

TECHNICAL SUPPLEMENT TO “SEMIPARAMETRIC STOCHASTIC
FRONTIER ESTIMATION VIA PROFILE LIKELIHOOD”

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Abstract. In this technical supplement to Martins-Filho and Yao (2011) we show that the skew-normal density satisfies all assumptions required in establishing the asymptotic properties of the estimators discussed therein. Also, we provide the proofs for Theorems 1, 2 and Lemma 1.

1 Introduction

Besides this introduction, this technical supplement has four sections. Section 2 provides proofs for Theorems 1, 2 and Lemma 1 in Martins-Filho and Yao (2011). Section 3 verifies that a skew-normal density satisfies all assumptions (A1-A7) required to prove Theorem 2. Section 4 verifies that assumptions PA1, PA2, PB, PC and PD used in Lemma 2 of Martins-Filho and Yao (2011) are also satisfied by the skew-normal density. Section 5 obtains the variance of the asymptotic distribution of $\sqrt{n}(\tilde{\theta} - \theta_0)$ when f_ϵ in Martins-Filho and Yao (2011) is a skew-normal. Throughout the note $\theta = (\sigma_u^2, \sigma_v^2)$ and we have

$$f_\epsilon(y - g(x); \theta) = \frac{2}{\sqrt{\sigma_u^2 + \sigma_v^2}} \phi\left(\frac{y - g(x)}{\sqrt{\sigma_u^2 + \sigma_v^2}}\right) \left(1 - \Phi\left(\frac{\sqrt{\sigma_u^2/\sigma_v^2}}{\sqrt{\sigma_u^2 + \sigma_v^2}}(y - g(x))\right)\right) \quad (1)$$

where $\sigma_u^2, \sigma_v^2 > 0$, $\lambda = \sqrt{\frac{\sigma_u^2}{\sigma_v^2}}$ and $s^2 = \sigma_u^2 + \sigma_v^2$. Whenever we need to distinguish the true values of the parameters and the function g we write $\theta_0 = \begin{pmatrix} \sigma_{u0}^2 \\ \sigma_{v0}^2 \end{pmatrix}$, λ_0 , s_0^2 and g_0 . C will always denote an arbitrary positive real number.

2 Proofs of Theorems 1, 2 and Lemma 1

Theorem 1: *Proof.* Given A1.1-3, A4 and the definition of $\hat{\theta}$, by Theorem 2.1 in Newey and McFadden (1994) it suffices to prove that $\sup_{\theta \in \Theta} |\bar{l}_n(\theta, \hat{m} + \gamma(\theta)) - E(\bar{l}_n(\theta, g_0))| = o_p(1)$. We do so by establishing that $\sup_{\theta \in \Theta} |\bar{l}_n(\theta, \hat{m} + \gamma(\theta)) - \bar{l}_n(\theta, g_0)| = o_p(1)$ and $\sup_{\theta \in \Theta} |\bar{l}_n(\theta, g_0) - E(\bar{l}_n(\theta, g_0))| = o_p(1)$. First, note that by A1.3 and A4.4 $\sup_{\theta \in \Theta} |\bar{l}_n(\theta, \hat{m} + \gamma(\theta)) - \bar{l}_n(\theta, g_0)| \leq \frac{1}{n} \sum_{i=1}^n \sup_{\theta \in \Theta} |b(y_i, x_i, \theta) \hat{m}(x_i) - m(x_i; \theta, g_0)|$. If $\frac{nh_n^3}{\log(n)} \rightarrow \infty$ as $n \rightarrow \infty$ and given A2.2 and A3, for a compact set G , we have $\sup_{x \in G} |\hat{m}(x) - m(x; \theta, g_0)| = o_p(1)$ (Martins-Filho and Yao, 2007). Given that $E(\sup_{\theta \in \Theta} |b(y_i, x_i, \theta)|) < \infty$ and the fact that (y_i, x_i) are i.i.d, we conclude that $\sup_{\theta \in \Theta} |\bar{l}_n(\theta, \hat{m} + \gamma(\theta)) - \bar{l}_n(\theta, g_0)| = o_p(1)$. Second, note that

$$|\bar{l}_n(\theta, g_0) - E(\bar{l}_n(\theta, g_0))| \leq \frac{1}{n} \sum_{i=1}^n |\log f_\epsilon(y_i - g_0(x_i); \theta) - E(\log f_\epsilon(y_i - g_0(x_i); \theta))|.$$

By the Heine-Borel theorem every open covering of Θ contains a finite subcover $\{S_k\}_{k=1}^K$ where $S_k = S(\theta_k, d(\theta_k))$ denotes an open sphere centered at θ_k with radius $d(\theta_k) > 0$. Now let

$$\mu(y_i, x_i, \theta, g_0, d(\theta)) = \sup_{\theta' \in S(\theta, d(\theta))} |\log f_\epsilon(y_i - g_0(x_i); \theta) - \log f_\epsilon(y_i - g_0(x_i); \theta')|.$$

By A4.2 $\mu(y_i, x_i, \theta, g_0, d(\theta)) \rightarrow 0$ for all $\theta \in \Theta$ as $d(\theta) \rightarrow 0$ almost everywhere according to $f(y, x)$. By the triangle inequality $\mu(y_i, x_i, \theta, g_0, d(\theta)) \leq 2 \sup_{\theta \in \Theta} |\log f_\varepsilon(y_i; \theta, g_0(x_i))|$. By A4.3 and Lebesgue's dominate convergence theorem (LDC) we conclude that for any $\epsilon, d > 0$, $E(\mu(y_i, x_i, \theta, g_0, d(\theta))) < \epsilon$ whenever $d(\theta) < d$. Letting $d(\theta_k) < d$ for all $k = 1, \dots, K$ we have $E(\mu(y_i, x_i, \theta_k, g_0, d(\theta_k))) < \epsilon$ for all k . Also, $|E(\log f_\varepsilon(y_i - g_0(x_i); \theta) - E(\log f_\varepsilon(y_i - g_0(x_i); \theta_k)))| \leq E(\mu(y_i, x_i, \theta_k, g_0, d(\theta_k))) < \epsilon$. Hence, for $\theta \in S_k$ we have

$$\begin{aligned} |\bar{l}_n(\theta, g_0) - E(\bar{l}_n(\theta, g_0))| &\leq n^{-1} \sum_{i=1}^n (\mu(y_i, x_i, \theta_k, g_0, d(\theta_k)) - E(\mu(y_i, x_i, \theta_k, g_0, d(\theta_k)))) \\ &\quad + \left| n^{-1} \sum_{i=1}^n (\log f_\varepsilon(y_i - g_0(x_i); \theta_k) - E(\log f_\varepsilon(y_i - g_0(x_i); \theta_k))) \right| + 2\epsilon \end{aligned}$$

Since $E(\mu(y_i, x_i, \theta_k, g_0, d(\theta_k))) < \infty$ and $E(|\log f_\varepsilon(y_i - g_0(x_i); \theta_k)|) < \infty$, we have, by the strong law of large numbers, that there exists $N_{\epsilon, k}$ such that $n > N_{\epsilon, k}$ gives

$$\left| n^{-1} \sum_{i=1}^n \mu(y_i, x_i, \theta_k, g_0, d(\theta_k)) - E(\mu(y_i, x_i, \theta_k, g_0, d(\theta_k))) \right| < \epsilon$$

and $n^{-1} \sum_{i=1}^n |\log f_\varepsilon(y_i - g_0(x_i); \theta_k) - E(\log f_\varepsilon(y_i - g_0(x_i); \theta_k))| < \epsilon$. Given that K is finite, for all $n > \max_k N_{k, \epsilon}$ we have $\sup_{\theta \in \Theta} |\bar{l}_n(\theta, g_0) - E(\bar{l}_n(\theta, g_0))| = o_p(1)$.

Theorem 2: Proof. Given A6.1 and Taylor's Theorem in Graves (1927),

$$\begin{aligned} \bar{l}_n(\theta, \hat{m} + \gamma(\theta)) &= \frac{1}{n} \sum_{i=1}^n \log f_\varepsilon(y_i - g_0(x_i); \theta) + \frac{1}{n} \sum_{i=1}^n \frac{d_F}{dg} \log f_\varepsilon(y_i - g_0(x_i), \theta) (\hat{m}(x_i) - m(x_i; \theta, g_0)) \\ &\quad + \frac{1}{2n} \sum_{i=1}^n (\hat{m}(x_i) - m(x_i; \theta, g_0))^2 \int_0^1 \frac{d_F^2}{dg^2} \log f_\varepsilon(y_i - g_0(x_i) - t(\hat{m}(x_i) - m(x_i; \theta, g_0)); \theta) \\ &\quad \times (1-t) dt. \end{aligned}$$

Denoting the last term in the above inequality by c_n and given that $\frac{d_F}{dg}$ is a bounded linear functional from $\mathcal{G}$ to $\mathcal{R}$, we have

$$\begin{aligned} |c_n| &\leq \frac{1}{2n} \sum_{i=1}^n \left(\sup_{x \in G} |\hat{m}(x) - m(x; \theta, g_0)| \right)^2 \int_0^1 C \sup_{x \in G} |g_0(x) + t(\hat{m}(x) - m(x; \theta, g_0))| (1-t) dt \\ &\leq \frac{1}{2} \left(\sup_{x \in G} |\hat{m}(x) - m(x; \theta, g_0)| \right)^2 \int_0^1 C \left(\sup_{x \in G} |g_0(x)| + t \sup_{x \in G} |\hat{m}(x) - m(x; \theta, g_0)| \right) (1-t) dt \\ &\leq C \left(\left(\sup_{x \in G} |\hat{m}(x) - m(x; \theta, g_0)| \right)^2 + \left(\sup_{x \in G} |\hat{m}(x) - m(x; \theta, g_0)| \right)^3 \right). \end{aligned}$$

Since $\sup_{x \in G} |\hat{m}(x) - m(x; \theta, g_0)| = O_p \left(\left(\frac{\log(n)}{nh_n} \right)^{1/2} + h_n^2 \right)$, it follows that if $h_n = O(n^{-1/5})$ we have that

$|c_n| = o_p(n^{-1/2})$. Consequently, we can write

$$\bar{l}_n(\theta, \hat{m} + \gamma(\theta)) = \bar{l}_n(\theta, g_0(x_i)) + \frac{1}{n} \sum_{i=1}^n \frac{d_F}{dg} \log f_\varepsilon(y_i - g_0(x_i), \theta)(\hat{m}(x_i) - m(x_i; \theta, g_0)) + o_p(n^{-1/2}).$$

Since $\frac{\partial}{\partial \theta} \bar{l}_n(\hat{\theta}, \hat{m} + \gamma(\hat{\theta})) = 0$ we have . By A5.1 and the mean value theorem there exists some $\bar{\theta} \in L(\hat{\theta}, \theta_0)$ (the line segment uniting $\hat{\theta}$ and θ_0) such that

$$-\frac{\partial^2}{\partial \theta \partial \theta'} \bar{l}_n(\bar{\theta}, \hat{m} + \gamma(\bar{\theta})) \sqrt{n}(\hat{\theta} - \theta_0) = \sqrt{n} \frac{\partial}{\partial \theta} \bar{l}_n(\theta_0, \hat{m} + \gamma(\theta_0)). \quad (2)$$

