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) k_{[2,2]}(x_{i_2,t}) \right) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) k_{[1,2]}(x_{i_1,t}) \right) k_{[2,2]}(x_{i_2,t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \\
& \frac{T^{1/2}}{(T-1)^2} \frac{1}{n} \sum_{i_2=1}^n \left(T^{1/2} \bar{k}_{i_2, [2,2]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) k_{[1,2]}(x_{i_1,t}) \right) k_{[2,1]}(x_{i_2,t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right)
\end{aligned}$$

Only the first assertion will be proved. Others can be established similarly. In order to prove the first assertion, it suffices to note that

$$\begin{aligned}
& E \left[\left| \frac{1}{n} \sum_{i_1=1}^n \left(T^{1/2} \bar{k}_{i_1, [1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T k_{[1,2]}(x_{i_1, t}) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) \right) \right) \right| \right] \\
& \leq \frac{1}{n^2 T} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T E \left[\left| T^{1/2} \bar{k}_{i_1, [1,1]} \right| M(x_{i_1, t}) M(x_{i_2, t})^2 \right] \\
& = \frac{1}{n^2 T} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T \left(E \left[\left| T^{1/2} \bar{k}_{i_1, [1,1]} \right|^2 \right] \right)^{1/2} \left(E \left[M(x_{i_1, t})^2 M(x_{i_2, t})^4 \right] \right)^{1/2} \\
& = O(1)
\end{aligned}$$

We now show that

$$\frac{1}{(T-1)^2} \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1, t}) k_{[1,2]}(x_{i_1, t}) k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) \right) = o_p \left(\frac{1}{\sqrt{T}} \right) \quad (43)$$

This follows easily from

$$\begin{aligned}
& E \left[\left| \frac{1}{n^2} \sum_{i_1=1}^n \sum_{i_2=1}^n \left(\frac{1}{T} \sum_{t=1}^T k_{[1,1]}(x_{i_1, t}) k_{[1,2]}(x_{i_1, t}) k_{[2,1]}(x_{i_2, t}) k_{[2,2]}(x_{i_2, t}) \right) \right| \right] \\
& \leq \frac{1}{n^2 T} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{t=1}^T E \left[M(x_{i_1, t})^2 M(x_{i_2, t})^2 \right] \\
& = O(1)
\end{aligned}$$

We now get back to the proof of Lemma 20. Using equations (40) and (41), (42), (43), we conclude

$$\frac{1}{T} \sum_{t=1}^T W_{T, (-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right)$$

■

Lemma 21 *Suppose that Condition 5 holds. When $\sum_{\ell} m_{\ell} = 4$, $L = 4$, $m_1 = 1$, $m_2 = 1$, $m_3 = 1$, $m_4 = 1$, we have*

$$\frac{1}{T} \sum_{t=1}^T W_{T, (-t)} = W_T + o_p \left(\frac{1}{\sqrt{T}} \right).$$

Proof. We have

$$\begin{aligned}
W_{[1], T} &= T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i, [1,1]}, & W_{[2], T} &= T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i, [2,1]}, \\
W_{[3], T} &= T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i, [3,1]}, & W_{[4], T} &= T^{1/2} \frac{1}{n} \sum_{i=1}^n \bar{k}_{i, [4,1]}
\end{aligned}$$

and therefore,

$$W_T = T^2 \frac{1}{n^4} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{i_3=1}^n \sum_{i_4=1}^n \bar{k}_{i_1, [1,1]} \bar{k}_{i_2, [2,1]} \bar{k}_{i_3, [3,1]} \bar{k}_{i_4, [4,1]}$$

and

$$\begin{aligned}
& \frac{1}{T} \sum_{t=1}^T W_{T,(-t)} \\
&= \frac{1}{T(T-1)^2} \frac{1}{n^4} \sum_{i_1=1}^n \sum_{i_2=1}^n \sum_{i_3=1}^n \sum_{i_4=1}^n \sum_{t=1}^T (T\bar{k}_{i_1,[1,1]} - k_{[1,1]}(x_{i_1,t})) (T\bar{k}_{i_2,[2,1]} - k_{[2,1]}(x_{i_2,t})) \\
&\quad \times (T\bar{k}_{i_3,[3,1]} - k_{[3,1]}(x_{i_3,t})) (T\bar{k}_{i_4,[4,1]} - k_{[4,1]}(x_{i_4,t})) \\
&= \frac{T^2 - 4T}{(T-1)^2} W_T \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{n} \sum_{i_2=1}^n T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \left(\frac{1}{n} \sum_{i_4=1}^n k_{[4,1]}(x_{i_4,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{n} \sum_{i_3=1}^n T^{1/2} \bar{k}_{i_3,[3,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_4=1}^n k_{[4,1]}(x_{i_4,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{n} \sum_{i_4=1}^n T^{1/2} \bar{k}_{i_4,[4,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_2=1}^n T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{n} \sum_{i_3=1}^n T^{1/2} \bar{k}_{i_3,[3,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_4=1}^n k_{[4,1]}(x_{i_4,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_2=1}^n T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{n} \sum_{i_4=1}^n T^{1/2} \bar{k}_{i_4,[4,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad + \frac{T}{(T-1)^2} \left(\frac{1}{n} \sum_{i_3=1}^n T^{1/2} \bar{k}_{i_3,[3,1]} \right) \left(\frac{1}{n} \sum_{i_4=1}^n T^{1/2} \bar{k}_{i_4,[4,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \left(\frac{1}{n} \sum_{i_1=1}^n T^{1/2} \bar{k}_{i_1,[1,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \left(\frac{1}{n} \sum_{i_4=1}^n k_{[4,1]}(x_{i_4,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \left(\frac{1}{n} \sum_{i_2=1}^n T^{1/2} \bar{k}_{i_2,[2,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \left(\frac{1}{n} \sum_{i_4=1}^n k_{[4,1]}(x_{i_4,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \left(\frac{1}{n} \sum_{i_3=1}^n T^{1/2} \bar{k}_{i_3,[3,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_4=1}^n k_{[4,1]}(x_{i_4,t}) \right) \right) \\
&\quad - \frac{T^{1/2}}{(T-1)^2} \left(\frac{1}{n} \sum_{i_4=1}^n T^{1/2} \bar{k}_{i_4,[4,1]} \right) \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \right) \\
&\quad + \frac{1}{(T-1)^2} \left(\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i_1=1}^n k_{[1,1]}(x_{i_1,t}) \right) \left(\frac{1}{n} \sum_{i_2=1}^n k_{[2,1]}(x_{i_2,t}) \right) \left(\frac{1}{n} \sum_{i_3=1}^n k_{[3,1]}(x_{i_3,t}) \right) \left(\frac{1}{n} \sum_{i_4=1}^n k_{[4,1]}(x_{i_4,t}) \right) \right) \tag{44}
\end{aligned}$$

Using equation (44) and lemmas in previous subsections, we can conclude that

$$\frac{1}{T} \sum_{t=1}^T W_{T,(-t)} = W_T + o_p\left(\frac{1}{\sqrt{T}}\right)$$

■

G Derivatives of θ when $\dim(\theta) = 1$

Recall that

$$h_i(\cdot, \epsilon) \equiv U_i(\cdot; \theta(F(\epsilon)), \alpha_i(\theta(F(\epsilon)), F_i(\epsilon)))$$

The first order condition may be written as

$$0 = \frac{1}{n} \sum_{i=1}^n \int h_i(\cdot, \epsilon) dF_i(\epsilon)$$

Differentiating repeatedly with respect to ϵ , we obtain

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{dh_i(\cdot, \epsilon)}{d\epsilon} dF_i(\epsilon) + \frac{1}{n} \sum_{i=1}^n \int h_i(\cdot, \epsilon) d\Delta_{iT} \quad (45)$$

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} dF_i(\epsilon) + 2 \frac{1}{n} \sum_{i=1}^n \int \frac{dh_i(\cdot, \epsilon)}{d\epsilon} d\Delta_{iT} \quad (46)$$

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{d^3 h_i(\cdot, \epsilon)}{d\epsilon^3} dF_i(\epsilon) + 3 \frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} d\Delta_{iT} \quad (47)$$

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{d^4 h_i(\cdot, \epsilon)}{d\epsilon^4} dF_i(\epsilon) + 4 \frac{1}{n} \sum_{i=1}^n \int \frac{d^3 h_i(\cdot, \epsilon)}{d\epsilon^3} d\Delta_{iT} \quad (48)$$

$$0 = \frac{1}{n} \sum_{i=1}^n \int \frac{d^5 h_i(\cdot, \epsilon)}{d\epsilon^5} dF_i(\epsilon) + 5 \frac{1}{n} \sum_{i=1}^n \int \frac{d^4 h_i(\cdot, \epsilon)}{d\epsilon^4} d\Delta_{iT} \quad (49)$$

G.1 $\theta^\epsilon(0)$

Evaluating (45) at $\epsilon = 0$, and noting that $E[U_i^{\alpha_i}] = 0$, we obtain

$$\theta^\epsilon(0) = \frac{\frac{1}{n} \sum_{i=1}^n \int U_i d\Delta_{iT}}{\frac{1}{n} \sum_{i=1}^n E[U_i^2]} \quad (50)$$

We therefore have

$$\sqrt{nT} \frac{1}{\sqrt{T}} \theta^\epsilon(0) = \frac{\frac{1}{\sqrt{n}\sqrt{T}} \sum_{i=1}^n \sum_{t=1}^T U_{it}}{\frac{1}{n} \sum_{i=1}^n E[U_i^2]}$$

G.2 α_i^θ and α_i^ϵ

In the i th stratum, $\alpha_i(\theta, F_i(\epsilon))$ solves the estimating equation

$$\int V_i[\theta, \alpha_i(\theta, F_i(\epsilon))] dF_i(\epsilon) = 0 \quad (51)$$

Differentiating the LHS with respect to θ and ϵ , we obtain

$$0 = \int V_i^\theta dF_i(\epsilon) + \alpha_i^\theta \int V_i^{\alpha_i} dF_i(\epsilon)$$

$$0 = \alpha_i^\epsilon \int V_i^{\alpha_i} dF_i(\epsilon) + \int V_i d\Delta_{iT}$$

where $\Delta_{iT} \equiv \frac{d}{d\epsilon} F_i(\epsilon) = \sqrt{T} (\hat{F}_i - F_i)$. Equating these equations to zero and solving for derivatives of α_i evaluated at $\epsilon = 0$ gives

$$\alpha_i^\theta = -\frac{E[V_i^\theta]}{E[V_i^{\alpha_i}]} = \frac{E[V_i^\theta]}{E[V_i^2]} = O(1) \quad (52)$$

$$\alpha_i^\epsilon = -\frac{\sum_{t=1}^T V_{it}}{\sqrt{T} E[V_i^{\alpha_i}]} = \frac{T^{-1/2} \sum_{t=1}^T V_{it}}{E[V_i^2]} = O_p(1) \quad (53)$$

