

SUPPLEMENT TO “INFERENCE FOR LOW-RANK MODELS”

VICTOR CHERNOZHUKOV, CHRISTIAN HANSEN, YUAN LIAO, AND YINCHU ZHU

ABSTRACT. This supplement contains all proofs.

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APPENDIX A. FROBENIUS-NORM MATRIX CONVERGENCE AND RANK CONSISTENCY

A.1. The convergence of $\|\tilde{\Theta}_S - \Theta_S\|_F$.

Lemma A.1. *Suppose the n rows of $\mathcal{E} \circ X$ are independent and that each is a $1 \times p$ sub-Gaussian vector. In addition, suppose $\|\frac{1}{n}\mathbf{E}(\mathcal{E} \circ X)(\mathcal{E} \circ X)'\|$ is bounded. Then*

$$\|\mathcal{E} \circ X\| = O_P(\sqrt{n} + \sqrt{p}).$$

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Proof. The eigenvalue-concentration inequality for independent sub-Gaussian random vectors (Theorem 5.39 of [6]) implies

$$\|(\mathcal{E} \circ X)(\mathcal{E} \circ X)' - \mathbb{E}(\mathcal{E} \circ X)(\mathcal{E} \circ X)'\| = O_P(\sqrt{np} + p),$$

which in turn shows

$$\|\mathcal{E} \circ X\|^2 \leq \|\mathbb{E}(\mathcal{E} \circ X)(\mathcal{E} \circ X)'\| + O_P(\sqrt{np} + p) = O_P(n + p).$$

□

To formally state the rate of convergence of the nuclear-norm penalized estimator, let

$$\omega_{np} := \nu\sqrt{J} + \|R\|_{(n)} \asymp (\sqrt{n} + \sqrt{p})\sqrt{J} + \|R\|_{(n)}.$$

Proposition A.1. *For $S \in \{\mathcal{I}, \mathcal{I}^c, \{1, \dots, n\}\}$, there is a $J \times J$ rotation matrix H_S satisfying $H_S' H_S = \mathbf{I}$, so that*

$$\|\tilde{\Theta}_S - \Theta_S\|_F^2 = O_P(\omega_{np}^2), \quad \|\tilde{V}_S - V_0 H_S\|_F = O_P(J^d \omega_{np} \psi_{np}^{-1}).$$

Proof. The convergence of $\|\tilde{\Theta}_S - \Theta_S\|_F^2$ follows from the standard arguments in the low-rank literature, e.g., [4]. Moreover, given the convergence (in Frobinus norm) of $\tilde{\Theta}$, the convergence of $\tilde{V} - V_0$ follows straightforward by applying the Weyl's theorem for bounding the eigenvalues and the sin-theta theorem for bounding the eigenvectors. The extra “ J^d ” term in the rate arises from the eigengap ψ_{np}/J^d . We omit details for brevity.

The only thing we would like to emphasize here is that the convergence requires the so-called “restrictive strong convexity”, which we shall give a formal prove in the following subsection. □

A.2. Proof of Restricted strong convexity. Recall the SVD of Θ_0 :

$$\Theta_0 = UDV', \quad U = (U_0, U_c), \quad V = (V_0, V_c).$$

Here (U_c, V_c) are the columns of U, V that correspond to the zero singular values, while (U_0, V_0) denote the columns of U, V associated with the non-zero singular values. In addition, for any $n \times p$ matrix A , let

$$\mathcal{P}(A) = U_c U_c' A V_c V_c' \quad \text{and} \quad \mathcal{M}(A) = A - \mathcal{P}(A).$$

Here $\mathcal{M}(\cdot)$ can be thought of as the projection matrix onto the columns of U_0 and V_0 , which is also the “low-rank” space of Θ_0 . $\mathcal{P}(\cdot)$ is then the projection onto the space orthogonal to this low-rank space.

Lemma A.2. *Suppose (i) $\max_{ij} |x_{ij}| < C$ and $\min_{ij} \mathbf{E}x_{ij}^2 > c_0$. (ii) Either $x_{ij} = c_j$ almost surely for some constants $c_j \neq 0$, or x_{ij} is independent across both (i, j) . In addition, define the restricted low-rank set as, for some $c > 0$,*

$$\mathcal{C}(c_1, c_2) = \{A \in \mathcal{A} : \|\mathcal{P}(A)\|_{(n)} \leq c_1 \|\mathcal{M}(A)\|_{(n)}, \|A\|_F^2 > c_2 \sqrt{np}\}.$$

For any $c_1, c_2 > 0$ there are constants $\kappa, B > 0$ so that with probability approaching one, uniformly for $A \in \mathcal{C}(c_1, c_2)$,

$$\|X \circ A\|_F^2 \geq \kappa \|A\|_F^2 - J(n+p)B$$

The same inequality holds when Θ_0 is replaced with its subsample versions: $\Theta_{0,\mathcal{I}}$ and Θ_{0,\mathcal{I}^c} .

Proof. For notational simplicity, write $X(A) = \|X \circ A\|_F^2$. Then for $\mathbf{E}x_{ij}^2 > c_0$,

$$\mathbf{E}X(A) = \sum_{ij} A_{ij}^2 \mathbf{E}x_{ij}^2 \geq c_0 \|A\|_F^2.$$

Define an event, for sufficiently large $B > 0$,

$$\mathcal{E}(A) := \{|X(A) - \mathbf{E}X(A)| > 0.5\mathbf{E}X(A) + J(n+p)B\}.$$

We aim to claim $P(\exists A \in \mathcal{C}(c_1, c_2), \mathcal{E}(A)) \rightarrow 0$. Once this is proved, then $P(\forall A \in \mathcal{C}(c_1, c_2), \mathcal{E}(A)^c) \rightarrow 1$. On $\mathcal{E}(A)^c$, the restricted strong convexity holds for $\kappa = c_0/2$, because:

$$X(A) \geq 0.5\mathbf{E}X(A) - J(n+p)B \geq \kappa \|A\|_F^2 - J(n+p)B.$$

To prove $P(\exists A \in \mathcal{C}(c_1, c_2), \mathcal{E}(A)) \rightarrow 0$, we use the standard peeling argument. Let

$$\Gamma_l = \{A \in \mathcal{C}(c_1, c_2) : 2^l v_n \leq \mathbf{E}X(A) \leq 2^{l+1} v_n\},$$

where $v_n = B\sqrt{np}$ and $l \in \mathbb{N}$. We let $c_2 = 2c_0^{-1}B$ in the definition of $\mathcal{C}(c_1, c_2)$.

Step 1: show $\mathcal{C}(c_1, c_2) \subset \cup_{l=1}^{\infty} \Gamma_l$. For $A \in \mathcal{C}(c_1, c_2)$ we have

$$\|A\|_F^2 \geq c_2 \sqrt{np} = 2c_0^{-1}B\sqrt{np} = 2c_0^{-1}v_n.$$

Then $\mathbf{E}X(A) \geq c_0 \|A\|_F^2 \geq 2v_n$. Hence there is $l \in \mathbb{N}$ so that $A \in \Gamma_l$ as long as $A \in \mathcal{C}(c_1, c_2)$. This shows $\mathcal{C}(c_1, c_2) \subset \cup_{l=1}^{\infty} \Gamma_l$.

Now let

$$\begin{aligned} \mathcal{D}(x) &:= \{A \in \mathcal{C}(c_1, c_2) : \|A\|_F^2 \leq x\} \\ \mathcal{F} &:= \{A : |X(A) - \mathbf{E}X(A)| - J(n+p)B > 0.25 \times 2^{l+1}v_n\}. \end{aligned}$$

and $x_l = c_0^{-1}2^{l+1}v_n$.

Step 2: show $\{A : \mathcal{E}(A) \text{ is true}\} \cap \Gamma_l \subset \mathcal{D}(x_l) \cap \mathcal{F}$. If $A \in \Gamma_l$ and $\mathcal{E}(A)$ holds, then $A \in \mathcal{F}$ because:

$$|X(A) - \mathbf{E}X(A)| - J(n+p)B > 0.5\mathbf{E}X(A) \geq 0.5 \times 2^l v_n = 0.25 \times 2^{l+1}v_n.$$

Also $\|A\|_F^2 \leq c_0^{-1}\mathbf{E}X(A) \leq c_0^{-1}2^{l+1}v_n$. This implies $A \in \mathcal{D}(x_l)$.

Now let

$$Z(x) := \sup_{A \in \mathcal{D}(x)} \left| \frac{1}{np} \sum_{ij} x_{ij}^2 A_{ij}^2 - \mathbf{E}x_{ij}^2 A_{ij}^2 \right|.$$

Step 3: bound $\mathbf{E}Z(x)$. For any $A \in \mathcal{D}(x) \subset \mathcal{C}(c_1, c_2)$, $C = 1 + c_1$,

$$\begin{aligned} \|A\|_{(n)} &= \|\mathcal{P}(A) + \mathcal{M}(A)\|_{(n)} \leq (1 + c_1) \|\mathcal{M}(A)\|_{(n)} \\ &\leq (1 + c_1) \sqrt{\text{rank}(\Theta_0)} \|\mathcal{M}(A)\|_F \leq C\sqrt{J} \|A\|_F \leq C\sqrt{Jx}. \end{aligned}$$

Let ϵ_{ij} be an i.i.d. Rademacher sequence. Let $G = (\epsilon_{ij}x_{ij})_{n \times p}$. Then $\mathbf{E}\|G\| \leq C_1\sqrt{n+p}$ for some constant C_1 . Then

$$\begin{aligned} \mathbf{E}Z(x) &\stackrel{(i)}{\leq} 2\mathbf{E} \sup_{A \in \mathcal{D}(x)} \left| \frac{1}{np} \sum_{ij} x_{ij}^2 A_{ij}^2 \epsilon_{ij} \right| \stackrel{(ii)}{\leq} C_2 \mathbf{E} \sup_{A \in \mathcal{D}(x)} \left| \frac{1}{np} \sum_{ij} x_{ij} A_{ij} \epsilon_{ij} \right| \\ &= C_2 \mathbf{E} \sup_{A \in \mathcal{D}(x)} \left| \frac{1}{np} \text{tr}(GA') \right| \leq C_2 \mathbf{E} \sup_{A \in \mathcal{D}(x)} \frac{1}{np} \|G\| \|A\|_{(n)} \\ &\leq C_3 \frac{\sqrt{n+p}}{np} \sup_{A \in \mathcal{D}(x)} \|A\|_{(n)} \leq C_4 \frac{\sqrt{n+p}}{np} \sqrt{Jx} = 2C_5 \frac{\sqrt{J(n+p)}}{\sqrt{npc_0}} \sqrt{\frac{c_0}{32np}} x \\ &\leq \frac{c_0 x}{32np} + \frac{C_5^2 J(n+p)}{c_0 np} \leq \frac{c_0 x}{32np} + B \frac{J(n+p)}{np} \end{aligned}$$

where (i) follows from the standard symmetrization argument; (ii) uses the contraction inequality (e.g., (2.3) of [3]), which requires $|x_{ij}| + |A|_{ij} \leq M$ for all (i, j) . This holds since $A \in \mathcal{A}$ and by the assumption. The last inequality holds for sufficiently large $B > 0$.

Step 4: bound the tail probability of $Z(x) - \mathbf{E}Z(x)$. The conditions that $|A_{ij}| < M$ (because $A \in \mathcal{A}$) and the independence of x_{ij} over (i, j) allow us to

apply the Massart inequality (e.g., Theorem 14.2 of [2]), so

$$P(Z(x) > \mathbf{E}Z(x) + t) \leq \exp(-C_6 n p t^2), \quad \forall t > 0,$$

Let $t = \frac{7c_0x}{32np}$. Then from Step 3,

$$\begin{aligned} P(Z(x) > \frac{J(n+p)}{np}B + \frac{1}{np}0.25c_0x) &\leq P(Z(x) > \mathbf{E}Z(x) - \frac{c_0x}{32np} + \frac{1}{np}0.25c_0x) \\ &= P(Z(x) > \mathbf{E}Z(x) + t) \leq \exp(-C_6 n p t^2) = \exp(-\frac{C_7 x^2}{np}). \end{aligned}$$

Step 5: Peeling device. Hence for c' that only depends on c_0 , but not on B ,

$$\begin{aligned} P(\exists A \in \mathcal{C}(c_1, c_2), \mathcal{E}(A)) &\leq \sum_{l=1}^{\infty} P(A \in \Gamma_l, \mathcal{E}(A)) = \sum_{l=1}^{\infty} P(A \in \mathcal{D}(x_l) \cap \mathcal{F}) \\ &\leq \sum_{l=1}^{\infty} P(\sup_{A \in \mathcal{D}(x_l)} |X(A) - \mathbf{E}X(A)| > J(n+p)B + 0.25c_0x_l) \\ &= \sum_{l=1}^{\infty} P(Z(x_l) > \frac{J(n+p)}{np}B + \frac{1}{np}0.25c_0x_l) \leq \sum_{l=1}^{\infty} \exp(-\frac{C_7 x_l^2}{np}) \\ &= \sum_{l=1}^{\infty} \exp(-\frac{C_8 4^{l+1} v_n^2}{np}) = \sum_{l=1}^{\infty} \exp(-C_8 4^{l+1} B^2) \leq \frac{\exp(-16C_8 B^2)}{1 - \exp(-16C_8 B^2)} < \epsilon \end{aligned}$$

for any $\epsilon > 0$ and sufficiently large B .

□

APPENDIX B. PROOF OF THEOREMS

We use the notation \mathbf{E}_I and \mathbf{Var}_I to denote the conditional expectation and variance given the subsamples in $S \in \{\mathcal{I}, \mathcal{I}^c\}$. We use \mathbf{I} to denote the identity matrix.

B.1. Convergence of $\widehat{\Gamma}_S$. Recall that columns of H_S are the eigenvectors of $\Gamma'_S \Gamma_S$. Note that $\theta_{ij} = \gamma'_i v_j + r_{ij}$. Throughout the proof, we use v_i and γ_j to denote the true values $\gamma_{i,0}$ and $v_{i,0}$ for notational simplicity.

Lemma B.1. *There are $J \times J$ rotation matrices H and B , so that for each $i \notin S$,*

$$\widehat{\gamma}_i - H' \gamma_i = B^{-1} H'_S \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + o_P(1).$$

The above $o_P(\cdot)$ is pointwise in i and in $\|\cdot\|$. Also $\|H' - H_S^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1})$, and $\|B\| + \|B^{-1}\| + \|H\| + \|H^{-1}\| = O_P(1)$. Note that both B and H' depend on S .

Proof. First recall that \tilde{V}_S is estimated using subsamples in S . Note that $\|\tilde{V}_S - V_0 H_S\| = O_P(J \omega_{np} \psi_{np}^{-1})$ for some rotation matrix H_S . For simplicity of notation, we simply write \tilde{v}'_j to denote the j th row of \tilde{V}_S . For each $i \notin S$, by definition in Step 3 of the estimation algorithm, and γ'_i as the i th row of Γ_0 ,

$$\hat{\gamma}_i - H_S^{-1} \gamma_i = \hat{B}_i^{-1} \sum_{j=1}^p [y_{ij} - x_{ij} \cdot \gamma'_i H_S^{-1} \tilde{v}_j] x_{ij} \tilde{v}_j,$$

and $\hat{B}_i = \sum_{j=1}^p x_{ij}^2 \tilde{v}_j \tilde{v}'_j$. Let $B = H'_S \sum_{j=1}^p (\mathbf{E} x_{ij}^2) v_j v'_j H_S$.

$$\begin{aligned} \hat{\gamma}_i - H_S^{-1} \gamma_i &= \hat{B}_i^{-1} \sum_{j=1}^p [\varepsilon_{ij} + x_{ij}(\theta_{ij} - \gamma'_i H_S^{-1} \tilde{v}_j)] x_{ij} \tilde{v}_j \\ &= B^{-1} H'_S \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + B^{-1} \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i + \sum_{k=1}^4 \Delta_{i,k}, \\ \Delta_{i,1} &= (\hat{B}_i^{-1} - B^{-1}) \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i, \quad \Delta_{i,2} = \hat{B}_i^{-1} \sum_{j=1}^p \varepsilon_{ij} x_{ij} (\tilde{v}_j - H'_S v_j), \\ \Delta_{i,3} &= \hat{B}_i^{-1} \sum_{j=1}^p x_{ij}^2 r_{ij} \tilde{v}_j, \quad \Delta_{i,4} = (\hat{B}_i^{-1} - B^{-1}) H'_S \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j. \end{aligned} \tag{B.1}$$

Lemma C.2 shows that $\sum_{k=1}^4 \Delta_{i,k} = o_P(1)$. So

$$\hat{\gamma}_i - H_S^{-1} \gamma_i = B^{-1} H'_S \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + B^{-1} \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i + o_P(1). \tag{B.2}$$

To bound the second term on the right hand side, we proceed below in different cases on the DGP of x_{ij} , corresponding to conditions (ii-a)-(ii-b) in Assumption 4.3.

Under condition (ii-a) x_{ij}^2 does not vary across $i \leq n$. We can write $x_{ij}^2 = x_j^2$, $B = H'_S \sum_{j=1}^p x_j^2 v_j v'_j H_S$ and

$$H' := H_S^{-1} + B^{-1} \sum_{j=1}^p \tilde{v}_j x_j^2 (v_j - \tilde{v}_j)', \quad \|H' - H_S^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1}).$$

From (B.1), moving $B^{-1} \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - \tilde{v}_j)' \gamma_i$ to the left hand side we have:

$$\hat{\gamma}_i - H' \gamma_i = B^{-1} H_S^{-1} \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + \sum_{k=1}^4 \Delta_{i,k} + o_P(1) = B^{-1} H_S^{-1} \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + o_P(1).$$

The fact that $\|B^{-1}\| = O_P(1)$ follows from the assumption that $\sum_{j=1}^p x_j^2 v_j v_j'$ is bounded away from zero.

