Supplementary Information for "Weighted Estimating Equations for Additive Hazards Models with Missing Covariates"

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Appendix S1. Derivation of asymptotic results

We first present two lemmas to assist the proofs of all the theorems. The key idea of the proofs is to approximate each of the corresponding weighted estimating functions by a sum of independent and identically distributed random variables to establish its asymptotic normality using the central limit theorem.

Lemma 1 *Suppose* $\sup_{t\in[0,\tau]} |h_n(t) - h(t)| \to 0$, $\sup_{t\in[0,\tau]} |g_n(t) - g(t)| \to 0$, *where*

(a) h is continuous on $[0,\tau]$

(b) $g_n(\cdot)$ and $g(\cdot)$ are left continuous on $[0,\tau]$ with total variations bounded by a constant $\bar{B}$, independent of n and t.

Then

$$\sup_{t\in[0,\tau]} |\int_0^t h_n(u)\, dg_n(u) - \int_0^t h(u)dg(u)| \to 0, \quad \sup_{t\in[0,\tau]} |\int_0^t h_n(u)\, dg_n(u) - \int_0^t h_n(u)dg(u)| \to 0,$$

$$\sup_{t\in[0,\tau]} |\int_0^t g_n(u)\, dh_n(u) - \int_0^t g(u)dh(u)| \to 0, \quad \sup_{t\in[0,\tau]} |\int_0^t g_n(u)\, dh_n(u) - \int_0^t g(u)dh_n(u)| \to 0.$$

Lemma 2 *Under the regularity conditions listed in the Appendix of the main manuscript, we have*

(1) $\bar{M}_{dn}(t) = n^{-1/2}\sum_{i=1}^n V_i\pi_i^{-2}(\widehat{\pi}_i - \pi_i)M_i(t)$ converges to a zero-mean Gaussian process W_{dM} with continuous sample paths.

(2) $\sup_{t\in[0,\tau]} ||\bar{M}_{Edn}(t)||\to 0$ in probability as $n\to\infty$, where

$$\bar{M}_{Edn}(t) = n^{-\frac{1}{2}}\sum_{i=1}^n \left(1 - \frac{V_i}{\pi_i}\right)\int_0^t [\hat{E}\{dM_i(s) \mid W_i\} - E\{dM_i(s) \mid W_i\}].$$

(3) $\bar{M}_{En}(t)$ converges to a zero-mean Gaussian process with continuous sample paths, where $\bar{M}_{En}(t) = n^{-1/2}\sum_{i=1}^n V_i(\hat{\pi}_i - \pi_i)\pi_i^{-2}E\{M_i(t) \mid W_i\}$.

(4) $\sup_{t\in[0,\tau]} ||\bar{M}_{Eqn}(t)||\to 0$ in probability as $n\to\infty$, where

$$\bar{M}_{Eqn}(t) = n^{-\frac{1}{2}}\sum_{i=1}^n \left(1 - \frac{V_i}{\pi_i}\right)\int_0^t [\hat{E}\{Z_i dM_i(s) \mid W_i\} - E\{Z_i dM_i(s) \mid W_i\}].$$

The proof of Lemma 1 is similar proof to Lemma A.3 of Bilias et al. (1997). The proof of Lemma 2 follows immediately from Lemma 1 to Lemma 4 in Wang and Wang (2001).

1 Proofs of Theorems 1 and 3

We only give the proof of Theorem 1. Theorem 3 can be proven in the same manner. There are four steps. The result in the first step, i.e., Eq. (1) is a direct application of Corollary III.2., a corollary to Theorem III.1, given in the Appendix (p. 1118) of Anderson and Gill (1982).

Step A1. Using Corollary III.2 given in the Appendix (p. 1118) of Anderson and Gill (1982), we have

$$\sup_{t\in[0,\tau]} ||S_{sw}^{(k)}(\pi,t) - s^{(k)}(t)||\to 0 \tag{1}$$

almost surely for $k = 0, 1$.