We now write

$$\begin{aligned} \sqrt{n} \frac{\partial}{\partial \theta} \bar{l}_n(\theta_0, \hat{m} + \gamma(\theta_0)) &= \sqrt{n} \frac{\partial}{\partial \theta} \bar{l}_n(\theta_0, g_0) + \frac{1}{\sqrt{n}} \frac{\partial}{\partial \theta} \sum_{i=1}^n \frac{d_F}{dg} \log f_\varepsilon(y_i - g_0(x_i), \theta_0)(\hat{m}(x_i) - m(x_i; \theta_0, g_0)) \\ &+ o_p(1). \end{aligned}$$

Due to the equality of Fréchet and Gateaux differentials, we have

$$\frac{d_F}{dg} \log f_\varepsilon(y_i - g_0(x_i), \theta)(\hat{m}(x_i) - m(x_i; \theta, g_0)) = \frac{\partial}{\partial \eta} \log f_\varepsilon(y_i - g_0(x_i); \theta)(\hat{m}(x_i) - m(x_i; \theta, g_0)).$$

Given A5.6 we have from Lemma 1 in Martins-Filho and Yao (2006),

$$\begin{aligned} \frac{1}{\sqrt{n}} \frac{\partial}{\partial \theta} \sum_{i=1}^n \frac{d_F}{dg} \log f_\varepsilon(y_i - g_0(x_i); \theta)(\hat{m}(x_i) - m(x_i; \theta, g_0)) &= \sqrt{n} \frac{\partial}{\partial \theta} \left(\frac{1}{n} \sum_{i=1}^n (y_i - m(x_i; \theta, g_0)) \times \right. \\ &\left. \int \frac{\partial}{\partial \eta} \log f_\varepsilon(y - g_0(x_i); \theta) f_\varepsilon(y - g_0(x_i); \theta_0) dy + \frac{1}{2} h_n^2 \sigma_K^2 E \left(g_0^{(2)}(x_i) \frac{\partial}{\partial \eta} \log f_\varepsilon(y_i - g_0(x_i); \theta) \right) \right) \\ &+ o_p(1) + \sqrt{n} o_p(h_n^2). \end{aligned}$$

We observe that the term $y_i - m(x_i; \theta, g_0)$ is a function of θ . Hence, when passing the $\frac{\partial}{\partial \theta}$ operator and evaluating at θ_0 we obtain,

$$\begin{aligned} &\frac{1}{\sqrt{n}} \frac{\partial}{\partial \theta} \sum_{i=1}^n \frac{d_F}{dg} \log f_\varepsilon(y_i - g_0(x_i); \theta_0)(\hat{m}(x_i) - m(x_i; \theta_0, g_0)) \\ &= \sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n \frac{\partial}{\partial \theta} \gamma(\theta_0) \int \frac{\partial}{\partial \eta} \log f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy + \frac{1}{n} \sum_{i=1}^n (y_i - m(x_i; \theta_0, g_0)) \right. \\ &\times \frac{\partial}{\partial \theta} \int \frac{\partial}{\partial \eta} \log f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy + \frac{1}{2} h_n^2 \sigma_K^2 \frac{\partial}{\partial \theta} E \left(g_0^{(2)}(x_i) \frac{\partial}{\partial \eta} \log f_\varepsilon(y_i - g_0(x_i); \theta_0) \right) \Big) \\ &+ o_p(1) + \sqrt{n} o_p(h_n^2). \end{aligned}$$

Given assumption A5.3, we have

$$\frac{\partial}{\partial \theta} \int \frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy = \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy$$

and

$$\frac{\partial}{\partial \theta} E \left(g_0^{(2)}(x_i) \frac{\partial}{\partial \eta} f_\varepsilon(y_i - g_0(x_i); \theta_0) \right) = E \left(g_0^{(2)}(x_i) \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) \right).$$

In addition, by A5.5

$$\begin{aligned} \int \frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy &= \frac{\partial}{\partial \eta} \int f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy \\ &= \frac{\partial}{\partial \eta} E(f_\varepsilon(y_i - g_0(x_i); \theta_0)) = 0. \end{aligned}$$

Hence, we can write

$$\begin{aligned} \sqrt{n} \frac{\partial}{\partial \theta} \bar{l}_n(\theta_0, \hat{m} + \gamma(\theta_0)) &= \sqrt{n} \frac{\partial}{\partial \theta} \bar{l}_n(\theta_0, g_0) + \sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n (y_i - m(x_i; \theta_0, g_0)) \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) \right. \\ &\quad \times f_\varepsilon(y) dy + \frac{1}{2} h_n^2 \sigma_K^2 E \left(g_0^{(2)}(x_i) \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y_i - g_0(x_i); \theta_0) \right) \Big) \\ &\quad + \sqrt{n} o_p(h_n^2) + o_p(1) \\ &= \sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n \frac{\partial}{\partial \theta} f_\varepsilon(y_i - g_0(x_i); \theta_0) + (y_i - m(x_i; \theta_0, g_0)) \right. \\ &\quad \times \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_{y|x}(y) dy \Big) \\ &\quad + \sqrt{n} \left(\frac{1}{2} h_n^2 \sigma_K^2 E \left(g_0^{(2)}(x_i) \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y_i - g_0(x_i); \theta_0) \right) + o_p(h_n^2) \right) + o_p(1). \end{aligned}$$

Let $Z_i = \frac{\partial}{\partial \theta} f_\varepsilon(y_i - g_0(x_i); \theta_0) + (y_i - m(x_i; \theta_0, g_0)) \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y) dy$ and observe that $E(Z_i) = 0$ since $E(y_i - m(x_i; \theta_0, g_0) | x_i) = 0$ and $E(f_\varepsilon(y - g_0(x_i); \theta))$ has a unique maximum at θ_0 . Let $\sigma_F^2 = E(Z_i Z_i')$, which exists as a positive definite matrix by A6.3 with

$$\begin{aligned} \sigma_F^2 &= E \left(\left(\frac{\partial}{\partial \theta} f_\varepsilon(y_i - g_0(x_i); \theta_0) + (y_i - m(x_i; \theta_0, g_0)) \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy \right) \right. \\ &\quad \times \left. \left(\frac{\partial}{\partial \theta} f_\varepsilon(y_i - g_0(x_i); \theta_0) + (y_i - m(x_i; \theta_0, g_0)) \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy \right) \right). \end{aligned}$$

Since Z_i is a continuous (measurable) function of $\begin{pmatrix} y_i \\ x_i \end{pmatrix}$, and given that the sequence $\left\{ \begin{pmatrix} y_i \\ x_i \end{pmatrix} \right\}_{i=1,2,\dots}$ is i.i.d., by the Cramer-Wold device and Lévy's central limit theorem, we have

$$\sqrt{n} \left(\frac{\partial}{\partial \theta} \bar{l}_n(\theta_0, \hat{m} + \gamma(\theta_0)) - B_{1n} \right) \xrightarrow{d} N(0, \sigma_F^2) \quad (3)$$

where $B_{1n} = \frac{1}{2} h_n^2 \sigma_K^2 E \left(g_0^{(2)}(x_i) \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y_i - g_0(x_i); \theta_0) \right) + o_p(h_n^2)$.

We now study the asymptotic behavior of $\frac{\partial^2}{\partial\theta\partial\theta'}\bar{l}_n(\bar{\theta}, \hat{m} + \gamma(\bar{\theta}))$. Note that,

$$\begin{aligned}\frac{\partial^2}{\partial\theta\partial\theta'}\bar{l}_n(\bar{\theta}, \hat{m} + \gamma(\bar{\theta})) &= \frac{1}{n} \sum_{i=1}^n \frac{\partial^2}{\partial\theta\partial\theta'} f_\varepsilon(y_i - g_0(x_i); \bar{\theta}) \\ &+ \frac{\partial^2}{\partial\theta\partial\theta'} \left(\frac{1}{n} \sum_{i=1}^n \frac{d_F}{dg} f_\varepsilon(y_i - g_0(x_i); \bar{\theta}) (\hat{m}(x_i) - m(x_i; \bar{\theta}, g_0)) \right) \\ &+ o_p(n^{-1/2}).\end{aligned}$$

Since $\hat{\theta} - \theta_0 = o_p(1)$ and $\bar{\theta} \in L(\hat{\theta}, \theta_0)$ we have that $\bar{\theta} - \theta_0 = o_p(1)$, that is, for sufficiently large n , $\bar{\theta} \in S_0$.

Denote the (i, j) element of $\frac{\partial^2}{\partial\theta\partial\theta'} f_\varepsilon(y_i - g_0(x_i); \bar{\theta})$ by $\frac{\partial^2}{\partial\theta_i\partial\theta_j} f_\varepsilon(y_i - g_0(x_i); \bar{\theta})$ and note that by A5.1 it is continuous on S_0 . Furthermore, by A5.2 and Theorem 1 we have that $E\left(\frac{\partial^2}{\partial\theta_i\partial\theta_j} f_\varepsilon(y_i - g_0(x_i); \theta)\right)$ is continuous at θ_0 and

$$\sup_{\theta \in S_0} \left| \frac{1}{n} \sum_{i=1}^n \frac{\partial^2}{\partial\theta_i\partial\theta_j} f_\varepsilon(y_i - g_0(x_i); \theta) - E\left(\frac{\partial^2}{\partial\theta_i\partial\theta_j} f_\varepsilon(y_i - g_0(x_i); \theta)\right) \right| = o_p(1).$$

By Theorem 21.6 in Davidson (1994) we conclude that

$$\frac{1}{n} \sum_{i=1}^n \frac{\partial^2}{\partial\theta_i\partial\theta_j} f_\varepsilon(y_i - g_0(x_i); \bar{\theta}) \xrightarrow{p} E\left(\frac{\partial^2}{\partial\theta_i\partial\theta_j} f_\varepsilon(y_i - g_0(x_i); \theta_0)\right) \text{ for all } (i, j).$$

Now, from earlier in the proof we have that

$$\begin{aligned}&\frac{\partial}{\partial\theta} \frac{1}{n} \sum_{i=1}^n \frac{d_F}{dg} f_\varepsilon(y_i - g_0(x_i); \theta) (\hat{m}(x_i) - m(x_i; \theta, g_0)) \\ &= \frac{1}{n} \sum_{i=1}^n \frac{\partial}{\partial\theta} \gamma(\theta) \int \frac{\partial}{\partial\eta} f_\varepsilon(y - g_0(x_i); \theta) f_\varepsilon(y - g_0(x_i); \theta_0) dy + \frac{1}{n} \sum_{i=1}^n (y_i - m(x_i; \theta, g_0)) \\ &\times \frac{\partial}{\partial\theta} \int \frac{\partial}{\partial\eta} f_\varepsilon(y - g_0(x_i); \theta) f_\varepsilon(y - g_0(x_i); \theta_0) dy + \frac{1}{2} h_n^2 \sigma_K^2 \frac{\partial}{\partial\theta} E\left(g_0^{(2)}(x_i) \frac{\partial}{\partial\eta} f_\varepsilon(y_i - g_0(x_i); \theta)\right) \\ &+ o_p(n^{-1/2}) + o_p(h_n^2) \text{ and therefore we write}\end{aligned}$$

