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**Working Paper**

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cemmap working paper, No. CWP31/19

**Provided in Cooperation with:**

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*Suggested Citation:* Chernozhukov, Victor; Hansen, Christian Bailey; Liao, Yuan; Zhu, Yinchu (2019) : Inference for heterogeneous effects using low-rank estimations, cemmap working paper, No. CWP31/19, Centre for Microdata Methods and Practice (cemmap), London, <https://doi.org/10.1920/wp.cem.2019.3119>

This Version is available at:

<https://hdl.handle.net/10419/211124>

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# Inference for heterogeneous effects using low-rank estimations

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**cemmap** working paper CWP31/19

# INFERENCE FOR HETEROGENEOUS EFFECTS USING LOW-RANK ESTIMATIONS

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**ABSTRACT.** We study a panel data model with general heterogeneous effects, where slopes are allowed to be varying across both individuals and times. The key assumption for dimension reduction is that the heterogeneous slopes can be expressed as a factor structure so that the high-dimensional slope matrix is of low-rank, so can be estimated using low-rank regularized regression. Our paper makes an important theoretical contribution on the “post-SVT (singular value thresholding) inference”. Formally, we show that the post-SVT inference can be conducted via three steps: (1) apply the nuclear-norm penalized estimation; (2) extract eigenvectors from the estimated low-rank matrices, and (3) run least squares to iteratively estimate the individual and time effect components in the slope matrix. To properly control for the effect of the penalized low-rank estimation, we argue that this procedure should be embedded with “partial out the mean structure” and “sample splitting”. The resulting estimators are asymptotically normal and admit valid inferences. Empirically, we apply the proposed methods to estimate the county-level minimum wage effects on the employment.

**Key words:** nuclear norm penalization, post-SVT, sample splitting, interactive effects

## 1. INTRODUCTION

This paper studies the estimation and inference about the following panel data model:

$$y_{it} = x'_{it}\theta_{it} + \alpha'_i g_t + u_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T,$$

where  $x_{it}$  is a  $d$ -dimensional vector of observed covariates;  $\alpha_i$  and  $g_t$  are unobserved fixed effects. Importantly, the model permits general heterogeneities, in the sense that not only the fixed effects appear in the model interactively, but also the slope  $\theta_{it}$  is allowed to vary across both  $i$  and  $t$ . The main dimension reduction assumption employed in this paper is that  $\theta_{it}$  can be expressed as:

$$\theta_{it} = \lambda'_i f_t,$$

that is, it can be represented by a factor structure, where  $\lambda_i$  is a matrix of loadings and  $f_t$  is a vector of factors. Here we allow  $f_t$  and  $g_t$  to have overlapping components. In particular, we allow either  $f_t$  or  $\lambda_i$  or both to be constant across  $i \leq N$  or  $t \leq T$ , so allow homogeneous slopes as special cases.

Let  $\Theta_r$  and  $X_r$  be the  $N \times T$  matrices of the  $r$ th component  $(\theta_{it,r})$  and  $x_{it,r}$ ; let  $M, Y, U$  be the  $N \times T$  matrices of  $\alpha'_i g_t$ ,  $y_{it}$  and  $u_{it}$ . Also let  $\odot$  denote the matrix element-wise product. We have the following matrix form:

$$Y = \sum_{r=1}^d X_r \odot \Theta_r + M + U.$$

With the factor structure in  $\Theta_r$  and  $M$ , both the slope and fixed effect matrices are of low-rank, whose ranks are at most equal to their associated numbers of factors. This motivates employing the low-rank estimation:

$$\begin{aligned} \min_{\{\Theta_1, \dots, \Theta_d, M\}} \quad & \|Y - \sum_{r=1}^d X_r \odot \Theta_r - M\|_F^2 + P_0(\Theta_1, \dots, \Theta_d, M) \\ \text{where} \quad & P_0(\Theta_1, \dots, \Theta_d, M) = \sum_{r=1}^d \nu_r \|\Theta_r\|_n + \nu_0 \|M\|_n, \end{aligned} \quad (1.1)$$

for some tuning parameters  $\nu_0, \nu_1, \dots, \nu_d > 0$ , where  $\|\cdot\|_F$  and  $\|\cdot\|_n$  respectively denote the matrix Frobenius norm and nuclear norm. In particular, let  $\psi_1(\Theta) \geq$

...  $\geq \psi_{\min\{T,N\}}(\Theta)$  be the sorted singular values of an  $N \times T$  matrix  $\Theta$ , then

$$\|\Theta\|_n := \sum_{i=1}^{\min\{T,N\}} \psi_i(\Theta),$$

which is a convex-relaxation of the rank of  $\Theta$ , and can be casted using efficient algorithms such as the singular value decomposition.

While the penalized low-rank estimation (1.1) produces consistent estimators for the low-rank matrices, however, it is subjected to shrinkage biases. As such, this paper makes an important theoretical contribution on the inference for low-rank matrices, after employing the singular value thresholding (SVT) type regularization, so-called “post-SVT inference”. Formally, we show that the post-SVT inference can be conducted via three steps:

- (1) apply the low-rank regularized estimation via SVT-based algorithms;
- (2) extract eigenvectors from the estimated low-rank matrices, and
- (3) run iterative least squares.

More specifically, we extract the eigenvectors of the estimated  $\Theta_r$  obtained in (1.1), which form as preliminary estimators for  $\lambda_i$ . We then apply least squares to obtain  $\hat{f}_t$  as the estimated  $f_t$ , and re-estimate  $\lambda_i$ , still using least squares to obtain  $\hat{\lambda}_i$ . This leads to our final estimator for  $\theta_{it}$  as, for each  $i, t$ ,

$$\hat{\theta}_{it} = \hat{\lambda}_i' \hat{f}_t.$$

We shall show that the shrinkage bias can be offset from this iterative least squares procedure. The final estimator is asymptotically normally distributed and admits an asymptotically valid inference for  $\theta_{it}$  at each fixed  $(i, t)$ .

In addition, we assume that the covariates are generated from the following model:

$$x_{it} = \mu_{it} + e_{it},$$

where  $e_{it}$  is a zero-mean process that is serially independent and cross-sectionally weakly dependent. Here  $\mu_{it}$  is the mean structure of  $x_{it}$ . We study two cases. The first case is:  $\mu_{it} = \mu_i$ , which assumes that  $x_{it}$  follows from a simple many-mean model. The second case is  $\mu_{it} = l_i' w_t$  which also allows a factor-structure that captures the cross-sectional and serial dependences in  $x_{it}$ , with  $l_i, w_t$  respectively denoting the loading and factors in  $x_{it}$ . On the other hand, to properly control for the effect of the penalized low-rank estimation (1.1), the iterative least squares

procedure should be embedded with “partial out the mean structure” and “sample splitting”, so that in effect, we are using  $e_{it}$  as the regressors to apply the iterative least squares. Section 2.2 explains this in details.

Employing the nuclear norm penalization has been a popular technique in the statistical literature to achieve low-rank estimations, e.g., Negahban and Wainwright (2011); Recht et al. (2010); Sun and Zhang (2012); Candès and Tao (2010); Koltchinskii et al. (2011). However, there is little study on the element-wise inference for the components. The only work that we are aware of on the related issue is Cai et al. (2016), who proposed a debiased estimator to make inference about the low-rank matrix after applying the nuclear-norm penalization. We note that their debiased procedure does not apply in the model we are considering. The main issue is that under proper conditions, low-rank matrices deduced from a high-dimensional factor structure have “very spiked” eigenvalues, possessing leading eigenvalues that grow at rate  $O(NT)^{1/2}$ . The presence of these fast-growing eigenvalues calls for distinguished asymptotic behaviors in covariance estimations, eigen-spectral analysis, as well as matrix completions. The related literature can be found in Fan et al. (2013); Wang and Fan (2017).

The nuclear-norm penalized estimation has also been applied in the recent econometric literature for panel data models. Bai and Ng (2017) studied its property in the pure factor model setting. Athey et al. (2018) applied matrix completion to estimate the causal effects. Moon and Weidner (2018) studied the inference for the homogeneous models (i.e.,  $\theta_{it} = \theta$  as a common coefficient for all  $(i, t)$ ) in panel data with interactive effects. They applied the nuclear-norm penalization to estimate the low-rank matrix of the interactive fixed effects. In addition, the literature on models with interactive fixed effects also includes, e.g., Bai (2009); Moon and Weidner (2015), but has been predominated by homogeneous models where  $\theta_{it} = \theta$  for some  $\theta$  and all  $(i, t)$ . In addition, Pesaran (2006); Ahn et al. (2013) studied time-invariant homogeneous models in which the slopes are allowed to vary across  $i$ . Su et al. (2015) considered nonlinear homogeneous effects where the effect of  $x_{it}$  is characterized by a nonparametric function that is time-invariant and common to all individuals. The homogeneity assumption, while simplifies the inference procedure and gains statistical efficiency if correctly specified, would lead to inconsistency and misleading inferences if fails to hold. Our standing point and recommended inference procedure is to start with a general heterogeneous model

as we are proposing, and formally conduct homogeneous tests as formalized in this paper. Then conduct inference and estimations using the homogeneous method only if the homogeneous hypothesis is accepted.

The rest of the paper is organized as follows. Section 2 introduces the post-SVT algorithms that define our estimators. It also explains the rationale of using partial-out and sample splitting techniques. Section 3 provides asymptotic inferential theory. Section 4 presents simulated results, and finally, Section 5 applies the proposed method to studying the county-level minimum wage effects. All proofs are presented in the appendix.

## 2. THE MODEL

We consider the following model

$$\begin{aligned} y_{it} &= x'_{it}\theta_{it} + \alpha'_i g_t + u_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T. \\ \theta_{it} &= \lambda'_i f_t. \end{aligned}$$

Here we observe  $(y_{it}, x_{it})$ . The goal is to make inference about  $\theta_{it}$ , which has a latent factor structure. The model also allows a general form of fixed effect. As explained in Bai (2009),  $\alpha'_i g_t$  can allow fixed effects that are either additive, or interactive, or both. We assume  $\dim(\lambda_i) = K_1$ ,  $\dim(\alpha_i) = K_2$ , both fixed. For ease of presentation, we focus on the case that  $x_{it}$  is a univariate regressor, that is,  $\dim(x_{it}) = 1$ . It is straightforward to extend to the multivariate case, which is presented in Appendix A.

We allow arbitrary dependences among  $\{\lambda_i, f_t : i \leq N, t \leq T\}$ , and impose nearly no restrictions on the sequence for  $\lambda_i$  and  $f_t$ . In particular, this allows homogeneous models as special cases. For instance, by setting  $\lambda_i = \lambda$  and  $f_t = f$  for all  $(i, t)$  and dimension  $\dim(\lambda_i) = \dim(f_t) = 1$ , we can allow  $\theta_{it} = \theta$  for all  $(i, t)$  and a common parameter  $\theta$ . This then reduces to the homogeneous interactive effect model, studied by Bai (2009); Moon and Weidner (2015). In addition,  $f_t$  can also be thought of as a serially independent process, which leads to pure heterogeneities.

**2.1. Nuclear norm penalized estimation and an iterative algorithm.** Let  $\Lambda, A$  respectively be  $N \times K_1$  and  $N \times K_2$  matrices of  $(\lambda_i)$  and  $(\alpha_i)$ ; let  $(F, G)$  be  $T \times K_i$  matrices of  $(f_t, g_t)$ ; let  $(Y, X, U)$  be  $N \times T$  matrices of  $(y_{it}, x_{it}, u_{it})$ . Then

the matrix form is:

$$Y = AG' + X \odot (\Lambda F') + U.$$

where  $\odot$  represents the element-wise product. Further let  $\Theta := \Lambda F'$  and  $M := AG'$ . Note that both of them are  $N \times T$  matrices, whose ranks are respectively  $(K_1, K_2)$ . We let  $N, T \rightarrow \infty$  but  $K_1, K_2$  be fixed constants. Thus both are low-rank matrices. Motivated by this, we shall estimate  $(M, \Theta)$  using the following penalized nuclear-norm optimization:

$$\begin{aligned} (\tilde{\Theta}, \tilde{M}) &= \min_{\Theta, M} F(\Theta, M), \\ F(\Theta, M) &:= \|Y - M - X \odot \Theta\|_F^2 + \nu_2 \|M\|_n + \nu_1 \|\Theta\|_n, \end{aligned} \quad (2.1)$$

for some tuning parameters  $\nu_2, \nu_1 > 0$ .

The computation of (2.1) can be carried out iteratively using *singular value thresholding estimations*. For a fixed matrix  $H$ , let  $UDV' = H$  be its singular value decomposition. Define the singular value thresholding operator  $S_\lambda(H) = UD_\lambda V'$ , where  $D_\lambda$  is defined by replacing the diagonal entry  $D_{ii}$  of  $D$  by  $\max\{D_{ii} - \lambda, 0\}$ . Given  $\Theta$ , solving for  $M$  in (2.1) leads to the following closed form solution: let  $Z_\Theta = Y - X \odot \Theta$ ,

$$S_{\nu_2/2}(Z_\Theta) = \arg \min_M \|Z_\Theta - M\|_F^2 + \nu_2 \|M\|_n,$$

which applies the singular value thresholding operator on  $Z_\Theta$ , with tuning  $\nu_2/2$ . On the other hand, given  $M$ , let  $Z_M = Y - M$ . Then the solution of  $\Theta$  to (2.1) is given by:

$$\Theta_M := \arg \min_{\Theta} \|Z_M - X \odot \Theta\|_F^2 + \nu_1 \|\Theta\|_n,$$

which satisfies the following KKT condition, for any  $\tau > 0$ , (Ma et al., 2011)

$$\Theta_M = S_{\tau\nu_1/2}(\Theta_M - \tau X \odot (X \odot \Theta_M - Z_M)).$$

As such, we employ the following algorithm to iteratively solve for  $\tilde{M}$  and  $\tilde{\Theta}$  as the global solution to (2.1).

**Algorithm 2.1.** Compute the nuclear-norm penalized regression as follows.

*Step 1:* Fix the “step size”  $\tau \in (0, 1/\max_{it} x_{it}^2)$ . Initialize  $\Theta_0, M_0$  and set  $k = 0$ .

*Step 2:* Let

$$\Theta_{k+1} = S_{\tau\nu_1/2}(\Theta_k - \tau X \odot (X \odot \Theta_k - Y + M_k)),$$



$$M_{k+1} = S_{\nu_2/2}(Y - X \odot \Theta_{k+1}).$$

Set  $k$  to  $k + 1$ .

*Step 3:* Repeat step 2 until convergence.

As for the convergence property of the algorithm, note that given  $M$ , updating  $\Theta_M$  is a standard gradient descent procedure (e.g., Beck and Teboulle (2009)), and therefore standard convergence analysis for the objective function  $F(\Theta, M)$  applies. As we shall show below, the evaluated objective function  $F(\Theta_{k+1}, M_{k+1})$  is monotonically decreasing, whose rate of convergence is  $O(k^{-1})$ .

**Proposition 2.1.** *Let  $(\tilde{\Theta}, \tilde{M})$  be a global minimum for  $F(\Theta, M)$ . Then for any  $\tau \in (0, 1/\max_{it} x_{it}^2)$ , and any initial  $\Theta_0, M_0$ , we have:*

$$F(\Theta_{k+1}, M_{k+1}) \leq F(\Theta_{k+1}, M_k) \leq F(\Theta_k, M_k),$$

for each  $k \geq 0$ . In addition, for all  $k \geq 1$ ,

$$F(\Theta_{k+1}, M_{k+1}) - F(\tilde{\Theta}, \tilde{M}) \leq \frac{1}{k\tau} \|\Theta_1 - \tilde{\Theta}\|_F^2. \quad (2.2)$$

Proposition 2.1 shows that the algorithm converges from an arbitrary initial value. The upper bound in (2.2) depends on the initial values through the accuracy of the first iteration  $\Theta_1 - \tilde{\Theta}$ . Not surprisingly, the upper bound does not depend on  $M_1 - \tilde{M}$ , because given  $\Theta_1$ , minimizing with respect to  $M$  has a one-step closed form solution, whose accuracy is completely determined by  $\Theta_1$ . In addition, the largest possible value for  $\tau$  to ensure the convergence is  $1/\max_{it} x_{it}^2$ . In practice, we set  $\tau = (1 - \epsilon)/\max_{it} x_{it}^2$  for some small  $\epsilon > 0$ .

**2.2. Post-SVT inference.** The estimated  $\Theta$  from the nuclear-norm penalized regression, however, cannot be used directly for inference because they are subjected to shrinkage biases. Our debiased method is based on iterative least squares, which iteratively estimates  $f_t$  and  $\lambda_i$  to control for the effect of shrinkage biases. We proceed in the following stages to obtain the final estimator of  $\theta_{it}$ .

*Stage 1:* obtain estimated  $(M, \Theta)$  from the nuclear norm optimization.

*Stage 2:* extract estimated loadings  $(\tilde{\alpha}_i, \tilde{\lambda}_i)$ 's from the singular vectors of the estimated  $(M, \Theta)$ .

*Stage 3:* iteratively estimate  $f_t$  and  $\lambda_i$  using least squares. More specifically:

- (i) obtain unbiased estimators  $\hat{f}_t$  for  $f_t$  using the estimated loadings.
- (ii) obtain unbiased estimators  $\hat{\lambda}_i$  for  $\lambda_i$  using  $\hat{f}_t$ .

(iii) obtain the final estimator  $\widehat{\theta}_{it} := \widehat{\lambda}_i' \widehat{f}_t$ .

As Stage 1 employs a singular value thresholding method, we call our procedure as the “post-SVT inference”. We shall show that  $\widehat{\theta}_{it}$  is  $C_{NT}$ -consistent, where  $C_{NT} = \sqrt{\min\{N, T\}}$ , and is asymptotically normally distributed, centered around  $\theta_{it}$ , for each fixed  $(i, t)$ . Also note that due to the rotation discrepancy,  $\lambda_i$  and  $f_t$  are not separately identified, so they can be estimated without biases subject to a rotation transformation. On the other hand, the effect coefficient  $\theta_{it}$  can be estimated well without rotation discrepancy.

To investigate the role of the dependence structure in  $x_{it}$ , we separately study two cases. In the first case, we assume  $x_{it}$  is serially independent, generated from the following mean process:

$$x_{it} = \mu_i + e_{it},$$

where  $e_{it}$  is a zero-mean process that is serially independent and cross-sectionally weakly dependent. In the second case, we relax this assumption and consider:

$$x_{it} = l_i' w_t + e_{it},$$

where  $w_t$  is a vector of (fixed dimensional) latent factors, with  $l_i$  as the loadings. Hence  $x_{it}$  also admits a factor structure, and  $w_t$ , or some of its components, are allowed to overlap with  $(f_t, g_t)$ .

In both cases, Stage 3 is the essential stage to obtain well-behaved unbiased estimators. In this stage,  $(\widetilde{\alpha}_i, \widetilde{\lambda}_i)$  are treated as the estimators for nuisance parameter, whose estimation error involves, among others, a term taking the form:

$$\Delta := \frac{1}{\sqrt{N}} \sum_{i=1}^N \lambda_i (\widetilde{\alpha}_i - H\alpha_i)' x_{it},$$

where  $H$  is a square rotation matrix. It is however challenging to argue that  $\Delta$  is negligible, due to two reasons. First, it can be shown that the nuclear-norm penalized estimator has a rate of convergence:

$$\frac{1}{N} \sum_{i=1}^N \|\widetilde{\alpha}_i - H\alpha_i\|^2 = O_P(C_{NT}^{-2}).$$

But this rate alone does not ensure  $\Delta = o_P(1)$  in the case  $N \geq T$ . Secondly, when  $x_{it}$  admits a factor structure, correlations in both cross-sectional and serial directions introduce additional technical difficulties.

We resolve the above technical difficulties through two procedures: (i) partialling out the mean of  $x_{it}$  (or the factor structures in  $x_{it}$ ) and (ii) sample splitting. When  $x_{it}$  admits a factor structure, note that the decomposition  $x_{it} = l'_i w_t + e_{it}$  yields

$$\dot{y}_{it} = \alpha'_i g_t + e_{it} \lambda'_i f_t + u_{it}, \quad \text{where } \dot{y}_{it} = y_{it} - l'_i w_t \theta_{it}. \quad (2.3)$$

We regress the estimated  $\dot{y}_{it}$  onto  $(\alpha_i, e_{it} \lambda_i)$  to estimate  $f_t$ . As such, the effect of estimating  $\alpha_i$  becomes

$$\Delta' := \frac{1}{\sqrt{N}} \sum_{i=1}^N \lambda_i (\tilde{\alpha}_i - H \alpha_i)' e_{it},$$

and now  $e_{it}$  is a zero-mean process and independent across  $t$ . Therefore, by subtracting the estimated  $l'_i w_t \theta_{it}$  from  $y_{it}$ , we have partialled out the strong dependent components in  $x_{it}$ , and essentially work with the following moment conditions for estimating  $f_t$ :

$$\mathbb{E} e_{it} (\dot{y}_{it} - \alpha'_i g_t - e_{it} \lambda'_i f_t) = 0, \quad \forall i = 1, \dots, N. \quad (2.4)$$

Importantly, this moment condition enjoys the *Neyman's orthogonality*:

$$\frac{\partial}{\partial \alpha_i} \mathbb{E} e_{it} (\dot{y}_{it} - \alpha'_i g_t - e_{it} \lambda'_i f_t) = \mathbb{E} e_{it} g_t = 0.$$

This ensures that the effect of estimating  $\alpha_i$  is indeed negligible. In the absence of factor structures in  $x_{it}$ , we shall simply partial out the sample mean  $\frac{1}{T} \sum_t x_{it}$  from  $x_{it}$  to obtain a zero-mean process.

Next, we use the sample splitting technique to continue arguing that  $\Delta' = o_P(1)$ . For the fixed  $t$ , let  $\{1, \dots, T\} = I \cup I^c \cup \{t\}$  be a random disjoint partition. The cardinality of  $I$  is  $[(T-1)/2]$  (the nearest integer to  $(T-1)/2$ ). Let

$$D_I = \{(y_{is}, x_{is}) : i \leq N, s \in I\}.$$

We explain the rationale of this splitting in more detail in Remark 2.1 later. We run the nuclear-norm optimization (2.1) using data  $D_I$  and estimate  $\tilde{\lambda}_i$ . Because  $e_{it}$  is serially independent, and  $t \notin I$ ,  $\tilde{\lambda}_i$  is independent of  $e_{it}$ . For example, in the case of cross-sectional independence, and  $\dim(\lambda_i) = 1$ , conditional on  $D_I$ , we have  $\mathbb{E}(\Delta' | D_I) = 0$ , whose variance is given by

$$\text{Var}(\Delta' | D_I) = \frac{1}{N} \sum_{i=1}^N \text{Var}(e_{it}) (\tilde{\alpha}_i - H \alpha_i) (\tilde{\alpha}_i - H \alpha_i)' \lambda_i^2.$$

This allows us to argue that  $\Delta' = o_P(1)$  so that the effect of estimating the nuisance parameters in Stage 3 is negligible.

### 2.3. Formal Estimation Algorithm. Let

$$x_{it} = \mu_{it} + e_{it}, \quad \mathbb{E}e_{it} = 0,$$

We present the estimation algorithm below, which works for both the cases of (i) many mean model, in which  $\mu_{it} = \mu_i$ , and (ii) factor model for the process of  $x_{it}$  in which  $\mu_{it} = l'_i w_t$ . When  $x_{it}$  admits a factor structure, we first apply the standard principal components method (PC) (e.g., Stock and Watson (2002)) to estimate  $l'_i w_t$  and obtain  $(\widehat{l'_i w_t}, \widehat{e_{it}})$ . In both cases, we partial out the “common components” by subtracting the estimated  $\mu_{it}$  from  $x_{it}$ , and essentially work with the model

$$\dot{y}_{it} = \alpha'_i g_t + e_{it} \theta_{it} + u_{it}, \quad \text{where } \dot{y}_{it} = y_{it} - \mu_{it} e_{it}. \quad (2.5)$$

Suppose we are interested in  $\theta_{it}$  for some fixed  $(i, t)$ . We propose the following steps to estimate  $\theta_{it}$ .

**Algorithm 2.2.** Estimate  $\theta_{it}$  as follows.

*Step 1. Estimate the number of factors.* Run nuclear-norm penalized regression:

$$(\widetilde{M}, \widetilde{\Theta}) := \arg \min_{M, \Theta} \|Y - M - X \odot \Theta\|_F^2 + \nu_2 \|M\|_n + \nu_1 \|\Theta\|_n. \quad (2.6)$$

Estimate  $K_1, K_2$  by

$$\widehat{K}_1 = \sum_i 1\{\psi_i(\widetilde{\Theta}) \geq (\nu_2 \|\widetilde{\Theta}\|)^{1/2}\}, \quad \widehat{K}_2 = \sum_i 1\{\psi_i(\widetilde{M}) \geq (\nu_1 \|\widetilde{M}\|)^{1/2}\}$$

where  $\psi_i(\cdot)$  denotes the  $i$ th largest singular-value.

*Step 2. Estimate the structure  $x_{it} = \mu_{it} + e_{it}$ .*

In the many mean model, let  $\widehat{e_{it}} = x_{it} - \frac{1}{T} \sum_{t=1}^T x_{it}$ . In the factor model, use the PC estimator to obtain  $(\widehat{l'_i w_t}, \widehat{e_{it}})$  for all  $i = 1, \dots, N, t = 1, \dots, T$ .

*Step 3: Sample splitting.* Randomly split the sample into  $\{1, \dots, T\}/\{t\} = I \cup I^c$ , so that  $|I|_0 = [(T-1)/2]$ . Denote by  $Y_I, X_I$  as the  $N \times |I|_0$  matrices of  $(y_{is}, x_{is})$  for observations at  $s \in I$ . Estimate the low-rank matrices  $\Theta$  and  $M$  as in (2.6), with  $(Y, X)$  replaced with  $(Y_I, X_I)$ , and obtain  $(\widetilde{M}_I, \widetilde{\Theta}_I)$ .

Let  $\widetilde{\Lambda}_I = (\widetilde{\lambda}_1, \dots, \widetilde{\lambda}_N)'$  be the  $N \times \widehat{K}_1$  matrix, whose columns are defined as  $\sqrt{N}$  times the first  $\widehat{K}_1$  eigenvectors of  $\widetilde{\Theta}_I \widetilde{\Theta}_I'$ . Let  $\widetilde{A}_I = (\widetilde{\alpha}_1, \dots, \widetilde{\alpha}_N)'$  be the  $N \times \widehat{K}_2$  matrix, whose columns are defined as  $\sqrt{N}$  times the first  $\widehat{K}_2$  eigenvectors of  $\widetilde{M}_I \widetilde{M}_I'$ .

*Step 4. Estimate the “partial-out” components.*

Substitute in  $(\tilde{\alpha}_i, \tilde{\lambda}_i)$ , and define

$$(\tilde{f}_s, \tilde{g}_s) := \arg \min_{f_s, g_s} \sum_{i=1}^N (y_{is} - \tilde{\alpha}'_i g_s - x_{is} \tilde{\lambda}'_i f_s)^2, \quad s \in I^c \cup \{t\}.$$

and

$$(\dot{\lambda}_i, \dot{\alpha}_i) = \arg \min_{\lambda_i, \alpha_i} \sum_{s \in I^c \cup \{t\}} (y_{is} - \alpha'_i \tilde{g}_s - x_{is} \lambda'_i \tilde{f}_s)^2, \quad i = 1, \dots, N.$$

*Step 5. Estimate  $(f_t, \lambda_i)$  for inferences.*

Motivated by (2.5), for all  $s \in I^c \cup \{t\}$ , let

$$(\hat{f}_{I,s}, \hat{g}_{I,s}) := \arg \min_{f_s, g_s} \sum_{i=1}^N (\hat{y}_{is} - \tilde{\alpha}'_i g_s - \hat{e}_{is} \tilde{\lambda}'_i f_s)^2.$$

Fix  $i \leq N$ ,

$$(\hat{\lambda}_{I,i}, \hat{\alpha}_{I,i}) = \arg \min_{\lambda_i, \alpha_i} \sum_{s \in I^c \cup \{t\}} (\hat{y}_{is} - \alpha'_i \hat{g}_{I,s} - \hat{e}_{is} \lambda'_i \hat{f}_{I,s})^2.$$

where  $\hat{y}_{is} = y_{is} - \bar{x}_i \dot{\lambda}'_i \tilde{f}_s$  and  $\hat{e}_{is} = x_{is} - \bar{x}_i$  in the many mean model, and  $\hat{y}_{is} = y_{is} - \widehat{l'_i w_s \dot{\lambda}'_i \tilde{f}_s}$ ,  $\hat{e}_{is} = x_{is} - \widehat{l'_i w_s}$  in the factor model.

*Step 6. Estimate  $\theta_{it}$ .* Repeat steps 3-5 with  $I$  and  $I^c$  exchanged, and obtain  $(\hat{\lambda}_{I^c,i}, \hat{f}_{I^c,s} : s \in I \cup \{t\}, i \leq N)$ . Define

$$\hat{\theta}_{it} := \frac{1}{2} [\hat{\lambda}'_{I,i} \hat{f}_{I,t} + \hat{\lambda}'_{I^c,i} \hat{f}_{I^c,t}].$$

**Remark 2.1.** We split the sample to  $\{1, \dots, T\} = I \cup I^c \cup \{t\}$ . As the partialled-out regressor  $e_{it}$  is serially independent, this ensures that at the fixed  $t$ ,  $e_{it}$  is independent of both splitted sample  $I$  and  $I^c$ . In steps 3-5 we estimate  $\theta_{is}$  for  $s \in \{t\} \cup I^c$ . In step 6 we switch the roles of  $I$  and  $I^c$  to estimate  $\theta_{is}$  for  $s \in \{t\} \cup I$ . As such, the parameter has been estimated twice at  $s = t$ . The final estimator is taken as the average of the two,  $\hat{\lambda}'_{I,i} \hat{f}_{I,t}$  and  $\hat{\lambda}'_{I^c,i} \hat{f}_{I^c,t}$ . This gains the asymptotic efficiency that would otherwise be lost due to the sample splitting. Finally, we have an expansion:

$$\hat{\theta}_{it} - \theta_{it} = \lambda'_i M_1 \frac{1}{N} \sum_{j=1}^N \lambda_j e_{jt} u_{jt} + f'_t M_1 \frac{1}{T} \sum_{t=1}^T f_s e_{is} u_{is} + \text{negligible},$$

for  $M_1, M_2$  to be defined later.

Note that step 4 is needed to obtain a consistent estimate for  $\dot{y}_{it} = y_{it} - \mu_{it}\lambda'_i f_t$ , in order to apply the “partialled out equation” (2.3). In particular, the consistency is required to hold for each fixed  $(i, t)$ , but  $(\tilde{\lambda}_i, \tilde{\alpha}_i)$  obtained in the low-rank estimation from step 1 does not satisfy this condition. This motivates the need for the estimators  $(\dot{\lambda}_i, \dot{\alpha}_i)$ . On the other hand, the estimators in step 4, however, are not suitable for inference, because at this step we use the regressor  $x_{it}$ , which is however, not a zero-mean or serially independent process. This gives rise to the need for step 5.

**2.4. Choosing the tuning parameters.** The “scores” of the nuclear-norm penalized regression are given by  $2\|U\|$  and  $2\|X \odot U\|$ , where  $\|\cdot\|$  denotes the matrix operator norm, and  $U = \{u_{it}\}$ , and  $X \odot U = (x_{it}u_{it})$ . The tuning parameters  $(\nu_2, \nu_1)$  are taken so that

$$2\|U\| < (1 - c)\nu_2, \quad 2\|X \odot U\| < (1 - c)\nu_1$$

for some  $c > 0$ .

To quantify the operator norm of these quantities, we shall assume that the columns of  $U$  and  $X \odot U$ , respectively  $\{u_t\}$  and  $\{x_t \odot u_t\}$ , are sub-Gaussian vectors. In the absence of serial correlations, by the eigenvalue-concentration inequality for independent sub-Gaussian random vectors (Theorem 5.39 of Vershynin (2010)):

$$\|(X \odot U)(X \odot U)' - \mathbb{E}(X \odot U)(X \odot U)'\| = O_P(\sqrt{NT} + N),$$

which provides a sharp bound for  $\|X \odot U\|$ , and a similar upper bound holds for  $\|UU' - \mathbb{E}UU'\|$ . Hence  $\nu_2$  and  $\nu_1$  can be chosen to satisfy  $\nu_2 \asymp \nu_1 \asymp \max\{\sqrt{N}, \sqrt{T}\}$ .

In the presence of serial correlations, we assume the following representation:

$$X \odot U = \Omega_{NT}\Sigma_T^{1/2}$$

where  $\Omega_{NT}$  is an  $N \times T$  matrix with independent, zero-mean, sub-Gaussian columns. Then still by the eigenvalue-concentration inequality for sub-Gaussian random vectors,

$$\|\Omega_{NT}\Omega'_{NT} - \mathbb{E}\Omega_{NT}\Omega'_{NT}\| = O_P(\sqrt{NT} + N).$$

In addition,  $\Sigma_T$  is a  $T \times T$  deterministic matrix, possibly non-diagonal, whose eigenvalues are bounded from both below and above by constants. Allowing  $\Sigma_T$  to be a non-diagonal matrix captures the serial-correlations in  $\{x_t \odot u_t\}$ . This also implies  $\|X \odot U\| \leq O_P(\max\{\sqrt{N}, \sqrt{T}\})$ . Therefore, the tuning parameters in

general can be chosen to satisfy

$$\nu_2 \asymp \nu_1 \asymp \max\{\sqrt{N}, \sqrt{T}\}.$$

In the Gaussian case, they can be computed via simulations. Suppose  $u_{it}$  is independent across both  $(i, t)$  and  $u_{it} \sim \mathcal{N}(0, \sigma_{ui}^2)$ . Let  $Z$  be an  $N \times T$  matrix whose element  $z_{it}$  is generated from  $\mathcal{N}(0, \sigma_{ui}^2)$ , independent across  $(i, t)$ . Then  $\|X \odot U\| =^d \|X \odot Z\|$  and  $\|U\| =^d \|Z\|$  where  $=^d$  means “identically distributed”. For a fixed  $\delta_{NT} = o(1)$ , let

$$\nu_2 = 2(1 + c_1)\bar{Q}(\|Z\|; 1 - \delta_{NT}), \quad \nu_1 = 2(1 + c_1)\bar{Q}(\|X \odot Z\|; 1 - \delta_{NT})$$

respectively denote  $(1 + c_1)$  multiplied by the  $1 - \delta_{NT}$  quantiles of  $\|Z\|$  and  $\|X \odot Z\|$ . Then

$$2\|U\| < (1 - \frac{c_1}{1 + c_1})\nu_2, \quad 2\|X \odot U\| < (1 - \frac{c_1}{1 + c_1})\nu_1$$

holds with probability  $1 - \delta_{NT}$ . In practice, we replace  $\sigma_{ui}^2$  with a consistent estimator, and take  $c_1 = 0.1$ ,  $\delta_{NT} = 0.05$ .

### 3. ASYMPTOTIC RESULTS

**3.1. The effect of low-rank estimations on inference.** We first heuristically discuss the main technical arguments.

Note that one of the key ingredients is to establish the asymptotic normality of  $\hat{f}_t$  for a fixed  $t$ . By definition, the estimation of  $\hat{f}_t$  depends on the SVT estimators (the nuclear-norm penalized regression),  $(\tilde{\alpha}_i, \tilde{\lambda}_i)$ , obtained as the eigenvectors of the estimated low-rank matrices. The main asymptotic effect of the SVT estimators give rise to the following two components:  $\frac{1}{\sqrt{N}} \sum_{i=1}^N \lambda_i (\tilde{\alpha}_i - H_2' \alpha_i)' e_{it}$ , and

$$\frac{1}{\sqrt{N}} \sum_{i=1}^N \lambda_i (\tilde{\lambda}_i - H_1' \lambda_i)' e_{it}^2, \quad (3.1)$$

where  $H_2, H_1$  are rotation matrices. As we have previously explained, the effect of  $\tilde{\alpha}_i - H_2' \alpha_i$  can be argued to be negligible using sample splitting. However, the effect of  $\tilde{\lambda}_i - H_1' \lambda_i$  in (3.1) is not necessarily  $o_P(1)$ , because the Neyman’s orthogonality does not hold in the moment conditions:

$$\frac{\partial}{\partial \lambda_i} \mathbb{E} e_{it} (\dot{y}_{it} - \alpha_i' g_t - e_{it} \lambda_i' f_t) \neq 0.$$

Indeed, it can be proved that, there is a matrix  $\mathcal{B}_{NT} \neq o_P(1)$ , the following expansion holds:

$$\sqrt{N}(\hat{f}_t - H_1^{-1}f_t) = H_1^{-1} \frac{1}{\sqrt{N}} \sum_{i=1}^N \lambda_i e_{it} u_{it} + \mathcal{B}_{NT} f_t + o_P(1),$$

where the presence of  $\mathcal{B}_{NT}$  is due to (3.1).

We shall argue that such an effect, however, does not affect our asymptotic inferential theory, by properly recentering  $\hat{f}_t$ . An important observation is that  $\mathcal{B}_{NT}$  is time-invariant and is associated with  $f_t$ , so the bias also belongs to the space of  $f_t$ . As such, we can define  $H_f := H_1^{-1} + \mathcal{B}_{NT}N^{-1/2}$  and establish that

$$\sqrt{N}(\hat{f}_t - H_f f_t) = H_1^{-1} \frac{1}{\sqrt{N}} \sum_{i=1}^N \lambda_i e_{it} u_{it} + o_P(1).$$

Therefore, the effect of  $\tilde{\lambda}_i - H_1' \lambda_i$  is “absorbed” by the adjusted rotation matrix. This is sufficient for the inferential theory of  $\hat{\theta}_{it}$ . Once  $f_t$  can be estimated without biases (up to rotation transformations), the least squares iteration using  $\hat{f}_t$  continues to producing unbiased estimators for  $\lambda_i$ .

**3.2. Estimating low rank matrices.** We first introduce a key assumption about the nuclear-norm SVT procedure. We require some “invertibility” condition for the operator:

$$(\Delta_1, \Delta_2) \mapsto \Delta_1 + \Delta_2 \odot X$$

when  $(\Delta_1, \Delta_2)$  is restricted on a “cone”, consisting of low-rank matrices, which we call *restricted low-rank set*, and was previously introduced and studied by Negahban and Wainwright (2011). To describe this cone, we first introduce some notation. Define

$$\Theta_I^0 = (\lambda_i' f_t : i \leq N, t \in I), \quad M_I^0 = (\alpha_i' g_t : i \leq N, t \in I).$$

Define  $U_1 D_1 V_1' = \Theta_I^0$  and  $U_2 D_2 V_2' = M_I^0$  as the singular values decompositions of  $M_I^0$  and  $\Theta_I^0$ , where the superscript 0 represents the “true” parameter values. Further decompose, for  $j = 1, 2$ ,

$$U_j = (U_{j,r}, U_{j,c}), \quad V_j = (V_{j,r}, V_{j,c})$$

Here  $(U_{j,r}, V_{j,r})$  corresponds to the nonzero singular values, while  $(U_{j,c}, V_{j,c})$  corresponds to the zero singular values. In addition, for any  $N \times T/2$  matrix  $\Delta$ ,



let

$$\mathcal{P}_j(\Delta) = U_{j,c}U'_{j,c}\Delta V_{j,c}V'_{j,c}, \quad \mathcal{M}_j(\Delta) = \Delta - \mathcal{P}_j(\Delta).$$

Here  $U_{j,c}U'_{j,c}$  and  $V_{j,c}V'_{j,c}$  respectively are the projection matrices onto the columns of  $U_{j,c}$  and  $V_{j,c}$ . Therefore,  $\mathcal{M}_1(\cdot)$  and  $\mathcal{M}_2(\cdot)$  can be considered as the projection matrices onto the “low-rank spaces” of  $\Theta_I^0$  and  $M_I^0$  respectively, and  $\mathcal{P}_1(\cdot)$  and  $\mathcal{P}_2(\cdot)$  are projections onto their orthogonal spaces.

**Assumption 3.1** (Restricted strong convexity). *Define restricted low-rank set to be: for some  $c > 0$ ,*

$$\mathcal{C}(c) = \{(\Delta_1, \Delta_2) : \|\mathcal{P}_1(\Delta_1)\|_1 + \|\mathcal{P}_2(\Delta_2)\|_1 \leq c\|\mathcal{M}_1(\Delta_1)\|_1 + c\|\mathcal{M}_2(\Delta_2)\|_1\}.$$

*If  $(\Delta_1, \Delta_2) \in \mathcal{C}(c)$  for some  $c > 0$ , then there is a constant  $\kappa_c > 0$ ,*

$$\|\Delta_1 + \Delta_2 \odot X\|_F^2 \geq \kappa_c \|\Delta_1\|_F^2 + \kappa_c \|\Delta_2\|_F^2.$$

*The same condition holds when  $(M_I^0, \Theta_I^0)$  are replaced with  $(M_{I^c}^0, \Theta_{I^c}^0)$ , or the full-sample  $(M^0, \Theta^0)$ .*

Our next assumption allows non-stationary or arbitrary dependence in the time-series for  $(f_t, g_t)$ . In particular, they hold for serially weakly dependent sequences, and even allow for perfect dependent sequence:  $(f_t, g_t) = (f, g)$  for some time-invariant  $(f, g)$  by setting  $\dim(f_t) = \dim(g_t) = 1$ .

**Assumption 3.2.** *As  $T \rightarrow \infty$ , the sub-samples  $(I, I^c)$  satisfy:*

$$\begin{aligned} \frac{1}{|I|_0} \sum_{t \in I} f_t f'_t &= \frac{1}{T} \sum_{t=1}^T f_t f'_t + O_P(T^{-1/2}) = \frac{1}{|I^c|_0} \sum_{t \in I^c} f_t f'_t, \\ \frac{1}{|I|_0} \sum_{t \in I} g_t g'_t &= \frac{1}{T} \sum_{t=1}^T g_t g'_t + O_P(T^{-1/2}) = \frac{1}{|I^c|_0} \sum_{t \in I^c} g_t g'_t. \end{aligned}$$

*In addition, there is  $c > 0$ , all the eigenvalues of  $\frac{1}{T} \sum_{t=1}^T f_t f'_t$  and  $\frac{1}{T} \sum_{t=1}^T g_t g'_t$  are bounded from below by  $c$  almost surely.*

**Assumption 3.3** (Valid factor structures with strong factors). *There are constants  $c_1 > \dots > c_{K_1} > 0$ , and  $c'_1 > \dots > c'_{K_2} > 0$ , so that, up to a term  $o_P(1)$ ,*

*(i)  $c'_j$  equals the  $j$  th largest eigenvalue of  $(\frac{1}{T} \sum_t g_t g'_t)^{1/2} \frac{1}{N} \sum_{i=1}^N \alpha_i \alpha'_i (\frac{1}{T} \sum_t g_t g'_t)^{1/2}$  for all  $j = 1, \dots, K_1$ , and*

*(ii)  $c_j$  equals the  $j$  th largest eigenvalue of  $(\frac{1}{T} \sum_t f_t f'_t)^{1/2} \frac{1}{N} \sum_{i=1}^N \lambda_i \lambda'_i (\frac{1}{T} \sum_t f_t f'_t)^{1/2}$  for all  $j = 1, \dots, K_2$ .*

The above assumption requires that the factors be strong. In addition, we require distinct eigenvalues in order to identify their corresponding eigenvectors, and therefore,  $(\lambda_i, \alpha_i)$ .

Recall that  $\widetilde{M}_S$  and  $\widetilde{\Theta}_S$  respectively are the estimated low-rank matrices obtained by the nuclear-norm penalized estimations on sample  $S \in \{I, I^c\}$ . Given the above assumption, we have the consistency-in-frobenius-norm for the estimated low-rank matrices,

**Proposition 3.1.** *Suppose  $2\|X \odot U\| < (1 - c)\nu_1$ ,  $2\|U\| < (1 - c)\nu_2$  and  $\nu_2 \asymp \nu_1$ . Then under Assumption 3.1, for  $S \in \{I, I^c, I \cup I^c\}$ , (i)*

$$\frac{1}{NT}\|\widetilde{M}_S - M_S\|_F^2 = O_P\left(\frac{\nu_2^2 + \nu_1^2}{NT}\right) = \frac{1}{NT}\|\widetilde{\Theta}_S - \Theta_S\|_F^2.$$

(ii) *Additionally with Assumption 3.3, there are square matrices  $H_{S1}, H_{S2}$ , so that*

$$\frac{1}{N}\|\widetilde{A}_S - AH_{S1}\|_F^2 = O_P\left(\frac{\nu_2^2 + \nu_1^2}{NT}\right), \quad \frac{1}{N}\|\widetilde{\Lambda}_S - \Lambda H_{S2}\|_F^2 = O_P\left(\frac{\nu_2^2 + \nu_1^2}{NT}\right).$$

(iii) *Furthermore,*

$$P(\widehat{K}_1 = K_1, \quad \widehat{K}_2 = K_2) \rightarrow 1.$$

**3.3. Asymptotic analysis when  $x_{it}$  admits a many mean model.** We now focus on the case  $x_{it} = \mu_i + e_{it}$ .

**Assumption 3.4.** *Let  $\omega_t = (x_{1t}u_{1t}, \dots, x_{Nt}u_{Nt}, u_{1t}, \dots, u_{Nt})'$ . Suppose  $\{\omega_t\}_{t \leq T}$  are independent sub-gaussian random vectors: there is  $C > 0$ ,*

$$\max_{t \leq T} \sup_{\|x\|=1} \mathbb{E} \exp(s\omega_t'x) \leq \exp(s^2C), \quad \forall s \in \mathbb{R}.$$

The sub-Gaussian condition allows us to apply the eigenvalue-concentration inequality for independent random vectors (Theorem 5.39 of Vershynin (2010)) to bound the scores  $\|X \odot U\|$  and  $\|U\|$ . Under Assumption 3.4, we can take  $\nu_2, \nu_1 = O_P(\sqrt{N + T})$ . Therefore

$$\frac{1}{N}\|\widetilde{A}_S - AH_{S1}\|_F^2 = O_P\left(\frac{1}{N} + \frac{1}{T}\right) = \frac{1}{N}\|\widetilde{\Lambda}_S - \Lambda H_{S2}\|_F^2.$$

The assumptions below are also needed to achieve the inferential theory for the estimated treatment effect.

**Assumption 3.5** (Dependence). *(i)  $\{e_{it}\}$  is serially stationary, and*

$$\mathbb{E}(e_{it}|u_{it}, g_t, f_t) = 0, \quad \mathbb{E}(u_{it}|e_{it}, g_t, f_t) = 0.$$

(ii)  $\{e_{it}, u_{it}\}$  are independent across  $t$ ;  $\{e_{it}\}$  are also conditionally independent across  $t$ , given  $\{f_t, g_t, u_t\}$ ;  $\{u_{it}\}$  are also conditionally independent across  $t$ , given  $\{f_t, g_t, e_t\}$ ;

(iii) Weak conditional cross-sectional dependence: Let  $\mathcal{W} = (F, G)$  and  $(E, U)$  be the  $N \times T$  matrices of  $(e_{it}, u_{it})$ . Let  $\omega_{it} = u_{it}e_{it}$ , and let  $c_i$  be a bounded nonrandom sequence. Almost surely,

$$\begin{aligned} \max_t \frac{1}{N^3} \sum_{ijkl} |\text{Cov}(e_{it}e_{jt}, e_{kt}e_{lt} | \mathcal{W}, U)| &< C \\ \max_{i,t} \sum_j |\text{Cov}(e_{it}^m, e_{jt}^r | \mathcal{W}, U)| &< C, \quad m, r \in \{1, 2\} \\ \max_t \|\mathbb{E}(u_t u_t' | \mathcal{W}, E)\| &< C \\ \max_t \mathbb{E}(|\frac{1}{\sqrt{N}} \sum_i c_i \omega_{it}|^4 | \mathcal{W}) &< C \\ \max_t \mathbb{E}(|\frac{1}{\sqrt{N}} \sum_i c_i e_{it}|^4 | \mathcal{W}, U) &< C \\ \max_t \mathbb{E}(|\frac{1}{\sqrt{N}} \sum_i c_i u_{it}|^4 | \mathcal{W}, E) &< C \end{aligned}$$

In addition, for each fixed  $i \leq N$ ,

$$\begin{aligned} \max_{s \leq T} \frac{1}{N} \sum_{kj} |\mathbb{E}(e_{ks}e_{is}e_{js} | \mathcal{W}, U)| &< C \\ \max_t \frac{1}{N} \sum_{kj} |\text{Cov}(\omega_{it}\omega_{jt}, \omega_{it}\omega_{kt} | \mathcal{W})| &< C \\ \max_t \sum_j |\text{Cov}(\omega_{it}, \omega_{jt} | \mathcal{W})| &< C. \end{aligned}$$

Let  $\text{diag}(X_s)$  be a diagonal matrix of  $x_{is}$  for a fixed  $s \leq T$ . Let  $M_\alpha = \mathbf{I}_N - A(A'A)^{-1}A$ ,  $M_g = \mathbf{I}_N - G(G'G)^{-1}G$ , and

$$\begin{aligned} D_{fs} &= \frac{1}{N} \Lambda' \text{diag}(X_s) M_\alpha \text{diag}(X_s) \Lambda, \quad D_{\lambda i} = \frac{1}{T} F' \text{diag}(X_i) M_g \text{diag}(X_i) F \\ D_f &= \frac{1}{N} \Lambda' \mathbb{E}(\text{diag}(X_s) M_\alpha \text{diag}(X_s)) \Lambda, \quad \bar{D}_{\lambda i} = \frac{1}{T} F' \mathbb{E}(\text{diag}(X_i) M_g \text{diag}(X_i)) F. \end{aligned}$$

**Assumption 3.6** (Moment bounds). (i)  $\max_i (\|\lambda_i\| + \|\alpha_i\| + \max_i |\mu_i|) < C$ .

(ii)  $\max_{it} \bar{e}_i^2 \max_{it} e_{it}^2 = O_P(\min\{N, T\})$ ,  $\max_i |\bar{e}_i| = O_P(1)$ ,

$C_{NT}^{-1} \max_{it} |e_{it}|^2 + \max_t \|\frac{1}{N} \sum_i e_{it} \alpha_i \lambda_i'\|_F + \max_t \|\frac{1}{N} \sum_i \lambda_i \lambda_i' \bar{e}_i e_{it}\|_F = o_P(1)$ ,

(iii) There is  $c > 0$ , so that almost surely, for all  $s \leq T$  and  $i \leq N$ ,  $\min_{j \leq K_2} \psi_j(D_{\lambda i}) > c$ ,  $\min_{j \leq K_2} \psi_j(D_{fs}) > c$ ,  $\min_{j \leq K_2} \psi_j(\bar{D}_{\lambda i}) > c$  and  $\min_{j \leq K_2} \psi_j(D_f) > c$ .

(iv)  $\max_{is} \mathbf{E}(e_{is}^6 | U, F) < C$ , and  $\max_{is} \mathbf{E}\|g_s\|^2 \|f_s\|^2 e_{is}^4 < \infty$ ,  $\mathbf{E}u_{ks}^2 \|f_s\|^2 e_{is}^2 e_{js}^2 < C$ .  $\mathbf{E}\|g_s\|^4 + \mathbf{E}\|f_s\|^4 < \infty$ .

**Theorem 3.1.** *Under assumptions 3.1- 3.6, for any fixed  $i \leq N$  and  $t \leq T$ , as  $N, T \rightarrow \infty$ ,*

$$\frac{\hat{\theta}_{it} - \theta_{it}}{(\frac{1}{N}\lambda_i' V_\lambda \lambda_i + \frac{1}{T}f_t' V_f f_t)^{1/2}} \rightarrow^d \mathcal{N}(0, 1),$$

where  $V_f = V_{f1}^{-1} V_{f2} V_{f1}^{-1}$  and  $V_\lambda = V_{\lambda1}^{-1} V_{\lambda2} V_{\lambda1}^{-1}$ , and the related quantities are defined as:

$$V_{f1} = \frac{1}{T} \sum_s f_s f_s' \mathbf{E}e_{is}^2, \quad V_{f2} = \frac{1}{T} \sum_s f_s f_s' \mathbf{E}(e_{is}^2 u_{is}^2 | F), \quad V_{\lambda1} = \frac{1}{N} \sum_j \lambda_j \lambda_j' \mathbf{E}e_{jt}^2, \quad \text{and} \\ V_{\lambda2} = \text{Var}(\frac{1}{\sqrt{N}} \sum_j \lambda_j e_{jt} u_{jt}).$$

While factors and loadings are estimated up to a rotation matrix, both  $\theta_{it}$  and its asymptotic variance are rotation free. On the other hand, the rotation matrices are different on the two splitted sample. Therefore, to preserve the rotation-free property of the asymptotic variance, the above quantities should be separately estimated on the two splitted sample, and the final asymptotic variance estimator should be taken as the average.