Step A2. We establish the asymptotic normality of $n^{-1/2}U_{sw}(\beta,\pi)$. Write $U_{sw}(\beta,\pi) = B_1 + B_2$, where

$$\begin{aligned} B_1 &= \sum_{i=1}^{n} \frac{V_i}{\pi_i} \int_0^\tau \{Z_i - e(t)\}\, dM_i(t), \\ B_2 &= -\sum_{i=1}^{n} \frac{V_i}{\pi_i} \int_0^\tau \{\bar{Z}_{sw}(\pi,t) - e(t)\}\, dM_i(t). \end{aligned}$$

Using Lemma 1 we can show that $n^{-1/2}B_2$ converges to 0 in probability. Let $\bar{M}_n(t) = n^{-1/2}\sum_{i=1}^{n} (V_i/\pi_i)M_i(t)$. Using regularity conditions (a4) and (a6) and that $\bar{M}_n(t)$ is the difference of two non-decreasing processes, $\bar{M}_n(t)$ converges weakly to a process $W_M(t)$ with continuous sample paths on $[0,\tau]$ by Example 2.11.16 of Van Der Vaart and Wellner (1996, pp. 215). By the strong embedding theorem (Shorack and Wellner 1986, pp. 47-48), there exists a new probability space where $\big(\bar{M}_n, S_{sw}^{(1)}(\pi,t), S_{sw}^{(0)}(\pi,t)\big)\to\big(W_M, s^{(1)}(t), s^{(0)}(t)\big)$ almost surely. For $S_{sw}^{(1)}(\pi,t)$ and $S_{sw}^{(0)}(\pi,t)$ are left continuous with bounded variations on $[0,\tau]$, applying Lemma 1 twice we have $\int_0^\tau \bar{Z}_{sw}(\pi,t)\, d\bar{M}_n(t)\to \int_0^\tau e(t)\, dW_M(t)$ almost surely. Similarly, $\int_0^\tau e(t)\, d\bar{M}_n(t)\to \int_0^\tau e(t)\, dW_M(t)$ almost surely. Hence $n^{-1/2}B_2\to 0$ almost surely in the new space, and the convergence is in probability back in the original probability space. So $n^{-1/2}U_{sw}(\beta,\pi)$ can be approximated by the sum of independent and identically distributed zero-mean random variables $n^{-1/2}\sum_{i=1}^{n}(V_i/\pi_i)M_{\tilde{Z},i}$, with variance equal to $\Sigma_{sw}(\pi) = var\{(V/\pi)M_{\tilde{Z}}\}$. By the central limit theorem,

$$n^{-\frac{1}{2}}U_{sw}(\beta,\pi)\to N(0,\Sigma_{sw}(\pi)) \text{ in distribution.} \tag{2}$$

Step A3. Applying (1) and Lemma 1, we can get

$$-\frac{1}{n}\frac{\partial}{\partial\beta}U_{sw}(\beta,\pi) - \Sigma\to 0 \text{ in probability.} \tag{3}$$

Step A4. We establish the asymptotic normality of $n^{1/2}\hat{\beta}_{sw}(\pi)$. Rearranging the Taylor expansion of $n^{-1/2}U_{sw}(\beta,\pi)$ at the true parameter value β, we obtain

$$n^{\frac{1}{2}}\{\hat{\beta}_{sw}(\pi)-\beta\} = -\Big\{\frac{1}{n}\frac{\partial}{\partial\beta}U_{sw}(\beta,\pi)|_{\beta=\beta^*}\Big\}^{-1} n^{-\frac{1}{2}}U_{sw}(\beta,\pi), \tag{4}$$

where β^* is in the interval between $\hat{\beta}_{sw}(\pi)$ and β. The asymptotic normality of $n^{1/2}\hat{\beta}_{sw}(\hat{\pi})$ follows from (2) - (3), and using the asymptotic normality the consistency of $\hat{\beta}_{sw}(\pi)$ can be derived.

2 Proof of Theorem 2

Theorem 2 presents the results for the simple weighted estimators with $\hat{\pi}$. The key steps to prove Theorem 2 are similar to those to derive Theorem 1 while complications are in the arguments concerning $\hat{\pi}(w)$. The following five steps are used.

Step B1. We show that

$$\sup_{t\in[0,\tau]} ||S_{sw}^{(k)}(\widehat{\pi},t) - s^{(k)}(t)|| \rightarrow 0 \text{ in probability.} \tag{5}$$

Using a Taylor expansion of $1/\hat{\pi}$ about π, we write $S_{sw}^{(k)}(\hat{\pi},t)$ as

$$S_{sw}^{(k)}(\pi,t) - \frac{1}{n}\sum_{j=1}^{n}\frac{V_j(\hat{\pi}_j-\pi_j)}{\pi_j^2}Y_j(t)Z_j^{\otimes k} + o_p(1)$$

Using (1), we only need show that the second term converges to 0 in probability uniformly in t. We give the proof for $k=0$ and the proof for $k=1$ is similar.