$\frac{\partial^2}{\partial\theta\partial\theta'} \left(\frac{1}{n} \sum_{i=1}^n \frac{d_F}{dg} f_\varepsilon(y_i - g_0(x_i); \bar{\theta}) (\hat{m}(x_i) - m(x_i; \bar{\theta}, g_0)) \right) = \sum_{j=1}^5 I_{4j} + o_p(n^{-1/2}) + o_p(h_n^2)$ where

$$\begin{aligned}I_{41} &= \frac{1}{n} \sum_{i=1}^n \frac{\partial^2}{\partial\theta\partial\theta'} \gamma(\bar{\theta}) \int \frac{\partial}{\partial\eta} f_\varepsilon(y - g_0(x_i); \bar{\theta}) f_\varepsilon(y - g_0(x_i); \theta_0) dy \\ I_{42} &= \frac{1}{n} \sum_{i=1}^n \frac{\partial}{\partial\theta} \int \frac{\partial}{\partial\eta} f_\varepsilon(y - g_0(x_i); \bar{\theta}) f_\varepsilon(y - g_0(x_i); \theta_0) dy \frac{\partial}{\partial\theta} \gamma(\bar{\theta}) \\ I_{43} &= \frac{1}{n} \sum_{i=1}^n \frac{\partial}{\partial\theta} \gamma(\bar{\theta}) \frac{\partial}{\partial\theta} \int \frac{\partial}{\partial\eta} f_\varepsilon(y - g_0(x_i); \bar{\theta}) f_\varepsilon(y - g_0(x_i); \theta_0) dy \\ I_{44} &= \frac{1}{n} \sum_{i=1}^n (y_i - m(x_i; \theta, g_0)) \frac{\partial^2}{\partial\theta\partial\theta'} \int \frac{\partial}{\partial\eta} f_\varepsilon(y - g_0(x_i); \bar{\theta}) f_\varepsilon(y - g_0(x_i); \theta_0) dy \\ I_{45} &= \frac{1}{2} h_n^2 \sigma_K^2 \frac{\partial^2}{\partial\theta\partial\theta'} E\left(g_0^{(2)}(x_i) \frac{\partial}{\partial\eta} f_\varepsilon(y_i - g_0(x_i); \bar{\theta})\right)\end{aligned}$$

The order of each term can be obtained by repeated use of Theorem 1 and Theorem 21.6 in Davidson (1994). We obtain,

$$\begin{aligned}
I_{41} &\xrightarrow{p} \frac{\partial^2}{\partial\theta\partial\theta'}\gamma(\theta_0)E\left(\frac{\partial}{\partial\eta}f_\varepsilon(y-g_0(x_i);\theta_0)\right) = 0 \text{ given A5.3, A5.6 and A7.1,} \\
I_{42} = I'_{43} &\xrightarrow{p} \frac{\partial}{\partial\theta}\gamma(\theta_0)E\left(\frac{\partial^2}{\partial\theta\partial\eta}f_\varepsilon(y-g_0(x_i);\theta_0)\right) \text{ given A5.3, A5.6, A7.2, A7.3} \\
I_{44} &\xrightarrow{p} 0 \text{ given A7.2, A7.4, A7.5 since } E(y_i - m(x_i; \theta_0, g_0)|x_i) = 0 \\
\frac{1}{h_n^2}I_{45} &\xrightarrow{p} \frac{1}{2}\sigma_K^2\frac{\partial^2}{\partial\theta\partial\theta'}E\left(g^{(2)}(x_i)\frac{\partial}{\partial\eta}f_\varepsilon(y-g_0(x_i);\theta_0)\right) \text{ given A7.2, A7.4, A7.6}
\end{aligned}$$

Combining all terms, we have

$$\begin{aligned}
\frac{\partial^2}{\partial\theta\partial\theta'}\bar{l}_n(\bar{\theta}, \hat{m} + \gamma(\bar{\theta})) &= E\left(\frac{\partial^2}{\partial\theta\partial\theta}f_\varepsilon(y_i - g_0(x_i); \theta_0)\right) \\
&+ \frac{\partial}{\partial\theta}\gamma(\theta_0)E\left(\frac{\partial^2}{\partial\theta\partial\eta}f_\varepsilon(y - g_0(x_i); \theta_0)\right) \\
&+ E\left(\frac{\partial^2}{\partial\theta\partial\eta}f_\varepsilon(y - g_0(x_i); \theta_0)\right)\frac{\partial}{\partial\theta}\gamma(\theta_0)' \\
&+ h_n^2 O_p(1) + o_p(h_n^2) + o_p(n^{-1/2}).
\end{aligned}$$

Using the last equation together with the results in equations (2) and (3) we conclude that,

$$\sqrt{n}(\hat{\theta} - \theta_0 - B_{2n}) \xrightarrow{d} N(0, \bar{H}^{-1}\sigma_F^2\bar{H}^{-1}) \quad (4)$$

where $B_{2n} = -\bar{H}^{-1}\left(\frac{1}{2}h_n^2\sigma_K^2E\left(g_0^{(2)}(x_i)\frac{\partial^2}{\partial\theta\partial\eta}f_\varepsilon(y - g_0(x_i); \theta_0)\right)\right) + o_p(h_n^2)$.

Lemma 1: *Proof.* Let $S_0(\theta, \eta, x) = \frac{1}{n}\sum_{i=1}^n \frac{1}{h_n}\frac{\partial}{\partial\eta}\log f_\varepsilon(y_i - \eta; \theta)K\left(\frac{x_i - x}{h_n}\right)$. For $x \in G$, since G is compact there exists a sphere $B(a; r)$ such that $G \subset B(a, r)$. For fixed n , by the Heine-Borel theorem there exist $\{B(x_k, \delta_n)\}_{k=1}^{l_n}$ for $x_k \in G$ such that $G \subseteq \cup_{k=1}^{l_n} B(x_k, \delta_n)$ with $l_n < r/\delta_n$. Similarly, there exists $\{B(\eta_k, \delta_n)\}_{k=1}^{l_{\eta n}}$ for $\eta_k \in \mathcal{H}$ such that $\mathcal{H} \subseteq \cup_{k=1}^{l_{\eta n}} B(\eta_k, \delta_n)$ with $l_{\eta n} < r'/\delta_n$ and $\{B(\theta_k, \delta_n)\}_{k=1}^{l_{\theta n}}$ for $\theta_k \in \Theta$ such that $\Theta \subseteq \cup_{k=1}^{l_{\theta n}} B(\theta_k, \delta_n)$ with $l_{\theta n} < r^P/\delta_n^P$.

$$\begin{aligned}
|S_0(\theta, \eta, x) - E(S_0(\theta, \eta, x))| &\leq |S_0(\theta, \eta, x) - S_0(\theta_{k_1}, \eta, x)| + |S_0(\theta_{k_1}, \eta, x) - S_0(\theta_{k_1}, \eta_{k_2}, x)| \\
&+ |S_0(\theta_{k_1}, \eta_{k_2}, x) - S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3})| + |E(S_0(\theta, \eta, x)) - E(S_0(\theta_{k_1}, \eta, x))| \\
&+ |E(S_0(\theta_{k_1}, \eta, x)) - E(S_0(\theta_{k_1}, \eta_{k_2}, x))| + |E(S_0(\theta, \eta, x)) - E(S_0(\theta, \eta, x))| \\
&+ |S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}) - E(S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}))|
\end{aligned}$$

where $k_1 \in \{1, \dots, l_{\theta n}\}$, $k_2 \in \{1, \dots, l_{\eta n}\}$, $k_3 \in \{1, \dots, l_n\}$. By construction of the open balls, for all $x \in G, \theta \in \Theta, \eta \in \mathcal{H}$ we can always find k_1, k_2, k_3 such that $\|\theta - \theta_{k_1}\| < \delta_n, |\eta - \eta_{k_2}| < \delta_n$ and

$$\|x - x_{k_3}\| < \delta_n.$$

$$|S_0(\theta, \eta, x) - S_0(\theta_{k_1}, \eta, x)| \leq \frac{1}{n} \sum_{i=1}^n \frac{1}{h_n} K\left(\frac{x_i - x}{h_n}\right) \left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta^*) \right\| \|(\theta - \theta_{k_1})\| \text{ for } \theta^* \in L(\theta, \theta_{k_1}).$$

By the c_r -inequality $\left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta^*) \right\| \leq \sum_{k=1}^P \left\| \frac{\partial^2}{\partial \eta \partial \theta_k} \log f_\varepsilon(y_i - \eta; \theta^*) \right\|$, and since by assumption $E\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta) \right\|^2\right) < \infty$, we have $E\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta^*) \right\|\right) \leq \sum_{k=1}^P E\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta \partial \theta_k} \log f_\varepsilon(y_i - \eta; \theta^*) \right\|^2\right) < \infty$. Since $\|\theta - \theta_{k_1}\| < \delta_n$ and $K(x) < C$

$$\begin{aligned} |S_0(\theta, \eta, x) - S_0(\theta_{k_1}, \eta, x)| &\leq \frac{1}{n} \sum_{i=1}^n \frac{1}{h_n} K\left(\frac{x_i - x}{h_n}\right) \delta_n \left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta^*) \right\| \\ &\leq C \delta_n \frac{1}{n} \sum_{i=1}^n \frac{1}{h_n} \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta) \right\| \end{aligned}$$

where $\frac{1}{n} \sum_{i=1}^n \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta^*) \right\| = O_p(1)$. By similar manipulations we have,

$$|S_0(\theta_{k_1}, \eta, x) - S_0(\theta_{k_1}, \eta_{k_2}, x)| \leq C \delta_n \frac{1}{n} \sum_{i=1}^n \frac{1}{h_n} \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y_i - \eta; \theta) \right\|$$

where $\frac{1}{n} \sum_{i=1}^n \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y_i - \eta; \theta) \right\| = O_p(1)$ using assumption PA2 with $s = 2, r = 0$. Similarly, we also obtain $|S_0(\theta_{k_1}, \eta_{k_2}, x) - S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3})| \leq C \frac{1}{h_n^2} \delta_n \frac{1}{n} \sum_{i=1}^n \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial}{\partial \eta} \log f_\varepsilon(y_i - \eta; \theta) \right\|$ where $\frac{1}{n} \sum_{i=1}^n \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial}{\partial \eta} \log f_\varepsilon(y_i - \eta; \theta) \right\| = O_p(1)$ using PA2 with $s = 1, r = 0$. In an analogous fashion we obtain, $|E(S_0(\theta, \eta, x)) - E(S_0(\theta_{k_1}, \eta, x))| \leq C \frac{1}{h_n} \delta_n E\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta \partial \theta} \log f_\varepsilon(y_i - \eta; \theta) \right\|\right)$, $|E(S_0(\theta_{k_1}, \eta, x)) - E(S_0(\theta_{k_1}, \eta_{k_2}, x))| \leq C \frac{1}{h_n} \delta_n E\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y_i - \eta; \theta) \right\|\right)$ and $|E(S_0(\theta_{k_1}, \eta_{k_2}, x)) - E(S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}))| \leq C \frac{1}{h_n^2} \delta_n E\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial}{\partial \eta} \log f_\varepsilon(y_i - \eta; \theta) \right\|\right)$. Hence, we can find k_1, k_2, k_3 such that

$$|S_0(\theta, \eta, x) - E(S_0(\theta, \eta, x))| \leq |E(S_0(\theta_{k_1}, \eta_{k_2}, x)) - E(S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}))| + 3C \delta_n h_n^{-2} \frac{1}{n} \sum_{i=1}^n M_i$$

where $M_i = \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \theta \partial \eta} \log f_\varepsilon(y_i - \eta; \theta) \right\| + \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y_i - \eta; \theta) \right\| + \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left\| \frac{\partial}{\partial \eta} \log f_\varepsilon(y_i - \eta; \theta) \right\| \right)$ and $E|M_i| < \infty$. Hence,

$$\begin{aligned} \sup_{\theta \in \Theta, \eta \in \mathcal{H}, x \in G} |S_0(\theta, \eta, x) - E(S_0(\theta, \eta, x))| &\leq \max_{1 \leq k_1 \leq l_{\theta_n}, 1 \leq k_2 \leq l_{\eta_n}, 1 \leq k_3 \leq l_n} |S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}) - E(S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}))| \\ &\quad + 3C \delta_n h_n^{-2} \frac{1}{n} \sum_{i=1}^n M_i = I_1 + I_2. \end{aligned}$$

