

Proofs

We first present several lemmas to deal with various terms concerning the bias and variance components in (8), (12), and (18). In the proofs, we use C to denote a generic positive constant that can take different values at different places.

Lemma 1. *Under assumptions (A1), (A2) and (A4), $E[(B(T) - A_0X)^{\otimes 2}]$ has eigenvalues bounded away from zero and infinity.*

Proof of Lemma 1. By the smoothness assumption (A4), there exists $\gamma = (\gamma_1, \dots, \gamma_p) \in R^{K \times p}$ such that

$$|E[X_j|T = t] - \gamma_j^T \mathbf{B}(t)| \leq CK^{-d'}. \quad (27)$$

Since $E[X_j|T = t]$ is assumed to be smooth for $t \in [0, 1]$, it is also bounded on $[0, 1]$. Then by (27), $\gamma_j^T \int_0^1 \mathbf{B}(t) \mathbf{B}^T(t) dt \gamma_j$ is bounded by a constant. By well-known properties of splines, eigenvalues of $\int_0^1 \mathbf{B}(t) \mathbf{B}^T(t) dt$ are bounded away from zero, and thus we can deduce that $\|\gamma_j\|$ is bounded. In turn this implies that the operator norm of γ is bounded.

Then we show that the operator norm of

$$\begin{pmatrix} \mathbf{I} & \mathbf{0} \\ -\gamma^T & \mathbf{I} \end{pmatrix} \quad (28)$$

is bounded. This is easily shown by definition, since

$$\begin{aligned} & \left\| \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ -\gamma^T & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{u} \\ \mathbf{v} \end{pmatrix} \right\|^2 \\ &= \left\| \begin{pmatrix} \mathbf{u} \\ \mathbf{v} - \gamma^T \mathbf{u} \end{pmatrix} \right\|^2 \\ &\leq \|\mathbf{u}\|^2 + 2(\|\mathbf{v}\|^2 + \|\gamma\|_{op}^2 \|\mathbf{u}\|^2) \leq C(\|\mathbf{u}\|^2 + \|\mathbf{v}\|^2), \end{aligned}$$

where $\|\cdot\|_{op}$ for a matrix denotes its operator norm (and we shall use $\|\cdot\|$ to denote its Frobenius norm). Note that the inverse of (28) is $\begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \gamma^T & \mathbf{I} \end{pmatrix}$ which also has a bounded operator norm.

Let

$$\mathbf{A} = E \left[\begin{pmatrix} B(T)B^T(T) & B(T)X^T \\ XB^T(T) & XX^T \end{pmatrix} \right] = E \left[\begin{pmatrix} B(T) \\ X \end{pmatrix} (B^T(T) \ X^T) \right].$$

Premultiplying \mathbf{A} by (28) and post-multiplying \mathbf{A} by the transpose of (28), we get the matrix

$$E \left[\begin{pmatrix} B(T) \\ X - \gamma^T B(T) \end{pmatrix} (B^T(T) \ X^T - B^T(T)\gamma) \right].$$

The operator norm for the difference between the above and

$$E \left[\begin{pmatrix} B(T) \\ X - E[X|T] \end{pmatrix} (B^T(T) \ X^T - E[X^T|T]) \right]$$

is (using operator norm is bounded by the maximum row sum of absolute values of entries) $O(K^{-d'}) = o(1)$. The displayed matrix above is block diagonal and the eigenvalues of both blocks are bounded and bounded away from zero by assumptions (A2) and (A3). This proves \mathbf{A} has eigenvalues bounded away from zero and infinity.