Let $a_n = n^{-1}\sum_{j=1}^{n} V_j(\hat{\pi}_j-\pi_j)\pi_j^{-2}Y_j(t)$, and let $\hat{f}(W_j) = (nh^d)^{-1}\sum_{l=1}^{n} K_h(W_j-W_l)$. Then

$$\begin{aligned} a_n &= \frac{1}{n}\sum_{j=1}^{n}\frac{\sum_{i=1}^{n} V_j(V_i-\pi_j)/\pi_j^2 K_h(W_j-W_i)Y_j(t)}{\sum_{l=1}^{n} K_h(W_j-W_l)} \\ &= \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{V_j(V_i-\pi_j)K_h(W_j-W_i)Y_j(t)}{\pi_j^2 h^d \hat{f}(W_j)}. \end{aligned} \tag{6}$$

By Taylor's expansion of $1/\hat{f}(W_j)$ about $f(W_j)$, (6) can be written as $S_{1n} - S_{2n} + o_p(1)$, where

$$S_{1n} = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{V_j(V_i-\pi_j)K_h(W_j-W_i)Y_j(t)}{\pi_j^2 h^d f(W_j)}$$

$$S_{2n} = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{V_j(V_i-\pi_j)K_h(W_j-W_i)Y_j(t)\{\hat{f}(W_j)-f(W_j)\}}{\pi_j^2 h^d f^2(W_j)}$$

After some tedious calculations, we can show that $var(S_{1n}) = O_p\{h^{2r}+(nh^{2d})^{-1}\} \rightarrow 0$, implying $S_{1n}\rightarrow 0$ in probability. Similarly, $S_{2n}\rightarrow 0$ in probability, thus $a_n\rightarrow 0$ in probability. Since a_n is monotone and bounded in t, the convergence is uniform in t.

Step B2. Using Taylor's expansion and through tedious calculations, we can show that

$$n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i}(\hat{\pi}_i-\pi_i)M_{\tilde{Z}i}=n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{(V_i-\pi_i)}{\pi_i}E(M_{\tilde{Z}_i}|W_i)+o_p(1). \tag{7}$$

Step B3. We establish the asymptotic normality of $n^{-1/2}U_{sw}(\beta,\widehat{\pi})$. By a Taylor expansion of $\widehat{\pi}$ about π, $n^{-1/2}U_{sw}(\beta,\widehat{\pi})=C_{1n}+C_{2n}+C_{3n}+C_{4n}$, where

$$\begin{aligned}
C_{1n}&=n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^\tau\{Z_i-e(t)\}dM_i(t)\\
C_{2n}&=-n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i^2}(\hat{\pi}_i-\pi_i)\int_0^\tau\{Z_i-e(t)\}dM_i(t)=-n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i^2}(\hat{\pi}_i-\pi_i)M_{\tilde{Z}i}\\
C_{3n}&=n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^\tau\{e(t)-\bar{Z}_{sw}(\hat{\pi},t)\}dM_i(t)\\
C_{4n}&=-n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i^2}(\hat{\pi}_i-\pi_i)\int_0^\tau\{e(t)-\bar{Z}_{sw}(\hat{\pi},t)\}dM_i(t)
\end{aligned}$$

Clearly, C_{1n} is a sum of independent and identically distributed random variables and C_{2n} can be approximated by a sum of independent and identically distributed random variables as in (7). We show that C_{3n} and C_{4n} converge to 0 in probability. It follows from Step B1 that $sup_{t\in[0,\tau]}||\bar{Z}_{sw}(\hat{\pi},t)-e(t)||\to 0$ in probability. Applying the strong embedding theorem (Shorack and Wellner (1986), Page 47-48) and the similar arguments as in Theorem 1 (with $\bar{Z}_{sw}(\pi,t)$ replaced by $\bar{Z}_{sw}(\hat{\pi},t)$), we have $C_{3n}\rightarrow 0$ in probability. To show $C_{4n}\rightarrow 0$ in probability, we use

$$C_{4n}\le sup_{t\in[0,\tau]}||\bar{Z}_{sw}(\hat{\pi},t)-e(t)||n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i^2}(\hat{\pi}_i-\pi_i)M_i(\tau).$$

Hence $n^{-1/2}U_{sw}(\beta,\hat{\pi})$ can be approximated by a sum of independent and identically distributed random variables:

$$n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^\tau\{Z_i-e(t)\}dM_i(t)+n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{(V_i-\pi_i)}{\pi_i}E(M_{\tilde{Z}_i}|W_i).$$

By the central limit theorem,

$$n^{-\frac{1}{2}}U_{sw}(\beta,\widehat{\pi})\rightarrow N(0,\Sigma_{sw}^{\widehat{\pi}}(\pi))\text{ in distribution.} \tag{8}$$