In addition, to estimate  $V_{\lambda2}$  we shall assume  $u_{jt}$  to be cross-sectionally independent given  $\{e_{jt}\}$  for simplicity. More specifically, given a splitted sample  $S \in \{I, I^c\}$ , we respectively estimate the above quantities on  $S$  by  $\hat{V}_{f,1}^S = \frac{1}{|S|_0} \sum_{s \in S} \hat{f}_s \hat{f}_s' \hat{e}_{is}^2$ ,  $\hat{V}_{f,2}^S = \frac{1}{|S|_0} \sum_{s \in S} \hat{f}_s \hat{f}_s' \hat{e}_{is}^2 \hat{u}_{is}^2$ ,  $\hat{V}_{\lambda,1}^S = \frac{1}{N} \sum_j \hat{\lambda}_j \hat{\lambda}_j' \hat{e}_{jt}^2$ , and  $\hat{V}_{\lambda,2}^S = \frac{1}{N} \sum_j \hat{\lambda}_j \hat{\lambda}_j' \hat{e}_{jt}^2 \hat{u}_{jt}^2$ . We have

$$\begin{aligned} \hat{v}_\lambda &= \frac{1}{2N} (\hat{\lambda}_{I,i}' \hat{V}_{\lambda,1}^{I-1} \hat{V}_{\lambda,2}^I \hat{V}_{\lambda,1}^{I-1} \hat{\lambda}_{I,i} + \hat{\lambda}_{I^c,i}' \hat{V}_{\lambda,1}^{I^c-1} \hat{V}_{\lambda,2}^{I^c} \hat{V}_{\lambda,1}^{I^c-1} \hat{\lambda}_{I^c,i}) \\ \hat{v}_f &= \frac{1}{2T} (\hat{f}_{I,t}' \hat{V}_{f,1}^{I-1} \hat{V}_{f,2}^I \hat{V}_{f,1}^{I-1} \hat{f}_{I,t} + \hat{f}_{I^c,t}' \hat{V}_{f,1}^{I^c-1} \hat{V}_{f,2}^{I^c} \hat{V}_{f,1}^{I^c-1} \hat{f}_{I^c,t}) \end{aligned}$$

and the estimated asymptotic variance of  $\hat{\theta}_{it}$  is  $\hat{v}_\lambda + \hat{v}_f$ .

**Corollary 3.1.** *In addition to the assumptions of Theorem 3.1, assume  $u_{it}$  to be cross-sectionally independent given  $\{e_{it}\}$ . For any fixed  $i \leq N$  and  $t \leq T$ ,*

$$\frac{\hat{\theta}_{it} - \theta_{it}}{(\hat{v}_\lambda + \hat{v}_f)^{1/2}} \rightarrow^d \mathcal{N}(0, 1).$$

**3.4. Asymptotic analysis when  $x_{it}$  admits a factor model.** In the presence of cross-sectional and serial dependence in  $x_{it}$ , we assume  $x_{it} = l_i' w_t + e_{it}$ .

**Assumption 3.7** (Dependence). (ii)  $\{e_{it}, u_{it}\}$  are independent across  $t$ ;  $\{e_{it}\}$  are also conditionally independent across  $t$ , given  $\{f_t, g_t, w_t, u_t\}$ ;  $\{u_{it}\}$  are also conditionally independent across  $t$ , given  $\{f_t, g_t, w_t, e_t\}$ ;

(ii)

$$\mathbb{E}(e_{it}|u_{it}, w_t, g_t, f_t) = 0, \quad \mathbb{E}(u_{it}|e_{it}, w_t, g_t, f_t) = 0.$$

(iii) The  $N \times T$  matrix  $X \odot U := (u_{it}x_{it})$  has the following decomposition:

$$X \odot U = \Omega_{NT} \Sigma_T^{1/2}$$

where : (a)  $\Omega_{NT} := (\omega_1, \dots, \omega_T)$  is an  $N \times T$  matrix, whose columns  $\{\omega_t\}_{t \leq T}$  are independent sub-gaussian random vectors, with  $\mathbb{E}\omega_t = 0$ , more specifically, there is  $C > 0$ ,

$$\max_{t \leq T} \sup_{\|x\|=1} \mathbb{E} \exp(s\omega_t'x) \leq \exp(s^2C), \quad \forall s \in \mathbb{R}.$$

(b)  $\Sigma_T$  is a  $T \times T$  deterministic matrix, whose eigenvalues are bounded from both below and above by constants.

(iv) Cross-sectional weak dependence: Assumption 3.5(iii) holds with  $\mathcal{W} = (F, G, W)$ .

Condition (iii) allows  $x_{it}$  to be serially weakly dependent, where the serial correlations are captured by  $\Sigma_T$ . The required conditions allow us to apply the eigenvalue-concentration inequality for independent sub-Gaussian random vectors on  $\Omega_{NT}$ . In addition, we allow arbitrary dependence among rows of  $\Omega_{NT}$ , and thus the strong cross-sectional dependence among  $x_{it}$  are allowed, which is desirable given the factor structure.

Next, define

$$\begin{aligned} b_{NT,1} &= \max_t \left\| \frac{1}{NT} \sum_{is} w_s (e_{is}e_{it} - \mathbb{E}e_{is}e_{it}) \right\| \\ b_{NT,2} &= \left( \max_t \frac{1}{T} \sum_s \left( \frac{1}{N} \sum_i e_{is}e_{it} - \mathbb{E}e_{is}e_{it} \right)^2 \right)^{1/2} \\ b_{NT,3} &= \max_t \left\| \frac{1}{N} \sum_i l_i e_{it} \right\| \\ b_{NT,4} &= \max_i \left\| \frac{1}{T} \sum_s e_{is} w_s \right\| \\ b_{NT,5} &= \max_i \left\| \frac{1}{NT} \sum_{js} l_j (e_{js}e_{is} - \mathbb{E}e_{js}e_{is}) \right\| \end{aligned}$$

In addition,

$$\begin{aligned} D_{fs} &= \frac{1}{N} \Lambda' (\text{diag}(X_s) M_\alpha \text{diag}(X_s) \Lambda \\ \bar{D}_{fs} &= \frac{1}{N} \Lambda' \mathbf{E}((\text{diag}(e_s) M_\alpha \text{diag}(e_s)) \Lambda) + \frac{1}{N} \Lambda' (\text{diag}(Lw_s) M_\alpha \text{diag}(Lw_s) \Lambda \\ D_{\lambda i} &= \frac{1}{T} F' (\text{diag}(X_i) M_g \text{diag}(X_i)) F \\ \bar{D}_{\lambda i} &= \frac{1}{T} F' \mathbf{E}(\text{diag}(E_i) M_g \text{diag}(E_i)) F + \frac{1}{T} F' (\text{diag}(Wl_i) M_g \text{diag}(Wl_i)) F. \end{aligned}$$

**Assumption 3.8** (Moment bounds). (i)  $\max_i (\|\lambda_i\| + \|\alpha_i\| + \|l_i\|) < C$ .

(ii) Let  $\delta_{NT} := (C_{NT}^{-1} + b_{NT,4} + b_{NT,5}) \max_t \|w_t\| + b_{NT,1} + b_{NT,3} + C_{NT}^{-1} b_{NT,2} + C_{NT}^{-1/2}$ .

Then  $\delta_{NT} \max_{it} |e_{it}| = o_P(1)$ ,  $\max_t \|\frac{1}{N} \sum_i e_{it} \alpha_i \lambda_i'\|_F = o_P(1)$ ,

(iii) There is  $c > 0$ , so that almost surely, for all  $s \leq T$  and  $i \leq N$ ,  $\min_{j \leq K_2} \psi_j(D_{\lambda i}) > c$ ,  $\min_{j \leq K_2} \psi_j(D_{fs}) > c$ ,  $\min_{j \leq K_2} \psi_j(\bar{D}_{\lambda i}) > c$  and  $\min_{j \leq K_2} \psi_j(\bar{D}_{fs}) > c$ . In addition,

$$\begin{aligned} c &< \min_j \psi_j \left( \frac{1}{N} \sum_i l_i l_i' \right) \leq \max_j \psi_j \left( \frac{1}{N} \sum_i l_i l_i' \right) < C \\ c &< \min_j \psi_j \left( \frac{1}{T} \sum_t w_t w_t' \right) \leq \max_j \psi_j \left( \frac{1}{T} \sum_t w_t w_t' \right) < C \end{aligned}$$

(iv)  $\max_{is} \mathbf{E}(e_{is}^8 | U, F) < C$ , and  $\mathbf{E}\|w_s\|^4 + \|g_s\|^4 + \mathbf{E}\|f_s\|^4 < C$ , and

$$\mathbf{E}\|g_s\|^4 \|f_s\|^4 + \mathbf{E}u_{ks}^4 \|f_s\|^4 + \mathbf{E}e_{jt}^4 \|f_t\|^8 + \mathbf{E}e_{jt}^4 \|f_t\|^4 \|g_t\|^4 + \mathbf{E}\|w_t\|^4 \|g_t\|^4 < C.$$

**Theorem 3.2.** For any fixed  $i \leq N$  and  $t \leq T$ , Under Assumptions 3.1-3.3, 3.7 and 3.8, as  $N, T \rightarrow \infty$ ,

$$\frac{\hat{\theta}_{it} - \theta_{it}}{\widehat{V}^{1/2}} \rightarrow^d \mathcal{N}(0, 1), \quad \frac{\hat{\theta}_{it} - \theta_{it}}{\widehat{V}^{1/2}} \rightarrow^d \mathcal{N}(0, 1),$$

where, for some invertible matrix  $H_f$ .

$$V = \frac{1}{N} \lambda_i' H_f^{-1} V_f H^{-1'} \lambda_i + \frac{1}{T} f_t' H_f' V_\lambda H_f f_t.$$

In addition, the conclusion of Corollary 3.1 continues to hold.

## 4. MONTE CARLO SIMULATIONS

**4.1. Static models.** We use simulations to assess the adequacy of the asymptotic distributions. We set

$$y_{it} = \alpha_i g_t + x_{it,1} \theta_{it} + x_{it,2} \beta_{it} + u_{it}$$

where  $\theta_{it} = \lambda'_{i,1}f_{t,1}$ , and  $\beta_{it} = \lambda'_{i,2}f_{t,2}$ . In addition, we have two processes for the regressors: either a many mean model

$$x_{it,r} = \mu_{i,r} + e_{it,r}, \quad r = 1, 2,$$

or a factor model:

$$x_{it,r} = l_{i,r}w_{t,r} + e_{it,r}, \quad r = 1, 2.$$

Here  $e_{it,r}$  are generated independently from the standard normal distribution across  $(i, t)$ . In addition, all the number of factors are set as one, and all the means, loadings and factors are independently generated from the standard normal distribution.

We define standardized estimates as:

$$\frac{\hat{\theta}_{it} - \theta_{it}}{(\hat{V}_\lambda + \hat{V}_f)^{1/2}}.$$

So the standardization is based on the theoretical mean and theoretical variance rather than the sample mean and sample variance from Monte Carlo repetitions. We next compute the sample mean and sample standard deviation (std) from 1,000 Monte Carlo repetitions of standardized estimates. If the asymptotic theory is adequate, the standardized estimates should be approximately  $\mathcal{N}(0, 1)$  and the std should be approximately one.

We only report the result for  $t = i = r = 1$ ; other values of  $(t, i, r)$  give similar results. In both processes that generated  $x_{it}$ , the sample means and sample standard deviations are close to zero and one, as is shown in Table 4.1. Figure 4.1 also plots the histogram of the standardized estimates, superimposed with the standard normal density. The histogram is scaled to be a density function. It appears that asymptotic theory provides a very good approximation to the finite sample distributions.

TABLE 4.1. Sample mean and standard deviations of the standardized estimate.

$N = T$	mean		standard deviation	
	many-mean	factor model	many-mean	factor model
50	0.110	-0.004	1.065	1.273
100	-0.010	0.002	0.944	1.329
200	0.002	-0.017	1.056	1.041

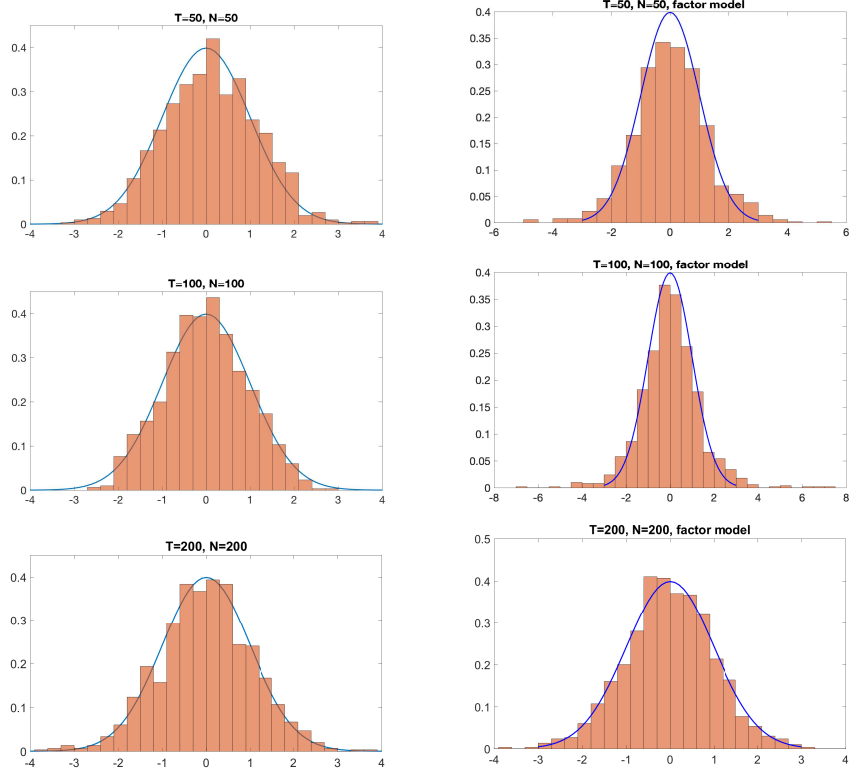


FIGURE 4.1. Histograms of standardized estimates in static models ( $\hat{\theta}_{11} - \theta_{11}$  divided by the estimated asymptotic standard deviation). The left three plots are from the many-mean model; the right three plots are from the factor model. The standard normal density function is superimposed on the histograms.

**4.2. Dynamic models.** Next we add lagged variables to allow for dynamics. We consider a model

$$y_{it} = \alpha'_i g_t + x_{it} \lambda'_{i,1} f_{t,1} + y_{i,t-1} \lambda'_{i,2} f_{t,2} + u_{it},$$

where  $x_{it} = l'_i w_t + e_{it}$ . Strictly speaking, our asymptotic theory does not allow the lagged variable  $y_{i,t-1}$  because it does not analytically admit a static factor model structure. But it can be approximated by using a static factor model so long as  $|\lambda'_{i,2} f_{t,2}|$  is bounded away from the unit root. So we investigate the finite sample performance of our method in this case.

We calibrate the parameters of the data generating process from an empirical application of the democracy-income model as in Acemoglu et al. (2008). Here  $y_{it}$  is the democracy score of country  $i$  in period  $t$ , and  $x_{it}$  is the GDP per capita



over the same period. We estimate their model and obtain the parameters for the simulated design. We assume all the factors and loadings are generated from normal distributions, whose mean vectors and covariance matrices are respectively calculated as the sample means and sample covariances of the estimators using the real democracy-income data. The number of factors in  $\alpha'_i g_t$  is estimated to be one, while all the other numbers of factors are estimated to be two. The following tables show the calibrated sample means and covariances. The error term  $u_{it}$  is generated independently from  $\mathcal{N}(0, \sigma^2)$  with  $\sigma = 0.1287$  calibrated from the real data.

TABLE 4.2. Calibrated means for the dynamic model

$\lambda_1$	$\lambda_2$	$f_1$	$f_2$	$l$	$w$	$\alpha$	$g$
-0.893	-0.863	-0.054	-0.056	-0.893	-0.054	0.298	0.005
0.075	0.045	-0.001	-0.001	0.075	-0.001		

TABLE 4.3. Calibrated covariances for the dynamic model

$\lambda_1$		$\lambda_2$		$f_1$		$f_2$		$l$		$w$		$\alpha$	$g$
0.20	0.06	0.25	0.04	0.33	-0.21	0.45	-0.22	0.20	0.06	0.33	-0.21	0.92	0.01
0.06	1.01	0.04	1.01	-0.21	0.21	-0.22	0.22	0.06	1.01	-0.21	0.21		

We generate  $y_{i1}$  independently from  $0.3\mathcal{N}(0, 1) + 0.497$ , whose parameters are calibrated from the real data at time  $t = 1$ , and then generate  $y_{it}$  iteratively. Let  $z_{it} := y_{i,t-1}$ . Figure 4.2 plots the first twenty eigenvalues of the  $N \times N$  sample covariance of  $z_{it}$  when  $N = T = 100$ , and demonstrates one very spiked eigenvalue. Therefore we estimate a one-factor model on  $z_{it}$  in our estimation procedure.

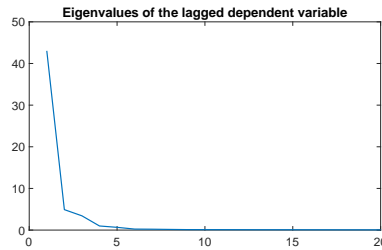


FIGURE 4.2. Sorted eigenvalues of the sample covariance of the lagged dependent variable

We calculate the t-statistic of the estimated  $\lambda'_{i,1}f_{t,1}$  and  $\lambda'_{i,2}f_{t,2}$  for  $t = i = 1$ , defined as

$$\frac{\hat{\theta}_{it} - \theta_{it}}{(\hat{V}_\lambda + \hat{V}_f)^{1/2}}.$$

Table 4.4 reports the sample means and standard deviations of the t-statistics, over 1,000 repetitions. Figure 4.2 plots their histograms. Above all, the results are satisfactory. The estimated effect for  $x_{it}$  is basically unbiased and distributed as standard normality. On the other hand, the estimated lagged effect for  $y_{i,t-1}$  is noticeably biased. As  $T, N$  become larger, the bias slowly decreases.

TABLE 4.4. Sample mean and standard deviations of the standardized estimated coefficients.

$N = T$	mean		standard deviation	
	$x_{it}$	$y_{i,t-1}$	$x_{it}$	$y_{i,t-1}$
50	0.019	-0.345	1.342	1.140
100	-0.096	-0.267	1.178	1.015
150	-0.010	-0.238	1.117	1.045

## 5. AN EMPIRICAL APPLICATION

**5.1. The background.** We illustrate our method in the application of studying the effect on employment of the minimum wage. Previous studies in the literature reach mixed conclusions. For instance, Card and Krueger (1994) find that the minimum wage has a positive effect on the employment using data of restaurants in New Jersey and Eastern Pennsylvania. Dube et al. (2010) concluded negative effects when county-level populations are controlled but also found no adverse employment effects from minimum wage increases when contiguous county-pairs are used for identifications. More recently, Wang et al. (2018) consider slope heterogeneity at the county level:

$$y_{it} = x_{it,1}\theta_i + x_{it,2}\beta_i + \alpha_i + g_t + u_{it} \quad (5.1)$$

where  $y_{it}$  is the log employment of county  $i$  at period  $t$ ;  $x_{it,1}$  is the log minimum wage, and  $x_{it,2}$  is the log population;  $\alpha_i$  and  $g_t$  are respectively the additive county and time fixed effects. They consider a grouping structure by assuming that  $\theta_i$  and  $\beta_i$  are clustered by a small number of unknown groups, and reach mixed effects of the minimum wage across different groups.

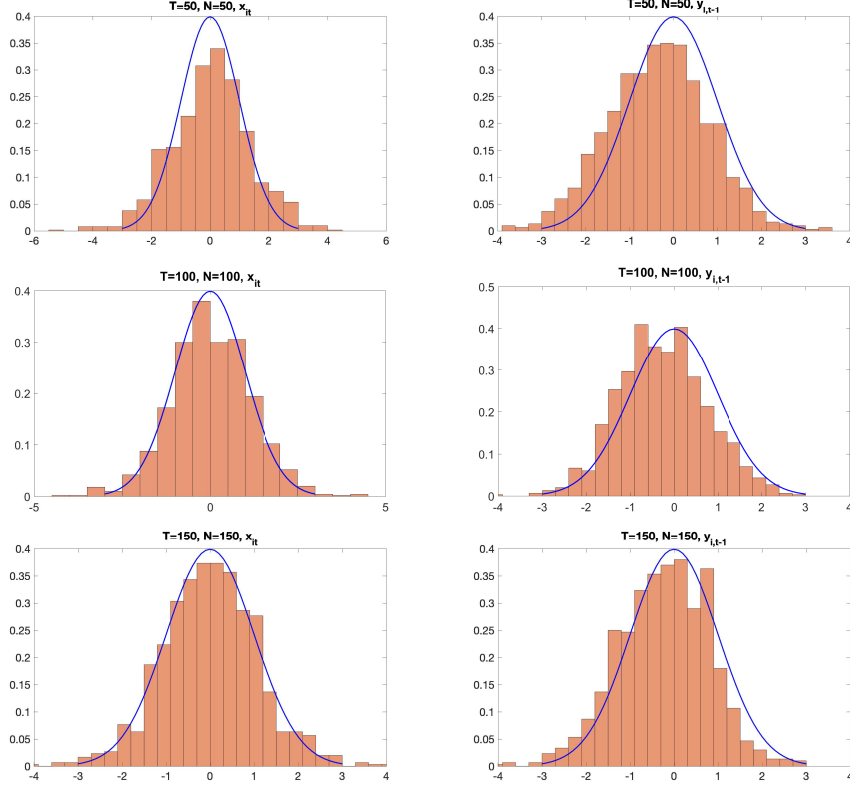


FIGURE 4.3. Histograms of standardized estimates in dynamic models ( $\hat{\theta}_{11} - \theta_{11}$  divided by the estimated asymptotic standard deviation). The left three plots are the effect of  $x_{i,t}$ ; the right three plots are for the effect of  $y_{i,t-1}$ . The standard normal density function is superimposed on the histograms.

While these results allow heterogeneity slopes across counties, the minimum wage effects have been treated as time invariant. However, these effects are decided by the equilibrium of both the supply and demand sides, which should vary over time. To illustrate this, we take the Baker County in Oregon for example, which has the highest average minimum wage during 1990-2006. Figure 5.1 plots the log minimum wage and the employment during this period. It is clear that while the minimum wage increases throughout years, the employment rate is very volatile, indicating a possible time-varying effect. In addition, using additive fixed effects in (5.1) may fail to control for complex unobserved heterogeneity correlated with minimum wages. To control for unobservable factors and heterogeneity that may change over time and counties interactively, we allow the interactive effect and

estimate the following model:

$$\begin{aligned} y_{it} &= x_{it,1}\theta_{it} + x_{it,2}\beta_{it} + \alpha'_i g_t + u_{it}, \\ \theta_{it} &= \lambda'_{i,1} f_{t,1}, \quad \beta_{it} = \lambda'_{i,2} f_{t,2}. \end{aligned}$$

We use the same county-level data as in Dube et al. (2010) and Wang et al. (2018).<sup>1</sup> The balanced panel contains data of 1378 counties in the US that ranges from the first quarter of 1990 to the second quarter of 2006, so  $T = 66$  and  $N = 1378$ . The preliminary analysis on the eigenvalues of the regressors  $x_{it,1}$  and  $x_{it,2}$  clearly demonstrates the presence of a single very spiked eigenvalue for each regressor, so we apply the “partial-out” approach by extracting one estimated factor from each regressor. The tuning parameters for the nuclear-norm regularization are chosen as in Section 2.4, where we estimate the noise variance  $\text{Var}(u_{it})$  by first setting it to  $\text{Var}(y_{it})$  and updating and iterating it in the tuning parameters. In addition, the numbers of factors in  $\theta_{it}$  and  $\beta_{it}$  are both selected as one by the algorithm.

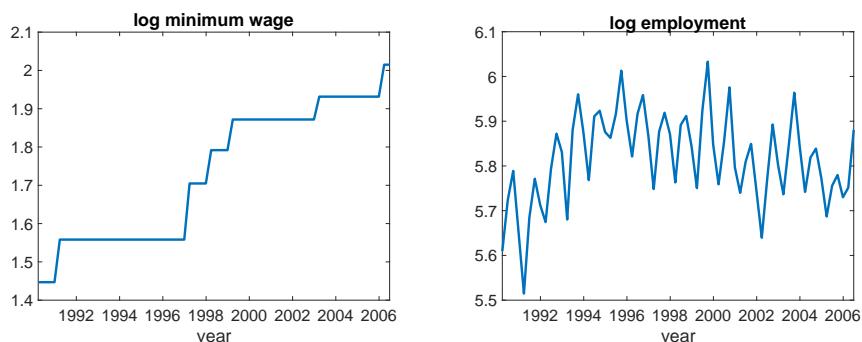


FIGURE 5.1. The minimum wage and employment in Baker County, Oregon. The left panel plots the log minimum wage, and the right panel plots the log employment, starting from the first quarter of 1990 and ending at the second quarter of 2006. Baker County in Oregon is one of the counties with the highest average minimum wage in this period.

**5.2. The results.** For each county, we estimate the minimum wage effect at each period. To present the results, we group the counties according to their averaged minimum wage throughout the time, and obtain three groups: high, medium and low minimum wage. Figure 5.2 plots the averaged effects within each group across time. The estimated effects of counties of either high or medium minimum wages

<sup>1</sup>We are grateful to Wuyi Wang for sharing the data with us.

are much more stable over time than counties of low minimum wages; the latter's effects are mostly negative, between -0.67 and -0.26 during 1992 through 1998, but then jump to between 0.64 and 1.78 during 2000 through 2004. In contrast, the estimated effects for counties of high minimum wages are between -0.05 and -0.02 during 1992 through 1998, and between 0.03 and 0.14 during 2000 through 2004. Table 5.1 summarizes the averaged effects (by counties) of the three groups during these two periods.

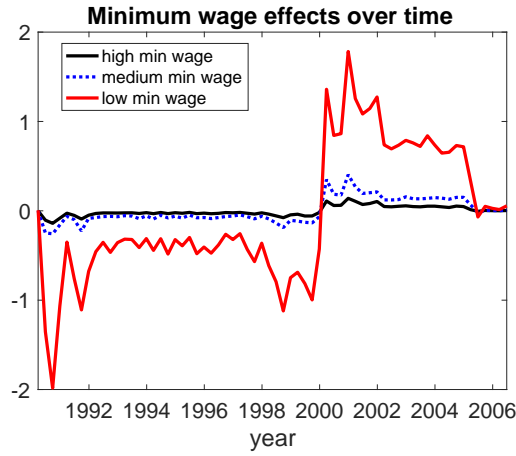


FIGURE 5.2. Averaged (by counties) minimum wage effects in each group

TABLE 5.1. Averaged (by counties) minimum wage effects of three groups

	1992 through 1998			2000 through 2004		
	mean	min	max	mean	min	max
high min wage	-0.026	-0.049	-0.018	0.065	0.037	0.139
medium min wage	-0.069	-0.092	-0.045	0.182	0.121	0.404
low min wage	-0.403	-0.677	-0.256	0.918	0.645	1.782

Our method also allows to study the dynamics of the county specific minimum wage effects. To illustrate this, we now focus on the Baker County in Oregon, which has the highest averaged (over time) minimum wage, and Uinta County in Wyoming, which has the lowest averaged (over time) minimum wage. Figure 5.2 plots the scatter plot and the least squares regression line between the estimated effects and the minimum wages for each county. In both counties, the effect is generally increasing with respect to the level of the minimum wage. This means,

during periods when the minimum wage is higher, the effect is also expected to become larger. We interpret the positive relationship between the minimum wage and its effect as the consequence of the increasing trend of the two throughout the sampling period in both counties.

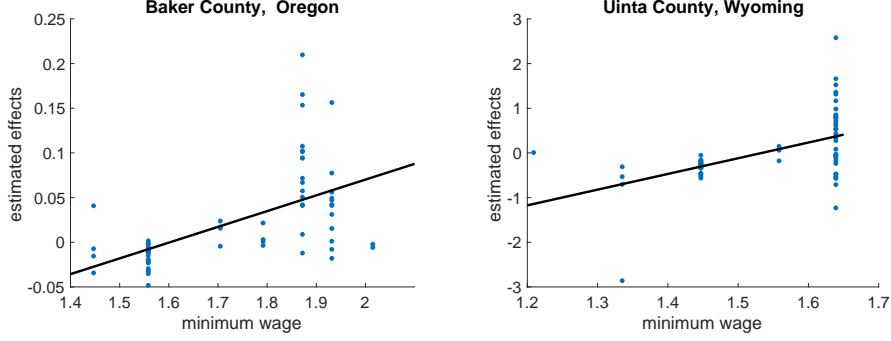


FIGURE 5.3. Scatter plots of estimated effects with respect to the minimum wage. Here dots represents different times. The left panel is for the Baker County (the highest averaged minimum wage), and the right panel is for the Uinta County (the lowest averaged minimum wage). Each plot is fitted using a least squares line.

## 6. CONCLUSION

We study a panel data model with general heterogeneous effects, in the sense that the slopes are allowed to be varying across both individuals and times, and the interactive fixed effects are allowed. The key assumption for dimension reduction is that the heterogeneous slopes can be expressed as a factor structure so that the high-dimensional slope matrix is of low-rank, so can be estimated using nuclear-norm based SVT regression. We show that the inference can be conducted via three steps:

- (1) apply the low-rank SVT estimation;
- (2) extract eigenvectors from the estimated low-rank matrices, and
- (3) run least squares to iteratively estimate the individual and time effect components in the slope matrix.

To properly control for the effect of the penalized low-rank estimation, we argue that this procedure should be embedded with “partial out the mean structure” and “sample splitting”. The resulting estimators are asymptotically normal and admit valid asymptotic inferences.

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## APPENDIX A. ESTIMATION ALGORITHM FOR THE MULTIVARIATE CASE

Consider

$$\begin{aligned} y_{it} &= \sum_{r=1}^R x_{it,r} \theta_{it,r} + \alpha'_i g_t + u_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T. \\ \theta_{it,r} &= \lambda'_{i,r} f_{t,r}. \end{aligned}$$

where  $(x_{it,1}, \dots, x_{it,R})'$  is an  $R$ -dimensional vector of covariate. Each coefficient  $\theta_{it,r}$  admits a factor structure with  $\lambda_{i,r}$  and  $f_{t,r}$  as the “loadings” and “factors”; the factors and loadings are  $\theta_{it,r}$  specific, but are allowed to have overlap. Here  $(R, \dim(\lambda_{i,1}), \dots, \dim(\lambda_{i,R}))$  are all assumed fixed.

Suppose  $x_{it,r} = \mu_{it,r} + e_{it,r}$ . For instance,  $\mu_{it,r} = l'_{i,r} w_{t,r}$  also admits a factor structure. Then after partialing out  $\mu_{it,r}$ , the model can also written as:

$$\dot{y}_{it} = \sum_{r=1}^R e_{it,r} \lambda'_{i,r} f_{t,r} + \alpha'_i g_t + u_{it}, \quad \dot{y}_{it} = y_{it} - \sum_{r=1}^R \mu_{it,r} \theta_{it,r}$$

As such, it is straightforward to extend the estimation algorithm to the multivariate case. Let  $X_r$  be the  $N \times T$  matrix of  $x_{it,r}$ , Let  $\Theta_r$  be the  $N \times T$  matrix of  $\theta_{it,r}$ . We first estimate these low rank matrices using penalized nuclear-norm regression. We then apply sample splitting, and employ steps 2-4 to iteratively estimate  $(f_{t,r}, \lambda_{i,r})$ . The formal algorithm is stated as follows.

**Algorithm A.1.** Estimate  $\theta_{it,r}$  as follows.

*Step 1. Estimate the number of factors.* Run nuclear-norm penalized regression:

$$(\widetilde{M}, \widetilde{\Theta}_r) := \arg \min_{M, \Theta_r} \|Y - M - \sum_{r=1}^R X_r \odot \Theta_r\|_F^2 + \nu_0 \|M\|_n + \sum_{r=1}^R \nu_r \|\Theta_r\|_n.$$

Estimate  $K_r = \dim(\lambda_{i,r})$ ,  $K_0 = \dim(\alpha_i)$  by

$$\widehat{K}_r = \sum_i 1\{\psi_i(\widetilde{\Theta}_r) \geq (\nu_r \|\widetilde{\Theta}_r\|)^{1/2}\}, \quad \widehat{K}_0 = \sum_i 1\{\psi_i(\widetilde{M}) \geq (\nu_0 \|\widetilde{M}\|)^{1/2}\}.$$

*Step 2. Estimate the structure  $x_{it,r} = \mu_{it,r} + e_{it,r}$ .*

In the many mean model, let  $\widehat{e}_{it,r} = x_{it,r} - \frac{1}{T} \sum_{t=1}^T x_{it,r}$ . In the factor model, use the PC estimator to obtain  $(\widehat{l'_{i,r} w_{t,r}}, \widehat{e}_{it,r})$  for all  $i = 1, \dots, N, t = 1, \dots, T$  and  $r = 1, \dots, R$ .

*Step 3: Sample splitting.* Randomly split the sample into  $\{1, \dots, T\}/\{t\} = I \cup I^c$ , so that  $|I|_0 = [(T-1)/2]$ . Denote by  $Y_I, X_{I,r}$  as the  $N \times |I|_0$  matrices of  $(y_{is}, x_{is,r})$

for observations at  $s \in I$ . Estimate the low-rank matrices  $\Theta$  and  $M$  as in step 1, with  $(Y, X_r)$  replaced with  $(Y_I, X_{I,r})$ , and obtain  $(\widetilde{M}_I, \widetilde{\Theta}_{I,r})$ .

Let  $\widetilde{\Lambda}_{I,r} = (\widetilde{\lambda}_{1,r}, \dots, \widetilde{\lambda}_{N,r})'$  be the  $N \times \widehat{K}_r$  matrix, whose columns are defined as  $\sqrt{N}$  times the first  $\widehat{K}_r$  eigenvectors of  $\widetilde{\Theta}_{I,r} \widetilde{\Theta}_{I,r}'$ . Let  $\widetilde{A}_I = (\widetilde{\alpha}_1, \dots, \widetilde{\alpha}_N)'$  be the  $N \times \widehat{K}_0$  matrix, whose columns are defined as  $\sqrt{N}$  times the first  $\widehat{K}_0$  eigenvectors of  $\widetilde{M}_I \widetilde{M}_I'$ .

*Step 4. Estimate the “partial-out” components.*

Substitute in  $(\widetilde{\alpha}_i, \widetilde{\lambda}_{i,r})$ , and define

$$(\widetilde{f}_{s,r}, \widetilde{g}_s) := \arg \min_{f_{s,r}, g_s} \sum_{i=1}^N (y_{is} - \widetilde{\alpha}_i' g_s - \sum_{r=1}^R x_{is,r} \widetilde{\lambda}_{i,r}' f_{s,r})^2, \quad s \in I^c \cup \{t\}.$$

and

$$(\dot{\lambda}_{i,r}, \dot{\alpha}_i) = \arg \min_{\lambda_{i,r}, \alpha_i} \sum_{s \in I^c \cup \{t\}} (y_{is} - \alpha_i' \widetilde{g}_s - \sum_{r=1}^R x_{is,r} \lambda_{i,r}' \widetilde{f}_{s,r})^2, \quad i = 1, \dots, N.$$

*Step 5. Estimate  $(f_{t,r}, \lambda_{i,r})$  for inferences.*

Motivated by (2.5), for all  $s \in I^c \cup \{t\}$ , let

$$(\widehat{f}_{I,s,r}, \widehat{g}_{I,s}) := \arg \min_{f_{s,r}, g_s} \sum_{i=1}^N (\widehat{y}_{is} - \widetilde{\alpha}_i' g_s - \sum_{r=1}^R \widehat{e}_{is,r} \widetilde{\lambda}_{i,r}' f_{s,r})^2.$$

Fix  $i \leq N$ ,

$$(\widehat{\lambda}_{I,i,r}, \widehat{\alpha}_{I,i}) = \arg \min_{\lambda_{i,r}, \alpha_i} \sum_{s \in I^c \cup \{t\}} (\widehat{y}_{is} - \alpha_i' \widehat{g}_{I,s} - \sum_{r=1}^R \widehat{e}_{is,r} \lambda_{i,r}' \widehat{f}_{I,s,r})^2.$$

where  $\widehat{y}_{is} = y_{is} - \bar{x}_{i,r} \dot{\lambda}_i' \widetilde{f}_s$  and  $\widehat{e}_{is,r} = x_{is,r} - \bar{x}_{i,r}$  in the many mean model, and  $\widehat{y}_{is} = y_{is} - \widehat{l}_{i,r}' w_{s,r} \dot{\lambda}_i' \widetilde{f}_{s,r}$ ,  $\widehat{e}_{is,r} = x_{is,r} - \widehat{l}_{i,r}' w_{s,r}$  in the factor model.

*Step 6. Estimate  $\theta_{it,r}$ .* Repeat steps 3-5 with  $I$  and  $I^c$  exchanged, and obtain  $(\widehat{\lambda}_{I^c,i,r}, \widehat{f}_{I^c,s,r} : s \in I \cup \{t\}, i \leq N, r \leq R)$ . Define

$$\widehat{\theta}_{it,r} := \frac{1}{2} [\widehat{\lambda}_{I,i,r}' \widehat{f}_{I,t,r} + \widehat{\lambda}_{I^c,i,r}' \widehat{f}_{I^c,t,r}].$$

The asymptotic variance can be estimated by  $\widehat{v}_{\lambda,r} + \widehat{v}_{f,r}$ , where

$$\begin{aligned} \widehat{v}_{\lambda,r} &= \frac{1}{2N} (\widehat{\lambda}_{I,i,r}' \widehat{V}_{\lambda,1}^{I-1} \widehat{V}_{\lambda,2}^I \widehat{V}_{\lambda,1}^{I-1} \widehat{\lambda}_{I,i,r} + \widehat{\lambda}_{I^c,i,r}' \widehat{V}_{\lambda,1}^{I^c-1} \widehat{V}_{\lambda,2}^{I^c} \widehat{V}_{\lambda,1}^{I^c-1} \widehat{\lambda}_{I^c,i,r}) \\ \widehat{v}_{f,r} &= \frac{1}{2T} (\widehat{f}_{I,t,r}' \widehat{V}_{f,1}^{I-1} \widehat{V}_{f,2}^I \widehat{V}_{f,1}^{I-1} \widehat{f}_{I,t,r} + \widehat{f}_{I^c,t,r}' \widehat{V}_{f,1}^{I^c-1} \widehat{V}_{f,2}^{I^c} \widehat{V}_{f,1}^{I^c-1} \widehat{f}_{I^c,t,r}) \end{aligned}$$

with  $\widehat{V}_{f,1}^S = \frac{1}{|S|_0} \sum_{s \in S} \widehat{f}_{s,r} \widehat{f}'_{s,r} \widehat{e}_{is,r}^2$ ,  $\widehat{V}_{f,2}^S = \frac{1}{|S|_0} \sum_{s \in S} \widehat{f}_{s,r} \widehat{f}'_{s,r} \widehat{e}_{is}^2 \widehat{u}_{is,r}^2$ ,  $\widehat{V}_{\lambda,1}^S = \frac{1}{N} \sum_j \widehat{\lambda}_{j,r} \widehat{\lambda}'_{j,r} \widehat{e}_{jt,r}^2$ , and  $\widehat{V}_{\lambda,2}^S = \frac{1}{N} \sum_j \widehat{\lambda}_{j,r} \widehat{\lambda}'_{j,r} \widehat{e}_{jt,r}^2 \widehat{u}_{jt,r}^2$ .

It is also straightforward to extend the univariate asymptotic analysis to the multivariate case, and establish the asymptotic normality for  $\widehat{\theta}_{it,r}$ . The proof techniques are the same, subjected to more complicated notation. Therefore our proofs below focus on the univariate case.

## APPENDIX B. PROOF OF PROPOSITION 2.1

Recall that  $\Theta_{k+1} = S_{\tau\nu_1/2}(\Theta_k - \tau A_k)$ , where

$$A_k = X \odot (X \odot \Theta_k - Y + M_k).$$

By Lemma B.2, set  $\Theta = \widetilde{\Theta}$  and  $M = \widetilde{M}$ , and replace  $k$  with subscript  $m$ ,

$$F(\widehat{\Theta}, \widehat{M}) - F(\Theta_{m+1}, M_{m+1}) \geq \frac{1}{\tau} \left( \|\Theta_{m+1} - \widehat{\Theta}\|_F^2 - \|\Theta_m - \widehat{\Theta}\|_F^2 \right).$$

Let  $m = 1, \dots, k$ , and sum these inequalities up, since  $F(\Theta_{m+1}, M_{m+1}) \geq F(\Theta_{k+1}, M_{k+1})$  by Lemma B.1,

$$\begin{aligned} kF(\widehat{\Theta}, \widehat{M}) - kF(\Theta_{k+1}, M_{k+1}) &\geq kF(\widehat{\Theta}, \widehat{M}) - \sum_{m=1}^k F(\Theta_{m+1}, M_{m+1}) \\ &\geq \frac{1}{\tau} \left( \|\Theta_{k+1} - \widehat{\Theta}\|_F^2 - \|\Theta_1 - \widehat{\Theta}\|_F^2 \right) \geq -\frac{1}{\tau} \|\Theta_1 - \widehat{\Theta}\|_F^2. \end{aligned}$$

Q.E.D.

The above proof depends on the following lemmas.

**Lemma B.1.** *We have: (i)*

$$\begin{aligned} \Theta_{k+1} &= \arg \min_{\Theta} p(\Theta, \Theta_k, M_k) + \nu_1 \|\Theta\|_n, \\ p(\Theta, \Theta_k, M_k) &:= \tau^{-1} \|\Theta_k - \Theta\|_F^2 - 2\text{tr}((\Theta_k - \Theta)' A_k). \end{aligned}$$

(ii) For any  $\tau \in (0, 1/\max x_{it}^2)$ ,

$$F(\Theta, M_k) \leq p(\Theta, \Theta_k, M_k) + \nu_1 \|\Theta\|_n + \nu_2 \|M_k\|_n + \|Y - M_k - X \odot \Theta_k\|_F^2.$$

(iii)  $F(\Theta_{k+1}, M_{k+1}) \leq F(\Theta_{k+1}, M_k) \leq F(\Theta_k, M_k)$ .

*Proof.* (i) We have  $\|\Theta_k - \tau A_k - \Theta\|_F^2 = \|\Theta_k - \Theta\|_F^2 + \tau^2 \|A_k\|_F^2 - 2\text{tr}[(\Theta_k - \Theta)' A_k] \tau$ . So

$$\begin{aligned} & \arg \min_{\Theta} \|\Theta_k - \tau A_k - \Theta\|_F^2 + \tau \nu_1 \|\Theta\|_n \\ &= \arg \min_{\Theta} \|\Theta_k - \Theta\|_F^2 - 2\text{tr}[(\Theta_k - \Theta)' A_k] \tau + \tau \nu_1 \|\Theta\|_n \\ &= \arg \min_{\Theta} \tau \cdot p(\Theta, \Theta_k, M_k) + \tau \nu_1 \|\Theta\|_n. \end{aligned}$$

On the other hand, it is well known that  $\Theta_{k+1} = S_{\tau \nu_1/2}(\Theta_k - \tau A_k)$  is the solution to the first problem in the above equalities (Ma et al., 2011). This proves (i).

(ii) Note that for  $\Theta_k = (\theta_{k,it})$  and  $\Theta = (\theta_{it})$ , and any  $\tau^{-1} > \max_{it} x_{it}^2$ , we have

$$\|X \odot (\Theta_k - \Theta)\|_F^2 = \sum_{it} x_{it}^2 (\theta_{k,it} - \theta_{it})^2 < \tau^{-1} \|\Theta_k - \Theta\|_F^2.$$

So

$$\begin{aligned} F(\Theta, M_k) &= \|Y - M_k - X \odot \Theta\|_F^2 + \nu_2 \|M_k\|_n + \nu_1 \|\Theta\|_n \\ &= \|Y - M_k - X \odot \Theta_k\|_F^2 + \|X \odot (\Theta_k - \Theta)\|_F^2 - 2\text{tr}[A'_k(\Theta_k - \Theta)] \\ &\quad + \nu_2 \|M_k\|_n + \nu_1 \|\Theta\|_n \\ &\leq \|Y - M_k - X \odot \Theta_k\|_F^2 + \tau^{-1} \|\Theta_k - \Theta\|_F^2 - 2\text{tr}[A'_k(\Theta_k - \Theta)] \\ &\quad + \nu_2 \|M_k\|_n + \nu_1 \|\Theta\|_n \\ &= p(\Theta, \Theta_k, M_k) + \|Y - M_k - X \odot \Theta_k\|_F^2 + \nu_2 \|M_k\|_n + \nu_1 \|\Theta\|_n. \end{aligned}$$

(iii) By definition,  $p(\Theta_k, \Theta_k, M_k) = 0$ . So

$$\begin{aligned} F(\Theta_{k+1}, M_{k+1}) &= \|Y - X \odot \Theta_{k+1} - M_{k+1}\|_F^2 + \nu_1 \|\Theta_{k+1}\|_n + \nu_2 \|M_{k+1}\|_n \\ &\stackrel{(a)}{\leq} \|Y - X \odot \Theta_{k+1} - M_k\|_F^2 + \nu_1 \|\Theta_{k+1}\|_n + \nu_2 \|M_k\|_n \\ &= F(\Theta_{k+1}, M_k) \\ &\stackrel{(b)}{\leq} p(\Theta_{k+1}, \Theta_k, M_k) + \nu_1 \|\Theta_{k+1}\|_n + \nu_2 \|M_k\|_n + \|Y - M_k - X \odot \Theta_k\|_F^2 \\ &\stackrel{(c)}{\leq} p(\Theta_k, \Theta_k, M_k) + \nu_1 \|\Theta_k\|_n + \nu_2 \|M_k\|_n + \|Y - M_k - X \odot \Theta_k\|_F^2 \\ &= F(\Theta_k, M_k). \end{aligned}$$

(a) is due to the definition of  $M_{k+1}$ ; (b) is due to (ii); (c) is due to (i). Q.E.D.

**Lemma B.2.** For any  $\tau \in (0, 1/\max_{it} x_{it}^2)$ , any  $(\Theta, M)$  and any  $k \geq 1$ ,

$$F(\Theta, M) - F(\Theta_{k+1}, M_{k+1}) \geq \frac{1}{\tau} (\|\Theta_{k+1} - \Theta\|_F^2 - \|\Theta_k - \Theta\|_F^2).$$

*Proof.* The proof is similar to that of Lemma 2.3 of Beck and Teboulle (2009), with the extension that  $M_{k+1}$  is updated after  $\Theta_{k+1}$ . The key difference here is that, while an update to  $M_{k+1}$  is added to the iteration, we show that the lower

bound does not depend on  $M_{k+1}$  or  $M_k$ . Therefore, the convergence property of the algorithm depends mainly on the step of updating  $\Theta$ .

Let  $\partial\|A\|_n$  be an element that belongs to the subgradient of  $\|A\|_n$ . Note that  $\partial\|A\|_n$  is convex in  $A$ . Also,  $\|Y - X \odot \Theta - M\|_F^2$  is convex in  $(\Theta, M)$ , so for any  $\Theta, M$ , we have the following three inequalities:

$$\begin{aligned} \|Y - X \odot \Theta - M\|_F^2 &\geq \|Y - X \odot \Theta_k - M_k\|_F^2 - 2\text{tr}[(\Theta - \Theta_k)'(X \odot (Y - X \odot \Theta_k - M_k))] \\ &\quad - 2\text{tr}[(M - M_k)'(Y - X \odot \Theta_k - M_k)] \\ \nu_1\|\Theta\|_n &\geq \nu_1\|\Theta_{k+1}\|_n + \nu_1\text{tr}[(\Theta - \Theta_{k+1})'\partial\|\Theta_{k+1}\|_n] \\ \nu_2\|M\|_n &\geq \nu_2\|M_k\|_n + \nu_2\text{tr}[(M - M_k)'\partial\|M_k\|_n]. \end{aligned}$$

In addition,

$$\begin{aligned} -F(\Theta_{k+1}, M_{k+1}) &\geq -F(\Theta_{k+1}, M_k) \\ &\geq -p(\Theta_{k+1}, \Theta_k, M_k) - \nu_1\|\Theta_{k+1}\|_n - \nu_2\|M_k\|_n - \|Y - M_k - X \odot \Theta_k\|_F^2. \end{aligned}$$

where the two inequalities are due to Lemma B.1. Sum up the above inequalities,

$$\begin{aligned} F(\Theta, M) - F(\Theta_{k+1}, M_{k+1}) &\geq (A) \\ (A) &:= -2\text{tr}[(\Theta - \Theta_k)'(X \odot (Y - X \odot \Theta_k - M_k))] - 2\text{tr}[(M - M_k)'(Y - X \odot \Theta_k - M_k)] \\ &\quad + \nu_1\text{tr}[(\Theta - \Theta_{k+1})'\partial\|\Theta_{k+1}\|_n] + \nu_2\text{tr}[(M - M_k)'\partial\|M_k\|_n] - p(\Theta_{k+1}, \Theta_k, M_k). \end{aligned}$$

We now simplify (A). Since  $k \geq 1$ , both  $M_k$  and  $\Theta_{k+1}$  should satisfy the KKT condition. By Lemma B.1, they are:

$$\begin{aligned} 0 &= \nu_1\partial\|\Theta_{k+1}\|_n - \tau^{-1}2(\Theta_k - \Theta_{k+1}) + 2A_k \\ 0 &= \nu_2\partial\|M_k\|_n - 2(Y - X \odot \Theta_k - M_k). \end{aligned}$$

Plug in, we have

$$\begin{aligned} (A) &= \tau^{-1}2\text{tr}[(\Theta - \Theta_{k+1})'(\Theta_k - \Theta_{k+1})] - \tau^{-1}\|\Theta_k - \Theta_{k+1}\|_F^2 \\ &= \frac{1}{\tau}(\|\Theta_{k+1} - \Theta\|_F^2 - \|\Theta_k - \Theta\|_F^2). \end{aligned}$$

Q.E.D.

## APPENDIX C. PROOF OF PROPOSITION 3.1

### C.1. Level of the Score.

**Lemma C.1.** *In the presence of serial correlations in  $x_{it}$  (Assumption 3.7),  $\|X \odot U\| = O_P(\sqrt{N+T}) = \|U\|$ . In addition, the chosen  $\nu_2, \nu_1$  in Section 2.4 are  $O_P(\sqrt{N+T})$ .*

*Proof.* The assumption that  $\Omega_{NT}$  contains independent sub-Gaussian columns ensures that, by the eigenvalue-concentration inequality for sub-Gaussian random vectors (Theorem 5.39 of Vershynin (2010)):

$$\|\Omega_{NT}\Omega'_{NT} - \mathbb{E}\Omega_{NT}\Omega'_{NT}\| = O_P(\sqrt{NT} + N).$$

In addition, let  $w_i$  be the  $T \times 1$  vector of  $\{x_{it}u_{it} : t \leq T\}$ . We have, for each  $(i, j, t, s)$ ,

$$\mathbb{E}(w_i w'_j)_{s,t} = \mathbb{E}x_{it}x_{js}u_{it}u_{js} = \begin{cases} \mathbb{E}x_{it}^2 u_{it}^2, & i = j, t = s \\ 0, & \text{otherwise} \end{cases}$$

due to the conditional cross-sectional and serial independence in  $u_{it}$ . Then for the  $(i, j)$ 'th entry of  $\mathbb{E}\Omega_{NT}\Omega'_{NT}$ ,

$$\begin{aligned} (\mathbb{E}\Omega_{NT}\Omega'_{NT})_{i,j} &= (\mathbb{E}(X \odot U)\Sigma_T^{-1}(X \odot U)')_{i,j} \\ &= \mathbb{E}w'_i \Sigma_T^{-1} w_j = \text{tr}(\Sigma_T^{-1} \mathbb{E}w_j w'_i) = \begin{cases} \sum_{t=1}^T (\Sigma_T^{-1})_{tt} \mathbb{E}x_{it}^2 u_{it}^2, & i = j \\ 0, & i \neq j. \end{cases} \end{aligned}$$

Hence  $\|\mathbb{E}\Omega_{NT}\Omega'_{NT}\| \leq O(T)$ . This implies  $\|\Omega_{NT}\Omega'_{NT}\| \leq O(T + N)$ . Hence  $\|X \odot U\| \leq \|\Omega_{NT}\| \|\Sigma_T^{1/2}\| \leq O_P(\max\{\sqrt{N}, \sqrt{T}\})$ . The rate for  $\|U\|$  follows from the same argument. The second claim that  $\nu_2, \nu_1$  satisfy the same rate constraint follows from the same argument, by replacing  $U$  with  $Z$ , and Assumption 3.7 is still satisfied by  $Z$  and  $X \odot Z$ . Q.E.D.