Since $A_0 = E[B(T)X^T](E[XX^T])^{-1}$, $E[(B(T) - A_0X)^{\otimes 2}] = E[B(T)B^T(T)] - E[B(T)X^T](E[XX^T])^{-1}E[XB^T(T)]$ has eigenvalues bounded away from zero by Lemma 2. \square

Lemma 2. *If a symmetric matrix $\begin{pmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}^T & \mathbf{C} \end{pmatrix}$ has all eigenvalues inside the interval $[c, C]$ for some $0 < c < C < \infty$, then $\mathbf{C} - \mathbf{B}^T \mathbf{A}^{-1} \mathbf{B}$ also has all its eigenvalues inside the interval $[c, C]$.*

Proof of Lemma 2. Obviously eigenvalues of $\mathbf{C} - \mathbf{B}^T \mathbf{A}^{-1} \mathbf{B}$ are no larger than

that of \mathbf{C} and thus bounded by C . Next, we have the identity

$$\begin{pmatrix} \mathbf{I} & \mathbf{0} \\ -\mathbf{B}^T \mathbf{A}^{-1} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}^T & \mathbf{C} \end{pmatrix} \begin{pmatrix} \mathbf{I} & -\mathbf{A}^{-1} \mathbf{B} \\ \mathbf{0} & \mathbf{I} \end{pmatrix} = \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0}^T & \mathbf{C} - \mathbf{B}^T \mathbf{A}^{-1} \mathbf{B} \end{pmatrix}$$

Thus for any vector \mathbf{b} with dimension same as that of \mathbf{C} , we have

$$\begin{aligned} & \mathbf{b}^T (\mathbf{C} - \mathbf{B}^T \mathbf{A}^{-1} \mathbf{B}) \mathbf{b} \\ &= (\mathbf{0}^T, \mathbf{b}^T) \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0}^T & \mathbf{C} - \mathbf{B}^T \mathbf{A}^{-1} \mathbf{B} \end{pmatrix} \begin{pmatrix} \mathbf{0} \\ \mathbf{b} \end{pmatrix} \\ &= (\mathbf{0}^T, \mathbf{b}^T) \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ -\mathbf{B}^T \mathbf{A}^{-1} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}^T & \mathbf{C} \end{pmatrix} \begin{pmatrix} \mathbf{I} & -\mathbf{A}^{-1} \mathbf{B} \\ \mathbf{0} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{0} \\ \mathbf{b} \end{pmatrix} \\ &= (-\mathbf{b}^T \mathbf{B}^T \mathbf{A}^{-1}, \mathbf{b}^T) \begin{pmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}^T & \mathbf{C} \end{pmatrix} \begin{pmatrix} -\mathbf{A}^{-1} \mathbf{B} \mathbf{b} \\ \mathbf{b} \end{pmatrix} \\ &\geq \|\mathbf{b}\|^2 c, \end{aligned}$$

which completes the proof. □

Lemma 3. *For any unit vector $\mathbf{a} \in R^K$, $\|\mathbf{a}^T (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{X}\| = O_p(1)$. If \mathbf{a} has bounded support, $\|\mathbf{a}^T (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{X}\| = O_p(K^{-1/2})$.*

Proof of Lemma 3. The first statement is easily obtained by the bound $\|(\mathbf{Z}^T \mathbf{Z})^{-1}\|_{op} = O_p(1/n)$ (using for example Lemma 3 in Wang et al. (2011)) and $\|\mathbf{Z}^T \mathbf{X}\| = O_p(n)$ (using that $E[B_k(T_i)X_{ij}] = E[B_k(T_i)E[X_{ij}|T_i]] \leq CE[B_k(T_i)] = O(1/\sqrt{K})$).

For the second statement, we assume $\mathbf{a} = (1, 0, \dots, 0)^T$ without loss of generality. We also condition on the event that eigenvalues of $(\mathbf{Z}^T \mathbf{Z}/n)^{-1}$ are bounded. By Lemma 6.3 of Zhou et al. (1998), the (j, j') entry of $(\mathbf{Z}^T \mathbf{Z})^{-1}$ is bounded by $(C/n)\gamma^{|j-j'|}$ for some $\gamma < 1$. This means the j -th component of $\mathbf{a}^T (\mathbf{Z}^T \mathbf{Z})^{-1}$ is bounded by $(C/n)\gamma^j$. Thus, denoting the j -th column of \mathbf{X} as \mathbf{X}_j ,

$$|\mathbf{a}^T (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{X}_j|$$

$$\leq C \sum_{k=1}^K \gamma^k \sum_{i=1}^n B_k(T_i) |X_{ij}| / n. \quad (29)$$

Since $E[B_k(T)|X_j] \leq CK^{-1/2}$, the above is $O_p(K^{-1/2})$ and the lemma is proved. \square