G.3 $\theta^{\epsilon\epsilon}(0)$

Evaluating each term of (46) at $\epsilon = 0$, we obtain

$$\begin{aligned} \frac{1}{n} \sum_{i=1}^n \int \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} dF_i(\epsilon) \Big|_{\epsilon=0} &= \theta^{\epsilon\epsilon}(0) \frac{1}{n} \sum_{i=1}^n E[U_i^\theta] \\ &+ 2\theta^\epsilon(0) \left(\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\alpha_i}] \alpha_i^\epsilon + \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] \alpha_i^\theta \alpha_i^\epsilon \right) \\ &+ (\theta^\epsilon(0))^2 \left(\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\theta}] + 2\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\alpha_i}] \alpha_i^\theta + \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] (\alpha_i^\theta)^2 \right) \\ &+ \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] (\alpha_i^\epsilon)^2 \end{aligned}$$

and

$$\begin{aligned} 2\frac{1}{n} \sum_{i=1}^n \int \frac{dh_i(\cdot, \epsilon)}{d\epsilon} d\Delta_{iT} \Big|_{\epsilon=0} &= 2\theta^\epsilon(0) \frac{1}{n} \sum_{i=1}^n \int U_i^\theta d\Delta_{iT} + 2\theta^\epsilon(0) \frac{1}{n} \sum_{i=1}^n \alpha_i^\theta \int U_i^{\alpha_i} d\Delta_{iT} \\ &+ 2\frac{1}{n} \sum_{i=1}^n \alpha_i^\epsilon \int U_i^{\alpha_i} d\Delta_{iT} \end{aligned}$$

from which we obtain

$$\begin{aligned} \theta^{\epsilon\epsilon}(0) \frac{1}{n} \sum_{i=1}^n E[U_i^2] &= \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] (\alpha_i^\epsilon)^2 + 2\frac{1}{n} \sum_{i=1}^n \alpha_i^\epsilon \int U_i^{\alpha_i} d\Delta_{iT} \\ &+ 2\theta^\epsilon(0) \left(\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\alpha_i}] \alpha_i^\epsilon + \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] \alpha_i^\theta \alpha_i^\epsilon + \frac{1}{n} \sum_{i=1}^n \int U_i^\theta d\Delta_{iT} + \frac{1}{n} \sum_{i=1}^n \alpha_i^\theta \int U_i^{\alpha_i} d\Delta_{iT} \right) \\ &+ (\theta^\epsilon(0))^2 \left(\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\theta}] + 2\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\alpha_i}] \alpha_i^\theta + \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] (\alpha_i^\theta)^2 \right) \end{aligned} \quad (54)$$

G.4 $\alpha_i^{\theta\theta}$, $\alpha_i^{\theta\epsilon}$, and $\alpha_i^{\epsilon\epsilon}$

Evaluating the second order derivatives $\left(\frac{\partial^2}{\partial\theta^2}, \frac{\partial^2}{\partial\theta\partial\epsilon}, \frac{\partial^2}{\partial\epsilon^2} \right)$ of (51) at $\epsilon = 0$, we obtain

$$\alpha_i^{\theta\theta} = \frac{E[V_i^{\theta\theta}]}{E[V_i^2]} + 2\alpha_i^\theta \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + (\alpha_i^\theta)^2 \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} = O(1), \quad (55)$$

$$\alpha_i^{\theta\epsilon} = \alpha_i^\epsilon \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + \alpha_i^\theta \alpha_i^\epsilon \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + \frac{\int V_i^\theta d\Delta_{iT}}{E[V_i^2]} + \alpha_i^\theta \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} = O_p(1), \quad (56)$$

and

$$\alpha_i^{\epsilon\epsilon} = (\alpha_i^\epsilon)^2 \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^\epsilon \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} = O_p(1). \quad (57)$$

G.5 $\theta^{\epsilon\epsilon\epsilon}(0)$

Evaluating each term of (47) at $\epsilon = 0$, it can be concluded that $\theta^{\epsilon\epsilon\epsilon}(0) \frac{1}{n} \sum_{i=1}^n E[U_i^2]$ can be expressed as a sum of normalized V-statistics of order 3.¹ Condition 4 along with Lemma 13 imply that $|\theta^{\epsilon\epsilon\epsilon}(0)| = O_p(1)$.

G.6 $\theta^{\epsilon\epsilon\epsilon\epsilon}(0)$

Evaluating each term of (48) at $\epsilon = 0$, it can be concluded that $\theta^{\epsilon\epsilon\epsilon\epsilon}(0) \frac{1}{n} \sum_{i=1}^n E[U_i^2]$ can be expressed as a sum of normalized V-statistics of order 4.² Condition 4 along with Lemma 13 imply that $|\theta^{\epsilon\epsilon\epsilon\epsilon}(0)| = O_p(1)$.

H “Jackknifing” $\hat{\theta}$

H.1 $T \left(\theta^\epsilon(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \theta_{(t)}^\epsilon(0) \right)$ and $\sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \theta_{(t)}^\epsilon(0)$

Because

$$\theta^\epsilon(0) = \frac{\frac{1}{n} \sum_{i=1}^n \int U_i d\Delta_{iT}}{\frac{1}{n} \sum_{i=1}^n E[U_i^2]},$$

we can use Lemma 14 and obtain

$$\frac{1}{T} \sum_{t=1}^T \theta_{(t)}^\epsilon(0) = \sqrt{\frac{T-1}{T}} \theta^\epsilon(0)$$

It therefore follows that

$$T \left(\sqrt{n} \theta^\epsilon(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n} \theta_{(t)}^\epsilon(0) \right) + \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n} \theta_{(t)}^\epsilon(0) = \sqrt{n} \theta^\epsilon(0) \quad (58)$$

H.2 $T \left(\sqrt{\frac{n}{T}} \theta^{\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0) \right)$ and $\sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0)$

Write

$$\theta^{\epsilon\epsilon}(0) \frac{1}{n} \sum_{i=1}^n E[U_i^2] = \frac{1}{n} \sum_{i=1}^n \mathcal{W}_{1,i,T} + \mathcal{W}_{2,T},$$

where

$$\begin{aligned} \mathcal{W}_{1,i,T} &\equiv E[U_i^{\alpha_i\alpha_i}] (\alpha_i^\epsilon)^2 + 2\alpha_i^\epsilon \int U_i^{\alpha_i} d\Delta_{iT} \\ &= 2 \left[\frac{1}{\sqrt{T}} \sum_{t=1}^T \frac{V_{it}}{E[V_i^2]} \right] \left[\frac{1}{\sqrt{T}} \sum_{t=1}^T \left(U_i^{\alpha_i} + \frac{E[U_i^{\alpha_i\alpha_i}]}{2E[V_i^2]} V_{it} \right) \right] \end{aligned}$$

¹For exact expression of the terms in (47), see Supplementary Appendix, which is available upon request.

²For exact expression of the terms in (48), see Supplementary Appendix, which is available upon request.

and

$$\begin{aligned}
\mathcal{W}_{2,T} &\equiv 2\theta^\epsilon(0) \left(\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\alpha_i}] \alpha_i^\epsilon + \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] \alpha_i^\theta \alpha_i^\epsilon + \frac{1}{n} \sum_{i=1}^n \int U_i^\theta d\Delta_{iT} + \frac{1}{n} \sum_{i=1}^n \alpha_i^\theta \int U_i^{\alpha_i} d\Delta_{iT} \right) \\
&\quad + (\theta^\epsilon(0))^2 \left(\frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\theta}] + 2 \frac{1}{n} \sum_{i=1}^n E[U_i^{\theta\alpha_i}] \alpha_i^\theta + \frac{1}{n} \sum_{i=1}^n E[U_i^{\alpha_i\alpha_i}] (\alpha_i^\theta)^2 \right) \\
&= O_p\left(\frac{1}{n}\right)
\end{aligned}$$

By Lemma 14, we obtain

$$\frac{1}{T} \sum_{t=1}^T \left(\frac{1}{n} \sum_{i=1}^n \mathcal{W}_{1,i,T,(-t)} \right) = \frac{T-2}{T-1} \frac{1}{n} \sum_{i=1}^n \mathcal{W}_{1,i,T} + \frac{1}{T(T-1)} \frac{1}{n} \sum_{i=1}^n \sum_{t=1}^T 2 \frac{V_{it}}{E[V_i^2]} \left(U_i^{\alpha_i} + \frac{E[U_i^{\alpha_i\alpha_i}]}{2E[V_i^2]} V_{it} \right)$$

By Lemma 15, we obtain

$$\frac{1}{T} \sum_{t=1}^T \mathcal{W}_{2,T,(-t)} = \frac{T-2}{T-1} \mathcal{W}_{2,T} + O_p\left(\frac{1}{nT}\right)$$

It therefore follows that

$$\begin{aligned}
&\left(\frac{1}{n} \sum_{i=1}^n E[U_i^2] \right) \cdot \frac{1}{2} T \left(\sqrt{\frac{n}{T}} \theta^{\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0) \right) \\
&\quad + \left(\frac{1}{n} \sum_{i=1}^n E[U_i^2] \right) \cdot \frac{1}{2} \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0) \\
&= \left(\frac{1}{n} \sum_{i=1}^n E[U_i^2] \right) \cdot \frac{\sqrt{nT}}{2} \left(\theta^{\epsilon\epsilon}(0) - \frac{1}{T} \sum_{t=1}^T \theta_{(t)}^{\epsilon\epsilon}(0) \right) \\
&= \frac{\sqrt{nT}}{2} \left(\frac{1}{n} \sum_{i=1}^n \mathcal{W}_{1,i,T} \right) \left(1 - \frac{T-2}{T-1} \right) \\
&\quad - \frac{\sqrt{nT}}{2} \left(\frac{1}{T(T-1)} \frac{1}{n} \sum_{i=1}^n \sum_{t=1}^T 2 \frac{V_{it}}{E[V_i^2]} \left(U_i^{\alpha_i} + \frac{E[U_i^{\alpha_i\alpha_i}]}{2E[V_i^2]} V_{it} \right) \right) \\
&\quad + \frac{\sqrt{nT}}{2} \left(1 - \frac{T-2}{T-1} \right) \mathcal{W}_{2,T} + O_p\left(\frac{1}{\sqrt{nT}}\right) \\
&= \frac{1}{2} \sqrt{nT} \frac{1}{T-1} \frac{1}{n} \sum_{i=1}^n \mathcal{W}_{1,i,T} \\
&\quad - \frac{1}{2} \sqrt{nT} \frac{1}{T-1} \frac{1}{nT} \sum_{i=1}^n \sum_{t=1}^T 2 \frac{V_{it}}{E[V_i^2]} \left(U_i^{\alpha_i} + \frac{E[U_i^{\alpha_i\alpha_i}]}{2E[V_i^2]} V_{it} \right) \\
&\quad + \frac{1}{2} \sqrt{nT} \frac{1}{T-1} \mathcal{W}_{2,T} + O_p\left(\frac{1}{\sqrt{nT}}\right) \\
&= o_p(1)
\end{aligned} \tag{59}$$

H.3 $T \left(\sqrt{\frac{n}{T}} \frac{1}{\sqrt{T}} \theta^{\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0) \right)$ and $\sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0)$

By Lemmas 14, 16, and 17, we obtain

$$\begin{aligned} \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0) &= \frac{\sqrt{nT}}{\sqrt{(T-1)^3}} \theta^{\epsilon\epsilon\epsilon}(0) + \frac{\sqrt{nT}}{\sqrt{(T-1)^3}} o_p\left(\frac{1}{\sqrt{T}}\right) \\ &= o_p(1) \end{aligned} \quad (60)$$

and

$$\begin{aligned} &T \left(\sqrt{\frac{n}{T}} \frac{1}{\sqrt{T}} \theta^{\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0) \right) \\ &= T \left(\sqrt{\frac{n}{T^2}} - \frac{\sqrt{nT}}{\sqrt{(T-1)^3}} \right) \theta^{\epsilon\epsilon\epsilon}(0) + \frac{T\sqrt{nT}}{\sqrt{(T-1)^3}} o_p\left(\frac{1}{\sqrt{T}}\right) \\ &= o_p(1) \end{aligned} \quad (61)$$

H.4 $T \left(\sqrt{\frac{n}{T}} \frac{1}{T} \theta^{\epsilon\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0) \right)$ and $\sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0)$

By Lemmas 14, 18, 19, 20, and 21, we obtain

$$\begin{aligned} \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0) &= \frac{\sqrt{nT}}{\sqrt{(T-1)^4}} \theta^{\epsilon\epsilon\epsilon\epsilon}(0) + \frac{\sqrt{nT}}{\sqrt{(T-1)^4}} o_p\left(\frac{1}{\sqrt{T}}\right) \\ &= o_p(1) \end{aligned} \quad (62)$$

and

$$\begin{aligned} &T \left(\sqrt{\frac{n}{T}} \frac{1}{T} \theta^{\epsilon\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0) \right) \\ &= T \left(\sqrt{\frac{n}{T^3}} - \frac{\sqrt{nT}}{\sqrt{(T-1)^4}} \right) \theta^{\epsilon\epsilon\epsilon\epsilon}(0) + \frac{T\sqrt{nT}}{\sqrt{(T-1)^4}} o_p\left(\frac{1}{\sqrt{T}}\right) \\ &= o_p(1) \end{aligned} \quad (63)$$