**C.2. Useful Claims.** The proof of Proposition 3.1 uses some claims that are proved in the following lemma. Let us first recall the notations. Define  $U_2 D_2 V'_2 = \Theta_I^0$  and  $U_1 D_1 V'_1 = M_I^0$  as the singular value decompositions of the true values  $\Theta_I^0$  and  $M_I^0$ . Further decompose, for  $j = 1, 2$ ,

$$U_j = (U_{j,r}, U_{j,c}), \quad V_j = (V_{j,r}, V_{j,c})$$

Here  $(U_{j,r}, V_{j,r})$  corresponds to the nonzero singular values, while  $(U_{j,c}, V_{j,c})$  corresponds to the zero singular values. In addition, for any  $N \times T/2$  matrix  $\Delta$ , let

$$\mathcal{P}_j(\Delta) = U_{j,c} U'_{j,c} \Delta V_{j,c} V'_{j,c}, \quad \mathcal{M}_j(\Delta) = \Delta - \mathcal{P}_j(\Delta).$$

Here  $U_{j,c}U'_{j,c}$  and  $V_{j,c}V'_{j,c}$  respectively are the projection matrices onto the columns of  $U_{j,c}$  and  $V_{j,c}$ . Therefore,  $\mathcal{M}_1(\cdot)$  and  $\mathcal{M}_2(\cdot)$  can be considered as the projection matrices onto the “low-rank” spaces of  $\Theta_I^0$  and  $M_I^0$  respectively, and  $\mathcal{P}_1(\cdot)$  and  $\mathcal{P}_2(\cdot)$  are projections onto their orthogonal spaces.

**Lemma C.2** (claims). *Same results below also apply to  $\mathcal{P}_2$   $\Theta_I^0$ , and samples on  $I^c$ . For any matrix  $\Delta$ ,*

- (i)  $\|\mathcal{P}_1(\Delta) + M_I^0\|_n = \|\mathcal{P}_1(\Delta)\|_n + \|M_I^0\|_n$ .
- (ii)  $\|\Delta\|_F^2 = \|\mathcal{M}_1(\Delta)\|_F^2 + \|\mathcal{P}_1(\Delta)\|_F^2$
- (iii)  $\text{rank}(\mathcal{M}_1(\Delta)) \leq 2K_1$ , where  $K_1 = \text{rank}(M_I^0)$ .
- (iv)  $\|\Delta\|_F^2 = \sum_j \sigma_j^2$  and  $\|\Delta\|_n^2 \leq \|\Delta\|_F^2 \text{rank}(\Delta)$ , with  $\sigma_j$  as the singular values of  $\Delta$ .
- (v) For any  $\Delta_1, \Delta_2$ ,  $|\text{tr}(\Delta_1\Delta_2)| \leq \|\Delta_1\|_n \|\Delta_2\|$ , Here  $\|\cdot\|$  denotes the operator norm.

*Proof.* (i) Note that  $M_I^0 = U_{1,r}D_{1,r}V'_{1,r}$  where  $D_{1,r}$  are the subdiagonal matrix of nonzero singular values. The claim follows from Lemma 2.3 of Recht et al. (2010).

(ii) Write

$$U'_1\Delta V_1 = \begin{pmatrix} A & B \\ C & U'_{1,c}\Delta V_{1,c} \end{pmatrix} = \begin{pmatrix} A & B \\ C & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & U'_{1,c}\Delta V_{1,c} \end{pmatrix} := H_2 + H_1.$$

Then  $\mathcal{P}_1(\Delta) = U_1H_1V'_1$  and  $\mathcal{M}_1(\Delta) = U_1H_2V'_1$ . So

$$\|\mathcal{P}_1(\Delta)\|_F^2 = \text{tr}(U_1H_1V'_1V_1H'_1U'_1) = \text{tr}(H_1H'_1) = \|H_1\|_F^2.$$

Similarly,  $\|\mathcal{M}_1(\Delta)\|_F^2 = \|H_2\|_F^2$ . So

$$\|H_2\|_F^2 + \|H_1\|_F^2 = \|U'_1\Delta V_1\|_F^2 = \|\Delta\|_F^2.$$

(iii) This is Lemma 1 of Negahban and Wainwright (2011).

(iv) The first is a basic equality, and the second follows from the Cauchy-Schwarz inequality.

(v) Let  $UDV' = \Delta_1$  be the singular value decomposition of  $\Delta_1$ , then

$$|\text{tr}(\Delta_1\Delta_2)| = \left| \sum_i D_{ii}(V'\Delta_2U)_{ii} \right| \leq \max_i |(V'\Delta_2U)_{ii}| \sum_i D_{ii} \leq \|\Delta_1\|_n \|\Delta_2\|.$$

**C.3. Proof of Proposition 3.1: convergence of  $\tilde{\Theta}_S, \tilde{M}_S$ .** In the proof below, we set  $S = I$ , that is, on the splitted sample  $t \in I$ , and set  $T_0 = |I|_0$ . The proof

carries over to  $S = I^c$  or  $S = I \cup I^c$ . We surpass the subscript  $S$  for notational simplicity. Let  $\Delta_1 = \widetilde{M} - M$  and  $\Delta_2 = \widetilde{\Theta} - \Theta$ . Then

$$\|Y - \widetilde{M} - X \odot \widetilde{\Theta}\|_F^2 = \|\Delta_1 + X \odot \Delta_2\|_F^2 + \|U\|_F^2 - 2\text{tr}[U'(\Delta_1 + X \odot \Delta_2)].$$

Note that  $\text{tr}(U'(X \odot \Delta_2)) = \text{tr}(\Delta_2'(X \odot U))$ . Thus by claim (v),

$$\begin{aligned} |2\text{tr}[U'(\Delta_1 + X \odot \Delta_2)]| &\leq 2\|U\|\|\Delta_1\|_n + 2\|X \odot U\|\|\Delta_2\|_n \\ &\leq (1-c)\nu_2\|\Delta_1\|_n + (1-c)\nu_1\|\Delta_2\|_n. \end{aligned}$$

Thus  $\|Y - \widetilde{M} - X \odot \widetilde{\Theta}\|_F^2 \leq \|Y - M - X \odot \Theta\|_F^2$  (evaluated at the true parameters) implies

$$\begin{aligned} \|\Delta_1 + X \odot \Delta_2\|_F^2 + \nu_2\|\widetilde{M}\|_n + \nu_1\|\widetilde{\Theta}\|_n &\leq (1-c)\nu_2\|\Delta_1\|_n + (1-c)\nu_1\|\Delta_2\|_n \\ &\quad + \nu_2\|M\|_n + \nu_1\|\Theta\|_n. \end{aligned}$$

Now

$$\begin{aligned} \|\widetilde{M}\|_n &= \|\Delta_1 + M\|_n = \|M + \mathcal{P}_1(\Delta_1) + \mathcal{M}_1(\Delta_1)\|_n \\ &\geq \|M + \mathcal{P}_1(\Delta_1)\|_n - \|\mathcal{M}_1(\Delta_1)\|_n \\ &= \|M\|_n + \|\mathcal{P}_1(\Delta_1)\|_n - \|\mathcal{M}_1(\Delta_1)\|_n, \end{aligned}$$

where the last equality follows from claim (i). Similar lower bound applies to  $\|\widetilde{\Theta}\|_n$ . Therefore,

$$\begin{aligned} &\|\Delta_1 + X \odot \Delta_2\|_F^2 + c\nu_2\|\mathcal{P}_1(\Delta_1)\|_n + c\nu_1\|\mathcal{P}_2(\Delta_2)\|_n \\ &\leq (2-c)\nu_2\|\mathcal{M}_1(\Delta_1)\|_n + (2-c)\nu_1\|\mathcal{M}_2(\Delta_2)\|_n. \end{aligned} \tag{C.1}$$

In the case  $U$  is Gaussian,  $\|U\|$  and  $\|X \odot U\| \asymp \max\{\sqrt{N}, \sqrt{T}\}$ , while in the more general case, set  $\nu_2 \asymp \nu_1 \asymp \max\{\sqrt{N}, \sqrt{T}\}$ . Thus the above inequality implies  $(\Delta_1, \Delta_2) \in \mathcal{C}(a)$  for some  $a > 0$ . Thus apply Assumption 3.1 and claims to (C.1), for a generic  $C > 0$ ,

$$\begin{aligned} \|\Delta_1\|_F^2 + \|\Delta_2\|_F^2 &\leq C\nu_2\|\mathcal{M}_1(\Delta_1)\|_n + C\nu_1\|\mathcal{M}_2(\Delta_2)\|_n \\ &\stackrel{\text{claim (iv)}}{\leq} C\nu_2\|\mathcal{M}_1(\Delta_1)\|_F\sqrt{\text{rank}(\mathcal{M}_2(\Delta_1))} \\ &\quad + C\nu_1\|\mathcal{M}_2(\Delta_2)\|_F\sqrt{\text{rank}(\mathcal{M}_2(\Delta_2))} \\ &\stackrel{\text{claim (iii)}}{\leq} C\nu_2\|\mathcal{M}_1(\Delta_1)\|_F\sqrt{2K_1} + C\nu_1\|\mathcal{M}_2(\Delta_2)\|_F\sqrt{2K_2} \\ &\stackrel{\text{claim (ii)}}{\leq} C\nu_2\|\Delta_1\|_F + C\nu_1\|\Delta_2\|_F \\ &\leq C\max\{\nu_2, \nu_1\}\sqrt{\|\Delta_1\|_F^2 + \|\Delta_2\|_F^2}. \end{aligned}$$

Thus  $\|\Delta_1\|_F^2 + \|\Delta_2\|_F^2 \leq C(\nu_2^2 + \nu_1^2)$ .



**C.4. Proof of Proposition 3.1: convergence of  $\tilde{\Lambda}_S, \tilde{A}_S$ .** We proceed the proof in the following steps.

**step 1: bound the eigenvalues**

Replace  $\nu_2^2 + \nu_1^2$  with  $O_P(N + T)$ , then

$$\|\tilde{\Theta}_S - \Theta_S\|_F^2 = O_P(N + T).$$

Let  $S_f = \frac{1}{T_0} \sum_{t \in I} f_t f_t'$ ,  $\Sigma_f = \frac{1}{T} \sum_{t=1}^T f_t f_t'$  and  $S_\Lambda = \frac{1}{N} \Lambda' \Lambda$ . Let  $\psi_{I,1}^2 \geq \dots \geq \psi_{I,K_1}^2$  be the  $K_1$  nonzero eigenvalues of  $\frac{1}{NT_0} \Theta_I \Theta_I' = \frac{1}{N} \Lambda S_f \Lambda'$ . Let  $\tilde{\psi}_1^2 \geq \dots \geq \tilde{\psi}_{K_2}^2$  be the first  $K_2$  nonzero singular values of  $\frac{1}{NT_0} \tilde{\Theta}_I \tilde{\Theta}_I'$ . Also, let  $\psi_j^2$  be the  $j$  th largest eigenvalue of  $\frac{1}{N} \Lambda \Sigma_f \Lambda'$ . Note that  $\psi_1^2 \dots \psi_{K_1}^2$  are the same as the eigenvalues of  $\Sigma_f^{1/2} S_\Lambda \Sigma_f^{1/2}$ . Hence by Assumption 3.3, there are constants  $c_1, \dots, c_{K_1} > 0$ , so that

$$\psi_j^2 = c_j, \quad j = 1, \dots, K_1.$$

Then by Weyl's theorem, for  $j = 1, \dots, \min\{T_0, N\}$ , with the assumption that  $\|S_f - \Sigma_f\| = O_P(\frac{1}{\sqrt{T}})$ ,  $|\psi_{I,j}^2 - \psi_j^2| \leq \frac{1}{N} \|\Lambda(S_f - \Sigma_f)\Lambda'\| \leq O(1) \|S_f - \Sigma_f\| = O_P(\frac{1}{\sqrt{T}})$ . This also implies  $\|\Theta_I\| = \psi_{I,1} \sqrt{NT_0} = \sqrt{(c_1 + o_P(1))T_0 N}$ .

Still by Weyl's theorem, for  $j = 1, \dots, \min\{T_0, N\}$ ,

$$\begin{aligned} |\tilde{\psi}_j^2 - \psi_{I,j}^2| &\leq \frac{1}{NT_0} \|\tilde{\Theta}_I \tilde{\Theta}_I' - \Theta_I \Theta_I'\| \\ &\leq \frac{2}{NT_0} \|\Theta_I\| \|\tilde{\Theta}_I - \Theta_I\| + \frac{1}{NT_0} \|\tilde{\Theta}_I - \Theta_I\|^2 = O_P\left(\frac{1}{\sqrt{N}} + \frac{1}{\sqrt{T}}\right). \end{aligned}$$

implying

$$|\tilde{\psi}_j^2 - \psi_j^2| = O_P\left(\frac{1}{\sqrt{N}} + \frac{1}{\sqrt{T}}\right).$$

Then for all  $j \leq K_1$ , with probability approaching one,

$$\begin{aligned} |\psi_{j-1}^2 - \tilde{\psi}_j^2| &\geq |\psi_{j-1}^2 - \psi_j^2| - |\psi_j^2 - \tilde{\psi}_j^2| \geq (c_{j-1} - c_j)/2 \\ |\tilde{\psi}_j^2 - \psi_{j+1}^2| &\geq |\psi_j^2 - \psi_{j+1}^2| - |\tilde{\psi}_j^2 - \psi_j^2| \geq (c_j - c_{j+1})/2 \end{aligned} \quad (\text{C.2})$$

with  $\psi_{K_1+1}^2 = c_{K_1+1} = 0$  because  $\Theta_I \Theta_I'$  has at most  $K_1$  nonzero eigenvalues.

**step 2: characterize the eigenvectors**

Next, we show that there is a  $K_1 \times K_1$  matrix  $H_1$ , so that the columns of  $\frac{1}{\sqrt{N}} \Lambda H_1$  are the first  $K_1$  eigenvectors of  $\Lambda \Sigma_f \Lambda'$ . Let  $L = S_\Lambda^{1/2} \Sigma_f S_\Lambda^{1/2}$ . Let  $R$  be a  $K_1 \times K_1$  matrix whose columns are the eigenvectors of  $L$ . Then  $D = R' L R$  is a diagonal matrix of the eigenvalues of  $L$  that are distinct nonzeros according to Assumption

3.3. Let  $H_1 = S_\Lambda^{-1/2}R$ . Then

$$\begin{aligned}\frac{1}{N}\Lambda\Sigma_f\Lambda'\Lambda H_1 &= \Lambda S_\Lambda^{-1/2}S_\Lambda^{1/2}\Sigma_f S_\Lambda^{1/2}S_\Lambda^{1/2}H_1 = \Lambda S_\Lambda^{-1/2}RR'LR \\ &= \Lambda H_1 D.\end{aligned}$$

Now  $\frac{1}{N}(\Lambda H_1)'\Lambda H_1 = H_1'S_\Lambda H_1 = R'R = I$ . So the columns of  $\Lambda H_1/\sqrt{N}$  are the eigenvectors of  $\Lambda\Sigma_f\Lambda'$ , corresponding to the eigenvalues in  $D$ .

Importantly, the rotation matrix  $H_1$ , by definition, depends only on  $S_\Lambda, \Sigma_f$ , which is time-invariant, and does not depend on the splitted sample.

**step 3: prove the convergence**

We first assume  $\hat{K}_1 = K_1$ . The proof of the consistency is given in step 4 below. Once this is true, then the following argument can be carried out conditional on the event  $\hat{K}_1 = K_1$ . Apply Davis-Kahan sin-theta inequality, and by (C.2),

$$\begin{aligned}\left\|\frac{1}{\sqrt{N}}\tilde{\Lambda}_I - \frac{1}{\sqrt{N}}\Lambda H_1\right\|_F &\leq \frac{\frac{1}{N}\|\Lambda\Sigma_f\Lambda' - \frac{1}{T_0}\tilde{\Theta}_I\tilde{\Theta}_I'\|}{\min_{j \leq K_2} \min\{|\psi_{j-1}^2 - \tilde{\psi}_j^2|, |\tilde{\psi}_j^2 - \psi_{j+1}^2|\}} \\ &\leq O_P(1)\frac{1}{N}\|\Lambda\Sigma_f\Lambda' - \frac{1}{T_0}\tilde{\Theta}_I\tilde{\Theta}_I'\| \\ &\leq O_P(1)\frac{1}{N}\|\Lambda(\Sigma_f - S_f)\Lambda'\| + \frac{1}{NT_0}\|\Theta_I\Theta_I' - \tilde{\Theta}_I\tilde{\Theta}_I'\| = O_P\left(\frac{1}{\sqrt{T}} + \frac{1}{\sqrt{N}}\right).\end{aligned}$$

**step 4: prove  $P(\hat{K}_1 = K_1) = 1$ .**

Note that  $\psi_j(\tilde{\Theta}) = \tilde{\psi}_j\sqrt{NT}$ . By step 1, for all  $j \leq K_1$ ,  $\tilde{\psi}_j^2 \geq c_j - o_P(1) \geq c_j/2$  with probability approaching one. Also,  $\tilde{\psi}_{K_1+1}^2 \leq O_P(T^{-1/2} + N^{-1/2})$ , implying that

$$\min_{j \leq K_1} \psi_j(\tilde{\Theta}) \geq c_{K_1}\sqrt{NT}/2, \quad \max_{j > K_1} \psi_j(\tilde{\Theta}) \leq O_P(T^{-1/2} + N^{-1/2})\sqrt{NT}.$$

In addition,  $(\nu_2\|\tilde{\Theta}\|)^{1/2} \asymp (\sqrt{N+T}\psi_1(\tilde{\Theta}))^{1/2} \asymp (\sqrt{N+T}\sqrt{NT})^{1/2}$ . Thus

$$\min_{j \leq K_1} \psi_j(\tilde{\Theta}) \geq (\nu_2\|\tilde{\Theta}\|)^{1/2}, \quad \max_{j > K_1} \psi_j(\tilde{\Theta}) \leq o_P(1)(\nu_2\|\tilde{\Theta}\|)^{1/2}.$$

This proves the consistency of  $\hat{K}_1$ .

Finally, the proof of the convergence for  $\tilde{A}_I$  and the consistency of  $\hat{K}_2$  follows from the same argument. Q.E.D.

## APPENDIX D. PROOF OF THEOREMS 3.1 AND 3.2

In the many mean model

$$x_{it} = \mu_i + e_{it},$$

we write  $\widehat{e}_{it} = x_{it} - \bar{x}_i$ ,  $\widehat{\mu}_{it} = \bar{x}_i$  and  $\mu_{it} = \mu_i$ . In the factor model

$$x_{it} = l'_i w_t + e_{it},$$

we write  $\widehat{e}_{it} = x_{it} - \widehat{l'_i w_t}$ ,  $\widehat{\mu}_{it} = \widehat{l'_i w_t}$  and  $\mu_{it} = l'_i w_t$ . The proof in this section works for both models.

Let

$$C_{NT} = \min\{\sqrt{N}, \sqrt{T}\}.$$

First recall that  $(\widetilde{f}_s, \dot{\lambda}_i)$  are computed as the preliminary estimators in step 3. The main technical requirement of these estimators is that their estimation effects are negligible, specifically, there is a rotation matrix  $H_1$  that is independent of the sample splitting, for each fixed  $s \in I^c \cup \{t\}$ , and fixed  $i \leq N$ ,

$$\begin{aligned} \frac{1}{N} \sum_j (H'_1 \lambda_j - \dot{\lambda}_j) e_{js} &= O_P(C_{NT}^{-2}), \\ \frac{1}{T} \sum_{s \in I^c \cup \{t\}} f_s (H_1^{-1} f_s - \widetilde{f}_s) e_{is} &= O_P(C_{NT}^{-2}). \end{aligned}$$

These are given in Lemmas E.2 and E.4 below for the many mean model, and Lemmas F.4 and F.6 for the factor model.

**D.1. Behavior of  $\widehat{f}_t$ .** Recall that for each  $t \notin I$ ,

$$(\widehat{f}_{I,t}, \widehat{g}_{I,t}) := \arg \min_{f_t, g_t} \sum_{i=1}^N (\widehat{y}_{it} - \widetilde{\alpha}'_i g_t - \widehat{e}_{it} \widetilde{\lambda}'_i f_t)^2.$$

For notational simplicity, we simply write  $\widehat{f}_t = \widehat{f}_{I,t}$  and  $\widehat{g}_t = \widehat{g}_{I,t}$ , but keep in mind that  $\widetilde{\alpha}$  and  $\widetilde{\lambda}$  are estimated through the low rank estimations on data  $I$ . Note that  $\widetilde{\lambda}_i$  consistently estimates  $\lambda_i$  up to a rotation matrix  $H'_1$ , so  $\widehat{f}_t$  is consistent for  $H_1^{-1} f_t$ . However, as we shall explain below, it is difficult to establish the asymptotic normality for  $\widehat{f}_t$  centered at  $H_1^{-1} f_t$ . Instead, we obtain a new centering quantity, and obtain an expansion for

$$\sqrt{N}(\widehat{f}_t - H_f f_t)$$

with a new rotation matrix  $H_f$  that is also independent of  $t$ . For the purpose of inference for  $\theta_{it}$ , this is sufficient.

Let  $\widehat{w}_{it} = (\widetilde{\lambda}'_i \widehat{e}_{it}, \widetilde{\alpha}'_i)'$ , and  $\widehat{B}_t = \frac{1}{N} \sum_i \widehat{w}_{it} \widehat{w}'_{it}$ . Define  $w_{it} = (\lambda'_i e_{it}, \alpha'_i)'$ , and

$$\widehat{Q}_t = \frac{1}{N} \sum_i \widehat{w}_{it} (\mu_{it} \lambda'_i f_t - \widehat{\mu}_{it} \dot{\lambda}'_i \widetilde{f}_t + u_{it}).$$

We have

$$\begin{aligned} \begin{pmatrix} \widehat{f}_t \\ \widehat{g}_t \end{pmatrix} &= \widehat{B}_t^{-1} \frac{1}{N} \sum_i \widehat{w}_{it} (y_{it} - \widehat{\mu}_{it} \dot{\lambda}'_i \widetilde{f}_t) \\ &= \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix} + \widehat{B}_t^{-1} \widehat{S}_t \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix} + \widehat{B}_t^{-1} \widehat{Q}_t \end{aligned} \quad (\text{D.1})$$

where

$$\widehat{S}_t = \frac{1}{N} \sum_i \begin{pmatrix} \widetilde{\lambda}_i \widehat{e}_{it} (\lambda'_i H_1 e_{it} - \widetilde{\lambda}'_i \widehat{e}_{it}) & \widetilde{\lambda}_i \widehat{e}_{it} (\alpha'_i H_2 - \widetilde{\alpha}'_i) \\ \widetilde{\alpha}_i (\lambda'_i H_1 e_{it} - \widetilde{\lambda}'_i \widehat{e}_{it}) & \widetilde{\alpha}_i (\alpha'_i H_2 - \widetilde{\alpha}'_i) \end{pmatrix}.$$

Note that the “upper block” of  $\widehat{B}_t^{-1} \widehat{S}_t$  is not first-order negligible. Essentially this is due to the fact that the moment condition

$$\frac{\partial}{\partial \lambda_i} \mathbb{E} e_{it} (\dot{y}_{it} - \alpha'_i g_t - e_{it} \lambda'_i f_t) \neq 0,$$

so is not “Neyman orthogonal” with respect to  $\lambda_i$ . On the other hand, we can get around such difficulty. In Lemma E.5 below, we show that  $\widehat{B}_t$  and  $\widehat{S}_t$  both converge in probability to block diagonal matrices that are independent of  $t$ . So  $g_t$  and  $f_t$  are “orthogonal”, and

$$\widehat{B}_t^{-1} \widehat{S}_t = \begin{pmatrix} \bar{H}_3 & 0 \\ 0 & \bar{H}_4 \end{pmatrix} + o_P(N^{-1/2}).$$

Define  $H_f := H_1^{-1} + \bar{H}_3 H_1^{-1}$ . Then (D.1) implies that

$$\widehat{f}_t = H_f f_t + \text{upper block of } \widehat{B}_t^{-1} \widehat{Q}_t.$$

Therefore  $\widehat{f}_t$  converges to  $f_t$  up to a new rotation matrix  $H_f$ , which equals  $H_1^{-1}$  up to an  $o_P(1)$  term  $\bar{H}_3 H_1^{-1}$ . While the effect of  $\bar{H}_3$  is not negligible, it is “absorbed” into the new rotation matrix. As such, we are able to establish the asymptotic normality for  $\sqrt{N}(\widehat{f}_t - H_f f_t)$ .

**Proposition D.1.** *For each fixed  $t \notin I$ , for both the (i) many mean model and (ii) factor model, we have*

$$\hat{f}_t - H_f f_t = H_f \left( \frac{1}{N} \sum_i \lambda_i \lambda_i' \mathbb{E} e_{it}^2 \right)^{-1} \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} + O_P(C_{NT}^{-2}).$$

*Proof.* Define

$$B = \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i \lambda_i' H_1 \mathbb{E} e_{it}^2 & 0 \\ 0 & H_2' \alpha_i \alpha_i' H_2 \end{pmatrix}, \quad S = \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') \mathbb{E} e_{it}^2 & 0 \\ 0 & \tilde{\alpha}_i' (\alpha_i' H_2 - \tilde{\alpha}_i') \end{pmatrix}.$$

Both  $B, S$  are independent of  $t$  due to the stationarity of  $e_{it}^2$ . But  $S$  depends on the sample splitting through  $(\tilde{\lambda}_i, \tilde{\alpha}_i)$ .

From (D.1),

$$\begin{aligned} \begin{pmatrix} \hat{f}_t \\ \hat{g}_t \end{pmatrix} &= (B^{-1}S + \mathbb{I}) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix} + B^{-1} \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i e_{it} \\ H_2' \alpha_i \end{pmatrix} u_{it} \\ &\quad + \sum_{d=1}^5 A_{dt}, \text{ where} \\ A_{1t} &= (\hat{B}_t^{-1} \hat{S}_t - B^{-1}S) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix} \\ A_{2t} &= (\hat{B}_t^{-1} - B^{-1}) \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i e_{it} \\ H_2' \alpha_i \end{pmatrix} u_{it} \\ A_{3t} &= \hat{B}_t^{-1} \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \hat{e}_{it} - H_1' \lambda_i e_{it} \\ \tilde{\alpha}_i - H_2' \alpha_i \end{pmatrix} u_{it} \\ A_{4t} &= \hat{B}_t^{-1} \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \hat{e}_{it} - H_1' \lambda_i e_{it} \\ \tilde{\alpha}_i - H_2' \alpha_i \end{pmatrix} (\mu_{it} \lambda_i' f_t - \hat{\mu}_{it} \dot{\lambda}_i' \tilde{f}_t) \\ A_{5t} &= (\hat{B}_t^{-1} - B^{-1}) \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i e_{it} \\ H_2' \alpha_i \end{pmatrix} (\mu_{it} \lambda_i' f_t - \hat{\mu}_{it} \dot{\lambda}_i' \tilde{f}_t) \\ A_{6t} &= B^{-1} \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i e_{it} \\ H_2' \alpha_i \end{pmatrix} (\mu_{it} \lambda_i' f_t - \hat{\mu}_{it} \dot{\lambda}_i' \tilde{f}_t). \end{aligned} \tag{D.2}$$

Note that  $B^{-1}S$  is a block-diagonal matrix, with the upper block being

$$\bar{H}_3 := H_1^{-1} \left( \frac{1}{N} \sum_i \lambda_i \lambda_i' \mathbb{E} e_{it}^2 \right)^{-1} \frac{1}{N} \sum_i \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') \mathbb{E} e_{it}^2.$$

Define

$$H_f := (\bar{H}_3 + \mathbb{I}) H_1^{-1}.$$

Fixed  $t \in I^c$ , in the many mean model, in Lemma E.7 we show that  $\sum_{d=1}^5 A_{dt} = O_P(C_{NT}^{-2})$  and for the “upper block” of  $A_{6t}$ ,  $\frac{1}{N} \sum_i \lambda_i e_{it} (\mu_i \lambda'_i f_t - \bar{x}_i \dot{\lambda}'_i \tilde{f}_t) = O_P(C_{NT}^{-2})$ .

On the other hand, in the factor model, in Lemma F.9 we show that  $\sum_{d=2}^5 A_{dt} = O_P(C_{NT}^{-2})$ , the “upper block” of  $A_{6t}$ ,  $\frac{1}{N} \sum_i \lambda_i e_{it} (\ell'_i w_t \lambda'_i f_t - \widehat{\ell'_i w_t} \dot{\lambda}'_i \tilde{f}_t) = O_P(C_{NT}^{-2})$  and the upper block of  $A_{1t}$  is  $O_P(C_{NT}^{-2})$ . Therefore, in both models,

$$\hat{f}_t = H_f f_t + H_1^{-1} \left( \frac{1}{N} \sum_i \lambda_i \lambda'_i \mathbf{E} e_{it}^2 \right)^{-1} \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} + O_P(C_{NT}^{-2}).$$

Given that  $\bar{H}_3 = O_P(C_{NT}^{-1})$  we have  $H_1^{-1} = H_f + O_P(C_{NT}^{-1})$ . By  $\frac{1}{N} \sum_i \lambda_i e_{it} u_{it} = O_P(N^{-1/2})$ ,

$$\hat{f}_t = H_f f_t + H_f \left( \frac{1}{N} \sum_i \lambda_i \lambda'_i \mathbf{E} e_{it}^2 \right)^{-1} \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} + O_P(C_{NT}^{-2}). \quad (\text{D.3})$$

Q.E.D.

**D.2. Behavior of  $\hat{\lambda}_i$ .** Recall that fix  $i \leq N$ ,

$$(\hat{\lambda}_{I,i}, \hat{\alpha}_{I,i}) = \arg \min_{\lambda_i, \alpha_i} \sum_{s \in I^c \cup \{t\}} (\hat{y}_{is} - \alpha'_i \hat{g}_{I,s} - \hat{e}_{is} \lambda'_i \hat{f}_{I,s})^2.$$

For notational simplicity, we simply write  $\hat{\lambda}_i = \hat{\lambda}_{I,i}$  and  $\hat{\alpha}_i = \hat{\alpha}_{I,i}$ , but keep in mind that  $\tilde{\alpha}$  and  $\tilde{\lambda}$  are estimated through the low rank estimations on data  $I$ . Write

$$T_0 = |I^c|_0.$$

$$(B^{-1}S + \mathbf{I}) \begin{pmatrix} H_1^{-1} & 0 \\ 0 & H_2^{-1} \end{pmatrix} := \begin{pmatrix} H_f & 0 \\ 0 & H_g \end{pmatrix}$$

$$\hat{D}_i = \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} \hat{f}_s \hat{f}'_s \hat{e}_{is}^2 & \hat{f}_s \hat{g}'_s \hat{e}_{is} \\ \hat{g}_s \hat{f}'_s \hat{e}_{is} & \hat{g}_s \hat{g}'_s \end{pmatrix}, \quad D_i = \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} H_f f_s f'_s H'_f \mathbf{E} e_{is}^2 & 0 \\ 0 & H_g g_s g'_s H'_g \end{pmatrix}$$

(D.4)

**Proposition D.2.** *For both the (i) many mean model and (ii) factor model,*

$$\hat{\lambda}_i = H_f'^{-1} \lambda_i + H_f'^{-1} \left( \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} f_s f'_s \mathbf{E} e_{is}^2 \right)^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} f_s e_{is} u_{is} + O_P(C_{NT}^{-2}).$$

*Proof.* By definition and (D.2),

$$\begin{pmatrix} \hat{\lambda}_i \\ \hat{\alpha}_i \end{pmatrix} = \hat{D}_i^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} \hat{f}_s \hat{e}_{is} \\ \hat{g}_s \end{pmatrix} (y_{is} - \hat{\mu}_{is} \dot{\lambda}'_i \tilde{f}_s)$$

$$\begin{aligned}
&= \begin{pmatrix} H_f'^{-1} \lambda_i \\ H_g'^{-1} \alpha_i \end{pmatrix} + D_i^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} H_f f_s e_{is} \\ H_g g_s \end{pmatrix} u_{is} + \sum_{d=1}^6 R_{di}, \quad \text{where,} \\
R_{1i} &= (\hat{D}_i^{-1} - D_i^{-1}) \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} H_f f_s e_{is} \\ H_g g_s \end{pmatrix} u_{is} \\
R_{2i} &= \hat{D}_i^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} H_f f_s (\hat{e}_{is} - e_{is}) u_{is} \\ 0 \end{pmatrix} \\
R_{3i} &= (\hat{D}_i^{-1} - D_i^{-1}) \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} \hat{f}_s \hat{e}_{is} \\ \hat{g}_s \end{pmatrix} (\mu_{is} \lambda_i' f_s - \hat{\mu}_{is} \dot{\lambda}_i' \tilde{f}_s) \\
R_{4i} &= D_i^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} \hat{f}_s \hat{e}_{is} \\ \hat{g}_s \end{pmatrix} (\mu_{is} \lambda_i' f_s - \hat{\mu}_{is} \dot{\lambda}_i' \tilde{f}_s) \\
R_{5i} &= \hat{D}_i^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} \hat{e}_{is} & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \hat{f}_s - H_f f_s \\ \hat{g}_s - H_g g_s \end{pmatrix} u_{is} \\
R_{6i} &= \hat{D}_i^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} \hat{f}_s \hat{e}_{is} \\ \hat{g}_s \end{pmatrix} (\lambda_i' H_f^{-1}, \alpha_i' H_g^{-1}) \begin{pmatrix} \hat{e}_{is} & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \hat{f}_s - H_f f_s \\ \hat{g}_s - H_g g_s \end{pmatrix} \quad \text{(D.5)}
\end{aligned}$$

In addition,  $\hat{D}_i - D_i = o_P(1)$  and the upper blocks of  $R_{di}$  are all  $O_P(C_{NT}^{-2})$  for  $d = 1, \dots, 6$ . This is proved by Lemmas E.9, E.10 in the many mean model, and by Lemma F.13, F.15 in the factor model. Hence

$$\hat{\lambda}_i = H_f'^{-1} \lambda_i + H_f'^{-1} \left( \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} f_s f_s' E e_{is}^2 \right)^{-1} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} f_s e_{is} u_{is} + O_P(C_{NT}^{-2}).$$

Q.E.D.

**D.3. Proof of normality of  $\hat{\theta}_{it}$ .** Suppose  $T$  is odd and  $|I|_0 = |I^c|_0 = (T-1)/2$ . By Propositions D.1 D.2, for fixed  $t \notin I$ ,

$$\begin{aligned}
\hat{\lambda}_{I,i}' \hat{f}_{I,t} - \lambda_i' f_t &= f_t' \left( \frac{1}{|I^c|_0} \sum_{s \in I^c \cup \{t\}} f_s f_s' E e_{is}^2 \right)^{-1} \frac{1}{|I^c|_0} \sum_{s \in I^c \cup \{t\}} f_s e_{is} u_{is} \\
&\quad + \lambda_i' \left( \frac{1}{N} \sum_i \lambda_i \lambda_i' E e_{it}^2 \right)^{-1} \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} \\
&\quad + O_P(C_{NT}^{-2}).
\end{aligned}$$

Exchanging  $I$  with  $I^c$ , we have, for  $t \notin I^c$ ,

$$\hat{\lambda}_{I^c,i}' \hat{f}_{I^c,t} - \lambda_i' f_t = f_t' \left( \frac{1}{|I|_0} \sum_{s \in I} f_s f_s' E e_{is}^2 \right)^{-1} \frac{1}{|I|_0} \sum_{s \in I} f_s e_{is} u_{is}$$

$$\begin{aligned}
& + \lambda'_i \left( \frac{1}{N} \sum_i \lambda_i \lambda'_i \mathbf{E} e_{it}^2 \right)^{-1} \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} \\
& + O_P(C_{NT}^{-2}).
\end{aligned}$$

Note that the fixed  $t \notin I \cup I^c$ , so take the average:

$$\begin{aligned}
\hat{\theta}_{it} - \lambda'_i f_t &= f'_t \left[ \left( \frac{1}{|I|_0} \sum_{s \in I} f_s f'_s \mathbf{E} e_{is}^2 \right)^{-1} \frac{1}{2|I|_0} \sum_{s \in I} f_s e_{is} u_{is} + \left( \frac{1}{|I^c|_0} \sum_{s \in I^c \cup \{t\}} f_s f'_s \mathbf{E} e_{is}^2 \right)^{-1} \frac{1}{2|I^c|_0} \sum_{s \in I^c \cup \{t\}} f_s e_{is} u_{is} \right. \\
& \left. + \lambda'_i \left( \frac{1}{N} \sum_i \lambda_i \lambda'_i \mathbf{E} e_{it}^2 \right)^{-1} \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} + O_P(C_{NT}^{-2}) \right].
\end{aligned}$$

Let  $V_{f1} = \frac{1}{T} \sum_{s=1}^T f_s f'_s \mathbf{E} e_{is}^2$ . By the assumption that

$$\frac{1}{|I|_0} \sum_{s \in I} f_s f'_s \mathbf{E} e_{is}^2 = V_{f1} + o_P(1) = \frac{1}{|I^c|_0} \sum_{s \in I^c \cup \{t\}} f_s f'_s \mathbf{E} e_{is}^2,$$

the first term in the above expansion is then  $o_P(T^{-1/2})$  plus

$$f'_t V_{f1}^{-1} \left[ \frac{1}{T} \sum_{s \in I} f_s e_{is} u_{is} + \frac{1}{T} \sum_{s \in I^c \cup \{t\}} f_s e_{is} u_{is} \right] = f'_t V_{f1}^{-1} \frac{1}{T} \sum_{s=1}^T f_s e_{is} u_{is} + O_P(T^{-1}).$$

In addition, let  $\xi_{NT} = \lambda'_i V_{\lambda 1}^{-1} \frac{1}{\sqrt{N}} \sum_j \lambda_j e_{jt} u_{jt}$  and  $\zeta_{NT} = f'_t V_{f1}^{-1} \frac{1}{\sqrt{T}} \sum_{s=1}^T f_s e_{is} u_{is}$ . Then

$$\hat{\theta}_{it} - \theta_{it} = \zeta_{NT} / \sqrt{T} + \xi_{NT} / \sqrt{N} + O_P(C_{NT}^{-2}) + o_P(T^{-1/2}).$$

Next, write  $\Sigma_{NT}^{1/2} = (\frac{1}{T} f'_t V_f f_t + \frac{1}{N} \lambda_i V_\lambda \lambda_i)^{1/2}$ . Then regardless of  $T/N \in [0, \infty]$ ,

$$\begin{aligned}
\left( \frac{O_P(C_{NT}^{-2}) + o_P(T^{-1/2})}{\Sigma_{NT}^{1/2}} \right)^2 &= O_P \left( \frac{1}{T f'_t V_f f_t + \frac{T^2}{N} \lambda_i V_\lambda \lambda_i} \right) \\
&+ O_P \left( \frac{1}{\frac{N^2}{T} f'_t V_f f_t + N \lambda_i V_\lambda \lambda_i} \right) + o_P(1) = o_P(1)
\end{aligned}$$

Next,  $\text{Cov}(\xi_{NT}, \zeta_{NT}) = \frac{1}{\sqrt{NT}} \sum_j \mathbf{E} \lambda'_i V_{\lambda 1}^{-1} \lambda_j f'_t V_{f1}^{-1} f_s e_{jt} e_{it} \mathbf{E}(u_{jt} u_{it} | E, F) \rightarrow 0$ . So  $(\zeta_{NT}, \xi_{NT}) \rightarrow^d (\zeta, \xi)$ , where  $(\zeta, \xi)$  is a bivariate Gaussian random vector, with mean zero, and covariance  $\text{diag}\{f'_t V_f f_t, \lambda'_i V_\lambda \lambda_i\}$ . We now use the same argument as the proof of Theorem 3 in Bai (2003). There exist  $(\zeta_{NT}^*, \xi_{NT}^*)$  and  $(\zeta^*, \xi^*)$  with the same distribution as  $(\zeta_{NT}, \xi_{NT})$  and  $(\zeta, \xi)$  such that  $(\zeta_{NT}^*, \xi_{NT}^*) \rightarrow (\zeta^*, \xi^*)$  almost



surely (almost sure representation). Then

$$\begin{aligned}
\frac{\zeta_{NT}/\sqrt{T} + \xi_{NT}/\sqrt{N}}{\Sigma_{NT}^{1/2}} &=^d \frac{\zeta_{NT}^*/\sqrt{T} + \xi_{NT}^*/\sqrt{N}}{\Sigma_{NT}^{1/2}} \\
&= \underbrace{\frac{\zeta^*/\sqrt{T} + \xi^*/\sqrt{N}}{\Sigma_{NT}^{1/2}}}_{\mathcal{N}(0,1)} + \underbrace{\frac{(\zeta_{NT}^* - \zeta^*)}{(f_t' V_f f_t + \frac{T}{N} \lambda_i V_\lambda \lambda_i)^{1/2}}}_{a_1} + \underbrace{\frac{(\xi_{NT}^* - \xi^*)}{(\frac{N}{T} f_t' V_f f_t + \lambda_i V_\lambda \lambda_i)^{1/2}}}_{a_2} \\
&=^d \mathcal{N}(0, 1) + o(1),
\end{aligned}$$

where  $a_1 \rightarrow 0$  and  $a_2 \rightarrow 0$  almost surely regardless of  $T/N \in [0, \infty]$ . Therefore,

$$\frac{\hat{\theta}_{it} - \theta_{it}}{\Sigma_{NT}^{1/2}} \rightarrow^d \mathcal{N}(0, 1).$$

Q.E.D.

## APPENDIX E. TECHNICAL LEMMAS IN THE MANY MEAN MODEL

**E.1. Behavior of the preliminary in the many mean model.** Recall that

$$(\tilde{f}_s, \tilde{g}_s) := \arg \min_{f_s, g_s} \sum_{i=1}^N (y_{is} - \tilde{\alpha}'_i g_s - x_{is} \tilde{\lambda}'_i f_s)^2, \quad s \in I^c \cup \{t\}.$$

and

$$(\dot{\lambda}_i, \dot{\alpha}_i) = \arg \min_{\lambda_i, \alpha_i} \sum_{s \in I^c \cup \{t\}} (y_{is} - \alpha'_i \tilde{g}_s - x_{is} \lambda'_i \tilde{f}_s)^2, \quad i = 1, \dots, N.$$

The goal of this section is to show that the effect of the preliminary estimation is negligible. Specifically, we aim to show, for each fixed  $t \in I^c$ , fixed  $i \leq N$ ,

$$\begin{aligned}
\frac{1}{\sqrt{N}} \sum_j (H_1' \lambda_j - \dot{\lambda}_j) e_{jt} &= O_P(\sqrt{N} C_{NT}^{-2}), \\
\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s (H_1^{-1} f_s - \tilde{f}_s) e_{is} &= O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

Throughout the proof below, we treat  $|I^c| = T$  instead of  $T/2$  to avoid keeping the constant “2”. In addition, for notational simplicity, we write  $\tilde{\Lambda} = \tilde{\Lambda}_I$  and  $\tilde{A} = \tilde{A}_I$  by suppressing the subscripts, but we should keep in mind that  $\tilde{\Lambda}$  and  $\tilde{A}$  are estimated on data  $D_I$  as defined in step 2. In addition, let  $\mathbf{E}_I$  and  $\mathbf{Var}_I$  be the conditional expectation and variance, given  $D_I$ . Recall that  $X_s$  be the vector of  $x_{is}$  fixing  $s \leq T$ , and  $M_{\tilde{\alpha}} = I_N - \tilde{A}(\tilde{A}'\tilde{A})^{-1}\tilde{A}'$ ;  $X_i$  be the vector of  $x_{is}$  fixing

$i \leq N$ , and  $M_{\tilde{g}} = I - \tilde{G}(\tilde{G}'\tilde{G})^{-1}\tilde{G}'$ , for  $\tilde{G}$  as the  $|I^c|_0 \times K_1$  matrix of  $\tilde{g}_s$ . Define  $\tilde{F}$  similarly.

Also,

$$\begin{aligned}\tilde{D}_{fs} &= \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) \tilde{\Lambda} \\ D_{fs} &= \frac{1}{N} \Lambda' (\text{diag}(X_s) M_{\alpha} \text{diag}(X_s) \Lambda \\ D_f &= \frac{1}{N} \Lambda' E((\text{diag}(X_s) M_{\alpha} \text{diag}(X_s)) \Lambda \\ \tilde{D}_{\lambda_i} &= \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) \tilde{F} \\ D_{\lambda_i} &= \frac{1}{T} F' (\text{diag}(X_i) M_g \text{diag}(X_i)) F \\ \bar{D}_{\lambda_i} &= \frac{1}{T} F' E(\text{diag}(X_i) M_g \text{diag}(X_i)) F\end{aligned}$$

By the stationarity,  $D_f$  does not depend on  $s$ .

**Lemma E.1.** *Suppose  $\max_{is} x_{is}^2 = o_P(C_{NT})$ . Also, there is  $c > 0$ , so that  $\min_s \min_j \psi_j(D_{fs}) > c$ . Then*

- (i)  $\max_s \|\tilde{D}_{fs}^{-1}\| = O_P(1)$ .
- (ii)  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\tilde{D}_{fs}^{-1} - (H_1' D_f H_1)^{-1}\|^2 = O_P(C_{NT}^{-2})$ .

*Proof.* (i) The eigenvalues of  $D_{fs}$  are bounded from zero uniformly in  $s \leq T$ . Also,

$$\begin{aligned}\tilde{D}_{fs} - H_1' D_{fs} H_1 &= \sum_l \delta_l, \quad \text{where} \\ \delta_1 &= \frac{1}{N} (\tilde{\Lambda} - \Lambda H_1)' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) \tilde{\Lambda}, \\ \delta_2 &= \frac{1}{N} H_1' \Lambda' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\tilde{\Lambda} - \Lambda H_1) \\ \delta_3 &= \frac{1}{N} H_1' \Lambda' \text{diag}(X_s) (M_{\tilde{\alpha}} - M_{\alpha}) \text{diag}(X_s) \Lambda H_1. \quad (\text{E.1})\end{aligned}$$

We now bound each term uniformly in  $s \leq T$ . The first term is

$$\frac{1}{N} (\tilde{\Lambda} - \Lambda H_1)' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) \tilde{\Lambda} \leq O_P(1) \frac{1}{\sqrt{N}} \|\tilde{\Lambda} - \Lambda H_1\|_F \max_{is} x_{is}^2 = o_P(1)$$

provided that  $\max_{is} x_{is}^2 = o_P(C_{NT})$ . The second term is bounded similarly. The third term is bounded by

$$O_P(1) \max_{is} x_{is}^2 \|M_{\tilde{\alpha}} - M_{\alpha}\| = O_P(1) \frac{1}{\sqrt{N}} \|\tilde{A} - A H_2\|_F \max_{is} x_{is}^2 = o_P(1).$$

This implies  $\max_s \|\tilde{D}_{fs} - H'_1 D_{fs} H_1\| = o_P(1)$ . In addition, because of the convergence of  $\|\frac{1}{\sqrt{N}}(\tilde{\Lambda} - \Lambda H_1)\|_F$ , we have  $\min_j \psi_j(H'_1 H_1) \geq C \min_j \psi_j(\frac{1}{N} H'_1 \Lambda' \Lambda H_1)$ , bounded away from zero. Thus  $\min_s \min_j \psi_j(H'_1 D_{fs} H_1) \geq \min_s \min_j \psi_j(D_{fs})C$ , bounded away from zero. This together with  $\max_s \|\tilde{D}_{fs} - H'_1 D_{fs} H_1\| = o_P(1)$  imply  $\min_s \|\tilde{D}_{fs}^{-1}\| = O_P(1)$ .

(ii) By (E.1),

$$\begin{aligned} & \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\tilde{D}_{fs}^{-1} - (H'_1 D_f H_1)^{-1}\|^2 \\ & \leq \frac{1}{T} \sum_s \|\tilde{D}_{fs} - (H'_1 D_f H_1)\|^2 \|(H'_1 D_f H_1)^{-2}\| \max_s \|\tilde{D}_{fs}^{-2}\| \\ & \leq O_P(1) \frac{1}{T} \sum_s \|\tilde{D}_{fs} - (H'_1 D_f H_1)\|^2 \\ & = O_P(1) \sum_{l=1}^3 \frac{1}{T} \sum_s \|\delta_l\|^2 + O_P(1) \frac{1}{T} \sum_s \|D_{fs} - D_f\|^2. \end{aligned}$$

We bound each term below.

$$\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\delta_1\|^2 \leq \frac{1}{N^2} \sum_{ij} \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \|\tilde{\lambda}_j\|^2 \frac{1}{T} \sum_{s \in I^c \cup \{t\}} x_{is}^2 x_{js}^2.$$

Note that  $\{e_{is}\}$  is serially independent, so  $x_{is}^2 x_{js}^2$  is independent of  $\|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \|\tilde{\lambda}_j - H'_1 \lambda_j\|^2$  for  $s \in I^c \cup \{t\}$ . Take the conditional expectation  $\mathbf{E}_I$ . Then  $\mathbf{E}_I x_{is}^2 x_{js}^2$  equals the unconditional expectation, and is bounded uniformly over  $(s, i, j)$ .

$$\begin{aligned} \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\delta_1\|^2 & \leq O_P(1) \frac{1}{N^2} \sum_{ij} \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \|\tilde{\lambda}_j\|^2 \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbf{E}_I x_{is}^2 x_{js}^2 \\ & \leq O_P(1) \frac{1}{N^2} \sum_{ij} \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \|\tilde{\lambda}_j\|^2 = O_P(C_{NT}^{-2}). \end{aligned}$$

Term of  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\delta_2\|^2$  is bounded similarly.

$$\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\delta_3\|^2 \leq O_P(1) \|M_{\tilde{\alpha}} - M_{\alpha}\| = O_P(C_{NT}^{-2}).$$

Finally, let  $M_{\alpha,ij}$  and  $P_{\alpha,ij}$  be the  $(i, j)$  th component of  $M_{\alpha}$  and  $A(A'A)^{-1}A'$ . Then  $P_{\alpha,ij} = \frac{1}{N} \alpha'_i (\frac{1}{N} A'A)^{-1} \alpha_j$ . Let  $p_i = (\frac{1}{N} A'A)^{-1/2} \alpha_i$ . We have,

$$\frac{1}{T} \sum_s \|D_{fs} - D_f\|^2 \leq \frac{1}{T} \sum_s \left\| \frac{1}{N} \sum_{ij} \lambda_i \lambda'_j M_{\alpha,ij} (x_{is} x_{js} - \mathbf{E} x_{is} x_{js}) \right\|_F^2$$

$$= \frac{1}{T} \sum_s \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i M_{\alpha,ii} (x_{is}^2 - \mathbb{E} x_{is}^2) - \frac{1}{N^2} \sum_{i \neq j} \lambda_i \lambda'_j p'_j p_j (x_{is} x_{js} - \mathbb{E} x_{is} x_{js}) \right\|_F^2.$$

As for the first term, it equals  $\frac{1}{T} \sum_s \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i M_{\alpha,ii} (e_{is}^2 - \mathbb{E} e_{is}^2) + \frac{2}{N} \sum_i \lambda_i \lambda'_i M_{\alpha,ii} \mu_i e_{is} \right\|_F^2 = O_P(N^{-1})$  provided that  $\frac{1}{N} \sum_{ij} |\text{Cov}(e_{is}^2, e_{js}^2)| < \infty$  and  $\|\mathbb{E} e_s e'_s\| < \infty$ . As for the second term, we can consider each element of  $\lambda_i$  and  $p_i$ , as the dimensions of both vectors are finite. So without loss of generality we assume  $\dim(\lambda_i) = \dim(p_i) = 1$ . Then,

$$\begin{aligned} & \mathbb{E} \frac{1}{T} \sum_s \left| \frac{1}{N^2} \sum_{i \neq j} \lambda_i \lambda_j p_i p_j (x_{is} x_{js} - \mathbb{E} x_{is} x_{js}) \right|^2 \\ & \leq 2 \frac{1}{T} \sum_s \mathbb{E} \left| \frac{1}{N^2} \sum_{ij} \lambda_i \lambda_j p_i p_j (x_{is} x_{js} - \mathbb{E} x_{is} x_{js}) \right|^2 + O(N^{-2}) \\ & \leq 8 \text{Var} \left( \frac{1}{N} \sum_j \lambda_j p_j e_{js} \right) \left( \frac{1}{N} \sum_i \lambda_i p_i \mu_i \right)^2 + \text{Var} \left( \left( \frac{1}{N} \sum_i \lambda_i p_i e_{is} \right)^2 \right) + O(N^{-2}) \\ & = O(N^{-1}). \end{aligned}$$

provided that  $\|\mathbb{E} e_s e'_s\| < \infty$  and  $\frac{1}{N^3} \sum_{ijkl} \text{Cov}(e_{is} e_{js}, e_{ks} e_{ls}) < C$ . So  $\frac{1}{T} \sum_s \|D_{fs} - D_f\|^2 = O_P(N^{-1})$ . Put together,  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\tilde{D}_{fs}^{-1} - (H_1' D_f H_1)^{-1}\|^2 = O_P(C_{NT}^{-2})$ .