Under condition (ii-b) x_{ij} is independent across $i \leq n$ and is weakly dependent across $j \leq p$. Let $B = H_S' \sum_{j=1}^p (\mathbf{E} x_{ij}^2) v_j v_j' H_S$. Define

$$\begin{aligned} \Delta_{i,5} &= B^{-1} \sum_{j=1}^p \tilde{v}_j (x_{ij}^2 - \mathbf{E} x_{ij}^2) (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i \\ H' &:= H_S^{-1} + B^{-1} \sum_{j=1}^p \tilde{v}_j (\mathbf{E} x_{ij}^2) (v_j - \tilde{v}_j)', \quad \|H' - H_S^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1}). \end{aligned}$$

where it is the assumption that $\mathbf{E} x_{ij}^2$ is stationary in i (does not vary across i). From (B.2), moving $B^{-1} \sum_{j=1}^p \tilde{v}_j (\mathbf{E} x_{ij}^2) (v_j - \tilde{v}_j)' \gamma_i$ to the left hand side we have:

$$\hat{\gamma}_i - H' \gamma_i = B^{-1} H_S^{-1} \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + \sum_{k=1}^5 \Delta_{i,k}.$$

Lemma C.2 bounds $\Delta_{i,1} \sim \Delta_{i,5}$.

Under condition (ii-c) In this case we focus on $x_{ij} \in \{0, 1\}$. Let $\mathcal{B}_i = \{j : x_{ij} = 1\}$. Then $B = H_S' \sum_{j \in \mathcal{B}} v_j v_j' H_S$. The fact $\|B^{-1}\| = O_P(1)$ follows from the assumption. In addition, let

$$\Delta_{i,6} := B^{-1} \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i - B^{-1} \sum_{j \in \mathcal{B}} \tilde{v}_j (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i.$$

We define

$$H' := H_S^{-1} + B^{-1} \sum_{j \in \mathcal{B}} \tilde{v}_j (v_j - \tilde{v}_j)', \quad \|H' - H_S^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1}).$$

From (B.1), moving $B^{-1} \sum_{j \in \mathcal{B}} \tilde{v}_j (v_j - \tilde{v}_j)' \gamma_i$ to the left hand side we have:

$$\hat{\gamma}_i - H' \gamma_i = B^{-1} H_S^{-1} \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + \sum_{k=1}^4 \Delta_{i,k} + \Delta_{i,6} = B^{-1} H_S^{-1} \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j + o_P(1).$$

Lemma C.2 shows that in this case $\Delta_{i,1} \sim \Delta_{i,4}$, $\Delta_{i,6} = o_P(1)$.

□

B.2. Convergence of $\widehat{V}_{\mathcal{I}}$. Let $L_{j,\mathcal{I}} = H' \sum_{i \notin \mathcal{I}} x_{ij}^2 \gamma_i \gamma_i' H$.

As the vector g can be either sparse (e.g., $g = (1, 0 \dots 0)'$) or dense (e.g., $g = (1, \dots, 1)'/p$), sometimes we shall use the following inequality to bound terms of the form: $\sum_{j=1}^p X_j L_{j,\mathcal{I}} g_j$:

Let $\mathcal{G} = \{j = 1, \dots, p : g_j \neq 0\}$ and $|\mathcal{G}|$ be its cardinality.

$$\sum_{j=1}^p X_j L_{j,\mathcal{I}} g_j \leq \sqrt{\sum_{j \in \mathcal{G}} L_{j,\mathcal{I}}^2} \sqrt{\sum_{j=1}^p X_j^2 g_j^2},$$

which is sharper than the usual bound $L := \sqrt{\sum_{j=1}^p L_{j,\mathcal{I}}^2} \sqrt{\sum_{j=1}^p X_j^2 g_j^2}$ when g is sparse, and reaches about the same order of L when g is dense.

Lemma B.2. *Given a $p \times 1$ fixed vector g , for the rotation matrix H in Lemma B.1 (which depends on the sample \mathcal{I}),*

$$\widehat{V}_{\mathcal{I}}' g - H^{-1} V_0' g = \sum_{j=1}^p \sum_{i \notin \mathcal{I}} L_{j,\mathcal{I}}^{-1} H' \gamma_i \varepsilon_{ij} x_{ij} g_j + O_P(\xi_{np})$$

where ξ_{np} is defined in (B.5). The above convergence is in $\|\cdot\|$.

Proof. Write $\widehat{V}_{\mathcal{I}} = (\widehat{v}_1, \dots, \widehat{v}_p)'$. Then for $\widehat{L}_{j,\mathcal{I}} = \sum_{i \notin \mathcal{I}} x_{ij}^2 \widehat{\gamma}_i \widehat{\gamma}_i'$,

$$\widehat{v}_j - H^{-1} v_j = \widehat{L}_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} [y_{ij} - x_{ij} \cdot \widehat{\gamma}_i' H^{-1} v_j] x_{ij} \widehat{\gamma}_i.$$

Therefore,

$$\widehat{V}_{\mathcal{I}}' g - H^{-1} V_0' g = \sum_{j=1}^p (\widehat{v}_j - H^{-1} v_j) g_j = \sum_{j=1}^p \sum_{i \notin \mathcal{I}} L_{j,\mathcal{I}}^{-1} H' \gamma_i \varepsilon_{ij} x_{ij} g_j + \sum_{d=1}^4 \Delta_d, \quad (\text{B.3})$$

where

$$\begin{aligned} \Delta_1 &= \sum_{j=1}^p \widehat{L}_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} x_{ij}^2 r_{ij} \widehat{\gamma}_i g_j, & \Delta_2 &= \sum_{j=1}^p [\widehat{L}_{j,\mathcal{I}}^{-1} - L_{j,\mathcal{I}}^{-1}] H' \sum_{i \notin \mathcal{I}} \gamma_i \varepsilon_{ij} x_{ij} g_j, \\ \Delta_3 &= \sum_{j=1}^p \widehat{L}_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} (\widehat{\gamma}_i - H' \gamma_i) \varepsilon_{ij} x_{ij} g_j, & \Delta_4 &= \sum_{j=1}^p \widehat{L}_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} x_{ij}^2 (\gamma_i' H - \widehat{\gamma}_i') H^{-1} v_j \widehat{\gamma}_i g_j. \end{aligned} \quad (\text{B.4})$$

By Lemmas C.4-C.6,

$$\begin{aligned}
\sum_{d=1}^4 \|\Delta_d\|^2 &= O_P(\xi_{np}^2) \\
\xi_{np}^2 &:= \left(J^{2+2d+4b} \omega_{np}^2 \mathbf{E} \max_{j \leq p} \|v_j\|^2 + np J^{2+2b} \max_{ij} r_{ij}^2 + \psi_{np}^{-2} J^{2+4d+4b} \omega_{np}^4 \right) \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 \psi_{np}^{-2} \\
&\quad + (\omega_{np}^4 \psi_{np}^{-2} J^{3+4d+8b} + J^{2+2b}) \sum_{j=1}^p \|v_j g_j\|^2 |\mathcal{G}| \psi_{np}^{-2} \\
&\quad + O_P \left(\omega_{np}^4 \psi_{np}^{-4} n J^{2+4d+6b} + \omega_{np}^2 \psi_{np}^{-2} J^{2+2d+6b} + J^{2b+1} \max_{ij} |r_{ij}|^2 n \right) \psi_{np}^{-2} \|g\|^2 |\mathcal{G}| \\
&\quad + O_P \left(1 + n J^{2d+1} \omega_{np}^2 \psi_{np}^{-2} + n J \sum_{j=1}^p \mathbf{E} \|v_j\|^4 \right) \omega_{np}^2 \psi_{np}^{-4} \|g\|^2 J^{1+2d+2b}. \tag{B.5}
\end{aligned}$$

where

$$\mu_{np}^2 := np^{-2} \omega_{np}^2 \psi_{np}^{-4} \|g\|^2 J^{4+2d+2b} \left[\sum_{\mathcal{B}_i \Delta \bar{\mathcal{B}}} 1 \right]^2.$$

□

B.3. Asymptotic normality of $\widehat{\theta}'_i g$. The asymptotic normality follows from Proposition B.1 below, whose condition (B.6) is verified by Lemma C.7 in the case of either sparse or dense g , and the primitive condition in Assumption 4.6.

Proposition B.1. *Let ξ_{np} be as defined in (B.5). Suppose*

$$|r'_i g| + J^b \|u_i\| \psi_{np} \xi_{np} = o_P(p^{-1/2} + \|u_i\| \|g\|). \tag{B.6}$$

Then for a fixed $i \leq n$,

$$\frac{\widehat{\theta}'_i g - \theta'_i g}{\sqrt{s_{np,1}^2 + s_{np,2}^2}} \rightarrow^d N(0, 1),$$

where, with $L_j = \sum_{i=1}^n x_{ij}^2 \gamma_i \gamma'_i$ and $\bar{B} = \sum_{j=1}^p (\mathbf{E} x_{ij}^2) v_j v'_j$,

$$\begin{aligned}
s_{np,1}^2 &:= \sum_{j=1}^p \sum_{t=1}^n \mathbf{Var}(\varepsilon_{tj} | \Theta, X) [\gamma'_i L_j^{-1} \gamma_t]^2 x_{ij}^2 g_j^2 \\
s_{np,2}^2 &:= \sum_{j=1}^p \mathbf{Var}(\varepsilon_{ij} | \Theta, X) x_{ij}^2 [v'_j \bar{B}^{-1} V'_0 g]^2.
\end{aligned}$$

Proof. Note that for fixed $i \leq n$, $\widehat{\theta}'_{\mathcal{I},i} = \widehat{\gamma}'_i \widehat{V}'_{\mathcal{I}}$ and $\theta'_i = \gamma'_i V'_0 + r'_i$, where r'_i denotes the i th row of R , the low-rank approximation error. By Lemmas B.1, B.2, for

$$\begin{aligned}
\bar{L}_{j,\mathcal{I}} &= \sum_{i \notin \mathcal{I}} x_{ij}^2 \gamma_i \gamma'_i, \\
(\widehat{\theta}_{\mathcal{I},i} - \theta_i)' g &= (\widehat{\gamma}'_i \widehat{V}'_{\mathcal{I}} - \gamma'_i V'_0) g - r'_i g \\
&= \gamma'_i \sum_{j=1}^p \sum_{t \notin \mathcal{I}} \bar{L}_{j,\mathcal{I}}^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j + \sum_{j=1}^p \varepsilon_{ij} x_{ij} v'_j \bar{B}^{-1} V'_0 g + \mathcal{R} \\
&= 2\gamma'_i \sum_{j=1}^p \sum_{t \notin \mathcal{I}} L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j + \sum_{j=1}^p \varepsilon_{ij} x_{ij} v'_j \bar{B}^{-1} V'_0 g + \mathcal{R} \\
\mathcal{R} &:= o_P(p^{-1/2} + \|u_i\| \|g\|) + O_P(J^{1+b} \|g\| \psi_{np}^{-1}) + \xi_{np} O_P(J^b \|u_i\| \psi_{np} + J^{1/2}) - r'_i g
\end{aligned}$$

where we used $\|H' - H_S^{-1}\| = (J^d \omega_{np} \psi_{np}^{-1})$ and $L_j = \sum_{i=1}^n x_{ij}^2 \gamma_i \gamma'_i$

$$\begin{aligned}
\left\| \sum_{j=1}^p \sum_{t \notin \mathcal{I}} L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j \right\| &= O_P(J^{1/2+b} \|g\| \psi_{np}^{-1}), \quad \left\| \sum_{j=1}^p \varepsilon_{ij} x_{ij} v'_j B^{-1} \right\| = O_P(\sqrt{J}). \\
\left| \gamma'_i \sum_{j=1}^p \sum_{t \notin \mathcal{I}} (2L_j^{-1} - \bar{L}_{j,\mathcal{I}}^{-1}) \gamma_t \varepsilon_{tj} x_{tj} g_j \right| &= \sqrt{O_P(J) \|u_i\|^2 \sum_{j=1}^p \left\| \frac{1}{2} L_j - \bar{L}_{j,\mathcal{I}} \right\|^2 g_j^2 \psi_{np}^{-4}} \\
&= o_P(\|u_i\| \|g\|).
\end{aligned}$$

Similarly, once we switch \mathcal{I} and \mathcal{I}^c , $(\widehat{\theta}_{\mathcal{I}^c,i} - \theta_i)g$ has a similar expansion. Hence

$$\begin{aligned}
\widehat{\theta}'_i g - \theta'_i g &= \gamma'_i \sum_{j=1}^p \sum_{t \notin \mathcal{I}} L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j + \gamma'_i \sum_{j=1}^p \sum_{t \notin \mathcal{I}^c} L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j \\
&\quad + \sum_{j=1}^p \varepsilon_{ij} x_{ij} v'_j \bar{B}^{-1} V'_0 g + \mathcal{R} \\
&= \gamma'_i \sum_{j=1}^p \sum_{t=1}^n L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j + \sum_{j=1}^p \varepsilon_{ij} x_{ij} v'_j \bar{B}^{-1} V'_0 g + \mathcal{R} + O_P(\|u_i\|^2 \|g\|)
\end{aligned}$$

where $\sum_{t \notin \mathcal{I}} + \sum_{t \notin \mathcal{I}^c} = \sum_{t=1}^n + 1\{t = i\}$, and $\gamma'_i \sum_{j=1}^p 1\{t = i\} L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j = O_P(\|u_i\|^2 \|g\|)$. Also note that $\|V'_0 g\| \asymp p^{-1/2}$ and $J^{1+b} \|g\| \psi_{np}^{-1} = o(p^{-1/2})$.

Next, we verify the Lindeberg condition for the first two leading terms of $\widehat{\theta}'_i g - \theta'_i g$. First, we emphasize that the defined $\mathcal{X}_{t,1}$ and $\mathcal{X}_{j,2}$ (as defined below) do not depend on the sample \mathcal{I} or \mathcal{I}^c . Let

$$\begin{aligned}
\mathcal{X}_{t,1} &:= \gamma'_i \sum_{j=1}^p L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j, \quad \mathcal{X}_{j,2} = \varepsilon_{ij} x_{ij} v'_j \bar{B}^{-1} V'_0 g \\
s_{np,1}^2 &:= \text{Var}\left(\sum_{t=1}^n \mathcal{X}_{t,1} \mid \Theta, X\right) = \sum_{j=1}^p \sum_{t=1}^n \text{Var}(\varepsilon_{tj} \mid \Theta, X) [\gamma'_i L_j^{-1} \gamma_t]^2 x_{tj}^2 g_j^2
\end{aligned}$$

$$\begin{aligned}
&\geq c \min_{j \leq p} \psi_{\min} \left(\sum_{t=1}^n x_{tj}^2 \gamma_t \gamma_t' \right) \psi_{\min}(L_j^{-2}) \|g\|^2 \|\gamma_i\|^2 \\
&\geq c \min_{j \leq p} \psi_{\min} \left(\sum_{t=1}^n x_{tj}^2 u_t u_t' \right) \psi_{\max}^{-2} \left(\sum_{t=1}^n x_{tj}^2 u_t u_t' \right) \|g\|^2 \|u_i\|^2 \geq c \|u_i\|^2 \|g\|^2. \\
s_{np,2}^2 &:= \text{Var} \left(\sum_{j=1}^p \mathcal{X}_{j,2} | \Theta, X \right) = \sum_{j=1}^p \text{Var}(\varepsilon_{ij} | \Theta, X) x_{ij}^2 [v_j' \bar{B}^{-1} V_0' g]^2 \\
&\geq c \|g' V_0\|^2 \min_i \psi_{\min} \left(\sum_{j=1}^p x_{ij}^2 v_j v_j' \right) \psi_{\max}^{-2}(\bar{B}) \geq cp^{-1}.
\end{aligned}$$

Write $\mathbb{E}_i(\cdot) := \mathbb{E}(\cdot | \Theta, X)$. We first bound $\sum_{t=1}^n \mathbb{E}_i \mathcal{X}_{t,1}^4$ and $\sum_{j=1}^p \mathbb{E}_i \mathcal{X}_{j,2}^4$. Write $\mathcal{Y}_{t,j} := \gamma_i' L_j^{-1} \gamma_t \varepsilon_{tj} x_{tj} g_j$, then $\mathcal{X}_{t,1} = \sum_{j=1}^p \mathcal{Y}_{t,j}$. Due to conditional independence,

$$\begin{aligned}
\sum_{t=1}^n \mathbb{E}_i(\mathcal{X}_{t,1}^4) &= \sum_{t=1}^n \mathbb{E}_i \left(\sum_{j=1}^p \mathcal{Y}_{t,j} \right)^4 \leq \sum_{t=1}^n \sum_{j=1}^p \mathbb{E}_i \mathcal{Y}_{t,j}^4 + 3 \sum_{t=1}^n \left[\sum_{j=1}^p \mathbb{E}_i \mathcal{Y}_{t,j}^2 \right]^2 \\
&\leq C \|u_i\|^4 \sum_{t=1}^n \|u_t\|^4 \left[\sum_{j=1}^p g_j^4 + \|g\|^4 \right] \\
\sum_{j=1}^p \mathbb{E}_i(\mathcal{X}_{j,2}^4) &\leq C \sum_{j=1}^p \|v_j\|^4 \|V_0' g\|^4 \leq C \sum_{j=1}^p \|v_j\|^4 p^{-2}.
\end{aligned}$$

Now for any $\epsilon > 0$, by Cauchy-Schwarz and Markov inequalities and

$$\sum_{j=1}^p \|v_j\|^4 = o_P(1), \quad \sum_{i=1}^n \|u_i\|^4 = o_P(1)$$

we have

$$\begin{aligned}
\frac{1}{s_{np,1}^2} \sum_{t=1}^n \mathbb{E}_i \mathcal{X}_{t,1}^2 \mathbf{1}\{|\mathcal{X}_{t,1}| > \epsilon s_{np,1}\} &\leq \frac{1}{s_{np,1}^2} \epsilon \sqrt{\sum_{t=1}^n \mathbb{E}_i \mathcal{X}_{t,1}^4} \\
&\leq \frac{C}{\epsilon} \sqrt{\sum_{t=1}^n \|u_t\|^4} \sqrt{\frac{\sum_{j=1}^p g_j^4}{\|g\|^4} + 1} = o_P(1). \\
\frac{1}{s_{np,2}^2} \sum_{j=1}^p \mathbb{E}_i \mathcal{X}_{j,1}^2 \mathbf{1}\{|\mathcal{X}_{j,1}| > \epsilon s_{np,2}\} &\leq Cp \sqrt{\sum_{j=1}^p \|v_j\|^4 p^{-2}} = o_P(1).
\end{aligned}$$

In addition,

$$\frac{1}{\|u_i\| \|g\| p^{-1/2}} \text{Cov} \left(\sum_{t=1}^n \mathcal{X}_{t,1}, \sum_{j=1}^p \mathcal{X}_{j,2} | \Theta, X \right) \leq C \|V_0\|_F \|u_i\| = o_P(1).$$

Also, $\mathcal{R} = o_P(p^{-1/2} + \|u_i\| \|g\|)$, given condition (B.6). Thus we have achieved

$$\widehat{\theta}'_i g - \theta'_i g = \sum_{t=1}^n \mathcal{X}_{t,1} + \sum_{j=1}^p \mathcal{X}_{j,2} + o_P(p^{-1/2} + \|u_i\| \|g\|) \quad (\text{B.7})$$

where $\sum_{t=1}^n \mathcal{X}_{t,1}/s_{np,1}$ and $\sum_{j=1}^p \mathcal{X}_{j,2}/s_{np,2}$ are asymptotically normal and independent. Hence we can apply the argument of the proof of Theorem 3 in [1] to conclude that, conditionally on (Θ, X) ,

$$\frac{\sum_{t=1}^n \mathcal{X}_{t,1} + \sum_{j=1}^p \mathcal{X}_{j,2}}{\sqrt{s_{np,1}^2 + s_{np,2}^2}} \rightarrow^d N(0, 1).$$

Also, $o_P(p^{-1/2} + \|u_i\| \|g\|)/\sqrt{s_{np,1}^2 + s_{np,2}^2} = o_P(1)$. This implies conditionally on (Θ, X) ,

$$\mathcal{Z} := \frac{\widehat{\theta}'_i g - \theta'_i g}{\sqrt{s_{np,1}^2 + s_{np,2}^2}} \rightarrow^d N(0, 1).$$

It remains to argue that the conditional weak convergence holds unconditionally. Let Φ denote the standard normal cumulative distribution function. Fix any $x \in \mathbb{R}$, let $f(\Theta, X) := P(\mathcal{Z} < x | \Theta, X)$. Then $f(\Theta, X) \rightarrow \Phi(x)$, pointwise in (Θ, X) . By the dominated convergence theorem and that f is dominated by 1,

$$P(\mathcal{Z} < x) = \mathbf{E}f(\Theta, X) \rightarrow \Phi(x).$$

This holds for any x , thus proves the weak convergence of \mathcal{Z} unconditionally. \square

B.4. Proof of Theorem 4.2: efficiency bound.