Note that $P(I_1 \geq \epsilon/2) \leq \sum_{k_1=1}^{l_{\theta n}} \sum_{k_2=1}^{l_{\eta n}} \sum_{k_3=1}^{l_n} P(|S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}) - E(S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}))|)$ and put

$$\begin{aligned} |S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}) - E(S_0(\theta_{k_1}, \eta_{k_2}, x_{k_3}))| &= \left| \frac{1}{n} \sum_{i=1}^n \left(\frac{1}{h_n} \frac{\partial}{\partial \eta} \log f_\epsilon(y_i - \eta_{k_2}; \theta_{k_1}) K\left(\frac{x_i - x_{k_3}}{h_n}\right) \right) \right. \\ &\quad \left. - E\left(\frac{1}{h_n} \frac{\partial}{\partial \eta} \log f_\epsilon(y_i - \eta_{k_2}; \theta_{k_1}) K\left(\frac{x_i - x_{k_3}}{h_n}\right)\right) \right| = \left| \frac{1}{n} \sum_{i=1}^n W_{in} \right| \end{aligned}$$

For fixed n , $E(W_{in}) = 0$. Furthermore, given that $K(x) < C$, $\frac{\partial}{\partial \eta} \log f_\epsilon(y - \eta; \theta)$ exists almost surely with $E(\frac{\partial}{\partial \eta} \log f_\epsilon(y - \eta; \theta)) < \infty$ by PA2 we have $|W_{in}| < c/h_n$. Furthermore, $\{W_{in}\}_{i \geq 1}$ forms an independent sequence since K and $\frac{\partial}{\partial \eta} \log f_\epsilon(y - \eta; \theta)$ are continuous (measurable) functions of $\{(y_i, x_i)\}_{i \geq 1}$, an independent sequence. By Bernstein's inequality we obtain, $P(I_1 \geq \epsilon/2) \leq 2l_{\theta n} l_{\eta n} l_n \exp\left(\frac{-nh_n(\epsilon^2/4)}{2h_n\bar{\sigma}^2 + (1/3)C\epsilon}\right)$ where $\bar{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \text{Var}(W_{in})$ and $h_n\bar{\sigma}^2 \rightarrow B_{\bar{\sigma}^2} = \int \left(\frac{\partial}{\partial \eta} \log f_\epsilon(y - \eta_{k_2}, \theta_{k_1})\right)^2 f(y, x_{k_3}) dy \int K^2(x) dx$. Since $l_{\theta n} < \frac{r^P}{\delta_n^P}$, $l_{\eta n} < \frac{r}{\delta_n}$, $l_n < \frac{r}{\delta_n}$ we have that $P(I_1 \geq \epsilon/2) < \frac{2r^{P+2}}{\delta_n^{P+2}} \exp\left(\frac{-nh_n(\epsilon^2/4)}{2h_n\bar{\sigma}^2 + (1/3)C\epsilon}\right)$. Now, by Markov's Inequality $P(I_2 \geq \epsilon/2) = P(\frac{1}{n} \sum_{i=1}^n M_i \geq \frac{h_n^2 \epsilon}{6\delta_n}) \leq \frac{E|M_i|}{\epsilon h_n^2} 6\delta_n$ and we have

$$P\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}, x \in G} |S_0(\theta, \eta, x) - E(S_0(\theta, \eta, x))| > \epsilon\right) \leq \frac{2r^{P+2}}{\delta_n^{P+2}} \exp\left(\frac{-nh_n(\epsilon^2/4)}{2h_n\bar{\sigma}^2 + (1/3)C\epsilon}\right) + \frac{E|M_i|}{\epsilon h_n^2} 6\delta_n.$$

The denominator in the first term converges as $n \rightarrow \infty$, so we set the two terms on the right hand side of the inequality to be of equal magnitude and solve for δ_n as a function of ϵ . As such, $\delta_n = O\left(\epsilon^{1/(p+3)} h_n^{2/(P+3)} \exp(-nh_n\epsilon^2/C)\right)$. Since we need $P\left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}, x \in G} |S_0(\theta, \eta, x) - E(S_0(\theta, \eta, x))| > \epsilon\right) \rightarrow 0$, we set $\epsilon = \left(\frac{\log(n)}{nh_n}\right)^{1/2} \Delta$ for some constant Δ . It is easy to verify that if $nh_n^{3m/(2-m)} \rightarrow \infty$ for $3/4 \leq m \leq 1$ then we have the desired convergence. Hence, if $nh_n^3 \rightarrow \infty$ ($m = 1$) we have that

$$\sup_{\theta \in \Theta, \eta \in \mathcal{H}, x \in G} |S_0(\theta, \eta, x) - E(S_0(\theta, \eta, x))| = O_p((\log(n)/nh_n)^{1/2}).$$

Now, let $S_1(\theta, \eta, x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h_n} \frac{\partial}{\partial \eta} \log f_\epsilon(y_i - \eta; \theta) K\left(\frac{x_i - x}{h_n}\right) \left(\frac{x_i - x}{h_n}\right)$ and since the kernel K has bounded support we immediately obtain, $\sup_{\theta \in \Theta, \eta \in \mathcal{H}, x \in G} |S_1(\theta, \eta, x) - E(S_1(\theta, \eta, x))| = O_p((\log(n)/nh_n)^{1/2})$ which completes the proof.

3 Verification of assumptions for Theorem 2

Since assumption A1 has been verified in Martins-Filho and Yao (2011) and assumptions A2 and A3 are unrelated to f_ϵ we will verify A4, A5, A6 and A7.

A4.1: For all $\theta \in \Theta$ we have that if $\theta \neq \theta_0$ then $f_\epsilon(y - g_0(x); \theta) \neq f_\epsilon(y - g_0(x); \theta_0)$ for all (y, x) .

Letting $e = y - g_0(x)$ for fixed x . Then, $f_\varepsilon(y - g_0(x); \theta) = f_e(e; \theta) = \frac{2}{s} \phi(e/s) \Phi(-\frac{\lambda}{s}e)$. Hence, f_e is a skew normal density with scale parameter s and skewness parameter λ . Identification of (s, λ) follows directly from Azzalini (1985). Identification of (σ_u^2, σ_v^2) follows from the uniqueness of the reparametrization given by $\lambda = \sqrt{\frac{\sigma_u^2}{\sigma_v^2}}$ and $s^2 = \sigma_u^2 + \sigma_v^2$. We also note that from property H and Lemma 2 in Azzalini (1985), all even moments of a skew-normal density with scale parameter $s = 1$ coincide with those of a standard normal, and all odd moments can be obtained by the moment generating function $M(t) = 2\exp(t^2/2)\Phi(\frac{\lambda}{\sqrt{1+\lambda^2}}t)$.

A4.2: If $\{\theta_i\}_{i=1,2,\dots}$ is a sequence in Θ such that $\theta_i \rightarrow \theta$ as $i \rightarrow \infty$, then

$$\log f_\varepsilon(y; \theta_i, g_0(x)) \rightarrow \log f_\varepsilon(y - g_0(x); \theta) \text{ as } i \rightarrow \infty \text{ for all } \theta \in \Theta.$$

This assumption requires continuity of $\log f_\varepsilon(y - g_0(x); \theta)$ with respect to θ . This is apparent from the structure of f_ε as a function of θ and continuity of the logarithm function.

A4.3: $E(\sup_{\theta \in \Theta} |\log f_\varepsilon(y - g_0(x); \theta)|) < \infty$.

Since $\theta \in \Theta$ a compact set, $\sigma_u^2, \sigma_v^2 > 0$, then $\sup_{\theta \in \Theta} |\log(\sigma_u^2 + \sigma_v^2)| < C$ and $E(\sup_{\theta \in \Theta} (y - g_0(x))^2 / (\sigma_u^2 + \sigma_v^2)) < C(\frac{\pi-2}{\pi}\sigma_u^2 + \sigma_v^2) < C$. Now, let $z = (-\lambda/s)e$ and note that by the mean value theorem

$$\begin{aligned} |\log \Phi(z)| &\leq |\log \Phi(0)| + \frac{\phi(z')}{\Phi(z')} |z| \text{ for } z' = \delta z \text{ where } \delta \in (0, 1). \\ &\leq |\log \Phi(0)| + C(1 + \delta|\lambda/s||e|)|e| \text{ and} \end{aligned}$$

$$\sup_{\theta \in \Theta} |\log \Phi(z)| \leq |\log \Phi(0)| + C(|e| + e^2) \text{ which gives}$$

$$E(\sup_{\theta \in \Theta} |\log \Phi(z)|) \leq |\log \Phi(0)| + CE(|e| + e^2) < C.$$

Combining the last inequality with the fact that $E(\sup_{\theta \in \Theta} (y - g_0(x))^2 / (\sigma_u^2 + \sigma_v^2)) < C$ and $\sup_{\theta \in \Theta} |\log(\sigma_u^2 + \sigma_v^2)| < C$ verifies A4.3.