I Proof of Theorem 3

Using the same argument as in the proof of Theorem 6, it can be shown that

$$\Pr \left[\left| \frac{1}{\sqrt{T}} \theta^{\epsilon\epsilon\epsilon\epsilon\epsilon}(\tilde{\epsilon}) \right| \geq \eta \right] = o\left(\frac{1}{T}\right).$$

Therefore,

$$T \cdot \frac{1}{120} \sqrt{\frac{n}{T}} \frac{1}{T\sqrt{T}} \theta^{\epsilon\epsilon\epsilon\epsilon\epsilon}(\tilde{\epsilon}) = o_p(1)$$

and

$$\begin{aligned}
\left| T \cdot \frac{1}{T} \sum_{t=1}^T \frac{1}{120} \sqrt{\frac{n}{T-1}} \frac{1}{(T-1)\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon\epsilon}(\tilde{\epsilon}_{(t)}) \right| &\leq \frac{1}{120} \sqrt{\frac{n}{T-1}} \frac{T}{(T-1)\sqrt{T-1}} \max_t \left| \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon\epsilon}(\tilde{\epsilon}_{(t)}) \right| \\
&= O\left(\max_t \left| \frac{1}{\sqrt{T}} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon\epsilon}(\tilde{\epsilon}_{(t)}) \right| \right) \\
&= o_p(1),
\end{aligned}$$

where $\theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon\epsilon}$ denotes the delete- t version of $\theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon\epsilon}$, and the second equality is based on

$$\Pr \left[\max_t \left| \frac{1}{\sqrt{T}} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon\epsilon}(\tilde{\epsilon}_{(t)}) \right| \geq \eta \right] \leq \sum_t \Pr \left[\left| \frac{1}{\sqrt{T}} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon\epsilon}(\tilde{\epsilon}_{(t)}) \right| \geq \eta \right] = T \cdot o\left(\frac{1}{T}\right) = o(1).$$

We may therefore write

$$\begin{aligned}
\sqrt{nT}(\tilde{\theta} - \theta_0) &= T \left(\sqrt{nT}(\hat{\theta} - \theta_0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n(T-1)}(\hat{\theta}_{(t)} - \theta_0) \right) \\
&\quad + \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n(T-1)}(\hat{\theta}_{(t)} - \theta_0)
\end{aligned}$$

or

$$\begin{aligned}
\sqrt{nT}(\tilde{\theta} - \theta_0) &= T \left(\sqrt{n}\theta^\epsilon(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n}\theta_{(t)}^\epsilon(0) \right) \\
&\quad + \frac{1}{2} T \left(\sqrt{\frac{n}{T}} \theta^{\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0) \right) \\
&\quad + \frac{1}{6} T \left(\sqrt{\frac{n}{T}} \frac{1}{\sqrt{T}} \theta^{\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0) \right) \\
&\quad + \frac{1}{24} T \left(\sqrt{\frac{n}{T}} \frac{1}{T} \theta^{\epsilon\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0) \right) \\
&\quad + \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n}\theta_{(t)}^\epsilon(0) \\
&\quad + \frac{1}{2} \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0) \\
&\quad + \frac{1}{6} \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0) \\
&\quad + \frac{1}{24} \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0) \\
&\quad + o_p(1)
\end{aligned}$$

Using equations (58), (59), (60), (61), (62), and (63) in Section H, we have

$$\begin{aligned}
& T \left(\sqrt{n}\theta^\epsilon(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n}\theta_{(t)}^\epsilon(0) \right) + \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{n}\theta_{(t)}^\epsilon(0) = \sqrt{n}\theta^\epsilon(0) \\
& \frac{1}{2} T \left(\sqrt{\frac{n}{T}} \theta^{\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0) \right) + \frac{1}{2} \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \theta_{(t)}^{\epsilon\epsilon}(0) = o_p(1) \\
& T \left(\sqrt{\frac{n}{T}} \frac{1}{\sqrt{T}} \theta^{\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0) \right) + \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{\sqrt{T-1}} \theta_{(t)}^{\epsilon\epsilon\epsilon}(0) = o_p(1) \\
& T \left(\sqrt{\frac{n}{T}} \frac{1}{T} \theta^{\epsilon\epsilon\epsilon\epsilon}(0) - \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0) \right) + \sqrt{\frac{T}{T-1}} \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{n}{T-1}} \frac{1}{T-1} \theta_{(t)}^{\epsilon\epsilon\epsilon\epsilon}(0) = o_p(1)
\end{aligned}$$

Supplementary Appendix for “Jackknife and Analytical Bias
Reduction for Nonlinear Panel Models” available upon request

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A Derivatives of h

A.1 First order derivative of h

$$\frac{dh_i(\cdot, \epsilon)}{d\epsilon} = \theta^\epsilon (U_i^\theta + U_i^{\alpha_i} \alpha_i^\theta) + U_i^{\alpha_i} \alpha_i^\epsilon$$

A.2 Second order derivative of h

$$\begin{aligned} \frac{d^2 h_i(\cdot, \epsilon)}{d\epsilon^2} &= \theta^{\epsilon\epsilon} (U_i^\theta + U_i^{\alpha_i} \alpha_i^\theta) \\ &\quad + 2\theta^\epsilon \left(U_i^{\theta\alpha_i} \alpha_i^\epsilon + U_i^{\alpha_i\alpha_i} \alpha_i^\theta \alpha_i^\epsilon + U_i^{\alpha_i} \alpha_i^{\theta\epsilon} \right) \\ &\quad + (\theta^\epsilon)^2 \left(U_i^{\theta\theta} + 2U_i^{\theta\alpha_i} \alpha_i^\theta + U_i^{\alpha_i\alpha_i} (\alpha_i^\theta)^2 + U_i^{\alpha_i} \alpha_i^{\theta\theta} \right) \\ &\quad + U_i^{\alpha_i\alpha_i} (\alpha_i^\epsilon)^2 + U_i^{\alpha_i} \alpha_i^{\epsilon\epsilon} \end{aligned}$$

A.3 Third order derivative of h

A.3.1 Coefficient of $\theta^{\epsilon\epsilon\epsilon}$

$$U_i^{\alpha_i} \alpha_i^\theta + U_i^\theta$$

A.3.2 Coefficient of $\theta^{\epsilon\epsilon}$

$$3U_i^{\theta\alpha_i} \alpha_i^\epsilon + 3U_i^{\alpha_i\alpha_i} \alpha_i^\theta \alpha_i^\epsilon + 3U_i^{\alpha_i} \alpha_i^{\theta\epsilon}$$

A.3.3 Coefficient of $\theta^{\epsilon\epsilon}\theta^\epsilon$

$$3U_i^{\theta\theta} + 3U_i^{\alpha_i\alpha_i} (\alpha_i^\theta)^2 + 3U_i^{\alpha_i} \alpha_i^{\theta\theta} + 6U_i^{\theta\alpha_i} \alpha_i^\theta$$

A.3.4 Coefficient of θ^ϵ

$$3U_i^{\alpha_i} \alpha_i^{\theta\epsilon\epsilon} + 3U_i^{\theta\alpha_i\alpha_i} (\alpha_i^\epsilon)^2 + 3U_i^{\theta\alpha_i} \alpha_i^{\epsilon\epsilon} + 6U_i^{\alpha_i\alpha_i} \alpha_i^{\theta\epsilon} \alpha_i^\epsilon + 3U_i^{\alpha_i\alpha_i} \alpha_i^{\epsilon\epsilon} \alpha_i^\theta + 3U_i^{\alpha_i\alpha_i\alpha_i} \alpha_i^\theta (\alpha_i^\epsilon)^2$$

A.3.5 Coefficient of $(\theta^\epsilon)^2$

$$3U_i^{\alpha_i} \alpha_i^{\theta\theta\epsilon} + 3U_i^{\theta\theta\alpha_i} \alpha_i^\epsilon + 6U_i^{\theta\alpha_i} \alpha_i^{\theta\epsilon} + 6U_i^{\theta\alpha_i\alpha_i} \alpha_i^\theta \alpha_i^\epsilon + 3U_i^{\alpha_i\alpha_i} (\alpha_i^\theta)^2 \alpha_i^\epsilon + 3U_i^{\alpha_i\alpha_i} \alpha_i^{\theta\theta} \alpha_i^\epsilon + 6U_i^{\alpha_i\alpha_i} \alpha_i^\theta \alpha_i^{\theta\epsilon}$$

A.3.6 Coefficient of $(\theta^\epsilon)^3$

$$U_i^{\alpha_i} \alpha_i^{\theta\theta\theta} + U_i^{\alpha_i\alpha_i\alpha_i} (\alpha_i^\theta)^3 + 3U_i^{\theta\theta\alpha_i} \alpha_i^\theta + 3U_i^{\theta\alpha_i\alpha_i} (\alpha_i^\theta)^2 + 3U_i^{\theta\alpha_i} \alpha_i^{\theta\theta} + 3U_i^{\alpha_i\alpha_i} \alpha_i^{\theta\theta} \alpha_i^\theta + U_i^{\theta\theta\theta}$$

A.3.7 "Constant" term

$$U_i^{\alpha_i} \alpha_i^{\epsilon\epsilon\epsilon} + 3U_i^{\alpha_i\alpha_i} \alpha_i^{\epsilon\epsilon} \alpha_i^\epsilon + U_i^{\alpha_i\alpha_i\alpha_i} (\alpha_i^\epsilon)^3$$

A.4 Fourth order derivative of h

A.4.1 Coefficient of $\theta^{\epsilon\epsilon\epsilon\epsilon}$

$$U_i^{\alpha_i} \alpha_i^\theta + U_i^\theta$$

A.4.2 Coefficient of $\theta^{\epsilon\epsilon\epsilon}$

$$4U_i^{\alpha_i \alpha_i} \alpha_i^\theta \alpha_i^\epsilon + 4U_i^{\theta \alpha_i} \alpha_i^\epsilon + 4U_i^{\alpha_i} \alpha_i^{\theta \epsilon}$$

A.4.3 Coefficient of $\theta^{\epsilon\epsilon\epsilon} \theta^\epsilon$

$$4U_i^{\theta \theta} + 4U_i^{\alpha_i \alpha_i} (\alpha_i^\theta)^2 + 8U_i^{\theta \alpha_i} \alpha_i^\theta + 4U_i^{\alpha_i} \alpha_i^{\theta \theta}$$

A.4.4 Coefficient of $\theta^{\epsilon\epsilon}$

$$6U_i^{\theta \alpha_i \alpha_i} (\alpha_i^\epsilon)^2 + 6U_i^{\theta \alpha_i} \alpha_i^{\epsilon\epsilon} + 6U_i^{\alpha_i} \alpha_i^{\theta \epsilon\epsilon} + 12U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \epsilon} \alpha_i^\epsilon + 6U_i^{\alpha_i \alpha_i \alpha_i} \alpha_i^\theta (\alpha_i^\epsilon)^2 + 6U_i^{\alpha_i \alpha_i} \alpha_i^\theta \alpha_i^{\epsilon\epsilon}$$

A.4.5 Coefficient of $\theta^{\epsilon\epsilon} \theta^\epsilon$

$$12U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \theta} \alpha_i^\epsilon + 24U_i^{\alpha_i \alpha_i} \alpha_i^\theta \alpha_i^{\theta \epsilon} + 24U_i^{\theta \alpha_i \alpha_i} \alpha_i^\theta \alpha_i^\epsilon + 12U_i^{\alpha_i \alpha_i \alpha_i} (\alpha_i^\theta)^2 \alpha_i^\epsilon + 24U_i^{\theta \alpha_i} \alpha_i^{\theta \epsilon} + 12U_i^{\theta \theta \alpha_i} \alpha_i^\epsilon + 12U_i^{\alpha_i} \alpha_i^{\theta \theta \epsilon}$$