Lemma 4. *For any unit vector $\mathbf{a} \in R^K$, $|\mathbf{a}^T(\mathbf{Z}^T\mathbf{Z})^{-1}\mathbf{Z}^T\mathbf{R}| = O_p(K^{-d})$. If \mathbf{a} has bounded support, $|\mathbf{a}^T(\mathbf{Z}^T\mathbf{Z})^{-1}\mathbf{Z}^T\mathbf{R}| = O_p(K^{-d-1/2})$.*

Proof of Lemma 4. Using that the components of \mathbf{R} are bounded by CK^{-d} , the proof is basically the same as the proof of Lemma 3 and thus omitted. \square

Lemma 5. *Suppose now $\boldsymbol{\theta}_0$ is chosen as in (19). For any unit vector $\mathbf{a} \in R^K$, $|\mathbf{a}^T(\mathbf{Z}^T\mathbf{Z})^{-1}\mathbf{Z}^T\mathbf{R}| = O_p(n^{-1/2}K^{-d+1/2})$. If \mathbf{a} is bounded support, it has order $O_p(n^{-1/2}K^{-d})$.*

Proof of Lemma 5. For general \mathbf{a} , this is easily proved by noting that $\sum_i B(T_i)r_i$ has mean zero and thus is $O_p(\sqrt{n}K^{-d})$ and thus $\|\mathbf{Z}^T\mathbf{R}\| = O_p(\sqrt{n}K^{-d+1/2})$. For \mathbf{a} with a bounded support, we can improve the rate as follows. Suppose without loss of generality $\mathbf{a} = (1, 0, \dots, 0)^T$. By Lemma 6.3 of Zhou et al. (1998), the (j, j') entry of $(\mathbf{Z}^T\mathbf{Z})^{-1}$ is bounded by $(C/n)\gamma^{|j-j'|}$ for some $\gamma < 1$. Thus

$$\begin{aligned} & |\mathbf{a}^T(\mathbf{Z}^T\mathbf{Z})^{-1}\mathbf{Z}^T\mathbf{R}| \\ & \leq (C/n) \sum_k \gamma^k \left| \sum_i B_k(T_i)r_i \right|. \end{aligned}$$

Let $b_k = |\sum_i B_k(T_i)r_i|$ and then $E b_k^2 \leq CnK^{-2d}$ and by Cauchy-Schwarz inequality $E[b_k b_{k'}] \leq CnK^{-2d}$. Thus

$$\begin{aligned} & E \left[\left(\sum_k \gamma^k \left| \sum_i B_{k'}(T_i)r_i \right| \right)^2 \right] \\ & = \sum_{k, k'} \gamma^{k+k'} E[b_k b_{k'}] \\ & \leq CnK^{-2d}, \end{aligned}$$

which implies $\mathbf{a}^T(\mathbf{Z}^T\mathbf{Z})^{-1}\mathbf{Z}^T\mathbf{R} = O_p(n^{-1/2}K^{-d})$. \square

Lemma 6.

$$\|(\mathbf{X}^T - \mathbf{X}^T \mathbf{P}_Z) \mathbf{R}\| = o_p(\sqrt{n}).$$

Proof of Lemma 6.

$$\begin{aligned} & \|(\mathbf{X}^T - \mathbf{X}^T \mathbf{P}_Z) \mathbf{R}\| \\ & \leq \|(\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T \mathbf{R}\| + \|(E[\mathbf{X}^T|\mathbf{T}] - \mathbf{X}^T \mathbf{P}_Z) \mathbf{R}\| \\ & \leq \|(\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T \mathbf{R}\| + \|(E[\mathbf{X}|\mathbf{T}] - \mathbf{X})^T \mathbf{Z}(\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{R}\| + \|(E[\mathbf{X}|\mathbf{T}])^T (\mathbf{I} - \mathbf{P}_Z) \mathbf{R}\| \\ & \leq \|(\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T \mathbf{R}\| + \|(E[\mathbf{X}|\mathbf{T}] - \mathbf{X})^T \mathbf{Z}(\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{R}\| + \|(E[\mathbf{X}|\mathbf{T}] - \mathbf{Z}\boldsymbol{\gamma})^T (\mathbf{I} - \mathbf{P}_Z) \mathbf{R}\|, \end{aligned}$$