A4.4: $E(\sup_{\theta \in \Theta} |\log f_\varepsilon(y - g_0(x); \theta)|) < \infty$. For all (y, x) , $g \in \mathcal{G}$ and $\theta \in \Theta$, $|\log f_\varepsilon(y; \theta, g(x)) - \log f_\varepsilon(y - g_0(x); \theta)| \leq b(y, x, \theta)|g(x) - g_0(x)| = b(y, x, \theta)|m(x; \theta, g) - m(x; \theta, g_0)|$ with $b(y, x, \theta) > 0$, and $E(\sup_{\theta \in \Theta} b(y, x, \theta)) < \infty$. We first observe that

$$\begin{aligned} |\log f_\varepsilon(y; \theta, g(x)) - \log f_\varepsilon(y - g_0(x); \theta)| &\leq \frac{1}{2s} |(y - g(x))^2 - (y - g_0(x))^2| \\ &+ \left| \log \left(\Phi(-\frac{\lambda}{s}(y - g(x))) \right) - \Phi(-\frac{\lambda}{s}(y - g_0(x))) \right| \\ &= I_1 + I_2. \end{aligned}$$

By Taylor's Theorem in Graves (1927), we have that $I_1 = \frac{1}{s^2}|y - g(x)||g(x) - g_0(x)| = b_1(y, x, \theta)|g(x) - g_0(x)|$. In addition, $\sup_{\theta \in \Theta} b_1(y, x, \theta) \leq C|y - g(x)|$ and given that $\sigma_u^2, \sigma_v^2 > 0$ and Θ is compact we have $E(\sup_{\theta \in \Theta} b_1(y, x, \theta)) < \infty$. Again, by Taylor's Theorem $I_2 \leq \frac{\lambda}{s} \int_0^1 \frac{\phi(w_1)}{\Phi(w_1)} dt |g(x) - g_0(x)| = b_2(y, x, \theta)|g(x) - g_0(x)|$ where $w_1 = y - g(x) + t(g(x) - g_0(x))$. Now,

$$\begin{aligned} b_2(y, x, \theta) &\leq \frac{\lambda}{s} \int_0^1 C(1 + w_1) dt \\ &\leq C \frac{\lambda}{s} + C \frac{\lambda^2}{s^2} (|e| + |g(x) - g_0(x)|). \end{aligned}$$

Since $E(|e|) < C$ we have given $\sigma_u^2, \sigma_v^2 > 0$, Θ compact and the results for I_1 that,

$$|\log f_\varepsilon(y - g(x); \theta) - \log f_\varepsilon(y - g_0(x); \theta)| \leq (b_1(y, x, \theta) + b_2(y, x, \theta))|g(x) - g_0(x)|$$

where $E(\sup_{\theta \in \Theta} (b_1(y, x, \theta) + b_2(y, x, \theta))) < C$.

A5.1 : For all $\eta = g(x) \in \mathcal{H}$, $\log f_\varepsilon(y - \eta; \theta)$ is twice continuously differentiable with respect to θ and $f_\varepsilon(y - \eta; \theta) > 0$ on some open ball $S_{0,\theta} = S(\theta_0, d(\theta_0))$ of θ_0 with $S_{0,\theta} \subset \Theta$ and $d(\theta_0)$ the radius of the ball.

For fixed $\eta = g(x)$ and given the structure of $\log f_\varepsilon$ as a function of θ , routine partial differentiation with respect to σ_u^2 and σ_v^2 show the existence of $\frac{\partial^3}{\partial(\sigma_u^2)^r \partial(\sigma_v^2)^s} \log f_\varepsilon(y - \eta; \theta)$ for $r + s \leq 3$ and $r, s = 0, 1, 2, 3$ provided that $\sigma_u^2 + \sigma_v^2 > 0$. That $f_\varepsilon(y - \eta; \theta) > 0$ on an open ball around θ_0 follows from the fact that $\sigma_u^2, \sigma_v^2 > 0$, $\exp(x) > 0$ and $\Phi(x) \in (0, 1)$.

A5.2 : $E\left(\sup_{\theta \in S_{0,\theta}} \left| \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f_\varepsilon(y - g_0(x); \theta) \right| \right) < \infty$ for $k, j = 1, \dots, P$

Routine partial differentiation of $\log f_\varepsilon(y - g(x); \theta)$ with respect to σ_u^2 gives

$$\begin{aligned} \left| \frac{\partial^2 \log f_\varepsilon(y - g(x); \theta)}{\partial(\sigma_u^2)^2} \right| &\leq \frac{1}{2s^2} + \frac{e^2}{s^6} + (1 - \Phi(e\lambda/s))^{-2} (\phi(e\lambda/s)ew)^2 + \frac{1}{2} (1 - \Phi(e\lambda/s))^{-1} \phi(e\lambda/s) |e^3| \frac{|w|}{s^4} \\ &+ (1 - \Phi(e\lambda/s))^{-1} \phi(e\lambda/s) |e| \left| \frac{\partial w}{\partial \sigma_u^2} \right| = I_1 + I_2 + I_3 + I_4 + I_5 \end{aligned}$$

where $w = \frac{1}{2\lambda s^3}$. $I_1 < C$ since $\sigma_u^2, \sigma_v^2 > 0$, $E(\sup_{\theta \in \Theta} I_2) < C$ since $1/s_6 < C$ and $E(e^2) < C$. Note that $I_3 < C(1 - \Phi(e\lambda/s))^{-2} \phi(e\lambda/s)^2 |e|^2$. Let $I = (1 - \Phi(e\lambda/s))^{-i} \phi(e\lambda/s)^i |e|^j$ and given the convexity of $\phi(x)/\Phi(x)$ and $\lim_{x \rightarrow \infty} (\phi(x)/\Phi(x)) = 0$, $\lim_{x \rightarrow -\infty} (\phi(x)/\Phi(x)) = -x$ we have that $|I| \leq C(|e|^j + |e|^{i+j}(\lambda/s)^i)$. In the case of I_3 , $i = j = 2$ and since $E(e^3), E(e^4) < C$ we have $E(\sup_{\theta \in \Theta} I_3) < C$. Using similar arguments $E(\sup_{\theta \in \Theta} I_4) < C$, $E(\sup_{\theta \in \Theta} I_5) < C$. The same arguments give the following bounds

$$E\left(\sup_{\theta \in \Theta} \left| \frac{\partial^2 \log f_\varepsilon(y - g(x); \theta)}{\partial(\sigma_v^2)^2} \right| \right) < C \text{ and } E\left(\sup_{\theta \in \Theta} \left| \frac{\partial^2 \log f_\varepsilon(y - g(x); \theta)}{\partial \sigma_u^2 \partial \sigma_v^2} \right| \right) < C.$$

A5.3 : $\frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x); \theta)$ is continuously differentiable in $S_{0,\theta}$. Furthermore,

$$\int \sup_{\theta \in S_{0,\theta}} \left\| \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x); \theta) \right\|_E f_\varepsilon(y - g_0(x); \theta_0) dy < \infty$$

and

$$E \left(\sup_{\theta \in S_{0,\theta}} \left\| \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x); \theta) \right\|_E |g_0^{(2)}(x)| \right) < \infty.$$

Taking partial derivatives we have $\frac{\partial}{\partial \eta} \log f_\varepsilon(y - \eta; \theta) = \frac{e}{s^2} + (1 - \Phi(e\lambda/s))^{-1} \phi(e\lambda/s) \frac{\lambda}{s}$. For fixed $\eta = g(x)$ and given the structure of $\frac{\partial}{\partial \eta} \log f_\varepsilon$ as a function of θ , routine partial differentiation with respect to σ_u^2 and σ_v^2 show the existence of $\frac{\partial^3}{\partial \eta \partial (\sigma_u^2)^r \partial (\sigma_v^2)^s} \log f_\varepsilon(y; \theta, \eta)$ for $r + s \leq 2$ and $r, s = 0, 1, 2$ provided that $\sigma_u^2 + \sigma_v^2 > 0$. For $x \in \mathbb{R}^2$, $\|x\|_E \leq x_1^2 + x_2^2$. Hence, we first show that $E \left(\sup_{\theta \in \Theta} \left| \frac{\partial^2}{\partial \eta \partial \sigma_u^2} \log f_\varepsilon(y - \eta; \theta) \right| |x \right) < C$. Using the structure of $\log f_\varepsilon(y - \eta; \theta)$ and taking partial derivatives shows that the components of $\frac{\partial^2}{\partial \eta \partial \sigma_u^2} \log f_\varepsilon(y - \eta; \theta)$ take the form $C(1 - \Phi(e\lambda/s))^{-i} \phi(e\lambda/s)^i |e|^j \leq C(|e|^j + |e|^{i+j} C)$ for $(i, j) = (0, 1), (2, 1), (1, 2)$, or $(1, 0)$. Since all finite order moments of skew normal densities exist (Azzalini(1985)), it follows that $E \left(\sup_{\theta \in \Theta} \left| \frac{\partial^2}{\partial \eta \partial \sigma_u^2} \log f_\varepsilon(y - \eta; \theta) \right| \right) < C$. The same argument provides

$$E \left(\sup_{\theta \in \Theta} \left| \frac{\partial^2}{\partial \eta \partial \sigma_v^2} \log f_\varepsilon(y - \eta; \theta) \right| \right) < C.$$

Finally, with the above given bounds $E \left(\sup_{\theta \in S_{0,\theta}} \left\| \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x); \theta) \right\|_E |g_0^{(2)}(x)| \right) < \infty$ provided that $|g_0^{(2)}(x)| < \infty$.

A5.4 : The matrix

$$\begin{aligned} \bar{H} &= E \left(\frac{\partial^2}{\partial \theta \partial \theta'} \log f_\varepsilon(y - g_0(x); \theta_0) \right) + \frac{\partial}{\partial \theta} \gamma(\theta_0) E \left(\frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x); \theta_0) \right)' \\ &+ E \left(\frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x); \theta_0) \right) \frac{\partial}{\partial \theta} \gamma(\theta_0)' \end{aligned}$$

exists and is nonsingular.

Given the structure of f_ε as a function of θ and the fact that $\gamma(\theta) = \sqrt{\frac{2}{\pi} \sigma_u^2}$, we have by routine partial differentiation that $\bar{H} = \begin{pmatrix} \bar{H}_{11} & \bar{H}_{12} \\ \bar{H}_{21} & \bar{H}_{22} \end{pmatrix}$ where $\bar{H}_{11} = -\frac{1}{2s^4} - w^2 I_1 + \sqrt{\frac{2}{\pi \sigma_u^2}} C_1$, $\bar{H}_{12} = -\frac{1}{2s^4} - ww_1 I_1 + \sqrt{\frac{2}{\pi \sigma_u^2}} C_2$, and $\bar{H}_{22} = -\frac{1}{2s^4} - w_1^2 I_1$. Here, $w = \frac{1}{2\lambda s^3}$, $w_1 = -\frac{1}{2\lambda} \frac{(\sigma_u^2 + 2\sigma_v^2)\sigma_u^2}{(\sigma_v^2)^2 s^3}$, $I = \int \frac{e^{-\frac{\sqrt{2}}{s} \pi^{3/2}}}{1 - \text{erf}(e^{-\frac{\lambda}{s\sqrt{2}}})} \exp(-e^2(\frac{\lambda^2}{s^2} + \frac{1}{2s^2})) de$, $I_1 = \int \frac{e^{-\frac{\sqrt{2}}{s} \pi^{3/2}}}{1 - \text{erf}(e^{-\frac{\lambda}{s\sqrt{2}}})} \exp(-e^2(\frac{\lambda^2}{s^2} + \frac{1}{2s^2})) de$, $C_1 = \frac{\gamma(\theta)}{s^4} + \frac{\lambda}{s} w I - (\frac{\lambda}{s})^2 w \sqrt{\frac{2}{\pi(\lambda^2+1)}} \frac{s^2}{\lambda^2+1} + w \sqrt{\frac{2}{\pi(\lambda^2+1)}}$, $C_2 = \frac{\gamma(\theta)}{s^4} + \frac{\lambda}{s} w_1 I - (\frac{\lambda}{s})^2 w_1 \sqrt{\frac{2}{\pi(\lambda^2+1)}} \frac{s^2}{\lambda^2+1} + w_1 \sqrt{\frac{2}{\pi(\lambda^2+1)}}$ where erf is the Gaussian error function. The determinant of $\bar{H}$ denoted by $\det(\bar{H}) = \bar{H}_{11}\bar{H}_{22} - \bar{H}_{21}\bar{H}_{12} = \frac{I_1}{2s^4}(w_1 - w)^2 + \frac{1}{\sqrt{2}s^4} \sqrt{\frac{1}{\pi \sigma_u^2}} (C_2 - C_1) + ww_1^2 I_1^2 (w_1 - w) + w_1 I_1 \sqrt{\frac{2}{\pi \sigma_u^2}} (wC_2 - w_1 C_1) - \frac{C_2^2}{2\pi \sigma_u^2} \neq 0$ given the structure of C_1, C_2 and $w \neq w_1, C_1 \neq C_2$.