Step B4. We show that $-\frac{1}{n}\frac{\partial}{\partial\beta}U_{sw}(\beta,\hat{\pi})-\Sigma\rightarrow 0$ in probability.

$$\begin{aligned}
-\frac{1}{n}\frac{\partial}{\partial\beta}U_{sw}(\beta,\widehat{\pi})&=\frac{1}{n}\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^\tau\{Z_i-e(t)\}Y_i(t)Z_i^T dt\\
&+\frac{1}{n}\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^\tau\{e(t)-\bar{Z}_{sw}(\widehat{\pi},t)\}Y_i(t)Z_i^T dt
\end{aligned}$$

By Step B1 and the Slutsky Theorem, $\sup_{t\in[0,\tau]} \|\bar{Z}_{sw}(\widehat{\pi},t) - e(t)\| \to 0$ in probability, with which we can show that $1/n \sum_{i=1}^n V_i/\widehat{\pi}_i \int_0^\tau \{e(t) - \bar{Z}_{sw}(\widehat{\pi},t)\} Y_i(t) Z_i^T dt \to 0$ in probability. By the Taylor expansion, the first term asymptotically equals the sum of the following two term:

$$B_1 = \frac{1}{n}\sum_{i=1}^n \frac{V_i}{\pi_i}\int_0^\tau \{Z_i - e(t)\} Y_i(t) Z_i^T(t) dt$$
$$B_2 = \frac{1}{n}\sum_{i=1}^n \frac{V_i}{\pi_i^2}(\widehat{\pi}_i - \pi_i)\int_0^\tau \{Z_i - e(t)\} Y_i(t) Z_i^T dt.$$

And $B_1 \to E[V/\pi \int_0^\tau \{Z - e(t)\} Y(t) Z^T dt] = \Sigma$ in probability. By similar arguments for (7), we can show B_2 converges to 0 in probability.

Step B5. The consistency of $\hat{\beta}_{sw}(\widehat{\pi})$ and asymptotic normality of $n^{1/2}\hat{\beta}_{sw}(\widehat{\pi})$ can be established in the same manner as for $n^{1/2}\hat{\beta}_{sw}(\pi)$ in Theorem 1.

3 Proofs of Theorem 4

Theorem 4 includes results for three FAWEs. The asymptotic distribution theory for $\widehat{\beta}_{faw}(\hat{\pi}, E)$ can be established similarly as for $\widehat{\beta}_{sw}(\hat{\pi})$ in Theorem 2. Also using similar techniques for developing the asymptotic distribution theory for $\widehat{\beta}_{sw}(\hat{\pi})$ and $\widehat{\beta}_{faw}(\pi, \hat{E})$, we can derive the asymptotic distribution theory for $\widehat{\beta}_{faw}(\hat{\pi}, \hat{E})$. So we only present the proofs for $\widehat{\beta}_{faw}(\pi, \hat{E})$. The key steps of the proofs are similar to those of Theorem 1. Complications are in the arguments regarding the conditional expectations estimated by the Nadaraya-Watson (Nadaraya 1964; Watson 1964) estimator.

We use the followng four steps to derive the asymptotic distribution theory for $\widehat{\beta}_{faw}(\pi, \hat{E})$.

Step C1. We show that

$$\sup_{t\in[0,\tau]} ||S_{faw}^{(k)}(\pi, \hat{E}, t) - s^{(k)}(t)|| \to 0 \text{ in probability.} \tag{9}$$

Write

$$S_{faw}(k)(\pi, \hat{E}, t) = \frac{1}{n}\sum_{j=1}^n \frac{V_j}{\pi_j} Y_j(t) Z_j^{\otimes k} + \frac{1}{n}\sum_{j=1}^n \left(1 - \frac{V_j}{\pi_j}\right) Y_j(t) E(Z_j^{\otimes k} | W_j)$$
$$+ \frac{1}{n}\sum_{j=1}^n \left(1 - \frac{V_j}{\pi_j}\right) Y_j(t)\{\hat{E}(Z_j^{\otimes k} \mid W_j) - E(Z_j^{\otimes k} \mid W_j)\}. \tag{10}$$

Using Corollary III.2 given in the Appendix (p. 1118) of Anderson and Gill (1982), the sum of the first two terms converges to $s^{(k)}(t)$ uniformly in t. With similar techniques in Step B1, we can show that the last term in (10) converges to 0 in probability.