Lemma B.3. *Let Z be a random variable with sub-Gaussian norm bounded by r . If $r \leq 1/3$, then $|\mathbf{E} \exp(Z) - 1| \leq cr$, where $c > 0$ is an absolute constant.*

Proof. By assumption, $[\mathbf{E}|Z|^j]^{1/j}/\sqrt{j} \leq r$ for any $j \geq 1$. Thus, $\mathbf{E}|Z|^j \leq r^j j^{j/2}$ for any $j \geq 1$. By Taylor's expansion, $\exp(Z) - 1 = \sum_{j=1}^{\infty} \frac{Z^j}{j!}$. Hence,

$$\begin{aligned} \mathbf{E} |\exp(Z) - 1| &= \sum_{j=1}^{\infty} \frac{\mathbf{E}|Z|^j}{j!} \leq \sum_{j=1}^{\infty} \frac{r^j j^{j/2}}{j!} \stackrel{(i)}{\leq} \sum_{j=1}^{\infty} \frac{r^j j^{j/2}}{(j/e)^j} \\ &= \sum_{j=1}^{\infty} (er)^j j^{-j/2} \leq \sum_{j=1}^{\infty} (er)^j \stackrel{(ii)}{=} \frac{er}{1-er} \stackrel{(iii)}{\leq} \frac{er}{1-e/3}, \end{aligned}$$

where (i) follows by $j! \geq (j/e)^j$ and (ii) and (iii) follow by $r \leq 1/3 < 1/e$. Thus, the result holds with $c = e/(1 - e/3)$. \square

Proof of Theorem 4.2. Let $\Theta = \Gamma V'$ be an arbitrary point in \mathcal{M} , where $\Gamma \in \mathbb{R}^{n \times J}$ and $V \in \mathbb{R}^{p \times J}$. We partition $\Gamma = \begin{pmatrix} \Gamma'_1 \\ \Gamma'_{-1} \end{pmatrix} \in \mathbb{R}^{n \times J}$ with $\Gamma_1 \in \mathbb{R}^J$ and $\Gamma_{-1} \in \mathbb{R}^{J \times (n-1)}$. By assumption, σ is bounded. Since X_{1j} is bounded, we have that μ_f is also bounded. It follows that $\kappa_1 \leq \sqrt{\mu_f}/(2\sigma) \leq \kappa_2$ for some constants $\kappa_1, \kappa_2 > 0$.

Consider $\tilde{\Theta} = \tilde{\Gamma} V'$, where $\tilde{\Gamma} = \begin{pmatrix} \tilde{\Gamma}'_1 \\ \Gamma'_{-1} \end{pmatrix} \in \mathbb{R}^{n \times J}$ with $\tilde{\Gamma}_1 = \Gamma_1 + qV'g$ and $q = t/\|V'g\|$. Here, $t \in (0, \kappa_1)$ is a fixed but arbitrary constant. Recall $s_*^2(\Theta, f, \sigma) = \sigma^2 \mu_f^{-1} \|V'g\|^2$ does not depend on Γ . So $s_*^2(\tilde{\Theta}, f, \sigma) = s_*^2(\Theta, f, \sigma)$. Let $\Delta = \tilde{\Theta} - \Theta = (\tilde{\Gamma} - \Gamma)V'$. Notice that

$$\Delta = \begin{pmatrix} q(V'g)'V' \\ 0 \end{pmatrix}$$

and

$$\|\Delta\|_F^2 = q^2 \|(V'g)'V'\|_F^2 = q^2 \|V'g\|^2 = t^2.$$

Let $\phi_{(\Theta, f, \sigma)}(Y, X)$ and $\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)$ be the density of the data (Y, X) under (Θ, f, σ) and $(\tilde{\Theta}, f, \sigma)$, respectively; we notice that

$$\phi_{(\Theta, f, \sigma)}(Y, X) = (2\pi)^{-np/2} \sigma^{-np} \exp\left(-\frac{1}{2\sigma^2} \|Y - X \circ \Theta\|_F^2\right) \cdot \prod_{i=1}^n \prod_{j=1}^p f(X_{ij}).$$

Then by the asymptotic unbiasedness, we have

$$\begin{aligned} \mathbf{E}_{(\tilde{\Theta}, f, \sigma)} T(Y, X) - \mathbf{E}_{(\Theta, f, \sigma)} T(Y, X) &= h(\tilde{\Theta}) - h(\Theta) + o(s_*(\Theta, f, \sigma)) + o(s_*(\tilde{\Theta}, f, \sigma)) \\ &\stackrel{(i)}{=} q \|V'g\|^2 + o(s_*(\Theta, f, \sigma)) \\ &= t \|V'g\| + o(s_*(\Theta, f, \sigma)), \end{aligned}$$

where (i) follows by $s_*^2(\tilde{\Theta}, f, \sigma) = s_*^2(\Theta, f, \sigma)$. On the other hand,

$$\begin{aligned} & \mathbf{E}_{(\tilde{\Theta}, f, \sigma)} T(Y, X) - \mathbf{E}_{(\Theta, f, \sigma)} T(Y, X) \\ &= \mathbf{E}_{(\Theta, f, \sigma)} [T(Y, X) - h(\Theta)] \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} - 1 \right) \\ &\leq \sqrt{\mathbf{Var}_{(\Theta, f, \sigma)} [T(Y, X)]} \times \sqrt{\mathbf{E}_{(\Theta, f, \sigma)} \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} - 1 \right)^2} \\ &= \sqrt{\mathbf{Var}_{(\Theta, f, \sigma)} [T(Y, X)]} \times \sqrt{\mathbf{E}_{(\Theta, f, \sigma)} \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} \right)^2 - 1}. \end{aligned}$$

It follows that

$$\mathbf{Var}_{(\Theta, f, \sigma)} [T(Y, X)] \geq \frac{[t\|V'g\|^2 + o(s_*(\Theta, f, \sigma))]^2}{\mathbf{E}_{(\Theta, f, \sigma)} \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} \right)^2 - 1}. \quad (\text{B.8})$$

The rest of the proof proceeds in two steps.

Step 1: compute $\mathbf{E}_{(\Theta, f, \sigma)} \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} \right)^2$. Under (Θ, f, σ) , $\varepsilon = Y - X \circ \Theta$ is a matrix with entries following $N(0, \sigma^2)$. By the explicit formulas above on $\phi_{(\Theta, f, \sigma)}(Y, X)$ and $\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)$, we have that

$$\begin{aligned} \mathbf{E}_{(\Theta, f, \sigma)} \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} \right)^2 &= \mathbf{E}_{(\Theta, f, \sigma)} \exp \left(-\frac{1}{\sigma^2} \|Y - X \circ \tilde{\Theta}\|_F^2 + \frac{1}{\sigma^2} \|Y - X \circ \Theta\|_F^2 \right) \\ &\stackrel{(i)}{=} \mathbf{E}_{(\Theta, f, \sigma)} \exp \left(\sigma^{-2} \sum_{j=1}^p X_{1j}^2 \Delta_{1j}^2 \right) \\ &= \exp \left(\sigma^{-2} \sum_{j=1}^p \mu_f \Delta_{1j}^2 \right) \times \mathbf{E}_{(\Theta, f, \sigma)} \exp \left(\sigma^{-2} \sum_{j=1}^p [X_{1j}^2 - \mu_f] \Delta_{1j}^2 \right), \end{aligned}$$

where (i) follows by the fact that under (Θ, f, σ) , $\varepsilon_{i,j}$ is i.i.d $N(0, \sigma^2)$ conditional on X .

Notice that under (Θ, f, σ) , X_{1j}^2 is i.i.d, bounded and has mean μ_f . By Hoeffding's inequality and equivalent bounds for sub-Gaussian distributions (e.g., Proposition 5.10 and Lemma 5.5 in Vershynin [6]), the variable $\sigma^{-2} \sum_{j=1}^p [X_{1j}^2 - \mu_f] \Delta_{1j}^2$ has sub-Gaussian norm bounded by $\kappa_3 \sigma^{-2} \sqrt{\sum_{j=1}^p \Delta_{1j}^4}$, where $\kappa_3 > 0$ is a constant

that only depends on the bound of X_{1j}^2 . We observe that

$$\begin{aligned} \sum_{j=1}^p \Delta_{1j}^4 &= \sum_{j=1}^p [q(V'g)'v_j]^4 = q^4 \left(\max_{1 \leq j \leq p} [(V'g)'v_j]^2 \right) \sum_{j=1}^p [(V'g)'v_j]^2 \\ &= q^4 \left(\max_{1 \leq j \leq p} [(V'g)'v_j]^2 \right) \|V'g\|^2 \leq q^4 \left(\|V'g\|^2 \max_{1 \leq j \leq p} \|v_j\|^2 \right) \|V'g\|^2 \\ &\lesssim q^4 \|V'g\|^4 (Jp^{-1}) \lesssim t^4 Jp^{-1} = o(1). \end{aligned}$$

By Lemma B.3, we have

$$\mathbb{E}_{(\Theta, f, \sigma)} \exp \left(\sigma^{-2} \sum_{i=1}^n \sum_{j=1}^p (X_{ij}^2 - \mu_f) \Delta_{ij}^2 \right) = 1 + o(1).$$

Moreover,

$$\sigma^{-2} \sum_{j=1}^p \mu_f \Delta_{1j}^2 = \mu_f \sigma^{-2} q^2 (V'g)'V'V(V'g) = \mu_f \sigma^{-2} q^2 \|V'g\|^2 = \mu_f \sigma^{-2} t^2.$$

By the above three displays, we have that

$$\mathbb{E}_{(\Theta, f, \sigma)} \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} \right)^2 = \exp(\mu_f \sigma^{-2} t^2) (1 + o(1)). \quad (\text{B.9})$$

Step 2: derive the final result.

Since t is fixed and $s_*(\Theta, f, \sigma) \asymp \|V'g\|$, it follows by (B.8) and (B.9) that

$$\begin{aligned} \text{Var}_{(\Theta, f, \sigma)} [T(Y, X)] &\geq \frac{[t\|V'g\| + o(s_*(\Theta, f, \sigma))]^2}{\mathbb{E}_{(\Theta, f, \sigma)} \left(\frac{\phi_{(\tilde{\Theta}, f, \sigma)}(Y, X)}{\phi_{(\Theta, f, \sigma)}(Y, X)} \right)^2 - 1} \\ &= \frac{[t\|V'g\| + o(s_*(\Theta, f, \sigma))]^2}{\exp(\mu_f \sigma^{-2} t^2) (1 + o(1)) - 1} \\ &= \frac{t^2 \|V'g\|^2 + o(s_*^2(\Theta, f, \sigma))}{\exp(\mu_f \sigma^{-2} t^2) - 1 + o(1) \cdot \exp(\mu_f \sigma^{-2} t^2)} \\ &= \frac{t^2 \|V'g\|^2 (1 + o(1))}{\exp(\mu_f \sigma^{-2} t^2) - 1 + o(1) \cdot \exp(\mu_f \sigma^{-2} t^2)}. \end{aligned}$$

Consider $r(a) = \exp(a)$. Notice that the second derivative is $r''(a) = \exp(a)$, which is increasing in a . We have that for any $a > 0$, $|r(a) - r(0) - r'(0)a| \leq \exp(a)a^2/2$. Thus, for any $a > 0$,

$$\exp(a) - 1 \leq r'(0)a + \exp(a)a^2/2 = a + \exp(a)a^2/2.$$

Since $t \in (0, \kappa_1)$ with $\kappa_1 \leq \sqrt{\mu_f}/(2\sigma)$, we have $\mu_f\sigma^{-2}t^2 \in (0, 1/4)$ and thus

$$\exp(\mu_f\sigma^{-2}t^2) - 1 \leq \mu_f\sigma^{-2}t^2 + \exp(1/4)\mu_f^2\sigma^{-4}t^4/2.$$

Therefore, we have

$$\begin{aligned} \text{Var}_{(\Theta, f, \sigma)}[T(Y, X)] &\geq \frac{t^2\|V'g\|^2(1+o(1))}{\exp(\mu_f\sigma^{-2}t^2) - 1 + o(1) \cdot \exp(\mu_f\sigma^{-2}t^2)} \\ &\geq \frac{t^2\|V'g\|^2(1+o(1))}{\mu_f\sigma^{-2}t^2 + \exp(1/4)\mu_f^2\sigma^{-4}t^4/2 + o(1) \cdot \exp(1/4)} \\ &= \frac{\|V'g\|^2(1+o(1))}{[\mu_f\sigma^{-2} + \exp(1/4)\mu_f^2\sigma^{-4}t^2/2](1+o(1))}. \end{aligned}$$

In other words,

$$\begin{aligned} \frac{\text{Var}_{(\Theta, f, \sigma)}[T(Y, X)]}{s_*^2(\Theta, f, \sigma)} &\geq \frac{1+o(1)}{\sigma^2\mu_f^{-1}[\mu_f\sigma^{-2} + \exp(1/4)\mu_f^2\sigma^{-4}t^2/2](1+o(1))} \\ &\stackrel{(i)}{\geq} \frac{1+o(1)}{[1 + 8\exp(1/4)\kappa_2^4t^2](1+o(1))}, \end{aligned}$$

where (i) follows by $\mu_f\sigma^{-2} \leq 4\kappa_2^2$. We take the limit and obtain

$$\liminf_{n, p \rightarrow \infty} \frac{\text{Var}_{(\Theta, f, \sigma)}[T(Y, X)]}{s_*^2(\Theta, f, \sigma)} \geq \frac{1}{1 + 8\exp(1/4)\kappa_2^4t^2}.$$

Notice that the left-hand side does not depend on the choice of t . Since the above bound holds for any $t \in (0, \kappa_1)$, we can choose small t and obtain

$$\liminf_{n, p \rightarrow \infty} \frac{\text{Var}_{(\Theta, f, \sigma)}[T(Y, X)]}{s_*^2(\Theta, f, \sigma)} \geq 1.$$

The proof is complete. \square

B.5. Proof of Theorem 4.3: minimax rate.

Proof. We provide proofs for both cases: sparse g ($g_1 = 1$ and $g_j = 0$ for $j \geq 2$) as well as dense g . The arguments and notations for these two cases are independent.

Case 1: sparse g

Fix any $\Theta_* \in \mathcal{S}$ with entries $\{\theta_{ij,*}\}$ such that $\text{rank}\Theta_* \leq J-1$ and $\max_{1 \leq i \leq n} \max_{1 \leq j \leq p} |\theta_{ij,*}| \leq c_1/2$. (This is always feasible because we can simply choose Θ_* to be the zero matrix.)

Let $\kappa > 0$ be a constant satisfying the following

$$\kappa \leq \min \{c_1/2, c_3/\sqrt{1-c_2}\}, \quad (\text{B.10})$$

Let Θ_{**} be a matrix with entries $\{\theta_{ij,**}\}$ defined as follows

$$\theta_{ij,**} = \begin{cases} \theta_{ij,*} + \kappa & \text{if } (i, j) = 1 \\ \theta_{1j,*} & \text{otherwise.} \end{cases}$$

Since Θ_* and Θ_{**} only differ in the $(1, 1)$ entry, it follows that $\text{rank}\Theta_{**} \leq \text{rank}\Theta_* + 1 \leq J-1+1 = J$. Since $|\theta_{11,**}| = |\theta_{11,*} + \kappa| \leq |\theta_{11,*}| + \kappa \leq c_1/2 + \kappa \leq c_1$. Therefore, $\Theta_{**} \in \mathcal{S}$.