**Lemma E.2.** (i) For each fixed  $t \in I^c$ ,  $H_1^{-1} f_t - \tilde{f}_t = O_P(C_{NT}^{-1})$ .

(ii) For each fixed  $i \leq N$ ,  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s (H_1^{-1} f_s - \tilde{f}_s) e_{is} = O_P(\sqrt{T} C_{NT}^{-2})$ .

*Proof.* Without loss of generality, we assume  $\dim(g_s) = \dim(f_s) = 1$ , as we can always work with their elements given that the number of factors is fixed. Then for  $y_s = A g_s + \text{diag}(X_s) \Lambda f_s + u_s$ ,

$$\begin{aligned} \tilde{f}_s &= \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} y_s \\ &= H_1^{-1} f_s + \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} (A H_2 - \tilde{A}) H_2^{-1} g_s \\ &\quad + \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \\ &\quad + \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s. \end{aligned} \tag{E.2}$$

Part (ii) that  $H_1^{-1} f_t - \tilde{f}_t = O_P(C_{NT}^{-1})$  follows from a straightforward calculation. So we omit the details. We now prove the much harder part (i) by plugging in each term in the above expansion to  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s (H_1^{-1} f_s - \tilde{f}_s) e_{is}$ .

First term: note that  $\frac{1}{NT} \sum_s \|g_s f_s e_{is}\|^2 \|\tilde{\Lambda}' \text{diag}(X_s)\|_F^2 < C$  provided that  $\mathbf{E} g_s^2 f_s^2 e_{is}^2 x_{is}^2 < \infty$ . So for a fixed  $i \leq N$ , by Lemma E.1.

$$\begin{aligned}
& \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (\tilde{D}_{fs}^{-1} - (H_1' D_x H_1)^{-1}) \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} (A H_2 - \tilde{A}) H_2^{-1} g_s \\
& \leq O_P(\sqrt{T} C_{NT}^{-1}) \left( \frac{1}{T} \sum_s \left\| \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) \right\|^2 \|g_s\|^2 \|f_s e_{is}\|^2 \|A H_2 - \tilde{A}\|^2 \right)^{1/2} \\
& \leq O_P(\sqrt{T} C_{NT}^{-2}) = o_P(1). \\
& \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} (A H_2 - \tilde{A}) H_2^{-1} g_s \\
& \leq O_P(C_{NT}^{-1}) \left\| \frac{1}{\sqrt{TN}} \sum_s f_s g_s e_{is} (H_1' D_x H_1)^{-1} \tilde{\Lambda}' \text{diag}(X_s) \right\| \\
& \leq O_P(\sqrt{T} C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \tilde{\lambda}_j^2 \left( \frac{1}{T} \sum_s f_s g_s e_{is} x_{js} \right)^2 \right]^{1/2}
\end{aligned}$$

To bound the last line, note that  $e_{is}$  is conditionally serially independent, given

$$\begin{aligned}
& \mathbf{E}_I \frac{1}{N} \sum_j \tilde{\lambda}_j^2 \left( \frac{1}{T} \sum_s f_s g_s e_{is} x_{js} \right)^2 = \frac{1}{N} \sum_j \tilde{\lambda}_j^2 \mathbf{E}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} x_{js} \right)^2 \\
& \leq \frac{1}{N} \sum_j (\tilde{\lambda}_j - H_1' \lambda_j)^2 + O_P(1) \frac{1}{N} \sum_j \mathbf{E}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} x_{js} \right)^2 \\
& = O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_j \mathbf{E}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} e_{js} \right)^2 + O_P(1) \mathbf{E}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} \right)^2 \\
& \leq O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbf{E}_I f_s g_s \mathbf{E}(e_{is} e_{js} | D_I, f_s, g_s) \right)^2 \\
& \quad + O_P(1) \text{Var}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} e_{js} \right) + O_P(1) \text{Var}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} \right) \\
& \leq^* O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_j \left| \frac{1}{T} \sum_s \mathbf{E}_I f_s g_s \mathbf{E}(e_{is} e_{js} | D_I, f_s, g_s) \right| + O_P(T^{-1}) \\
& \leq O_P(C_{NT}^{-2}) + O_P(N^{-1}) \frac{1}{T} \sum_s \mathbf{E}_I |f_s g_s| \max_{i,s,f_s,g_s} \sum_j |\mathbf{E}(e_{is} e_{js} | f_s, g_s)| + O_P(T^{-1}) \\
& \leq O_P(C_{NT}^{-2}),
\end{aligned}$$

where  $\leq^*$  is due to  $|\mathbf{E}_I f_s g_s e_{is} e_{js}| < \infty$ . Put together,

$$\frac{1}{\sqrt{T}} \sum_s f_s e_{is} \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} (A H_2 - \tilde{A}) H_2^{-1} g_s = O_P(\sqrt{T} C_{NT}^{-2}).$$

Second term: recall that  $M_{\tilde{\alpha},ij}$  and  $P_{\tilde{\alpha},ij}$  are the  $(i,j)$  th component of  $M_{\tilde{\alpha}}$  and  $\tilde{A}(\tilde{A}'\tilde{A})^{-1}\tilde{A}'$  and  $P_{\tilde{\alpha},ij} = \frac{1}{N}p'_ip_j$ .

$$\begin{aligned}
& \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (\tilde{D}_{fs}^{-1} - (H'_1 D_x H_1)^{-1}) \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \\
& \leq O_P(\sqrt{TN} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \left\| \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) \right\|^2 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& \leq O_P(\sqrt{TN} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \frac{1}{N^2} \sum_j \tilde{\lambda}_j^2 x_{js}^4 M_{\tilde{\alpha},jj}^2 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& \quad + O_P(\sqrt{TN} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \frac{1}{N^2} \sum_j \left[ \frac{1}{N} \sum_{k \neq j} \tilde{\lambda}_k x_{ks} p'_k p_j x_{js} \right]^2 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& \leq O_P(\sqrt{T} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \frac{1}{N} \sum_j \tilde{\lambda}_j^2 \mathbb{E}_I x_{js}^4 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& \quad + O_P(\sqrt{T} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \frac{1}{N^2} \sum_{k \neq j} x_{ks}^2 (p'_k p_j)^2 x_{js}^2 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& = O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

It is also straightforward to prove that

$$\begin{aligned}
& \left( \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (H'_1 D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) (M_{\tilde{\alpha}} - M_{\alpha}) \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \right)^2 \\
& \leq O_P(T) \frac{1}{T} \sum_s \|f_s^2 e_{is} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s)\|^2 \frac{1}{T} \sum_s \|\text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda})\|^2 \|M_{\tilde{\alpha}} - M_{\alpha}\|^2 \\
& \leq O_P(T C_{NT}^{-4}).
\end{aligned}$$

Next, let  $z_{js} = \sum_k \tilde{\lambda}_k M_{\alpha,kj} x_{ks}$ ,

$$\begin{aligned}
& \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (H'_1 D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\alpha} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \\
& \leq O_P(\sqrt{T} C_{NT}^{-1}) \left\| \frac{1}{T} \sum_s f_s^2 e_{is} (H'_1 D_x H_1)^{-1} \frac{1}{\sqrt{N}} \tilde{\Lambda}' \text{diag}(X_s) M_{\alpha} \text{diag}(X_s) \right\| \\
& \leq O_P(\sqrt{T} C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s f_s^2 e_{is} z_{js} x_{js} \right)^2 \right]^{1/2}
\end{aligned}$$

To bound the last line, note that

$$\frac{1}{N} \sum_j \mathbb{E}_I \left( \frac{1}{T} \sum_s f_s^2 e_{is} z_{js} x_{js} \right)^2 = \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 z_{js} e_{is} x_{js} \right)^2 + \frac{1}{N} \sum_j \text{Var}_I \left( \frac{1}{T} \sum_s f_s^2 e_{is} z_{js} x_{js} \right)$$

$$\begin{aligned}
&\leq \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{is} x_{js}^2 \right)^2 (\tilde{\lambda}_j M_{\alpha, jj})^2 + O_P(1) \frac{1}{N} \sum_j \frac{1}{N} \sum_{k \neq j} \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 x_{ks} e_{is} x_{js} \right)^2 \\
&\quad + \frac{1}{N} \sum_j \text{Var}_I \left( \frac{1}{T} \sum_s f_s^2 e_{is} z_{js} x_{js} \right) \\
&\leq \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{is} x_{js}^2 \right)^2 (\tilde{\lambda}_j - H_1' \lambda_j)^2 + O_P(1) \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{is} x_{js}^2 \right)^2 \\
&\quad + O_P(1) \frac{1}{N} \sum_j \frac{1}{N} \sum_{k \neq j} \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 x_{ks} e_{is} x_{js} \right)^2 + O_P(T^{-1}) \\
&\leq O_P(1) \frac{1}{N} \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 \sum_j |\mathbb{E}_I(e_{is} e_{js}^2 | f_s)| + O_P(1) \frac{1}{N} \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 \sum_j |\mathbb{E}_I(e_{is} e_{js} | f_s)| \\
&\quad + O_P(1) \frac{1}{N} \frac{1}{N} \sum_{k \neq j} \left| \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{ks} e_{is} e_{js} \right| + O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2})
\end{aligned}$$

given that  $\sum_j |\mathbb{E}_I(e_{is} e_{js}^2 | f_s)| + \sum_j |\mathbb{E}_I(e_{is} e_{js} | f_s)| + \frac{1}{N} \sum_{k \neq j} |\mathbb{E}_I(e_{ks} e_{is} e_{js} | f_s)| < \infty$ .

Put together,

$$\frac{1}{\sqrt{T}} \sum_s f_s e_{is} \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s = O_P(\sqrt{T} C_{NT}^{-2}).$$

Third term: note that  $\mathbb{E}_I(u_s u_s' | X_s, f_s) < C$ .

$$\begin{aligned}
&\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (\tilde{D}_{fs}^{-1} - (H_1' D_x H_1)^{-1}) \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s \\
&\leq O_P(\sqrt{T} C_{NT}^{-1}) \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} |f_s e_{is} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s|^2 \right)^{1/2} \\
&= O_P(\sqrt{T} C_{NT}^{-1}) \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbb{E}_I |f_s e_{is} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s|^2 \right)^{1/2} \\
&= O_P(\sqrt{T} C_{NT}^{-1}) \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbb{E}_I f_s^2 e_{is}^2 \frac{1}{N^2} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \mathbb{E}_I(u_s u_s' | X_s, f_s) M_{\tilde{\alpha}} \text{diag}(X_s) \tilde{\Lambda} \right)^{1/2} \\
&\leq O_P(\sqrt{T} C_{NT}^{-1}) \frac{1}{N} \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbb{E}_I f_s^2 e_{is}^2 \|\tilde{\Lambda}' \text{diag}(X_s)\|^2 \right)^{1/2} \\
&\leq O_P(\sqrt{T} C_{NT}^{-1}) \frac{1}{N} \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbb{E}_I f_s^2 e_{is}^2 \sum_j \tilde{\lambda}_j^2 x_{js}^2 \right)^{1/2} = O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

Next, due to  $\mathbb{E}(u_s | f_s, D_I, e_s) = 0$ , and  $e_s$  is conditionally serially independent given  $(f_s, u_s)$ ,

$$\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) (M_{\tilde{\alpha}} - M_{\alpha}) u_s$$

$$\begin{aligned}
&= \text{tr} \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} u_s f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) (M_{\tilde{\alpha}} - M_{\alpha}) \\
&\leq O_P(\sqrt{T} C_{NT}^{-1}) \left\| \frac{1}{T} \sum_{s \in I^c \cup \{t\}} u_s f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) \right\|_F \\
&\leq O_P(\sqrt{T} C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \left\| \frac{1}{T} \sum_{s \in I^c \cup \{t\}} u_s f_s e_{is} \frac{1}{\sqrt{N}} x_{js} \right\|_F^2 \tilde{\lambda}_j^2 \right)^{1/2} \\
&\leq O_P(\sqrt{T} C_{NT}^{-1}) \left( \max_j \mathbb{E}_I \left\| \frac{1}{T} \sum_{s \in I^c \cup \{t\}} u_s f_s e_{is} \frac{1}{\sqrt{N}} x_{js} \right\|_F^2 \right)^{1/2} \\
&\leq O_P(C_{NT}^{-1}) \left( \max_{jk} \frac{1}{T} \text{Var}_I \left( \sum_{s \in I^c \cup \{t\}} u_{ks} f_s e_{is} x_{js} \right) \right)^{1/2} \\
&\leq O_P(C_{NT}^{-1}) \left( \max_{jks} \text{Var}_I(u_{ks} f_s e_{is} x_{js}) \right)^{1/2} = O_P(C_{NT}^{-1}) = O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

Next,

$$\begin{aligned}
&\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} (\tilde{\Lambda} - \Lambda H_1)' \text{diag}(X_s) M_{\alpha} u_s \\
&\leq O_P(1) \frac{1}{N} \sum_j (\tilde{\lambda}_j - H_1' \lambda_j) \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} M'_{\alpha,j} u_s x_{js} \\
&\leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \left( \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} M'_{\alpha,j} u_s x_{js} \right)^2 \right)^{1/2} \\
&\leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \text{Var}_I(f_s e_{is} M'_{\alpha,j} u_s x_{js}) \right)^{1/2} \\
&= O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbb{E}_I f_s^2 x_{js}^2 e_{is}^2 M'_{\alpha,j} \text{Var}_I(u_s | e_s, f_s) M_{\alpha,j} \right)^{1/2} \\
&\leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbb{E}_I f_s^2 x_{js}^2 e_{is}^2 \|M_{\alpha,j}\|^2 \right)^{1/2} = O_P(C_{NT}^{-1}) = O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

Finally,

$$\begin{aligned}
&\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} H_1' \Lambda' \text{diag}(X_s) M_{\alpha} u_s \\
&\leq O_P(N^{-1}) (\mathbb{E}_I f_s^2 e_{is}^2 \Lambda' \text{diag}(X_s) M_{\alpha} \mathbb{E}_I(u_s u_s' | e_s, f_s) M_{\alpha} \text{diag}(X_s) \Lambda)^{1/2} \\
&\leq O_P(N^{-1}) (\mathbb{E}_I f_s^2 e_{is}^2 \|\Lambda' \text{diag}(X_s)\|^2)^{1/2} \\
&\leq O_P(N^{-1/2}) \left( \frac{1}{N} \sum_j \mathbb{E}_I f_s^2 e_{is}^2 x_{js}^2 \right)^{1/2} = O_P(N^{-1/2}) = O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

Put together, we have  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s = O_P(\sqrt{T} C_{NT}^{-2})$ .



Thus  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s(H_1^{-1}f_s - \tilde{f}_s)e_{is} = O_P(\sqrt{T}C_{NT}^{-2})$ .  
Q.E.D.

**Lemma E.3.** Suppose  $\max_{it} e_{it}^4 = O_P(\min\{N, T\})$ . (i)  $\frac{1}{T} \|\tilde{F} - FH_1^{-1'}\|_F^2 = O_P(C_{NT}^{-2}) = \frac{1}{T} \|\tilde{G} - GH_2^{-1'}\|_F^2$ , and  $\frac{1}{T} \sum_{t \in I^c} \|\tilde{f}_t - H_1^{-1}f_t\|^2 e_{it}^2 u_{it}^2 = O_P(C_{NT}^{-2})$ .  
(ii)  $\max_i \|\tilde{D}_{\lambda i}^{-1}\| = O_P(1)$ .  
(iii)  $\frac{1}{N} \sum_i \|\tilde{D}_{\lambda i}^{-1} - (H_1^{-1}\bar{D}_{\lambda i}H_1^{-1'})^{-1}\|^2 = O_P(C_{NT}^{-2})$ .

*Proof.* (i) The proof is straightforward given the expansion of (E.2) and  $\max_s \|\tilde{D}_{fs}^{-1}\| = O_P(1)$ . So we omit the details for brevity. (ii) Note that

$$\begin{aligned} \tilde{D}_{\lambda i} - H_1^{-1}D_{\lambda i}H_1^{-1'} &= \sum_l \delta_l, \quad \text{where} \\ \delta_1 &= \frac{1}{T}(\tilde{F} - FH_1^{-1'})'\text{diag}(X_i)M_{\tilde{g}}\text{diag}(X_i)\tilde{F}, \\ \delta_2 &= \frac{1}{T}H_1^{-1}F'\text{diag}(X_i)M_{\tilde{g}}\text{diag}(X_i)(\tilde{F} - FH_1^{-1'}) \\ \delta_3 &= \frac{1}{T}H_1^{-1}F'\text{diag}(X_i)(M_{\tilde{g}} - M_g)\text{diag}(X_i)FH_1^{-1'}. \quad (\text{E.3}) \end{aligned}$$

The proof is very similar to that of Lemma E.1.

(iii)

$$\begin{aligned} &\frac{1}{N} \sum_i \|\tilde{D}_{\lambda i}^{-1} - (H_1^{-1}\bar{D}_{\lambda i}H_1^{-1'})^{-1}\|^2 \\ &\leq \frac{1}{N} \sum_i \|\tilde{D}_{\lambda i} - (H_1^{-1}\bar{D}_{\lambda i}H_1^{-1'})\|^2 \max_i \|(H_1^{-1}\bar{D}_{\lambda i}H_1^{-1'})^{-2}\| \|\tilde{D}_{\lambda i}^{-2}\| \\ &\leq O_P(1) \frac{1}{N} \sum_i \|\tilde{D}_{\lambda i} - (H_1^{-1}\bar{D}_{\lambda i}H_1^{-1'})\|^2 \\ &= O_P(1) \sum_{l=1}^3 \frac{1}{N} \sum_i \|\delta_l\|^2 + O_P(1) \frac{1}{N} \sum_i \|D_{\lambda i} - \bar{D}_{\lambda i}\|^2. \end{aligned}$$

We now bound each term. With the assumption that  $\max_{it} x_{it}^4 = O_P(\min\{N, T\})$ ,

$$\begin{aligned} \frac{1}{N} \sum_i \|\delta_1\|^2 &\leq \frac{1}{T} \|\tilde{F} - FH_1^{-1'}\|_F^2 \|M_{\tilde{g}} - M_g\|^2 \frac{1}{T} \|\tilde{F}\|_F^2 \frac{1}{N} \sum_i \|\text{diag}(X_i)\|^4 \\ &\quad + \frac{1}{T^2} \|\tilde{F} - FH_1^{-1'}\|_F^4 \frac{1}{N} \sum_i \|\text{diag}(X_i)\|^4 \\ &\quad + \frac{1}{N} \sum_i \left\| \frac{1}{T} (\tilde{F} - FH_1^{-1'})' \text{diag}(X_i) M_g \text{diag}(X_i) FH_1^{-1'} \right\|^2 \\ &\leq O_P(C_{NT}^{-4}) \max_{it} x_{it}^4 + \frac{1}{NT} \sum_i \sum_t x_{it}^2 \left( \sum_s M_{g,ts} x_{is} f_s \right)^2 O_P(C_{NT}^{-2}) \end{aligned}$$

$$\leq O_P(C_{NT}^{-2}).$$

$\frac{1}{N} \sum_i \|\delta_2\|^2$  is bounded similarly.  $\frac{1}{N} \sum_i \|\delta_3\|^2 \leq O_P(1) \|M_{\tilde{g}} - M_g\|^2 = O_P(C_{NT}^{-2})$ . Finally,

$$\frac{1}{N} \sum_i \|D_{\lambda_i} - \bar{D}_{\lambda_i}\|^2 \leq \frac{1}{N} \sum_i \left\| \frac{1}{T} \sum_{st} f_s f'_t M_{g,st} (x_{is} x_{it} - \mathbb{E} x_{is} x_{it}) \right\|_F^2 = O_P(C_{NT}^{-2}).$$

The proof of above is essentially the same as that of  $\frac{1}{T} \sum_s \|D_{f_s} - D_f\|^2$  in Lemma E.1 (ii), provided that  $e_{it}$  is conditionally serially independent given  $f_t$ , so we omit the details for brevity.

**Lemma E.4.** Suppose  $\text{Var}(u_s | e_t, e_s) < C$ .

- (i) For each fixed  $t \in I^c$ ,  $\frac{1}{\sqrt{N}} \sum_i (H'_1 \lambda_i - \dot{\lambda}_i) e_{it} = O_P(\sqrt{N} C_{NT}^{-2})$ .
- (ii) For each  $i \leq N$ ,  $\lambda_i - \dot{\lambda}_i = O_P(C_{NT}^{-1})$ .
- (iii) For each fixed  $j \leq N$ ,  $\frac{1}{T} \sum_{t \in I^c} \|e_{jt} f'_t\|^2 \left\| \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i (\dot{\lambda}_i - H'_1 \lambda_i)' \right\|^2 = O_P(C_{NT}^{-4})$ .

Part (iii) is used for deriving the expansion of  $\hat{\lambda}_i$  later.

*Proof.* Given that the  $|I^c| \times 1$  vector  $y_i = G\alpha_i + \text{diag}(X_i)F\lambda_i + u_i$  where  $u_i$  is a  $|I^c| \times 1$  vector and  $G$  is an  $|I^c| \times K_1$  matrix, we have

$$\begin{aligned} \dot{\lambda}_i &= \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} y_i \\ &= H'_1 \lambda_i + \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (GH_2^{-1'} - \tilde{G}) H'_2 \alpha_i \\ &\quad + \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (FH_1^{-1'} - \tilde{F}) H'_1 \lambda_i + \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} u_i \end{aligned}$$

Part (ii) that  $\lambda_i - \dot{\lambda}_i = O_P(C_{NT}^{-1})$  follows from a straightforward calculation. So we omit the details. We now prove the much harder part (i) by plugging in each term in the above expansion to  $\frac{1}{\sqrt{N}} \sum_i (H'_1 \lambda_i - \dot{\lambda}_i) e_{it}$ .

First term:  $\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (GH_2^{-1'} - \tilde{G}) H'_2 \alpha_i$ .

$$\begin{aligned} &\frac{1}{\sqrt{N}} \sum_i e_{it} (\tilde{D}_{\lambda_i}^{-1} - (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1}) \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (GH_2^{-1'} - \tilde{G}) H'_2 \alpha_i \\ &\leq O_P(\sqrt{N} C_{NT}^{-2}) \left( \frac{1}{N} \sum_i e_{it}^2 \frac{1}{T} \sum_s \tilde{f}_s^2 x_{is}^2 \right)^{1/2} \\ &\leq O_P(\sqrt{N} C_{NT}^{-2}) + O_P(\sqrt{N} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 \right)^{1/2} \max_{is} |x_{is}| \\ &\leq O_P(\sqrt{N} C_{NT}^{-2}) + O_P(\sqrt{N} C_{NT}^{-3}) \max_{is} |x_{is}| = O_P(\sqrt{N} C_{NT}^{-2}). \end{aligned}$$

Given  $F, G$ ,  $\bar{D}_{\lambda i}^{-1}$  is nonrandom. So

$$\begin{aligned}
& \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (G H_2^{-1'} - \tilde{G}) H_2' \alpha_i \\
& \leq O_P(\sqrt{N} C_{NT}^{-1}) \left( \frac{1}{T} \sum_s \tilde{f}_s^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2 \right)^{1/2} \\
& \leq O_P(\sqrt{N} C_{NT}^{-1}) (a^{1/2} + b^{1/2}) \quad \text{where} \\
a &= \frac{1}{T} \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2 \\
b &= \frac{1}{T} \sum_s f_s^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2.
\end{aligned}$$

We now bound each term. As for  $b$ , note that for each fixed  $t$ ,

$$\begin{aligned}
& \mathbb{E} \left( \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2 \middle| F, G, u_s \right) \\
& \leq \mathbb{E} \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} e_{is} \middle| F, G, u_s \right)^2 + \mathbb{E} \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} \mu_i \middle| F, G, u_s \right)^2 \\
& \leq \text{Var} \left( \frac{1}{N} \sum_i \alpha_i e_{it} e_{is} \bar{D}_{\lambda i}^{-1} \middle| F, G, u_s \right) + \left( \mathbb{E} \frac{1}{N} \sum_i \alpha_i e_{it} e_{is} \bar{D}_{\lambda i}^{-1} \middle| F, G, u_s \right)^2 \\
& \quad + \text{Var} \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} \mu_i \middle| F, G, u_s \right) \\
& \leq \frac{1}{N} \max_i \|\bar{D}_{\lambda i}^{-2}\| \frac{1}{N} \sum_{ij} |\text{Cov}(e_{jt} e_{js}, e_{it} e_{is} | F, G, u_s)| + \left( \mathbb{E} \frac{1}{N} \sum_i \alpha_i e_{it} e_{is} \bar{D}_{\lambda i}^{-1} \middle| F, G, u_s \right)^2 \\
& \quad + \frac{1}{N} \max_i \|\bar{D}_{\lambda i}^{-2}\| \frac{1}{N} \sum_{ij} |\text{Cov}(e_{it}, e_{jt} | F, G, u_s)| \\
& \leq \frac{C}{N} + \left( \mathbb{E} \frac{1}{N} \sum_i \alpha_i e_{it} e_{is} \bar{D}_{\lambda i}^{-1} \middle| F, G, u_s \right)^2 \tag{E.5}
\end{aligned}$$

with the assumption  $\frac{1}{N} \sum_{ij} |\text{Cov}(e_{jt} e_{js}, e_{it} e_{is} | F, G, u_s)| < C$ . So

$$\begin{aligned}
\mathbb{E} b &\leq \frac{1}{T} \sum_s \mathbb{E} f_s^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2 \\
&\leq \frac{1}{T} \sum_s \mathbb{E} f_s^2 \frac{C}{N} + \frac{1}{T} \sum_s \mathbb{E} f_s^2 \left( \mathbb{E} \frac{1}{N} \sum_i \alpha_i e_{it} e_{is} \bar{D}_{\lambda i}^{-1} \middle| F, G \right)^2 \\
&\leq \frac{C}{N} + \frac{1}{T} \mathbb{E} f_t^2 \left( \mathbb{E} \frac{1}{N} \sum_i \alpha_i e_{it}^2 \bar{D}_{\lambda i}^{-1} \middle| F, G \right)^2 = O(C_{NT}^{-2}). \\
a &= \frac{1}{T} \sum_s f_s^2 \left( \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) \right)^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2
\end{aligned}$$

$$\begin{aligned}
& + \frac{1}{T} \sum_s (\tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s)^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 \\
& + \frac{1}{T} \sum_s (\tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s)^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2
\end{aligned}$$

The first line of  $a$  is bounded by, using the upper bound of  $\mathbb{E}b$ , and  $\max \|\tilde{D}_{fs}^{-1}\| = O_P(1)$ ,

$$\begin{aligned}
& O_P(C_{NT}^{-2}) \max_{is} x_{is}^4 \frac{1}{T} \sum_s f_s^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 \leq O_P(1) \frac{1}{T} \sum_s \mathbb{E} f_s^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 \\
& = O_P(C_{NT}^{-2}).
\end{aligned}$$

The second line of  $a$  is bounded similarly. The third line is bounded by:

$$\begin{aligned}
& O_P(1) \frac{1}{T} \sum_s (\frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s)^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 \\
& \leq O_P(1) \frac{1}{T} \sum_s \mathbb{E} (\frac{1}{N} \Lambda' \text{diag}(X_s) M_{\alpha} u_s)^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 \\
& \quad + O_P(C_{NT}^{-2}) \max_{is} x_{is}^2 \frac{1}{TN} \sum_s \mathbb{E} \|u_s\|^2 \mathbb{E} ((\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 | u_s) \\
& := O_P(1)(a.1 + a.2).
\end{aligned}$$

We now respectively bound  $a.1$  and  $a.2$ . As for  $a.1$ , note that  $\text{Var}(u_s | e_t, e_s) < C$  almost surely, thus

$$\begin{aligned}
& \mathbb{E} (\frac{1}{N} \Lambda' \text{diag}(X_s) M_{\alpha} u_s | e_t, e_s)^2 = \frac{1}{N} \frac{1}{N} \Lambda' \text{diag}(X_s) M_{\alpha} \text{Var}(u_s | e_t, e_s) M_{\alpha} \text{diag}(X_s) \Lambda \\
& \leq C \frac{1}{N} \frac{1}{N} \Lambda' \text{diag}(X_s)^2 \Lambda.
\end{aligned}$$

As for  $a.2$ , we use (E.5). Thus,

$$\begin{aligned}
a.1 & \leq \frac{1}{T} \sum_s \mathbb{E} (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 \mathbb{E} (\frac{1}{N} \Lambda' \text{diag}(X_s) M_{\alpha} u_s | e_t, e_s)^2 \\
& \leq \frac{C}{N} \frac{1}{T} \sum_s \mathbb{E} (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 \frac{1}{N} \Lambda' \text{diag}(X_s)^2 \Lambda = O(N^{-1}). \\
a.2 & \leq C_{NT}^{-2} \max_{is} x_{is}^2 \frac{1}{TN} \sum_s \mathbb{E} \|u_s\|^2 \mathbb{E} ((\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is})^2 | u_s) \\
& \leq C_{NT}^{-2} \max_{is} x_{is}^2 \frac{1}{TN} \sum_s \mathbb{E} \|u_s\|^2 \frac{C}{N} \\
& \quad + C_{NT}^{-2} \max_{is} x_{is}^2 \frac{1}{TN} \sum_s \mathbb{E} \|u_s\|^2 (\mathbb{E} \frac{1}{N} \sum_i \alpha_i e_{it} e_{is} \bar{D}_{\lambda i}^{-1} | F, u_s)^2
\end{aligned}$$

$$\leq O(C_{NT}^{-2}).$$

Put together,  $a^{1/2} + b^{1/2} = O(C_{NT}^{-1})$ . So the first term in the expansion of  $\frac{1}{\sqrt{N}} \sum_i (H_1' \lambda_i - \dot{\lambda}_i) e_{it}$  is

$$\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (G H_2^{-1'} - \tilde{G}) H_2' \alpha_i = O_P(\sqrt{N} C_{NT}^{-2}).$$

Second term:  $\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i$ .

$$\begin{aligned} & \frac{1}{\sqrt{N}} \sum_i e_{it} (\tilde{D}_{\lambda_i}^{-1} - (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1}) \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}) \left( \frac{1}{NT} \sum_i e_{it}^2 \|F' \text{diag}(X_i) M_g \text{diag}(X_i)\|^2 \right)^{1/2} \\ & \quad + O_P(\sqrt{N} C_{NT}^{-2}) \left( \frac{1}{N} \sum_i e_{it}^2 \|\text{diag}(X_i)\|^4 \right)^{1/2} [\|M_g - M_{\tilde{g}}\| \frac{1}{\sqrt{T}} \|\tilde{F}\| + \frac{1}{\sqrt{T}} \|\tilde{F} - F H_1^{-1'}\|] \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}) \left( \frac{1}{NT} \sum_i \sum_s e_{it}^2 f_s^2 x_{is}^4 \right)^{1/2} \\ & \quad + O_P(\sqrt{N} C_{NT}^{-2}) \left( \frac{1}{NT} \sum_i \sum_s x_{is}^2 e_{it}^2 g_s^2 \left( \frac{1}{T} \sum_k f_k g_k x_{ik} \right)^2 \right)^{1/2} \\ & \quad + O_P(\sqrt{N} C_{NT}^{-3}) \max_{it} x_{it}^2 = O_P(\sqrt{N} C_{NT}^{-2}). \end{aligned}$$

Also, plug in (E.2) for  $\tilde{f}_s - H_1^{-1} f_s$ , and note  $\frac{1}{T} \sum_s (\frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} e_{is}^2)^2 = O_P(C_{NT}^{-2})$ ,

$$\begin{aligned} & \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1} \frac{1}{T} (\tilde{F} - F H_1^{-1'})' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\ & \leq O_P(\sqrt{N} C_{NT}^{-3}) \max_{it} x_{it}^2 \\ & \quad + \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1} \frac{1}{T} (\tilde{F} - F H_1^{-1'})' \text{diag}(X_i) M_g \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}) + \sqrt{N} \frac{1}{T} \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 \frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} e_{is}^2 \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}) + \max_{is} x_{is}^2 O_P(\sqrt{N} C_{NT}^{-2}) \frac{1}{NT} \sum_s g_s^2 \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} e_{is}^2 \\ & \quad + \max_{is} x_{is}^2 O_P(\sqrt{N} C_{NT}^{-2}) \frac{1}{T} \sum_s \frac{1}{N} \sum_j \lambda_j^2 x_{js}^2 f_s^2 \frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} e_{is}^2 \\ & \quad + \sqrt{N} \frac{1}{T} \sum_s \left( \frac{1}{N} \Lambda' \text{diag}(X_s) M_{\alpha} u_s \right)^2 \frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} e_{is}^2 \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}). \end{aligned}$$

Next,

$$\begin{aligned}
& \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1} \frac{1}{T} F' \text{diag}(X_i) (M_{\tilde{g}} - M_g) \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\
& \leq O_P(\sqrt{N} C_{NT}^{-1}) \left( \frac{1}{N} \sum_i \lambda_i^2 e_{it}^2 \frac{1}{T} \sum_k f_k^2 x_{ik}^2 \right)^{1/2} \left( \frac{1}{NT} \sum_i \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 e_{is}^2 \right)^{1/2} \\
& = O_P(\sqrt{N} C_{NT}^{-2}),
\end{aligned}$$

where the last equality is due to  $\frac{1}{NT} \sum_i \sum_{s \in I^c \cup \{t\}} (\tilde{f}_s - H_1^{-1} f_s)^2 e_{is}^2 = O_P(C_{NT}^{-2})$ , proved as below. Use (E.2) for  $\tilde{f}_s - H_1^{-1} f_s$ ,

$$\begin{aligned}
& \frac{1}{NT} \sum_i \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 e_{is}^2 \\
& = \frac{1}{NT} \sum_i \sum_{s \in I^c \cup \{t\}} e_{is}^2 \frac{1}{N} \|\Lambda' \text{diag}(X_s)\|^2 [g_s^2 + \frac{1}{N} \|u_s\|^2] O_P(C_{NT}^{-2}) \\
& \quad + O_P(1) \frac{1}{N} \sum_j (H_1 \lambda_j - \tilde{\lambda}_j)^2 \max_j \frac{1}{NT} \sum_i \sum_{s \in I^c \cup \{t\}} \mathbb{E}_I e_{is}^2 f_s^2 \frac{1}{N} \|\Lambda' \text{diag}(X_s)\|^2 x_{js}^2 \\
& \quad + \frac{1}{NT} \sum_i \sum_s e_{is}^2 \left( \frac{1}{N} \Lambda' \text{diag}(X_s) M_\alpha u_s \right)^2 \\
& \quad + \frac{1}{NT} \sum_i \sum_s e_{is}^2 \frac{1}{N} \|\text{diag}(X_s) M_\alpha u_s\|^2 O_P(C_{NT}^{-2}) \\
& = O_P(C_{NT}^{-2}).
\end{aligned}$$

Next,

$$\begin{aligned}
& \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1} \frac{1}{T} F' \text{diag}(X_i) M_g \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\
& \leq O_P(\sqrt{N} C_{NT}^{-1}) \left\| \frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda i}^{-1} \frac{1}{\sqrt{T}} F' \text{diag}(X_i) M_g \text{diag}(X_i) \right\| \\
& \leq O_P(\sqrt{N} C_{NT}^{-1}) \left( \frac{1}{T} \sum_s f_s^2 \left( \frac{1}{N} \sum_i \lambda_i x_{is}^2 e_{it} \bar{D}_{\lambda i}^{-1} \right)^2 \right)^{1/2} \\
& \quad + O_P(\sqrt{N} C_{NT}^{-1}) \left( \frac{1}{T} \sum_s g_s^2 \left( \frac{1}{N} \sum_i x_{is} \lambda_i e_{it} \bar{D}_{\lambda i}^{-1} \frac{1}{T} \sum_k f_k x_{ik} g_k \right)^2 \right)^{1/2} \\
& = O_P(\sqrt{N} C_{NT}^{-1}) (a^{1/2} + b^{1/2}).
\end{aligned}$$

We aim to show  $a = O_P(C_{NT}^{-2}) = b$ .

$$\mathbb{E} a := \frac{1}{T} \sum_s \mathbb{E} f_s^2 \left( \frac{1}{N} \sum_i \lambda_i x_{is}^2 e_{it} \bar{D}_{\lambda i}^{-1} \right)^2$$

$$\begin{aligned}
&\leq \frac{1}{T} \sum_s \frac{1}{N^2} \sum_{ij} \mathbb{E} f_s^2 \lambda_i \bar{D}_{\lambda i}^{-1} \lambda_j \bar{D}_{\lambda j}^{-1} \mathbb{E}(e_{is}^2 e_{js}^2 | F) \text{Cov}(e_{it}, e_{jt} | F) \\
&\quad + \frac{1}{T} \sum_s \mathbb{E} f_s^2 \frac{1}{N^2} \sum_{ij} \lambda_i \mu_i^2 \bar{D}_{\lambda i}^{-1} \lambda_j \mu_j^2 \bar{D}_{\lambda j}^{-1} \text{Cov}(e_{it}, e_{jt} | F) \\
&\quad + \frac{2}{T} \sum_s \mathbb{E} f_s^2 \frac{1}{N^2} \sum_{ij} \lambda_i \mu_i \bar{D}_{\lambda i}^{-1} \bar{D}_{\lambda j}^{-1} \lambda_i \mu_j \mathbb{E}(e_{js} e_{is} | F) \text{Cov}(e_{jt} e_{it} | F) \\
&= O_P(N^{-1}). \\
\text{Eb} &:= \frac{1}{T} \sum_s \mathbb{E} g_s^2 \left( \frac{1}{N} \sum_i x_{is} \lambda_i e_{it} \bar{D}_{\lambda i}^{-1} \frac{1}{T} \sum_k f_k x_{ik} g_k \right)^2 \\
&= O(T^{-1}) + O(1) \frac{1}{T} \sum_s \mathbb{E} g_s^2 \frac{1}{N^2} \sum_{ij} |\mathbb{E}(x_{js} x_{is} | F) \text{Cov}(e_{it}, e_{jt} | F)| \\
&= O_P(C_{NT}^{-2}).
\end{aligned}$$

Therefore the second term is

$$\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i = O_P(\sqrt{N} C_{NT}^{-2}).$$

The third term:  $\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} u_i$ . First,

$$\begin{aligned}
&\frac{1}{\sqrt{N}} \sum_i e_{it} (\tilde{D}_{\lambda i}^{-1} - (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1}) \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} u_i \\
&\leq O_P(\sqrt{N} C_{NT}^{-2}) + O_P(1) \frac{1}{\sqrt{N}} \sum_i e_{it} (\tilde{D}_{\lambda i}^{-1} - (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1}) \frac{1}{T} F' \text{diag}(X_i) M_g u_i \\
&\leq O_P(\sqrt{N} C_{NT}^{-2}) + O_P(\sqrt{N} C_{NT}^{-1}) \frac{1}{N} \sum_i |e_{it}| \left| \frac{1}{T} \sum_s f_s x_{is} u_{is} \right| \\
&\quad + O_P(\sqrt{N} C_{NT}^{-1}) \frac{1}{N} \sum_i |e_{it}| \left| \frac{1}{T} \sum_s f_s x_{is} g_s \right| \left| \frac{1}{T} \sum_k g_k u_{ik} \right| \\
&= O_P(\sqrt{N} C_{NT}^{-2}).
\end{aligned}$$

Second,

$$\begin{aligned}
&\frac{1}{\sqrt{N}} \sum_i e_{it} \bar{D}_{\lambda i}^{-1} \frac{1}{T} (\tilde{F} - F H_1^{-1'})' \text{diag}(X_i) M_{\tilde{g}} u_i \\
&\leq \frac{1}{\sqrt{N}} \sum_i e_{it} \bar{D}_{\lambda i}^{-1} \frac{1}{T} (\tilde{F} - F H_1^{-1'})' \text{diag}(X_i) M_g u_i \\
&\quad + O_P(\sqrt{N} C_{NT}^{-1}) \left( \frac{1}{NT} \sum_i e_{it}^2 \|u_i\|^2 \right)^{1/2} \left( \frac{1}{NT} \sum_i \|(\tilde{F} - F H_1^{-1'})' \text{diag}(X_i)\|^2 \right)^{1/2} \\
&\leq O_P(\sqrt{N} C_{NT}^{-2}) + O_P(\sqrt{N} C_{NT}^{-1}) \left\| \frac{1}{N} \sum_i \frac{1}{\sqrt{T}} \text{diag}(X_i) M_g u_i e_{it} \bar{D}_{\lambda i}^{-1} \right\|
\end{aligned}$$

$$\begin{aligned}
&\leq O_P(\sqrt{N}C_{NT}^{-2}) + O_P(\sqrt{N}C_{NT}^{-1})\left(\frac{1}{T}\sum_s\left(\frac{1}{N}\sum_i x_{is}M'_{g,s}u_ie_{it}\bar{D}_{\lambda i}^{-1}\right)^2\right)^{1/2} \\
&= O_P(\sqrt{N}C_{NT}^{-2}),
\end{aligned}$$

where the last equality is due to  $\frac{1}{T}\sum_s\left(\frac{1}{N}\sum_i x_{is}M'_{g,s}u_ie_{it}\bar{D}_{\lambda i}^{-1}\right)^2 = O_P(C_{NT}^{-2})$ , proved as follows:

$$\begin{aligned}
&\frac{1}{T}\sum_s \mathbb{E}\left(\frac{1}{N}\sum_i x_{is}M'_{g,s}u_ie_{it}\bar{D}_{\lambda i}^{-1}\right)^2 \\
&\leq \frac{1}{T}\sum_s \mathbb{E}\left(\frac{1}{N}\sum_i x_{is}u_{is}e_{it}\bar{D}_{\lambda i}^{-1}\right)^2 + \frac{1}{T}\sum_s \mathbb{E}\left(\frac{1}{NT}\sum_i\sum_k x_{is}g_kg_su_{ik}e_{it}\bar{D}_{\lambda i}^{-1}\right)^2 \\
&\leq O(T^{-1}) + \frac{1}{T}\sum_{s \neq t} \frac{1}{N^2}\sum_{ij} \mathbb{E}|\mathbb{E}(e_{jt}e_{it}|F)|\mathbb{E}(u_{is}u_{js}x_{js}x_{is}|F)| \\
&\quad + \frac{1}{T}\sum_s \mathbb{E}\frac{1}{NT}\sum_i\sum_k \bar{D}_{\lambda i}^{-1}\frac{1}{NT}\sum_j\sum_l \bar{D}_{\lambda j}^{-1}|x_{js}g_lg_su_{jl}x_{is}g_kg_su_{ik}||\text{Cov}(e_{it}, e_{jt}|F)| \\
&\leq O(T^{-1}) + O(N^{-1})
\end{aligned}$$

where the last equality is due to  $\max_j \sum_i |\text{Cov}(e_{it}, e_{jt}|F)| < C$ .

Next,

$$\begin{aligned}
&\frac{1}{\sqrt{N}}\sum_i e_{it}\bar{D}_{\lambda i}^{-1}\frac{1}{T}F'\text{diag}(X_i)(M_{\tilde{g}} - M_g)u_i \\
&= \text{tr}\frac{1}{\sqrt{N}}\sum_i u_ie_{it}\bar{D}_{\lambda i}^{-1}\frac{1}{T}F'\text{diag}(X_i)(M_{\tilde{g}} - M_g) \\
&\leq O_P(\sqrt{N}C_{NT}^{-1})\frac{1}{T}\left\|\frac{1}{N}\sum_i u_ie_{it}\bar{D}_{\lambda i}^{-1}F'\text{diag}(X_i)\right\|_F \\
&\leq O_P(\sqrt{N}C_{NT}^{-1})\left(\frac{1}{T^2}\sum_{sk} \mathbb{E}\left(\frac{1}{N}\sum_i u_{is}e_{it}\bar{D}_{\lambda i}^{-1}f_kx_{ik}\right)^2\right)^{1/2} = O_P(\sqrt{N}C_{NT}^{-2})
\end{aligned}$$

where the last equality is due to  $\frac{1}{T^2}\sum_{sk} \mathbb{E}\left(\frac{1}{N}\sum_i u_{is}e_{it}\bar{D}_{\lambda i}^{-1}f_kx_{ik}\right)^2 = O_P(C_{NT}^{-2})$ .

$$\begin{aligned}
&\frac{1}{T^2}\sum_{sk} \mathbb{E}\left(\frac{1}{N}\sum_i u_{is}e_{it}\bar{D}_{\lambda i}^{-1}f_kx_{ik}\right)^2 \\
&= \frac{1}{T^2}\sum_{sk} \mathbb{E}\frac{1}{N}\sum_i \bar{D}_{\lambda i}^{-1}\frac{1}{N}\sum_j \bar{D}_{\lambda j}^{-1}f_k^2x_{jk}u_{is}x_{ik}u_{js}e_{jt}e_{it} \\
&\leq O(T^{-1}) + \frac{1}{T^2}\sum_{sk} \frac{1}{N^2}\sum_{ij} \mathbb{E}\bar{D}_{\lambda i}^{-1}\bar{D}_{\lambda j}^{-1}f_k^2\mathbb{E}(x_{jk}u_{is}x_{ik}u_{js}|F)|\text{Cov}(e_{jt}, e_{it}|F) \\
&\leq O_P(C_{NT}^{-2}).
\end{aligned}$$



Finally, since  $u_{it}$  is conditionally serially independent given  $E, F$ ,

$$\begin{aligned}
& \mathbb{E}\left(\frac{1}{\sqrt{N}} \sum_i e_{it} \bar{D}_{\lambda_i}^{-1} \frac{1}{T} F' \text{diag}(X_i) M_g u_i\right)^2 \\
&= \mathbb{E} \frac{1}{N} \sum_{ij} \sum_s \bar{D}_{\lambda_j}^{-1} \bar{D}_{\lambda_i}^{-1} \frac{1}{T} (F' \text{diag}(X_i) M_{g,s})^2 e_{jt} e_{it} \frac{1}{T} u_{js} u_{is} \\
&\leq \frac{C}{T^2 N} \sum_{ij} \sum_s \mathbb{E} u_{js} u_{is} \mathbb{E} ((F' \text{diag}(X_i) M_{g,s})^2 e_{jt} e_{it} | U) \\
&\leq \frac{C}{T^2 N} \sum_{ij} \sum_s |\text{Cov}(u_{js}, u_{is})| = O(T^{-1}) = O_P(C_{NT}^{-2}).
\end{aligned}$$

Together,  $\frac{1}{\sqrt{N}} \sum_i (H'_1 \lambda_i - \dot{\lambda}_i) e_{it} = O_P(\sqrt{T} C_{NT}^{-2})$ . Q.E.D.

The proof of part (iii) follows from the same arguments as in part (i). While a rigorous proof still follows from substituting in the expansion of  $\dot{\lambda}_i - H'_1 \lambda_i$ , the details would be mostly very similar. So we omit it for brevity.

## E.2. Technical lemmas for $\hat{f}_t$ .

**Lemma E.5.** Suppose  $\max_i |\bar{e}_i| = O_P(1)$ . For each fixed  $t$ , (i)  $\hat{B}_t - B = O_P(C_{NT}^{-1})$ . (ii)  $\hat{S}_t - S = O_P(C_{NT}^{-2})$ .

*Proof.* Throughout the proof, we assume  $\dim(\alpha_i) = \dim(\lambda_i) = 1$  without loss of generality.

(i)  $\hat{B}_t - B = b_1 + b_2$ , where

$$\begin{aligned}
b_1 &= \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \tilde{\lambda}'_i \hat{e}_{it}^2 - H'_1 \lambda_i \lambda'_i H_1 e_{it}^2 & \tilde{\lambda}_i \tilde{\alpha}'_i \hat{e}_{it} - H'_1 \lambda_i \alpha_i H'_2 e_{it} \\ \tilde{\alpha}_i \tilde{\lambda}'_i \hat{e}_{it} - H'_2 \alpha_i \lambda_i H'_1 e_{it} & \tilde{\alpha}_i \tilde{\alpha}'_i - H'_2 \alpha_i \alpha'_i H_2 \end{pmatrix} \\
b_2 &= \frac{1}{N} \sum_i \begin{pmatrix} H'_1 \lambda_i \lambda'_i H_1 (e_{it}^2 - \mathbb{E} e_{it}^2) & H'_1 \lambda_i \alpha_i H'_2 e_{it} \\ H'_2 \alpha_i \lambda_i H'_1 e_{it} & 0 \end{pmatrix}.
\end{aligned}$$

To prove the convergence of  $b_1$ , first note that

$$\begin{aligned}
& \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) = \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it} - e_{it})^2 + \frac{2}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it} - e_{it}) e_{it} \\
&\leq \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\tilde{\lambda}_i - H'_1 \lambda_i)' (\hat{e}_{it} - e_{it})^2 + \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) \lambda'_i H'_1 (\hat{e}_{it} - e_{it})^2 \\
&\quad + O_P(1) \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 + \frac{2}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\tilde{\lambda}_i - H'_1 \lambda_i)' (\hat{e}_{it} - e_{it}) e_{it} \\
&\quad + \frac{2}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) \lambda'_i H'_1 (\hat{e}_{it} - e_{it}) e_{it} + O_P(1) \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it}) e_{it}
\end{aligned}$$

$$\begin{aligned}
&\leq O_P(C_{NT}^{-2}) \max_{it} |\hat{e}_{it} - e_{it}| \max_{it} |e_{it}| + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 \right)^{1/2} \\
&\quad + O_P(1) \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 e_{it}^2 \right)^{1/2} \\
&\quad + O_P(1) \frac{1}{N} \sum_i \lambda_i \lambda_i' (\hat{e}_{it} - e_{it}) e_{it}.
\end{aligned} \tag{E.6}$$

In addition,

$$\begin{aligned}
&\frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\alpha}_i' (\hat{e}_{it} - e_{it}) = \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) (\tilde{\alpha}_i - H_2' \alpha_i)' (\hat{e}_{it} - e_{it}) \\
&\quad + \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) \alpha_i' H_2 (\hat{e}_{it} - e_{it}) + O_P(1) \frac{1}{N} \sum_i \lambda_i \alpha_i' (\hat{e}_{it} - e_{it}) \\
&\leq O_P(C_{NT}^{-2}) \max_{it} |\hat{e}_{it} - e_{it}| + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2} \\
&\quad + O_P(1) \frac{1}{N} \sum_i \lambda_i \alpha_i' (\hat{e}_{it} - e_{it}).
\end{aligned} \tag{E.7}$$

When  $\hat{e}_{it} - e_{it} = \mu_i - \bar{x}_i = -\bar{e}_i$ , we assume that  $C_{NT}^{-1} \max_{it} |\bar{e}_i| \max_{it} |e_{it}| = O_P(1)$ .