A5.5 : Let $\eta_0 = g_0(x)$ for any $x \in G$ and denote by $S_{0,\eta} = S(\eta_0, d(\eta_0))$. $f_\varepsilon(y - \eta; \theta)$ is continuously differentiable on $S_{0,\eta}$, an open interval of $\mathcal{H}$, $E \left(\sup_{\eta \in S_{0,\eta}} \left| \frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \right| \right) < \infty$ and for all $x \in G$, $\frac{\partial}{\partial \eta} E(f_\varepsilon(y - g_0(x); \theta_0)|x) = 0$.

From A5.3 we have $\frac{\partial}{\partial \eta} \log f_\varepsilon(y - \eta; \theta) = \frac{e}{s^2} + (1 - \Phi(e \frac{\lambda}{s}))^{-1} \phi(e \frac{\lambda}{s}) \frac{\lambda}{s}$ and taking a second partial derivative with respect to η gives $\frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) = -\frac{1}{s^2} - (1 - \Phi(e \frac{\lambda}{s}))^{-2} \phi(e \frac{\lambda}{s})^2 (\frac{\lambda}{s})^2 + (1 - \Phi(e \frac{\lambda}{s}))^{-1} \phi(e \frac{\lambda}{s}) (\frac{\lambda}{s})^3 e$ establishing continuous differentiability of $\log f_\varepsilon(y - \eta; \theta)$ with respect to the argument η . Now,

$$E \left(\sup_{\eta \in S_{0,\eta}} |f_\varepsilon(y - \eta; \theta)| \right) \leq \frac{1}{s^2} E(\sup_{\eta \in S_{0,\eta}} |y - \eta|) + (\lambda/s) E \left(\sup_{\eta \in S_{0,\eta}} \left| \left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-1} \phi(e \frac{\lambda}{s}) \right| \right).$$

The first term on the right hand side of the inequality is bounded since $\eta \in \mathcal{H}$ a compact set in $\Re$ and $E(|y|) \leq E(|g_0(x)|) + E(|e|) < C$. For the second term, note that

$$E \left(\sup_{\eta \in S_{0,\eta}} \left| \left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-1} \phi(e \frac{\lambda}{s}) \right| \right) \leq C (1 + (\lambda/s) E(\sup_{\eta \in S_{0,\eta}} |y - \eta|)) < C.$$

Lastly, $\frac{\partial}{\partial \eta} E(f_\varepsilon(y - g_0(x); \theta_0)) = E \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x); \theta_0) \right)$ and

$$\begin{aligned} E \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x); \theta_0) \right) &= -\frac{1}{s^2} \sqrt{\frac{2}{\pi} \sigma_u^2} + \frac{\lambda}{s} E \left(\left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-1} \phi(e \frac{\lambda}{s}) |x \right) \\ &= -\frac{1}{s^2} \sqrt{\frac{2}{\pi} \sigma_u^2} + \frac{\lambda}{s} \sqrt{\frac{2}{\pi(\lambda^2 + 1)}} = 0 \end{aligned}$$

given the definition of s and λ .

A5.6 : For all $\theta \in \Theta$, $\frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x); \theta)$ is continuous at x ,

$$E \left(\sup_{\theta \in \Theta} \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \right)^2 \right) < \infty \text{ and } E \left(\sup_{\theta \in \Theta} \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \right)^2 y^2 \right) < \infty.$$

Continuity of $\frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x); \theta)$ at x follows directly from the existence $\frac{\partial^2}{\partial \eta \partial x} f_\varepsilon(y - g_0(x); \theta)$, which follows given that $\sigma_u^2, \sigma_v^2 > 0$ and differentiability of $g_0(x)$ with respect to x . Now,

$$\begin{aligned} E \left(\sup_{\theta \in \Theta} \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \right)^2 \right) &= E \left(\sup_{\theta \in \Theta} \left(\frac{1}{s^2} + \left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-1} \phi(e \frac{\lambda}{s}) \left(\frac{\lambda}{s} \right) \right)^2 \right) \\ &\leq CE(e^2) + CE \left(\sup_{\theta \in \Theta} \left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-1} \phi(e \frac{\lambda}{s}) |e| \right) \\ &\quad + CE \left(\sup_{\theta \in \Theta} \left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-2} \phi(e \frac{\lambda}{s})^2 \right) < C \end{aligned}$$

given that $\sigma_u^2, \sigma_v^2 > 0$ and the arguments made to verify A5.2. Given that $E(e^2 y^2) \leq C(E(e^2 g_0(x)^2) + E(e^4)) < C(E(e^2) + E(e^4)) < C$ from Azzalini(1985) and the fact that $g_0(x) \in \mathcal{H}$ a compact set, we im-

mediately have $E \left(\sup_{\theta \in \Theta} \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \right)^2 y^2 \right) < \infty$ using the same arguments that gave the boundedness of $E \left(\sup_{\theta \in \Theta} \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \right)^2 \right)$.

A6.1 : $\log f_\varepsilon(y - g_0(x); \theta)$ is twice Fréchet differentiable at g_0 with increment $h(x) = g(x) - g_0(x)$ and denote the Fréchet derivatives of order $i = 1, 2$ at g_0 by $\frac{d_F^i}{dg} \log f_\varepsilon(y - g_0(x); \theta)$.

Let $T(g_0) = f_\varepsilon(y - g_0(x); \theta)$. It follows directly from the definition of the first order Gateaux differential with increment $h = g - g_0$ that $\delta_G T(g_0, h) = \frac{d}{d\alpha} T(g_0 + \alpha(g - g_0))|_{\alpha=0} = \frac{e}{s^2}(g(x) - g_0(x)) + (1 - \Phi(e \frac{\lambda}{s}))^{-1} \phi(e \frac{\lambda}{s}) \frac{\lambda}{s}(g(x) - g_0(x))$. We will establish that $\delta_G T(g_0, h) = \delta_F T(g_0, h)$. First, observe that

$$\begin{aligned} |T(g) - T(g_0) - \delta_G T(g_0, h)| &\leq \left| -\frac{1}{2s^2}(y - g(x))^2 + \frac{1}{2s^2}(y - g_0(x))^2 - \frac{e}{s^2}(g(x) - g_0(x)) \right| \\ &\quad + \left| \log \left(1 - \Phi((y - g(x)) \frac{\lambda}{s}) \right) - \log \left(1 - \Phi((y - g_0(x)) \frac{\lambda}{s}) \right) \right. \\ &\quad \left. - \log \left(1 - \Phi((y - g(x)) \frac{\lambda}{s}) \right)^{-1} \phi(e \frac{\lambda}{s}) \frac{\lambda}{s}(g(x) - g_0(x)) \right| \\ &= I_1 + I_2. \end{aligned}$$

Let $T_1(g) = -\frac{1}{2s^2}(y - g(x))^2$, then $\delta_G T_1(g_0, h) = \frac{e}{s^2}(g(x) - g_0(x))$ and $\delta_G^2 T_1(g_0, h) = -\frac{1}{s^2}(g(x) - g_0(x))^2$.

By Taylor's Theorem $T_1(g) = T_1(g_0) + \delta_G T_1(g_0, h) + \int_0^1 \delta_G^2 T_1(g_0, h)(1-t)dt$, therefore $I_1 \leq \frac{1}{2s^2} \|g - g_0\|^2$.

Setting $T_2(g) = \log \left(1 - \Phi((y - g(x)) \frac{\lambda}{s}) \right)$ and taking Gateaux differentials of order 2 and using Taylor's Theorem as in the case for T_1 gives

$$\begin{aligned} I_2 &= \left| \int_0^1 (1-t) \left(- \left(1 - \Phi(e^* \frac{\lambda}{s}) \right)^{-2} \phi(e^* \frac{\lambda}{s})^2 \left(\frac{\lambda}{s} \right)^2 \right. \right. \\ &\quad \left. \left. + \left(1 - \Phi(e^* \frac{\lambda}{s}) \right)^{-1} \phi(e^* \frac{\lambda}{s})^2 e^* \left(\frac{\lambda}{s} \right)^3 \right) dt \right| (g(x) - g_0(x)) \\ &\leq \int_0^1 (1-t) \left(C(1 + |e^*| \frac{\lambda}{s})^2 + C(1 + |e^*| \frac{\lambda}{s}) |e^*| \right) dt \|g(x) - g_0(x)\|^2 \end{aligned}$$

where $e^* = y - (g_0 + th)(x)$. Since $|e^*| \leq |e| + t|g(x) - g_0(x)|$, $E(e^2) < C$ and $g \in \mathcal{G}$ we have that

$I_2 = O_p(1) \|g - g_0\|^2$. Since $I_1 = O(1) \|g - g_0\|^2$ we have combining the two orders that $\delta_G T(g_0, h) =$

$\delta_F T(g_0, h) = \frac{d_F}{dg} f_\varepsilon(y - g_0(x); \theta)(g(x) - g_0(x))$ where $\frac{d_F}{dg} f_\varepsilon(y - g_0(x); \theta) = \frac{e}{s^2} + (1 - \Phi(e \frac{\lambda}{s}))^{-1} \phi(e \frac{\lambda}{s}) \frac{\lambda}{s}$

is the first order Fréchet derivative. The same arguments show the existence and equivalence of second order Gateaux and Fréchet differentials. In this case,

$$\begin{aligned} \delta_F^2 T(g_0, h) &= -\frac{1}{s^2}(g(x) - g_0(x))^2 + \left(- \left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-2} \phi(e \frac{\lambda}{s})^2 \left(\frac{\lambda}{s} \right)^2 \right. \\ &\quad \left. + \left(1 - \Phi(e \frac{\lambda}{s}) \right)^{-1} \phi(e \frac{\lambda}{s})^2 e \left(\frac{\lambda}{s} \right)^3 \right) (g(x) - g_0(x)). \end{aligned}$$

A6.2 : $\frac{d_F}{dg} \log f_\varepsilon(y - g_0(x); \theta_0)$ is continuous at every $x \in G$.

From A6.1 $\frac{d_F}{dg} \log f_\varepsilon(y - g_0(x); \theta_0) = \frac{e}{s^2} + (1 - \Phi(e\frac{\lambda}{s}))^{-1} \phi(e\frac{\lambda}{s})\frac{\lambda}{s}$ which is clearly continuous in x given differentiability of $g(x)$ and the structure of $\log f_\varepsilon(y - g_0(x); \theta_0)$ as a function of x .

A6.3 : The matrix

$$\begin{aligned} \sigma_F^2 &= E \left(\left(\frac{\partial}{\partial \theta} f_\varepsilon(y_i - g_0(x_i); \theta_0) + (y_i - m(x_i; \theta_0, g_0)) \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy \right) \right. \\ &\quad \times \left. \left(\frac{\partial}{\partial \theta} f_\varepsilon(y_i - g_0(x_i); \theta_0) + (y_i - m(x_i; \theta_0, g_0)) \int \frac{\partial^2}{\partial \theta \partial \eta} f_\varepsilon(y - g_0(x_i); \theta_0) f_\varepsilon(y - g_0(x_i); \theta_0) dy \right) \right). \end{aligned}$$

exists and is positive definite.