We now compare the Kullback–Leibler divergence between $P_{(\Theta_*, \rho, \sigma)}$ and $P_{(\Theta_{**}, \rho, \sigma)}$:

$$KL(P_{(\Theta_*, \rho, \sigma)}, P_{(\Theta_{**}, \rho, \sigma)}) = \int \left(\log \frac{dP_{(\Theta_*, \rho, \sigma)}}{dP_{(\Theta_{**}, \rho, \sigma)}} \right) dP_{(\Theta_*, \rho, \sigma)}.$$

By the formula of Gaussian densities, we have that

$$\frac{dP_{(\Theta_*, \rho, \sigma)}}{dP_{(\Theta_{**}, \rho, \sigma)}} = \frac{\exp\left(-\frac{1}{2}(y_{11} - \theta_{1j,*}x_{11})^2\sigma_{11}^{-2}\right)}{\exp\left(-\frac{1}{2}(y_{11} - \theta_{1j,**}x_{11})^2\sigma_{11}^{-2}\right)}.$$

Therefore,

$$\begin{aligned} KL(P_{(\Theta_*, \rho, \sigma)}, P_{(\Theta_{**}, \rho, \sigma)}) &= \int \left(\log \frac{dP_{(\Theta_*, \rho, \sigma)}}{dP_{(\Theta_{**}, \rho, \sigma)}} \right) dP_{(\Theta_*, \rho, \sigma)} \\ &= \mathbb{E}_{(\Theta_*, \rho, \sigma)} \left(-\frac{1}{2} \sum_{j=1}^p [(y_{11} - \theta_{1j,*}x_{11})^2 - (y_{11} - \theta_{1j,**}x_{11})^2] \sigma_{1j}^{-2} \right) \\ &= \mathbb{E}_{(\Theta_*, \rho, \sigma)} \left(\left[\frac{1}{2} \kappa^2 x_{11} - (y_{11} - \theta_{11,*}x_{11})\kappa x_{11} \right] \sigma_{11}^{-2} \right) \\ &= \frac{1}{2} \kappa^2 \rho_1 \sigma_{11}^{-2} \leq \frac{1}{2} \kappa^2 (1 - c_2) c_3^{-2} \stackrel{(i)}{\leq} 1/2, \end{aligned}$$

where (i) follows by (B.10).

We notice that $|h(\Theta_*) - h(\Theta_{**})| = \kappa$. By Theorem 2.2 in Tsybakov [5] and Equation (2.9) therein, we have that

$$\inf_T \sup_{\Theta \in \mathcal{S}} P_{(\Theta, \rho, \sigma)} (|T - h(\Theta)| > \kappa) \geq \max \left(\frac{1}{4} \exp(-1/2), \frac{1 - \sqrt{(1/2)/2}}{2} \right) = 1/4.$$

Case 2: dense g

Fix any $\Theta_* \in \mathcal{S}$ with entries $\{\theta_{ij,*}\}$ such that $\text{rank}\Theta_* \leq J-1$ and $\max_{1 \leq i \leq n} \max_{1 \leq j \leq p} |\theta_{ij,*}| \leq c_1/2$. (This is always feasible because we can simply choose Θ_* to be the zero matrix.)

Let $\kappa > 0$ be a constant satisfying the following

$$\kappa \leq c_1 c_5 / 2 \quad \text{and} \quad \frac{\kappa^2(1-c_2)}{2c_3^2 c_5^2} \leq 1/2. \quad (\text{B.11})$$

Define $\Delta_j = \kappa p^{-3/2}/g_j$. Let Θ_{**} be a matrix with entries $\{\theta_{ij,**}\}$ defined as follows

$$\theta_{ij,**} = \begin{cases} \theta_{ij,*} & \text{if } i \neq 1 \\ \theta_{1j,*} + \Delta_j & \text{if } i = 1. \end{cases}$$

Since Θ_* and Θ_{**} only differ in the first row, it follows that $\text{rank}\Theta_{**} \leq \text{rank}\Theta_* + 1 \leq J - 1 + 1 = J$. Since

$$\begin{aligned} \max_{1 \leq j \leq p} |\theta_{1j,**}| &= \max_{1 \leq j \leq p} |\theta_{1j,*} + \Delta_j| \leq \max_{1 \leq j \leq p} |\theta_{1j,*}| + \max_{1 \leq j \leq p} |\Delta_j| \\ &\leq \frac{c_1}{2} + \frac{\kappa p^{-3/2}}{\min_j |g_j|} \leq \frac{c_1}{2} + \frac{\kappa p^{-3/2}}{c_5/p} \stackrel{(i)}{\leq} c_1, \end{aligned}$$

where (i) follows by $\kappa \leq c_1 c_5 p^{1/2}/2$ (due to (B.11) and $p \geq 1$). Therefore, $\Theta_{**} \in \mathcal{S}$.

We now compare the Kullback–Leibler divergence between $P_{(\Theta_*, \rho, \sigma)}$ and $P_{(\Theta_{**}, \rho, \sigma)}$:

$$KL(P_{(\Theta_*, \rho, \sigma)}, P_{(\Theta_{**}, \rho, \sigma)}) = \int \left(\log \frac{dP_{(\Theta_*, \rho, \sigma)}}{dP_{(\Theta_{**}, \rho, \sigma)}} \right) dP_{(\Theta_*, \rho, \sigma)}.$$

By the formula of Gaussian densities, we have that

$$\frac{dP_{(\Theta_*, \rho, \sigma)}}{dP_{(\Theta_{**}, \rho, \sigma)}} = \frac{\exp\left(-\frac{1}{2} \sum_{j=1}^p (y_{1j} - \theta_{1j,*} x_{1j})^2 \sigma_{1j}^{-2}\right)}{\exp\left(-\frac{1}{2} \sum_{j=1}^p (y_{1j} - \theta_{1j,**} x_{1j})^2 \sigma_{1j}^{-2}\right)}.$$

Therefore,

$$\begin{aligned}
KL(P_{(\Theta_*, \rho, \sigma)}, P_{(\Theta_{**}, \rho, \sigma)}) &= \int \left(\log \frac{dP_{(\Theta_*, \rho, \sigma)}}{dP_{(\Theta_{**}, \rho, \sigma)}} \right) dP_{(\Theta_*, \rho, \sigma)} \\
&= \mathbb{E}_{(\Theta_*, \rho, \sigma)} \left(-\frac{1}{2} \sum_{j=1}^p [(y_{1j} - \theta_{1j,*} x_{1j})^2 - (y_{1j} - \theta_{1j,**} x_{1j})^2] \sigma_{1j}^{-2} \right) \\
&= \mathbb{E}_{(\Theta_*, \rho, \sigma)} \left(\sum_{j=1}^p \left[\frac{1}{2} \Delta_j^2 x_{1j} - (y_{1j} - \theta_{1j,*} x_{1j}) \Delta_j x_{1j} \right] \sigma_{1j}^{-2} \right) \\
&= \frac{\kappa^2 p^{-3}}{2} \sum_{j=1}^p \sigma_{1j}^{-2} \rho_j g_j^{-2} \leq \frac{\kappa^2 (1 - c_2)}{2c_3^2 c_5^2} \stackrel{(i)}{\leq} 1/2,
\end{aligned}$$

where (i) follows by (B.11).

We notice that

$$|h(\Theta_*) - h(\Theta_{**})| = \left| \sum_{j=1}^p g_j \Delta_j \right| = \kappa p^{-1/2}.$$

By Theorem 2.2 in Tsybakov [5] and Equation (2.9) therein, we have that

$$\inf_T \sup_{\Theta \in \mathcal{S}} P_{(\Theta, \rho, \sigma)} (|T - h(\Theta)| > \kappa p^{-1/2}) \geq \max \left(\frac{1}{4} \exp(-1/2), \frac{1 - \sqrt{(1/2)/2}}{2} \right) = 1/4.$$

The proof is complete. \square

B.6. Proof of Theorem 4.4.

Proof. We write $\widehat{\mu}_{j,i}^2 = \widehat{\mu}_{j,i}^2$ for simplicity because we fix i of interest. Note that $g_j y_{ij} x_{ij} = g_j x_{ij}^2 \theta_{ij} + g_j e_{ij}$, where $e_{ij} = x_{ij} \varepsilon_{ij}$. Let $\mu_j^2 = \mathbb{E} x_{kj}^2$.

$$\begin{aligned}
\widehat{h}_i(\widehat{\Theta}) - \theta_i' g &= \sum_{j=1}^p \mu_j^{-2} g_j [x_{ij} \varepsilon_{ij} + (x_{ij}^2 - \mu_j^2) \theta_{ij}] + (a) \dots + (d) \\
(a) &= \sum_{j=1}^p (\widehat{\mu}_j^{-2} - \mu_j^{-2}) \mu_j^{-2} (\mu_j^2 - \widehat{\mu}_j^2) g_j x_{ij}^2 \theta_{ij} \\
(b) &= \sum_{j=1}^p \mu_j^{-4} (\mu_j^2 - \widehat{\mu}_j^2) g_j x_{ij}^2 \theta_{ij} \\
(c) &= \sum_{j=1}^p (\widehat{\mu}_j^{-2} - \mu_j^{-2}) \mu_j^{-2} (\mu_j^2 - \widehat{\mu}_j^2) g_j e_{ij}
\end{aligned}$$

$$(d) = \sum_{j=1}^p \mu_j^{-4} (\mu_j^2 - \widehat{\mu}_j^2) g_j e_{ij}.$$

We now bound each term.

For (a)(c), note $\max_j |\widehat{\mu}_j^2 - \mu_j^2| = \max_j \left| \frac{1}{n-1} \sum_{k \neq i} x_{kj}^2 - \mathbb{E} x_{kj}^2 \right| = O_P(\sqrt{\frac{\log p}{n}})$.

Hence $\max_j \widehat{\mu}_j^2 = O_P(1)$, and $\max_j |\widehat{\mu}_j^{-2} - \mu_j^{-2}| = O_P(\sqrt{\frac{\log p}{n}})$. Hence

$$(a) \leq O_P\left(\frac{\log p}{n}\right) \max_j |\mu_j^{-2} x_{ij} g_j| \sum_{j=1}^p |\theta_{ij}| \leq O_P\left(\frac{\log p}{n}\right)$$

$$(c) \leq O_P\left(\frac{\log p}{n}\right) \max_j |\mu_j^{-2}| \sum_j |g_j e_{ij}| \leq O_P\left(\frac{\log p}{n}\right).$$

For (b)(d), let $v_{kj} = x_{kj}^2 - \mathbb{E} x_{kj}^2$ and $c_j = \mu_j^{-4} \theta_{ij}$. Then v_{kj} is independent over k .

$$\begin{aligned} \mathbb{E}(b)^2 &= \mathbb{E} \left(\frac{1}{n-1} \sum_{j=1}^p \sum_{k \neq i} v_{kj} g_j x_{ij}^2 c_j \right)^2 \\ &\leq O\left(\frac{1}{n^2}\right) \sum_{j,l \leq p} \sum_{k \neq i} g_j g_l \mathbb{E} v_{kj} v_{kl} \mathbb{E} c_j c_l \mathbb{E} x_{ij}^2 x_{il}^2 \\ &\leq O\left(\frac{1}{np^2}\right) \max_{i \leq n} \sum_{j,l \leq p} |\text{Cov}(x_{ij}^2, x_{il}^2)| = O\left(\frac{1}{np}\right) \\ \mathbb{E}(d)^2 &= \mathbb{E} \left(\frac{1}{n-1} \sum_{j=1}^p \sum_{k \neq i} v_{kj} g_j x_{ij} \mu_j^{-4} \varepsilon_{ij} \right)^2 \\ &\leq O\left(\frac{1}{np^2}\right) \max_{k \leq n} \sum_{j,l \leq p} |\text{Cov}(x_{kl}^2, x_{kj}^2) \mathbb{E} x_{ij} \varepsilon_{ij} x_{il} \varepsilon_{il}| = O\left(\frac{1}{np}\right). \end{aligned}$$

Hence provided that $\sqrt{p} \log p = o(n)$, we have

$$\sqrt{p} [\widehat{h}_i(\Theta) - \theta'_i g] = \sum_{j=1}^p Z_j + o_P(1)$$

where $Z_j = \sqrt{p} \mu_j^{-2} g_j W_{ij}$ with $W_{ij} = x_{ij} \varepsilon_{ij} + x_{ij}^2 \theta_{ij}$.

We now verify the Lindeberg condition. Suppose $\mu_j > c > 0$. Let $s_n^2 = \sum_{j=1}^p \text{Var}(Z_j)$. Note that $\mathbb{E} Z_j^4 = O(p^{-2}) \mathbb{E} W_{ij}^4 = O(p^{-2})$. Also $\text{Var}(Z_j) \leq \sqrt{\mathbb{E} Z_j^4} = O(p^{-1})$. Also $\text{Var}(Z_j) \geq cp^{-1}$. Hence $s_n^{-1} = O(1)$. Then for any $\epsilon > 0$,

$$s_n^{-2} \sum_j \mathbb{E} (Z_j - \mathbb{E} Z_j)^2 \mathbb{1}\{|Z_j - \mathbb{E} Z_j| > \epsilon s_n\} \leq \epsilon^{-1} s_n^{-3} \sum_j \sqrt{\mathbb{E} (Z_j - \mathbb{E} Z_j)^4} \sqrt{\text{Var}(Z_j)} = O(p^{-1/2}).$$

Thus $s_n^{-1} \sqrt{p} [\widehat{h_i(\Theta)} - \theta'_i g] \rightarrow^d N(0, 1)$. In particular, $s_n^2 = p \sum_{j=1}^p g_j^2 \mu_j^{-4} \text{Var}(W_{ij})$. \square

B.7. Proof of Theorem 5.2: the Treatment Effect Study.

B.7.1. *Proof of Lemma 5.1.* We now prove Lemma 5.1 which verifies the SSV and incoherence condition in the treatment effect study. For ease of readability, this lemma is restated below.

Lemma B.4. (i) *The minimum nonzero singular value ψ_{np}^2 for $\Theta_0(m)$ can be taken as*

$$\psi_{np}^2 \asymp J^{-1} \sum_{i=1}^n \sum_{j=1}^p h_{j,m}(\eta_i)^2, \quad m = 0, 1,$$

which means $\psi_J(\Theta_0(m)) \geq c\psi_{np}^2$ for this choice of ψ_{np} .

(ii) *The incoherence Assumption 4.4 holds.*

(iii) *The low-rank approximation error satisfies $\|R(m)\|_{(n)} \leq CJ^{-(a-1)} \max\{p, n\}$.*

Proof. Fix $m \in \{0, 1\}$, we drop the dependence on m for notational simplicity.

(i) SSV: Let $\psi_j(A)$ be the j th largest singular value of A . Then $\psi_j(\Theta_0) = \psi_j(A_m)$. Now for any $\epsilon > 0$, with probability approaching one,

$$\begin{aligned} \sum_{i=1}^n \sum_{j=1}^p h_j(\eta_i)^2 &= \|\Theta\|_F^2 \leq (1 + \epsilon) \|\Theta_0\|_F^2 = (1 + \epsilon) \sum_{k=1}^J \psi_k^2(\Theta_0) \\ &\leq (1 + \epsilon) J \psi_1^2(A) \stackrel{(1)}{\leq} C(1 + \epsilon) J^{2b+1} \psi_J^2(A) \\ &= C(1 + \epsilon) J^{2b+1} \psi_J^2(\Theta_0) \\ \sum_{i=1}^n \sum_{j=1}^p h_j(\eta_i)^2 &= \|\Theta\|_F^2 \geq (1 - \epsilon) \|\Theta_0\|_F^2 = (1 - \epsilon) \sum_{k=1}^J \psi_k^2(\Theta_0) \\ &\geq (1 - \epsilon) J \psi_J^2(\Theta_0). \end{aligned}$$

where (1) follows from Assumption 5.1.

(ii) Incoherence: We derive the singular vectors and singular values of Θ_0 . Note that we can write

$$\Theta = \underbrace{\Phi \Lambda'}_{\Theta_0} + R.$$

where Φ is the $n \times J$ matrix of ϕ_i ; Λ is the $p \times J$ matrix of λ_j ; R is the $n \times p$ matrix of r_{ij} . Write $S_\Lambda = \frac{1}{p} \Lambda' \Lambda$, $S_\Phi = \frac{1}{n} \Phi' \Phi$, $A = S_\Phi^{1/2} S_\Lambda S_\Phi^{1/2}$. Also let G_Φ be a $J \times J$ matrix whose columns are the eigenvectors of A , and T be the diagonal matrix of

corresponding eigenvalues. Let $H_\Phi := S_\Phi^{-1/2}G_\Phi$, it can be verified that

$$\Theta_0\Theta_0'\Phi H_\Phi = pn\Phi H_\Phi T, \quad \frac{1}{n}(\Phi H_\Phi)'\Phi H_\Phi = I.$$

This shows that the columns of ΦH_Φ are the left singular-vectors of Θ_0 ; the eigenvalues of A equal the the first J eigenvalues of $\Theta_0'\Theta_0$. Similarly, we can define $H_\Lambda = S_\Lambda^{-1/2}G_\Lambda$, where G_Λ is a $J \times J$ matrix whose columns are the eigenvectors of $S_\Lambda^{1/2}S_\Phi S_\Lambda^{1/2}$. Hence we have

$$U_0 = n^{-1/2}\Phi H_\Phi, \quad V_0 = p^{-1/2}\Lambda H_\Lambda. \quad (\text{B.12})$$

The $h_j(\cdot)$ function belongs to the Hilber space with uniformly-bounded L^2 norm, meaning that $\max_{j \leq p} \|h_j\|_{L^2}^2 = \max_{j \leq p} \sum_{k=1}^{\infty} \lambda_{j,k}^2 < \infty$. Thus

$$\begin{aligned} \mathbf{E} \max_{j \leq p} \|v_j\|^2 &\leq \max_{j \leq p} \|\lambda_j\|^2 \psi_{\min}^{-1}\left(\frac{1}{p}\Lambda'\Lambda\right) p^{-1} \\ &\leq \max_{j \leq p} \sum_{k=1}^{\infty} \lambda_{j,k}^2 p^{-1} \psi_{\min}^{-1}\left(\frac{1}{p}\Lambda'\Lambda\right) \leq O(p^{-1}) \\ \sum_{i=1}^n \|u_i\|^4 &\leq \sum_{i=1}^n \|\phi_i\|^4 \psi_{\min}^{-2}(S_\Phi) \leq \sum_{i=1}^n \|\Phi_i\|^4 \psi_{\min}^{-2}\left(\frac{1}{n}\Phi'\Phi\right) n^{-2} \\ &\leq \frac{1}{n} \sum_{i=1}^n \|\Phi_i\|^4 O_P(J^2 n^{-1}) = o_P(1) \\ \mathbf{E} \max_{i \leq n} \|u_i\|^2 &\leq \mathbf{E} \max_{i \leq n} \|\Phi_i\|^2 \psi_{\min}^{-1}(S_\Phi) \\ &\leq n^{-1} J \sup_{\eta} \max_{j \leq J} |\phi_j(\eta)|^2 \mathbf{E} \psi_{\min}^{-1}(S_\Phi) = O(Jn^{-1}). \end{aligned}$$