Also,

$\frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 = \frac{1}{N} \sum_i \bar{e}_i^4 = O_P(T^{-1})$  and  $\frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 = \frac{1}{N} \sum_i \bar{e}_i^2 = O_P(T^{-1})$ . Also,  $\frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 e_{it}^2 = O_P(T^{-1})$  and  $\frac{1}{N} \sum_i \lambda_i \lambda_i' (\hat{e}_{it} - e_{it}) e_{it} = O_P(C_{NT}^{-2})$ , and  $\frac{1}{N} \sum_i \lambda_i \alpha_i' (\hat{e}_{it} - e_{it}) = O_P(C_{NT}^{-2})$ . Thus

$$\frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' (\hat{e}_{it}^2 - e_{it}^2) = O_P(C_{NT}^{-2}), \text{ and } \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\alpha}_i' (\hat{e}_{it} - e_{it}) = O_P(C_{NT}^{-1}). \tag{E.8}$$

So the first term of  $b_1$  is, due to the serial independence of  $e_{it}^2$ ,

$$\begin{aligned}
&\frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' \hat{e}_{it}^2 - H_1' \lambda_i \lambda_i' H_1 e_{it}^2 \\
&\leq \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' (\hat{e}_{it}^2 - e_{it}^2) + \frac{1}{N} \sum_i (\tilde{\lambda}_i \tilde{\lambda}_i' - H_1' \lambda_i \lambda_i' H_1) e_{it}^2 \\
&\leq O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_i \|\tilde{\lambda}_i \tilde{\lambda}_i' - H_1' \lambda_i \lambda_i' H_1\|_F \mathbf{E}_I e_{it}^2 \\
&\leq O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_i \|\tilde{\lambda}_i \tilde{\lambda}_i' - H_1' \lambda_i \lambda_i' H_1\|_F = O_P(C_{NT}^{-1}).
\end{aligned}$$

The second term is,

$$\begin{aligned} & \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\alpha}'_i \hat{e}_{it} - H'_1 \lambda_i \alpha_i H'_2 e_{it} \\ & \leq O_P(C_{NT}^{-1}) + O_P(1) \frac{1}{N} \sum_i \|\tilde{\lambda}_i \tilde{\alpha}'_i - H'_1 \lambda_i \alpha_i H'_2\|_F \mathbf{E}_I |e_{it}| \leq O_P(C_{NT}^{-1}). \end{aligned}$$

The third term of  $b_1$  is bounded similarly. The last term of  $b_1$  is easy to show to be  $O_P(C_{NT}^{-1})$ . As for  $b_2$ , by the assumption that  $\frac{1}{N} \sum_{ij} |\text{Cov}(e_{it}^2, e_{jt}^2)| < C$ , thus  $b_2 = O_P(N^{-1/2})$ . Hence  $\hat{B}_t - B = O_P(C_{NT}^{-1})$ .

(ii)  $\hat{S}_t - S = c_t + d_t$ ,

$$\begin{aligned} c_t &= \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \lambda'_i H_1 e_{it} (\hat{e}_{it} - e_{it}) + \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) & \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ \tilde{\alpha}_i \lambda'_i H_1 (e_{it} - \hat{e}_{it}) + \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (\hat{e}_{it} - e_{it}) & 0 \end{pmatrix} \\ d_t &= \frac{1}{N} \sum_i \begin{pmatrix} (\tilde{\lambda}_i \lambda'_i H_1 - \tilde{\lambda}_i \tilde{\lambda}'_i) e_{it}^2 - H'_1 \lambda_i (\lambda'_i H_1 - \tilde{\lambda}'_i) \mathbf{E} e_{it}^2 & \tilde{\lambda}_i e_{it} (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) e_{it} & 0 \end{pmatrix}. \end{aligned}$$

As for  $c_t$ , note that when  $\hat{e}_{it} - e_{it} = -\bar{e}_i$ , we have

$$\begin{aligned} & \frac{1}{N} \sum_i \tilde{\lambda}_i \lambda'_i H_1 e_{it} (\hat{e}_{it} - e_{it}) \leq \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) \lambda'_i e_{it} (\hat{e}_{it} - e_{it}) + O_P(1) \frac{1}{N} \sum_i \lambda_i \lambda_i e_{it} (\hat{e}_{it} - e_{it}) \\ & \leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i e_{it}^2 \bar{e}_i^2 \right)^{1/2} + O_P(1) \frac{1}{N} \sum_i \lambda_i \lambda_i e_{it} \bar{e}_i = O_P(C_{NT}^{-2}). \end{aligned}$$

Also, by (E.8),  $\frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) = O_P(C_{NT}^{-2})$ . For the second term of  $c$ ,

$$\begin{aligned} & \frac{1}{N} \sum_i \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ & \leq \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) + O_P(1) \frac{1}{N} \sum_i \lambda_i (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ & \leq O_P(C_{NT}^{-2}) \max_i |\bar{e}_i| + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i \bar{e}_i^2 \right)^{1/2} = O_P(C_{NT}^{-2}) \end{aligned}$$

given that  $\max_i |\bar{e}_i| = O_P(1)$ . For the third term of  $c_t$ , similarly,

$\frac{1}{N} \sum_i \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (\hat{e}_{it} - e_{it}) = O_P(C_{NT}^{-2})$ . Also,

$$\begin{aligned} & \frac{1}{N} \sum_i \tilde{\alpha}_i \lambda'_i H_1 (e_{it} - \hat{e}_{it}) \\ & \leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2} + O_P(1) \frac{1}{N} \sum_i \lambda_i \alpha'_i (\hat{e}_{it} - e_{it}) \\ & \leq O_P(C_{NT}^{-2}). \end{aligned}$$

So  $c_t = O_P(C_{NT}^{-2})$ .

As for  $d_t$ , we first prove that  $\frac{1}{N} \sum_i \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') (e_{it}^2 - \mathbb{E} e_{it}^2) = O_P(C_{NT}^{-1} N^{-1/2})$ . Note that  $\mathbb{E}_I \frac{1}{N} \sum_i \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') (e_{it}^2 - \mathbb{E} e_{it}^2) = 0$ . Let  $\Upsilon_t$  be an  $N \times 1$  vector of  $e_{it}^2$ , and  $\text{diag}(\Lambda)$  be diagonal matrix consisting of elements of  $\Lambda$ . Then

$$\|\text{Var}(\Upsilon_t)\| \leq \max_i \sum_j |\text{Cov}(e_{it}^2, e_{jt}^2)| < C,$$

and  $\frac{1}{N} \sum_i \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') e_{it}^2 = \frac{1}{N} (H_1 \Lambda - \tilde{\Lambda})' \text{diag}(\Lambda) \Upsilon_t$ . So

$$\begin{aligned} \text{Var}_I \left( \frac{1}{N} \sum_i \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') e_{it}^2 \right) &= \frac{1}{N^2} (H_1 \Lambda - \tilde{\Lambda})' \text{diag}(\Lambda) \text{Var}(\Upsilon_t) \text{diag}(\Lambda) (H_1 \Lambda - \tilde{\Lambda}) \\ &\leq C \frac{1}{N^2} \|H_1 \Lambda - \tilde{\Lambda}\|_F^2 = O_P(C_{NT}^{-2} N^{-1}). \end{aligned}$$

This implies  $\frac{1}{N} \sum_i \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') (e_{it}^2 - \mathbb{E} e_{it}^2) = O_P(C_{NT}^{-1} N^{-1/2})$ .

Thus the first term of  $d_t$  is

$$\begin{aligned} &\frac{1}{N} \sum_i (\tilde{\lambda}_i \lambda_i' H_1 - \tilde{\lambda}_i \tilde{\lambda}_i') e_{it}^2 - H_1' \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') \mathbb{E} e_{it}^2 \\ &\leq \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) (\lambda_i' H_1 - \tilde{\lambda}_i') e_{it}^2 + \frac{1}{N} \sum_i H_1' \lambda_i (\lambda_i' H_1 - \tilde{\lambda}_i') (e_{it}^2 - \mathbb{E} e_{it}^2) \\ &= O_P(1) \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) (\lambda_i' H_1 - \tilde{\lambda}_i') \mathbb{E}_I e_{it}^2 + O_P(C_{NT}^{-1} N^{-1/2}) = O_P(C_{NT}^{-2}). \end{aligned}$$

As for the second term of  $d_t$ ,  $\frac{1}{N} \sum_i \tilde{\lambda}_i e_{it} (\alpha_i' H_2 - \tilde{\alpha}_i')$ , note that

$$\begin{aligned} &\frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) e_{it} (\alpha_i' H_2 - \tilde{\alpha}_i') = O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i e_{it}^2 (\alpha_i' H_2 - \tilde{\alpha}_i')^2 \right)^{1/2} \\ &\leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\alpha_i' H_2 - \tilde{\alpha}_i')^2 \mathbb{E}_I e_{it}^2 \right)^{1/2} = O_P(C_{NT}^{-2}). \end{aligned}$$

And,  $\mathbb{E}_I \frac{1}{N} \sum_i \tilde{\lambda}_i e_{it} (\alpha_i' H_2 - \tilde{\alpha}_i') = 0$ .

$$\begin{aligned} \text{Var}_I \left( \frac{1}{N} \sum_i \lambda_i e_{it} (\alpha_i' H_2 - \tilde{\alpha}_i') \right) &= \frac{1}{N^2} \text{Var}_I ((A H_2 - \tilde{A})' \text{diag}(\Lambda) e_t) \\ &\leq \frac{1}{N^2} (A H_2 - \tilde{A})' \text{diag}(\Lambda) \text{Var}(e_t) \text{diag}(\Lambda) (A H_2 - \tilde{A}) = O_P(C_{NT}^{-2} N^{-1}), \end{aligned}$$

implying  $\frac{1}{N} \sum_i \tilde{\lambda}_i e_{it} (\alpha_i' H_2 - \tilde{\alpha}_i') = O_P(C_{NT}^{-2})$ . Finally, the third term of  $d_t$ ,  $\frac{1}{N} \sum_i \tilde{\lambda}_i e_{it} (\alpha_i' H_2 - \tilde{\alpha}_i')$ , is bounded similarly. So  $d_t = O_P(C_{NT}^{-2})$ .

Q.E.D.

**Lemma E.6.** Suppose  $C_{NT}^{-1} \max_{it} |e_{it}|^2 + \max_t \|\frac{1}{N} \sum_i \lambda_i \lambda_i' \bar{e}_i e_{it}\|_F = o_P(1)$ .

- (i)  $\max_t \|\hat{B}_t^{-1}\| = O_P(1)$ .
- (ii)  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\hat{B}_s^{-1} - B^{-1}\|^2 = O_P(C_{NT}^{-2})$ .
- (iii)  $\frac{1}{T} \sum_{t \in I^c} \|\hat{S}_t - S\|^2 = O_P(C_{NT}^{-4})$ .

*Proof.* Define

$$B_t = \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i \lambda_i' H_1 e_{it}^2 & 0 \\ 0 & H_2' \alpha_i \alpha_i' H_2 \end{pmatrix}.$$

Then  $\hat{B}_t - B_t = b_{1t} + b_{2t}$ ,

$$\begin{aligned} b_{1t} &= \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \tilde{\lambda}_i' \hat{e}_{it}^2 - H_1' \lambda_i \lambda_i' H_1 e_{it}^2 & \tilde{\lambda}_i \tilde{\alpha}_i' \hat{e}_{it} - H_1' \lambda_i \alpha_i H_2' e_{it} \\ \tilde{\alpha}_i \tilde{\lambda}_i' \hat{e}_{it} - H_2' \alpha_i \lambda_i H_1' e_{it} & \tilde{\alpha}_i \tilde{\alpha}_i' - H_2' \alpha_i \alpha_i' H_2 \end{pmatrix} \\ b_{2t} &= \frac{1}{N} \sum_i \begin{pmatrix} 0 & H_1' \lambda_i \alpha_i H_2' e_{it} \\ H_2' \alpha_i \lambda_i H_1' e_{it} & 0 \end{pmatrix}. \end{aligned}$$

(i) We now show  $\max_t |b_{1t}| = o_P(1)$ . In addition, by assumption  $\max_t |b_{2t}| = o_P(1)$ . Thus  $\max_t |\hat{B}_t - B_t| = o_P(1)$ , and thus  $\max_t \|\hat{B}_t^{-1}\| = o_P(1) + \max_t \|B_t^{-1}\| = O_P(1)$ , by the assumption that  $\|B_t^{-1}\| = O_P(1)$  uniformly in  $t$ . To show  $\max_t |b_{1t}| = o_P(1)$ , note that:

First term:

$$\begin{aligned} & \max_t \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' (\hat{e}_{it}^2 - e_{it}^2) \right\| \\ & \leq O_P(1) \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 \right)^{1/2} \max_t \left[ \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 + (\hat{e}_{it} - e_{it})^2 e_{it}^2 \right]^{1/2} \\ & \quad + \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 [2 \max_t |(\hat{e}_{it} - e_{it}) e_{it}| + \max_t (\hat{e}_{it} - e_{it})^2] \\ & \quad + O_P(1) \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' (\hat{e}_{it} - e_{it}) e_{it} \right\|_F \\ & \quad + O_P(1) \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' (\hat{e}_{it} - e_{it})^2 \right\|_F. \end{aligned} \tag{E.9}$$

When  $\hat{e}_{it} - e_{it} = -\bar{e}_i$ , we have

$$\max_t \left[ \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 + (\hat{e}_{it} - e_{it})^2 e_{it}^2 \right]^{1/2} \leq \left[ \frac{1}{N} \sum_i \bar{e}_i^4 \right]^{1/2} + \left[ \frac{1}{N} \sum_i \bar{e}_i^2 \right]^{1/2} \max_{it} |e_{it}|$$

and  $2 \max_t |(\widehat{e}_{it} - e_{it})e_{it}| + \max_t (\widehat{e}_{it} - e_{it})^2 \leq 2|\bar{e}_i| \max_t |e_{it}| + \bar{e}_i^2$ ,

$$\begin{aligned} \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' (\widehat{e}_{it} - e_{it})^2 \right\|_F &\leq \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' \bar{e}_i^2 \right\|_F = O_P(T^{-1}) \\ \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' (\widehat{e}_{it} - e_{it}) e_{it} \right\|_F &\leq \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' \bar{e}_i e_{it} \right\|_F. \end{aligned}$$

Thus, with the assumption  $C_{NT}^{-1} \max_{it} |e_{it}|^2 + \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' \bar{e}_i e_{it} \right\|_F = o_P(1)$ ,

$$\max_t \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' (\widehat{e}_{it}^2 - e_{it}^2) \right\| = o_P(1) + O_P(C_{NT}^{-2}) \max_{it} |e_{it}| + \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' \bar{e}_i e_{it} \right\|_F = o_P(1).$$

In addition,  $\max_t \left\| \frac{1}{N} \sum_i (\tilde{\lambda}_i \tilde{\lambda}_i' - H_1' \lambda_i \lambda_i' H_1) e_{it}^2 \right\| \leq O_P(C_{NT}^{-1}) \max_{it} e_{it}^2 = o_P(1)$ . So the first term of  $\max_t |b_{1t}|$  is  $o_P(1)$ .

Second term,

$$\begin{aligned} &\max_t \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\alpha}_i' (\widehat{e}_{it} - e_{it}) \right\|_F \\ &\leq \max_{it} |\widehat{e}_{it} - e_{it}| \frac{1}{N} \sum_i \left\| (\tilde{\lambda}_i - H_1' \lambda_i) (\tilde{\alpha}_i - H_2' \alpha_i)' \right\|_F \\ &\quad + O_P(1) \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 + \left( \frac{1}{N} \sum_i \|\tilde{\alpha}_i - H_2' \alpha_i\|^2 \right)^{1/2} \max_t \left( \frac{1}{N} \sum_i (\widehat{e}_{it} - e_{it})^2 \right)^{1/2} \right. \\ &\quad \left. + O_P(1) \max_t \left\| \frac{1}{N} \sum_i \lambda_i \alpha_i' (\widehat{e}_{it} - e_{it}) \right\|_F \right). \end{aligned} \tag{E.10}$$

When  $\widehat{e}_{it} - e_{it} = -\bar{e}_i$ , the above is  $o_P(1)$  given that  $C_{NT}^{-2} \max_i |\bar{e}_i| = o_P(1)$ . Next,

$$\max_t \left\| \frac{1}{N} \sum_i (\tilde{\lambda}_i \tilde{\alpha}_i' - H_1' \lambda_i \alpha_i' H_2) e_{it} \right\|_F = O_P(C_{NT}^{-1}) \max_{it} |e_{it}| = o_P(1).$$

So the second term of  $\max_t |b_{1t}|$  is  $o_P(1)$ . Similarly, the third term is also  $o_P(1)$ .

Finally, the last term  $\left\| \frac{1}{N} \sum_i \tilde{\alpha}_i \tilde{\alpha}_i' - H_2' \alpha_i \alpha_i' H_2 \right\|_F = o_P(1)$ .

(ii) Because we have proved  $\max_t \|\widehat{B}_t^{-1}\| = O_P(1)$ , it suffices to prove

$$\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\widehat{B}_s - B\|_F^2 = O_P(C_{NT}^{-2}), \text{ or } \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{1t}\|_F^2 = O_P(C_{NT}^{-2}) = \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{2t}\|_F^2.$$

First term of  $b_{1t}$ : by (E.6), the first term is bounded by

$$\begin{aligned} &\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' \widehat{e}_{it}^2 - H_1' \lambda_i \lambda_i' H_1 e_{it}^2 \right\|_F^2 \\ &\leq \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' (\widehat{e}_{it}^2 - e_{it}^2) \right\|_F^2 + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i (\tilde{\lambda}_i \tilde{\lambda}_i' - H_1' \lambda_i \lambda_i' H_1) e_{it}^2 \right\|_F^2 \end{aligned}$$

$$\begin{aligned}
&\leq O_P(C_{NT}^{-4}) \max_{it} |\widehat{e}_{it} - e_{it}|^2 \max_{it} |e_{it}|^2 + O_P(C_{NT}^{-2}) \frac{1}{T} \sum_{t \in I^c} \frac{1}{N} \sum_i (\widehat{e}_{it} - e_{it})^4 \\
&\quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i (\widehat{e}_{it} - e_{it})^2 \right)^2 + O_P(C_{NT}^{-2}) \frac{1}{T} \sum_{t \in I^c} \frac{1}{N} \sum_i (\widehat{e}_{it} - e_{it})^2 e_{it}^2 \\
&\quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i \lambda_i \lambda'_i (\widehat{e}_{it} - e_{it}) e_{it} \right)^2 \\
&\quad + O_P(1) \text{tr} \left( \frac{1}{N^2} \sum_{ij} (\widetilde{\lambda}_i \widetilde{\lambda}'_i - H'_1 \lambda_i \lambda'_i H_1) (\widetilde{\lambda}_j \widetilde{\lambda}'_j - H'_1 \lambda_j \lambda'_j H_1) \right) \frac{1}{T} \sum_{t \in I^c} \mathbb{E}_I e_{jt}^2 e_{it}^2 \\
&\leq O_P(C_{NT}^{-2}) + O_P(1) \left( \frac{1}{N} \sum_i \|(\widetilde{\lambda}_i \widetilde{\lambda}'_i - H'_1 \lambda_i \lambda'_i H_1)\|_F^2 \right) = O_P(C_{NT}^{-2}). \quad (\text{E.11})
\end{aligned}$$

Second term of  $b_{1t}$ :

$$\begin{aligned}
&\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \widetilde{\lambda}_i \widetilde{\alpha}'_i \widehat{e}_{it} - H'_1 \lambda_i \alpha_i H'_2 e_{it} \right\|_F^2 \\
&\leq \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \widetilde{\lambda}_i \widetilde{\alpha}'_i (\widehat{e}_{it} - e_{it}) \right\|_F^2 + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i (\widetilde{\lambda}_i \widetilde{\alpha}'_i - H'_1 \lambda_i \alpha_i H'_2) e_{it} \right\|_F^2 \\
&\leq O_P(C_{NT}^{-4}) \max_i \frac{1}{T} \sum_t (\widehat{e}_{it} - e_{it})^2 + O_P(C_{NT}^{-2}) \frac{1}{NT} \sum_{it} (\widehat{e}_{it} - e_{it})^2 \\
&\quad + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \alpha'_i (\widehat{e}_{it} - e_{it}) \right\|_F^2 \\
&\quad + O_P(1) \text{tr} \frac{1}{N^2} \sum_{ij} (\widetilde{\lambda}_i \widetilde{\alpha}'_i - H'_1 \lambda_i \alpha_i H'_2) (\widetilde{\lambda}_j \widetilde{\alpha}'_j - H'_1 \lambda_j \alpha_j H'_2) \frac{1}{T} \sum_{t \in I^c} \mathbb{E}_I e_{it} e_{jt} \\
&= O_P(C_{NT}^{-2}). \quad (\text{E.12})
\end{aligned}$$

The third term of  $b_{1t}$  is bounded similarly. Finally, it is straightforward to see that fourth term of  $b_{1t}$  is  $\left\| \frac{1}{N} \sum_i \widetilde{\alpha}_i \widetilde{\alpha}'_i - H'_2 \alpha_i \alpha'_i H_2 \right\|_F^2 = O_P(C_{NT}^{-2})$ . Thus  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{1t}\|_F^2 = O_P(C_{NT}^{-2})$ .

As for  $b_{2t}$ , it suffices to prove

$$\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i e_{it} \right\|_F^2 = O_P(1) \frac{1}{T} \sum_{t \in I^c} \mathbb{E} \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i e_{it} \right\|_F^2 = O_P(N^{-1}).$$

Thus  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{2t}\|_F^2 = O_P(C_{NT}^{-2})$ . Q.E.D.

(iii) Note that  $\frac{1}{T} \sum_{t \in I^c} \|\widehat{S}_t - S\|^2 \leq \frac{2}{T} \sum_{t \in I^c} \|c_t\|^2 + \frac{2}{T} \sum_{t \in I^c} \|d_t\|^2$ , where

$$c_t = \frac{1}{N} \sum_i \begin{pmatrix} \widetilde{\lambda}_i \lambda'_i H_1 e_{it} (\widehat{e}_{it} - e_{it}) + \widetilde{\lambda}_i \widetilde{\lambda}'_i (\widehat{e}_{it}^2 - e_{it}^2) & \widetilde{\lambda}_i (\widehat{e}_{it} - e_{it}) (\alpha'_i H_2 - \widetilde{\alpha}'_i) \\ \widetilde{\alpha}_i \lambda'_i H_1 (e_{it} - \widehat{e}_{it}) + \widetilde{\alpha}_i (\lambda'_i H_1 - \widetilde{\lambda}'_i) (\widehat{e}_{it} - e_{it}) & 0 \end{pmatrix}$$

$$d_t = \frac{1}{N} \sum_i \begin{pmatrix} (\tilde{\lambda}_i \lambda'_i H_1 - \tilde{\lambda}_i \tilde{\lambda}'_i) e_{it}^2 - H'_1 \lambda_i (\lambda'_i H_1 - \tilde{\lambda}'_i) \mathbb{E} e_{it}^2 & \tilde{\lambda}_i e_{it} (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) e_{it} & 0 \end{pmatrix}.$$

As for  $\frac{1}{T} \sum_{t \in I^c} \|c_t\|_F^2$ , we have

$$\begin{aligned} & \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \lambda'_i H_1 e_{it} (\hat{e}_{it} - e_{it}) \right\|_F^2 \\ & \leq O_P(1) \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \frac{1}{NT} \sum_i \sum_{t \in I^c} e_{it}^2 (\hat{e}_{it} - e_{it})^2 \\ & \quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i e_{it} (\hat{e}_{it} - e_{it}) \right\|_F^2 \\ & \leq O_P(C_{NT}^{-2}) \frac{1}{NT} \sum_i \sum_{t \in I^c} e_{it}^2 \bar{e}_i^2 + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i e_{it} \bar{e}_i \right\|_F^2 \\ & = O_P(C_{NT}^{-4}) \\ & \quad \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) \right\|_F^2 \\ & \leq \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \right)^2 \max_{it} [(\hat{e}_{it} - e_{it})^4] \\ & \quad + \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 |e_{it}| \right)^2 \max_{it} |\hat{e}_{it} - e_{it}|^2 \\ & \quad + \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \frac{1}{NT} \sum_{t \in I^c} \sum_i [(\hat{e}_{it} - e_{it})^4 + (\hat{e}_{it} - e_{it})^2 e_{it}^2] \\ & \quad + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it}) e_{it} \right\|_F^2 + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it})^2 \right\|_F^2. \end{aligned}$$

Note that

$$\begin{aligned} & \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 |e_{it}| \right)^2 \\ & = O_P(1) \frac{1}{N^2} \sum_{ij} \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \|\tilde{\lambda}_j - H'_1 \lambda_j\|^2 \frac{1}{T} \sum_{t \in I^c} \mathbb{E}_I |e_{jt} e_{it}| \\ & = O_P(1) \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \right)^2 = O_P(C_{NT}^{-4}). \end{aligned}$$

So when  $\hat{e}_{it} - e_{it} = -\bar{e}_i$ , with the assumption that  $\max_{it} |\bar{e}_i| = O_P(1)$ , we have

$$\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) \right\|_F^2 = O_P(C_{NT}^{-4}).$$



Also,

$$\begin{aligned}
& \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) \right\|_F^2 \\
& \leq \frac{1}{N} \sum_i \|\alpha'_i H_2 - \tilde{\alpha}'_i\|^2 \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \max_{it} (\hat{e}_{it} - e_{it})^2 \\
& \quad + O_P(1) \frac{1}{N} \sum_i \|\alpha'_i H_2 - \tilde{\alpha}'_i\|^2 \frac{1}{N} \sum_i \frac{1}{T} \sum_{t \in I^c} (\hat{e}_{it} - e_{it})^2 = O_P(C_{NT}^{-4}).
\end{aligned}$$

Similarly,  $\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (\hat{e}_{it} - e_{it}) \right\|_F^2 = O_P(C_{NT}^{-4})$ . Finally,

$$\begin{aligned}
\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\alpha}_i \lambda'_i H_1 (e_{it} - \hat{e}_{it}) \right\|_F^2 &= O_P(C_{NT}^{-4}) + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i (e_{it} - \hat{e}_{it}) \right\|_F^2 \\
&= O_P(C_{NT}^{-4}).
\end{aligned}$$

So  $\frac{1}{T} \sum_{t \in I^c} \|c_t\|_F^2 = O_P(C_{NT}^{-4})$ .

As for  $\frac{1}{T} \sum_{t \in I^c} \|d_t\|_F^2$ , its first term depends on  $\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (e_{it}^2 - \mathbf{E} e_{it}^2) \right\|_F^2$ . Let  $\Upsilon_t$  be an  $N \times 1$  vector of  $e_{it}^2$ , and  $\text{diag}(\Lambda)$  be diagonal matrix consisting of elements of  $\Lambda$ . Suppose  $\dim(\lambda_i) = 1$  (focus on each element), then the first term of  $\frac{1}{T} \sum_{t \in I^c} \|d_t\|_F^2$  is bounded by

$$\begin{aligned}
& \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i (\tilde{\lambda}_i \lambda'_i H_1 - \tilde{\lambda}_i \tilde{\lambda}'_i) e_{it}^2 - H'_1 \lambda_i (\lambda'_i H_1 - \tilde{\lambda}'_i) \mathbf{E} e_{it}^2 \right\|_F^2 \\
& \leq \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\lambda'_i H_1 - \tilde{\lambda}'_i) e_{it}^2 \right\|_F^2 \\
& \quad + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i H'_1 \lambda_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (e_{it}^2 - \mathbf{E} e_{it}^2) \right\|_F^2 \\
& \leq O_P(1) \frac{1}{N^2} \sum_{ij} \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \|\tilde{\lambda}_j - H'_1 \lambda_j\|^2 \frac{1}{T} \sum_{t \in I^c} \mathbf{E} e_{jt}^2 e_{it}^2 \\
& \quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \frac{1}{N^2} (\tilde{\Lambda} - \Lambda H_1)' \text{diag}(\Lambda) \text{Var}_I(\Upsilon_t) \text{diag}(\Lambda) (\tilde{\Lambda} - \Lambda H_1) \\
& = O_P(C_{NT}^{-4}).
\end{aligned}$$

In addition, using the same technique, it is easy to show

$$\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i e_{it} (\alpha'_i H_2 - \tilde{\alpha}'_i) \right\|_F^2 = O_P(C_{NT}^{-4}) = \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) e_{it} \right\|_F^2.$$

Put together,  $\frac{1}{T} \sum_{t \in I^c} \|\hat{S}_t - S\|^2 \leq \frac{2}{T} \sum_{t \in I^c} \|c_t\|^2 + \frac{2}{T} \sum_{t \in I^c} \|d_t\|^2 = O_P(C_{NT}^{-4})$ .  
Q.E.D.

**Lemma E.7.** For terms defined in (D.2), and for each fixed  $t \in I^c$ ,  $\sum_{d=1}^5 A_{dt} = O_P(C_{NT}^{-2})$  and for the “upper block” of  $A_{6t}$ ,  $\frac{1}{N} \sum_i \lambda_i e_{it} (\mu_i \lambda_i' f_t - \bar{x}_i \dot{\lambda}_i' \tilde{f}_t) = O_P(C_{NT}^{-2})$ .

*Proof.* (i) Term  $A_{1t}$ . It suffices to show  $\hat{B}_t^{-1} \hat{S}_t - B^{-1} S = O_P(C_{NT}^{-2})$ . By Lemma E.5,

$$\begin{aligned} B_t^{-1} \hat{S}_t - B^{-1} S &= (B_t^{-1} - B^{-1})(\hat{S}_t - S) + (B_t^{-1} - B^{-1})S + B^{-1}(\hat{S}_t - S) \\ &= O_P(C_{NT}^{-2}) + O_P(C_{NT}^{-1})S = O_P(C_{NT}^{-2}), \end{aligned}$$

where the last equality is due to  $S = O_P(C_{NT}^{-1})$ .

(ii) Term  $A_{2t}$ . Given  $B_t^{-1} - B^{-1} = O_P(C_{NT}^{-1})$  and the cross-sectional weak correlations in  $u_{it}$ , it is easy to see  $A_{2t} = O_P(C_{NT}^{-2})$ .

(iii) Term  $A_{3t}$ . It suffices to prove:

$$\begin{aligned} \frac{1}{N} \sum_i (\tilde{\lambda}_i \hat{e}_{it} - H_1' \lambda_i e_{it}) u_{it} &= O_P(C_{NT}^{-2}) \\ \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) u_{it} &= O_P(C_{NT}^{-2}). \end{aligned} \quad (\text{E.13})$$

First, let  $\Upsilon_t$  be an  $N \times 1$  vector of  $e_{it} u_{it}$ . Due to the serial independence of  $(u_{it}, e_{it})$ , we have

$$\begin{aligned} \mathbb{E}_I \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) e_{it} u_{it} &= 0, \\ \text{Var}_I \left( \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) e_{it} u_{it} \right) &= \frac{1}{N^2} (\tilde{\Lambda} - \Lambda H_1)' \text{Var}_I(\Upsilon_t) (\tilde{\Lambda} - \Lambda H_1) \\ &\leq O_P(C_{NT}^{-2} N^{-1}) \max_i \sum_j |\text{Cov}(e_{it} u_{it}, e_{jt} u_{jt})| = O_P(C_{NT}^{-2} N^{-1}). \end{aligned}$$

Similarly,  $\mathbb{E}_I \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) u_{it} = 0$  and  $\text{Var}_I \left( \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) u_{it} \right) = O_P(C_{NT}^{-2} N^{-1})$ .

$$\begin{aligned} \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) e_{it} u_{it} &= O_P(C_{NT}^{-1} N^{-1/2}) \\ \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) u_{it} &= O_P(C_{NT}^{-1} N^{-1/2}) \\ \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 u_{it}^2 &= O_P(1) \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 \mathbb{E}_I u_{it}^2 = O_P(C_{NT}^{-2}) \end{aligned} \quad (\text{E.14})$$

Thus, the first term of (E.13) is

$$\frac{1}{N} \sum_i (\tilde{\lambda}_i \hat{e}_{it} - H_1' \lambda_i e_{it}) u_{it} \leq \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 u_{it}^2 \right)^{1/2} \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2}$$

$$\begin{aligned}
& + H_1' \frac{1}{N} \sum_i \lambda_i (\hat{e}_{it} - e_{it}) u_{it} + \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) e_{it} u_{it} \\
& \leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2} + O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_i \lambda_i (\hat{e}_{it} - e_{it}) u_{it}
\end{aligned} \tag{E.15}$$

When  $\hat{e}_{it} - e_{it} = -\bar{e}_i$  in the many mean model, the above is  $O_P(C_{NT}^{-2})$ .

(iv) Term  $A_{5t}$ . Given  $B_t^{-1} - B^{-1} = O_P(C_{NT}^{-1})$ , it suffices to prove the following terms are  $O_P(C_{NT}^{-2})$ .

$$\begin{aligned}
B_{1t} &= \frac{1}{N} \sum_i \lambda_i e_{it} (\bar{x}_i - \mu_i) (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
B_{2t} &= \frac{1}{N} \sum_i \lambda_i e_{it} (\bar{x}_i - \mu_i) \lambda_i' H_1 \tilde{f}_t \\
B_{3t} &= \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
B_{4t} &= \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i \lambda_i' H_1 (\tilde{f}_t - H_1^{-1} f_t) \\
B_{5t} &= \frac{1}{N} \sum_i \alpha_i (\bar{x}_i - \mu_i) (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t
\end{aligned} \tag{E.16}$$

and that the following terms are  $O_P(C_{NT}^{-1})$ :

$$\begin{aligned}
B_{6t} &= \frac{1}{N} \sum_i \alpha_i (\bar{x}_i - \mu_i) \lambda_i' H_1 \tilde{f}_t \\
B_{7t} &= \frac{1}{N} \sum_i \alpha_i \mu_i (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
B_{8t} &= \frac{1}{N} \sum_i \alpha_i \mu_i \lambda_i' H_1 (\tilde{f}_t - H_1^{-1} f_t).
\end{aligned} \tag{E.17}$$

In fact, we have,

$$\begin{aligned}
B_{1t} &\leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i e_{it}^2 \bar{e}_i^2 \right)^{1/2} = O_P(C_{NT}^{-2}). \\
B_{2t} &= O_P(1) \frac{1}{NT} \sum_{is} \lambda_i \lambda_i' e_{it} e_{is} \\
&\leq O_P(1) \left( \frac{1}{N^2 T^2} \sum_{ij} \sum_{sk} |E e_{it} e_{jt} e_{is} e_{jk}| \right)^{1/2} = O_P(C_{NT}^{-2}).
\end{aligned}$$

By Lemma E.4, note that  $t \in I^c$ ,  $B_{3t} = O_P(1) \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i (\dot{\lambda}_i - H'_1 \lambda_i)' = O_P(C_{NT}^{-2})$ . Finally, still by Lemma E.4 that for each fixed  $t$ ,  $\tilde{f}_t - H_1^{-1} f_t = O_P(C_{NT}^{-1})$ . Thus

$$B_{4t} = O_P(C_{NT}^{-1}) \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i \lambda_i' = O_P(C_{NT}^{-2}).$$

The proofs for  $B_{5t} \sim B_{8t}$  from the similar argument, using the Cauchy-Schwarz inequality. In addition, it is also straightforward to prove, for each fixed  $j$ ,

$$\sum_{d=1}^5 \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 (1 + e_{jt}^4) = O_P(C_{NT}^{-4}), \quad \sum_{d=6}^8 \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 (1 + e_{jt}^4) = O_P(C_{NT}^{-2}). \quad (\text{E.18})$$

(v) “upper block” of  $A_{6t}$ . From the proof of (iv), we have  $B_{dt} = O_P(C_{NT}^{-2})$ , for  $d = 1, \dots, 4$ . It follows immediately that  $\frac{1}{N} \sum_i \lambda_i e_{it} (\mu_i \lambda_i' f_t - \bar{x}_i \dot{\lambda}_i' \tilde{f}_t) = O_P(C_{NT}^{-2})$ .

(vi) Term  $A_{4t}$ . Note that  $\bar{x}_i - \mu_i = e_{it} - \hat{e}_{it}$ . It suffices to prove each of the following terms is  $O_P(C_{NT}^{-2})$ : note that  $\mu_{it} = \mu_i$ .

$$\begin{aligned} C_{1t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) e_{it} (\hat{e}_{it} - e_{it}) (\dot{\lambda}_i - H'_1 \lambda_i)' \tilde{f}_t \\ C_{2t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\hat{e}_{it} - e_{it})^2 (\dot{\lambda}_i - H'_1 \lambda_i)' \tilde{f}_t \\ C_{3t} &= \frac{1}{N} \sum_i H'_1 \lambda_i (\hat{e}_{it} - e_{it})^2 (\dot{\lambda}_i - H'_1 \lambda_i)' \tilde{f}_t \\ C_{4t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) e_{it} (\hat{e}_{it} - e_{it}) \lambda_i' H_1 \tilde{f}_t \\ C_{5t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\hat{e}_{it} - e_{it})^2 \lambda_i' H_1 \tilde{f}_t \\ C_{6t} &= \frac{1}{N} \sum_i H'_1 \lambda_i (\hat{e}_{it} - e_{it})^2 \lambda_i' H_1 \tilde{f}_t \\ C_{7t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) e_{it} \mu_{it} (\dot{\lambda}_i - H'_1 \lambda_i)' \tilde{f}_t \\ C_{8t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\hat{e}_{it} - e_{it}) \mu_{it} (\dot{\lambda}_i - H'_1 \lambda_i)' \tilde{f}_t \\ C_{9t} &= \frac{1}{N} \sum_i H'_1 \lambda_i (\hat{e}_{it} - e_{it}) \mu_{it} (\dot{\lambda}_i - H'_1 \lambda_i)' \tilde{f}_t \\ C_{10t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) e_{it} \mu_{it} \lambda_i' H_1 (\tilde{f}_t - H_1^{-1} f_t) \\ C_{11t} &= \frac{1}{N} \sum_i (\tilde{\lambda}_i - H'_1 \lambda_i) (\hat{e}_{it} - e_{it}) \mu_{it} \lambda_i' H_1 (\tilde{f}_t - H_1^{-1} f_t) \end{aligned}$$

$$\begin{aligned}
C_{12t} &= \frac{1}{N} \sum_i H_1' \lambda_i (\hat{e}_{it} - e_{it}) \mu_{it} \lambda_i' H_1 (\tilde{f}_t - H_1^{-1} f_t) \\
C_{13t} &= \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) (\hat{e}_{it} - e_{it}) (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
C_{14t} &= \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) (\hat{e}_{it} - e_{it}) \lambda_i' H_1 \tilde{f}_t \\
C_{15t} &= \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) \mu_{it} (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
C_{16t} &= \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) \mu_{it} \lambda_i' H_1 (\tilde{f}_t - H_1^{-1} f_t). \tag{E.19}
\end{aligned}$$

The proof follows from repeatedly applying the Cauchy-Schwarz inequality and is straightforward. In addition, it is also straightforward to apply Cauchy-Schwarz to prove that

$$\frac{1}{T} \sum_{t \in I^c} \|C_{dt}\|^2 = O_P(C_{NT}^{-4}) = \frac{1}{T} \sum_{t \in I^c} \|C_{dt}\|^2 e_{it}^2, \quad d = 1, \dots, 16. \text{ and fixed } i. \tag{E.20}$$

We omit the details for brevity. Q.E.D.

**Lemma E.8.** (i)  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\hat{f}_s - H_f f_s\|^2 = O_P(C_{NT}^{-2})$ .  
(ii) For each fixed  $i$ ,  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) e_{is} f_s' = O_P(C_{NT}^{-2})$ .

This lemma is needed to prove the performance for  $\hat{\lambda}_i$ , which controls the effect of  $\hat{f}_s - H_f f_s$  on the estimation of  $\lambda_i$ .

*Proof.* (i) Given (D.2), the proof is very similar to that of Lemma E.7. We omit the details for brevity. We now turn to the much harder part (ii).

(ii) Use (D.2),  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) e_{is} f_s'$  equals, up to a multiplier of order  $O_P(1)$ ,

$$\frac{1}{NT} \sum_{t \in I^c} \sum_i e_{it}^2 u_{it} f_t' + \sum_{d=1}^5 \frac{1}{T} \sum_{t \in I^c} a_{dt} e_{it} f_t'.$$

where  $a_{dt}$  is the upper block of  $A_{dt}$ . Given that  $E(u_t u_t' | e_y, f_t) < C$  and that  $u_t$  is conditionally serially independent, we have  $\frac{1}{NT} \sum_{t \in I^c} \sum_i e_{it}^2 u_{it} f_t' = O_P(C_{NT}^{-2})$ . Next, up to a multiplier of order  $O_P(1)$ , by Lemma E.6,

$$\frac{1}{T} \sum_{t \in I^c} a_{1t} e_{it} f_t' \leq \frac{1}{T} \sum_{t \in I^c} \|\hat{B}_t^{-1} \hat{S}_t - B^{-1} S\| (\|f_t\| + \|g_t\|) \|f_t'\| |e_{it}|$$

$$\begin{aligned}
& \leq \left(\frac{1}{T} \sum_{t \in I^c} \|\hat{B}_t - B\|^2\right)^{1/2} \|S\| + \left(\frac{1}{T} \sum_{t \in I^c} \|\hat{S}_t - S\|^2\right)^{1/2} \\
& = O_P(C_{NT}^{-2}) \\
\frac{1}{T} \sum_{t \in I^c} a_{2t} e_{it} f'_t & \leq \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \|\hat{B}_t^{-1} - B^{-1}\| \left\| \frac{1}{N} \sum_j \lambda_j e_{jt} u_{jt} \right\| + \left\| \frac{1}{N} \sum_j \alpha_j u_{jt} \right\| \\
& \leq \left(\frac{1}{T} \sum_{t \in I^c} \|\hat{B}_t - B\|^2\right)^{1/2} \left(\frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\|^2 \left\| \frac{1}{N} \sum_j \lambda_j e_{jt} u_{jt} \right\| + \left\| \frac{1}{N} \sum_j \alpha_j u_{jt} \right\|^2\right)^{1/2} \\
& \leq O_P(C_{NT}^{-1}) \left(\frac{1}{T} \sum_{t \in I^c} \mathbb{E} \|e_{it} f'_t\|^2 \mathbb{E} \left\| \frac{1}{N} \sum_j \lambda_j e_{jt} u_{jt} \right\|^2 + \left\| \frac{1}{N} \sum_j \alpha_j u_{jt} \right\|^2 |e_t, f_t|\right)^{1/2} \\
& = O_P(C_{NT}^{-2}) \\
\frac{1}{T} \sum_{t \in I^c} a_{3t} e_{it} f'_t & \leq \max_t \|\hat{B}_t^{-1}\| \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \left\| \frac{1}{N} \sum_j (\tilde{\lambda}_j \hat{e}_{jt} - H'_1 \lambda_j e_{jt}) u_{jt} \right\| \\
& \quad + \max_t \|\hat{B}_t^{-1}\| \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \left\| \frac{1}{N} \sum_j (\tilde{\alpha}_j - H'_2 \alpha_j) u_{jt} \right\| \\
& \leq O_P(1) \left(\frac{1}{T} \sum_{t \in I^c} \mathbb{E}_I \left\| \frac{1}{N} \sum_j (\tilde{\lambda}_j - H'_1 \lambda_j) e_{jt} u_{jt} \right\|^2\right)^{1/2} \\
& \quad + O_P(1) \left(\frac{1}{T} \sum_{t \in I^c} \mathbb{E}_I \left\| \frac{1}{N} \sum_j (\tilde{\alpha}_j - H'_2 \alpha_j) u_{jt} \right\|^2\right)^{1/2} \\
& \quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \left\| \frac{1}{N} \sum_j (\tilde{\lambda}_j - H'_1 \lambda_j) (\hat{e}_{jt} - e_{jt}) u_{jt} \right\| \\
& \quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \left\| \frac{1}{N} \sum_j \lambda_j (\hat{e}_{jt} - e_{jt}) u_{jt} \right\| \\
& = O_P(C_{NT}^{-2}) \\
\frac{1}{T} \sum_{t \in I^c} a_{4t} e_{it} f'_t & \leq \max_t \|\hat{B}_t^{-1}\| \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \|C_{dt}\|, \quad d = 1 \dots 16
\end{aligned}$$

where  $C_{dt}$ 's are defined in the proof of Lemma E.7. By (E.20),  $\frac{1}{T} \sum_{t \in I^c} \|C_{dt}\|^2 = O_P(C_{NT}^{-4})$  for  $d \leq 16$ . Thus  $\frac{1}{T} \sum_{t \in I^c} a_{4t} e_{it} f'_t = O_P(C_{NT}^{-2})$ , still following from Cauchy-Schwarz.

Next, for  $B_{dt}$  defined in the proof of Lemma E.7,

$$\frac{1}{T} \sum_{t \in I^c} a_{5t} e_{it} f'_t \leq \sum_{d=1}^8 \frac{1}{T} \sum_{t \in I^c} \|\hat{B}_t - B\| \|B_{dt} e_{it} f'_t\|.$$

Repeatedly using Cauchy-Schwarz, it can be shown that  $\frac{1}{T} \sum_{t \in I^c} a_{5t} e_{it} f'_t = O_P(C_{NT}^{-2})$ . Finally, using Cauchy-Schwarz,

$$\frac{1}{T} \sum_{t \in I^c} a_{6t} e_{it} f'_t \leq O_P(1) \sum_{d=1}^4 \left\| \frac{1}{T} \sum_{t \in I^c} B_{dt} e_{it} f'_t \right\| = O_P(C_{NT}^{-2}).$$

Therefore,  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) e_{is} f'_s = O_P(C_{NT}^{-2})$ .

Q.E.D.

### E.3. Technical lemmas for $\hat{\lambda}_i$ .

**Lemma E.9.** *For each fixed  $i$ ,  $\hat{D}_i - D_i = O_P(C_{NT}^{-1})$ .*

*Proof.*  $\hat{D}_i - D_i$  is a two-by-two block matrix. The first block is

$$\begin{aligned} & \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \hat{f}_s \hat{f}'_s \hat{e}_{is}^2 - H_f f_s f'_s H'_f \mathbf{E} e_{is}^2 \\ &= \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) (\hat{f}_s - H_f f_s)' [(\hat{e}_{is} - e_{is})^2 + (\hat{e}_{is} - e_{is}) e_{is} + e_{is}^2] \\ & \quad + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) f'_s H'_f [(\hat{e}_{is} - e_{is})^2 + (\hat{e}_{is} - e_{is}) e_{is} + e_{is}^2] \\ & \quad + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} H_f f_s (\hat{f}_s - H_f f_s)' [(\hat{e}_{is} - e_{is})^2 + (\hat{e}_{is} - e_{is}) e_{is} + e_{is}^2] \\ & \quad + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} H_f f_s f'_s H'_f [(\hat{e}_{is} - e_{is})^2 + (\hat{e}_{is} - e_{is}) e_{is}] + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} H_f f_s f'_s H'_f (e_{is}^2 - \mathbf{E} e_{is}^2). \end{aligned}$$

The second block is

$$\begin{aligned} \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \hat{f}_s \hat{g}'_s \hat{e}_{is} &= \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) (\hat{g}_s - H_g g_s)' \hat{e}_{is} + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) g'_s H'_g \hat{e}_{is} \\ & \quad + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} H_f f_s (\hat{g}_s - H_g g_s)' \hat{e}_{is} + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} H_f f_s g'_s H'_g (\hat{e}_{is} - e_{is}) \\ & \quad + \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} H_f f_s g'_s H'_g e_{is} \end{aligned}$$

The third block is similar. The fourth block is  $\frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \hat{g}_s \hat{g}'_s - H_g g_s g'_s H'_g$ . Given  $\hat{e}_{is} - e_{is} = -\bar{e}_i$  and Lemma E.9, it is straightforward to see each term in the above expansions is  $O_P(C_{NT}^{-1})$ . Q.E.D.

**Lemma E.10.** *For each fixed  $i \leq N$ ,*

$$\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \widehat{f}_s \widehat{e}_{is} (\mu_i \lambda'_i f_s - \bar{x}_i \dot{\lambda}'_i \widetilde{f}_s) = O_P(C_{NT}^{-2}), \quad \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \widehat{g}_s (\mu_i \lambda'_i f_s - \bar{x}_i \dot{\lambda}'_i \widetilde{f}_s) = O_P(C_{NT}^{-1}).$$

*Note that the first term is  $O_P(C_{NT}^{-2})$  while the second term is  $O_P(C_{NT}^{-1})$ .*

*Proof.* It suffices to prove that the following statements.

$$\begin{aligned} R_{3i,1} &:= \frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\widehat{f}_s - H_f f_s) (\widehat{e}_{is} - e_{is}) \mu_i \lambda'_i f_s = O_P(C_{NT}^{-2}) \\ R_{3i,2} &:= \frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\widehat{f}_s \widehat{e}_{is} - H_f f_s e_{is}) (\mu_{it} \lambda'_i f_s - \widehat{\mu}_{it} \dot{\lambda}'_i \widetilde{f}_s) = O_P(C_{NT}^{-2}) \\ R_{3i,3} &:= \frac{1}{T} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (\widehat{e}_{is} - e_{is}) \dot{\lambda}'_i \widetilde{f}_s = O_P(C_{NT}^{-2}) \\ R_{3i,4} &:= \frac{1}{T} \sum_{s \in I^c \cup \{t\}} f_s e_{is} \mu_i (\dot{\lambda}_i - H'_1 \lambda_i)' \widetilde{f}_s = O_P(C_{NT}^{-2}) \\ R_{3i,5} &:= \frac{1}{T} \sum_{s \in I^c \cup \{t\}} f_s e_{is} \mu_i \lambda'_i (\widetilde{f}_s - H_1^{-1} f_s) = O_P(C_{NT}^{-2}) \\ R_{3i,6} &:= \frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\widehat{f}_s - H_f f_s) e_{is} \mu_i \lambda'_i f_s = O_P(C_{NT}^{-2}) \\ R_{3i,7} &:= \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \widehat{g}_s (\mu_i \lambda'_i f_s - \bar{x}_i \dot{\lambda}'_i \widetilde{f}_s) = O_P(C_{NT}^{-1}) \end{aligned} \tag{E.21}$$

where  $\widehat{e}_{is} - e_{is} = \bar{e}_i$  and  $\mu_{it} = \mu_i$ ,  $\widehat{\mu}_{it} = \bar{x}_i$  in the above.

Note that all terms but the last one in the above are  $O_P(C_{NT}^{-2})$ . For the preliminary estimators, we have  $\dot{\lambda}_i - H'_1 \lambda_i = O_P(C_{NT}^{-1})$  and  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\widetilde{f}_s - H_1^{-1} f_s\|^2 = O_P(C_{NT}^{-2})$ , by Lemmas E.3 and E.4. Then using the Cauchy-Schwarz inequality, it is easy to show that  $R_{3i,1}$  through  $R_{3i,4}$  are  $O_P(C_{NT}^{-2})$  and  $R_{3i,7} = O_P(C_{NT}^{-1})$ . Next, By Lemmas E.2, E.9,

$$\frac{1}{T} \sum_{s \in I^c \cup \{t\}} f_s (H_1^{-1} f_s - \widetilde{f}_s) e_{is} = O_P(C_{NT}^{-2}) = \frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\widehat{f}_s - H_f f_s) e_{is} f'_s.$$

So  $R_{3i,5} = O_P(C_{NT}^{-2}) = R_{3i,6}$ . (Note that the above two equalities involve in two factor estimators: the preliminary  $\widetilde{f}_s$  and the final  $\widehat{f}_s$ .) This concludes that  $R_{3i,d} = O_P(C_{NT}^{-2})$  for all  $d \leq 7$  defined above, and completes the proof. Q.E.D.



**Lemma E.11.** For  $B_{dt}$  defined in the proof of Lemma E.7, and a fixed  $j \leq N$ ,  
for  $d = 1 \dots 4$ ,  $\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{dt} = O_P(C_{NT}^{-2})$ ,  $r = 0, 1, 2$ .  
for  $d = 5 \dots 8$ ,  $\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{dt} = O_P(C_{NT}^{-2})$ .