We start by noting that routine partial differentiation with respect to σ_u^2 gives, $\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} = -\frac{1}{2s^2} + \frac{e^2}{2s^4} - \Phi(-e\frac{\lambda}{s})^{-1} \phi(-e\frac{\lambda}{s})ew$ and consequently $E \left(\left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} \right)^2 \right) = \frac{1}{4s^4} + \frac{1}{4s^6} E(e^4) + w^2 E(\Phi(-e\frac{\lambda}{s})^{-2} \phi(-e\frac{\lambda}{s})^2 e^2) < C$ by the arguments used in verifying A5.2. Now,

$$\begin{aligned} E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} \right) &= -e \frac{1}{4s^4} - \Phi \left(-e \frac{\lambda}{s} \right)^{-2} \phi \left(-e \frac{\lambda}{s} \right)^2 \left(-\frac{\lambda}{s} \right) ew \\ &\quad - \Phi \left(-e \frac{\lambda}{s} \right)^{-1} \phi \left(-e \frac{\lambda}{s} \right) \left(\frac{\lambda}{s} \right) e^2 w + \Phi \left(-e \frac{\lambda}{s} \right)^{-1} \phi \left(-e \frac{\lambda}{s} \right) \left(\frac{\lambda}{s} \right) w \end{aligned}$$

and by the Cauchy-Schwarz inequality

$$\begin{aligned} E \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} e E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} \middle| x \right) \right) &\leq \left(E \left(e^2 \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} \right)^2 \right) \right)^{1/2} \\ &\quad \times \left(E \left(\left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} \right)^2 \right) \right)^{1/2}. \end{aligned}$$

We observe that

$$\begin{aligned} E \left(e^2 \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} \right)^2 \right) &= E \left(\frac{1}{4s^4} + \frac{e^4}{4s^8} + \Phi \left(-e \frac{\lambda}{s} \right)^{-2} \phi \left(-e \frac{\lambda}{s} \right)^2 e^2 w^2 - \frac{e^2}{2s^6} \right. \\ &\quad + \frac{1}{s^2} \Phi \left(-e \frac{\lambda}{s} \right)^{-1} \phi \left(-e \frac{\lambda}{s} \right) ew - \frac{1}{s^4} \Phi \left(-e \frac{\lambda}{s} \right)^{-1} \phi \left(-e \frac{\lambda}{s} \right) e^3 w \left. \right) \\ &\times (e^2 + 2e\gamma(\theta) + \gamma(\theta)^2) \end{aligned}$$

and note that the leading expectation takes the form

$$E \left(C(s^2)^{-i} \Phi \left(-e \frac{\lambda}{s} \right)^{-j} \phi \left(-e \frac{\lambda}{s} \right)^j e^q w^h \right)$$

where $(s^2)^{-i} w^h < C$ for all i, h nonnegative and (j, q) is either (0,2), (0,1), (0,0), (0,6), (0,5), (0,4), (2,4), (2,3), (0,2), (2,2), (0,3), (0,2), (1,3), (1,2), (1,1), (1,5), (1,4), (1,3). In all cases, given the existence of all

moments for a skew normal we have $E \left(e^2 \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} \right)^2 \right) < C$. Similarly, $E \left(\left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} \right)^2 \right) < C$ and consequently $E \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} e E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} | x \right) \right) < C$. By the definition of conditional expectation,

$$\begin{aligned} E \left(e^2 \left(E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} | x \right) \right)^2 \right) &= E(e^2) E \left(E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} | x \right)^2 \right) \\ &\leq E(e^2 + 2e\gamma(\theta) + \gamma(\theta)^2) E \left(\left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} \right)^2 \right) \\ &\leq C \end{aligned}$$

given the existence of all moments for a skew normal. Hence, we conclude that

$$E \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} + e E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} | x \right) \right)^2 < C.$$

Repeating the same sequence of arguments for σ_v^2 gives

$$E \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_v^2} + e E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_v^2 \partial \eta} | x \right) \right)^2 < C.$$

Lastly, by the Cauchy-Schwarz inequality

$$\begin{aligned} E \left(\left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2} + e E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_u^2 \partial \eta} | x \right) \right) \times \right. \\ \left. \left(\frac{\partial f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_v^2} + e E \left(\frac{\partial^2 f_\varepsilon(y - g_0(x); \theta)}{\partial \sigma_v^2 \partial \eta} | x \right) \right) \right) \leq C \end{aligned}$$

by the bound obtained above. In addition, σ_F^2 is positive definite.

$$\mathbf{A7.1} : \sup_{\theta \in S_{0,\theta}} \left| E \left(\frac{\partial}{\partial \eta} f_\varepsilon(y - g_0(x_i); \theta) | x_i \right) \right| < \infty$$

Using the same steps taken to verify A5.3 we have that

$$\begin{aligned} \sup_{\theta \in S_{0,\theta}} \left| E \left(\frac{\partial}{\partial \eta} f_\varepsilon(y; \theta, g_0(x_i)) | x_i \right) \right| &\leq \sup_{\theta \in S_{0,\theta}} \frac{1}{s^2} E(|e|) + \sup_{\theta \in S_{0,\theta}} \frac{\lambda}{s} E \left(\left| 1 - \Phi \left(e \frac{\lambda}{s} \right)^{-1} \phi \left(e \frac{\lambda}{s} \right) \right| \right) \\ &= I_1 + I_2 < C \end{aligned}$$

by the same arguments we have used above.

A7.2 : $\frac{\partial^2}{\partial \theta_i \partial \eta} f_\varepsilon(y - g_0(x_i); \theta)$ is continuously differentiable in $S_{0,\theta}$ and

$$E \left(\sup_{\theta \in S_{0,\theta}} \left| \frac{\partial^3}{\partial \theta_i \partial \theta_j \partial \eta} f_\varepsilon(y - g_0(x_i); \theta) \right| | x_i \right) < \infty$$

for all $x_i \in G$ almost surely.

We verify that $\frac{\partial^2}{\partial\theta_i\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)$ is continuously differentiable in $S_{0,\theta}$ by taking routine partial derivatives of $\frac{\partial^2}{\partial\theta_i\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)$ and establishing that $\frac{\partial^4}{\partial\theta_i^k\partial\theta_j^l\partial\eta}f_\varepsilon(y-g_0(x_i);\theta) < C$ for all $k, l = 0, 1, 2, 3$ and $k + l \leq 3$. The fact that

$$E\left(\sup_{\theta \in S_{0,\theta}} \left| \frac{\partial^3}{\partial\theta_i\partial\theta_j\partial\eta}f_\varepsilon(y-g_0(x_i);\theta) \right| |x_i\right) < \infty$$

follows directly from the arguments used to verify A5.3.

$$\mathbf{A7.3} : \sup_{\theta \in S_{0,\theta}} \left| E\left(\frac{\partial^2}{\partial\theta_i\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)|x_i\right) \right| < \infty.$$

$$\begin{aligned} \sup_{\theta \in S_{0,\theta}} \left| E\left(\frac{\partial^2}{\partial\sigma_u^2\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)|x_i\right) \right| &\leq \sup_{\theta \in S_{0,\theta}} \frac{1}{s^4} |E(e)| + \sup_{\theta \in S_{0,\theta}} |w\frac{\lambda}{s}| \left| E\left(1 - \Phi\left(e\frac{\lambda}{s}\right)^{-2} \phi\left(e\frac{\lambda}{s}\right)^2 e\right) \right| \\ &+ \sup_{\theta \in S_{0,\theta}} \left| \frac{\lambda}{2s^5} \right| E\left(1 - \Phi\left(e\frac{\lambda}{s}\right)^{-1} \phi\left(e\frac{\lambda}{s}\right)\right) \\ &+ \sup_{\theta \in S_{0,\theta}} |w| E\left(1 - \Phi\left(e\frac{\lambda}{s}\right)^{-1} \phi\left(e\frac{\lambda}{s}\right)\right) < C \end{aligned}$$

by the arguments repeatedly used above. In a similar fashion we have $\sup_{\theta \in S_{0,\theta}} \left| E\left(\frac{\partial^2}{\partial\sigma_v^2\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)|x_i\right) \right| < C$.

A7.4 : $E\left(\frac{\partial^3}{\partial\theta_i\partial\theta_j\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)|x_i\right)$ is continuous in $S_{0,\theta}$ almost surely.

In verifying A7.2 we obtained the existence of $\frac{\partial^4}{\partial\theta_i^k\partial\theta_j^l\partial\eta}f_\varepsilon(y-g_0(x_i);\theta) < C$ for all $k, l = 0, 1, 2, 3$ and $k + l \leq 3$. Hence following the argument in A7.3 we verify that $E\left(\frac{\partial^4}{\partial\theta_i^k\partial\theta_j^l\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)\right) < C$ given the existence of moments of a skew normal. This implies continuity of $E\left(\frac{\partial^3}{\partial\theta_i\partial\theta_j\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)|x_i\right)$ in $S_{0,\theta}$.

A7.5 : Follows from Azzalini (1985).

A7.6 : $\frac{\partial^2}{\partial\theta_i\partial\theta_j}E\left(g_0^{(2)}(x_i)\frac{\partial}{\partial\eta}f_\varepsilon(y-g_0(x_i);\theta)\right)$ is continuous in $S_{0,\theta}$ almost surely.

This follows directly from A7.2 and A7.4.

4 Verification of assumptions PA1, PA2, PB, PC and PD for Lemma 2

Before we verify that the assumptions in Lemma 2 are met by the density in (1) we note that in the statement of Lemma 2 $\alpha_\theta(x)$ is assumed to be the unique maximizer of $E(f_\varepsilon(y-\eta;\theta))$ for fixed x and θ and satisfies $\frac{\partial}{\partial\eta}E(\log f_\varepsilon(y-\alpha_\theta(x);\theta)|x) = 0$. This must be verified for the density in (1). For this purpose,

we will show that for given $\theta \in \Theta$ and $x \in G$, there exists a unique maximizer of $E(\log f_\varepsilon(y - \eta; \theta)|x)$ with respect to η given by $\alpha_\theta(x)$ such that

$$(i) \frac{\partial}{\partial \eta} E(\log f_\varepsilon(y - \alpha_\theta(x); \theta)|x) = 0, \quad (ii) \inf_{\theta \in \Theta, x \in G} -\frac{\partial^2}{\partial \eta^2} E(\log f_\varepsilon(y - \alpha_\theta(x); \theta)|x) > 0.$$

(i) for fixed θ , $\log f_\varepsilon(y - \eta; \theta) = \frac{1}{2} \log(\frac{2}{\pi}) - \frac{1}{2} \log(\sigma_u^2 + \sigma_v^2) - \frac{1}{2} \frac{e^2}{\sigma_u^2 + \sigma_v^2} + \log(\Phi(-\frac{\lambda e}{s}))$, and only the last two terms depend on η . If each is a strictly concave function e then $\log f_\varepsilon(y - \eta; \theta)$ is a strictly concave function of η since η enters e linearly. Note that $\frac{e^2}{2(\sigma_u^2 + \sigma_v^2)}$ is strictly concave in e , hence we only need to show that $\log(\Phi(-\frac{\lambda e}{s}))$ is a strictly concave function of e . Let $u = -\frac{\lambda e}{s}$ and note that for fixed $-\frac{\lambda}{s}$, e enters u linearly, i.e., $\frac{\partial u}{\partial e} = -\frac{\lambda}{s}$ does not depend on e . Consequently, if we show $\log(\Phi(-\frac{\lambda e}{s}))$ is strictly concave in u , then it is also strictly concave in e since $\frac{\partial^2}{\partial u^2} \log(\Phi(u)) = \frac{1}{\Phi^2(u)} [\phi'(u)\Phi(u) - \phi^2(u)]$. Inspired by Burrige (1981), we consider three cases:

- (a) if $\phi'(u) < 0$, then it is clear that $\frac{\partial^2}{\partial u^2} \log(\Phi(u)) < 0$;
- (b) if $\phi'(u) = 0$, then $\frac{\partial^2}{\partial u^2} \log(\Phi(u)) < 0$;
- (c) if $\phi'(u) > 0$, then we show that $\frac{\partial^2}{\partial u^2} \log(\Phi(u)) < 0$.