(iii) Sieve error:

$$\|R\|_{(n)} \leq \|R\|_F (p \vee n)^{1/2} \leq C(p \vee n)^{3/2} J^{-a}.$$

□

B.7.2. *Proof of Lemma 5.3.* In this lemma, we verify the following condition:

$$\begin{aligned} \psi_1\left(\frac{1}{np}\Theta\Theta'\right) / \psi_J\left(\frac{1}{np}\Theta\Theta'\right) &\leq O_P(J^\alpha) \\ \min_{k=1 \dots J-1} \psi_k\left(\frac{1}{np}\Theta\Theta'\right) - \psi_{k+1}\left(\frac{1}{np}\Theta\Theta'\right) &\geq cJ^{-(\alpha+1)}. \end{aligned}$$

Proof. Since and h_j are independently generated from the Gaussian process prior, we have

$$\max_{i,l} \left| \frac{1}{p} \sum_{j=1}^p h_j(\eta_i) h_j(\eta_l) - K(\eta_i, \eta_l) \right| = O_P\left(\sqrt{\frac{\log n}{p}}\right).$$

Hence for $r_J := \sup_{\eta_1, \eta_2} |\sum_{k>J} \nu_k \phi_k(\eta_1) \phi_k(\eta_2)|$,

$$\left\| \frac{1}{np} \Theta \Theta' - \frac{1}{n} \Phi D_\lambda \Phi' \right\| \leq O_P\left(\sqrt{\frac{\log n}{p}}\right) + r_J.$$

Thus

$$\max_{j \leq J} |\psi_j(\frac{1}{np} \Theta \Theta') - \psi_j(\frac{1}{n} \Phi D_\lambda \Phi')| \leq \underbrace{\left\| \frac{1}{np} \Theta \Theta' - \frac{1}{n} \Phi D_\lambda \Phi' \right\|}_{O_P\left(\sqrt{\frac{\log n}{p}} + r_J\right)}.$$

We now show that the eigenvalues of $\frac{1}{n} \Phi D_\lambda \Phi'$ are approximately D_λ . In fact, the top J eigenvalues equal those of $(\frac{1}{n} \Phi' \Phi)^{1/2} D_\lambda (\frac{1}{n} \Phi' \Phi)^{1/2}$. Because η_i are i.i.d Unif[0, 1], and ϕ_j are eigenfunctions of the operator T , so $\int \phi_{k_1}(\eta) \phi_{k_2}(\eta) d\eta = 1\{k_1 = k_2\}$, showing $\mathbb{E} \frac{1}{n} \Phi' \Phi = I$. Hence $\|\frac{1}{n} \Phi' \Phi - I\| = O_P(\frac{J}{\sqrt{n}})$. This implies

$$\max_{j \leq J} |\psi_j(\frac{1}{n} \Phi D_\lambda \Phi') - \nu_j| \leq \left\| (\frac{1}{n} \Phi' \Phi)^{1/2} D_\lambda (\frac{1}{n} \Phi' \Phi)^{1/2} - D_\lambda \right\| \leq \|D_\lambda\| O_P\left(\frac{J}{\sqrt{n}}\right).$$

Together, for $w_n := \sqrt{\frac{\log n}{p}} + r_J + \|D_\lambda\| \frac{J}{\sqrt{n}}$,

$$\max_{j \leq J} |\psi_j(\frac{1}{np} \Theta \Theta') - \nu_j| \leq O_P(w_n) = o_P(\nu_J/J).$$

This implies

$$\frac{\psi_1(\frac{1}{np} \Theta \Theta')}{\psi_J(\frac{1}{np} \Theta \Theta')} \leq \frac{O_P(w_n)}{\nu_J - O_P(w_n)} + \frac{2\nu_1}{\nu_J} \leq O_P(J^\alpha).$$

Also, for any $k \leq J - 1$, the mean value theorem implies

$$\psi_k(\frac{1}{np} \Theta \Theta') - \psi_{k+1}(\frac{1}{np} \Theta \Theta') \geq M(k^{-\alpha} - (k+1)^{-\alpha}) - O_P(w_n) \geq \alpha M J^{-\alpha-1} - O_P(w_n).$$

The lower bound also holds (up to a constant) for $\psi_k(\frac{1}{\sqrt{np}} \Theta) - \psi_{k+1}(\frac{1}{\sqrt{np}} \Theta)$ because $\psi_1(\frac{1}{\sqrt{np}} \Theta) = O_P(1)$.

□

B.7.3. *Proof of Theorem 5.2.*

Proof. Let the columns of $V_0(m) = (v_j(m) : j \leq p)$ be the right singular vectors of $\Theta_0(m)$ and $\bar{B}(0) = \sum_{j \in T_0} x_{ij}(0)v_j(0)v_j(0)'$ and $\bar{B}(1) = \sum_{j \in T_1} x_{ij}(1)v_j(1)v_j(1)'$.

Note that condition (12) implies Assumption 4.3 (ii-c) when $\{1, \dots, p\}$ is replaced with T_0 and for $x_{ij} = x_{ij}(0)$. Hence (B.7) holds, for $g_0 = \frac{1}{p_0}(1, \dots, 1)'$, on T_0 and $m = 0$. We then have

$$\begin{aligned} \hat{\theta}_i(0)'g_0 - \theta_i(0)'g_0 &= \sum_{j \in T_0} e_{ij}x_{ij}(0)v_j(0)'\bar{B}(0)^{-1}V_0(0)'g_0 + o_P(p_0^{-1/2}) \\ &:= \sum_{j \in T_0} e_{ij}\zeta_{ij}(0) + o_P(p_0^{-1/2}). \end{aligned}$$

Similarly, for $g_1 = \frac{1}{p_1}(1, \dots, 1)'$, on T_1 and $m = 1$, we have

$$\hat{\theta}_i(1)'g_1 - \theta_i(1)'g_1 = \sum_{j \in T_1} e_{ij}\zeta_{ij}(1) + o_P(p_1^{-1/2}).$$

Together, we reach

$$\begin{aligned} \hat{\tau}_i - \tau_i &= \hat{\theta}_i(1)'g_1 - \hat{\theta}_i(0)'g_0 - \left[\frac{1}{p} \sum_{j=1}^p \theta_{ij}(1) - \frac{1}{p} \sum_{j=1}^p \theta_{ij}(0) \right] \\ &= \hat{\theta}_i(1)'g_1 - \theta_i(1)'g_1 - [\hat{\theta}_i(0)'g_0 - \theta_i(0)'g_0] \\ &\quad + \theta_i(1)'g_1 - \frac{1}{p} \sum_{j=1}^p \theta_{ij}(1) + \frac{1}{p} \sum_{j=1}^p \theta_{ij}(0) - \theta_i(0)'g_0 \\ &= \sum_{j \in T_1} e_{ij}\zeta_{ij}(1) - \sum_{j \in T_0} e_{ij}\zeta_{ij}(0) + o_P(p_0^{-1/2} + p_1^{-1/2}) \\ &= \sum_{j=1}^p e_{ij}\Delta_{ij} + o_P(\min\{p_0, p_1\}^{-1/2}) \\ \Delta_{ij} &:= \zeta_{ij}(1)1\{j \in T_1\} - \zeta_{ij}(0)1\{j \in T_0\}, \\ \bar{s}_{np,i}^2 &:= \sum_{j \in T_0} \text{Var}(e_{ij}|X, g(\eta))\zeta_{ij}(0)^2 + \sum_{j \in T_1} \text{Var}(e_{ij}|X, g(\eta))\zeta_{ij}(1)^2 \end{aligned}$$

Note that e_{ij} is independent over j conditioning on $x_{ij}(m)$ and $\Theta(m)$, $m = 0, 1$.

We verify the Lindeberg condition: for any $\epsilon > 0$,

$$\begin{aligned} &\frac{1}{\bar{s}_{np,i}^2} \sum_{j=1}^p \mathbb{E}[e_{ij}^2 \Delta_{ij}^2 1\{|e_{ij}\Delta_{ij}\} > \epsilon \bar{s}_{np,i}\}|X, g(\eta)] \leq \frac{1}{\bar{s}_{np,i}^4 \epsilon^2} \sum_{j=1}^p \mathbb{E}[e_{ij}^4 \Delta_{ij}^4 |X, g(\eta)] \\ &\leq \frac{C}{\bar{s}_{np,i}^4} \sum_{j \in T_0} \zeta_{ij}(0)^4 + \frac{C}{\bar{s}_{np,i}^4} \sum_{j \in T_1} \zeta_{ij}(1)^4 \leq \frac{C}{\bar{s}_{np,i}^4 p_0^2} \sum_{j \in T_0} \|v_j(0)\|^4 + \frac{C}{\bar{s}_{np,i}^4 p_1^2} \sum_{j \in T_1} \|v_j(1)\|^4 \end{aligned}$$

$$\leq \frac{CJ^2}{\bar{s}_{np,i}^4 p_0^3} + \frac{CJ^2}{\bar{s}_{np,i}^4 p_1^3} = o_P(1).$$

Thus with the condition that $\bar{s}_{np,i}^2 \min\{p_0, p_1\} \geq c$ for some $c > 0$ with probability approaching one, we have $\bar{s}_{np,i}^{-1}(\hat{\tau}_i - \tau_i) \rightarrow^d N(0, 1)$. \square

APPENDIX C. TECHNICAL LEMMAS

Lemma C.1. *Suppose $\sum_{j=1}^p \mathbf{E}\|v_j\|^4 = o(1)$ and $\min_{i \leq n} \|\sum_{j=1}^p v_j v_j' x_{ij}^2\| \geq c$. Let $\hat{B}_i = \sum_{j=1}^p x_{ij}^2 \tilde{v}_j \tilde{v}_j'$ and $B = H_S' \sum_{j=1}^p (\mathbf{E}x_{ij}^2) v_j v_j' H_S$. Then*

(i) $\max_{i \leq n} \|\hat{B}_i^{-1}\| = O_P(1)$.

(ii) *Consider the DGP of x_{ij} , corresponding to conditions (ii-a)-(ii-b) in Assumption 4.3.*

For each fixed $i \leq n$,

$$\|\hat{B}_i^{-1} - B^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1} + \sqrt{\sum_{j=1}^p \mathbf{E}\|v_j\|^4}), \text{ and}$$

$$\sum_{i \notin \mathcal{I}} \|\hat{B}_i^{-1} - B^{-1}\|^2 = O_P(nJ^{2d} \omega_{np}^2 \psi_{np}^{-2} + n \sum_{j=1}^p \mathbf{E}\|v_j\|^4).$$

In case (ii-c), For each fixed $i \leq n$,

$$\|\hat{B}_i^{-1} - B^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1} + Jp^{-1} \sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1), \text{ and}$$

$$\sum_{i \notin \mathcal{I}} \|\hat{B}_i^{-1} - B^{-1}\|^2 = O_P(nJ^{2d} \omega_{np}^2 \psi_{np}^{-2}) + O_P(nJ^2 p^{-2}) [\sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1]^2.$$

Proof. (i) Note that for $\max_{ij} |x_{ij}| = O_P(1)$,

$$\begin{aligned} \max_{i \leq n} \|\hat{B}_i - H_S' \sum_{j=1}^p x_{ij}^2 v_j v_j' H_S\| &\leq O_P(1) [\max_{i \leq n} \|\sum_{j=1}^p x_{ij}^2 (\tilde{v}_j - H_S' v_j) v_j'\| \\ &+ \max_{i \leq n} \sum_{j=1}^p x_{ij}^2 \|\tilde{v}_j - H_S' v_j\|^2] \\ &\leq O_P(1) \|\tilde{V}_S - V_0 H_S\| = O_P(J^d \omega_{np} \psi_{np}^{-1}) = o_P(1). \end{aligned}$$

On the other hand, by the assumption $\min_{i \leq n} \|\sum_{j=1}^p v_j v_j' x_{ij}^2\| \geq c$ almost surely. We have $\max_{i \leq n} \|\hat{B}_i^{-1}\| \leq \max_{i \leq n} \|(\sum_{j=1}^p x_{ij}^2 v_j v_j')^{-1}\| + o_P(1) = O_P(1)$.

To prove (ii), we proceed below corresponding to conditions (ii-a)-(ii-b) in Assumption 4.3.

Under condition (ii-a) x_{ij}^2 does not vary across $i \leq n$. We can write $x_{ij}^2 = x_j^2$. In this case $B = H_S' \sum_{j=1}^p x_j^2 v_j v_j' H_S$.

We have

$$\|\widehat{B}_i^{-1} - B^{-1}\| \leq O_P(1) \|\widehat{B}_i - H'_S \sum_{j=1}^p x_{ij}^2 v_j v'_j H_S\| \leq O_P(J^d \omega_{np} \psi_{np}^{-1}).$$

In addition, $\sum_{i \notin \mathcal{I}} \|\widehat{B}_i - B\|^2 \leq O_P(n J^{2d} \omega_{np}^2 \psi_{np}^{-2})$.

Under condition (ii-b) x_{ij} is independent across $i \leq n$ and is weakly dependent across $j \leq p$. In this case $B = H'_S \sum_{j=1}^p (\mathbb{E} x_{ij}^2) v_j v'_j H_S$.

We now bound $\sum_{j=1}^p (x_{ij}^2 - \mathbb{E} x_{ij}^2) v_j v'_j$ for fixed $i \leq n$. By the assumption x_{ij}^2 is weakly dependent across j . Also $\mathbb{E}((x_{ij}^2 - \mathbb{E} x_{ij}^2) | \Theta_0) = 0$. Let $X_i^2 = (x_{i1}^2, \dots, x_{ip}^2)'$. $\max_i \|\text{Var}(X_i^2 | \Theta_0)\|^2 < C$. Let $V_{k_1, k_2} = p \times 1$ vector of $v_{j, k_1} v_{j, k_2}$. Then with the assumption $\sum_{j=1}^p \mathbb{E} \|v_j\|^4 = o(1)$,

$$\begin{aligned} \mathbb{E} \left\| \sum_{j=1}^p (x_{ij}^2 - \mathbb{E} x_{ij}^2) v_j v'_j \right\|_F^2 &= \sum_{k_1, k_2 \leq J} \mathbb{E} \text{Var} \left[\sum_{j=1}^p x_{ij}^2 v_{j, k_1} v_{j, k_2} \mid \Theta_0 \right] \\ &= \sum_{k_1, k_2 \leq J} \mathbb{E} V'_{k_1, k_2} \text{Var}[X_i^2 | \Theta_0] V_{k_1, k_2} \leq C \sum_{j=1}^p \mathbb{E} \|v_j\|^4 \leq o(1). \end{aligned}$$

Hence $\|\widehat{B}_i^{-1} - B^{-1}\| \leq O_P(1) \|\widehat{B}_i - B\| \leq O_P(J^d \omega_{np} \psi_{np}^{-1} + \sqrt{\sum_{j=1}^p \mathbb{E} \|v_j\|^4})$.

In addition, by the proof of part (i),

$$\sum_{i \notin \mathcal{I}} \|\widehat{B}_i - B\|^2 \leq O_P(n J^{2d} \omega_{np}^2 \psi_{np}^{-2}) + \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p (x_{ij}^2 - \mathbb{E} x_{ij}^2) v_j v'_j \right\|^2.$$

By a similar argument of part (ii), $\mathbb{E} \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p (x_{ij}^2 - \mathbb{E} x_{ij}^2) v_j v'_j \right\|^2 \leq n \sum_{j=1}^p \mathbb{E} \|v_j\|^4$. Together, $\|B\|^2 = O_P(1)$ and $\max \|\widehat{B}_i^{-1}\| = O_P(1)$ so

$$\begin{aligned} \sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 &\leq \|B^{-1}\|^2 \max_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1}\|^2 \sum_{i \notin \mathcal{I}} \|\widehat{B}_i - B\|^2 \\ &= O_P(n J^{2d} \omega_{np}^2 \psi_{np}^{-2} + n \sum_{j=1}^p \mathbb{E} \|v_j\|^4). \end{aligned}$$

Under condition (ii-c) There is a common $\bar{\mathcal{B}}$. In this case we restrict to $x_{ij} \in \{0, 1\}$, and let $B = H'_S \sum_{j \in \bar{\mathcal{B}}} v_j v'_j H_S$. Let $\mathcal{B}_i = \{j : x_{ij} = 1\}$.

We have

$$\|\widehat{B}_i^{-1} - B^{-1}\| \leq O_P(1) \|\widehat{B}_i - H'_S \sum_{j=1}^p x_{ij}^2 v_j v'_j H_S\| + O_P(1) \left\| \sum_{j \in \mathcal{B}_i} v_j v'_j - \sum_{j \in \bar{\mathcal{B}}} v_j v'_j \right\|$$

$$\begin{aligned}
&\leq O_P(J^d \omega_{np} \psi_{np}^{-1}) + O_P(1) \max_{j \leq p} \|v_j\|^2 \sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1 \\
&\leq O_P(J^d \omega_{np} \psi_{np}^{-1}) + O_P(Jp^{-1}) \sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1.
\end{aligned}$$

In addition,

$$\begin{aligned}
\sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 &\leq O_P(1) \sum_{i \notin \mathcal{I}} \|\widehat{B}_i - B\|^2 \\
&= O_P(nJ^{2d} \omega_{np}^2 \psi_{np}^{-2}) + O_P(nJ^2 p^{-2}) \left[\sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1 \right]^2
\end{aligned}$$

□

Lemma C.2. For $d = 1 \sim 4$, consider $\Delta_{i,d}$ as defined in (B.1). In addition, let

$$\Delta_{i,5} := B^{-1} \sum_{j=1}^p \tilde{v}_j (x_{ij}^2 - \mathbf{E}x_{ij}^2) (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i$$

Also, consider the three different cases on the DGP of x_{ij} , corresponding to conditions (ii-a)-(ii-c) in Assumption 4.3. Then:

- (i) Under conditions either (ii-a) or (ii-b), for each $i \notin \mathcal{I}$, and $d = 1 \sim 4$, $\|\Delta_{i,d}\| = o_P(1)$ and $\sum_{i \notin \mathcal{I}} \|\Delta_{i,d}\|^2 = O_P(J^{1+2d+2b} \omega_{np}^2) = o_P(\psi_{np}^2)$.
- (ii) Under condition (ii-b), for each $i \notin \mathcal{I}$, $\|\Delta_{i,5}\| = o_P(1)$ and $\sum_{i \notin \mathcal{I}} \|\Delta_{i,5}\|^2 = O_P(J^{1+2d+2b} \omega_{np}^2) = o_P(\psi_{np}^2)$.
- (iii) Under conditions (ii-c), for each for each $i \notin \mathcal{I}$, and $d = 1 \sim 4, 6$, $\|\Delta_{i,d}\| = o_P(1)$ and $\sum_{i \notin \mathcal{I}} \|\Delta_{i,d}\|^2 = O_P(J^{1+2d+2b} \omega_{np}^2) = o_P(\psi_{np}^2)$.