where $E[\mathbf{X}|\mathbf{T}] = (E[X|T = T_1], \dots, E[X|T = T_n])^T$, $\boldsymbol{\gamma}$ is such that $\|E[\mathbf{X}|\mathbf{T}] - \mathbf{Z}\boldsymbol{\gamma}\| = O_p(\sqrt{n}K^{-d'})$, and the last equality is due to that $(\mathbf{I} - \mathbf{P}_Z)\mathbf{Z} = 0$. Since $E[X|T]$ is the projection of X to the space of square-integrable functions of T , $X - E[X|T]$ is orthogonal to this space and thus $(\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T \mathbf{R}$ and $(E[\mathbf{X}|\mathbf{T}] - \mathbf{X})^T \mathbf{Z}$ both have mean zero. Thus by direct calculation of their variances the first and the second terms in the displayed above are $O_p(\sqrt{n}K^{-d})$ and $O_p(\sqrt{n}K^{-d+1/2})$, respectively, using that $\|\mathbf{Z}^T \mathbf{R}\| = O_p(nK^{-d})$. The third term above is bounded by $\|(E[\mathbf{X}|\mathbf{T}] - \mathbf{Z}\boldsymbol{\gamma})\| \cdot \|\mathbf{R}\| = O_p(nK^{-d-d'})$. This completes the proof since we assumed $\sqrt{n}K^{-d-d'} = o(1)$. \square

Lemma 7. $\|(\mathbf{X} - \mathbf{P}_Z \mathbf{X})^{\otimes 2}/n - E[(X - E[X|T])^{\otimes 2}]\| = o_p(1)$.

Proof of Lemma 7. Let $E[\mathbf{X}|\mathbf{T}] = (E[X|T = T_1], \dots, E[X|T = T_n])^T$. Law of large numbers implies

$$\left\| \frac{1}{n} (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T (\mathbf{X} - E[\mathbf{X}|\mathbf{T}]) - E[(X - E[X|T])^{\otimes 2}] \right\| = o_p(1).$$

Since $(\mathbf{X} - \mathbf{P}_Z \mathbf{X})^T (\mathbf{X} - \mathbf{P}_Z \mathbf{X}) = (\mathbf{X} - \mathbf{P}_Z \mathbf{X})^T \mathbf{X}$, we have

$$\begin{aligned} & (\mathbf{X} - \mathbf{P}_Z \mathbf{X})^T (\mathbf{X} - \mathbf{P}_Z \mathbf{X}) - (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T (\mathbf{X} - E[\mathbf{X}|\mathbf{T}]) \\ & = (\mathbf{X} - \mathbf{P}_Z \mathbf{X})^T \mathbf{X} - (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T \mathbf{X} + (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T E[\mathbf{X}|\mathbf{T}] \\ & = (E[\mathbf{X}|\mathbf{T}] - \mathbf{P}_Z \mathbf{X})^T \mathbf{X} + (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T E[\mathbf{X}|\mathbf{T}] \end{aligned}$$

$$\begin{aligned}
&= \mathbf{X}^T \mathbf{Z} (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T (\mathbf{X} - E[\mathbf{X}|\mathbf{T}]) + \mathbf{X}^T (\mathbf{I} - \mathbf{P}_Z) E[\mathbf{X}|\mathbf{T}] + (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T E[\mathbf{X}|\mathbf{T}] \\
&= \mathbf{X}^T \mathbf{Z} (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T (\mathbf{X} - E[\mathbf{X}|\mathbf{T}]) + \mathbf{X}^T (\mathbf{I} - \mathbf{P}_Z) (E[\mathbf{X}|\mathbf{T}] - \mathbf{Z}\gamma) + (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T E[\mathbf{X}|\mathbf{T}],
\end{aligned}$$