*Proof.* For  $r = 0, 1, 2$ ,

$$\begin{aligned}
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{1t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r \frac{1}{N} \sum_i \lambda_i e_{it} \bar{e}_i (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
&\leq \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r \frac{1}{N} \sum_i \lambda_i e_{it} \bar{e}_i (\dot{\lambda}_i - H_1' \lambda_i)' f_t \\
&\quad + O_P(C_{NT}^{-2}) \left( \frac{1}{N} \sum_i \bar{e}_i^2 \frac{1}{T_0} \sum_{t \in I^c} f_t^2 e_{jt}^{2r} e_{it}^2 \right)^{1/2} \\
&\leq O_P(C_{NT}^{-2}) \\
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{2t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r \frac{1}{N} \sum_i \lambda_i e_{it} \bar{e}_i \lambda_i' H_1 \tilde{f}_t \\
&= \left( \mathbb{E} \left( \frac{1}{T_0} \sum_{t \in I^c} \frac{1}{N} \sum_i \lambda_i^2 e_{it} \bar{e}_i f_t^2 e_{jt}^r \right)^2 \right)^{1/2} + O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2}) \\
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{3t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
&\leq \frac{1}{T_0} \sum_{t \in I^c} f_t^2 e_{jt}^r \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i (\dot{\lambda}_i - H_1' \lambda_i) + O_P(C_{NT}^{-2}) \\
&\leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i \mathbb{E} \left( \frac{1}{T_0} \sum_{t \in I^c} f_t^2 e_{jt}^r e_{it} \right)^2 \right)^{1/2} + O_P(C_{NT}^{-2}) \\
&\leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i \frac{1}{T_0^2} \sum_{s \neq t} \mathbb{E} f_t^2 f_s^2 \mathbb{E}(e_{jt}^r e_{it} | F) \mathbb{E} e_{js}^r e_{is} | F) \right)^{1/2} + O_P(C_{NT}^{-2}) \\
&\leq O_P(C_{NT}^{-2}) \left( \sum_i |\text{Cov}(e_{js}^r, e_{is} | F)| \right)^{1/2} + O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2}) \\
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{4t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r \frac{1}{N} \sum_i \lambda_i e_{it} \mu_i \lambda_i' H_1 (\tilde{f}_t - H_1^{-1} f_t) = O_P(C_{NT}^{-2}).
\end{aligned}$$

Next, for  $d = 5 \sim 8$ ,

$$\begin{aligned}
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{5t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} \frac{1}{N} \sum_i \alpha_i \bar{e}_i (\dot{\lambda}_i - H_1' \lambda_i)' \tilde{f}_t \\
&= O_P(C_{NT}^{-2}), \quad (\text{similar to } \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{1t}) \\
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{6t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} \tilde{f}_t \left( \frac{1}{N} \sum_i \alpha_i \bar{e}_i \lambda_i' H_1 \right) = O_P(C_{NT}^{-2})
\end{aligned}$$

$$\begin{aligned}
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{7t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} (\tilde{f}_t - H_1^{-1} f_t) \frac{1}{N} \sum_i \alpha_i \mu_i (\dot{\lambda}_i - H_1' \lambda_i)' \\
&\quad + \left( \frac{1}{T_0} \sum_{t \in I^c} f_t^2 e_{jt} \right) \left( \frac{1}{N} \sum_i \alpha_i \mu_i (\dot{\lambda}_i - H_1' \lambda_i) \right) = O_P(C_{NT}^{-2}) \\
\frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{8t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} (\tilde{f}_t - H_1^{-1} f_t) \frac{1}{N} \sum_i \alpha_i \mu_i \lambda_i' H_1 \\
&= O_P(C_{NT}^{-2}), \quad \text{by lemma E.2.}
\end{aligned}$$

Q.E.D.

**Lemma E.12.** *For  $R_{di}$  defined in (D.5), and for each fixed  $j \leq N$ ,  $R_{dj} = O_P(C_{NT}^{-2})$  for  $d = 1, \dots, 3$ . The upper blocks of  $R_{4j} \sim R_{6j}$  are  $O_P(C_{NT}^{-2})$ .*

*Proof.* (i) It is easy to see that  $R_{1j} = O_P(C_{NT}^{-2}) = R_{2j}$ . Also, it follows from Lemmas E.9, E.10 that both  $R_{3j}$  and the upper block of  $R_{4j}$  are  $O_P(C_{NT}^{-2})$ . Next, by (D.2),

$$\begin{aligned}
R_{5j} &= \hat{D}_j^{-1} \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{e}_{jt} & 0 \\ 0 & \mathbf{I} \end{pmatrix} \begin{pmatrix} \hat{f}_t - H_f f_t \\ \hat{g}_t - H_g g_t \end{pmatrix} u_{jt} \\
&= \hat{D}_j^{-1} \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{e}_{jt} & 0 \\ 0 & \mathbf{I} \end{pmatrix} B^{-1} \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i e_{it} \\ H_2' \alpha_i \end{pmatrix} u_{it} u_{jt} \\
&\quad + \sum_{d=1}^5 \hat{D}_j^{-1} \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{e}_{jt} & 0 \\ 0 & \mathbf{I} \end{pmatrix} A_{dt} u_{jt} \\
&\leq O_P(C_{NT}^{-1}) \left\| \frac{1}{T_0} \sum_{t \in I^c} \hat{e}_{jt} \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} u_{jt} \right\| + O_P(C_{NT}^{-1}) \left\| \frac{1}{T_0} \sum_{t \in I^c} \frac{1}{N} \sum_i \alpha_i u_{it} u_{jt} \right\| \\
&\quad + D_j^{-1} B^{-1} \frac{1}{T_0} \sum_{t \in I^c} \frac{1}{N} \sum_i \begin{pmatrix} \lambda_i e_{it} \hat{e}_{jt} \\ \alpha_i \end{pmatrix} u_{it} u_{jt} + \sum_{d=1}^5 \Upsilon_d, \tag{E.22}
\end{aligned}$$

where, for  $A_{dt}$  defined in (D.2),

$$\Upsilon_d = \hat{D}_j^{-1} \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{e}_{jt} & 0 \\ 0 & \mathbf{I} \end{pmatrix} A_{dt} u_{jt}.$$

The first two terms of  $R_{5j}$  are  $O_P(C_{NT}^{-2})$ ; the upper block of the third term is bounded by

$$O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \frac{1}{N} \sum_i \lambda_i e_{it} \hat{e}_{jt} u_{it} u_{jt} = O_P(C_{NT}^{-2})$$

granted by the assumption that  $\text{Var}(\frac{1}{\sqrt{N}} \sum_i w_{it} w_{jt}) < C$  and  $\sum_i |\text{Cov}(w_{it}, w_{jt})| < C$  for  $w_{it} = u_{it} e_{it}$ . To finish the proof for  $R_{5j}$ , we show  $\Upsilon_d = O_P(C_{NT}^{-2})$  for  $d = 1 \dots 5$ .

Term  $\Upsilon_1$  is bounded by (Lemma E.6),

$$O_P(1) \left( \frac{1}{T_0} \sum_{t \in I^c} \|\hat{B}_t^{-1} \hat{S}_t - B^{-1} S\|^2 \right)^{1/2} = O_P(C_{NT}^{-2}).$$

Term  $\Upsilon_2$  is bounded by

$$O_P(C_{NT}^{-2}) + O_P(C_{NT}^{-1}) \left( \frac{1}{T_0} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i w_{it} \right\|^4 + \left\| \frac{1}{N} \sum_i \alpha_i u_{it} \right\|^4 \right)^{1/2} = O_P(C_{NT}^{-2})$$

with the assumption that  $\max_t \mathbb{E} \left\| \frac{1}{\sqrt{N}} \sum_i \lambda_i w_{it} \right\|^4 < C$ , and  $\max_t \mathbb{E} \left\| \frac{1}{\sqrt{N}} \sum_i \alpha_i u_{it} \right\|^4 < C$ .

Term  $\Upsilon_3$  is bounded by  $O_P(C_{NT}^{-2})$  plus

$$O_P(1) \left( \frac{1}{T_0} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i (\tilde{\lambda}_i \hat{e}_{it} - H'_1 \lambda_i e_{it}) u_{it} \right\|^2 + \left\| \frac{1}{N} \sum_i (\tilde{\alpha}_i - H'_2 \alpha_i) u_{it} \right\|^2 \right)^{1/2} = O_P(C_{NT}^{-2}).$$

Term  $\Upsilon_4$  is bounded by  $O_P(C_{NT}^{-2})$  plus

$$\begin{aligned} & O_P(1) \left( \frac{1}{T_0} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \hat{e}_{it} - H'_1 \lambda_i e_{it} \\ \tilde{\alpha}_i - H'_2 \alpha_i \end{pmatrix} (\mu_i \lambda'_i f_t - \bar{x}_i \dot{\lambda}'_i \tilde{f}_t) \right\|^2 \right)^{1/2} \\ & \leq O_P(1) \left( \sum_{d=1}^{16} \frac{1}{T_0} \sum_{t \in I^c} \|C_{dt}\|^2 \right)^{1/2} = O_P(C_{NT}^{-2}) \end{aligned}$$

where  $C_{dt}$  are defined in the proof of Lemma E.7.

Term  $\Upsilon_5$  is bounded by, ( $B_{dt}$  is defined in the proof of Lemma E.7)

$$O_P(C_{NT}^{-2}) + O_P(1) \sum_{d=1}^8 \frac{1}{T_0} \sum_{t \in I^c} \|\hat{B}_t - B_t\| \|B_{dt}\| |u_{jt}| (|e_{jt}| + 1),$$

which is  $O_P(C_{NT}^{-2})$ , using Lemma E.3 that  $\frac{1}{T} \sum_{t \in I^c} \|\tilde{f}_t - H_1^{-1} f_t\|^2 e_{it}^2 u_{it}^2 = O_P(C_{NT}^{-2})$ .

Finally, the upper block of  $\Upsilon_6$  is bounded by

$$\begin{aligned} & \|\hat{D}_j^{-1} - D_j^{-1}\| O_P(1) \sum_{d=1}^8 \frac{1}{T_0} \sum_{t \in I^c} \|\hat{B}_t - B_t\| \|B_{dt}\| |u_{jt}| (|\hat{e}_{jt}| + 1) \\ & + O_P(1) \sum_{d=1}^4 \left\| \frac{1}{T_0} \sum_{t \in I^c} \hat{e}_{jt} u_{jt} B_{dt} \right\| = O_P(C_{NT}^{-2}). \end{aligned}$$

Therefore, the upper block of  $R_{5j}$  is  $O_P(C_{NT}^{-2})$ .

(ii) We now show the upper block of  $R_{6j}$  is  $O_P(C_{NT}^{-2})$ . Let

$$\begin{aligned}\Gamma &:= \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \begin{pmatrix} \widehat{f}_s \widehat{e}_{js} \\ \widehat{g}_s \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{js} \mathbf{l} & 0 \\ 0 & \mathbf{l} \end{pmatrix} \begin{pmatrix} \widehat{f}_s - H_f f_s \\ \widehat{g}_s - H_g g_s \end{pmatrix} \\ &= \Gamma_0 + \Gamma_1 + \dots + \Gamma_6,\end{aligned}$$

where, by (D.2),

$$\begin{aligned}\Gamma_0 &:= \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{f}_t \widehat{e}_{jt} \\ \widehat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} \mathbf{l} & 0 \\ 0 & \mathbf{l} \end{pmatrix} B^{-1} \frac{1}{N} \sum_i \begin{pmatrix} H'_1 \lambda_i e_{it} \\ H'_2 \alpha_i \end{pmatrix} u_{it} \\ \Gamma_d &:= \sum_{d=1}^6 \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{f}_t \widehat{e}_{jt} \\ \widehat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} \mathbf{l} & 0 \\ 0 & \mathbf{l} \end{pmatrix} A_{dt}, \quad d = 1, \dots, 6.\end{aligned}$$

Then  $R_{6j} = \widehat{D}_j^{-1} \Gamma$ . We aim to show that  $\Gamma_0 \dots \Gamma_5$  are each  $O_P(C_{NT}^{-2})$ . In addition, the upper block of  $\Gamma_6$  is  $O_P(C_{NT}^{-2})$ , while its lower block is  $O_P(C_{NT}^{-1})$ . Once this is done, we then have:  $\widehat{D}_j^{-1}(\Gamma_0 + \dots + \Gamma_5) = O_P(C_{NT}^{-2})$ . Also, due to  $\widehat{D}_j^{-1} - D_j^{-1} = O_P(C_{NT}^{-1})$  and  $D_j$  is block diagonal (defined in (D.4)), the upper block of  $\widehat{D}_j^{-1} \Gamma_6$  is also  $O_P(C_{NT}^{-2})$ . It then implies that the upper block of  $R_{6j}$  is  $O_P(C_{NT}^{-2})$ .

The upper block of  $\Gamma_0$  is

$$\begin{aligned}& \frac{1}{T_0} \sum_{s \in I^c \cup \{t\}} \widehat{f}_t \widehat{e}_{jt} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} \mathbf{l} & 0 \\ 0 & \mathbf{l} \end{pmatrix} B^{-1} \frac{1}{N} \sum_i \begin{pmatrix} H'_1 \lambda_i e_{it} \\ H'_2 \alpha_i \end{pmatrix} u_{it} \\ &= O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \widehat{f}_t \widehat{e}_{jt}^2 \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} + O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \widehat{f}_t \widehat{e}_{jt} \frac{1}{N} \sum_i \alpha_i u_{it} \\ &= O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \widehat{f}_t \widehat{e}_{jt}^2 \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} + O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \widehat{f}_t \widehat{e}_{jt} \frac{1}{N} \sum_i \alpha_i u_{it} \\ &= O_P(C_{NT}^{-2}).\end{aligned}$$

Similarly, the lower block of  $\Gamma_0$  is

$$O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \widehat{g}_t \frac{1}{N} \sum_i \lambda_i e_{it} u_{it} + O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \widehat{g}_t \frac{1}{N} \sum_i \alpha_i u_{it} = O_P(C_{NT}^{-2}).$$

$$\begin{aligned}\Gamma_1 &= \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{f}_t \widehat{e}_{jt} \\ \widehat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} \mathbf{l} & 0 \\ 0 & \mathbf{l} \end{pmatrix} A_{1t} \\ &= \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{f}_t \widehat{e}_{jt} \\ \widehat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} \mathbf{l} & 0 \\ 0 & \mathbf{l} \end{pmatrix} (\widehat{B}_t^{-1} \widehat{S}_t - B^{-1} S) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix}\end{aligned}$$

$$\begin{aligned}
&\leq O_P(C_{NT}^{-2}) \left( \frac{1}{T_0} \sum_{t \in I^c} (\|\widehat{f}_t \widehat{e}_{jt}\| + \|\widehat{g}_t\|)^2 (\widehat{e}_{jt}^2 + 1) (\|f_t\| + \|g_t\|)^2 \right)^{1/2} \\
&= O_P(C_{NT}^{-2}).
\end{aligned}$$

Now let

$$\mathcal{D} = \left( \frac{1}{T_0} \sum_{t \in I^c} \|\widehat{f}_t - H_f f_t\|^2 + \|\widehat{g}_t - H_g g_t\|^2 \right)^{1/2} = O_P(C_{NT}^{-1}).$$

Then

$$\begin{aligned}
\Gamma_2 &= \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{f}_t \widehat{e}_{jt} \\ \widehat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} A_{2t} \\
&= \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{f}_t \widehat{e}_{jt} \\ \widehat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} (\widehat{B}_t^{-1} - B^{-1}) \frac{1}{N} \sum_i \begin{pmatrix} H'_1 \lambda_i e_{it} \\ H'_2 \alpha_i \end{pmatrix} u_{it} \\
&\leq O_P(1) \mathcal{D} \left( \frac{1}{T_0} \sum_{t \in I^c} (|\widehat{e}_{jt}|^2 + 1)^2 \left\| \frac{1}{N} \sum_i \begin{pmatrix} \lambda_i e_{it} \\ \alpha_i \end{pmatrix} u_{it} \right\|^2 \right)^{1/2} \\
&\quad + O_P(C_{NT}^{-1}) \left( \frac{1}{T_0} \sum_{t \in I^c} \left\| \begin{pmatrix} f_t \widehat{e}_{jt} \\ g_t \end{pmatrix} \right\|^2 (|\widehat{e}_{jt}| + 1)^2 \left\| \frac{1}{N} \sum_i \begin{pmatrix} \lambda_i e_{it} \\ \alpha_i \end{pmatrix} u_{it} \right\|^2 \right)^{1/2} \\
&= O_P(C_{NT}^{-2}).
\end{aligned}$$

Next, let

$$\mathcal{A}_t = \frac{1}{N} \sum_i \begin{pmatrix} \widetilde{\lambda}_i \widehat{e}_{it} - H'_1 \lambda_i e_{it} \\ \widetilde{\alpha}_i - H'_2 \alpha_i \end{pmatrix} u_{it}.$$

Then

$$\begin{aligned}
\Gamma_3 &= \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{f}_t \widehat{e}_{jt} \\ \widehat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} \widehat{B}_t^{-1} \mathcal{A}_t \\
&\leq O_P(1) \mathcal{D} \left( \frac{1}{T_0} \sum_{t \in I^c} (|\widehat{e}_{jt}|^2 + 1)^2 \|\mathcal{A}_t\|^2 \right)^{1/2} + O_P(1) \frac{1}{T_0} \sum_{t \in I^c} \left\| \begin{pmatrix} f_t \widehat{e}_{jt} \\ g_t \end{pmatrix} \right\| (|\widehat{e}_{jt}| + 1) \|\mathcal{A}_t\|.
\end{aligned}
\tag{E.23}$$

Cauchy Schwarz implies  $\frac{1}{T_0} \sum_{t \in I^c} (|\widehat{e}_{jt}|^2 + 1)^2 \|\mathcal{A}_t\|^2 = O_P(C_{NT}^{-2})$ . Therefore, the first term in (E.23) is  $O_P(C_{NT}^{-2})$ . As for the second term in (E.23),

$$\frac{1}{T_0} \sum_{t \in I^c} (\|f_t e_{jt}\| + \|g_t\|) (1 + |e_{jt}|) \left| \frac{1}{N} \sum_i (\widetilde{\lambda}_i \widehat{e}_{it} - H'_1 \lambda_i e_{it}) u_{it} \right|$$

$$\begin{aligned}
&\leq O_P(1) \left( \frac{1}{T_0} \sum_{t \in I^c} \left| \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) e_{it} u_{it} \right|^2 \right)^{1/2} \\
&\quad + O_P(1) \left( \frac{1}{T_0} \sum_{t \in I^c} \left| \frac{1}{N} \sum_i \lambda_i (\hat{e}_{it} - e_{it}) u_{it} \right|^2 \right)^{1/2} + O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2}),
\end{aligned}$$

where the last equality is due to:

$$\begin{aligned}
&\frac{1}{T_0} \sum_{t \in I^c} \mathbb{E} \left[ \left| \frac{1}{N} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i) e_{it} u_{it} \right|^2 \middle| E, I \right] \\
&= \frac{1}{T_0} \sum_{t \in I^c} \frac{1}{N^2} (\tilde{\Lambda} - \Lambda H_1)' \text{diag}(e_t) \text{Var}(u_t | E, I) \text{diag}(e_t) (\tilde{\Lambda} - \Lambda H_1) \\
&\leq O_P(1) \frac{1}{N^2} \sum_i (\tilde{\lambda}_i - H_1' \lambda_i)^2 \frac{1}{T_0} \sum_{t \in I^c} \mathbb{E}_I e_{it}^2 = O_P(C_{NT}^{-4}).
\end{aligned}$$

Also similarly,  $\frac{1}{T_0} \sum_{t \in I^c} \mathbb{E} \left( \left| \frac{1}{N} \sum_i (\tilde{\alpha}_i - H_2' \alpha_i) u_{it} \right|^2 \middle| I \right) = O_P(C_{NT}^{-4})$ . Therefore, the second term in (E.23) is  $O_P(C_{NT}^{-2})$ . Thus  $\Gamma_3 = O_P(C_{NT}^{-2})$ .

Next, for  $C_{dt}$  defined in the proof of Lemma E.7

$$\begin{aligned}
\Gamma_4 &= \sum_{d=1}^{16} \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{f}_t \hat{e}_{jt} \\ \hat{g}_t \end{pmatrix} (\lambda_j' H_f^{-1}, \alpha_j' H_g^{-1}) \begin{pmatrix} \hat{e}_{jt} \mathbf{1} & 0 \\ 0 & \mathbf{1} \end{pmatrix} \hat{B}_t^{-1} C_{dt} \\
&\leq O_P(1) \sum_{d=1}^{16} \mathcal{D} \left[ \frac{1}{T_0} \sum_{t \in I^c} |e_{jt}|^4 \|C_{dt}\|^2 \right]^{1/2} + O_P(1) \sum_{d=1}^{16} \left( \frac{1}{T_0} \sum_{t \in I^c} \|C_{dt}\|^2 \right)^{1/2} \\
&= O_P(C_{NT}^{-2}), \quad \text{by (E.20).}
\end{aligned}$$

For  $B_{dt}$  defined in the proof of Lemma E.7

$$\begin{aligned}
\Gamma_5 &= \sum_{d=1}^8 \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{f}_t \hat{e}_{jt} \\ \hat{g}_t \end{pmatrix} (\lambda_j' H_f^{-1}, \alpha_j' H_g^{-1}) \begin{pmatrix} \hat{e}_{jt} \mathbf{1} & 0 \\ 0 & \mathbf{1} \end{pmatrix} (\hat{B}_t^{-1} - B^{-1}) B_{dt} \\
&\leq O_P(1) \max_t \|\hat{B}_t^{-1} - B^{-1}\| \sum_{d=1}^8 \mathcal{D} \left[ \frac{1}{T_0} \sum_{t \in I^c} (|e_{jt}|^2 + 1)^2 \|B_{dt}\|^2 \right]^{1/2} \\
&\quad + O_P(1) \left( \frac{1}{T_0} \sum_{t \in I^c} \|\hat{B}_t^{-1} - B^{-1}\|^2 \right)^{1/2} \sum_{d=1}^8 \left( \frac{1}{T_0} \sum_{t \in I^c} \|B_{dt}\|^2 \right)^{1/2} \\
&= O_P(C_{NT}^{-2}), \quad \text{by (E.18).}
\end{aligned}$$

Finally, the upper block of  $\Gamma_6$  is

$$\frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt} (\hat{e}_{jt} \lambda_j' H_f^{-1}, \alpha_j' H_g^{-1}) B^{-1} \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i e_{it} \\ H_2' \alpha_i \end{pmatrix} (\mu_i \lambda_i' f_t - \bar{x}_i \dot{\lambda}_i' \tilde{f}_t)$$

$$\begin{aligned}
&= O_P(1) \sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt}^2 B_{dt} + O_P(1) \sum_{d=5}^8 \frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt} B_{dt} \\
&\leq O_P(1) \sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^2 B_{dt} + O_P(1) \sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} f_t (\hat{e}_{jt} - e_{jt})^2 B_{dt} \\
&\quad + O_P(1) \sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} f_t (\hat{e}_{jt} - e_{jt}) e_{jt} B_{dt} \\
&\quad + O_P(1) \sum_{d=5}^8 \frac{1}{T_0} \sum_{t \in I^c} f_t (\hat{e}_{jt} - e_{jt}) B_{dt} + O_P(1) \sum_{d=5}^8 \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{dt} \\
&\quad + O_P(C_{NT}^{-1}) \left( \sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} e_{jt}^4 \|B_{dt}\|^2 \right)^{1/2} + O_P(C_{NT}^{-1}) \left( \sum_{d=1}^8 \frac{1}{T_0} \sum_{t \in I^c} e_{jt}^2 \|B_{dt}\|^2 \right)^{1/2} \\
&= O_P(C_{NT}^{-2}), \quad \text{by (E.18) and Lemma E.11.}
\end{aligned}$$

The lower block of  $\Gamma_6$  is, by repeatedly using Cauchy-Schwarz,

$$\sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} \hat{g}_t \hat{e}_{jt} B_{dt} + \sum_{d=5}^8 \frac{1}{T_0} \sum_{t \in I^c} \hat{g}_t B_{dt} = O_P(C_{NT}^{-1}).$$

Q.E.D.

## APPENDIX F. TECHNICAL LEMMAS IN THE FACTOR MODEL

Here we present the intermediate results when  $x_{it}$  admits a factor structure:

$$x_{it} = l'_i w_t + e_{it}.$$

The proof is similar to that of the many mean model, while the main difference lies on dealing with the effect of  $\hat{e}_{it} - e_{it}$ .

**F.1. The effect of  $\hat{e}_{it} - e_{it}$  in the factor model.** Let  $\hat{w}_t$  be the PC estimator of  $w_t$ . Then  $\hat{l}'_i = \frac{1}{T} \sum_s x_{is} \hat{w}'_s$  and  $\hat{e}_{it} - e_{it} = l'_i H_x (\hat{w}_t - H_x^{-1} w_t) + (\hat{l}'_i - l'_i H_x) \hat{w}_t$ .

**Lemma F.1.** (i)  $\max_{it} |\hat{e}_{it} - e_{it}| = O_P(\phi_{NT})$ , where

$$\phi_{NT} := (C_{NT}^{-2} (\max_i \frac{1}{T} \sum_s e_{is}^2)^{1/2} + b_{NT,4} + b_{NT,5}) (1 + \max_t \|w_t\|) + (b_{NT,1} + C_{NT}^{-1} b_{NT,2} + b_{NT,3}).$$

So  $\max_{it} |\hat{e}_{it} - e_{it}| \max_{it} |e_{it}| = O_P(1)$ .

- (ii) All terms below are  $O_P(C_{NT}^{-2})$ , for a fixed  $t$ :  $\frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4$ ,  $\frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2$ , and  $\frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 e_{it}^2$ ,  $\frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it}) e_{it}$ ,  $\frac{1}{N} \sum_i \lambda_i (\hat{e}_{it} - e_{it}) u_{it}$ .
- (iii)  $\frac{1}{N} \sum_i \lambda_i \alpha'_i (\hat{e}_{it} - e_{it}) = O_P(C_{NT}^{-1})$  for a fixed  $t$ .

(iv) All terms below are  $O_P(C_{NT}^{-2})$ , for a fixed  $j \leq N$ :

$$\begin{aligned} & \frac{1}{T} \sum_t \left\| \frac{1}{N} \sum_i \alpha_i \lambda_i' (e_{it} - \hat{e}_{it}) \right\|^2 \|f_t\|^2 (\|f_t\| + \|g_t\|)^2 |e_{jt}|^{2(1+r)}, \quad r \in \{0, 1\}, \\ & \frac{1}{T_0} \sum_{t \in I^c} \|f_t\|^2 |\hat{e}_{jt} - e_{jt}|^2, \quad \frac{1}{T} \sum_{t \notin I} f_t e_{jt} (\hat{e}_{jt} - e_{jt}) \tilde{f}_t, \quad \frac{1}{T} \sum_t f_t (\hat{e}_{jt} - e_{jt}) u_{jt} \end{aligned}$$

*Proof.* Below we first simplify the expansion of  $\hat{e}_{it} - e_{it}$ . Let  $K_3 = \dim(l_i)$ . Let  $\mathcal{Q}$  be a diagonal matrix consisting of the reciprocal of the first  $K_3$  eigenvalues of  $XX'/(NT)$ . Let

$$\begin{aligned} \zeta_{st} &= \frac{1}{N} \sum_i (e_{is} e_{it} - \mathbb{E} e_{is} e_{it}), \quad \eta_t = \frac{1}{N} \sum_i l_i e_{it}, \\ \sigma^2 &= \frac{1}{N} \sum_i \mathbb{E} e_{it}^2. \end{aligned}$$

For the PC estimator, there is a rotation matrix  $\bar{H}_x$ , by (A.1) of Bai (2003), (which can be simplified due to the serial independence in  $e_{it}$ )

$$\begin{aligned} \hat{w}_t - \bar{H}_x w_t &= \mathcal{Q} \frac{\sigma^2}{T} (\hat{w}_t - \bar{H}_x w_t) + \mathcal{Q} \left[ \frac{\sigma^2}{T} \bar{H}_x + \frac{1}{TN} \sum_{is} \hat{w}_s l_i' e_{is} \right] w_t \\ &\quad + \mathcal{Q} \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} + \mathcal{Q} \frac{1}{T} \sum_s \hat{w}_s w_s' \eta_t. \end{aligned}$$

Move  $\mathcal{Q} \frac{\sigma^2}{T} (\hat{w}_t - \bar{H}_x w_t)$  to the left hand side (LHS); then LHS becomes  $(I - \mathcal{Q} \frac{\sigma^2}{T}) (\hat{w}_t - \bar{H}_x w_t)$ . Note that  $\|\mathcal{Q}\| = O_P(1)$  so  $\mathcal{Q}_1 := (I - \mathcal{Q} \frac{\sigma^2}{T})^{-1}$  exists whose eigenvalues all converge to one. Then multiply  $\mathcal{Q}_1$  on both sides, we reach

$$\begin{aligned} \hat{w}_t - \bar{H}_x w_t &= \mathcal{Q}_1 \mathcal{Q} \left[ \frac{\sigma^2}{T} \bar{H}_x + \frac{1}{TN} \sum_{is} \hat{w}_s l_i' e_{is} \right] w_t \\ &\quad + \mathcal{Q}_1 \mathcal{Q} \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} + \mathcal{Q}_1 \mathcal{Q} \frac{1}{T} \sum_s \hat{w}_s w_s' \eta_t. \end{aligned}$$

Next, move  $\mathcal{Q}_1 \mathcal{Q} \left[ \frac{\sigma^2}{T} \bar{H}_x + \frac{1}{TN} \sum_{is} \hat{w}_s l_i' e_{is} \right] w_t$  to LHS, combined with  $-\bar{H}_x w_t$ , then LHS becomes  $\hat{w}_t - H_x^{-1} w_t$ , where  $H_x^{-1} = (I + \mathcal{Q}_1 \mathcal{Q} \frac{\sigma^2}{T}) \bar{H}_x + \mathcal{Q}_1 \mathcal{Q} \frac{1}{TN} \sum_{is} \hat{w}_s l_i' e_{is}$ , where

$\mathcal{Q}_1 \mathcal{Q} \frac{1}{TN} \sum_{is} \hat{w}_s l_i' e_{is} = o_P(1)$ . So the eigenvalues of  $H_x^{-1}$  converge to those of  $\bar{H}_x$ , which are well known to be bounded away from both zero and infinity (Bai, 2003).

Finally, let  $R_1 = \mathcal{Q}_1 \mathcal{Q}$  and  $R_2 = \mathcal{Q}_1 \mathcal{Q} \frac{1}{T} \sum_s \hat{w}_s w_s'$ , we reach

$$\hat{w}_t - H_x^{-1} w_t = R_1 \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} + R_2 \eta_t. \quad (\text{F.1})$$

with  $\|R_1\| + \|R_2\| = O_P(1)$ .



Also,  $\widehat{l}'_i = \frac{1}{T} \sum_s x_{is} \widehat{w}'_s$ , for  $\mathcal{Q}_3 = -H_x(R_1 \frac{1}{T^2} \sum_{m,s \leq T} \zeta_{ms} \widehat{w}_m \widehat{w}'_s + R_2 \frac{1}{T} \sum_s \eta_s \widehat{w}'_s) = O_P(C_{NT}^{-2})$ ,

$$\begin{aligned}
\widehat{e}_{it} - e_{it} &= l'_i H_x (\widehat{w}_t - H_x^{-1} w_t) + (\widehat{l}'_i - l'_i H_x) \widehat{w}_t \\
&= l'_i H_x (\widehat{w}_t - H_x^{-1} w_t) + \frac{1}{T} \sum_s e_{is} (\widehat{w}'_s - w'_s H_x^{-1'}) \widehat{w}_t \\
&\quad + \frac{1}{T} \sum_s e_{is} w'_s H_x^{-1'} \widehat{w}_t + l'_i H_x \frac{1}{T} \sum_s (H_x^{-1} w_s - \widehat{w}_s) \widehat{w}'_s \widehat{w}_t \\
&= \frac{1}{T} \sum_s e_{is} w'_s H_x^{-1'} \widehat{w}_t + \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}'_m R'_1 \widehat{w}_t + \frac{1}{T} \sum_s e_{is} \eta'_s R'_2 \widehat{w}_t \\
&\quad + l'_i \mathcal{Q}_3 \widehat{w}_t + l'_i H_x R_1 \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} + l'_i H_x R_2 \eta_t. \tag{F.2}
\end{aligned}$$

(i) We first show that  $\max_t \|\widehat{w}_t - H_x^{-1} w_t\| = O_P(1)$ . Define

$$\begin{aligned}
b_{NT,1} &= \max_t \left\| \frac{1}{NT} \sum_{is} w_s (e_{is} e_{it} - \mathbb{E} e_{is} e_{it}) \right\| \\
b_{NT,2} &= \left( \max_t \frac{1}{T} \sum_s \left( \frac{1}{N} \sum_i e_{is} e_{it} - \mathbb{E} e_{is} e_{it} \right)^2 \right)^{1/2} \\
b_{NT,3} &= \max_t \left\| \frac{1}{N} \sum_i l_i e_{it} \right\| \\
b_{NT,4} &= \max_i \left\| \frac{1}{T} \sum_s e_{is} w_s \right\| \\
b_{NT,5} &= \max_i \left\| \frac{1}{NT} \sum_{js} l_j (e_{js} e_{is} - \mathbb{E} e_{js} e_{is}) \right\|
\end{aligned}$$

Then

$$\begin{aligned}
\max_t \left\| \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right\| &\leq O_P(1) \max_t \left\| \frac{1}{T} \sum_s w_s \zeta_{st} \right\| + O_P(C_{NT}^{-1}) \left( \max_t \frac{1}{T} \sum_s \zeta_{st}^2 \right)^{1/2} \\
&= O_P(b_{NT,1} + C_{NT}^{-1} b_{NT,2}).
\end{aligned}$$

Then by assumption,  $\max_t \|\widehat{w}_t - H_x^{-1} w_t\| = O_P(b_{NT,1} + C_{NT}^{-1} b_{NT,2} + b_{NT,3}) = O_P(1)$ .

As such  $\max_t \|\widehat{w}_t\| = O_P(1) + \max_t \|w_t\|$ .

In addition,

$$\begin{aligned}
\max_i \left\| \frac{1}{T^2} \sum_{m \leq T} \sum_{s \leq T} e_{is} \zeta_{ms} \widehat{w}'_m \right\| &\leq O_P(C_{NT}^{-1}) \left( \max_i \frac{1}{T} \sum_{s \leq T} e_{is}^2 \right)^{1/2} \left( \frac{1}{T^2} \sum_{s,t \leq T} \zeta_{st}^2 \right)^{1/2} \\
&\quad + O_P(1) \left( \max_i \frac{1}{T} \sum_s e_{is}^2 \right)^{1/2} \left( \frac{1}{T} \sum_s \left\| \frac{1}{TN} \sum_{jt} (e_{jt} e_{js} - \mathbb{E} e_{jt} e_{js}) w_t \right\|^2 \right)^{1/2}
\end{aligned}$$

$$= O_P(C_{NT}^{-2})(\max_i \frac{1}{T} \sum_s e_{is}^2)^{1/2}.$$

So  $\max_{it} |\widehat{e}_{it} - e_{it}| = O_P(\phi_{NT})$ , where

$$\phi_{NT} := (C_{NT}^{-2}(\max_i \frac{1}{T} \sum_s e_{is}^2)^{1/2} + b_{NT,4} + b_{NT,5})(1 + \max_t \|w_t\|) + (b_{NT,1} + C_{NT}^{-1}b_{NT,2} + b_{NT,3}).$$

(ii) Let  $a \in \{1, 2, 4\}$ , and  $b \in \{0, 1, 2\}$ , and a bounded constant sequence  $c_i$ , consider, up to a  $O_P(1)$  multiplier that is independent of  $(t, i)$ ,

$$\begin{aligned} \frac{1}{N} \sum_i c_i e_{it}^b (\widehat{e}_{it} - e_{it})^a &= \frac{1}{N} \sum_i c_i e_{it}^b \left( \frac{1}{T} \sum_s e_{is} w_s \right)^a \widehat{w}_t^a \\ &+ \frac{1}{N} \sum_i c_i e_{it}^b \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right)^a \widehat{w}_t^a \\ &+ \frac{1}{N} \sum_i c_i e_{it}^b \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^a \widehat{w}_t^a + \frac{1}{N} \sum_i c_i e_{it}^b l_i^a \mathcal{Q}_3^a \widehat{w}_t^a \\ &+ \frac{1}{N} \sum_i c_i e_{it}^b l_i^a \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right)^a + \frac{1}{N} \sum_i c_i e_{it}^b l_i^a \eta_t^a. \quad (\text{F.3}) \end{aligned}$$

Note that

$$\begin{aligned} \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} &\leq O_P(1) \frac{1}{TN} \sum_{is} w_s (e_{is} e_{it} - \mathbb{E} e_{is} e_{it}) \\ &+ \left( \frac{1}{T} \sum_s \left( \frac{1}{N} \sum_i (e_{is} e_{it} - \mathbb{E} e_{is} e_{it}) \right)^2 \right)^{1/2} O_P(C_{NT}^{-1}) = O_P(C_{NT}^{-2}) \\ \frac{1}{N} \sum_i e_{it}^b \left( \frac{1}{T} \sum_s e_{is} w_s \right)^a &= O(T^{-a/2}), \quad a = 2, 4, \quad b = 0, 2 \\ \frac{1}{N} \sum_i \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right)^4 &\leq \left( \frac{1}{T^2} \sum_{m,s \leq T} \zeta_{ms}^2 \right)^2 \left( \frac{1}{T} \sum_m w_m^2 \right)^2 \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is}^2 \right)^2 \\ &+ \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_{m \leq T} \left( \frac{1}{T} \sum_{s \leq T} e_{is} \zeta_{ms} \right)^2 \right)^2 O_P(C_{NT}^{-4}) = O_P(C_{NT}^{-4}) \\ \frac{1}{N} \sum_i \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right)^2 &\leq \frac{1}{N} \sum_i \frac{1}{T} \sum_m \left( \frac{1}{T} \sum_s e_{is} \zeta_{ms} \right)^2 \frac{1}{T} \sum_m w_m^2 \\ &+ \frac{1}{N} \sum_i \frac{1}{T} \sum_{m \leq T} \left( \frac{1}{T} \sum_{s \leq T} e_{is} \zeta_{ms} \right)^2 O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2}) \\ \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^4 &\leq \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is}^2 \right)^2 \left( \frac{1}{T} \sum_t \eta_t^2 \right)^2 = O_P(C_{NT}^{-4}) \\ \frac{1}{N} \sum_i e_{it}^2 \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^2 &= O_P(C_{NT}^{-2}) \end{aligned}$$

$$\begin{aligned}
\frac{1}{N} \sum_i e_{it}^2 l_i^2 \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right)^2 &\leq \frac{1}{N} \sum_i e_{it}^2 l_i^2 \left( \frac{1}{T} \sum_s w_s \zeta_{st} \right)^2 + O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2}) \\
\frac{1}{T} \sum_t \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right)^2 &\leq O_P(C_{NT}^{-4}) \\
\frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T} \sum_s e_{is} w_s \right) &= O_P(1) \left( \frac{1}{N^2 T^2} \sum_{ij \leq N} \sum_{sl \leq T} c_i c_j \mathbb{E} w_s w_l \mathbb{E}(e_{it} e_{jt} e_{is} e_{jl} | W) \right)^{1/2} \\
&= O_P(C_{NT}^{-2}) \\
\frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T^2} \sum_{s, m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right) &\leq O_P(C_{NT}^{-2}) + \frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T} \sum_{s \leq T} \frac{1}{T} \sum_{m \leq T} e_{is} \zeta_{ms} w_m \right) \\
&\leq O_P(C_{NT}^{-2}) + O_P(1) \left( \frac{1}{T} \sum_{s \leq T} \mathbb{E} \left( \frac{1}{T} \sum_{m \leq T} \zeta_{ms} w_m \right)^2 \right)^{1/2} \\
&= O_P(C_{NT}^{-2}).
\end{aligned}$$

where the last equality follows from the following:

$$\begin{aligned}
\frac{1}{T} \sum_{s \leq T} \mathbb{E} \left( \frac{1}{T} \sum_{m \leq T} \zeta_{ms} w_m \right)^2 &= O(T^{-2}) + \frac{1}{T} \sum_{s \leq T} \frac{1}{T^2} \sum_{t \neq s} \mathbb{E} w_s w_t \text{Cov}(\zeta_{ss}, \zeta_{ts} | W) \\
&+ \frac{1}{T} \sum_{s \leq T} \frac{1}{T} \sum_{m \neq s} \frac{1}{T} \sum_{t \leq T} \mathbb{E} w_m w_t \text{Cov}(\zeta_{ms}, \zeta_{ts} | W) \\
&= O(T^{-2}) + \frac{1}{T} \sum_{s \leq T} \frac{1}{T} \sum_{t \neq s} \frac{1}{T} \mathbb{E} w_t^2 \frac{1}{N^2} \sum_{ij} \mathbb{E}(e_{is} e_{js} | W) \mathbb{E}(e_{it} e_{jt} | W) = O(C_{NT}^{-4}).
\end{aligned}$$

With the above results ready, we can proceed proving (ii)(iii) as follows.

Now for  $a = 4, b = 0, c_i = 1$ , up to a  $O_P(1)$  multiplier

$$\begin{aligned}
\frac{1}{N} \sum_i (\widehat{e}_{it} - e_{it})^4 &= \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} w_s \right)^4 + \frac{1}{N} \sum_i \left( \frac{1}{T^2} \sum_{s, m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right)^4 \\
&+ \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^4 + \mathcal{Q}_3^4 + \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right)^4 + \eta_t^4 \\
&\leq O_P(C_{NT}^{-4}).
\end{aligned}$$

For  $a = 2, b = 0, c_i = 1$ ,

$$\begin{aligned}
\frac{1}{N} \sum_i (\widehat{e}_{it} - e_{it})^2 &\leq \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} w_s \right)^2 + \frac{1}{N} \sum_i \left( \frac{1}{T^2} \sum_{s, m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right)^2 \\
&+ \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^2 + \mathcal{Q}_3^2 + \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right)^2 + \eta_t^2 \\
&\leq O_P(C_{NT}^{-2}).
\end{aligned}$$

For  $a = 2$ ,  $b = 2$ ,  $c_i = 1$ ,

$$\begin{aligned} \frac{1}{N} \sum_i e_{it}^2 (\widehat{e}_{it} - e_{it})^2 &= \frac{1}{N} \sum_i e_{it}^2 \left( \frac{1}{T} \sum_s e_{is} w_s \right)^2 + \frac{1}{N} \sum_i e_{it}^2 \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right)^2 \\ &\quad + \frac{1}{N} \sum_i e_{it}^2 \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^2 + \mathcal{Q}_3^2 + \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right)^2 + \eta_t^2 \\ &\leq O_P(C_{NT}^{-2}). \end{aligned}$$

Next, let  $a = b = 1$  and  $c_i$  be any element of  $\lambda_i \lambda'_i$ ,

$$\begin{aligned} \frac{1}{N} \sum_i c_i e_{it} (\widehat{e}_{it} - e_{it}) &= \frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T} \sum_s e_{is} w_s \right) + \frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right) \\ &\quad + \frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right) + \frac{1}{N} \sum_i c_i e_{it} l_i \mathcal{Q}_3 \\ &\quad + \frac{1}{N} \sum_i c_i e_{it} l_i \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right) + \frac{1}{N} \sum_i c_i e_{it} l_i \eta_t \\ &\leq O_P(C_{NT}^{-2}). \end{aligned}$$

Next, ignoring an  $O_P(1)$  multiplier,

$$\begin{aligned} \frac{1}{N} \sum_i \lambda_i (\widehat{e}_{it} - e_{it}) u_{it} &\leq \frac{1}{N} \sum_i \lambda_i \frac{1}{T} \sum_s e_{is} w_s u_{it} \\ &\quad + \frac{1}{N} \sum_i \lambda_i \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}_m u_{it} + \frac{1}{N} \sum_i \lambda_i \frac{1}{T} \sum_s e_{is} \eta_s u_{it} \\ &\quad + \frac{1}{N} \sum_i \lambda_i l'_i \mathcal{Q}_3 u_{it} + \frac{1}{N} \sum_i \lambda_i l_i u_{it} \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} + \frac{1}{N} \sum_i \lambda_i l_i \eta_t u_{it} \\ &\leq O_P(C_{NT}^{-2}). \end{aligned}$$

(iii) Let  $a = 1$ ,  $b = 0$  and  $c_i$  be any element of  $\lambda_i \alpha'_i$ ,

$$\begin{aligned} \frac{1}{N} \sum_i c_i (\widehat{e}_{it} - e_{it}) &= \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} w_s \right) + \frac{1}{N} \sum_i c_i \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \widehat{w}_m \right) \\ &\quad + \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right) + \mathcal{Q}_3 + \left( \frac{1}{T} \sum_s \widehat{w}_s \zeta_{st} \right) + \eta_t \\ &\leq O_P(C_{NT}^{-1}), \end{aligned}$$

where the dominating term is  $\eta_t = O_P(C_{NT}^{-1})$ .

(iv) Up to an  $O_P(1)$  multiplier, for  $r \in \{0, 1\}$ ,

$$\frac{1}{T} \sum_t \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i (e_{it} - \widehat{e}_{it}) \right\|^2 \|f_t\|^2 (\|f_t\| + \|g_t\|)^2 |e_{jt}|^{2(1+r)}$$

$$\begin{aligned}
&\leq \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i \frac{1}{T} \sum_s e_{is} w_s \right\|^2 O_P(1) + \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i \frac{1}{T} \sum_s e_{is} \eta_s \right\|^2 O_P(1) \\
&\quad + O_P(1) \mathcal{Q}_3^2 + \frac{1}{T^2} \sum_{mt \leq T} \zeta_{mt}^2 \frac{1}{T} \sum_s \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i e_{is} \right\|^2 O_P(1) \\
&\quad + \left\| \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \right\|^2 O_P(1) + \frac{1}{T} \sum_t \eta_t^2 \|f_t\|^2 (\|f_t\| + \|g_t\|)^2 |e_{jt}|^{2(1+r)} \\
&= O_P(C_{NT}^{-2}) + \left( \frac{1}{T} \sum_t \eta_t^4 \right)^{1/2} O_P(1) = O_P(C_{NT}^{-2}),
\end{aligned}$$

with the assumptions that  $\mathbb{E} e_{jt}^4 \|f_t\|^8 + \mathbb{E} e_{jt}^4 \|f_t\|^4 \|g_t\|^4 + \mathbb{E} e_{jt}^2 \|f_t\|^4 \|w_t\|^2 < C$  and

$$\mathbb{E} e_{jt}^2 \|f_t\|^2 \|w_t\|^2 \|g_t\|^2 < C, \quad \mathbb{E} \frac{1}{\sqrt{N}} \sum_i l_i e_{it} \|^4 < C.$$

Similarly,  $\frac{1}{T_0} \sum_{t \in I^c} \|f_t\|^2 |\hat{e}_{jt} - e_{jt}|^2 = O_P(C_{NT}^{-2})$ .