Proof. (i) **For term $\Delta_{i,1}$.**

Lemma C.1 shows $\|\widehat{B}_i^{-1} - B^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1} + \sqrt{\sum_{j=1}^p \mathbf{E}\|v_j\|^4})$ and $\|\widehat{B}_i^{-1}\| = O_P(1)$. Also let $X_i^2 = (x_{i1}^2, \dots, x_{ip}^2)'$. Note $\|\gamma_i\| \leq O_P(J^b \psi_{np}) \|u_i\|$.

$$\left\| \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i \right\| \leq \|\gamma_i\| \|\tilde{V}' \text{diag}(X_i^2) (\tilde{V} H_S^{-1} - V)\| \leq \|u_i\| O_P(J^{b+g} \omega_{np}).$$

Hence $\|\Delta_{i,1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1} + \sqrt{\sum_{j=1}^p \mathbf{E}\|v_j\|^4}) \|u_i\| \omega_{np} J^{b+g} = o_P(1)$.

In addition, note that $\sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 = O_P(J^{1+2b} \psi_{np}^2)$. Hence

$$\sum_{i \notin \mathcal{I}} \|\Delta_{i,1}\|^2 \leq O_P(1) \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i \right\|^2$$

$$\leq O_P(1) \sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 \|\tilde{V}' \text{diag}(X_i^2)(\tilde{V}_S - VH_S)\|^2 = O_P(J^{1+2d+2b}\omega_{np}^2) = o_P(\psi_{np}^2).$$

For term $\Delta_{i,2}$.

By assumption ε_{ij} is independent across $i \leq n$. Because $\tilde{V}_{\mathcal{I}}$ is estimated using subsamples excluding i , $\mathbf{E}(\varepsilon_{ij} | \tilde{V}_{\mathcal{I}}, \Theta_0, X) = 0$. Let \tilde{P}_{ik} be $p \times 1$ vector of $x_{ij}(\tilde{v}_{j,k} - v_{j,k})$. By the assumption $\text{Var}[\varepsilon_i | X, \Theta_0] < C$,

$$\begin{aligned} \mathbf{E}_I(\|\sum_{j=1}^p \varepsilon_{ij} x_{ij}(\tilde{v}_j - H'_S v_j)\|^2 | \Theta_0) &= \sum_{k \leq J} \mathbf{E}_I \tilde{P}'_{ik} \text{Var}_I[\varepsilon_i | \tilde{V}_{\mathcal{I}}, X, \Theta_0] \tilde{P}_{ik} \\ &\leq \mathbf{E}_I(\sum_{j=1}^p x_{ij}^2 \|\tilde{v}_j - H'_S v_j\|^2 | \Theta_0) \leq \|\tilde{V}_{\mathcal{I}} - VH_S\|_F^2 = O_P(J^{2d}\omega_{np}^2\psi_{np}^{-2}) = o_P(1). \end{aligned} \tag{C.1}$$

Hence $\|\Delta_{i,2}\| = o_P(1)$. In addition, $\sum_{i \notin \mathcal{I}} \|\sum_{j=1}^p \varepsilon_{ij} x_{ij}(\tilde{v}_j - v_j)\|^2 = O_P(nJ^{2d}\omega_{np}^2\psi_{np}^{-2})$ implies $\sum_{i \notin \mathcal{I}} \|\Delta_{i,2}\|^2 \leq O_P(nJ^{2d}\omega_{np}^2\psi_{np}^{-2}) = O_P(J^{1+2d+2b}\omega_{np}^2) = o_P(\psi_{np}^2)$.

For term $\Delta_{i,3}$.

$$\begin{aligned} \max_{i \leq n} \|\Delta_{i,3}\| &\leq O_P(1) \|\sum_{j=1}^p r_{ij} \tilde{v}_j\| \leq \max_{ij} |r_{ij}| \sqrt{pJ} = o_P(1) \\ \sum_{i \notin \mathcal{I}} \|\Delta_{i,3}\|^2 &\leq n \max_i \|\Delta_{i,3}\|^2 \leq npJ \max_{ij} r_{ij}^2 = O_P(J^{1+2d+2b}\omega_{np}^2) = o_P(\psi_{np}^2). \end{aligned} \tag{C.2}$$

For term $\Delta_{i,4}$.

Note $\mathbf{E} \|\sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j\|^2 \leq C \sum_{j=1}^p x_{ij}^2 \|v_j\|^2 \leq CJ$. So

$$\Delta_{i4} = O_P(\sqrt{J})(J^d \omega_{np} \psi_{np}^{-1} + \sqrt{\sum_{j=1}^p \mathbf{E} \|v_j\|^4}) = o_P(1).$$

$$\sum_{i \notin \mathcal{I}} \|\Delta_{i,4}\|^2 \leq O_P(1) \sum_{i \notin \mathcal{I}} \|\sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j\|^2 \leq O_P(nJ) = O_P(J^{1+2d+2b}\omega_{np}^2) = o_P(\psi_{np}^2).$$

(ii) **For term $\Delta_{i,5}$ under Assumption 4.3 (ii-b).**

First, $\|\gamma_i\| \leq O_P(J^b \psi_{np}) \|u_i\|$. So

$$\begin{aligned} &\|\sum_{j=1}^p (\tilde{v}_j - H'_S v_j)(v_j - H_S^{-1'} \tilde{v}_j)' \gamma_i (x_{ij}^2 - \mathbf{E} x_{ij}^2)\| \\ &\leq O_P(\|\gamma_i\|) \|\tilde{V}_{\mathcal{I}} - VH_S\|_F^2 = O_P(J^{b+2d}\omega_{np}^2\psi_{np}^{-1} \|u_i\|) = o_P(1). \end{aligned}$$

Next, by the assumption x_{ij}^2 is independent across i . Let \tilde{P}_{ki} denote $p \times 1$ vector of $v_{j,k}(v_j - \tilde{v}_j)' \gamma_i$ and recall $X_i^2 = (\dot{m}_{i1}^2, \dots, \dot{m}_{ip}^2)'$. Since $i \notin \mathcal{I}$, $\tilde{V}_{\mathcal{I}}$ is estimated using subsample in \mathcal{I} , and x_{ij} is independent of Θ_0 , we have that

$$\begin{aligned} \mathbf{E}_I \left\| \sum_{j=1}^p v_j (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i (x_{ij}^2 - \mathbf{E} x_{ij}^2) \right\|^2 &= \sum_{k \leq J} \mathbf{E}_I \text{Var}_I [\tilde{P}_{ki}' X_i^2 | \Theta_0] \\ &\leq (\mathbf{E} \max_{j \leq p} \|v_j\|^2) \|\tilde{V}_{\mathcal{I}} - V H_S\|_F^2 \|\gamma_i\|^2. \end{aligned}$$

This makes $\left\| \sum_{j=1}^p v_j (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i (x_{ij}^2 - \mathbf{E} x_{ij}^2) \right\| = O_P(\sqrt{\mathbf{E} \max_{j \leq p} \|v_j\|^2}) \omega_{np} \|u_i\| J^{g+b}$. The last term is assumed to be $o_P(1)$. Hence $\|\Delta_{i,5}\| = o_P(1)$.

In addition,

$$\begin{aligned} \sum_{i \notin \mathcal{I}} \|\Delta_{i,5}\|^2 &\leq C \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p (\tilde{v}_j - H_S' v_j) (x_{ij}^2 - \mathbf{E} x_{ij}^2) (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i \right\|^2 \\ &\quad + C \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p v_j (x_{ij}^2 - \mathbf{E} x_{ij}^2) (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i \right\|^2 \\ &\leq C \sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 \left\| (\tilde{V}_{\mathcal{I}} - V H_S)' \text{diag}\{X_i^2 - \mathbf{E} X_i^2\} (\tilde{V}_{\mathcal{I}} - V H_S) \right\|^2 \\ &\quad + O_P(1) \sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 (\mathbf{E} \max_{j \leq p} \|v_j\|^2) \|\tilde{V}_{\mathcal{I}} - V H_S\|_F^2 \\ &\leq O_P(J^{1+2b+4g} \omega_{np}^4 \psi_{np}^{-2} + J^{1+2d+2b} \omega_{np}^2 \mathbf{E} \max_{j \leq p} \|v_j\|^2) = O_P(J^{1+2d+2b} \omega_{np}^2) = o_P(\psi_{np}^2). \end{aligned} \tag{C.3}$$

(iii) We now focus on condition (ii-c) of Assumption 4.3.

For terms $\Delta_{i,2}, \Delta_{i,3}$.

These two terms are the same as under Assumption 4.3 (ii-a) and (ii-b), so their bounds are the same as that of part (i).

For terms $\Delta_{i,1}, \Delta_{i,4}$.

By Lemma C.1, $\|\hat{B}_i^{-1} - B^{-1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1} + J p^{-1} \sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1)$. Also

$$\left\| \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i \right\| \leq \|\gamma_i\| \left\| \tilde{V}' \text{diag}(X_i^2) (\tilde{V} H_S^{-1} - V) \right\| \leq \|u_i\| O_P(\omega_{np} J^{b+g}).$$

Hence $\|\Delta_{i,1}\| = O_P(J^d \omega_{np} \psi_{np}^{-1} + J p^{-1} \sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1) \|u_i\| \omega_{np} J^{b+g} = o_P(1)$.

Also, $\sum_{i \notin \mathcal{I}} \|\Delta_{i,1}\|^2 \leq O_P(J^{1+2d+2b} \omega_{np}^2) = o_P(\psi_{np}^2)$.

Finally, $\mathbb{E} \|\sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j\|^2 \leq C \sum_{j=1}^p x_{ij}^2 \|v_j\|^2 \leq CJ$. So

$$\Delta_{i4} = O_P(\sqrt{J})(J^d \omega_{np} \psi_{np}^{-1} + Jp^{-1} \sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1) = o_P(1).$$

$$\sum_{i \notin \mathcal{I}} \|\Delta_{i,4}\|^2 \leq O_P(1) \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p \varepsilon_{ij} x_{ij} v_j \right\|^2 \leq O_P(nJ) = o_P(\psi_{np}^2).$$

For term $\Delta_{i,6}$.

Uniformly in i ,

$$\begin{aligned} |\Delta_{i,6}| &= \left| B^{-1} \sum_{j \in \mathcal{B}_i} \tilde{v}_j (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i - B^{-1} \sum_{j \in \bar{\mathcal{B}}} \tilde{v}_j (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i \right| \\ &\leq O_P(1) \sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} \|\tilde{v}_j (v_j - H_S^{-1} \tilde{v}_j)' \gamma_i\| \\ &\leq O_P(1) \|\gamma_i\| \|\tilde{V}_S - V_0 H_S\|^2 + O_P(1) \|\gamma_i\| \|\tilde{V}_S - V_0 H_S\| \max_j \|v_j\| \sqrt{\sum_j 1\{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}\}} \\ &\leq O_P(J^{2d} \omega_{np}^2 \psi_{np}^{-2}) \|\gamma_i\| + O_P(J^d \omega_{np} \psi_{np}^{-1}) \|\gamma_i\| \max_j \|v_j\| \sqrt{\sum_j 1\{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}\}} \\ &\leq O_P(J^{2d+b} \omega_{np}^2 \psi_{np}^{-1} \sqrt{Jn^{-1}}) + O_P(J^{g+b+1} \omega_{np} \sqrt{(np)^{-1}}) \sqrt{\sum_j 1\{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}\}} = o_P(1), \end{aligned} \tag{C.4}$$

where we used $\|\gamma_i\| = O_P(J^b \psi_{np}) \|u_i\| = O_P(J^b \psi_{np} \sqrt{Jn^{-1}})$ and $\max_j \|v_j\| = O_P(\sqrt{Jp^{-1}})$ from Assumption 4.4. Finally,

$$\begin{aligned} \sum_{i \notin \mathcal{I}} \|\Delta_{i,6}\|^2 &\leq \max_i \|\Delta_{i,6}\|^2 n \\ &\leq O_P(\omega_{np}^4 \psi_{np}^{-2} J^{1+4d+2b} + \omega_{np}^2 J^{2+2d+2b} p^{-1} \sum_j 1\{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}\}) \\ &= O_P(J^{1+2d+2b} \omega_{np}^2). \end{aligned}$$

□

Lemma C.3. (i) $\|\hat{\Gamma}_S - \Gamma_{0,S} H\|_F^2 = O_P(J^{1+2d+2b} \omega_{np}^2) = o_P(\psi_{np}^2)$ where $\Gamma_{0,S}$ is the submatrix of Γ_0 corresponding to the rows in \mathcal{S} (i.e., sample splitting).

(ii) $\max_{j \leq p} \|\hat{L}_{j,\mathcal{S}}^{-1}\| = O_P(\psi_{np}^{-2})$. Recall that $L_j = \sum_i x_{ij}^2 \gamma_i \gamma_i'$

(iii) $\sum_{j \in \mathcal{G}} \|\hat{L}_{j,\mathcal{S}}^{-1} - L_{j,\mathcal{S}}^{-1}\|^2 = O_P(\omega_{np}^2 J^{1+2d+4b} \psi_{np}^{-6} |\mathcal{G}|)$. Here $\mathcal{G} = \{j : g_j \neq 0\}$.

Proof. (i) First note that $\|\Gamma_{0,S}\|^2 = O_P(J^{2b}\psi_{np}^2)$. It follows from (B.1) and Lemma C.2

$$\begin{aligned} \|\widehat{\Gamma}_S - \Gamma_{0,S}H\|_F^2 &\leq \sum_{i \notin S} \|B^{-1}H'_S \sum_{j=1}^p \varepsilon_{ij}x_{ij}v_j\|^2 + \sum_{k=1}^5 \sum_{i \notin \mathcal{I}} \|\Delta_{i,k}\|^2 \\ &= O_P(\omega_{np}^2 J^{1+2d+2b}) = O_P(\psi_{np}^2). \end{aligned}$$

(ii) Now set $S = \mathcal{I}$. Write $\text{diag}\{X_j^2\}$ be $|\mathcal{I}|_0 \times |\mathcal{I}|_0$ diagonal matrix of x_{ij}^2 . Then

$$\widehat{L}_{j,\mathcal{I}} = \widehat{\Gamma}'_{\mathcal{I}} \text{diag}\{X_j^2\} \widehat{\Gamma}_{\mathcal{I}}, \quad L_{j,\mathcal{I}} = H' \Gamma'_{0,\mathcal{I}} \text{diag}\{X_j^2\} \Gamma_{0,\mathcal{I}} H.$$

$$\begin{aligned} \max_{j \leq p} \|\widehat{L}_{j,\mathcal{I}} - L_{j,\mathcal{I}}\| &\leq 2 \max_{j \leq p} \|(\widehat{\Gamma}_{\mathcal{I}} - \Gamma_{0,\mathcal{I}}H)' \text{diag}\{X_j^2\} \Gamma_{0,\mathcal{I}} H\| \\ &\quad + \max_{j \leq p} \|(\widehat{\Gamma}_{\mathcal{I}} - \Gamma_{0,\mathcal{I}}H)' \text{diag}\{X_j^2\} (\widehat{\Gamma}_{\mathcal{I}} - \Gamma_{0,\mathcal{I}}H)\| \\ &= O_P(\omega_{np} J^{1/2+d+2b} \psi_{np} + \omega_{np}^2 J^{1+2d+2b}) = O_P(\psi_{np}^2). \end{aligned} \tag{C.5}$$

Also, $\min_j \psi_{\min}(L_{j,\mathcal{I}}) \geq c\psi_{\min}(\Theta_0)^2 \geq c\psi_{np}^2$. Thus $\min_j \psi_{\min}(\widehat{L}_{j,\mathcal{I}}) \geq (c - o_P(1))\psi_{np}^2$.

(iii) $\sum_{j \in \mathcal{G}} \|\widehat{L}_{j,\mathcal{I}} - L_{j,\mathcal{I}}\|^2 \leq O_P(J^{1+2d+4b} \omega_{np}^2 \psi_{np}^2 |\mathcal{G}|)$. So

$$\sum_{j \in \mathcal{G}} \|\widehat{L}_{j,\mathcal{I}}^{-1} - L_{j,\mathcal{I}}^{-1}\|^2 \leq \max_j \|\widehat{L}_{j,\mathcal{I}}^{-2}\| \|L_{j,\mathcal{I}}^{-2}\| \sum_{j \in \mathcal{G}} \|\widehat{L}_{j,\mathcal{I}} - L_{j,\mathcal{I}}\|^2 = O_P(\omega_{np}^2 \psi_{np}^{-6} |\mathcal{G}| J^{1+2d+4b}).$$

□

In lemmas below, Δ_d , $d = 1 \sim 4$ are defined in (B.4).

Lemma C.4. $\|\Delta_1\| + \|\Delta_2\| = O_P(\omega_{np} \psi_{np}^{-1} J^{1+d+3b} + J^{b+1/2} \max_{ij} |r_{ij}| \sqrt{n} \psi_{np}^{-1} \|g\| \sqrt{|\mathcal{G}|})$.

Proof. First $\mathbb{E} \sum_{j=1}^p \|\sum_{i \notin \mathcal{I}} H'_S \gamma_i \varepsilon_{ij} x_{ij} g_j\|^2 \leq C J^{2b+1} \psi_{np}^2 \|g\|^2$.