where γ is such that $\|E[\mathbf{X}|\mathbf{T}] - \mathbf{Z}\gamma\| = O_p(\sqrt{n}K^{-d'})$, and the last equality is due to that $(\mathbf{I} - \mathbf{P}_Z)\mathbf{Z} = 0$. Using $\|E[\mathbf{X}|\mathbf{T}] - \mathbf{Z}\gamma\| = O_p(\sqrt{n}K^{-d'})$ and that $\|\mathbf{I} - \mathbf{P}_Z\|_{op} \leq 1$, the second term above is $O_p(nK^{-d'})$. Since $\mathbf{Z}^T(\mathbf{X} - E[\mathbf{X}|\mathbf{T}])$ and $(\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T E[\mathbf{X}|\mathbf{T}]$ both have mean zero by the characterization of conditional expectation as a projection, the first term and the third term above are $O_p(\sqrt{nK})$ and $O_p(\sqrt{n})$, respectively. These bounds show that

$$\left\| \frac{1}{n} (\mathbf{X} - \mathbf{P}_Z \mathbf{X})^T (\mathbf{X} - \mathbf{P}_Z \mathbf{X}) - \frac{1}{n} (\mathbf{X} - E[\mathbf{X}|\mathbf{T}])^T (\mathbf{X} - E[\mathbf{X}|\mathbf{T}]) \right\| = o_p(1),$$

which completes the proof. \square

Lemma 8. $\|(\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^{\otimes 2}/n - E[(B(T) - A_0 X)^{\otimes 2}]\| = o_p(1)$ if $K^2 \log n/n \rightarrow 0$; $\|(\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^{\otimes 2}/n - E[(B(T) - A_0 X)^{\otimes 2}]\| = o_p(K^{-1/2})$ if $K^3 \log n/n \rightarrow 0$.

Proof of Lemma 8. Let $\mathbf{X}A_0^T = (A_0 X_1, \dots, A_0 X_n)^T$. We first show

$$\left\| \frac{1}{n} (\mathbf{Z} - \mathbf{X}A_0^T)^T (\mathbf{Z} - \mathbf{X}A_0^T) - E[(B(T) - A_0 X)^{\otimes 2}] \right\| = o_p(1). \quad (30)$$

Since $|B_k(t)B_{k'}(t)| \leq K$ and $E|B_k(T)B_{k'}(T)|^2 \leq CK$ (because B_k is bounded by \sqrt{K} and it has a support on an interval with length $O(1/K)$), by Bernstein's inequality,

$$P \left(\left| \frac{1}{n} \sum_i B_k(T_i)B_{k'}(T_i) - E[B_k(T)B_{k'}(T)] \right| > t \right) \leq C \exp\left\{-C \frac{n^2 t^2}{nK + nKt}\right\},$$

and thus

$$\|\mathbf{Z}^{\otimes 2}/n - E[B(T)^{\otimes 2}]\| = o_p(1),$$

if $K \log n/n \rightarrow 0$.

We have $\|X_{ij}B_k(T_i)\|_{\psi_1} \leq C\|X_{ij}\|_{\psi_2}\|B_k(T_i)\|_{\psi_2} \leq C\sqrt{K}$, where ψ_1 and ψ_2 are the sub-exponential norm and the sub-gaussian norm, respectively (see for example Definition 5.7 and 5.13 in Vershynin (2011)). Again by Bernstein's inequality,

$$P \left(\left| \frac{1}{n} \sum_i X_{ij}B_k(T_i) - E[X_{ij}B_k(T_i)] \right| > t \right) \leq C \exp\left\{-C \frac{nt^2}{K + \sqrt{K}t}\right\},$$

and thus

$$\|\mathbf{Z}^T \mathbf{X} A_0 / n - E[B(T) X A_0^T]\| = o_p(1),$$

if $K^2 \log n / n \rightarrow 0$.