Step C2. We establish the asymptotic normality of $n^{-1/2}\widehat{U}_{faw}(\beta,\pi)$. Write

$$\begin{aligned}\widehat{U}_{faw}(\beta,\pi) &= \sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^{\tau}\left\{Z_i-\bar{Z}_{faw}(\pi,\hat{E},t)\right\}dM_i(t)\\&+\sum_{i=1}^{n}\left(1-\frac{V_i}{\pi_i}\right)\int_0^{\tau}[\hat{E}\{Z_i dM_i(t)\mid W_i\}-\bar{Z}_{faw}(\pi,\hat{E},t)\hat{E}\{dM_i(t)\mid W_i\}]\\&=U_{1n}-U_{2n}+U_{3n}+U_{4n}-U_{5n},\end{aligned}$$

where

$$\begin{aligned}U_{1n}&=\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^{\tau}\{Z_i-e(t)\}\,dM_i(t)\\U_{2n}&=\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^{\tau}\{\bar{Z}_{faw}(\pi,\hat{E},t)-e(t)\}\,dM_i(t)\\U_{3n}&=\sum_{i=1}^{n}\left(1-\frac{V_i}{\pi_i}\right)\int_0^{\tau}[E\{Z_i\,dM_i(t)\mid W_i\}-e(t)E\{\,dM_i(t)\mid W_i\}]\\U_{4n}&=\sum_{i=1}^{n}\left(1-\frac{V_i}{\pi_i}\right)\int_0^{\tau}[\hat{E}\{Z_i\,dM_i(t)\mid W_i\}-E\{Z_i\,dM_i(t)\mid W_i\}]\\U_{5n}&=\sum_{i=1}^{n}\left(1-\frac{V_i}{\pi_i}\right)\int_0^{\tau}[\bar{Z}_{faw}(\pi,\hat{E},t)\hat{E}\{\,dM_i(t)\mid W_i\}-e(t)E\{\,dM_i(t)\mid W_i\}].\end{aligned}$$

Following similar arguments and techniques in Step B2, we can show that $n^{-1/2}U_{2n}$, $n^{-1/2}U_{4n}$ and $n^{-1/2}U_{5n}$ converge to 0 in probability.

Then $n^{-1/2}\widehat{U}_{faw}(\beta,\pi)$ can be approximated by the sum of independent and identically distributed random variables:

$$n^{-\frac{1}{2}}\sum_{i=1}^{n}\frac{V_i}{\pi_i}\left\{\int_0^{\tau}\{Z_i-e(t)\}\,dM_i(t)+\left(1-\frac{V_i}{\pi_i}\right)E[\{Z_i-e(t)\}\,dM_i(t)\mid W_i]\right\}.$$

By the central limit theorem,

$$n^{-\frac{1}{2}}\widehat{U}_{faw}(\beta,\pi)\rightarrow N\big(0,\Sigma_{faw}(\pi)\big)\text{in distribution.} \tag{11}$$

Step C3. We show that

$$-\frac{1}{n}\frac{\partial}{\partial\beta}\widehat{U}_{faw}(\beta,\pi)-\Sigma\rightarrow 0\text{ in probability.} \tag{12}$$

Write $-1/n \, \partial\widehat{U}_{faw}(\beta,\pi)/\partial\beta = U_1 + U_2$, where

$$U_1 = \frac{1}{n}\sum_{i=1}^{n}\frac{V_i}{\pi_i}\int_0^{\tau} Y_i(t)Z^{\otimes 2}dt + \frac{1}{n}\sum_{i=1}^{n}\left(1-\frac{V_i}{\pi_i}\right)\int_0^{\tau}\widehat{E}\{Y_i(t)Z^{\otimes 2}dt \mid W_i\}$$

$$U_2 = -\int_0^{\tau}\bar{Z}_{faw}(\pi,\hat{E},t)\left[\frac{1}{n}\sum_{i=1}^{n}\frac{V_i}{\pi_i}Y_i(t)Z^Tdt + \frac{1}{n}\sum_{i=1}^{n}\left(1-\frac{V_i}{\pi_i}\right)\widehat{E}\{Y_i(t)Z_i^T \mid W_i\}dt\right]$$

$$= -\int_0^{\tau}\bar{Z}_{faw}(\pi,\hat{E},t)S^{(1)}_{faw}(\pi,\hat{E},t).$$

And the results can be shown by applying similar arguments used in Step B2.

Step C4. The existence and the consistency of $\widehat{\beta}_{faw}(\pi,\hat{E})$ as well as the asymptotic normality of $n^{1/2}\widehat{\beta}_{faw}(\pi,\hat{E})$ can be established similarly as that of $n^{1/2}\widehat{\beta}_{sw}(\pi)$ in Theorem 1.

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Appendix S2. Acknowledgement

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