By Lemma C.3, note $\sum_{j=1}^p |g_j| \leq \|g\| \sqrt{|\mathcal{G}|}$,

$$\begin{aligned} \|\Delta_1\| &\leq \max_{ij} \|\widehat{L}_{j,\mathcal{I}}^{-1} r_{ij} x_{ij}^2\| \sum_{j=1}^p |g_j| \sum_{i \notin \mathcal{I}} \|\widehat{\gamma}_i\| \leq J^b \max_{ij} |r_{ij}| \sqrt{n} J \psi_{np}^{-1} \|g\| \sqrt{|\mathcal{G}|}. \\ \|\Delta_2\| &\leq \left(\sum_{k \in \mathcal{G}} \|\widehat{L}_{k,\mathcal{I}}^{-1} - L_{k,\mathcal{I}}^{-1}\|^2 \sum_{j=1}^p \|\sum_{i \notin \mathcal{I}} H'_S \gamma_i \varepsilon_{ij} x_{ij} g_j\|^2 \right)^{1/2} \leq O_P(\omega_{np} \psi_{np}^{-2} |\mathcal{G}|^{1/2} J^{1+d+3b} \|g\|). \end{aligned}$$

□

Lemma C.5. *Suppose $\mathbb{E}(\varepsilon_{ij}|X, \Theta) = 0$. Then*

$$\|\Delta_3\|^2 \leq \sum_{j \in \mathcal{G}} \|v_j\|^2 \|g\|^2 \psi_{np}^{-4} n^2 + \omega_{np}^4 \psi_{np}^{-6} n J^{2+4d+6b} \|g\|^2 |\mathcal{G}| + O_P(J^{1+2b+2d} \psi_{np}^{-4} \|g\|^2 \omega_{np}^2).$$

$$+O_P\left(J^{2d}\omega_{np}^2\psi_{np}^{-2} + \sum_{j=1}^p \mathbb{E}\|v_j\|^4 + J^2p^{-2}[\sum_{\mathcal{B}_i\Delta\bar{\mathcal{B}}} 1]^2\right)\omega_{np}^2\psi_{np}^{-4}\|g\|^2nJ^{2d+2+2b}.$$

Proof. Let $S = \mathcal{I}$. We now bound $\|\Delta_3\|$. First, $\sum_{j=1}^p \sum_{i \notin \mathcal{I}} \varepsilon_{ij}^2 x_{ij}^2 g_j^2 = O_P(n\|g\|^2)$.

$$\begin{aligned} \|\Delta_3\|^2 &\leq \left\| \sum_{j=1}^p \widehat{L}_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} (\widehat{\gamma}_i - H'\gamma_i) \varepsilon_{ij} x_{ij} g_j \right\|^2 \leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} (\widehat{\gamma}_i - H'\gamma_i) \varepsilon_{ij} x_{ij} g_j \right\|^2 \\ &\quad + \sum_{j \in \mathcal{G}} \|\widehat{L}_{j,\mathcal{I}}^{-1} - L_{j,\mathcal{I}}^{-1}\|^2 \|\widehat{\Gamma}_{\mathcal{I}} - \Gamma_{0,\mathcal{I}} H\|_F^2 \sum_{j=1}^p \sum_{i \notin \mathcal{I}} \varepsilon_{ij}^2 x_{ij}^2 g_j^2 \\ &\leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} B^{-1} \sum_{k=1}^p v_k \varepsilon_{ik} \varepsilon_{ij} x_{ij} x_{ik} g_j \right\|^2 + \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \sum_{k=1}^5 \Delta_{i,k} \varepsilon_{ij} x_{ij} g_j \right\|^2 \\ &\quad + O_P(\omega_{np}^4 \psi_{np}^{-6} n J^{2+4d+6b} \|g\|^2 |\mathcal{G}|). \end{aligned}$$

The first term is, let $L_{j,\mathcal{I}}^{-1} B^{-1} v_k = (a_{jk,1}, \dots, a_{jk,J})'$. Then

$$\begin{aligned} &\mathbb{E} \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} B^{-1} \sum_{k=1}^p v_k \varepsilon_{ik} \varepsilon_{ij} x_{ij} x_{ik} g_j \right\|^2 \leq \sum_{t=1}^J \mathbb{E} \left[\sum_{j=1}^p \sum_{i \notin \mathcal{I}} \sum_{k=1}^p a_{jk,t} \varepsilon_{ik} \varepsilon_{ij} x_{ij} x_{ik} g_j \right]^2 \\ &\leq \sum_{t=1}^J \sum_{j=1}^p \sum_{i \notin \mathcal{I}} \sum_{k=1}^p g_j g_k \mathbb{E} a_{jk,t} x_{ij}^2 x_{ik}^2 a_{kj,t} \mathbb{E} \varepsilon_{ik}^2 \mathbb{E} \varepsilon_{ij}^2 \\ &\quad + \sum_{t=1}^J \sum_{j=1}^p \sum_{i \notin \mathcal{I}} \sum_{j'=1}^p \sum_{i' \neq i} \mathbb{E} a_{jj,t} x_{ij}^2 g_j (\mathbb{E} \varepsilon_{ij}^2) a_{j'j',t} \dot{m}_{i'j'}^2 g_{j'} \mathbb{E} \varepsilon_{i'j'}^2 \\ &\leq \mathbb{E} \left[\sum_{j=1}^p \|v_j g_j\| \right]^2 O_P(\psi_{np}^{-4} n^2) \leq \mathbb{E} \sum_{j \in \mathcal{G}} \|v_j\|^2 \|g\|^2 O_P(\psi_{np}^{-4} n^2). \end{aligned}$$

We now bound the second term. Note

$$\mathbb{E} \left\| \sum_{j=1}^p \varepsilon_{ij} x_{ij} g_j L_{j,\mathcal{I}}^{-1} \right\|_F^2 = O(\|g\|^2 \psi_{np}^{-4} J).$$

(i) Lemma C.1 shows

$$\sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 = O_P(nJ^{2d}\omega_{np}^2\psi_{np}^{-2} + n \sum_{j=1}^p \mathbb{E}\|v_j\|^4 + nJ^2p^{-2}[\sum_{\mathcal{B}_i\Delta\bar{\mathcal{B}}} 1]^2).$$

Then

$$\begin{aligned} d &:= \sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 \|\widetilde{V}_{\mathcal{I}} - V_{0,\mathcal{I}} H_S\|^2 \\ &= O_P\left(J^{2d}\omega_{np}^2\psi_{np}^{-2} + \sum_{j=1}^p \mathbb{E}\|v_j\|^4 + J^2p^{-2}[\sum_{\mathcal{B}_i\Delta\bar{\mathcal{B}}} 1]^2\right)\omega_{np}^2\psi_{np}^{-2} J^{2d}n. \end{aligned}$$

Next, let b'_{ju} be the u th row of $L_{j,\mathcal{I}}^{-1}$ and $a_{ij} = \sum_{k=1}^p \tilde{v}_k x_{ik}^2 (v_k - \tilde{v}_k H_S^{-1})' \gamma_i \varepsilon_{ij} x_{ij} g_j$. Then

$$\begin{aligned}
& \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \Delta_{i,1} \varepsilon_{ij} x_{ij} g_j \right\|^2 \\
& \leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} (\widehat{B}_i^{-1} - B^{-1}) \sum_{k=1}^p \tilde{v}_k x_{ik}^2 (v_k - \tilde{v}_k H_S^{-1})' \gamma_i \varepsilon_{ij} x_{ij} g_j \right\|^2 \\
& \leq \sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 \sum_{u=1}^J \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p a_{ij} b'_{ju} \right\|_F^2 \leq O_P(d) \sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 \sum_{j=1}^p \varepsilon_{ij} x_{ij} g_j L_{j,\mathcal{I}}^{-1} \Big\|_F^2 \\
& \leq O_P \left(J^{2d} \omega_{np}^2 \psi_{np}^{-2} + \sum_{j=1}^p \mathbb{E} \|v_j\|^4 + J^2 p^{-2} \left[\sum_{\mathcal{B}_i \Delta \bar{\mathcal{B}}} 1 \right]^2 \right) \omega_{np}^2 \psi_{np}^{-4} \|g\|^2 n J^{2d+2+2b}.
\end{aligned}$$

(ii) Let $a_i = \sum_{k=1}^p \varepsilon_{ik} x_{ik} (\tilde{v}_k - H'_S v_k)$, $b_{ij} = L_{j,\mathcal{I}}^{-1} \varepsilon_{ij} x_{ij} g_j$. First, by (C.1),

$$\begin{aligned}
& \sum_{i \notin \mathcal{I}} \|a_i\|^2 = O_P(n J^{2d} \omega_{np}^2 \psi_{np}^{-2}). \\
& \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \Delta_{i,2} \varepsilon_{ij} x_{ij} g_j \right\|^2 \leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \widehat{B}_i^{-1} \sum_{k=1}^p \varepsilon_{ik} x_{ik} (\tilde{v}_k - H'_S v_k) \varepsilon_{ij} x_{ij} g_j \right\|^2 \\
& \leq \sum_{i \notin \mathcal{I}} \|a_i\|^2 \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p b_{ij} \right\|^2 \max_i \|\widehat{B}_i^{-1}\|^2 \leq O_P(\omega_{np}^4 \psi_{np}^{-6} n J^{2+4d+6b} \|g\|^2 |\mathcal{G}|).
\end{aligned}$$

(iii) Note that $\mathbb{E}(\varepsilon_{ij} | \widetilde{V}_{\mathcal{I}}, X, \Theta) = 0$. Let $a_{jk,d}$ be the d th element of $L_{j,\mathcal{I}}^{-1} B^{-1} \tilde{v}_k$.

$$\begin{aligned}
& \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \Delta_{i,3} \varepsilon_{ij} x_{ij} g_j \right\|^2 \leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} (\widehat{B}_i^{-1} - B^{-1}) \sum_{k=1}^p \tilde{v}_k x_{ik}^2 r_{ik} \varepsilon_{ij} x_{ij} g_j \right\|^2 \\
& + \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} B^{-1} \sum_{k=1}^p \tilde{v}_k x_{ik}^2 r_{ik} \varepsilon_{ij} x_{ij} g_j \right\|^2 \\
& \leq J \sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 \sum_{i \notin \mathcal{I}} \sum_{k=1}^p x_{ik}^4 r_{ik}^2 \left\| \sum_{j=1}^p \varepsilon_{ij} x_{ij} g_j L_{j,\mathcal{I}}^{-1} \right\|_F^2 \\
& + O_P(1) \mathbb{E}_I \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} B^{-1} \sum_{k=1}^p \tilde{v}_k x_{ik}^2 r_{ik} \varepsilon_{ij} x_{ij} g_j \right\|^2 \\
& \leq \left(J \sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 + 1 \right) \|R\|_F^2 \|g\|^2 \psi_{np}^{-4} J \\
& \leq \left(J^{1+2d} n \omega_{np}^2 \psi_{np}^{-2} + n J^2 \mathbb{E} \max_{j \leq p} \|v_j\|^2 + n J^3 p^{-2} \left[\sum_{\mathcal{B}_i \Delta \bar{\mathcal{B}}} 1 \right]^2 + 1 \right) \|R\|_F^2 \|g\|^2 \psi_{np}^{-4} J.
\end{aligned}$$

We note that this term is dominated by other terms. In particular,

$$\begin{aligned} & \left(nJ^3 p^{-2} \left[\sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1 \right]^2 \right) \|R\|_F^2 \|g\|^2 \psi_{np}^{-4} J \\ &= o_P \left(\frac{np}{(n+p)J^3 + J\|R\|_{(n)}^2} \right)^2 \|R\|_F^2 \|g\|^2 \psi_{np}^{-4} nJ^4 p^{-2} \\ &\leq o_P \left(\frac{n}{J^2} \right) \|R\|_F^2 \|g\|^2 \psi_{np}^{-4} \text{ dominated by the (v) term below.} \end{aligned}$$

(iv) Let b'_{ju} be the u th row of $L_{j,\mathcal{I}}^{-1}$ and $a_{ij} = \sum_{k=1}^p \varepsilon_{ik} x_{ik} v_k \varepsilon_{ij} x_{ij} g_j$, and $f := \sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2$, $c_{iutqkj} = v_{k,q} x_{ij} x_{ik} g_j b_{ju,t}$

$$\begin{aligned} & \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \Delta_{i,4} \varepsilon_{ij} x_{ij} g_j \right\|^2 \leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} (\widehat{B}_i^{-1} - B^{-1}) \sum_{k=1}^p \varepsilon_{ik} x_{ik} v_k \varepsilon_{ij} x_{ij} g_j \right\|^2 \\ &\leq f \sum_{u=1}^J \sum_{i \notin \mathcal{I}} \sum_{j=1}^p \| \sum_{k=1}^p a_{ij} b'_{ju} \|_F^2 \leq O_P(f) \sum_{t,q,u \leq J} \sum_{i \notin \mathcal{I}} \mathbb{E} \left[\left| \sum_{j=1}^p \sum_{k=1}^p \varepsilon_{ik} \varepsilon_{ij} c_{ikjutq} \right|^2 \middle| X, \Theta \right] \\ &\leq O_P(f) \sum_{t,q,u \leq J} \sum_{i \notin \mathcal{I}} \sum_{k=1}^p \sum_{j=1}^p c_{iutqkj}^2 + O_P(f) \sum_{t,q,u \leq J} \sum_{i \notin \mathcal{I}} \left(\sum_{k=1}^p c_{iutqkk} \right)^2 \\ &\leq O_P(fn) \sum_{j=1}^p J g_j^2 \|L_j^{-1}\|_F^2 \leq \text{the bound for } \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \Delta_{i,1} \varepsilon_{ij} x_{ij} g_j \right\|^2. \end{aligned}$$

(v) Let $a_{jk,t}$ be the t th element of $L_{j,\mathcal{I}}^{-1} B^{-1} \tilde{v}_k$. Because $\mathbb{E}(\varepsilon_{ij} | \Theta, X, \mathcal{I}) = 0$, and $\mathbb{E}(x_{ik}^2 - \mathbb{E}x_{ik}^2 | \Theta, \mathcal{I}) = 0$. Let A_{ijt} be p -dimensional vector of $a_{jk,t}(v_k - \tilde{v}_k)' \gamma_i$. Let $e'_k = (0, \dots, 0, 1, 0, \dots)$. Then $\max_{k \leq p} \|\tilde{v}_k\| = \max_k \|e'_k \tilde{V}\| \leq \max_k \|e_k\| = 1$. Under Assumption 4.3 (ii-b),

$$\begin{aligned} & \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \Delta_{i,5} \varepsilon_{ij} x_{ij} g_j \right\|^2 \\ &\leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} B^{-1} \sum_{k=1}^p \tilde{v}_k (x_{ik}^2 - \mathbb{E}x_{ik}^2) (v_k - H_S^{-1} \tilde{v}_k)' \gamma_i \varepsilon_{ij} x_{ij} g_j \right\|^2 \\ &\leq O_P(1) \sum_{t \leq J} \sum_{i \notin \mathcal{I}} \sum_{j=1}^p \mathbb{E}_I \text{Var}_I \left[\sum_{k=1}^p a_{jk,t} (x_{ik}^2 - \mathbb{E}x_{ik}^2) (v_k - H_S^{-1} \tilde{v}_k)' \gamma_i \varepsilon_{ij} \middle| \Theta, X \right] x_{ij}^2 g_j^2 \\ &\leq O_P(1) \sum_{t \leq J} \sum_{i \notin \mathcal{I}} \sum_{j=1}^p \mathbb{E}_I A'_{ijt} \text{Var}_I [X_i^2 | \Theta] A_{ijt} g_j^2 \end{aligned}$$

$$\begin{aligned}
&\leq O_P(1) \sum_{i \notin \mathcal{I}} \sum_{j=1}^p \mathbf{E}_I \sum_{k=1}^p \|a_{jk}\|^2 [(v_k - H_S^{-1'} \tilde{v}_k)' \gamma_i]^2 g_j^2 \\
&\leq O_P(J^{1+2b} \psi_{np}^{-2}) \|g\|^2 \max_k \|\tilde{v}_k\|^2 \|V - \tilde{V} H_S^{-1}\|^2 \leq O_P(J^{1+2b+2d} \psi_{np}^{-4} \|g\|^2 \omega_{np}^2).
\end{aligned}$$

(vi) Recall $\Delta_{i,6} = B^{-1} \sum_{j=1}^p \tilde{v}_j x_{ij}^2 (v_j - H_S^{-1'} \tilde{v}_j)' \gamma_i - B^{-1} \sum_{j \in \mathcal{B}} \tilde{v}_j (v_j - H_S^{-1'} \tilde{v}_j)' \gamma_i$. Because $\mathbf{E}(\varepsilon_{ij} | \Theta, X, \mathcal{I}) = 0$, we have $\mathbf{E}(\varepsilon_{ij} | \Theta, X, \mathcal{I}, \Delta_{i,6}) = 0$. So by the bound for $\max_i \Delta_{i,6}$ in (C.4),

$$\begin{aligned}
&\left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} \Delta_{i,6} \varepsilon_{ij} x_{ij} g_j \right\|^2 \leq O_P(1) \sum_{j=1}^p \sum_{i \notin \mathcal{I}} \|L_{j,\mathcal{I}}^{-1}\|^2 \|\Delta_{i,6}\|^2 g_j^2 x_{ij}^2 \text{Var}(\varepsilon_{ij} | \Theta, X, \mathcal{I}) \\
&\leq O_P(n \psi_{np}^{-4} \|g\|^2) \max_i \|\Delta_{i,6}\|^2 \leq O_P(J^{1+2b+2d} \psi_{np}^{-4} \|g\|^2 \omega_{np}^2).
\end{aligned}$$

Putting together we obtain the desired result. \square

Lemma C.6. *Suppose $\mathbf{E}(\varepsilon_{ij} | X, \Theta) = 0$. Then*

$$\begin{aligned}
\|\Delta_4\|^2 &\leq O_P \left(J^{2+2d+2b} \omega_{np}^2 \mathbf{E} \max_{j \leq p} \|v_j\|^2 + np J^2 \max_{ij} r_{ij}^2 + \psi_{np}^{-2} J^{2+4d+2b} \omega_{np}^4 \right) \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 \psi_{np}^{-2} J^{2b} \\
&\quad + (\omega_{np}^4 \psi_{np}^{-2} J^{3+4d+8b} + J^{2+2b}) \sum_{j=1}^p \|v_j g_j\|^2 |\mathcal{G}| \psi_{np}^{-2}.
\end{aligned}$$

Proof. First,

$$\begin{aligned}
&\sum_{j=1}^p \sum_{i \notin \mathcal{I}} \|H^{-1} v_j \hat{\gamma}_i' x_{ij}^2 g_j\|^2 \leq \sum_{i \notin \mathcal{I}} \|\hat{\gamma}_i\|^2 \sum_{j=1}^p \|v_j\|^2 g_j^2 = O_P(J^{1+2b} \psi_{np}^2) \sum_{j=1}^p \|v_j\|^2 g_j^2 \\
&\mathbf{E} \left\| \sum_{i \notin \mathcal{I}} x_{ij}^2 \sum_{k=1}^p \gamma_i \varepsilon_{ik} x_{ik} v_k' \right\|^2 \leq O(J^{2+2b} \psi_{np}^2), \quad \mathbf{E} \left\| \sum_{k=1}^p \varepsilon_{ik} x_{ik} H^{-1'} v_k \right\|^2 = O(J).
\end{aligned}$$