A.4.6 Coefficient of $\theta^{\epsilon\epsilon} (\theta^\epsilon)^2$

$$6U_i^{\theta \theta \theta} + 18U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \theta} \alpha_i^\theta + 6U_i^{\alpha_i \alpha_i \alpha_i} (\alpha_i^\theta)^3 + 18U_i^{\theta \alpha_i} \alpha_i^{\theta \theta} + 18U_i^{\theta \theta \alpha_i} \alpha_i^\theta + 18U_i^{\theta \alpha_i \alpha_i} (\alpha_i^\theta)^2 + 6U_i^{\alpha_i} \alpha_i^{\theta \theta \theta}$$

A.4.7 Coefficient of $(\theta^{\epsilon\epsilon})^2$

$$3U_i^{\alpha_i} \alpha_i^{\theta \theta} + 6U_i^{\theta \alpha_i} \alpha_i^\theta + 3U_i^{\alpha_i \alpha_i} (\alpha_i^\theta)^2 + 3U_i^{\theta \theta}$$

A.4.8 Coefficient of θ^ϵ

$$4U_i^{\theta \alpha_i} \alpha_i^{\epsilon\epsilon\epsilon} + 4U_i^{\theta \alpha_i \alpha_i} (\alpha_i^\epsilon)^3 + 4U_i^{\alpha_i} \alpha_i^{\theta \epsilon\epsilon\epsilon} + 12U_i^{\alpha_i \alpha_i} \alpha_i^\theta \alpha_i^{\epsilon\epsilon} \alpha_i^\epsilon + 12U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \epsilon\epsilon} \alpha_i^\epsilon + 4U_i^{\alpha_i \alpha_i \alpha_i} \alpha_i^\theta (\alpha_i^\epsilon)^3 + 4U_i^{\alpha_i \alpha_i} \alpha_i^\theta \alpha_i^{\epsilon\epsilon\epsilon} + 12U_i^{\alpha_i \alpha_i \alpha_i} \alpha_i^{\theta \epsilon} (\alpha_i^\epsilon)^2 + 12U_i^{\theta \alpha_i \alpha_i} \alpha_i^{\epsilon\epsilon} \alpha_i^\epsilon + 12U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \epsilon} \alpha_i^{\epsilon\epsilon}$$

A.4.9 Coefficient of $(\theta^\epsilon)^2$

$$6U_i^{\alpha_i} \alpha_i^{\theta \theta \epsilon\epsilon} + 6U_i^{\theta \theta \alpha_i} (\alpha_i^\epsilon)^2 + 6U_i^{\theta \theta \alpha_i} \alpha_i^{\epsilon\epsilon} + 12U_i^{\theta \alpha_i} \alpha_i^{\theta \epsilon\epsilon} + 12U_i^{\alpha_i \alpha_i} (\alpha_i^{\theta \epsilon})^2 + 24U_i^{\alpha_i \alpha_i} \alpha_i^\theta \alpha_i^{\theta \epsilon} \alpha_i^\epsilon + 12U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \theta \epsilon} \alpha_i^\epsilon + 12U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \epsilon\epsilon} \alpha_i^\theta + 6U_i^{\alpha_i \alpha_i} (\alpha_i^\theta)^2 \alpha_i^{\epsilon\epsilon} + 6U_i^{\alpha_i \alpha_i \alpha_i} (\alpha_i^\theta)^2 (\alpha_i^\epsilon)^2 + 6U_i^{\alpha_i \alpha_i \alpha_i} \alpha_i^{\theta \theta} (\alpha_i^\epsilon)^2 + 12U_i^{\theta \alpha_i \alpha_i} \alpha_i^\theta (\alpha_i^\epsilon)^2 + 12U_i^{\theta \alpha_i \alpha_i} \alpha_i^{\theta \epsilon} \alpha_i^{\epsilon\epsilon} + 24U_i^{\theta \alpha_i \alpha_i} \alpha_i^{\theta \epsilon} \alpha_i^\epsilon + 6U_i^{\alpha_i \alpha_i} \alpha_i^{\theta \theta} \alpha_i^{\epsilon\epsilon}$$

A.4.10 Coefficient of $(\theta^\epsilon)^3$

$$\begin{aligned}
& 12U_i^{\theta\theta\alpha_i}\alpha_i^{\theta\epsilon} + 4U_i^{\theta\theta\theta\alpha_i}\alpha_i^\epsilon + 12U_i^{\theta\alpha_i}\alpha_i^{\theta\theta\epsilon} + 4U_i^{\alpha_i}\alpha_i^{\theta\theta\theta\epsilon} + 12U_i^{\alpha_i\alpha_i\alpha_i}\alpha_i^{\theta\theta}\alpha_i^\theta\alpha_i^\epsilon + 4U_i^{\alpha_i\alpha_i\alpha_i\alpha_i}(\alpha_i^\theta)^3\alpha_i^\epsilon \\
& + 4U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\theta\theta}\alpha_i^\epsilon + 12U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\theta}\alpha_i^{\theta\epsilon} + 12U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\theta\alpha_i}\alpha_i^\theta + 12U_i^{\alpha_i\alpha_i\alpha_i}(\alpha_i^\theta)^2\alpha_i^{\theta\epsilon} \\
& + 12U_i^{\theta\theta\alpha_i\alpha_i}\alpha_i^\theta\alpha_i^\epsilon + 24U_i^{\theta\alpha_i\alpha_i}\alpha_i^{\theta\epsilon}\alpha_i^\theta + 12U_i^{\theta\alpha_i\alpha_i\alpha_i}(\alpha_i^\theta)^2\alpha_i^\epsilon + 12U_i^{\theta\alpha_i\alpha_i}\alpha_i^{\theta\theta}\alpha_i^\epsilon
\end{aligned}$$

A.4.11 Coefficient of $(\theta^\epsilon)^4$

$$\begin{aligned}
& U_i^{\alpha_i\alpha_i\alpha_i\alpha_i}(\alpha_i^\theta)^4 + 6U_i^{\theta\theta\alpha_i}\alpha_i^{\theta\theta} + 6U_i^{\theta\theta\alpha_i\alpha_i}(\alpha_i^\theta)^2 + 4U_i^{\theta\theta\theta\alpha_i}\alpha_i^\theta + 4U_i^{\theta\alpha_i}\alpha_i^{\theta\theta\theta} + 4U_i^{\theta\alpha_i\alpha_i\alpha_i}(\alpha_i^\theta)^3 \\
& + U_i^{\alpha_i}\alpha_i^{\theta\theta\theta\theta} + 3U_i^{\alpha_i\alpha_i}(\alpha_i^{\theta\theta})^2 + 4U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\theta\theta}\alpha_i^\theta + 6U_i^{\alpha_i\alpha_i\alpha_i}\alpha_i^{\theta\theta}(\alpha_i^\theta)^2 + 12U_i^{\theta\alpha_i\alpha_i}\alpha_i^{\theta\theta}\alpha_i^\theta + U_i^{\theta\theta\theta\theta}
\end{aligned}$$

A.4.12 “Constant” term

$$6U_i^{\alpha_i\alpha_i\alpha_i}\alpha_i^{\epsilon\epsilon}(\alpha_i^\epsilon)^2 + 4U_i^{\alpha_i\alpha_i}\alpha_i^{\epsilon\epsilon\epsilon}\alpha_i^\epsilon + 3U_i^{\alpha_i\alpha_i}(\alpha_i^{\epsilon\epsilon})^2 + U_i^{\alpha_i}\alpha_i^{\epsilon\epsilon\epsilon\epsilon} + U_i^{\alpha_i\alpha_i\alpha_i\alpha_i}(\alpha_i^\epsilon)^4$$

A.5 Fifth Order Derivative of h

A.5.1 Coefficient of $\theta^{\epsilon\epsilon\epsilon\epsilon}$

$$U_i^{\alpha_i}\alpha_i^\theta + U_i^\theta$$

A.5.2 Coefficient of $\theta^{\epsilon\epsilon\epsilon\epsilon}$

$$5U_i^{\alpha_i\alpha_i}\alpha_i^\theta\alpha_i^\epsilon + 5U_i^{\alpha_i}\alpha_i^{\theta\epsilon} + 5U_i^{\theta\alpha_i}\alpha_i^\epsilon$$

A.5.3 Coefficient of $\theta^{\epsilon\epsilon\epsilon\epsilon\theta^\epsilon}$

$$5U_i^{\alpha_i\alpha_i}(\alpha_i^\theta)^2 + 5U_i^{\alpha_i}\alpha_i^{\theta\theta} + 10U_i^{\theta\alpha_i}\alpha_i^\theta + 5U_i^{\theta\theta}$$

A.5.4 Coefficient of $\theta^{\epsilon\epsilon\epsilon}$

$$10U_i^{\alpha_i\alpha_i}\alpha_i^\theta\alpha_i^{\epsilon\epsilon} + 20U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\epsilon}\alpha_i^\epsilon + 10U_i^{\alpha_i\alpha_i\alpha_i}\alpha_i^\theta(\alpha_i^\epsilon)^2 + 10U_i^{\alpha_i}\alpha_i^{\theta\epsilon\epsilon} + 10U_i^{\theta\alpha_i\alpha_i}(\alpha_i^\epsilon)^2 + 10U_i^{\theta\alpha_i}\alpha_i^{\epsilon\epsilon}$$

A.5.5 Coefficient of $\theta^{\epsilon\epsilon\epsilon\theta^\epsilon}$

$$20U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\theta}\alpha_i^\epsilon + 20U_i^{\alpha_i\alpha_i\alpha_i}(\alpha_i^\theta)^2\alpha_i^\epsilon + 40U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\epsilon}\alpha_i^\theta + 40U_i^{\theta\alpha_i\alpha_i}\alpha_i^\theta\alpha_i^\epsilon + 20U_i^{\alpha_i}\alpha_i^{\theta\theta\epsilon} + 40U_i^{\theta\alpha_i}\alpha_i^{\theta\epsilon} + 20U_i^{\theta\theta\alpha_i}\alpha_i^\epsilon$$

A.5.6 Coefficient of $\theta^{\epsilon\epsilon\epsilon}(\theta^\epsilon)^2$

$$10U_i^{\alpha_i\alpha_i\alpha_i}(\alpha_i^\theta)^3 + 30U_i^{\alpha_i\alpha_i}\alpha_i^{\theta\theta}\alpha_i^\theta + 10U_i^{\alpha_i}\alpha_i^{\theta\theta\theta} + 30U_i^{\theta\theta\alpha_i}\alpha_i^\theta + 30U_i^{\theta\alpha_i}\alpha_i^{\theta\theta} + 30U_i^{\theta\alpha_i\alpha_i}(\alpha_i^\theta)^2 + 10U_i^{\theta\theta\theta}$$

A.5.7 Coefficient of $\theta^{\epsilon\epsilon\epsilon\theta^\epsilon}$

$$10U_i^{\alpha_i\alpha_i}(\alpha_i^\theta)^2 + 10U_i^{\alpha_i}\alpha_i^{\theta\theta} + 20U_i^{\theta\alpha_i}\alpha_i^\theta + 10U_i^{\theta\theta}$$

A.5.19 “Constant” term

$$U_i^{\alpha_i \alpha_i \alpha_i \alpha_i \alpha_i} (\alpha_i^\xi)^5 + 10U_i^{\alpha_i \alpha_i \alpha_i \alpha_i} \alpha_i^{\xi\xi} (\alpha_i^\xi)^3 + 15U_i^{\alpha_i \alpha_i \alpha_i} (\alpha_i^{\xi\xi})^2 \alpha_i^\xi + 5U_i^{\alpha_i \alpha_i} \alpha_i^{\xi\xi\xi} \alpha_i^\xi \\ + 10U_i^{\alpha_i \alpha_i} \alpha_i^{\xi\xi\xi} \alpha_i^{\xi\xi} + 10U_i^{\alpha_i \alpha_i} \alpha_i^{\xi\xi\xi} (\alpha_i^\xi)^2 + U_i^{\alpha_i} \alpha_i^{\xi\xi\xi\xi}$$