Furthermore,

$$\|A_0(\mathbf{X}^T \mathbf{X} / n - E[XX^T])A_0^T\| = o_p(1)$$

by law of large numbers and that $\|A_0\|_{op}$ is bounded. The latter can be shown as follows.

Since $A_0 = E[B(T)X^T](E[XX^T])^{-1}$, we only need to show $\|E[B(T)X^T]\|_{op}$ is bounded. In turn, this is seen by $|\mathbf{a}^T E[B(T)X^T] \mathbf{b}| \leq (\mathbf{a}^T E[B(T)B(T)^T] \mathbf{a})^{1/2} (\mathbf{b}^T E[XX^T] \mathbf{b})^{1/2}$.

Thus we complete the proof of (30).

Since $(\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T (\mathbf{Z} - \mathbf{P}_X \mathbf{Z}) = (\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T \mathbf{Z}$, we have

$$\begin{aligned} & (\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T (\mathbf{Z} - \mathbf{P}_X \mathbf{Z}) - (\mathbf{Z} - \mathbf{X} A_0^T)^T (\mathbf{Z} - \mathbf{X} A_0^T) \\ &= (\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T \mathbf{Z} - (\mathbf{Z} - \mathbf{X} A_0^T)^T \mathbf{Z} + (\mathbf{Z} - \mathbf{X} A_0^T)^T \mathbf{X} A_0^T \\ &= (\mathbf{X} A_0^T - \mathbf{P}_X \mathbf{Z})^T \mathbf{Z} + (\mathbf{Z} - \mathbf{X} A_0^T)^T \mathbf{X} A_0^T \\ &= -\mathbf{Z}^T \mathbf{X} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T (\mathbf{Z} - \mathbf{X} A_0^T) + (\mathbf{Z} - \mathbf{X} A_0^T)^T \mathbf{X} A_0^T. \end{aligned}$$

Since $\mathbf{X}^T (\mathbf{Z} - \mathbf{X} A_0^T)$ has mean zero, and $\|\mathbf{Z}^T \mathbf{X}\| = O_p(n)$ as shown in the proof of Lemma 3, the two terms above are $O_p(\sqrt{nK})$. Thus

$$\left\| \frac{1}{n} (\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T (\mathbf{Z} - \mathbf{P}_X \mathbf{Z}) - \frac{1}{n} (\mathbf{Z} - \mathbf{X} A_0^T)^T (\mathbf{Z} - \mathbf{X} A_0^T) \right\| = o_p(1),$$

which completes the proof. \square

Lemma 9.

$$\left(\mathbf{a}^T (nE[(B(T) - A_0 X)^{\otimes 2}])^{-1} \mathbf{a} \right)^{-1/2} \mathbf{a}^T ((\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T (\mathbf{Z} - \mathbf{P}_X \mathbf{Z}))^{-1} (\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T \boldsymbol{\epsilon} \xrightarrow{d} N(0, 1).$$

Proof of Lemma 9. Obviously $\mathbf{a}^T (nE[(B(T) - A_0 X)^{\otimes 2}])^{-1} \mathbf{a} \asymp 1/n$ by Lemma 1.

We have

$$\mathbf{a}^T ((\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T (\mathbf{Z} - \mathbf{P}_X \mathbf{Z}))^{-1} (\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T \boldsymbol{\epsilon} - \mathbf{a}^T ((\mathbf{Z} - \mathbf{P}_X \mathbf{Z})^T (\mathbf{Z} - \mathbf{P}_X \mathbf{Z}))^{-1} (\mathbf{Z} - \mathbf{X} A_0^T)^T \boldsymbol{\epsilon}$$

$$\begin{aligned}
&= \mathbf{a}^T((\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z})^T(\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z}))^{-1}(\mathbf{X}A_0^T - \mathbf{P}_\mathbf{X}\mathbf{Z})^T\boldsymbol{\epsilon} \\
&= \mathbf{a}^T((\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z})^T(\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z}))^{-1}(\mathbf{X}A_0^T - \mathbf{Z})^T\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\boldsymbol{\epsilon} \\
&= O_p(\sqrt{K}/n) = o_p(n^{-1/2}),
\end{aligned}$$