Next, for a fixed  $i \leq N$ ,

$$\begin{aligned}
\frac{1}{T} \sum_t f_t e_{it} \hat{w}_t \tilde{f}_t &= O_P(C_{NT}^{-1}), \quad \frac{1}{T} \sum_t f_t u_{it} \hat{w}_t = O_P(C_{NT}^{-1}) \\
\frac{1}{T} \sum_{t \notin I} f_t e_{it} \tilde{f}_t &= O_P(C_{NT}^{-1}), \quad \frac{1}{T} \sum_{t \notin I} f_t e_{it} \eta_t \tilde{f}_t = O_P(C_{NT}^{-2})
\end{aligned}$$

Also,  $h_i := \frac{1}{T} \sum_s e_{is} w_s + \frac{1}{T} \sum_s e_{is} \eta_s + \mathcal{Q}_3 + \frac{1}{T^2} \sum_{s, m \leq T} e_{is} \zeta_{ms} \hat{w}_m = O_P(C_{NT}^{-1})$ . So

$$\begin{aligned}
\frac{1}{T} \sum_{t \notin I} f_t e_{it} (\hat{e}_{it} - e_{it}) \tilde{f}_t &\leq \frac{1}{T} \sum_{t \notin I} f_t e_{it} \hat{w}_t \tilde{f}_t h_i + \frac{1}{T} \sum_{t \notin I} f_t e_{it} \tilde{f}_t \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} + \frac{1}{T} \sum_{t \notin I} f_t e_{it} \eta_t \tilde{f}_t \\
&= O_P(C_{NT}^{-2}) \\
\frac{1}{T} \sum_t f_t (\hat{e}_{it} - e_{it}) u_{it} &\leq \frac{1}{T} \sum_t f_t u_{it} \hat{w}_t h_i + \frac{1}{T} \sum_t f_t u_{it} \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} + \frac{1}{T} \sum_t f_t u_{it} \eta_t \\
&= O_P(C_{NT}^{-2}).
\end{aligned}$$

**Lemma F.2.** Assume  $\max_{it} |e_{it}| C_{NT}^{-1} = O_P(1)$  and  $\mathbb{E} e_{it}^8 < C$ .

Let  $c_i$  be a non-random bounded sequence.

$$\begin{aligned}
(i) \max_t \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 &= O_P(1 + \max_t \|w_t\|^4 + b_{NT,2}^4) C_{NT}^{-4} + O_P(b_{NT,1}^4 + b_{NT,3}^4). \\
\max_t \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 e_{it}^2 &\leq O_P(1 + \max_t \|w_t\|^2 + b_{NT,2}^2) \max_{it} |e_{it}|^2 C_{NT}^{-2} \\
&\quad + O_P(b_{NT,1}^2 + b_{NT,3}^2) \max_t \frac{1}{N} \sum_i e_{it}^2. \\
\max_t \left| \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it}) e_{it} \right| &\leq O_P(1 + \max_t \|w_t\| + b_{NT,2}) \max_{it} |e_{it}| C_{NT}^{-1} \\
&\quad + \max_t \left\| \frac{1}{N} \sum_i c_i e_{it} \right\|_F O_P(b_{NT,1} + b_{NT,3}). \\
\max_t \left| \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it})^2 \right| &\leq O_P(1 + \max_t \|w_t\|^2 + b_{NT,2}^2) C_{NT}^{-2} + O_P(b_{NT,1}^2 + b_{NT,3}^2). \\
\max_t \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 &\leq O_P(1 + \max_t \|w_t\|^2 + b_{NT,2}^2) C_{NT}^{-2} + O_P(b_{NT,1}^2 + b_{NT,3}^2) \\
\max_t \left| \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it}) \right| &\leq O_P(1 + \max_t \|w_t\|) C_{NT}^{-1} + O_P(b_{NT,1} + b_{NT,3} + C_{NT}^{-1} b_{NT,2}).
\end{aligned}$$

$$\begin{aligned}
& \max_i \frac{1}{T} \sum_t (\hat{e}_{it} - e_{it})^2 \leq O_P(b_{NT,4}^2 + b_{NT,5}^2 + C_{NT}^{-2}). \\
& (ii) \text{ All terms below are } O_P(C_{NT}^{-2}): \frac{1}{NT} \sum_{it} (\hat{e}_{it} - e_{it})^4 \\
& \frac{1}{NT} \sum_{it} (\hat{e}_{it} - e_{it})^2, \frac{1}{NT} \sum_{it} e_{it}^2 (\hat{e}_{it} - e_{it})^2, \frac{1}{T} \sum_t \left| \frac{1}{N} \sum_i c_i (e_{it} - \hat{e}_{it}) \right|^2, \text{ and} \\
& \frac{1}{TN} \sum_{t \in I^c} \sum_i \tilde{f}_t f_t e_{jt}^r c_i e_{it} (\hat{e}_{it} - e_{it}) \text{ for } r = \{0, 1, 2\}, \text{ for a fixed } j. \\
& \frac{1}{TN} \sum_{t \in I^c} \sum_i f_t f_t e_{jt} c_i (\hat{e}_{it} - e_{it}) \text{ for a fixed } j. \\
& (iii) \text{ All terms below are } O_P(C_{NT}^{-4}): \frac{1}{T} \sum_t \left| \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it}) e_{it} \right|^2, \\
& \frac{1}{T} \sum_t \left| \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it})^2 \right|^2, \frac{1}{T} \sum_t \left| \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it}) u_{it} \right|^2, \\
& \text{For a fixed } j \leq N, \text{ and } r \leq 2, \\
& \frac{1}{T} \sum_t \left| \frac{1}{N} \sum_i c_i e_{it} e_{jt}^r (\hat{e}_{it} - e_{it}) f_t \right|^2 + \frac{1}{T} \sum_{t \in I^c} (|e_{jt}| + 1)^2 u_{jt}^2 \left| \frac{1}{N} \sum_i c_i e_{it} (\hat{e}_{it} - e_{it}) \right|^2
\end{aligned}$$

*Proof.* (i) First, in the proof of Lemma F.1(i), we showed  $\max_t \|\hat{w}_t\| \leq O_P(1 + \max_t \|w_t\|)$ . By the proof of Lemma F.1(ii),

$$\begin{aligned}
& \max_t \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 \leq \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} w_s \right)^4 \max_t \hat{w}_t^4 + \frac{1}{N} \sum_i \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m \right)^4 \max_t \hat{w}_t^4 \\
& + \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^4 \max_t \hat{w}_t^4 + \mathcal{Q}_3^4 \max_t \hat{w}_t^4 + \max_t \left( \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \right)^4 + \max_t \eta_t^4 \\
& \leq O_P(1 + \max_t \|w_t\|^4 + b_{NT,2}^4)(C_{NT}^{-4}) + O_P(b_{NT,1}^4 + b_{NT,3}^4).
\end{aligned}$$

Next,

$$\begin{aligned}
\max_t \frac{1}{N} \sum_i e_{it}^2 (\hat{e}_{it} - e_{it})^2 &= \max_t \frac{1}{N} \sum_i e_{it}^2 \left( \frac{1}{T} \sum_s e_{is} w_s \right)^2 \max_t \hat{w}_t^2 + \max_t \frac{1}{N} \sum_i e_{it}^2 l_i^4 \mathcal{Q}_3^2 \max_t \hat{w}_t^2 \\
&+ \max_t \frac{1}{N} \sum_i e_{it}^2 \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m \right)^2 \max_t \hat{w}_t^2 \\
&+ \max_t \frac{1}{N} \sum_i e_{it}^2 \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^2 \max_t \hat{w}_t^2 \\
&+ \max_t \frac{1}{N} \sum_i e_{it}^2 l_i^2 \left( \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \right)^2 + \max_t \frac{1}{N} \sum_i e_{it}^2 l_i^2 \eta_t^2 \\
&\leq O_P(1 + \max_t \|w_t\|^2 + b_{NT,2}^2) \max_{it} |e_{it}|^2 C_{NT}^{-2} \\
&+ O_P(b_{NT,1}^2 + b_{NT,3}^2) \max_t \frac{1}{N} \sum_i e_{it}^2. \\
\frac{1}{N} \sum_i c_i e_{it} (\hat{e}_{it} - e_{it}) &\leq \max_t \frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T} \sum_s e_{is} w_s \right) \hat{w}_t \\
&+ \max_t \frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m \right) \hat{w}_t \\
&+ \max_t \frac{1}{N} \sum_i c_i e_{it} \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right) \hat{w}_t + \max_t \frac{1}{N} \sum_i c_i e_{it} l_i \mathcal{Q}_3 \max_t \hat{w}_t
\end{aligned}$$

$$\begin{aligned}
& + \max_t \frac{1}{N} \sum_i c_i e_{it} l_i \left( \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \right) + \max_t \frac{1}{N} \sum_i c_i e_{it} l_i \max_t \eta_t \\
& \leq O_P(1 + \max_t \|w_t\| + b_{NT,2}) \max_{it} |e_{it}| C_{NT}^{-1} \\
& \quad + \max_t \left\| \frac{1}{N} \sum_i c_i e_{it} l_i \right\|_F O_P(b_{NT,1} + b_{NT,3}). \\
\max_t \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it})^2 & \leq \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} w_s \right)^2 \max_t \hat{w}_t^2 + \max_t \left( \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \right)^2 + \max_t \eta_t^2 \\
& \quad + \frac{1}{N} \sum_i c_i \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m \right)^2 \max_t \hat{w}_t^2 \\
& \quad + \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right)^2 \max_t \hat{w}_t^2 + \max_t \mathcal{Q}_3^2 \hat{w}_t^2 \\
& \leq O_P(1 + \max_t \|w_t\|^2 + b_{NT,2}^2) C_{NT}^{-2} + O_P(b_{NT,1}^2 + b_{NT,3}^2), \\
\max_t \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it}) & \leq \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} w_s \right) \max_t \hat{w}_t \\
& \quad + \frac{1}{N} \sum_i c_i \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m \right) \max_t \hat{w}_t \\
& \quad + \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} \eta'_s \right) \max_t \hat{w}_t + \mathcal{Q}_3 \max_t \hat{w}_t \\
& \quad + \max_t \left( \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \right) + \max_t \eta_t \\
& \leq O_P(1 + \max_t \|w_t\|) C_{NT}^{-2} + O_P(b_{NT,1} + b_{NT,3} + C_{NT}^{-1} b_{NT,2}).
\end{aligned}$$

Finally,

$$\begin{aligned}
\max_i \frac{1}{T} \sum_t (\hat{e}_{it} - e_{it})^2 & \leq \max_i \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{T} \sum_s e_{is} w'_s H_x^{-1'} \right)^2 + \max_i \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}'_m R'_1 \right)^2 \\
& \quad + \max_i \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{T} \sum_s e_{is} \eta'_s R'_2 \right)^2 + \max_i \frac{1}{T} \sum_t \hat{w}_t^2 (l'_i \mathcal{Q}_3)^2 \\
& \quad + \max_i \frac{1}{T} \sum_t (l'_i H_x R_1 \frac{1}{T} \sum_s \hat{w}_s \zeta_{st})^2 + \max_i \frac{1}{T} \sum_t \eta_t^2 (l'_i H_x R_2)^2 \\
& \leq O_P(b_{NT,4}^2 + b_{NT,5}^2 + C_{NT}^{-2}).
\end{aligned}$$

(ii) Note that  $\max_t \|\hat{w}_t\|^2 = O_P(1) + O_P(1) \max_t \|w_t\|^2 \leq O_P(1) + o_P(C_{NT})$ , where the last inequality follows from the assumption that  $\max_t \|w_t\|^2 = o_P(C_{NT})$ .

$$\frac{1}{NT} \sum_{it} (\hat{e}_{it} - e_{it})^4 \leq \frac{1}{T} \sum_t \|\hat{w}_t\|^2 \max_t \|\hat{w}_t\|^2 \left[ \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} w_s \right)^4 + O_P(1) \left( \frac{1}{T^2} \sum_{s,m \leq T} \zeta_{ms}^2 \right)^2 \right]$$

$$\begin{aligned}
& + \frac{1}{T} \sum_t \|\hat{w}_t\|^2 \max_t \|\hat{w}_t\|^2 \left[ \frac{1}{N} \sum_i \left( \frac{1}{T} \sum_s e_{is} \eta_s \right)^4 + \mathcal{Q}_3^4 \right] \\
& + \frac{1}{T} \sum_t \left( \frac{1}{T} \sum_s \zeta_{st}^2 \right)^2 O_P(C_{NT}^{-4}) + \frac{1}{T} \sum_t \eta_t^4 + \frac{1}{T} \sum_t \left( \frac{1}{T} \sum_s w_s \zeta_{st} \right)^4 \\
& \leq (O_P(1) + o_P(C_{NT})) C_{NT}^{-4} + O_P(C_{NT}^{-2}) \\
& + O_P(1) \frac{1}{T} \sum_t \frac{1}{T^4} \sum_{s,k,l,m \leq T} \mathbb{E} w_l w_m w_k w_s \mathbb{E}(\zeta_{st} \zeta_{kt} \zeta_{lt} \zeta_{mt} | W) \\
& = O_P(C_{NT}^{-2}).
\end{aligned}$$

Similarly,  $\frac{1}{NT} \sum_{it} (\hat{e}_{it} - e_{it})^2 = O_P(C_{NT}^{-2})$ .

$$\begin{aligned}
\frac{1}{NT} \sum_{it} e_{it}^2 (\hat{e}_{it} - e_{it})^2 & \leq \frac{1}{NT} \sum_{it} e_{it}^2 \hat{w}_t^2 \left( \frac{1}{T} \sum_s e_{is} \eta_s \right)^2 + \frac{1}{NT} \sum_{it} e_{it}^2 \hat{w}_t^2 \left( \frac{1}{T} \sum_s e_{is} w_s \right)^2 \\
& + \frac{1}{NT} \sum_{it} e_{it}^2 \hat{w}_t^2 \left( \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m \right)^2 + \frac{1}{NT} \sum_{it} e_{it}^2 \hat{w}_t^2 (l'_i \mathcal{Q}_3)^2 \\
& + \frac{1}{NT} \sum_{it} e_{it}^2 (l'_i \frac{1}{T} \sum_s \hat{w}_s \zeta_{st})^2 + \frac{1}{NT} \sum_{it} e_{it}^2 (l'_i \eta_t)^2 = O_P(C_{NT}^{-2}).
\end{aligned}$$

Next,

$$\begin{aligned}
\frac{1}{T} \sum_t \left( \frac{1}{N} \sum_i c_i (e_{it} - \hat{e}_{it}) \right)^2 & \leq \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{N} \sum_i c_i \frac{1}{T} \sum_s e_{is} w_s \right)^2 \\
& + \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{N} \sum_i c_i \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m \right)^2 \\
& + \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{N} \sum_i c_i \frac{1}{T} \sum_s e_{is} \eta_s \right)^2 \\
& + \frac{1}{T} \sum_t \hat{w}_t^2 \mathcal{Q}_3^2 + \frac{1}{T} \sum_t \left( \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \right)^2 + \frac{1}{T} \sum_t \eta_t^2 \\
& = O_P(C_{NT}^{-2}).
\end{aligned}$$

Finally, for  $r = 0, 1, 2$ , and  $p = 0, 1$ ,

$$\begin{aligned}
& \frac{1}{TN} \sum_{t \in I^c} \sum_i f_t^2 e_{jt}^r c_i e_{it}^p (\hat{e}_{it} - e_{it}) \\
& = \frac{1}{TN} \sum_{t \in I^c} f_t^2 e_{jt}^r \sum_i c_i e_{it}^p \hat{w}_t \frac{1}{T^2} \sum_{s,m \leq T} e_{is} \zeta_{ms} \hat{w}_m + \frac{1}{TN} \sum_{t \in I^c} f_t^2 e_{jt}^r \sum_i c_i e_{it}^p l'_i \frac{1}{T} \sum_s \hat{w}_s \zeta_{st} \\
& + \frac{1}{TN} \sum_{t \in I^c} \hat{w}_t f_t^2 e_{jt}^r \sum_i c_i e_{it}^p l'_i \mathcal{Q}_3 + \frac{1}{TN} \sum_{t \in I^c} f_t \hat{w}_t^2 e_{jt}^r \sum_i c_i e_{it}^p \frac{1}{T} \sum_s e_{is} (w_s + \eta_s) \\
& + \frac{1}{TN} \sum_{t \in I^c} f_t^2 e_{jt}^r \sum_i c_i e_{it}^p l'_i \eta_t
\end{aligned}$$



$$= \frac{1}{TN} \sum_{t \in I^c} f_t \hat{w}_t^2 e_{jt}^r \sum_i c_i e_{it}^p \frac{1}{T} \sum_s e_{is} (w_s + \eta_s) + \frac{1}{TN} \sum_{t \in I^c} f_t^2 e_{jt}^r \sum_i c_i e_{it}^p l_i \eta_t + O_P(C_{NT}^{-2}),$$

where the last equality is due to:  $\frac{1}{T} \sum_s (\frac{1}{T} \sum_t w_t \zeta_{ts})^2 = O_P(C_{NT}^{-4})$  and  $\mathcal{Q}_3 = O_P(C_{NT}^{-2})$ . Now for  $p = 1$ ,

$$\begin{aligned} & \frac{1}{TN} \sum_{t \in I^c} \sum_i \tilde{f}_t f_t e_{jt}^r c_i e_{it} (\hat{e}_{it} - e_{it}) = O_P(C_{NT}^{-2}) + \frac{1}{TN} \sum_{t \in I^c} \sum_i f_t^2 e_{jt}^r c_i e_{it} (\hat{e}_{it} - e_{it}) \\ &= \frac{1}{TN} \sum_{t \in I^c} f_t \hat{w}_t^2 e_{jt}^r \sum_i c_i e_{it} \frac{1}{T} \sum_s e_{is} (w_s + \eta_s) + \frac{1}{TN} \sum_{t \in I^c} f_t^2 e_{jt}^r \sum_i c_i e_{it} l_i \eta_t + O_P(C_{NT}^{-2}) \\ &= O_P(C_{NT}^{-2}) \end{aligned}$$

where the last equality is due to  $\frac{1}{T} \sum_t (\frac{1}{TN} \sum_{is} (w_s + \eta_s) e_{is} e_{it} c_i)^2 = O_P(C_{NT}^{-4})$ ; and  $\frac{1}{T} \sum_t (\frac{1}{N} \sum_i e_{it} c_i)^2 \eta_t^2 = O_P(C_{NT}^{-4})$ .

For  $p = 0$  and  $r = 1$ ,

$$\begin{aligned} & \frac{1}{TN} \sum_{t \in I^c} \sum_i f_t^2 e_{jt} c_i (\hat{e}_{it} - e_{it}) \\ &= O_P(1) \frac{1}{N} \sum_i c_i \frac{1}{T} \sum_s e_{is} (w_s + \eta_s) + O_P(1) \frac{1}{T} \sum_{t \in I^c} f_t^2 e_{jt} \eta_t + O_P(C_{NT}^{-2}), \\ &= O_P(C_{NT}^{-2}). \end{aligned}$$

(iii)

$$\begin{aligned} & \frac{1}{T} \sum_t \left( \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it}) e_{it} \right)^2 \\ &\leq \max_t \|\hat{w}_t - H_x w_t\|^2 \frac{1}{T} \sum_t \left[ \left( \frac{1}{N} \sum_i c_i \frac{1}{T} \sum_s e_{is} w_s e_{it} \right)^2 + \frac{1}{T} \sum_m \left( \frac{1}{N} \sum_i c_i e_{it} \frac{1}{T} \sum_{s \leq T} e_{is} \zeta_{ms} \right)^2 \right] \\ &+ \frac{1}{T} \sum_t w_t^2 \left[ \left( \frac{1}{N} \sum_i c_i \frac{1}{T} \sum_s e_{is} w_s e_{it} \right)^2 + \frac{1}{T} \sum_m \left( \frac{1}{N} \sum_i c_i e_{it} \frac{1}{T} \sum_{s \leq T} e_{is} \zeta_{ms} \right)^2 \right] \\ &+ \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{N} \sum_i c_i \frac{1}{T} \sum_s e_{is} \eta_s e_{it} \right)^2 + \frac{1}{T} \sum_t \hat{w}_t^2 \left( \frac{1}{N} \sum_i c_i l'_i e_{it} \right)^2 \mathcal{Q}_3^2 \\ &+ \frac{1}{T} \sum_t \left( \frac{1}{N} \sum_i c_i l_i e_{it} \right)^2 \frac{1}{T} \sum_s \zeta_{st}^2 + \frac{1}{T} \sum_t \eta_t^2 \left( \frac{1}{N} \sum_i c_i l_i e_{it} \right)^2 = O_P(C_{NT}^{-4}) \end{aligned}$$

Similarly,  $\frac{1}{T} \sum_t (\frac{1}{N} \sum_j c_j (\hat{e}_{it} - e_{it}) u_{jt})^2$ ,  $\frac{1}{T} \sum_{t \in I^c} (|e_{jt}| + 1)^2 u_{jt}^2 (\frac{1}{N} \sum_i c_i e_{it} (\hat{e}_{it} - e_{it}))^2$  and

$\frac{1}{T} \sum_t e_{jt}^{2r} f_t^2 (\frac{1}{N} \sum_i c_i e_{it} (\hat{e}_{it} - e_{it}))^2$  are all  $O_P(C_{NT}^{-4})$  (for fixed  $j$  and  $r \leq 2$ ).

Next, to bound  $\frac{1}{T} \sum_t (\frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it})^2)^2$ , we first bound  $\frac{1}{T} \sum_t \hat{w}_t^4$ . By (F.1),

$$\begin{aligned} \frac{1}{T} \sum_t \hat{w}_t^4 &\leq O_P(1) + \frac{1}{T} \sum_t \|\hat{w}_t - H_x^{-1} w_t\|^4 \\ &\leq O_P(1) + \frac{1}{T} \sum_t \|\eta_t\|^4 + \frac{1}{T} \sum_t \left\| \frac{1}{T} \sum_s w_s \zeta_{st} \right\|^4 + \frac{1}{T} \sum_t \left( \frac{1}{T} \sum_s \zeta_{st}^2 \right)^2 O_P(C_{NT}^{-4}) \\ &= O_P(1). \end{aligned}$$

Thus

$$\begin{aligned} &\frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i c_i (\hat{e}_{it} - e_{it})^2 \right)^2 \\ &\leq \frac{1}{T} \sum_{t \in I^c} \hat{w}_t^4 \left( \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} w_s \right)^2 \right)^2 + \frac{1}{T} \sum_{t \in I^c} \hat{w}_t^4 \left( \frac{1}{N} \sum_i c_i \left( \frac{1}{T} \sum_s e_{is} \eta_s \right)^2 \right)^2 \\ &\quad + \frac{1}{T} \sum_{t \in I^c} \hat{w}_t^4 \mathcal{Q}_3^4 + \frac{1}{T} \sum_{t \in I^c} \eta_t^4 + \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{T} \sum_s w_s \zeta_{st} \right)^4 + \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{T} \sum_s \zeta_{st}^2 \right)^2 O_P(C_{NT}^{-4}) \\ &\quad + \frac{1}{T} \sum_{t \in I^c} \hat{w}_t^4 \left( \frac{1}{N} \sum_i c_i \frac{1}{T} \sum_{m \leq T} \left( \frac{1}{T} \sum_{s \leq T} e_{is} \zeta_{ms} \right)^2 \right)^2 = O_P(C_{NT}^{-4}). \end{aligned}$$

**F.2. Behavior of the preliminary in the factor model.** Recall that

$$(\tilde{f}_s, \tilde{g}_s) := \arg \min_{f_s, g_s} \sum_{i=1}^N (y_{is} - \tilde{\alpha}'_i g_s - x_{is} \tilde{\lambda}'_i f_s)^2, \quad s \in I^c \cup \{t\}.$$

and

$$(\dot{\lambda}_i, \dot{\alpha}_i) = \arg \min_{\lambda_i, \alpha_i} \sum_{s \in I^c \cup \{t\}} (y_{is} - \alpha'_i \tilde{g}_s - x_{is} \lambda'_i \tilde{f}_s)^2, \quad i = 1, \dots, N.$$

The goal of this section is still to show that the effect of the preliminary estimation is negligible. Specifically, we aim to show, for each fixed  $t \in I^c$ , fixed  $i \leq N$ ,

$$\begin{aligned} \frac{1}{\sqrt{N}} \sum_j (H_1' \lambda_j - \dot{\lambda}_j) e_{jt} &= O_P(\sqrt{N} C_{NT}^{-2}), \\ \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s (H_1^{-1} f_s - \tilde{f}_s) e_{is} &= O_P(\sqrt{T} C_{NT}^{-2}). \end{aligned}$$

Let  $L$  denote  $N \times K_3$  matrix of  $l_i$ , so  $X_s = L w_s + e_s$ . Also let  $W$  be  $T \times K_3$  matrix of  $w_t$ .

Define

$$\tilde{D}_{fs} = \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) \tilde{\Lambda}$$

$$\begin{aligned}
D_{fs} &= \frac{1}{N} \Lambda' (\text{diag}(X_s) M_\alpha \text{diag}(X_s) \Lambda \\
\bar{D}_{fs} &= \frac{1}{N} \Lambda' \mathbb{E}((\text{diag}(e_s) M_\alpha \text{diag}(e_s)) \Lambda) + \frac{1}{N} \Lambda' (\text{diag}(Lw_s) M_\alpha \text{diag}(Lw_s) \Lambda \\
\tilde{D}_{\lambda i} &= \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) \tilde{F} \\
D_{\lambda i} &= \frac{1}{T} F' (\text{diag}(X_i) M_g \text{diag}(X_i)) F \\
\bar{D}_{\lambda i} &= \frac{1}{T} F' \mathbb{E}(\text{diag}(E_i) M_g \text{diag}(E_i)) F + \frac{1}{T} F' (\text{diag}(Wl_i) M_g \text{diag}(Wl_i)) F
\end{aligned}$$

**Lemma F.3.** Suppose  $\max_{it} e_{it}^2 + \max_t \|w_t\|^2 = o_P(C_{NT})$ . Also, there is  $c > 0$ , so that

$\min_s \min_j \psi_j(D_{fs}) > c$ . Then

- (i)  $\max_s \|\tilde{D}_{fs}^{-1}\| = O_P(1)$ .
- (ii)  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\tilde{D}_{fs}^{-1} - (H_1' \bar{D}_{fs} H_1)^{-1}\|^2 = O_P(C_{NT}^{-2})$ .

*Proof.* The proof is mostly the same as that of Lemma E.1. The only difference is in the proof of (ii), where we need to show  $\frac{1}{T} \sum_s \|D_{fs} - \bar{D}_{fs}\|^2 = O_P(C_{NT}^{-2})$ .

$$\begin{aligned}
& \frac{1}{T} \sum_s \|D_{fs} - \bar{D}_{fs}\|^2 \leq \frac{1}{T} \sum_s \left\| \frac{1}{N} \sum_{ij} \lambda_i \lambda_j' M_{\alpha, ij} (x_{is} x_{js} - \mathbb{E} e_{is} e_{js} - l_i' w_s l_j' w_s) \right\|_F^2 \\
& \leq \frac{1}{T} \sum_s \left\| \frac{1}{N} \sum_{ij} \lambda_i \lambda_j' M_{\alpha, ij} (e_{is} e_{js} - \mathbb{E} e_{is} e_{js}) \right\|_F^2 \\
& \quad + \frac{2}{T} \sum_s \left\| \frac{1}{N} \sum_{ij} \lambda_i \lambda_j' M_{\alpha, ij} l_i' w_s l_j' w_s \right\|_F^2
\end{aligned}$$

We assume  $\dim(\lambda_i) = \dim(p_i) = 1$ . As for the first term, it is less than

$$\begin{aligned}
& \frac{1}{T} \sum_s \text{Var} \left( \frac{1}{N} \sum_{ij} \lambda_i \lambda_j' M_{\alpha, ij} e_{is} e_{js} \right) \\
& \leq \frac{1}{T} \sum_s \frac{1}{N^4} \sum_{ijkl} |\text{Cov}(e_{is} e_{js}, e_{ks} e_{ls})| = O(N^{-1})
\end{aligned}$$

provided that  $\frac{1}{N^3} \sum_{ijkl} \text{Cov}(e_{is} e_{js}, e_{ks} e_{ls}) < C$ . As for the second term, it is less than

$$O_P(1) \frac{1}{T} \sum_s \mathbb{E} w_s^2 \frac{1}{N^2} \sum_{ij} |\text{Cov}(e_{js}, e_{ls} | w_s)| = O(N^{-1})$$

provided that  $\frac{1}{N} \sum_{ij} |\text{Cov}(e_{is}, e_{js} | w_s)| < \infty$  and  $\|\mathbb{E} e_s e_s'\| < \infty$ . So  $\frac{1}{T} \sum_s \|D_{fs} - \bar{D}_{fs}\|^2 = O_P(N^{-1})$ .

- Lemma F.4.** (i) For each fixed  $t \in I^c$ ,  $H_1^{-1}f_t - \tilde{f}_t = O_P(C_{NT}^{-1})$ .  
(ii) For each fixed  $i \leq N$ ,  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s(H_1^{-1}f_s - \tilde{f}_s)e_{is} = O_P(\sqrt{T}C_{NT}^{-2})$ .  
(iii) For each fixed  $i \leq N$ ,  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} w_s f_s(H_1^{-1}f_s - \tilde{f}_s)e_{is} = O_P(\sqrt{T}C_{NT}^{-2})$ .

*Proof.* We highlight the similarity and main differences from the proof of Lemma E.2.

We have the same expansion.

$$\begin{aligned}
\tilde{f}_s &= \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} y_s \\
&= H_1^{-1} f_s + \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} (A H_2 - \tilde{A}) H_2^{-1} g_s \\
&\quad + \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \\
&\quad + \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s.
\end{aligned} \tag{F.4}$$

Step 1, the same proof yields

$$\begin{aligned}
&\frac{1}{\sqrt{T}} \sum_s f_s e_{is} (\tilde{D}_{fs}^{-1} - (H_1' D_x H_1)^{-1}) \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} (A H_2 - \tilde{A}) H_2^{-1} g_s \\
&\leq O_P(\sqrt{T}C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \tilde{\lambda}_j^2 \left( \frac{1}{T} \sum_s f_s g_s e_{is} x_{js} \right)^2 \right]^{1/2} \\
&\leq O_P(\sqrt{T}C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \tilde{\lambda}_j^2 \left( \frac{1}{T} \sum_s f_s g_s e_{is} e_{js} \right)^2 \right]^{1/2} \\
&\quad + O_P(\sqrt{T}C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \tilde{\lambda}_j^2 l_j^2 \left( \frac{1}{T} \sum_s f_s g_s e_{is} w_s \right)^2 \right]^{1/2} \\
&\leq O_P(\sqrt{T}C_{NT}^{-2}) + O_P(\sqrt{T}C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \mathbb{E}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} e_{js} \right)^2 \right]^{1/2} \\
&\quad + O_P(\sqrt{T}C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \mathbb{E}_I \left( \frac{1}{T} \sum_s f_s g_s e_{is} w_s \right)^2 \right]^{1/2} \\
&= O_P(\sqrt{T}C_{NT}^{-2}).
\end{aligned}$$

Put together,

$$\frac{1}{\sqrt{T}} \sum_s f_s e_{is} \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} (A H_2 - \tilde{A}) H_2^{-1} g_s = O_P(\sqrt{T}C_{NT}^{-2}).$$

Step 2: recall that  $M_{\tilde{\alpha},ij}$  and  $P_{\tilde{\alpha},ij}$  are the  $(i,j)$  th component of  $M_{\tilde{\alpha}}$  and  $\tilde{A}(\tilde{A}'\tilde{A})^{-1}\tilde{A}'$  and write  $P_{\tilde{\alpha},ij} := \frac{1}{N}p'_ip_j$ .

$$\begin{aligned}
& \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (\tilde{D}_{fs}^{-1} - (H'_1 D_x H_1)^{-1}) \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \\
& \leq O_P(\sqrt{TN} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \frac{1}{N^2} \sum_j \tilde{\lambda}_j^2 \mathbb{E}_I e_{js}^4 M_{\tilde{\alpha},jj}^2 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& \quad + O_P(\sqrt{TN} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \frac{1}{N^2} \sum_j \tilde{\lambda}_j^2 l_j^4 w_s^4 M_{\tilde{\alpha},jj}^2 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& \quad + O_P(\sqrt{T} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s \frac{1}{N^2} \sum_{k \neq j} x_{ks}^2 (p'_k p_j)^2 x_{js}^2 \|f_s\|^2 \|f_s e_{is}\|^2 \right)^{1/2} \\
& = O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

Step 3: the same proof yields:

$$\begin{aligned}
& \left( \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (H'_1 D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) (M_{\tilde{\alpha}} - M_{\alpha}) \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \right)^2 \\
& \leq O_P(T C_{NT}^{-4}).
\end{aligned}$$

Step 4: let  $z_{js} = \sum_k \tilde{\lambda}_k M_{\alpha,kj} x_{ks}$ ,

$$\begin{aligned}
& \frac{1}{\sqrt{T}} \sum_s f_s e_{is} (H'_1 D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\alpha} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s \\
& \leq O_P(\sqrt{T} C_{NT}^{-1}) \left[ \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s f_s^2 e_{is} z_{js} x_{js} \right)^2 \right]^{1/2}
\end{aligned}$$

To bound the last line, note that

$$\begin{aligned}
& \frac{1}{N} \sum_j \mathbb{E}_I \left( \frac{1}{T} \sum_s f_s^2 e_{is} z_{js} x_{js} \right)^2 \\
& \leq \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I (f_s^2 e_{is} x_{js}^2)^2 (\tilde{\lambda}_j M_{\alpha,jj})^2 + O_P(1) \frac{1}{N} \sum_j \frac{1}{N} \sum_{k \neq j} \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 x_{ks} e_{is} x_{js} \right)^2 \right. \\
& \quad \left. + \frac{1}{N} \sum_j \text{Var}_I \left( \frac{1}{T} \sum_s f_s^2 e_{is} z_{js} x_{js} \right) \right) \\
& \leq \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I (f_s^2 e_{is} x_{js}^2)^2 (\tilde{\lambda}_j - H'_1 \lambda_j)^2 + O_P(1) \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{is} e_{js}^2 \right)^2 \right. \\
& \quad \left. + O_P(1) \frac{1}{N} \sum_j \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{is} l_j w_s e_{js} \right)^2 + O_P(1) \frac{1}{N} \sum_j \frac{1}{N} \sum_{k \neq j} \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{ks} e_{is} e_{js} \right)^2 \right. \\
& \quad \left. + O_P(1) \frac{1}{N} \sum_j \frac{1}{N} \sum_{k \neq j} \left( \frac{1}{T} \sum_s \mathbb{E}_I f_s^2 e_{ks} e_{is} l_j w_s \right)^2 \right)
\end{aligned}$$

$$+O_P(1)\frac{1}{N}\sum_j\frac{1}{N}\sum_{k\neq j}\left(\frac{1}{T}\sum_s\mathbf{E}_I f_s^2 l_k w_s e_{is} e_{js}\right)^2 + O_P(T^{-1}) = O_P(C_{NT}^{-2})$$

given that  $\sum_j |\mathbf{E}_I(e_{is} e_{js} | f_s, w_s)| + \frac{1}{N} \sum_{k\neq j} |\mathbf{E}_I(e_{ks} e_{is} e_{js} | f_s, w_s)| < \infty$ . Put together,

$$\frac{1}{\sqrt{T}}\sum_s f_s e_{is} \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s = O_P(\sqrt{T} C_{NT}^{-2}).$$

Step 5:

$$\begin{aligned} & \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (\tilde{D}_{fs}^{-1} - (H_1' D_x H_1)^{-1}) \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s \\ & \leq O_P(\sqrt{T} C_{NT}^{-1}) \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} |f_s e_{is} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s|^2 \right)^{1/2} \\ & \leq O_P(\sqrt{T} C_{NT}^{-2}) \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbf{E}_I f_s^2 e_{is}^2 \frac{1}{N} \sum_j \tilde{\lambda}_j^2 x_{js}^2 \right)^{1/2} \\ & \leq O_P(\sqrt{T} C_{NT}^{-2}) \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \frac{1}{N} \sum_j \tilde{\lambda}_j^2 \mathbf{E}_I f_s^2 e_{is}^2 e_{js}^2 \right)^{1/2} \\ & \quad + O_P(\sqrt{T} C_{NT}^{-2}) \left( \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbf{E}_I f_s^2 e_{is}^2 w_s^2 \right)^{1/2} \left( \frac{1}{N} \sum_j \tilde{\lambda}_j^2 l_j^2 \right)^{1/2} = O_P(\sqrt{T} C_{NT}^{-2}). \end{aligned}$$

Step 6:

$$\begin{aligned} & \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) (M_{\tilde{\alpha}} - M_{\alpha}) u_s \\ & \leq O_P(\sqrt{T} C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \left\| \frac{1}{T} \sum_{s \in I^c \cup \{t\}} u_s f_s e_{is} \frac{1}{\sqrt{N}} x_{js} \right\|_F^2 \tilde{\lambda}_j^2 \right)^{1/2} \\ & \leq O_P(\sqrt{T} C_{NT}^{-1}) \left( \max_j \mathbf{E}_I \mathbf{E}_I \left( \left\| \frac{1}{T} \sum_{s \in I^c \cup \{t\}} u_s f_s e_{is} \frac{1}{\sqrt{N}} x_{js} \right\|_F^2 \middle| X, E, F \right) \right)^{1/2} \\ & \leq O_P(C_{NT}^{-1}) \left( \max_{jks} \text{Var}_I(u_{ks} f_s e_{is} x_{js}) \right)^{1/2} = O_P(C_{NT}^{-1}) = O_P(\sqrt{T} C_{NT}^{-2}). \end{aligned}$$

Step 7:

$$\begin{aligned} & \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} (\tilde{\Lambda} - \Lambda H_1)' \text{diag}(X_s) M_{\alpha} u_s \\ & \leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbf{E}_I f_s^2 x_{js}^2 e_{is}^2 M'_{\alpha,j} \text{Var}_I(u_s | e_s, w_s, f_s) M_{\alpha,j} \right)^{1/2} \\ & \leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_j \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \mathbf{E}_I f_s^2 x_{js}^2 e_{is}^2 \|M_{\alpha,j}\|^2 \right)^{1/2} = O_P(C_{NT}^{-1}) = O_P(\sqrt{T} C_{NT}^{-2}). \end{aligned}$$

Finally,

$$\begin{aligned}
& \frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} (H_1' D_x H_1)^{-1} \frac{1}{N} H_1' \Lambda' \text{diag}(X_s) M_\alpha u_s \\
& \leq O_P(N^{-1}) (\mathbf{E}_I f_s^2 e_{is}^2 \Lambda' \text{diag}(X_s) M_\alpha \mathbf{E}_I (u_s u_s' | e_s, f_s) M_\alpha \text{diag}(X_s) \Lambda)^{1/2} \\
& \leq O_P(N^{-1/2}) \left( \frac{1}{N} \sum_j \mathbf{E}_I f_s^2 e_{is}^2 x_{js}^2 \right)^{1/2} = O_P(N^{-1/2}) = O_P(\sqrt{T} C_{NT}^{-2}).
\end{aligned}$$

Put together, we have  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s e_{is} \tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s = O_P(\sqrt{T} C_{NT}^{-2})$ .

Thus  $\frac{1}{\sqrt{T}} \sum_{s \in I^c \cup \{t\}} f_s (H_1^{-1} f_s - \tilde{f}_s) e_{is} = O_P(\sqrt{T} C_{NT}^{-2})$ . Q.E.D.

(iii) The proof is the same as that of (ii).

**Lemma F.5.** Suppose  $\max_{it} e_{it}^4 = O_P(\min\{N, T\})$ . (i)  $\frac{1}{T} \|\tilde{F} - F H_1^{-1'}\|_F^2 = O_P(C_{NT}^{-2}) = \frac{1}{T} \|\tilde{G} - G H_2^{-1'}\|_F^2$ , and  $\frac{1}{T} \sum_{t \in I^c} \|\tilde{f}_t - H_1^{-1} f_t\|^2 e_{it}^2 u_{it}^2 = O_P(C_{NT}^{-2})$ .  
(ii)  $\max_i \|\tilde{D}_{\lambda_i}^{-1}\| = O_P(1)$ .  
(iii)  $\frac{1}{N} \sum_i \|\tilde{D}_{\lambda_i}^{-1} - (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1}\|^2 = O_P(C_{NT}^{-2})$ .

*Proof.* (i) The proof is very similar to that of Lemma E.1, hence we omit the details for (i)(ii). As for (iii), the same proof as in Lemma E.3 shows

$$\begin{aligned}
& \frac{1}{N} \sum_i \|\tilde{D}_{\lambda_i}^{-1} - (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1}\|^2 \\
& \leq O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_i \left\| \frac{1}{T} \sum_{st} f_s f_t' M_{g,st} (x_{is} x_{it} - \mathbf{E} e_{is} e_{it} - l_i' w_s l_i' w_t) \right\|_F^2 \\
& \leq O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_i \left\| \frac{1}{T} \sum_{st} f_s f_t' M_{g,st} (e_{is} e_{it} - \mathbf{E} e_{is} e_{it}) \right\|_F^2 \\
& \quad + O_P(1) \frac{1}{N} \sum_i \left\| \frac{1}{T} \sum_{st} f_s f_t' M_{g,st} w_s e_{it} \right\|_F^2 \\
& \leq O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_i \left\| \frac{1}{T} \sum_t f_t^2 w_t e_{it} \right\|_F^2 + O_P(1) \frac{1}{N} \sum_i \left\| \frac{1}{T} \sum_t f_t g_t e_{it} \right\|_F^2 \\
& = O_P(C_{NT}^{-2}).
\end{aligned}$$

Q.E.D.

**Lemma F.6.** Suppose  $\text{Var}(u_s | e_t, e_s, w_s) < C$  and  $C_{NT}^{-1} \max_{is} |x_{is}|^2 = O_P(1)$ .

(i) For each fixed  $t \in I^c$ ,  $\frac{1}{\sqrt{N}} \sum_i (H_1' \lambda_i - \dot{\lambda}_i) e_{it} = O_P(\sqrt{N} C_{NT}^{-2})$ .

(ii) For each  $i \leq N$ ,  $\lambda_i - \dot{\lambda}_i = O_P(C_{NT}^{-1})$ .

(iii) For each fixed  $j \leq N$ ,  $\frac{1}{T} \sum_{t \in I^c} \|w_t e_{jt} f_t'\|^2 \left\| \frac{1}{N} \sum_i \lambda_i e_{it} l_i (\dot{\lambda}_i - H_1' \lambda_i)' \right\|^2 = O_P(C_{NT}^{-4})$ .

*Proof.* We have the same expansion

$$\begin{aligned}\dot{\lambda}_i &= \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} y_i \\ &= H_1' \lambda_i + \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (GH_2^{-1'} - \tilde{G}) H_2' \alpha_i \\ &\quad + \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (FH_1^{-1'} - \tilde{F}) H_1' \lambda_i + \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} u_i.\end{aligned}$$

We highlight the similarity and differences from the proof of Lemma E.4.

Step 1: given  $\mathbb{E} e_{it}^4 f_t^2 + e_{it}^2 f_t^2 w_t^2 < C$ ,

$$\begin{aligned}& \frac{1}{\sqrt{N}} \sum_i e_{it} (\tilde{D}_{\lambda i}^{-1} - (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1}) \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (GH_2^{-1'} - \tilde{G}) H_2' \alpha_i \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}) + O_P(\sqrt{N} C_{NT}^{-2}) \left( \frac{1}{T} \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 \right)^{1/2} \max_{is} |x_{is}| \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}) + O_P(\sqrt{N} C_{NT}^{-3}) \max_{is} |x_{is}| = O_P(\sqrt{N} C_{NT}^{-2}).\end{aligned}$$

Step 2:  $\bar{D}_{\lambda i}$  is nonrandom given  $W, G, F$ ,

$$\begin{aligned}& \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (GH_2^{-1'} - \tilde{G}) H_2' \alpha_i \\ & \leq O_P(\sqrt{N} C_{NT}^{-1}) (a^{1/2} + b^{1/2}) \quad \text{where} \\ a &= \frac{1}{T} \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2 \\ b &= \frac{1}{T} \sum_s f_s^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2.\end{aligned}$$

We now bound each term. As for  $b$ , note that for each fixed  $t$ ,

$$\begin{aligned}& \mathbb{E} \left( \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2 \middle| F, G, W, u_s \right) \\ & \leq \mathbb{E} \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} e_{is} \middle| F, G, W, u_s \right)^2 + \mathbb{E} \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} l'_i w_s \middle| F, G, W, u_s \right)^2 \\ & \leq \frac{C}{N} + \frac{C \|w_s\|^2}{N} + \left( \mathbb{E} \frac{1}{N} \sum_i \alpha_i e_{it} e_{is} \bar{D}_{\lambda i}^{-1} \middle| F, G, W, u_s \right)^2\end{aligned} \tag{F.5}$$

with the assumption  $\frac{1}{N} \sum_{ij} |\text{Cov}(e_{jt} e_{js}, e_{it} e_{is})| < C$ . So

$$\begin{aligned}Eb &\leq \frac{1}{T} \sum_s \mathbb{E} f_s^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2 \leq O(C_{NT}^{-2}). \\ a &= \frac{1}{T} \sum_s f_s^2 \left( \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) \right)^2 \left( \frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda i}^{-1} x_{is} \right)^2\end{aligned}$$



$$\begin{aligned}
& + \frac{1}{T} \sum_s (\tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} \text{diag}(X_s) (\Lambda H_1 - \tilde{\Lambda}) H_1^{-1} f_s)^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda_i}^{-1} x_{is})^2 \\
& + \frac{1}{T} \sum_s (\tilde{D}_{fs}^{-1} \frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s)^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda_i}^{-1} x_{is})^2 \\
& \leq O_P(C_{NT}^{-2}) \max_{is} x_{is}^4 \frac{1}{T} \sum_s \mathbb{E} f_s^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda_i}^{-1} x_{is})^2 \\
& \quad + O_P(1) \frac{1}{T} \sum_s (\frac{1}{N} \tilde{\Lambda}' \text{diag}(X_s) M_{\tilde{\alpha}} u_s)^2 (\frac{1}{N} \sum_i \alpha_i e_{it} \bar{D}_{\lambda_i}^{-1} x_{is})^2 \\
& \leq O_P(C_{NT}^{-2})
\end{aligned}$$

where reaching the last inequality is similar to the proof in Lemma E.4, based on (F.5).

Put together,  $a^{1/2} + b^{1/2} = O(C_{NT}^{-1})$ . So the first term in the expansion of  $\frac{1}{\sqrt{N}} \sum_i (H_1' \lambda_i - \dot{\lambda}_i) e_{it}$  is

$$\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda_i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} (G H_2^{-1'} - \tilde{G}) H_2' \alpha_i = O_P(\sqrt{N} C_{NT}^{-2}).$$

Step 3: the same proof as in Lemma E.4 yields

$$\begin{aligned}
& \frac{1}{\sqrt{N}} \sum_i e_{it} (\tilde{D}_{\lambda_i}^{-1} - (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1}) \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\
& \leq O_P(\sqrt{N} C_{NT}^{-2}).
\end{aligned}$$

Step 4: similar to the proof in Lemma E.4

$$\begin{aligned}
& \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda_i} H_1^{-1'})^{-1} \frac{1}{T} (\tilde{F} - F H_1^{-1'})' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\
& \leq O_P(\sqrt{N} C_{NT}^{-2}) + \sqrt{N} \frac{1}{T} \sum_s (\tilde{f}_s - H_1^{-1} f_s)^2 \frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} x_{is}^2 \\
& \leq O_P(\sqrt{N} C_{NT}^{-2}) + \max_{is} x_{is}^2 O_P(\sqrt{N} C_{NT}^{-2}) \frac{1}{NT} \sum_s g_s^2 w_s^2 \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} l_i^2 \\
& \quad + \max_{is} x_{is}^2 O_P(\sqrt{N} C_{NT}^{-2}) \frac{1}{T} \sum_s w_s^2 \frac{1}{N} \sum_j \lambda_j^2 x_{js}^2 f_s^2 \frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} l_i^2 \\
& \quad + \sqrt{N} \frac{1}{T} \sum_s w_s^2 (\frac{1}{N} \Lambda' \text{diag}(X_s) M_{\alpha} u_s)^2 \frac{1}{N} \sum_i \lambda_i e_{it} \bar{D}_{\lambda_i}^{-1} l_i^2 \\
& \leq O_P(\sqrt{N} C_{NT}^{-2}).
\end{aligned}$$

Step 5: the same proof as in Lemma E.4 yields

$$\begin{aligned} & \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1} \frac{1}{T} F' \text{diag}(X_i) (M_{\tilde{g}} - M_g) \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\ & \leq O_P(\sqrt{N} C_{NT}^{-2}), \end{aligned}$$

Step 6:

$$\begin{aligned} & \frac{1}{\sqrt{N}} \sum_i e_{it} (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1} \frac{1}{T} F' \text{diag}(X_i) M_g \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i \\ & \leq O_P(\sqrt{N} C_{NT}^{-1}) \left( \frac{1}{T} \sum_s f_s^2 \left( \frac{1}{N} \sum_i \lambda_i x_{is}^2 e_{it} \bar{D}_{\lambda i}^{-1} \right)^2 \right)^{1/2} \\ & \quad + O_P(\sqrt{N} C_{NT}^{-1}) \left( \frac{1}{T} \sum_s g_s^2 \left( \frac{1}{N} \sum_i x_{is} \lambda_i e_{it} \bar{D}_{\lambda i}^{-1} \frac{1}{T} \sum_k f_k x_{ik} g_k \right)^2 \right)^{1/2} \\ & = O_P(\sqrt{N} C_{NT}^{-1}) (a^{1/2} + b^{1/2}). \end{aligned}$$

We aim to show  $a = O_P(C_{NT}^{-2}) = b$ .

$$\begin{aligned} \text{Ea} &:= \frac{1}{T} \sum_s \text{E} f_s^2 \left( \frac{1}{N} \sum_i \lambda_i x_{is}^2 e_{it} \bar{D}_{\lambda i}^{-1} \right)^2 \\ &\leq \frac{1}{T} \sum_s \frac{1}{N^2} \sum_{ij} \text{E} f_s^2 \lambda_i \bar{D}_{\lambda i}^{-1} \lambda_j \bar{D}_{\lambda j}^{-1} \text{E}(e_{is}^2 e_{js}^2 | F) \text{Cov}(e_{it}, e_{jt} | F, G, W) \\ &\quad + \frac{1}{T} \sum_s \text{E} f_s^2 \frac{1}{N^2} \sum_{ij} \lambda_i l_i^2 w_s^2 \bar{D}_{\lambda i}^{-1} \lambda_j \mu_j^2 \bar{D}_{\lambda j}^{-1} \text{Cov}(e_{it}, e_{jt} | F, G, W) \\ &\quad + \frac{2}{T} \sum_s \text{E} f_s^2 \frac{1}{N^2} \sum_{ij} \lambda_i l_i w_s \bar{D}_{\lambda i}^{-1} \bar{D}_{\lambda j}^{-1} \lambda_i l_j w_s \text{E}(e_{js} e_{is} | F) \text{Cov}(e_{jt}, e_{it} | F, G, W) \\ &= O_P(N^{-1}). \\ \text{Eb} &:= \frac{1}{T} \sum_s \text{E} g_s^2 \left( \frac{1}{N} \sum_i x_{is} \lambda_i e_{it} \bar{D}_{\lambda i}^{-1} \frac{1}{T} \sum_k f_k x_{ik} g_k \right)^2 \\ &= O_P(C_{NT}^{-2}). \end{aligned}$$

Therefore the second term is

$$\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} \text{diag}(X_i) (F H_1^{-1'} - \tilde{F}) H_1' \lambda_i = O_P(\sqrt{N} C_{NT}^{-2}).$$

Step 7:  $\frac{1}{\sqrt{N}} \sum_i e_{it} \tilde{D}_{\lambda i}^{-1} \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} u_i$ . The same proof yields

$$\frac{1}{\sqrt{N}} \sum_i e_{it} (\tilde{D}_{\lambda i}^{-1} - (H_1^{-1} \bar{D}_{\lambda i} H_1^{-1'})^{-1}) \frac{1}{T} \tilde{F}' \text{diag}(X_i) M_{\tilde{g}} u_i \leq O_P(\sqrt{N} C_{NT}^{-2}).$$

$$\begin{aligned} \frac{1}{\sqrt{N}} \sum_i e_{it} \bar{D}_{\lambda_i}^{-1} \frac{1}{T} (\tilde{F} - F H_1^{-1'})' \text{diag}(X_i) M_{\tilde{g}} u_i &\leq O_P(\sqrt{N} C_{NT}^{-2}) \\ \frac{1}{\sqrt{N}} \sum_i e_{it} \bar{D}_{\lambda_i}^{-1} \frac{1}{T} F' \text{diag}(X_i) (M_{\tilde{g}} - M_g) u_i &\leq O_P(\sqrt{N} C_{NT}^{-2}). \end{aligned}$$

Step 8:

$$\mathbb{E} \left( \frac{1}{\sqrt{N}} \sum_i e_{it} \bar{D}_{\lambda_i}^{-1} \frac{1}{T} F' \text{diag}(X_i) M_g u_i \right)^2 = O_P(C_{NT}^{-2}).$$

Together,  $\frac{1}{\sqrt{N}} \sum_i (H_1' \lambda_i - \dot{\lambda}_i) e_{it} = O_P(\sqrt{T} C_{NT}^{-2})$ . Q.E.D.

The proof of part (iii) follows from the same arguments as in part (i). While a rigorous proof still follows from substituting in the expansion of  $\dot{\lambda}_i - H_1' \lambda_i$ , the details would be mostly very similar. So we omit it for brevity.

### F.3. Technical lemmas for $\hat{f}_t$ in the factor model.

**Lemma F.7.** For each fixed  $t$ , (i)  $\hat{B}_t - B = O_P(C_{NT}^{-1})$ .

(ii) The upper two blocks of  $\hat{B}_t^{-1} \hat{S}_t - B^{-1} S$  are both  $O_P(C_{NT}^{-2})$ .

*Proof.* Throughout the proof, we assume  $\dim(\alpha_i) = \dim(\lambda_i) = 1$  without loss of generality. We highlight the similarity and differences from the proofs of Lemma E.5.

(i)  $\hat{B}_t - B = b_1 + b_2$ , where

$$\begin{aligned} b_1 &= \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \tilde{\lambda}_i' \hat{e}_{it}^2 - H_1' \lambda_i \lambda_i' H_1 e_{it}^2 & \tilde{\lambda}_i \tilde{\alpha}_i' \hat{e}_{it} - H_1' \lambda_i \alpha_i H_2' e_{it} \\ \tilde{\alpha}_i \tilde{\lambda}_i' \hat{e}_{it} - H_2' \alpha_i \lambda_i H_1' e_{it} & \tilde{\alpha}_i \tilde{\alpha}_i' - H_2' \alpha_i \alpha_i' H_2 \end{pmatrix} \\ b_2 &= \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i \lambda_i' H_1 (e_{it}^2 - \mathbb{E} e_{it}^2) & H_1' \lambda_i \alpha_i H_2' e_{it} \\ H_2' \alpha_i \lambda_i H_1' e_{it} & 0 \end{pmatrix}. \end{aligned}$$

To prove the convergence of  $b_1$ , the same proof as in Lemma E.5 yields (by Lemma F.1),

$$\begin{aligned} &\frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' (\hat{e}_{it}^2 - e_{it}^2) \\ &\leq O_P(C_{NT}^{-2}) \max_{it} |\hat{e}_{it} - e_{it}| \max_{it} |e_{it}| + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 \right)^{1/2} \\ &\quad + O_P(1) \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 e_{it}^2 \right)^{1/2} \\ &\quad + O_P(1) \frac{1}{N} \sum_i \lambda_i \lambda_i' (\hat{e}_{it} - e_{it}) e_{it} = O_P(C_{NT}^{-2}) \end{aligned}$$

In addition,

$$\begin{aligned}
& \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\alpha}'_i (\hat{e}_{it} - e_{it}) \\
& \leq O_P(C_{NT}^{-2}) \max_{it} |\hat{e}_{it} - e_{it}| + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2} \\
& \quad + O_P(1) \frac{1}{N} \sum_i \lambda_i \alpha'_i (\hat{e}_{it} - e_{it}) = O_P(C_{NT}^{-2})
\end{aligned}$$

So the same proof as in Lemma E.5 yields  $b_1 = O_P(C_{NT}^{-1})$ . In addition,  $b_2 = O_P(N^{-1/2})$ . Hence  $\hat{B}_t - B = O_P(C_{NT}^{-1})$ .

(ii) We first bound the four blocks of  $\hat{S}_t - S$ . We have  $\hat{S}_t - S = c_t + d_t$ ,

$$\begin{aligned}
c_t &= \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \lambda'_i H_1 e_{it} (\hat{e}_{it} - e_{it}) + \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) & \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ \tilde{\alpha}_i \lambda'_i H_1 (e_{it} - \hat{e}_{it}) + \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (\hat{e}_{it} - e_{it}) & 0 \end{pmatrix} \\
d_t &= \frac{1}{N} \sum_i \begin{pmatrix} (\tilde{\lambda}_i \lambda'_i H_1 - \tilde{\lambda}_i \tilde{\lambda}'_i) e_{it}^2 - H_1' \lambda_i (\lambda'_i H_1 - \tilde{\lambda}'_i) E e_{it}^2 & \tilde{\lambda}_i e_{it} (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) e_{it} & 0 \end{pmatrix}.
\end{aligned}$$

Call each block of  $c_t$  to be  $c_{t,1} \dots c_{t,4}$  in the clockwise order. Note that  $c_{t,4} = 0$ .

As for  $c_{t,1}$ , it follows from Lemma F.1 that

$$\begin{aligned}
& \frac{1}{N} \sum_i \tilde{\lambda}_i \lambda'_i H_1 e_{it} (\hat{e}_{it} - e_{it}) \leq \left( \frac{1}{N} \sum_i e_{it}^2 (\hat{e}_{it} - e_{it})^2 \right)^{1/2} O_P(C_{NT}^{-1}) \\
& \quad + O_P(1) \frac{1}{N} \sum_i \lambda_i \lambda_i e_{it} (\hat{e}_{it} - e_{it}) \leq O_P(C_{NT}^{-2}).
\end{aligned}$$

We have also shown  $\frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) = O_P(C_{NT}^{-2})$ . Thus  $c_{t,1} = O_P(C_{NT}^{-2})$ .

For  $c_{t,2}$ , from Lemma F.1,

$$\begin{aligned}
& \frac{1}{N} \sum_i \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) \\
& \leq O_P(C_{NT}^{-2}) \max_i |e_{it} - \hat{e}_{it}| + O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2} = O_P(C_{NT}^{-2}).
\end{aligned}$$

For the third term of  $c_t$ , similarly,  $\frac{1}{N} \sum_i \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (\hat{e}_{it} - e_{it}) = O_P(C_{NT}^{-2})$ . Also, by Lemma F.1,

$$\begin{aligned}
& \frac{1}{N} \sum_i \tilde{\alpha}_i \lambda'_i H_1 (e_{it} - \hat{e}_{it}) \\
& \leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2} + O_P(1) \frac{1}{N} \sum_i \lambda_i \alpha'_i (\hat{e}_{it} - e_{it})
\end{aligned}$$

$$\leq O_P(C_{NT}^{-1}).$$

So  $c_{t,3} = O_P(C_{NT}^{-1})$ . As for  $d_t$ , the same proof of Lemma E.5 shows that  $d_t = O_P(C_{NT}^{-2})$ .