B “Derivatives” of α_i

Recall that, in the i th stratum, $\alpha_i(\theta, F_i(\epsilon))$ solves the estimating equation

$$\int V_i[\theta, \alpha_i(\theta, F_i(\epsilon))] dF_i(\epsilon) = 0 \quad (\text{B1})$$

B.1 $\alpha_i^{\theta\theta}$, $\alpha_i^{\theta\epsilon}$, and $\alpha_i^{\xi\xi}$

Second order differentiation $\left(\frac{\partial^2}{\partial\theta^2}, \frac{\partial^2}{\partial\theta\partial\epsilon}, \frac{\partial^2}{\partial\epsilon^2}\right)$ of (B1) yields

$$0 = \int V_i^{\theta\theta} dF_i(\epsilon) + 2\alpha_i^\theta \int V_i^{\theta\alpha_i} dF_i(\epsilon) + \alpha_i^{\theta\theta} \int V_i^{\alpha_i} dF_i(\epsilon) + (\alpha_i^\theta)^2 \int V_i^{\alpha_i \alpha_i} dF_i(\epsilon) \\ 0 = \alpha_i^\xi \int V_i^{\theta\alpha_i} dF_i(\epsilon) + \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i} dF_i(\epsilon) + \alpha_i^\theta \alpha_i^\xi \int V_i^{\alpha_i \alpha_i} dF_i(\epsilon) + \int V_i^\theta d\Delta_{iT} + \alpha_i^\theta \int V_i^{\alpha_i} d\Delta_{iT} \\ 0 = \alpha_i^{\xi\xi} \int V_i^{\alpha_i} dF_i(\epsilon) + (\alpha_i^\xi)^2 \int V_i^{\alpha_i \alpha_i} dF_i(\epsilon) + 2\alpha_i^\xi \int V_i^{\alpha_i} d\Delta_{iT}$$

Evaluating at $\epsilon = 0$, we obtain

$$0 = E[V_i^{\theta\theta}] + 2\frac{E[V_i^{\theta\theta}]}{E[V_i^2]} E[V_i^{\theta\alpha_i}] - \alpha_i^{\theta\theta} E[V_i^2] + \left(\frac{E[V_i^{\theta\theta}]}{E[V_i^2]}\right)^2 E[V_i^{\alpha_i \alpha_i}] \\ 0 = \frac{T^{-1/2} \sum_{t=1}^T V_{it}}{E[V_i^2]} E[V_i^{\theta\alpha_i}] - \alpha_i^{\theta\epsilon} E[V_i^2] + \frac{E[V_i^{\theta\theta}]}{E[V_i^2]} \frac{T^{-1/2} \sum_{t=1}^T V_{it}}{E[V_i^2]} E[V_i^{\alpha_i \alpha_i}] \\ + T^{-1/2} \sum_{t=1}^T (V_i^\theta - E[V_i^\theta]) + \frac{E[V_i^{\theta\theta}]}{E[V_i^2]} T^{-1/2} \sum_{t=1}^T (V_i^{\alpha_i} - E[V_i^{\alpha_i}]) \\ 0 = -\alpha_i^{\xi\xi} E[V_i^2] + \left(\frac{T^{-1/2} \sum_{t=1}^T V_{it}}{E[V_i^2]}\right)^2 E[V_i^{\alpha_i \alpha_i}] + 2\frac{T^{-1/2} \sum_{t=1}^T V_{it}}{E[V_i^2]} T^{-1/2} \sum_{t=1}^T (V_i^{\alpha_i} - E[V_i^{\alpha_i}])$$

from which we obtain

$$\alpha_i^{\theta\theta} = \frac{E[V_i^{\theta\theta}]}{E[V_i^2]} + 2\alpha_i^\theta \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + (\alpha_i^\theta)^2 \frac{E[V_i^{\alpha_i \alpha_i}]}{E[V_i^2]} = O_p(1), \\ \alpha_i^{\theta\epsilon} = \alpha_i^\xi \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + \alpha_i^\theta \alpha_i^\xi \frac{E[V_i^{\alpha_i \alpha_i}]}{E[V_i^2]} + \frac{\int V_i^\theta d\Delta_{iT}}{E[V_i^2]} + \alpha_i^\theta \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} = O_p(1),$$

and

$$\alpha_i^{\xi\xi} = (\alpha_i^\xi)^2 \frac{E[V_i^{\alpha_i \alpha_i}]}{E[V_i^2]} + 2\alpha_i^\xi \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} = O_p(1).$$

B.2 $\alpha_i^{\theta\theta\theta}$, $\alpha_i^{\theta\theta\epsilon}$, $\alpha_i^{\theta\epsilon\epsilon}$, and $\alpha_i^{\epsilon\epsilon\epsilon}$

Third order differentiation $\left(\frac{\partial^3}{\partial\theta^3}, \frac{\partial^3}{\partial\theta^2\partial\epsilon}, \frac{\partial^3}{\partial\theta\partial\epsilon^2}, \frac{\partial^3}{\partial\epsilon^3}\right)$ of (B1) yields

$$0 = \int V_i^{\theta\theta\theta} dF(\epsilon) + 3\alpha_i^\theta \int V_i^{\theta\theta\alpha_i} dF(\epsilon) + 3(\alpha_i^\theta)^2 \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i} dF(\epsilon) \\ + (\alpha_i^\theta)^3 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^\theta \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i} dF(\epsilon)$$

$$0 = \alpha_i^\epsilon \int V_i^{\theta\theta\alpha_i} dF(\epsilon) + 2\alpha_i^\epsilon \alpha_i^\theta \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 2\alpha_i^{\theta\epsilon} \int V_i^{\theta\alpha_i} dF(\epsilon) \\ + \alpha_i^\epsilon (\alpha_i^\theta)^2 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 2\alpha_i^\theta \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\ + \alpha_i^\epsilon \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\theta\theta\epsilon} \int V_i^{\alpha_i} dF(\epsilon) + \int V_i^{\theta\theta} d\Delta_{iT} \\ + 2\alpha_i^\theta \int V_i^{\theta\alpha_i} d\Delta_{iT} + (\alpha_i^\theta)^2 \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + \alpha_i^{\theta\theta} \int V_i^{\alpha_i} d\Delta_{iT}$$

$$0 = (\alpha_i^\epsilon)^2 \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon} \int V_i^{\theta\alpha_i} dF(\epsilon) \\ + (\alpha_i^\epsilon)^2 \alpha_i^\theta \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon} \alpha_i^\theta \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\ + 2\alpha_i^\epsilon \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\theta\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) + 2\alpha_i^\epsilon \int V_i^{\theta\alpha_i} d\Delta_{iT} \\ + 2\alpha_i^\epsilon \alpha_i^\theta \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 2\alpha_i^{\theta\epsilon} \int V_i^{\alpha_i} d\Delta_{iT}$$

$$0 = (\alpha_i^\epsilon)^3 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) \\ + 3(\alpha_i^\epsilon)^2 \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 3\alpha_i^{\epsilon\epsilon} \int V_i^{\alpha_i} d\Delta_{iT}$$

Evaluating at $\epsilon = 0$, we obtain

$$\alpha_i^{\theta\theta\theta} = \frac{E[V_i^{\theta\theta\theta}]}{E[V_i^2]} + 3\alpha_i^\theta \frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} + 3(\alpha_i^\theta)^2 \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\theta} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} \\ + (\alpha_i^\theta)^3 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\theta \alpha_i^{\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]}$$

$$\alpha_i^{\theta\theta\epsilon} = \alpha_i^\epsilon \frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} + 2\alpha_i^\epsilon \alpha_i^\theta \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^{\theta\epsilon} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} \\ + \alpha_i^\epsilon (\alpha_i^\theta)^2 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^\theta \alpha_i^{\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\ + \frac{\int V_i^{\theta\theta} d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^\theta \frac{\int V_i^{\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} + (\alpha_i^\theta)^2 \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + \alpha_i^{\theta\theta} \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]}$$

$$\begin{aligned}
\alpha_i^{\theta\epsilon\epsilon} &= (\alpha_i^\epsilon)^2 \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^2 \alpha_i^\theta \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ \alpha_i^{\epsilon\epsilon} \alpha_i^\theta \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^\epsilon \alpha_i^{\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 2\alpha_i^\epsilon \frac{\int V_i^{\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^\epsilon \alpha_i^\theta \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^{\theta\epsilon} \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
\alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) &= (\alpha_i^\epsilon)^3 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 3(\alpha_i^\epsilon)^2 \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon} \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]}
\end{aligned}$$

B.3 $\alpha_i^{\theta\theta\theta\theta}$, $\alpha_i^{\theta\theta\theta\epsilon}$, $\alpha_i^{\theta\theta\epsilon\epsilon}$, $\alpha_i^{\theta\epsilon\epsilon\epsilon}$, and $\alpha_i^{\epsilon\epsilon\epsilon\epsilon}$

Fourth order differentiation $\left(\frac{\partial^4}{\partial\theta^4}, \frac{\partial^4}{\partial\theta^3\partial\epsilon}, \frac{\partial^4}{\partial\theta^2\partial\epsilon^2}, \frac{\partial^4}{\partial\theta\partial\epsilon^3}, \frac{\partial^4}{\partial\epsilon^4}\right)$ of (B1) yields

$$\begin{aligned}
0 &= 6(\alpha_i^\theta)^2 \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 12\alpha_i^\theta \alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 4\alpha_i^\theta \alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
&+ 3(\alpha_i^{\theta\theta})^2 \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + (\alpha_i^\theta)^4 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 4(\alpha_i^\theta)^3 \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
&+ \alpha_i^{\theta\theta\theta\theta} \int V_i^{\alpha_i} dF(\epsilon) + 6(\alpha_i^\theta)^2 \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) + 6\alpha_i^{\theta\theta} \int V_i^{\theta\theta\alpha_i} dF(\epsilon) \\
&+ 4\alpha_i^\theta \int V_i^{\theta\theta\theta\alpha_i} dF(\epsilon) + \int V_i^{\theta\theta\theta\theta} dF(\epsilon) + 4\alpha_i^{\theta\theta\theta} \int V_i^{\theta\alpha_i} dF(\epsilon) \\
0 &= 3\alpha_i^\theta \alpha_i^\epsilon \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^\epsilon \alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^\epsilon \alpha_i^\theta \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) \\
&+ 3(\alpha_i^\theta)^2 \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^\epsilon (\alpha_i^\theta)^3 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 6\alpha_i^\theta \alpha_i^{\theta\epsilon} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) \\
&+ 3\alpha_i^\epsilon (\alpha_i^\theta)^2 \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^\epsilon \alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\epsilon} \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
&+ 3\alpha_i^\theta \alpha_i^{\theta\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^\epsilon \int V_i^{\theta\theta\theta\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\epsilon} \int V_i^{\theta\theta\alpha_i} dF(\epsilon) \\
&+ 3\alpha_i^{\theta\theta\epsilon} \int V_i^{\theta\alpha_i} dF(\epsilon) + \alpha_i^{\theta\theta\theta\epsilon} \int V_i^{\alpha_i} dF(\epsilon) \\
&+ \int V_i^{\theta\theta\theta} d\Delta_{iT} + 3\alpha_i^\theta \int V_i^{\theta\theta\alpha_i} d\Delta_{iT} + 3(\alpha_i^\theta)^2 \int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT} + 3\alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i} d\Delta_{iT} \\
&+ (\alpha_i^\theta)^3 \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + 3\alpha_i^\theta \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + \alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i} d\Delta_{iT}
\end{aligned}$$