Next, define and bound: (using Lemmas C.2 C.3)

$$\begin{aligned}
I &:= \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} x_{ij}^2 B^{-1} \sum_{k=1}^p \varepsilon_{ik} x_{ik} v_k' H^{-1} v_j \hat{\gamma}_i g_j \right\|^2 \\
&\leq \sum_{j \in \mathcal{G}} \|L_{j,\mathcal{I}}^{-1} B^{-1}\|^2 \left\| \sum_{i \notin \mathcal{I}} x_{ij}^2 \sum_{k=1}^p \gamma_i \varepsilon_{ik} x_{ik} v_k' \right\|^2 \|H^{-1}\|^2 \sum_{j \in \mathcal{G}} \|v_j g_j\|^2 \\
&\quad + \sum_{i \notin \mathcal{I}} \left\| \sum_{j=1}^p x_{ij}^2 g_j L_{j,\mathcal{I}}^{-1} B^{-1} v_j \right\|^2 \left\| \sum_{k=1}^p \varepsilon_{ik} x_{ik} H^{-1'} v_k \right\|^2 \sum_{i \notin \mathcal{I}} \|(\hat{\gamma}_i - H' \gamma_i)\|^2 \\
&\leq O_P(|\mathcal{G}| \psi_{np}^{-2} J^{2+2b} \sum_{j \in \mathcal{G}} \|v_j g_j\|^2 + n \psi_{np}^{-4} \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 J^{2+2d+2b} \omega_{np}^2).
\end{aligned}$$

$$\begin{aligned}
II &:= \sum_{d=1}^6 \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} x_{ij}^2 \Delta'_{i,d} H^{-1} v_j (\widehat{\gamma}_i - H' \gamma_i) g_j \right\|^2 \\
&\leq O_P(1) \left[\sum_{d=1}^6 \sum_{i \notin \mathcal{I}} \|\Delta_{i,d}\|^2 \right] \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 \sum_{i \notin \mathcal{I}} \|(\widehat{\gamma}_i - H' \gamma_i)\|^2 \max_j \|L_{j,\mathcal{I}}^{-1}\|^2 \\
&\leq O_P(J^{2+4d+4b} \omega_{np}^4 \|g\|^2) \sum_{j \in \mathcal{G}} \|v_j\|^2 \psi_{np}^{-4}. \\
III &:= \sum_{j \in \mathcal{G}} \|\widehat{L}_{j,\mathcal{I}}^{-1} - L_{j,\mathcal{I}}^{-1}\|^2 \sum_{i \notin \mathcal{I}} \|\gamma'_i H - \widehat{\gamma}'_i\|^2 \sum_{j=1}^p \sum_{i \notin \mathcal{I}} \|H^{-1} v_j \widehat{\gamma}'_i x_{ij}^2 g_j\|^2 \\
&= O_P(\omega_{np}^4 \psi_{np}^{-4} |\mathcal{G}| J^{3+4d+8b} \sum_{j=1}^p \|v_j\|^2 g_j^2). \\
\|\Delta_4\|^2 &= \left\| \sum_{j=1}^p \widehat{L}_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} x_{ij}^2 (\gamma'_i H - \widehat{\gamma}'_i) H^{-1} v_j \widehat{\gamma}_i g_j \right\|^2 \\
&\leq I + II + III + \sum_{d=1}^6 \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} \sum_{i \notin \mathcal{I}} H' \gamma_i x_{ij}^2 v'_j H^{-1'} \Delta_{i,d} g_j \right\|^2 \\
&\leq (\omega_{np}^4 \psi_{np}^{-2} J^{3+4d+8b} + J^{2+2b}) \sum_{j=1}^p \|v_j g_j\|^2 |\mathcal{G}| \psi_{np}^{-2} + \sum_{j \in \mathcal{G}} \|v_j\|^2 \|g\|^2 \psi_{np}^{-4} J^{2+4d+4b} \omega_{np}^4 \\
&\quad + \sum_{d=1}^6 \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} H' \sum_{i \notin \mathcal{I}} g_j \gamma_i x_{ij}^2 v'_j H^{-1'} \Delta_{i,d} \right\|^2.
\end{aligned}$$

We now bound the last term on the right hand side. Recall that

$$\sum_{i \notin \mathcal{I}} \|(\widehat{B}_i^{-1} - B^{-1})\|^2 = O_P(J^{2d} n \omega_{np}^2 \psi_{np}^{-2} + n \sum_{j=1}^p \mathbb{E} \|v_j\|^4 + n J^2 p^{-2} [\sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1]^2).$$

(i) Recall $\sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 = O_P(J^{1+2b} \psi_{np}^2)$.

$$\begin{aligned}
&\left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} H' \sum_{i \notin \mathcal{I}} g_j \gamma_i x_{ij}^2 v'_j H^{-1'} \Delta_{i,1} \right\|^2 \\
&\leq O_P(1) \sum_{i \notin \mathcal{I}} \|(\widehat{B}_i^{-1} - B^{-1})\|^2 \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 J \|\widetilde{V}_S - V_0 H_S\|_F^2 \sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 \max_j \|L_{j,\mathcal{I}}^{-1} H'\|^2 \\
&\leq O_P(\omega_{np}^2 \psi_{np}^{-2} J^{2d} + \sum_{j=1}^p \mathbb{E} \|v_j\|^4 + J^2 p^{-2} [\sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1]^2) \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 n \omega_{np}^2 \psi_{np}^{-4} J^{2d+1+2b}.
\end{aligned}$$

We note that the term involving $\sum_{j \in \mathcal{B}_i \Delta \bar{\mathcal{B}}} 1$ is dominated by other terms so can be ignored.

(ii) As $\mathbf{E}_I(\varepsilon_{ik}|\widehat{B}_i, \widetilde{V}, \Theta, X) = 0$ for $i \notin \mathcal{I}$, ($\widehat{B}_i, \widetilde{V}$ are estimated using data in \mathcal{I}),

$$\begin{aligned}
& \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} H' \sum_{i \notin \mathcal{I}} g_j \gamma_i x_{ij}^2 v_j' H^{-1'} \Delta_{i,2} \right\|^2 \\
& \leq \left\| \sum_{j \in \mathcal{G}} g_j L_{j,\mathcal{I}}^{-1} H' \sum_{i \notin \mathcal{I}} \gamma_i x_{ij}^2 v_j' H^{-1'} \widehat{B}_i^{-1} \sum_{k=1}^p \varepsilon_{ik} x_{ik} (\widetilde{v}_k - H'_S v_k) \right\|^2 \\
& \leq O_P(1) \sum_{j \in \mathcal{G}} \|g_j L_{j,\mathcal{I}}^{-1} H'\|^2 \sum_{t=1}^J \sum_{j \in \mathcal{G}} \text{Var}_I \left[\sum_{k=1}^p \sum_{i \notin \mathcal{I}} \gamma_{i,t} x_{ij}^2 v_j' H^{-1'} \widehat{B}_i^{-1} \varepsilon_{ik} x_{ik} (\widetilde{v}_k - H'_S v_k) \right] \\
& \leq O_P(1) \sum_{j \in \mathcal{G}} \|g_j L_{j,\mathcal{I}}^{-1} H'\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 \sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 \|\widetilde{V}_S - V_0 H_S\|_F^2 \\
& \leq O_P(\psi_{np}^{-4} \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 J^{1+2b+2d} \omega_{np}^2)
\end{aligned}$$

(iii) By (C.2)(C.3) $\sum_{d=3,5} \sum_i \|\Delta_{i,d}\|^2 = O_P(a_n)$, (sharper bound than the conclusion in Lemmas C.2), where

$$a_n := J^{1+2b+4g} \omega_{np}^4 \psi_{np}^{-2} + J^{1+2d+2b} \omega_{np}^2 \mathbf{E} \max_{j \leq p} \|v_j\|^2 + npJ \max_{ij} r_{ij}^2.$$

Hence

$$\begin{aligned}
& \sum_{d=3,5} \left\| \sum_{i \notin \mathcal{I}} \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} H' g_j \gamma_i x_{ij}^2 v_j' H^{-1'} \Delta_{i,d} \right\|^2 \\
& \leq \sum_{i \notin \mathcal{I}} \|\gamma_i\|^2 \sum_{j=1}^p \|L_{j,\mathcal{I}}^{-1} H' g_j\|^2 \sum_{j \in \mathcal{G}} \|v_j'\|^2 \sum_{d=3,5} \sum_{i \notin \mathcal{I}} \|\Delta_{i,d}\|^2 \\
& \leq O_P(J^{1+2b} \psi_{np}^{-2} \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2) \sum_{d=3,5} \sum_{i \notin \mathcal{I}} \|\Delta_{i,d}\|^2 \leq O_P(a_n) J^{1+2b} \psi_{np}^{-2} \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2.
\end{aligned}$$

This is the leading term.

(iv) $\mathbf{E}_I(\varepsilon_{ik}|H, \widehat{B}_i, \widetilde{V}, \Theta, X) = 0$,

$$\begin{aligned}
& \left\| \sum_{i \notin \mathcal{I}} \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} H' g_j \gamma_i x_{ij}^2 v_j' H^{-1'} \Delta_{i,4} \right\|^2 \\
& \leq \left\| \sum_{j=1}^p L_{j,\mathcal{I}}^{-1} H' g_j \sum_{k=1}^p \sum_{i \notin \mathcal{I}} \gamma_i x_{ij}^2 v_j' H^{-1'} (\widehat{B}_i^{-1} - B^{-1}) \varepsilon_{ik} x_{ik} v_k \right\|^2 \\
& \leq O_P(1) \sum_{j=1}^p \|L_{j,\mathcal{I}}^{-1} H' g_j\|^2 \sum_{j \in \mathcal{G}} \sum_{t=1}^J \text{Var}_I \left[\sum_{k=1}^p \sum_{i \notin \mathcal{I}} \gamma_{i,t} x_{ij}^2 v_j' H^{-1'} (\widehat{B}_i^{-1} - B^{-1}) v_k \varepsilon_{ik} x_{ik} \right] \\
& \leq O_P(1) \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 \sum_{i \notin \mathcal{I}} \|\widehat{B}_i^{-1} - B^{-1}\|^2 \|\gamma_i\|^2 J \psi_{np}^{-4}
\end{aligned}$$

$$\leq O_P(1) \left(\max_i \|u_i\|^2 n J^{2d} \omega_{np}^2 \psi_{np}^{-2} + n \max_i \|u_i\|^2 \sum_{j=1}^p \mathbb{E} \|v_j\|^4 \right) J^{2b} \psi_{np}^{-2} \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2.$$

This is dominated by other terms. Also the last term involving $\Delta_{i,6}$, depending on $\bar{\mathcal{B}} \Delta \mathcal{B}_i$, is dominated by other terms. So together leads to the desired result. \square

We now verify (B.6) using more primitive conditions.

Lemma C.7. *Suppose $\max_{ij} |r_{ij}|^2 (p \vee n)^3 J^3 = o(1)$. Then*

$$|r'_i g| + J^b \|u_i\| \psi_{np} \xi_{np} = o_P(p^{-1/2} + \|u_i\| \|g\|).$$

holds true when either case (I) or case (II) below holds:

(I) sparse g : $\|g\| \leq C$,

$(p \vee n)^{3/4} J^{1+d+2b} = o(\psi_{np})$ and $J^{3+2d+6b} = o(\min(\sqrt{p}, p/\sqrt{n}))$.

(II) dense g : $\max_{j \leq p} |g_j| \leq Cp^{-1}$.

$(p \vee n)^{3/4} J^{5/4+d+2b} + J^{7/2+5b+2d} p n^{-1/2} = o(\psi_{np})$, and $J^{3+3b+g} = o(\min(\sqrt{n}, \sqrt{p}))$.

Proof. First,

$$\begin{aligned} \xi_{np}^2 &:= \sum_{d=1}^6 a_d + \mu_{np}^2 \\ a_1 &= \left(\omega_{np}^4 \psi_{np}^{-2} J^{3+4d+8b} + J^{2+2b} \right) \sum_{j=1}^p \|v_j g_j\|^2 |\mathcal{G}| \psi_{np}^{-2} \\ a_{25} &= \left(J^{2+2d+4b} \omega_{np}^2 \mathbb{E} \max_{j \leq p} \|v_j\|^2 + \psi_{np}^{-2} J^{2+4d+4b} \omega_{np}^4 \right) \|g\|^2 \sum_{j \in \mathcal{G}} \|v_j\|^2 \psi_{np}^{-2} \\ a_3 &= \left(\omega_{np}^2 \psi_{np}^{-2} n J^{2d} + 1 \right) \psi_{np}^{-4} \|g\|^2 |\mathcal{G}| \omega_{np}^2 J^{2+2d+6b} \\ a_4 &= \left(1 + n J^{2d+1} \omega_{np}^2 \psi_{np}^{-2} + n J \sum_{j=1}^p \mathbb{E} \|v_j\|^4 \right) \omega_{np}^2 \psi_{np}^{-4} \|g\|^2 J^{1+2d+2b} \\ a_5 &= \left(p J \sum_{j \in \mathcal{G}} \|v_j\|^2 + |\mathcal{G}| \right) n \max_{ij} |r_{ij}|^2 \|g\|^2 \psi_{np}^{-2} J^{2b+1} \\ \mu_{np}^2 &:= n p^{-2} \omega_{np}^2 \psi_{np}^{-4} \|g\|^2 J^{4+2d+2b} \left[\sum_{\mathcal{B}_i \Delta \bar{\mathcal{B}}} 1 \right]^2. \end{aligned}$$

Therefore, we aim to show

$$|r'_i g|^2 + J^{2b} \|u_i\|^2 \psi_{np}^2 a_5 = o_P(p^{-1} + \|u_i\|^2 \|g\|^2) \quad (\text{C.6})$$

$$J^{2b} \|u_i\|^2 \psi_{np}^2 (a_1 + \dots + a_4) = o_P(p^{-1} + \|u_i\|^2 \|g\|^2) \quad (\text{C.7})$$

$$J^b \|u_i\| \psi_{np} \mu_{np} = o_P(p^{-1/2} + \|u_i\| \|g\|). \quad (\text{C.8})$$

Under $\max_{ij} |r_{ij}|^2 (p \vee n)^2 J^{3+4b} = o(1)$, (C.6) holds. In particular, $pJ \sum_{j \in \mathcal{G}} \|v_j\|^2 + |\mathcal{G}| \leq O_P(pJ^2)$ and

$$J^{2b} \psi_{np}^2 a_5 = o_P(\|g\|^2). \quad (\text{C.9})$$

Proof of (C.7). We consider two cases.

CASE I: sparse g . In this case, $\|g\| + |\mathcal{G}| < C$ and we use bound: $\sum_{j \in \mathcal{G}} \|v_j\|^2 \leq \max_{j \in \mathcal{G}} \|v_j\|^2 |\mathcal{G}| \leq O_P(J/p)$. We have the following bounds

$$\begin{aligned} a_1 + a_2 &\leq O_P(\omega_{np}^2 \psi_{np}^{-2} J^{2d+4b} + p^{-1}) J^{4+2d+4b} p^{-1} \omega_{np}^2 \psi_{np}^{-2} \|g\|^2 \\ a_3 &= O_P(\omega_{np}^2 \psi_{np}^{-2} n J^{2d} + 1) \psi_{np}^{-4} \omega_{np}^2 J^{2+2d+6b} \|g\|^2 \\ a_4 &= O_P(1 + n J^{2d+1} \omega_{np}^2 \psi_{np}^{-2} + n J^3 p^{-1}) \omega_{np}^2 \psi_{np}^{-4} J^{1+2d+2b} \|g\|^2 \end{aligned}$$

So $J^{2b} \|u_i\|^2 \psi_{np}^2 (a_1 + \dots + a_4) = o_P(\|u_i\|^2 \|g\|^2)$ holds as long as: $(p \vee n)^{3/4} J^{1+d+2b} = o(\psi_{np})$ and $J^{3+2d+6b} \ll \min(\sqrt{p}, p/\sqrt{n})$.

CASE II: dense g . In this case $\max_{j \leq p} |g_j| \leq Cp^{-1}$, $\|g\|^2 \leq Cp^{-1}$, and $|\mathcal{G}| = O(p)$. We use the bounds $\sum_{j=1}^p \|v_j g_j\|^2 \leq CJ \|g\|^2/p$, $\sum_{j \in \mathcal{G}} \|v_j\|^2 \leq J$. Then

$$a_1 + \dots + a_4 \leq (\omega_{np}^2 \psi_{np}^{-2} J^{2+2d+4b} + J^2 p^{-1} + pn \omega_{np}^2 \psi_{np}^{-4} J^{2d+2b} + \psi_{np}^{-2} J^{2b} p) J^{2+2d+4b} \|g\|^2 \psi_{np}^{-2} \omega_{np}^2.$$

Hence $J^{2b} \|u_i\|^2 \psi_{np}^2 (a_1 + \dots + a_4) = o_P(p^{-1})$ holds as long as: $J^{7/2+5b+2d} pn^{-1/2} = o(\psi_{np})$, $J^{3+3b+g} = o(\min(\sqrt{n}, \sqrt{p}))$ and $(p \vee n)^{3/4} J^{5/4+d+2b} = o(\psi_{np})$.

Proof of (C.8). We divide into two cases.

CASE I: sparse g .

We have $J^b \|u_i\| \psi_{np} \mu_{np} = o_P(\|u_i\| \|g\|)$.

CASE II: dense g .

We have $\|u_i\| \psi_{np} \mu_{np} = o_P(p^{-1/2})$.

These hold under the condition

$$\max_{i \leq n} \sum_{j=1}^p 1\{j \in \bar{\mathcal{B}} \triangle \mathcal{B}_i\} = o_P\left(\frac{\min\{n, p, \psi_{np}\} p}{(n+p)J + \|R\|_{(n)}^2}\right) J^{-(2+d+2b)}.$$

□

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DEPARTMENT OF ECONOMICS, MIT, CAMBRIDGE, MA 02139

Email address: vchern@mit.edu

BOOTH SCHOOL OF BUSINESS, UNIVERSITY OF CHICAGO, CHICAGO, IL 60637

Email address: Christian.Hansen@chicagobooth.edu

DEPARTMENT OF ECONOMICS, RUTGERS UNIVERSITY, NEW BRUNSWICK, NJ 08901

Email address: yuan.liao@rutgers.edu

DEPARTMENT OF ECONOMICS, BRANDEIS UNIVERSITY, 415 SOUTH ST, WALTHAM, MA 02453

Email address: yinchuzhu@brandeis.edu