Put together, we have:  $\widehat{S}_t - S = c_t + d_t = O_P(C_{NT}^{-1})$ . On the other hand, the upper two blocks of  $\widehat{S}_t - S$  are  $O_P(C_{NT}^{-2})$ , determined by  $c_{t,1}, c_{t,2}$  and the upper blocks of  $d_t$ . In addition, note that both  $B, S$  are block diagonal matrices, and the diagonal blocks of  $S$  are  $O_P(C_{NT}^{-1})$ . Due to

$$\widehat{B}_t^{-1}\widehat{S}_t - B^{-1}S = (\widehat{B}_t^{-1} - B^{-1})(\widehat{S}_t - S) + (\widehat{B}_t^{-1} - B^{-1})S + B^{-1}(\widehat{S}_t - S),$$

hence the upper blocks of  $\widehat{B}_t^{-1}\widehat{S}_t - B^{-1}S$  are both  $O_P(C_{NT}^{-2})$ .

Q.E.D.

**Lemma F.8.** Suppose  $C_{NT}^{-1} \max_{it} |e_{it}|^2 + \max_t \|\frac{1}{N} \sum_i \lambda_i \lambda_i' \bar{e}_i e_{it}\|_F = o_P(1)$ .

(i)  $\max_t \|\widehat{B}_t^{-1}\| = O_P(1)$ .

(ii)  $\frac{1}{T} \sum_{s \neq I} \|\widehat{B}_s^{-1} - B^{-1}\|^2 = O_P(C_{NT}^{-2})$ ,

(iii) Write

$$\widehat{S}_t - S = \begin{pmatrix} \Delta_{t1} \\ \Delta_{t2} \end{pmatrix},$$

whose partition matches with that of  $(f_t', g_t')'$ . Then  $\frac{1}{T} \sum_{t \in I^c} \|\Delta_{t1}\|^2 = O_P(C_{NT}^{-4})$  and  $\frac{1}{T} \sum_{t \in I^c} \|\Delta_{t2}\|^2 = O_P(C_{NT}^{-2})$ .

*Proof.* Define

$$B_t = \frac{1}{N} \sum_i \begin{pmatrix} H_1' \lambda_i \lambda_i' H_1 e_{it}^2 & 0 \\ 0 & H_2' \alpha_i \alpha_i' H_2 \end{pmatrix}.$$

Then  $\widehat{B}_t - B_t = b_{1t} + b_{2t}$ ,

$$\begin{aligned} b_{1t} &= \frac{1}{N} \sum_i \begin{pmatrix} \widetilde{\lambda}_i \widetilde{\lambda}_i' \widehat{e}_{it}^2 - H_1' \lambda_i \lambda_i' H_1 e_{it}^2 & \widetilde{\lambda}_i \widetilde{\alpha}_i' \widehat{e}_{it} - H_1' \lambda_i \alpha_i H_2' e_{it} \\ \widetilde{\alpha}_i \widetilde{\lambda}_i' \widehat{e}_{it} - H_2' \alpha_i \lambda_i H_1' e_{it} & \widetilde{\alpha}_i \widetilde{\alpha}_i' - H_2' \alpha_i \alpha_i' H_2 \end{pmatrix} \\ b_{2t} &= \frac{1}{N} \sum_i \begin{pmatrix} 0 & H_1' \lambda_i \alpha_i H_2' e_{it} \\ H_2' \alpha_i \lambda_i H_1' e_{it} & 0 \end{pmatrix}. \end{aligned}$$

The proof is similar to that of Lemma E.6, with the main difference from dealing with terms involving  $\widehat{e}_{it} - e_{it}$ . Those are bounded by Lemma F.2.

(i) By assumption  $\max_t |b_{2t}| = o_P(1)$ . It suffices to show  $\max_t |b_{1t}| = o_P(1)$ .

First term: it follows from Lemma F.2 that

$$\begin{aligned}
& \max_t \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) \right\| \\
& \leq O_P(1) \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 \right)^{1/2} \max_t \left[ \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 + (\hat{e}_{it} - e_{it})^2 e_{it}^2 \right]^{1/2} \\
& \quad + \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 [2 \max_t |(\hat{e}_{it} - e_{it}) e_{it}| + \max_t (\hat{e}_{it} - e_{it})^2] \\
& \quad + O_P(1) \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it}) e_{it} \right\|_F \\
& \quad + O_P(1) \max_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it})^2 \right\|_F \\
& \leq O_P(1 + \max_t \|w_t\|^2 + b_{NT,2}^2) C_{NT}^{-2} + O_P(b_{NT,1}^2 + b_{NT,3}^2) \\
& \quad + O_P(1 + \max_t \|w_t\| + b_{NT,2}) \max_{it} |e_{it}| C_{NT}^{-1} + O_P(b_{NT,1} + b_{NT,3}) \left( \max_t \frac{1}{N} \sum_i e_{it}^2 \right)^{1/2} C_{NT}^{-1} \\
& \quad + O_P(\phi_{NT}^2 C_{NT}^{-2}) + \phi_{NT} \max_{it} |e_{it}| C_{NT}^{-2} + \max_t \left\| \frac{1}{N} \sum_i c_i e_{it} l_i \right\|_F O_P(b_{NT,1} + b_{NT,3}) \\
& = o_P(1),
\end{aligned}$$

given assumptions  $C_{NT}^{-1}(b_{NT,2} + \max_t \|w_t\|) \max_{it} |e_{it}| = o_P(1)$ ,  $\phi_{NT} \max_{it} |e_{it}| = O_P(1)$ ,  $\max_t \left\| \frac{1}{N} \sum_i e_{it} \alpha_i \lambda'_i \right\|_F = o_P(1)$ , and  $(b_{NT,1} + b_{NT,3})[(\max_t \frac{1}{N} \sum_i e_{it}^2)^{1/2} C_{NT}^{-1} + 1] = o_P(1)$ .

In addition,  $\max_t \left\| \frac{1}{N} \sum_i (\tilde{\lambda}_i \tilde{\lambda}'_i - H'_1 \lambda_i \lambda'_i H_1) e_{it}^2 \right\| \leq O_P(C_{NT}^{-1}) \max_{it} e_{it}^2 = o_P(1)$ . So the first term of  $\max_t |b_{1t}|$  is  $o_P(1)$ .

Second term,

$$\begin{aligned}
& \max_t \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\alpha}'_i (\hat{e}_{it} - e_{it}) \right\|_F \\
& \leq \max_{it} |\hat{e}_{it} - e_{it}| \frac{1}{N} \sum_i \|(\tilde{\lambda}_i - H'_1 \lambda_i)(\tilde{\alpha}_i - H'_2 \alpha_i)'\|_F \\
& \quad + O_P(1) \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H'_1 \lambda_i\|^2 + \left( \frac{1}{N} \sum_i \|\tilde{\alpha}_i - H'_2 \alpha_i\|^2 \right)^{1/2} \max_t \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^{1/2} \right) \\
& \quad + O_P(1) \max_t \left\| \frac{1}{N} \sum_i \lambda_i \alpha'_i (\hat{e}_{it} - e_{it}) \right\|_F \\
& \leq O_P(\phi_{NT} + 1 + \max_t \|w_t\|) C_{NT}^{-2} + O_P(b_{NT,1} + b_{NT,3} + C_{NT}^{-1} b_{NT,2}) = o_P(1).
\end{aligned}$$

The rest of the proof is the same as that of Lemma E.6.

(ii) It suffices to prove  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{1t}\|_F^2 = O_P(C_{NT}^{-2}) = \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{2t}\|_F^2$ .

First term of  $b_{1t}$ : by Lemma F.2,

$$\begin{aligned}
& \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}'_i \hat{e}_{it}^2 - H'_1 \lambda_i \lambda'_i H_1 e_{it}^2 \right\|_F^2 \\
& \leq O_P(C_{NT}^{-4}) \max_{it} |\hat{e}_{it} - e_{it}|^2 \max_{it} |e_{it}|^2 + O_P(C_{NT}^{-2}) \frac{1}{T} \sum_{t \in I^c} \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^4 \\
& \quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 \right)^2 + O_P(C_{NT}^{-2}) \frac{1}{T} \sum_{t \in I^c} \frac{1}{N} \sum_i (\hat{e}_{it} - e_{it})^2 e_{it}^2 \\
& \quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it}) e_{it} \right)^2 + O_P(C_{NT}^{-2}) \\
& \leq O_P(C_{NT}^{-4} \phi_{NT}^2) \max_{it} |e_{it}|^2 + O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2}).
\end{aligned}$$

Second term of  $b_{1t}$ : still by Lemma F.2,

$$\begin{aligned}
& \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\alpha}'_i \hat{e}_{it} - H'_1 \lambda_i \alpha_i H'_2 e_{it} \right\|_F^2 \\
& \leq O_P(C_{NT}^{-4}) \max_i \frac{1}{T} \sum_t (\hat{e}_{it} - e_{it})^2 + O_P(C_{NT}^{-2}) \frac{1}{NT} \sum_{it} (\hat{e}_{it} - e_{it})^2 \\
& \quad + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \alpha'_i (\hat{e}_{it} - e_{it}) \right\|_F^2 + O_P(C_{NT}^{-2}) \\
& \leq O_P(b_{NT,4}^2 + b_{NT,5}^2 + C_{NT}^{-2}) C_{NT}^{-4} + O_P(C_{NT}^{-2}) = O_P(C_{NT}^{-2}).
\end{aligned}$$

The rest of the proof for  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{1t}\|_F^2 = O_P(C_{NT}^{-2}) = \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|b_{2t}\|_F^2$  is the same as that of Lemma E.6.

(iii) Note that  $\hat{S}_t - S = c_t + d_t$ , where

$$\begin{aligned}
c_t &= \frac{1}{N} \sum_i \begin{pmatrix} \tilde{\lambda}_i \lambda'_i H_1 e_{it} (\hat{e}_{it} - e_{it}) + \tilde{\lambda}_i \tilde{\lambda}'_i (\hat{e}_{it}^2 - e_{it}^2) & \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ \tilde{\alpha}_i \lambda'_i H_1 (e_{it} - \hat{e}_{it}) + \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (\hat{e}_{it} - e_{it}) & 0 \end{pmatrix} \\
d_t &= \frac{1}{N} \sum_i \begin{pmatrix} (\tilde{\lambda}_i \lambda'_i H_1 - \tilde{\lambda}_i \tilde{\lambda}'_i) e_{it}^2 - H'_1 \lambda_i (\lambda'_i H_1 - \tilde{\lambda}'_i) E e_{it}^2 & \tilde{\lambda}_i e_{it} (\alpha'_i H_2 - \tilde{\alpha}'_i) \\ \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) e_{it} & 0 \end{pmatrix}.
\end{aligned}$$

As for the upper blocks of  $c_t$ , by Lemma F.2,

$$\begin{aligned}
& \text{(ii) All terms below are } O_P(C_{NT}^{-2}): \frac{1}{NT} \sum_{it} (\hat{e}_{it} - e_{it})^4 \\
& \quad \frac{1}{NT} \sum_{it} (\hat{e}_{it} - e_{it})^2, \frac{1}{NT} \sum_{it} e_{it}^2 (\hat{e}_{it} - e_{it})^2 \text{ and } \frac{1}{T} \sum_t \left\| \frac{1}{N} \sum_i \alpha_i \lambda'_i (e_{it} - \hat{e}_{it}) \right\|_F^2. \\
& \text{(iii) All terms below are } O_P(C_{NT}^{-4}): \frac{1}{T} \sum_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it}) e_{it} \right\|_F^2, \\
& \quad \frac{1}{T} \sum_t \left\| \frac{1}{N} \sum_i \lambda_i \lambda'_i (\hat{e}_{it} - e_{it})^2 \right\|_F^2.
\end{aligned}$$

$$\begin{aligned}
& \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \lambda_i' H_1 e_{it} (\hat{e}_{it} - e_{it}) \right\|_F^2 \\
& \leq O_P(1) \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 \frac{1}{NT} \sum_i \sum_{t \in I^c} e_{it}^2 (\hat{e}_{it} - e_{it})^2 \\
& \quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' e_{it} (\hat{e}_{it} - e_{it}) \right\|_F^2 \\
& = O_P(C_{NT}^{-4}) \\
& \quad \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i \tilde{\lambda}_i' (\hat{e}_{it}^2 - e_{it}^2) \right\|_F^2 \\
& \leq \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 \right)^2 \max_{it} [(\hat{e}_{it} - e_{it})^4] \\
& \quad + \frac{1}{T} \sum_{t \in I^c} \left( \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 |e_{it}| \right)^2 \max_{it} |\hat{e}_{it} - e_{it}|^2 \\
& \quad + \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 \frac{1}{NT} \sum_{t \in I^c} \sum_i [(\hat{e}_{it} - e_{it})^4 + (\hat{e}_{it} - e_{it})^2 e_{it}^2] \\
& \quad + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' (\hat{e}_{it} - e_{it}) e_{it} \right\|_F^2 + \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' (\hat{e}_{it} - e_{it})^2 \right\|_F^2 \\
& = O_P(C_{NT}^{-4}).
\end{aligned}$$

Also,

$$\begin{aligned}
& \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) (\alpha_i' H_2 - \tilde{\alpha}_i') \right\|_F^2 \\
& \leq \frac{1}{N} \sum_i \|\alpha_i' H_2 - \tilde{\alpha}_i'\|^2 \frac{1}{N} \sum_i \|\tilde{\lambda}_i - H_1' \lambda_i\|^2 \max_{it} (\hat{e}_{it} - e_{it})^2 \\
& \quad + O_P(1) \frac{1}{N} \sum_i \|\alpha_i' H_2 - \tilde{\alpha}_i'\|^2 \frac{1}{N} \sum_i \frac{1}{T} \sum_{t \in I^c} (\hat{e}_{it} - e_{it})^2 = O_P(C_{NT}^{-4}).
\end{aligned}$$

Similarly,  $\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\alpha}_i (\lambda_i' H_1 - \tilde{\lambda}_i') (\hat{e}_{it} - e_{it}) \right\|_F^2 = O_P(C_{NT}^{-4})$ . Finally,

$$\begin{aligned}
\frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\alpha}_i \lambda_i' H_1 (e_{it} - \hat{e}_{it}) \right\|_F^2 &= O_P(C_{NT}^{-4}) + O_P(1) \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \alpha_i \lambda_i' (e_{it} - \hat{e}_{it}) \right\|_F^2 \\
&= O_P(C_{NT}^{-2}).
\end{aligned}$$

So if we let the two upper blocks of  $c_t$  be  $c_{t,1}, c_{t,2}$ , and the third block of  $c_t$  be  $c_{t,3}$ , then  $\frac{1}{T} \sum_{t \in I^c} \|c_{t,1}\|_F^2 + \frac{1}{T} \sum_{t \in I^c} \|c_{t,2}\|_F^2 = O_P(C_{NT}^{-4})$  while  $\frac{1}{T} \sum_{t \in I^c} \|c_{t,3}\|_F^2 = O_P(C_{NT}^{-2})$ .



As for the blocks of  $d_t$ , let  $d_{t,1}, \dots, d_{t,3}$  denote the nonzero blocks, then the same proof as in Lemma E.6 shows  $\frac{1}{T} \sum_{t \in I^c} \|d_{t,k}\|_F^2 = O_P(C_{NT}^{-4})$  for  $k = 1, 2, 3$ .

Together, we have

$$\frac{1}{T} \sum_{t \in I^c} \|\Delta_{t1}\|^2 \leq \frac{1}{T} \sum_{t \in I^c} \|c_{t,1} + d_{t,1}\|^2 + \frac{1}{T} \sum_{t \notin I} \|c_{t,2} + d_{t,2}\|^2 = O_P(C_{NT}^{-4})$$

and  $\frac{1}{T} \sum_{t \notin I} \|\Delta_{t2}\|^2 = \frac{1}{T} \sum_{t \notin I} \|c_{t,3} + d_{t,3}\|^2 = O_P(C_{NT}^{-2})$ .

Q.E.D.

**Lemma F.9.** *For terms defined in (D.2), and for each fixed  $t \in I^c$ ,*

- (i)  $\sum_{d=2}^5 A_{dt} = O_P(C_{NT}^{-2})$
- (ii) For the “upper block” of  $A_{6t}$ ,  $\frac{1}{N} \sum_i \lambda_i e_{it} (l'_i w_t \lambda'_i f_t - \widehat{l'_i w_t \lambda'_i f_t}) = O_P(C_{NT}^{-2})$ .
- (iii) The upper block of  $A_{1t}$  is  $O_P(C_{NT}^{-2})$ .

*Proof.* Term  $A_{2t}$  is the same as that of Lemma E.7.

Term  $A_{3t}$ : based on the proof of Lemma E.7, the only difference is to bound the following term, which involves  $\widehat{e}_{it} - e_{it}$ :

$$\begin{aligned} & \frac{1}{N} \sum_i (\widetilde{\lambda}_i \widehat{e}_{it} - H'_1 \lambda_i e_{it}) u_{it} \\ & \leq O_P(C_{NT}^{-1}) \left( \frac{1}{N} \sum_i (\widehat{e}_{it} - e_{it})^2 \right)^{1/2} + O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{N} \sum_i \lambda_i (\widehat{e}_{it} - e_{it}) u_{it} \\ & = O_P(C_{NT}^{-2}) \end{aligned}$$

where the last equality follows from Lemma F.1.

Term  $A_{4t}$ . It suffices to prove each of the terms defined in (E.19), with  $\mu_{it} = l'_i w_t$ , is  $O_P(C_{NT}^{-2})$ . Given Lemma F.1, the proof follows from repeatedly applying the Cauchy-Schwarz inequality and is straightforward.

Term  $A_{5t}$ . Given  $B_t^{-1} - B^{-1} = O_P(C_{NT}^{-1})$ , it suffices to prove the following terms are  $O_P(C_{NT}^{-2})$ .

$$\begin{aligned} B_{1t} &= \frac{1}{N} \sum_i \lambda_i e_{it} (\widehat{e}_{it} - e_{it}) (\dot{\lambda}_i - H'_1 \lambda_i)' \widetilde{f}_t \\ B_{2t} &= \frac{1}{N} \sum_i \lambda_i e_{it} (\widehat{e}_{it} - e_{it}) \lambda'_i H_1 \widetilde{f}_t \\ B_{3t} &= \frac{1}{N} \sum_i \lambda_i e_{it} l'_i w_t (\dot{\lambda}_i - H'_1 \lambda_i)' \widetilde{f}_t \\ B_{4t} &= \frac{1}{N} \sum_i \lambda_i e_{it} l'_i w_t \lambda'_i H_1 (\widetilde{f}_t - H_1^{-1} f_t) \end{aligned}$$

$$B_{5t} = \frac{1}{N} \sum_i \alpha_i (\widehat{e}_{it} - e_{it}) (\dot{\lambda}_i - H_1' \lambda_i)' \widetilde{f}_t \quad (\text{F.6})$$

and that the following terms are  $O_P(C_{NT}^{-1})$ :

$$\begin{aligned} B_{6t} &= \frac{1}{N} \sum_i \alpha_i (\widehat{e}_{it} - e_{it}) \lambda_i' H_1 \widetilde{f}_t \\ B_{7t} &= \frac{1}{N} \sum_i \alpha_i l_i' w_t (\dot{\lambda}_i - H_1' \lambda_i)' \widetilde{f}_t \\ B_{8t} &= \frac{1}{N} \sum_i \alpha_i l_i' w_t \lambda_i' H_1 (\widetilde{f}_t - H_1^{-1} f_t). \end{aligned} \quad (\text{F.7})$$

In fact,  $B_{1t}, B_{5,t} \sim B_{8t}$  follow immediately from the Cauchy-Schwarz inequality.  $B_{2t} = O_P(C_{NT}^{-2})$  due to Lemma F.1. Term  $B_{3,t}$  follows from Lemma F.6. Finally,  $B_{4t} = O_P(C_{NT}^{-1}) \frac{1}{N} \sum_i \lambda_i e_{it} l_i \lambda_i' = O_P(C_{NT}^{-2})$ .

(ii) “upper block” of  $A_{6t}$ . Note that  $l_i' w_t - \widehat{l_i' w_t} = \widehat{e}_{it} - e_{it}$ .

From the proof of (i), we have  $B_{dt} = O_P(C_{NT}^{-2})$ , for  $d = 1, \dots, 4$ . It follows immediately that  $\frac{1}{N} \sum_i \lambda_i e_{it} (l_i' w_t \lambda_i' f_t - \widehat{l_i' w_t \lambda_i' f_t}) = O_P(C_{NT}^{-2})$ .

(iii) Lastly, note that the upper block of  $A_{1t}$  is determined by the upper blocks of  $\widehat{B}_t^{-1} \widehat{S}_t - B^{-1} S$ , and are both  $O_P(C_{NT}^{-2})$  by Lemma F.7.

Q.E.D.

**Lemma F.10.** For terms  $B_{dt}$  defined in (F.6) (F.7), and  $C_{dt}$  defined in (E.19), with  $\mu_{it} = l_i' w_t$ , we have for a fixed  $j \leq N$ ,

$$\begin{aligned} (i) \quad & \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 = O_P(C_{NT}^{-4}) \text{ for } d = 1, 3, 4, 5. \\ & \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 = O_P(C_{NT}^{-2}) \text{ for } d = 2, 6, 7, 8. \\ (ii) \quad & \sum_{d=1}^5 \frac{1}{T} \sum_{t \in I^c} \|B_{dt} e_{jt}^r f_t'\| = O_P(C_{NT}^{-2}) \text{ for } r = 0, 1, 2. \\ & \sum_{d=1}^5 \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\| |u_{jt}| (|e_{jt}| + 1) + \sum_{d=6}^8 \left\| \frac{1}{T_0} \sum_{t \in I^c} B_{dt} e_{jt} f_t \right\| = O_P(C_{NT}^{-2}) \\ (iii) \quad & \sum_{d=6}^8 \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 e_{jt}^2 \|f_t\|^2 + \sum_{d=1}^8 \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 e_{jt}^4 = O_P(C_{NT}^{-2}), \\ & \sum_{d=1}^8 \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 u_{jt}^2 (|e_{jt}| + 1)^2 = O_P(C_{NT}^{-2}), \sum_{d=1}^{16} \frac{1}{T} \sum_{t \in I^c} \|C_{dt}\|^2 e_{jt}^4 = O_P(C_{NT}^{-2}), \\ \text{and } & \sum_{d=1}^{16} \frac{1}{T} \sum_{t \in I^c} \|C_{dt}\|^2 = O_P(C_{NT}^{-4}). \end{aligned}$$

*Proof.* (i) Note that  $\frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 = O_P(C_{NT}^{-4})$  for  $d = 1, 4, 5$ , following from Cauchy Schwarz. Also, Cauchy-Schwarz and Lemma F.6 imply that  $\frac{1}{T} \sum_{t \in I^c} \|B_{3t}\|^2 = O_P(C_{NT}^{-4})$ .

Next,  $\max_{it} |e_{it}(\hat{e}_{it} - e_{it})| = O_P(1)$  by the assumption that  $\phi_{NT} \max_{it} |e_{it}| = O_P(1)$ .

$$\begin{aligned} \frac{1}{T} \sum_{t \in I^c} \|B_{2t}\|^2 &\leq O_P(1) \frac{1}{T} \sum_{t \in I^c} \|\tilde{f}_t - H_1^{-1} f_t\|^2 \max_{it} |e_{it}(\hat{e}_{it} - e_{it})|^2 \\ &\quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \|f_t\|^2 \frac{1}{N} \sum_i \lambda_i e_{it}(\hat{e}_{it} - e_{it}) \lambda_i' \\ &= O_P(C_{NT}^{-2}). \end{aligned}$$

Also,  $\sum_{d=6}^8 \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\|^2 = O_P(C_{NT}^{-2})$  following from Cauchy-Schwarz.

(ii) By (i),  $\frac{1}{T} \sum_{t \in I^c} \|B_{dt} e_{jt}^r f_t'\| + \frac{1}{T} \sum_{t \in I^c} \|B_{dt}\| |u_{jt}| (|e_{jt}| + 1) = O_P(C_{NT}^{-2})$  for  $d = 1, 3, 4, 5$ , using Cauchy Schwarz. In addition, it follows from Lemma F.2 that

$$\begin{aligned} \frac{1}{T} \sum_{t \in I^c} \|B_{2t} e_{jt}^r f_t'\| &\leq O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' e_{jt}^r e_{it} (\hat{e}_{it} - e_{it}) f_t \right\|^2 \right)^{1/2} = O_P(C_{NT}^{-2}) \\ \frac{1}{T} \sum_{t \in I^c} \|B_{2t}\| |u_{jt}| (|e_{jt}| + 1) &\leq O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} (|e_{jt}| + 1)^2 u_{jt}^2 \left\| \frac{1}{N} \sum_i \lambda_i \lambda_i' e_{it} (\hat{e}_{it} - e_{it}) \right\|^2 \right)^{1/2} \\ &= O_P(C_{NT}^{-2}). \end{aligned}$$

For  $d = 6 \sim 8$ ,

$$\begin{aligned} \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{6t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} \frac{1}{N} \sum_i \alpha_i (\hat{e}_{it} - e_{it}) \lambda_i' H_1 \tilde{f}_t = O_P(C_{NT}^{-2}) \\ &\quad (\text{by Lemma F.2}) \\ \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{7t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} (\tilde{f}_t - H_1^{-1} f_t) \frac{1}{N} \sum_i \alpha_i l_i' w_t (\dot{\lambda}_i - H_1' \lambda_i)' \\ &\quad + \left( \frac{1}{T_0} \sum_{t \in I^c} f_t^2 e_{jt} w_t \right) \left( \frac{1}{N} \sum_i \alpha_i l_i (\dot{\lambda}_i - H_1' \lambda_i) \right) = O_P(C_{NT}^{-2}) \\ \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} B_{8t} &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} (\tilde{f}_t - H_1^{-1} f_t) w_t \frac{1}{N} \sum_i \alpha_i l_i \lambda_i' H_1 \\ &= O_P(C_{NT}^{-2}), \quad \text{by lemma F.4.} \end{aligned}$$

(iii) follows from applying the Cauchy-Schwarz inequality.

Q.E.D.

**Lemma F.11.** (i)  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\hat{f}_s - H_f f_s\|^2 (1 + e_{jt}^4) = O_P(C_{NT}^{-2})$  for a fixed  $j \leq N$ .  
(ii) For each fixed  $i$ ,  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) e_{is} f_s' = O_P(C_{NT}^{-2})$ .

*Proof.* We only prove the harder part (ii). The proof is similar to that of Lemma E.9. By the proof of Lemma E.9, it suffices to prove  $\sum_{d=1}^5 \frac{1}{T} \sum_{t \in I^c} a_{dt} e_{it} f_t' = O_P(C_{NT}^{-2})$ , where  $a_{dt}$  is the upper block of  $A_{dt}$ .

By Lemma F.8,  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \|\hat{B}_s^{-1} - B^{-1}\|^2 = O_P(C_{NT}^{-2})$ . So the proof of  $\frac{1}{T} \sum_{t \in I^c} a_{2t} e_{it} f'_t \leq O_P(C_{NT}^{-2})$  follows from the same argument as that of Lemma E.9. Next, for  $B_{dt}$  defined in the proof of Lemma E.7, by Lemma F.10,

$$\begin{aligned} \frac{1}{T} \sum_{t \in I^c} a_{5t} e_{it} f'_t &\leq \sum_{d=1}^8 \frac{1}{T} \sum_{t \in I^c} \|\hat{B}_t^{-1} - B^{-1}\| \|B_{dt} e_{it} f'_t\| \\ &\leq \max_t \|\hat{B}_t^{-1} - B^{-1}\| \sum_{d=1}^5 \frac{1}{T} \sum_{t \in I^c} \|B_{dt} e_{it} f'_t\| \\ &\quad + \left( \frac{1}{T} \sum_t \|\hat{B}_t^{-1} - B^{-1}\|^2 \right)^{1/2} \sum_{d=6}^8 \left( \frac{1}{T} \sum_t \|B_{dt} e_{it} f'_t\|^2 \right)^{1/2} \\ &= O_P(C_{NT}^{-2}). \end{aligned}$$

Next,  $\frac{1}{T} \sum_t \left\| \frac{1}{N} \sum_j \lambda_j (\hat{e}_{jt} - e_{jt}) u_{jt} \right\|^2 = O_P(C_{NT}^{-4})$  by Lemma F.2,

$$\begin{aligned} \frac{1}{T} \sum_{t \in I^c} a_{3t} e_{it} f'_t &\leq O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} \mathbb{E}_I \left\| \frac{1}{N} \sum_j (\tilde{\lambda}_j - H'_1 \lambda_j) e_{jt} u_{jt} \right\|^2 \right)^{1/2} \\ &\quad + O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} \mathbb{E}_I \left\| \frac{1}{N} \sum_j (\tilde{\alpha}_j - H'_2 \alpha_j) u_{jt} \right\|^2 \right)^{1/2} \\ &\quad + O_P(1) \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \left\| \frac{1}{N} \sum_j (\tilde{\lambda}_j - H'_1 \lambda_j) (\hat{e}_{jt} - e_{jt}) u_{jt} \right\| \\ &\quad + O_P(1) \left( \frac{1}{T} \sum_t \left\| \frac{1}{N} \sum_j \lambda_j (\hat{e}_{jt} - e_{jt}) u_{jt} \right\|^2 \right)^{1/2} \\ &= O_P(C_{NT}^{-2}) \\ \frac{1}{T} \sum_{t \in I^c} a_{4t} e_{it} f'_t &\leq \max_t \|\hat{B}_t^{-1}\| \frac{1}{T} \sum_{t \in I^c} \|e_{it} f'_t\| \sum_{d=1}^{16} \|C_{dt}\|, \end{aligned}$$

where  $C_{dt}$ 's are defined in the proof of Lemma E.7. By Lemma F.10,  $\frac{1}{T} \sum_{t \in I^c} \|C_{dt}\|^2 = O_P(C_{NT}^{-4})$  for  $d \leq 16$ . Thus  $\frac{1}{T} \sum_{t \in I^c} a_{4t} e_{it} f'_t = O_P(C_{NT}^{-2})$ , still following from Cauchy-Schwarz.

Below we present the proof for  $\frac{1}{T} \sum_{t \in I^c} a_{1t} e_{it} f'_t$ , which is different from that of Lemma E.9. Note that

$$A_{1t} = (\hat{B}_t^{-1} \hat{S}_t - B^{-1} S) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix} := (A_{1t,a} + A_{1t,b} + A_{1t,c}) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix},$$

where

$$A_{1t,a} = (\hat{B}_t^{-1} - B^{-1})(\hat{S}_t - S)$$

$$\begin{aligned} A_{1t,b} &= (\hat{B}_t^{-1} - B^{-1})S \\ A_{1t,c} &= B^{-1}(\hat{S}_t - S). \end{aligned}$$

Let  $(a_{1t,a}, a_{1t,b}, a_{1t,c})$  respectively be the upper blocks of  $(A_{1t,a}, A_{1t,b}, A_{1t,c})$ . Then

$$\frac{1}{T} \sum_{t \in I^c} a_{1t} e_{it} f'_t \leq \frac{1}{T} \sum_{t \in I^c} (\|a_{1t,a}\| + \|a_{1t,b}\| + \|a_{1t,c}\|) \|e_{it} f_t\| (\|f_t\| + \|g_t\|).$$

By the Cauchy-Schwarz and Lemma F.8, and  $B$  is a block diagonal matrix,

$$\begin{aligned} \frac{1}{T} \sum_{t \in I^c} \|a_{1t,b}\| \|e_{it} f_t\| (\|f_t\| + \|g_t\|) &\leq O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} \|A_{1t,b}\|^2 \right)^{1/2} \\ &\leq O_P(\|S\|) \left( \frac{1}{T} \sum_{t \in I^c} \|\hat{B}_t - B\|^2 \right)^{1/2} = O_P(C_{NT}^{-2}) \\ \frac{1}{T} \sum_{t \in I^c} \|a_{1t,c}\| \|e_{it} f_t\| (\|f_t\| + \|g_t\|) &\leq O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} \|a_{1t,c}\|^2 \right)^{1/2} \\ &\leq O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} \|\Delta_{t1}\|^2 \right)^{1/2} = O_P(C_{NT}^{-2}), \end{aligned}$$

where  $\Delta_{t1}$  is defined in Lemma F.8, the upper block of  $\hat{S}_t - S$ . The treatment of  $\frac{1}{T} \sum_{t \in I^c} \|a_{1t,a}\| \|e_{it} f_t\| (\|f_t\| + \|g_t\|)$  is slightly different. Note that  $\max_t \|\hat{B}_t^{-1}\| + \|B^{-1}\| = O_P(1)$ , shown in Lemma F.8. Partition

$$\hat{S}_t - S = \begin{pmatrix} \Delta_{t1} \\ (\Delta_{t2,1} + \Delta_{t2,2}, 0) \end{pmatrix}$$

where the notation  $\Delta_{t1}$  is defined in the proof of Lemma F.8. The proof of Lemma F.8 also gives

$$\begin{aligned} \Delta_{t2,1} &= \frac{1}{N} \sum_i \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) e_{it} + \frac{1}{N} \sum_i \tilde{\alpha}_i (\lambda'_i H_1 - \tilde{\lambda}'_i) (\hat{e}_{it} - e_{it}) \\ &\quad + \frac{1}{N} \sum_i (\tilde{\alpha}_i - H'_2 \alpha_i) \lambda'_i H_1 (e_{it} - \hat{e}_{it}) \\ \Delta_{t2,2} &= H'_2 \frac{1}{N} \sum_i \alpha_i \lambda'_i (e_{it} - \hat{e}_{it}) H_1. \end{aligned}$$

Therefore,

$$\begin{aligned} \|a_{1t,a}\| &\leq \|(\hat{B}_t^{-1} - B^{-1})(\hat{S}_t - S)\| \\ &\leq (\max_t \|\hat{B}_t^{-1}\| + \|B^{-1}\|) (\|\Delta_{t1}\| + \|\Delta_{t2,1}\|) + \|\hat{B}_t^{-1} - B^{-1}\| \|\Delta_{t2,2}\|. \end{aligned}$$

Note that the above bound treats  $\Delta_{t1}$  and  $\Delta_{t2}$  differently because by the proof of Lemma F.8,  $\frac{1}{T} \sum_{t \in I^c} \|\Delta_{t1}\|^2 = O_P(C_{NT}^{-4}) = \frac{1}{T} \sum_{t \in I^c} \|\Delta_{t2,1}\|^2$  but the rate of convergence for  $\frac{1}{T} \sum_{t \in I^c} \|\Delta_{t2,2}\|^2$  is slower ( $= O_P(C_{NT}^{-2})$ ). Hence

$$\begin{aligned} & \frac{1}{T} \sum_{t \in I^c} \|a_{1t,a}\| \|e_{it} f_t\| (\|f_t\| + \|g_t\|) \leq O_P(1) \left( \frac{1}{T} \sum_{t \in I^c} \|\Delta_{t1}\|^2 + \|\Delta_{t2,1}\|^2 \right)^{1/2} \\ & + \left( \frac{1}{T} \sum_{t \in I^c} \|\hat{B}_t^{-1} - B^{-1}\|^2 \right)^{1/2} \left( \frac{1}{T} \sum_{t \in I^c} \|\Delta_{t2,2}\|^2 \|e_{it} f_t\|^2 (\|f_t\| + \|g_t\|)^2 \right)^{1/2} \\ & \leq^{(a)} O_P(C_{NT}^{-2}) + O_P(C_{NT}^{-1}) \left( \frac{1}{T} \sum_{t \in I^c} \|\Delta_{t2,2}\|^2 \|e_{it} f_t\|^2 (\|f_t\| + \|g_t\|)^2 \right)^{1/2} \\ & \leq^{(b)} O_P(C_{NT}^{-2}). \end{aligned}$$

where (a) follows from the proof of Lemma F.8, while (b) follows from Lemma F.1.

Thus

$$\frac{1}{T} \sum_{t \in I^c} a_{1t} e_{it} f_t' \leq O_P(C_{NT}^{-2}).$$

Therefore,  $\frac{1}{T} \sum_{s \in I^c \cup \{t\}} (\hat{f}_s - H_f f_s) e_{is} f_s' = O_P(C_{NT}^{-2})$ .

Q.E.D.

**Lemma F.12.**  $\frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt}^2 B_{dt} = O_P(C_{NT}^{-2})$ , for  $d = 1 \dots 4$ ,  
 $\frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt} B_{dt} = O_P(C_{NT}^{-2})$  for  $d = 5 \dots 8$ .

*Proof.* By Lemmas F.10 and F.11, for  $r = 1, 2$  and  $d \leq 8$ ,

$$\begin{aligned} \frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt}^r B_{dt} & \leq \max_{jt} |\hat{e}_{jt}^r - e_{jt}^r| \left( \frac{1}{T_0} \sum_{t \in I^c} \|\hat{f}_t - H_f f_t\|^2 \right)^{1/2} \left( \frac{1}{T_0} \sum_{t \in I^c} \|B_{dt}\|^2 \right)^{1/2} \\ & + \left( \frac{1}{T_0} \sum_{t \in I^c} \|\hat{f}_t - H_f f_t\|^2 e_{jt}^{2r} \right)^{1/2} \left( \frac{1}{T_0} \sum_{t \in I^c} \|B_{dt}\|^2 \right)^{1/2} \\ & + \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{dt} + \frac{1}{T_0} \sum_{t \in I^c} \|f_t B_{dt}\| |\hat{e}_{jt}^r - e_{jt}^r| \\ & \leq O_P(C_{NT}^{-2}) + \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt}^r B_{dt} + \frac{1}{T_0} \sum_{t \in I^c} \|f_t B_{dt}\| |\hat{e}_{jt}^r - e_{jt}^r|. \end{aligned}$$

Hence by Lemmas F.10, the above is further bounded by

$$\begin{aligned} \sum_{d=1}^4 \left\| \frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt}^r B_{dt} \right\| & \leq O_P(C_{NT}^{-2}) + \max_t |\hat{e}_{jt}^r - e_{jt}^r| \sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} \|f_t B_{dt}\| = O_P(C_{NT}^{-2}) \\ \sum_{d=5}^8 \frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt} B_{dt} & \leq O_P(C_{NT}^{-2}) + \sum_{d=5}^8 \left( \frac{1}{T_0} \sum_{t \in I^c} \|B_{dt}\|^2 \right)^{1/2} \left( \frac{1}{T_0} \sum_{t \in I^c} \|f_t\|^2 |\hat{e}_{jt} - e_{jt}|^2 \right)^{1/2} \end{aligned}$$

$$\leq O_P(C_{NT}^{-2}).$$

Q.E.D.

#### F.4. Technical lemmas for $\widehat{\lambda}_i$ .

**Lemma F.13.** *For each fixed  $i$ ,  $\widehat{D}_i - D_i = O_P(C_{NT}^{-1})$ .*

*Proof.* The proof is very similar to that of Lemma E.9. The only difference arises from bounding  $\widehat{e}_{is} - e_{is}$  in the factor model. Examining the proof of Lemma E.9, in the current context, the proof still carries over by applying Cauchy Schwarz.

Q.E.D.

**Lemma F.14.** *For each fixed  $i \leq N$ ,*

$$\frac{1}{T} \sum_{s \in I^c \cup \{t\}} \widehat{f}_s \widehat{e}_{is} (l'_i w_t \lambda'_i f_s - \widehat{l'_i w_t \lambda'_i f_s}) = O_P(C_{NT}^{-2}), \quad \frac{1}{T} \sum_{s \in I^c \cup \{t\}} \widehat{g}_s (l'_i w_t \lambda'_i f_s - \widehat{l'_i w_t \lambda'_i f_s}) = O_P(C_{NT}^{-1}).$$

*Proof.* It suffices to show (E.21) as in the proof of Lemma E.10, with  $\mu_{is} = l'_i w_s$  and  $\widehat{\mu}_{is} = \widehat{l'_i w_s}$ . Using the Cauchy-Schwarz inequality, it is easy to show that  $R_{3i,1}, R_{3i,2}$  and  $R_{3i,4}$  are  $O_P(C_{NT}^{-2})$  and  $R_{3i,7} = O_P(C_{NT}^{-1})$ . Next, by Lemma F.1,  $R_{3i,3} = O_P(C_{NT}^{-2})$ . In addition, by Lemmas F.4 and F.11,  $R_{3i,5} = O_P(C_{NT}^{-2})$  and  $R_{3i,6} = O_P(C_{NT}^{-2})$ .

This concludes that  $R_{3i,d} = O_P(C_{NT}^{-2})$  for all  $d \leq 7$  defined in Lemma E.10, and completes the proof. Q.E.D.

**Lemma F.15.** *For  $R_{di}$  defined in (D.5), and for each fixed  $j \leq N$ ,  $R_{dj} = O_P(C_{NT}^{-2})$  for  $d = 1, \dots, 3$ . The upper blocks of  $R_{4j} \sim R_{6j}$  are  $O_P(C_{NT}^{-2})$ .*

*Proof.* (i) It is easy to see that  $R_{1j} = O_P(C_{NT}^{-2})$ . Lemma F.1 implies  $R_{2j} = O_P(C_{NT}^{-2})$ . Also, it follows from Lemmas F.13, F.14 that both  $R_{3j}$  and the upper block of  $R_{4j}$  are  $O_P(C_{NT}^{-2})$ .

(ii) We now show the upper blocks of  $R_{5j}$  are  $O_P(C_{NT}^{-2})$ . Similar to the proof of Lemma E.12,

$$R_{5j} = \widehat{D}_j^{-1} \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \widehat{f}_t - H_f f_t \\ \widehat{g}_t - H_g g_t \end{pmatrix} u_{jt} \leq \sum_{d=1}^5 \Upsilon_d + O_P(C_{NT}^{-2}),$$

where, for  $A_{dt}$  defined in (D.2), with  $\mu_{it} = l'_i w_t$  and  $\widehat{\mu}_{it} = \widehat{l'_i w_t}$ ,

$$\Upsilon_d = \widehat{D}_j^{-1} \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \widehat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} A_{dt} u_{jt}.$$

We now show  $\Upsilon_d = O_P(C_{NT}^{-2})$  for  $d = 1 \dots 5$ .

The proof for terms  $\Upsilon_1$  and  $\Upsilon_2$  is the same as in Lemma E.12. Next,

$$\Upsilon_3 \leq O_P(C_{NT}^{-2}) + \left( \frac{1}{T_0} \sum_{t \in I^c} \left\| \frac{1}{N} \sum_i \tilde{\lambda}_i (\hat{e}_{it} - e_{it}) u_{it} \right\|^2 \right)^{1/2}$$

where the last equality follows from Lemma F.2 and the Cauchy Schwarz.

$$\Upsilon_4 \leq O_P(C_{NT}^{-2}) + O_P(1) \left( \sum_{d=1}^{16} \frac{1}{T_0} \sum_{t \in I^c} \|C_{dt}\|^2 \right)^{1/2} = O_P(C_{NT}^{-2})$$

where the last equality is due to Lemma F.10.

$$\begin{aligned} \Upsilon_5 &\leq O_P(C_{NT}^{-2}) + O_P(1) \sum_{d=1}^8 \frac{1}{T_0} \sum_{t \in I^c} \|\hat{B}_t - B_t\| \|B_{dt}\| |u_{jt}| (|e_{jt}| + 1) \\ &\leq O_P(C_{NT}^{-2}) + O_P(1) \sum_{d=1}^5 \frac{1}{T_0} \sum_{t \in I^c} \|B_{dt}\| |u_{jt}| (|e_{jt}| + 1) \\ &\quad + O_P(C_{NT}^{-1}) \sum_{d=6}^8 \left( \frac{1}{T_0} \sum_{t \in I^c} \|B_{dt}\|^2 u_{jt}^2 (|e_{jt}| + 1)^2 \right)^{1/2} = O_P(C_{NT}^{-2}), \end{aligned}$$

where the last equality follows from Lemma F.10.

Finally, the upper block of  $\Upsilon_6$  is bounded by, still by Lemma F.10,

$$O_P(1) \sum_{d=1}^4 \left\| \frac{1}{T_0} \sum_{t \in I^c} \hat{e}_{jt} u_{jt} B_{dt} \right\| + O_P(C_{NT}^{-2}).$$

Therefore, the upper block of  $R_{5j}$  is  $O_P(C_{NT}^{-2})$ .

(iii) We now show the upper block of  $R_{6j}$  is  $O_P(C_{NT}^{-2})$ . Let

$$\begin{aligned} \Gamma &:= \Gamma_0 + \Gamma_1 + \dots + \Gamma_6, \\ \Gamma_0 &:= \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{f}_t \hat{e}_{jt} \\ \hat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \hat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} B^{-1} \frac{1}{N} \sum_i \begin{pmatrix} H'_1 \lambda_i e_{it} \\ H'_2 \alpha_i \end{pmatrix} u_{it} \\ \Gamma_d &:= \sum_{d=1}^6 \frac{1}{T_0} \sum_{t \in I^c} \begin{pmatrix} \hat{f}_t \hat{e}_{jt} \\ \hat{g}_t \end{pmatrix} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \hat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} A_{dt}, \quad d = 1, \dots, 6. \end{aligned}$$

Then  $R_{6j} = \hat{D}_j^{-1} \Gamma$ . Similar to the proof of Lemma E.12, we aim to show that  $\Gamma_0, \Gamma_2 \dots \Gamma_5$  are each  $O_P(C_{NT}^{-2})$ . In addition, the upper blocks of  $\Gamma_1$  and  $\Gamma_6$  are  $O_P(C_{NT}^{-2})$ , while their lower blocks are  $O_P(C_{NT}^{-1})$ .

First,  $\Gamma_0 + \Gamma_2 = O_P(C_{NT}^{-2})$  follows from the same proof as in Lemma E.12.



Next, the upper block of  $\Gamma_1$  is

$$\begin{aligned}
& \frac{1}{T_0} \sum_{t \in I^c} \widehat{f}_t \widehat{e}_{jt} (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} (\widehat{B}_t^{-1} \widehat{S}_t - B^{-1} S) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix} \\
& \leq a1 + a2 + O_P(C_{NT}^{-2}) \\
a1 &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} (\lambda'_j H_f^{-1} e_{jt}, \alpha'_j H_g^{-1}) (\widehat{B}_t^{-1} - B^{-1}) (\widehat{S}_t - S) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix} \\
a2 &= \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} (\lambda'_j H_f^{-1} e_{jt}, \alpha'_j H_g^{-1}) B^{-1} (\widehat{S}_t - S) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix}.
\end{aligned}$$

By the proof of lemma F.11, we have

$$\widehat{S}_t - S = \begin{pmatrix} \Delta_{t1} \\ (\Delta_{t2,1} + \Delta_{t2,2}, 0) \end{pmatrix}, \quad \Delta_{t2,2} = H_2' \frac{1}{N} \sum_i \alpha_i \lambda'_i (e_{it} - \widehat{e}_{it}) H_1.$$

As for  $a1$ , by the proof of Lemma F.8,  $\frac{1}{T} \sum_{t \in I^c} \|\Delta_{t1}\|^2 = O_P(C_{NT}^{-4}) = \frac{1}{T} \sum_{t \in I^c} \|\Delta_{t2,1}\|^2$ ,

$$\begin{aligned}
a1 &\leq O_P(1) (\max_t \|\widehat{B}_t^{-1}\| + \|B^{-1}\|) \left( \frac{1}{T} \sum_t \|\Delta_{t1}\|^2 + \|\Delta_{t2,1}\|^2 \right)^{1/2} \\
&\quad + O_P(1) \left( \frac{1}{T} \sum_t \|\widehat{B}_t^{-1} - B^{-1}\|^2 \right)^{1/2} \left( \frac{1}{T} \sum_t \|\Delta_{t2,2}\|^2 \|f_t\|^2 (\|f_t\| + \|g_t\|)^2 |e_{jt}|^4 \right)^{1/2} \\
&= O_P(C_{NT}^{-2})
\end{aligned}$$

where the last equality uses Lemma F.8 that  $\max_t \|\widehat{B}_t^{-1}\| = O_P(1)$ , Lemma F.1 that  $\frac{1}{T} \sum_t \|\Delta_{t2,2}\|^2 \|f_t\|^2 (\|f_t\| + \|g_t\|)^2 |e_{jt}|^4 = O_P(C_{NT}^{-2})$  and  $\frac{1}{T} \sum_{s \notin I} \|\widehat{B}_s^{-1} - B^{-1}\|^2 = O_P(C_{NT}^{-2})$ .

As for  $a2$ , still by  $\frac{1}{T} \sum_{t \in I^c} \|\Delta_{t1}\|^2 = O_P(C_{NT}^{-4}) = \frac{1}{T} \sum_{t \in I^c} \|\Delta_{t2,1}\|^2$ , and by Lemma F.2,

$$\begin{aligned}
a2 &\leq O_P(1) \left( \frac{1}{T} \sum_t \|\Delta_{t1}\|^2 + \|\Delta_{t2,1}\|^2 \right)^{1/2} + O_P(1) \frac{1}{T_0} \sum_{t \in I^c} f_t e_{jt} \Delta_{t2,2} f_t \\
&\leq O_P(C_{NT}^{-2}) + O_P(1) \frac{1}{TN} \sum_{it} f_t e_{jt} f_t \alpha_i \lambda'_i (e_{it} - \widehat{e}_{it}) = O_P(C_{NT}^{-2}).
\end{aligned}$$

Together, the upper block of  $\Gamma_1$  is  $O_P(C_{NT}^{-2})$ .

The lower block of  $\Gamma_1$  is

$$\frac{1}{T_0} \sum_{t \in I^c} \widehat{g}_t (\lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) \begin{pmatrix} \widehat{e}_{jt} & 0 \\ 0 & 1 \end{pmatrix} (\widehat{B}_t^{-1} \widehat{S}_t - B^{-1} S) \begin{pmatrix} H_1^{-1} f_t \\ H_2^{-1} g_t \end{pmatrix}$$

$$\leq O_P(C_{NT}^{-1}) \left( \frac{1}{T_0} \sum_{t \in I^c} \|\hat{g}_t\|^2 (\hat{e}_{jt}^2 + 1) (\|f_t\| + \|g_t\|)^2 \right)^{1/2} = O_P(C_{NT}^{-1}).$$

Next,  $\Gamma_3 = O_P(C_{NT}^{-2})$  follows from the same proof as in Lemma E.12. The only difference is to bound  $\frac{1}{T} \sum_t \left| \frac{1}{N} \sum_i \lambda_i (\hat{e}_{it} - e_{it}) u_{it} \right|^2 = O_P(C_{NT}^{-4})$  by Lemma F.2.

Next,  $\Gamma_4 + \Gamma_5 = O_P(C_{NT}^{-2})$  follows from the same proof as in Lemma E.12, whose proof in the current context uses Lemma F.10 that  $\sum_{d=1}^{16} \frac{1}{T_0} \sum_{t \in I^c} |e_{jt}|^4 \|C_{dt}\|^2 = O_P(C_{NT}^{-2})$ ,  $\sum_{d=1}^{16} \frac{1}{T_0} \sum_{t \in I^c} \|C_{dt}\|^2 = O_P(C_{NT}^{-4})$ , and  $\sum_{d=1}^8 \left[ \frac{1}{T_0} \sum_{t \in I^c} (|e_{jt}|^2 + 1)^2 \|B_{dt}\|^2 \right] = O_P(C_{NT}^{-2})$ .

Finally, the upper block of  $\Gamma_6$  is

$$\frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt} (\hat{e}_{jt} \lambda'_j H_f^{-1}, \alpha'_j H_g^{-1}) B^{-1} \begin{pmatrix} H'_1 & 0 \\ 0 & H_2 \end{pmatrix} \begin{pmatrix} \sum_{d=1}^4 B_{dt} \\ \sum_{d=5}^8 B_{dt} \end{pmatrix}.$$

Now Lemma F.12 implies  $\frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt}^2 B_{dt} = O_P(C_{NT}^{-2})$  for  $d = 1 \sim 4$ , and  $\frac{1}{T_0} \sum_{t \in I^c} \hat{f}_t \hat{e}_{jt} B_{dt} = O_P(C_{NT}^{-2})$  for  $d = 5 \sim 8$ . So the above is  $O_P(C_{NT}^{-2})$ .

The lower block of  $\Gamma_6$  is, by repeatedly using Cauchy-Schwarz,

$$\sum_{d=1}^4 \frac{1}{T_0} \sum_{t \in I^c} \hat{g}_t \hat{e}_{jt} B_{dt} + \sum_{d=5}^8 \frac{1}{T_0} \sum_{t \in I^c} \hat{g}_t B_{dt} = O_P(C_{NT}^{-1}).$$

Q.E.D.

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