$$\begin{aligned}
0 &= 2(\alpha_i^\epsilon)^2 \alpha_i^\theta \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 2\alpha_i^{\epsilon\epsilon} \alpha_i^\theta \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 4\alpha_i^\epsilon \alpha_i^{\theta\epsilon} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) \\
&+ (\alpha_i^\epsilon)^2 (\alpha_i^\theta)^2 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 2\alpha_i^\theta \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + (\alpha_i^\epsilon)^2 \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
&+ \alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 2\alpha_i^\epsilon \alpha_i^{\theta\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon} (\alpha_i^\theta)^2 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
&+ \alpha_i^{\theta\theta\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) + (\alpha_i^\epsilon)^2 \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon} \int V_i^{\theta\theta\alpha_i} dF(\epsilon) \\
&+ 2\alpha_i^{\theta\epsilon\epsilon} \int V_i^{\theta\alpha_i} dF(\epsilon) + 2(\alpha_i^{\theta\epsilon})^2 \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 4\alpha_i^\theta \alpha_i^\epsilon \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
&+ 2\alpha_i^\epsilon \int V_i^{\theta\theta\alpha_i} d\Delta_{iT} + 4\alpha_i^{\theta\epsilon} \int V_i^{\theta\alpha_i} d\Delta_{iT} + 2\alpha_i^{\theta\theta\epsilon} \int V_i^{\alpha_i} d\Delta_{iT} + 2\alpha_i^\epsilon (\alpha_i^\theta)^2 \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} \\
&+ 4\alpha_i^\theta \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 2\alpha_i^\epsilon \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 4\alpha_i^\epsilon \alpha_i^\theta \int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT} \\
0 &= (\alpha_i^\epsilon)^3 \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\theta\alpha_i} dF(\epsilon) \\
&+ (\alpha_i^\epsilon)^3 \alpha_i^\theta \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^\epsilon \alpha_i^\theta \alpha_i^{\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3(\alpha_i^\epsilon)^2 \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
&+ \alpha_i^{\epsilon\epsilon\epsilon} \alpha_i^\theta \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^\epsilon \alpha_i^{\theta\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
&+ \alpha_i^{\theta\epsilon\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) \\
&+ 3(\alpha_i^\epsilon)^2 \int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT} + 3\alpha_i^{\epsilon\epsilon} \int V_i^{\theta\alpha_i} d\Delta_{iT} + 3(\alpha_i^\epsilon)^2 \alpha_i^\theta \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} \\
&+ 3\alpha_i^{\epsilon\epsilon} \alpha_i^\theta \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 6\alpha_i^\epsilon \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 3\alpha_i^{\theta\epsilon\epsilon} \int V_i^{\alpha_i} d\Delta_{iT} \\
0 &= (\alpha_i^\epsilon)^4 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 6(\alpha_i^\epsilon)^2 \alpha_i^{\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3(\alpha_i^{\epsilon\epsilon})^2 \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
&+ 4\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) \\
&+ 4(\alpha_i^\epsilon)^3 \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + 12\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 4\alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\alpha_i} d\Delta_{iT}
\end{aligned}$$

Evaluating at $\epsilon = 0$, we obtain

$$\begin{aligned}
\alpha_i^{\theta\theta\theta\theta} &= 6(\alpha_i^\theta)^2 \alpha_i^{\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 12\alpha_i^\theta \alpha_i^{\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 4\alpha_i^\theta \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 3(\alpha_i^{\theta\theta})^2 \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ (\alpha_i^\theta)^4 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 4(\alpha_i^\theta)^3 \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6(\alpha_i^\theta)^2 \frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\theta\theta} \frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} \\
&+ 4\alpha_i^\theta \frac{E[V_i^{\theta\theta\theta\alpha_i}]}{E[V_i^2]} + \frac{E[V_i^{\theta\theta\theta\theta}]}{E[V_i^2]} + 4\alpha_i^{\theta\theta\theta} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]}
\end{aligned}$$

$$\begin{aligned}
\alpha_i^{\theta\theta\theta\epsilon} &= 3\alpha_i^\theta\alpha_i^\epsilon\alpha_i^{\theta\theta}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon\alpha_i^{\theta\theta}\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon\alpha_i^\theta\frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 3(\alpha_i^\theta)^2\alpha_i^{\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ \alpha_i^\epsilon(\alpha_i^\theta)^3\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^\theta\alpha_i^{\theta\epsilon}\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon(\alpha_i^\theta)^2\frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^\epsilon\alpha_i^{\theta\theta\theta}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 3\alpha_i^{\theta\epsilon}\alpha_i^{\theta\theta}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\theta\alpha_i^{\theta\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^\epsilon\frac{E[V_i^{\theta\theta\theta\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\epsilon}\frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\theta\epsilon}\frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} \\
&+ \frac{\int V_i^{\theta\theta\theta}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^\theta\frac{\int V_i^{\theta\theta\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3(\alpha_i^\theta)^2\frac{\int V_i^{\theta\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\theta\theta}\frac{\int V_i^{\theta\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
&+ (\alpha_i^\theta)^3\frac{\int V_i^{\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^\theta\alpha_i^{\theta\theta}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + \alpha_i^{\theta\theta\theta}\frac{\int V_i^{\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
\alpha_i^{\theta\theta\epsilon\epsilon} &= 2(\alpha_i^\epsilon)^2\alpha_i^\theta\frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^{\epsilon\epsilon}\alpha_i^\theta\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 4\alpha_i^\epsilon\alpha_i^{\theta\epsilon}\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^2(\alpha_i^\theta)^2\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 2\alpha_i^\theta\alpha_i^{\theta\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^2\alpha_i^{\theta\theta}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon}\alpha_i^{\theta\theta}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^\epsilon\alpha_i^{\theta\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ \alpha_i^{\epsilon\epsilon}(\alpha_i^\theta)^2\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^2\frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} + 2\alpha_i^{\theta\epsilon\epsilon}\frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} \\
&+ 2(\alpha_i^{\theta\epsilon})^2\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 4\alpha_i^\theta\alpha_i^\epsilon\alpha_i^{\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 2\alpha_i^\epsilon\frac{\int V_i^{\theta\theta\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 4\alpha_i^{\theta\epsilon}\frac{\int V_i^{\theta\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^{\theta\theta\epsilon}\frac{\int V_i^{\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^\epsilon(\alpha_i^\theta)^2\frac{\int V_i^{\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
&+ 4\alpha_i^\theta\alpha_i^{\theta\epsilon}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^\epsilon\alpha_i^{\theta\theta}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 4\alpha_i^\epsilon\alpha_i^\theta\frac{\int V_i^{\theta\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
\alpha_i^{\theta\epsilon\epsilon\epsilon} &= (\alpha_i^\epsilon)^3\frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon\alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon\epsilon}\frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^3\alpha_i^\theta\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 3\alpha_i^\epsilon\alpha_i^\theta\alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3(\alpha_i^\epsilon)^2\alpha_i^{\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon\epsilon}\alpha_i^\theta\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon}\alpha_i^{\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 3\alpha_i^\epsilon\alpha_i^{\theta\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 3(\alpha_i^\epsilon)^2\frac{\int V_i^{\theta\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon}\frac{\int V_i^{\theta\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3(\alpha_i^\epsilon)^2\alpha_i^\theta\frac{\int V_i^{\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon}\alpha_i^\theta\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
&+ 6\alpha_i^\epsilon\alpha_i^{\theta\epsilon}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\theta\epsilon\epsilon}\frac{\int V_i^{\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
\alpha_i^{\epsilon\epsilon\epsilon\epsilon} &= (\alpha_i^\epsilon)^4\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6(\alpha_i^\epsilon)^2\alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3(\alpha_i^{\epsilon\epsilon})^2\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 4\alpha_i^\epsilon\alpha_i^{\epsilon\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 4(\alpha_i^\epsilon)^3\frac{\int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 12\alpha_i^\epsilon\alpha_i^{\epsilon\epsilon}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 4\alpha_i^{\epsilon\epsilon\epsilon}\frac{\int V_i^{\alpha_i}d\Delta_{iT}}{E[V_i^2]}
\end{aligned}$$

B.4 $\alpha_i^{\theta\theta\theta\theta}$, $\alpha_i^{\theta\theta\theta\epsilon}$, $\alpha_i^{\theta\theta\epsilon\epsilon}$, $\alpha_i^{\theta\theta\epsilon\epsilon\epsilon}$, $\alpha_i^{\theta\epsilon\epsilon\epsilon\epsilon}$, and $\alpha_i^{\epsilon\epsilon\epsilon\epsilon\epsilon}$

Fifth order differentiation $\left(\frac{\partial^5}{\partial\theta^5}, \frac{\partial^5}{\partial\theta^4\partial\epsilon}, \frac{\partial^5}{\partial\theta^3\partial\epsilon^2}, \frac{\partial^5}{\partial\theta^2\partial\epsilon^3}, \frac{\partial^5}{\partial\theta\partial\epsilon^4}, \frac{\partial^5}{\partial\epsilon^5}\right)$ of (B1) yields

$$\begin{aligned}
0 = & 10\alpha_i^{\theta\theta} \int V_i^{\theta\theta\theta\alpha_i} dF(\epsilon) + 5\alpha_i^{\theta} \int V_i^{\theta\theta\theta\theta\alpha_i} dF(\epsilon) + 30\alpha_i^{\theta}\alpha_i^{\theta\theta} \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) \\
& + 20\alpha_i^{\theta}\alpha_i^{\theta\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 30(\alpha_i^{\theta})^2\alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 10\alpha_i^{\theta\theta}\alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
& + 5\alpha_i^{\theta}\alpha_i^{\theta\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 15\alpha_i^{\theta}(\alpha_i^{\theta\theta})^2 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 10(\alpha_i^{\theta})^3\alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 10(\alpha_i^{\theta})^2\alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 10\alpha_i^{\theta\theta\theta} \int V_i^{\theta\theta\alpha_i} dF(\epsilon) + 5\alpha_i^{\theta\theta\theta\theta} \int V_i^{\theta\alpha_i} dF(\epsilon) \\
& + (\alpha_i^{\theta})^5 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 5(\alpha_i^{\theta})^4 \int V_i^{\theta\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 15(\alpha_i^{\theta\theta})^2 \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) \\
& + 10(\alpha_i^{\theta})^3 \int V_i^{\theta\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\theta\theta\theta\theta} \int V_i^{\alpha_i} dF(\epsilon) + 10(\alpha_i^{\theta})^2 \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) + \int V_i^{\theta\theta\theta\theta\theta} dF(\epsilon)
\end{aligned}$$