since its (conditional) second moment is

$$\sigma^2 \left\| \mathbf{a}^T((\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z})^T(\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z}))^{-1}(\mathbf{X}A_0^T - \mathbf{Z})^T\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1/2} \right\|^2 = O_p(K/n^2),$$

using Lemma 8 and that $\|(\mathbf{X}A_0^T - \mathbf{Z})^T\mathbf{X}\| = O_p(\sqrt{nK})$ (note $(\mathbf{X}A_0^T - \mathbf{Z})^T\mathbf{X}$ has mean zero). Furthermore,

$$\begin{aligned}
&\mathbf{a}^T((\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z})^T(\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z}))^{-1}(\mathbf{Z} - \mathbf{X}A_0^T)^T\boldsymbol{\epsilon} - \mathbf{a}^T(nE[(B(T) - A_0X)^{\otimes 2}])^{-1}(\mathbf{Z} - \mathbf{X}A_0^T)^T\boldsymbol{\epsilon} \\
&= \mathbf{a}^T((\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z})^T(\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z}))^{-1} (E[(B(T) - A_0X)^{\otimes 2}] - (\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z})^T(\mathbf{Z} - \mathbf{P}_\mathbf{X}\mathbf{Z})/n) \\
&\quad (E[(B(T) - A_0X)^{\otimes 2}])^{-1}(\mathbf{Z} - \mathbf{X}A_0)^T\boldsymbol{\epsilon} \\
&= o_p(n^{-1/2}),
\end{aligned}$$

using again Lemma 8 and that $\|\mathbf{Z} - \mathbf{X}A_0^T\| \leq \|\mathbf{Z}\| + \|\mathbf{X}\|\|A_0\|_{op} = O_p(\sqrt{nK})$. The proof would be complete if we show

$$(\sigma^2 \mathbf{a}^T(nE[(B(T) - A_0X)^{\otimes 2}])^{-1}\mathbf{a})^{-1/2} \mathbf{a}^T(E[(B(T) - A_0X)^{\otimes 2}])^{-1}(\mathbf{Z} - \mathbf{X}A_0^T)^T\boldsymbol{\epsilon} \rightarrow N(0, 1).$$

By Lemma 3.1 of Huang (2003), we only need to show that

$$\frac{\max_i \alpha_i^2}{\sum_i \alpha_i^2} = o_p(1),$$

where $\alpha_i = \mathbf{a}^T(E[(B(T) - A_0X)^{\otimes 2}])^{-1}(B(T_i) - A_0X_i)$. It is easy to see that $\sum_i \alpha_i^2$ is of order n while $|\alpha_i| \leq \|B(T_i) - A_0X_i\| = O_p(\sqrt{K})$ since $B_k(T_i)$ is bounded by \sqrt{K} and only at most s basis functions B_k are nonzero at the point T_i (s is the order of the splines), thus the above displayed is verified and the proof of the Lemma is complete.

□

Proof of Theorem 1. Most of the results are derived based on the expression (11). (20) is standard and well-known and thus omitted from the proof. The stochastic

terms (12) are order $O_p(n^{-1/2})$ whether or not \mathbf{a} has bounded support, by (17) and Lemmas 3 and 7. The first bias term in (18) is dealt with in Lemma 4 while the second bias term in (18) is dealt with in Lemmas 3, 6 and 7 which is $o_p(n^{-1/2})$ whether \mathbf{a} has bounded support or not. These proved (21) and (22).

When $\boldsymbol{\theta}_0$ is chosen as in (9), the bias term is of order $o_p(n^{-1/2})$ by Lemma 5 which established (23).

Asymptotic normality (24) is obtained by Lemma 9 and (8) and noting that the second term in the bias (18) is $o_p(n^{-1/2})$. The equivalence between (24) and (25) when \mathbf{a} has bounded support is due to that (17) is $o_p(1/n)$ by Lemmas 3 and 7. When $\boldsymbol{\theta}_0$ is chosen as in (9), the bias term can be removed from (24) and (25) since the bias term is of order $o_p(n^{-1/2})$ by Lemma 5. \square