$$\begin{aligned}
0 = & 6\alpha_i^{\epsilon}(\alpha_i^{\theta})^2 \int V_i^{\theta\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 12\alpha_i^{\theta}\alpha_i^{\theta\epsilon} \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) + 4\alpha_i^{\epsilon}(\alpha_i^{\theta})^3 \int V_i^{\theta\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 12(\alpha_i^{\theta})^2\alpha_i^{\theta\epsilon} \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 12\alpha_i^{\theta}\alpha_i^{\theta\theta\epsilon} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 12\alpha_i^{\theta\epsilon}\alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) \\
& + 4\alpha_i^{\theta}\alpha_i^{\theta\theta\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon}(\alpha_i^{\theta})^4 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 4(\alpha_i^{\theta})^3\alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 6(\alpha_i^{\theta})^2\alpha_i^{\theta\theta\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 4\alpha_i^{\theta\epsilon}\alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\epsilon}(\alpha_i^{\theta\theta})^2 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 6\alpha_i^{\theta\theta}\alpha_i^{\theta\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 6\alpha_i^{\epsilon}\alpha_i^{\theta\theta} \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) + 4\alpha_i^{\epsilon}\alpha_i^{\theta} \int V_i^{\theta\theta\theta\alpha_i\alpha_i} dF(\epsilon) \\
& + 4\alpha_i^{\epsilon}\alpha_i^{\theta\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon}\alpha_i^{\theta\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 12\alpha_i^{\theta}\alpha_i^{\epsilon}\alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 4\alpha_i^{\theta}\alpha_i^{\epsilon}\alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 12\alpha_i^{\theta}\alpha_i^{\theta\epsilon}\alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 6(\alpha_i^{\theta})^2\alpha_i^{\epsilon}\alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + \alpha_i^{\theta\theta\theta\theta\epsilon} \int V_i^{\alpha_i} dF(\epsilon) + 4\alpha_i^{\theta\theta\theta\epsilon} \int V_i^{\theta\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon} \int V_i^{\theta\theta\theta\theta\alpha_i} dF(\epsilon) \\
& + 4\alpha_i^{\theta\epsilon} \int V_i^{\theta\theta\theta\alpha_i} dF(\epsilon) + 6\alpha_i^{\theta\theta\epsilon} \int V_i^{\theta\theta\alpha_i} dF(\epsilon) \\
& + 4\alpha_i^{\theta}\alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 6(\alpha_i^{\theta})^2\alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + 12\alpha_i^{\theta}\alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT} \\
& + 3(\alpha_i^{\theta\theta})^2 \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 6(\alpha_i^{\theta})^2 \int V_i^{\theta\theta\alpha_i\alpha_i} d\Delta_{iT} + 4(\alpha_i^{\theta})^3 \int V_i^{\theta\alpha_i\alpha_i\alpha_i} d\Delta_{iT} \\
& + 4\alpha_i^{\theta\theta\theta} \int V_i^{\theta\alpha_i} d\Delta_{iT} + \alpha_i^{\theta\theta\theta\theta} \int V_i^{\alpha_i} d\Delta_{iT} + 4\alpha_i^{\theta} \int V_i^{\theta\theta\theta\alpha_i} d\Delta_{iT} + 6\alpha_i^{\theta\theta} \int V_i^{\theta\theta\alpha_i} d\Delta_{iT} \\
& + (\alpha_i^{\theta})^4 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + \int V_i^{\theta\theta\theta\theta} d\Delta_{iT}
\end{aligned}$$

$$\begin{aligned}
0 = & 6\alpha_i^\theta (\alpha_i^{\theta\epsilon})^2 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3(\alpha_i^\epsilon)^2 \alpha_i^\theta \int V_i^{\theta\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\epsilon\epsilon} \alpha_i^\theta \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) \\
& + 3(\alpha_i^\epsilon)^2 \alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + (\alpha_i^\epsilon)^2 \alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) \\
& + \alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 6\alpha_i^\epsilon \alpha_i^{\theta\epsilon} \int V_i^{\theta\theta\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\theta\epsilon\epsilon} \alpha_i^\theta \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
& + 3(\alpha_i^\epsilon)^2 (\alpha_i^\theta)^2 \int V_i^{\theta\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\epsilon\epsilon} (\alpha_i^\theta)^2 \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) + (\alpha_i^\epsilon)^2 (\alpha_i^\theta)^3 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 6\alpha_i^\epsilon \alpha_i^{\theta\theta\epsilon} \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon} (\alpha_i^\theta)^3 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 6\alpha_i^{\theta\epsilon} \int \alpha_i^{\theta\theta\epsilon} V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
& + 2\alpha_i^\epsilon \alpha_i^{\theta\theta\theta\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 6\alpha_i^{\theta\epsilon\epsilon} \alpha_i^\theta \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\epsilon\epsilon} (\alpha_i^\theta)^2 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 3\alpha_i^{\theta\epsilon\epsilon} \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\theta} \alpha_i^{\epsilon\epsilon} \alpha_i^\theta \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\theta} (\alpha_i^\epsilon)^2 \alpha_i^\theta \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 6\alpha_i^{\theta\theta} \alpha_i^\epsilon \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 6\alpha_i^{\theta\epsilon} \alpha_i^\epsilon (\alpha_i^\theta)^2 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 12\alpha_i^{\theta\epsilon} \alpha_i^\epsilon \alpha_i^\theta \int V_i^{\theta\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
& + 6\alpha_i^{\theta\theta\epsilon} \alpha_i^\epsilon \alpha_i^\theta \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 6(\alpha_i^{\theta\epsilon})^2 \int V_i^{\theta\alpha_i\alpha_i} dF(\epsilon) + (\alpha_i^\epsilon)^2 \int V_i^{\theta\theta\theta\alpha_i\alpha_i} dF(\epsilon) \\
& + \alpha_i^{\theta\theta\theta\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\epsilon\epsilon} \int V_i^{\theta\theta\alpha_i} dF(\epsilon) + 3\alpha_i^{\theta\theta\epsilon\epsilon} \int V_i^{\theta\alpha_i} dF(\epsilon) + \alpha_i^{\epsilon\epsilon} \int V_i^{\theta\theta\theta\alpha_i} dF(\epsilon) \\
& + 12\alpha_i^\theta \alpha_i^{\theta\epsilon} \int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT} + 2\alpha_i^\epsilon (\alpha_i^\theta)^3 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + 6(\alpha_i^\theta)^2 \alpha_i^{\theta\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} \\
& + 6\alpha_i^\theta \alpha_i^{\theta\theta\epsilon} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 6\alpha_i^{\theta\epsilon} \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 6\alpha_i^\epsilon \alpha_i^\theta \int V_i^{\theta\theta\alpha_i\alpha_i} d\Delta_{iT} \\
& + 6\alpha_i^\epsilon \alpha_i^{\theta\theta} \int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT} + 2\alpha_i^\epsilon \alpha_i^{\theta\theta\theta} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 6\alpha_i^\epsilon (\alpha_i^\theta)^2 \int V_i^{\theta\alpha_i\alpha_i\alpha_i} d\Delta_{iT} \\
& + 6\alpha_i^\theta \alpha_i^\epsilon \alpha_i^{\theta\theta} \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + 6\alpha_i^{\theta\epsilon} \int V_i^{\theta\theta\alpha_i} d\Delta_{iT} + 6\alpha_i^{\theta\theta\epsilon} \int V_i^{\theta\alpha_i} d\Delta_{iT} \\
& + 2\alpha_i^{\theta\theta\theta\epsilon} \int V_i^{\alpha_i} d\Delta_{iT} + 2\alpha_i^\epsilon \int V_i^{\theta\theta\theta\alpha_i} d\Delta_{iT}
\end{aligned}$$

$$\begin{aligned}
0 &= \alpha_i^{\epsilon\epsilon\epsilon\epsilon} \int V_i^{\alpha_i} dF(\epsilon) + 10(\alpha_i^\epsilon)^2 \alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) + (\alpha_i^\epsilon)^5 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
&+ 10(\alpha_i^\epsilon)^3 \alpha_i^{\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} dF(\epsilon) + 10\alpha_i^{\epsilon\epsilon} \alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) + 5\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i} dF(\epsilon) \\
&+ 15\alpha_i^\epsilon (\alpha_i^{\epsilon\epsilon})^2 \int V_i^{\alpha_i\alpha_i\alpha_i} dF(\epsilon) \\
&+ 5(\alpha_i^\epsilon)^4 \int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + 15(\alpha_i^{\epsilon\epsilon})^2 \int V_i^{\alpha_i\alpha_i} d\Delta_{iT} + 5\alpha_i^{\epsilon\epsilon\epsilon\epsilon} \int V_i^{\alpha_i} d\Delta_{iT} \\
&+ 30(\alpha_i^\epsilon)^2 \alpha_i^{\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT} + 20\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon\epsilon} \int V_i^{\alpha_i\alpha_i} d\Delta_{iT}
\end{aligned}$$

Evaluating at $\epsilon = 0$, we obtain

$$\begin{aligned}
\alpha_i^{\theta\theta\theta\theta} &= 10\alpha_i^{\theta\theta} \frac{E[V_i^{\theta\theta\theta\theta\alpha_i}]}{E[V_i^2]} + 5\alpha_i^\theta \frac{E[V_i^{\theta\theta\theta\theta\alpha_i}]}{E[V_i^2]} + 30\alpha_i^\theta \alpha_i^{\theta\theta} \frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 20\alpha_i^\theta \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 30(\alpha_i^\theta)^2 \alpha_i^{\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 10\alpha_i^{\theta\theta} \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 5\alpha_i^\theta \alpha_i^{\theta\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 15\alpha_i^\theta (\alpha_i^{\theta\theta})^2 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 10(\alpha_i^\theta)^3 \alpha_i^{\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 10(\alpha_i^\theta)^2 \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 10\alpha_i^{\theta\theta\theta} \frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} + 5\alpha_i^{\theta\theta\theta\theta} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + (\alpha_i^\theta)^5 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 5(\alpha_i^\theta)^4 \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
&+ 15(\alpha_i^{\theta\theta})^2 \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 10(\alpha_i^\theta)^3 \frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 10(\alpha_i^\theta)^2 \frac{E[V_i^{\theta\theta\theta\alpha_i}]}{E[V_i^2]} \\
&+ \frac{E[V_i^{\theta\theta\theta\theta\theta}]}{E[V_i^2]}
\end{aligned}$$

$$\begin{aligned}
\alpha_i^{\theta\theta\theta\theta\epsilon} = & 6\alpha_i^\epsilon (\alpha_i^\theta)^2 \frac{E[V_i^{\theta\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 12\alpha_i^\theta \alpha_i^{\theta\epsilon} \frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 4\alpha_i^\epsilon (\alpha_i^\theta)^3 \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 12(\alpha_i^\theta)^2 \alpha_i^{\theta\epsilon} \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 12\alpha_i^\theta \alpha_i^{\theta\theta\epsilon} \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 12\alpha_i^{\theta\epsilon} \alpha_i^{\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 4\alpha_i^\theta \alpha_i^{\theta\theta\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^\epsilon (\alpha_i^\theta)^4 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 4(\alpha_i^\theta)^3 \alpha_i^{\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6(\alpha_i^\theta)^2 \alpha_i^{\theta\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 4\alpha_i^{\theta\epsilon} \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon (\alpha_i^{\theta\theta})^2 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6\alpha_i^{\theta\theta} \alpha_i^{\theta\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^\epsilon \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 4\alpha_i^\epsilon \alpha_i^\theta \frac{E[V_i^{\theta\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 4\alpha_i^\epsilon \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^\epsilon \alpha_i^{\theta\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 12\alpha_i^\theta \alpha_i^\epsilon \alpha_i^{\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 4\alpha_i^\theta \alpha_i^\epsilon \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 12\alpha_i^\theta \alpha_i^{\theta\epsilon} \alpha_i^{\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6(\alpha_i^\theta)^2 \alpha_i^\epsilon \alpha_i^{\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 4\alpha_i^{\theta\theta\theta\epsilon} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + \alpha_i^\epsilon \frac{E[V_i^{\theta\theta\theta\theta\alpha_i}]}{E[V_i^2]} + 4\alpha_i^{\theta\epsilon} \frac{E[V_i^{\theta\theta\theta\alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\theta\theta\epsilon} \frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} \\
& + 4\alpha_i^\theta \alpha_i^{\theta\theta\theta} \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6(\alpha_i^\theta)^2 \alpha_i^{\theta\theta} \frac{\int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 12\alpha_i^\theta \alpha_i^{\theta\theta} \frac{\int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 3(\alpha_i^{\theta\theta})^2 \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6(\alpha_i^\theta)^2 \frac{\int V_i^{\theta\theta\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 4(\alpha_i^\theta)^3 \frac{\int V_i^{\theta\alpha_i\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 4\alpha_i^{\theta\theta\theta} \frac{\int V_i^{\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} + \alpha_i^{\theta\theta\theta\theta} \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 4\alpha_i^\theta \frac{\int V_i^{\theta\theta\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^{\theta\theta} \frac{\int V_i^{\theta\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + (\alpha_i^\theta)^4 \frac{\int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + \frac{\int V_i^{\theta\theta\theta\theta} d\Delta_{iT}}{E[V_i^2]}
\end{aligned}$$

$$\begin{aligned}
\alpha_i^{\theta\theta\theta\epsilon\epsilon} = & 6\alpha_i^\theta (\alpha_i^{\theta\epsilon})^2 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3(\alpha_i^\epsilon)^2 \alpha_i^\theta \frac{E[V_i^{\theta\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon} \alpha_i^\theta \frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 3(\alpha_i^\epsilon)^2 \alpha_i^{\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^2 \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\theta} \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + \alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^\epsilon \alpha_i^{\theta\epsilon} \frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\theta\epsilon\epsilon} \alpha_i^\theta \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 3(\alpha_i^\epsilon)^2 (\alpha_i^\theta)^2 \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon} (\alpha_i^\theta)^2 \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^2 (\alpha_i^\theta)^3 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6\alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\theta\epsilon} \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon} (\alpha_i^\theta)^3 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\theta\epsilon} \alpha_i^{\theta\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 2\alpha_i^\epsilon \alpha_i^{\theta\theta\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\theta\epsilon\epsilon} \alpha_i^\theta \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\epsilon\epsilon} (\alpha_i^\theta)^2 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 3\alpha_i^{\theta\epsilon\epsilon} \alpha_i^{\theta\theta} \frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\theta} \alpha_i^{\epsilon\epsilon} \alpha_i^\theta \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\theta} (\alpha_i^\epsilon)^2 \alpha_i^\theta \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6\alpha_i^{\theta\theta} \alpha_i^\epsilon \alpha_i^{\theta\epsilon} \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\theta\epsilon} \alpha_i^\epsilon (\alpha_i^\theta)^2 \frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 12\alpha_i^{\theta\epsilon} \alpha_i^\epsilon \alpha_i^\theta \frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6\alpha_i^{\theta\theta\epsilon} \alpha_i^\epsilon \alpha_i^\theta \frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6(\alpha_i^{\theta\epsilon})^2 \frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^2 \frac{E[V_i^{\theta\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 3\alpha_i^{\theta\epsilon\epsilon} \frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} + 3\alpha_i^{\theta\theta\epsilon\epsilon} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon} \frac{E[V_i^{\theta\theta\theta\alpha_i}]}{E[V_i^2]} \\
& + 12\alpha_i^\theta \alpha_i^{\theta\epsilon} \frac{\int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^\epsilon (\alpha_i^\theta)^3 \frac{\int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6(\alpha_i^\theta)^2 \alpha_i^{\theta\epsilon} \frac{\int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 6\alpha_i^\theta \alpha_i^{\theta\theta\epsilon} \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^{\theta\epsilon} \alpha_i^{\theta\theta} \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^\epsilon \alpha_i^\theta \frac{\int V_i^{\theta\theta\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 6\alpha_i^\epsilon \alpha_i^{\theta\theta} \frac{\int V_i^{\theta\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^\epsilon \alpha_i^{\theta\theta\theta} \frac{\int V_i^{\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^\epsilon (\alpha_i^\theta)^2 \frac{\int V_i^{\theta\alpha_i\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 6\alpha_i^\theta \alpha_i^\epsilon \alpha_i^{\theta\theta} \frac{\int V_i^{\alpha_i\alpha_i\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^{\theta\epsilon} \frac{\int V_i^{\theta\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^{\theta\theta\epsilon} \frac{\int V_i^{\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 2\alpha_i^{\theta\theta\theta\epsilon} \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 2\alpha_i^\epsilon \frac{\int V_i^{\theta\theta\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]}
\end{aligned}$$

$$\begin{aligned}
\alpha_i^{\theta\theta\epsilon\epsilon\epsilon} = & 3\alpha_i^{\epsilon\epsilon}\alpha_i^{\theta\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 2(\alpha_i^\epsilon)^3\alpha_i^\theta\frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6(\alpha_i^\epsilon)^2\alpha_i^{\theta\epsilon}\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + \alpha_i^{\epsilon\epsilon\epsilon}(\alpha_i^\theta)^2\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^3(\alpha_i^\theta)^2\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^{\theta\epsilon\epsilon\epsilon}\alpha_i^\theta\frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + \alpha_i^{\epsilon\epsilon\epsilon}\alpha_i^{\theta\theta}\frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^3\alpha_i^{\theta\theta}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 2\alpha_i^{\epsilon\epsilon\epsilon}\alpha_i^\theta\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 3\alpha_i^\epsilon\alpha_i^{\theta\theta\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 3(\alpha_i^\epsilon)^2\alpha_i^{\theta\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\theta\epsilon\epsilon}\alpha_i^\epsilon\alpha_i^\theta\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 3\alpha_i^\epsilon\alpha_i^{\theta\theta}\alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^\theta\alpha_i^{\epsilon\epsilon}\alpha_i^{\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^\epsilon\alpha_i^\theta\alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6\alpha_i^\theta(\alpha_i^\epsilon)^2\alpha_i^{\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon(\alpha_i^\theta)^2\alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^3\frac{E[V_i^{\theta\theta\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 2\alpha_i^{\theta\epsilon\epsilon\epsilon}\frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon\epsilon}\frac{E[V_i^{\theta\theta\alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\epsilon\epsilon}\alpha_i^{\theta\epsilon}\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^\epsilon(\alpha_i^{\theta\epsilon})^2\frac{E[V_i^{\alpha_i\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6\alpha_i^{\theta\epsilon\epsilon}\alpha_i^{\theta\epsilon}\frac{E[V_i^{\alpha_i\alpha_i}]}{E[V_i^2]} + 6\alpha_i^\epsilon\alpha_i^{\theta\epsilon\epsilon}\frac{E[V_i^{\theta\alpha_i\alpha_i}]}{E[V_i^2]} + 3\alpha_i^\epsilon\alpha_i^{\epsilon\epsilon}\frac{E[V_i^{\theta\theta\alpha_i\alpha_i}]}{E[V_i^2]} \\
& + 6(\alpha_i^\epsilon)^2\alpha_i^\theta\frac{\int V_i^{\theta\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^\theta\alpha_i^{\theta\epsilon\epsilon}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 12\alpha_i^\epsilon\alpha_i^{\theta\epsilon}\frac{\int V_i^{\theta\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
& + 6\alpha_i^\epsilon\alpha_i^{\theta\theta\epsilon}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon}\alpha_i^{\theta\theta}\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3(\alpha_i^\epsilon)^2\alpha_i^{\theta\theta}\frac{\int V_i^{\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
& + 3\alpha_i^{\epsilon\epsilon}(\alpha_i^\theta)^2\frac{\int V_i^{\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3(\alpha_i^\epsilon)^2(\alpha_i^\theta)^2\frac{\int V_i^{\alpha_i\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^{\epsilon\epsilon}\alpha_i^\theta\frac{\int V_i^{\theta\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
& + 12\alpha_i^\theta\alpha_i^\epsilon\alpha_i^{\theta\epsilon}\frac{\int V_i^{\alpha_i\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\theta\theta\epsilon\epsilon}\frac{\int V_i^{\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3\alpha_i^{\epsilon\epsilon}\frac{\int V_i^{\theta\theta\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 6\alpha_i^{\theta\epsilon\epsilon}\frac{\int V_i^{\theta\alpha_i}d\Delta_{iT}}{E[V_i^2]} \\
& + 6(\alpha_i^{\theta\epsilon})^2\frac{\int V_i^{\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]} + 3(\alpha_i^\epsilon)^2\frac{\int V_i^{\theta\theta\alpha_i\alpha_i}d\Delta_{iT}}{E[V_i^2]}
\end{aligned}$$

$$\begin{aligned}
\alpha_i^{\theta\epsilon\epsilon\epsilon\epsilon} = & 6(\alpha_i^\epsilon)^2 \alpha_i^\theta \alpha_i^{\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + 4(\alpha_i^\epsilon)^3 \alpha_i^{\theta\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + 6(\alpha_i^\epsilon)^2 \alpha_i^{\theta\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} \\
& + 6(\alpha_i^\epsilon)^2 \alpha_i^{\epsilon\epsilon} \frac{E[V_i^{\theta\alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + 4\alpha_i^{\epsilon\epsilon\epsilon} \alpha_i^{\theta\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + 6\alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i}]}{E[V_i^2]} \\
& + \alpha_i^{\epsilon\epsilon\epsilon\epsilon} \alpha_i^\theta \frac{E[V_i^{\alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + 3(\alpha_i^{\epsilon\epsilon})^2 \alpha_i^\theta \frac{E[V_i^{\alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^4 \alpha_i^\theta \frac{E[V_i^{\alpha_i \alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} \\
& + 4\alpha_i^\epsilon \alpha_i^{\theta\epsilon\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i}]}{E[V_i^2]} + 12\alpha_i^\epsilon \alpha_i^{\theta\epsilon} \alpha_i^{\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + \alpha_i^{\epsilon\epsilon\epsilon\epsilon} \frac{E[V_i^{\theta\alpha_i}]}{E[V_i^2]} \\
& + 4\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon\epsilon} \frac{E[V_i^{\theta\alpha_i \alpha_i}]}{E[V_i^2]} + 4\alpha_i^\epsilon \alpha_i^\theta \alpha_i^{\epsilon\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + 3(\alpha_i^{\epsilon\epsilon})^2 \frac{E[V_i^{\theta\alpha_i \alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^4 \frac{E[V_i^{\theta\alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} \\
& + 12\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon} \frac{\int V_i^{\theta\alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} + 12(\alpha_i^\epsilon)^2 \alpha_i^{\theta\epsilon} \frac{\int V_i^{\alpha_i \alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} + 4(\alpha_i^\epsilon)^3 \alpha_i^\theta \frac{\int V_i^{\alpha_i \alpha_i \alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 4\alpha_i^{\epsilon\epsilon\epsilon} \alpha_i^\theta \frac{\int V_i^{\alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} + 12\alpha_i^\epsilon \alpha_i^\theta \alpha_i^{\epsilon\epsilon} \frac{\int V_i^{\alpha_i \alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} + 4(\alpha_i^\epsilon)^3 \frac{\int V_i^{\theta\alpha_i \alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 4\alpha_i^{\epsilon\epsilon\epsilon} \frac{\int V_i^{\theta\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 4\alpha_i^{\theta\epsilon\epsilon\epsilon} \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} + 12\alpha_i^{\epsilon\epsilon} \alpha_i^{\theta\epsilon} \frac{\int V_i^{\alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 12\alpha_i^\epsilon \alpha_i^{\theta\epsilon\epsilon} \frac{\int V_i^{\alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]}
\end{aligned}$$

$$\begin{aligned}
\alpha_i^{\epsilon\epsilon\epsilon\epsilon\epsilon} = & 10(\alpha_i^\epsilon)^2 \alpha_i^{\epsilon\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + (\alpha_i^\epsilon)^5 \frac{E[V_i^{\alpha_i \alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} + 10(\alpha_i^\epsilon)^3 \alpha_i^{\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} \\
& + 10\alpha_i^{\epsilon\epsilon} \alpha_i^{\epsilon\epsilon\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i}]}{E[V_i^2]} + 5\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon\epsilon\epsilon} \frac{E[V_i^{\alpha_i \alpha_i}]}{E[V_i^2]} + 15\alpha_i^\epsilon (\alpha_i^{\epsilon\epsilon})^2 \frac{E[V_i^{\alpha_i \alpha_i \alpha_i}]}{E[V_i^2]} \\
& + 5(\alpha_i^\epsilon)^4 \frac{\int V_i^{\alpha_i \alpha_i \alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} + 15(\alpha_i^{\epsilon\epsilon})^2 \frac{\int V_i^{\alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} + 5\alpha_i^{\epsilon\epsilon\epsilon\epsilon} \frac{\int V_i^{\alpha_i} d\Delta_{iT}}{E[V_i^2]} \\
& + 30(\alpha_i^\epsilon)^2 \alpha_i^{\epsilon\epsilon} \frac{\int V_i^{\alpha_i \alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]} + 20\alpha_i^\epsilon \alpha_i^{\epsilon\epsilon\epsilon} \frac{\int V_i^{\alpha_i \alpha_i} d\Delta_{iT}}{E[V_i^2]}
\end{aligned}$$