For $x \neq y$, since $\phi(x)$ is log-concave, we have $\log(\phi(x)) < \log(\phi(y)) + h(y)(x - y)$, where $h(y) = \frac{\phi'(y)}{\phi(y)}$. So $\phi(x) < \phi(y) \exp(h(y)(x - y))$. Integrating with respect to x from $-\infty$ to z , we obtain

$$\Phi(z) < \int_{-\infty}^z \phi(y) \exp(h(y)(x - y)) dx = \frac{\phi(y)}{h(y)} [\exp(h(y)(z - y)) - \exp(h(y)(x - y))]|_{x=-\infty}$$

If we let $y = u$, and $z = u$, then $h(y) = g(u) = \frac{\phi'(u)}{\phi(u)} > 0$, so $\Phi(u) < \frac{\phi(u)}{h(u)} = \frac{\phi^2(u)}{\phi'(u)}$ hence $\frac{\partial^2}{\partial u^2} \log(\Phi(u)) < 0$.

In all, $\log f_\varepsilon(y - \eta; \theta)$ is strictly concave in η , so $E(\log f_\varepsilon(y - \eta; \theta))$ is strictly concave in η . Given PA2, we

have $\frac{\partial}{\partial \eta} E(\log f_\varepsilon(y - \eta; \theta)|x) = E(\frac{\partial}{\partial \eta} \log f_\varepsilon(y - \eta; \theta)|x) = \frac{E(y - \eta)}{\sigma_u^2 + \sigma_v^2} + E[\Phi(-\frac{\lambda e}{s})]^{-1} \phi(-\frac{\lambda e}{s}) \frac{\lambda}{s}$. Since the second

term is greater than zero, and the first term could be less than zero for large value of η , $\frac{\partial}{\partial \eta} E(\log f_\varepsilon(y -$

$\eta; \theta)|x)$ could take positive or negative values. Since $\frac{\partial}{\partial \eta} E(\log f_\varepsilon(y - \eta; \theta)|x)$ is continuous and decreasing

with η , there exists a unique value η^* such that $\frac{\partial}{\partial \eta} E(\log f_\varepsilon(y - \eta^*; \theta)|x) = 0$. Since $\frac{\partial}{\partial \eta} E(\log f_\varepsilon(y - \eta; \theta)|x)$ is

continuous with respect to x, θ, η in a neighborhood of x, θ , and η^* and $|\frac{\partial^2}{\partial \eta^2} E(\log f_\varepsilon(y - \eta^*; \theta)|x)| \neq 0$ (see

(ii) below). By the Implicit Function Theorem, there exists a neighborhood of x, θ and η^* such that for

every x, θ in it, there is a unique $\alpha_\theta(x)$ in the neighborhood of η^* such that $\frac{\partial}{\partial \eta} E(\log f_\varepsilon(y - \alpha_\theta(x); \theta)|x) = 0$.

To verify (ii) note that as in (i) $E(\log f_\varepsilon(y - \eta; \theta)|x)$ is strictly concave in η , $\log f_\varepsilon(y - \eta; \theta)$ does not depend

on x and $\sigma_u^2, \sigma_v^2 > 0$, so $\inf_{\theta \in \Theta, x \in G} -\frac{\partial^2}{\partial \eta^2} E(\log f_\varepsilon(y - \alpha_\theta(x); \theta)|x) > \inf_{\theta \in \Theta, x \in G, \eta \in \mathcal{H}} -\frac{\partial^2}{\partial \eta^2} E(\log f_\varepsilon(y - \eta; \theta)|x) > 0$.

We now turn to the verification of PA1, PA2, PB, PC and PD.

PA1: 1. For fixed (but arbitrary) $\theta' \in \Theta$ and $\eta' \in \mathcal{H}$ and for all $\theta \in \Theta$ and $\eta \in \mathcal{H}$, let $\rho(\theta, \eta) = \int \log f_\varepsilon(y - \eta; \theta) f_\varepsilon(y - \eta'; \theta') dy$. If $\theta \neq \theta'$ then $\rho(\theta, \eta) < \rho(\theta', \eta')$; 2. $\tilde{I}_\theta(\theta, \eta) > 0$ for all $\theta \in \Theta$ and $\eta \in \mathcal{H}$ where

$$\begin{aligned} \tilde{I}_\theta(\theta, \eta) &= E \left(\frac{\partial}{\partial \theta} f_\varepsilon(y - \eta; \theta) \frac{\partial}{\partial \theta} f_\varepsilon(y - \eta; \theta)' \right) \\ &\quad - \frac{E(\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \frac{\partial}{\partial \theta} f_\varepsilon(y - \eta; \theta)) E(\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \frac{\partial}{\partial \theta'} f_\varepsilon(y - \eta; \theta))}{E((\frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta))^2)} \end{aligned}$$

Since $f_\varepsilon(y - \eta; \theta)$ is a density function, $\int f_\varepsilon(y - \eta; \theta) dy = 1$. By the strict version of Jensen's inequality, for any nonconstant positive random variable a , $E(-\ln(a)) > -\ln E(a)$. If $\theta \neq \theta'$ implies $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$, then for $a = \frac{f_\varepsilon(y - \eta; \theta)}{f_\varepsilon(y - \eta'; \theta')}$ and $\theta \neq \theta'$,

$$\begin{aligned} \int (-\log(a)) f_\varepsilon(y - \eta'; \theta') dy &= \int \log(f_\varepsilon(y - \eta'; \theta')) f_\varepsilon(y - \eta'; \theta') dy - \int \log(f_\varepsilon(y - \eta; \theta)) f_\varepsilon(y - \eta'; \theta') dy \\ &> -\log \int a f_\varepsilon(y - \eta'; \theta') dy = -\log \int \frac{f_\varepsilon(y - \eta; \theta)}{f_\varepsilon(y - \eta'; \theta')} f_\varepsilon(y - \eta'; \theta') dy = 0. \end{aligned}$$

So we only need to show if $\theta \neq \theta'$ then $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$.

We consider two cases: (i) If $\eta = \eta'$, and if further $E(y - \eta)^2 > 0$, then as in the verification of A4.1, we have $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$.

(ii) If $\eta \neq \eta'$ and if $\frac{\lambda}{s} \neq \frac{\lambda'}{s'}$, then $(y - \eta) \frac{\lambda}{s} \neq (y - \eta') \frac{\lambda'}{s'}$ and since $\Phi(x)$ is strictly increasing, $1 - \Phi((y - \eta) \frac{\lambda}{s}) \neq 1 - \Phi((y - \eta') \frac{\lambda'}{s'})$. We consider three subcases:

(1) If $\sigma_v^2 = \sigma_v'^2$, then $\sigma_u^2 = \sigma_u'^2$ since $\theta \neq \theta'$. We also have $1 - \Phi((y - \eta) \frac{\lambda}{s}) \neq 1 - \Phi((y - \eta') \frac{\lambda'}{s'})$,

$$\begin{aligned} &\frac{2}{\sqrt{\sigma_u^2 + \sigma_v^2}} \phi \left(\frac{y - \eta}{\sqrt{\sigma_u^2 + \sigma_v^2}} \right) \neq \frac{2}{\sqrt{\sigma_u'^2 + \sigma_v'^2}} \phi \left(\frac{y - \eta'}{\sqrt{\sigma_u'^2 + \sigma_v'^2}} \right). \text{ So } f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta') \text{ except on the set} \\ A &= \left\{ \frac{2}{\sqrt{\sigma_u^2 + \sigma_v^2}} \phi \left(\frac{y - \eta}{\sqrt{\sigma_u^2 + \sigma_v^2}} \right) \left(1 - \Phi \left(\frac{\sqrt{\sigma_u^2 / \sigma_v^2}}{\sqrt{\sigma_u^2 + \sigma_v^2}} (y - \eta) \right) \right) = \frac{2}{\sqrt{\sigma_u'^2 + \sigma_v'^2}} \phi \left(\frac{y - \eta'}{\sqrt{\sigma_u'^2 + \sigma_v'^2}} \right) \left(1 - \Phi \left(\frac{\sqrt{\sigma_u'^2 / \sigma_v'^2}}{\sqrt{\sigma_u'^2 + \sigma_v'^2}} (y - \eta') \right) \right) \right\} \\ &= \left\{ -\frac{1}{2} \frac{(y - \eta)^2}{\sigma_u^2 + \sigma_v^2} + \log[(\sigma_u^2 + \sigma_v^2)^{-\frac{1}{2}} (1 - \Phi(\frac{\lambda}{s}(y - \eta)))] = -\frac{1}{2} \frac{(y - \eta')^2}{\sigma_u'^2 + \sigma_v'^2} + \log[(\sigma_u'^2 + \sigma_v'^2)^{-\frac{1}{2}} (1 - \Phi(\frac{\lambda'}{s'}(y - \eta')))] \right\} \end{aligned}$$

Since the two quadratic functions of y are not equal, $\log[(\sigma_u^2 + \sigma_v^2)^{-\frac{1}{2}} (1 - \Phi(\frac{\lambda}{s}(y - \eta)))]$ is a monotonic function of y , set A contains at most finite discrete points which make the equality to be true and $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$ almost everywhere.

(2) If $\sigma_v^2 \neq \sigma_v'^2$, and $\frac{\sigma_u^2}{\sigma_v^2} = \frac{\sigma_u'^2}{\sigma_v'^2}$, then $\sigma_u^2 \neq \sigma_u'^2$. We consider two subcases:

(a) If $\sigma_u^2 + \sigma_v^2 = \sigma_u'^2 + \sigma_v'^2$, then $\frac{2}{\sqrt{\sigma_u^2 + \sigma_v^2}} \phi \left(\frac{y - \eta}{\sqrt{\sigma_u^2 + \sigma_v^2}} \right) \neq \frac{2}{\sqrt{\sigma_u'^2 + \sigma_v'^2}} \phi \left(\frac{y - \eta'}{\sqrt{\sigma_u'^2 + \sigma_v'^2}} \right)$. Since $\frac{\lambda}{s} \neq \frac{\lambda'}{s'}$, $1 - \Phi((y - \eta) \frac{\lambda}{s}) \neq 1 - \Phi((y - \eta') \frac{\lambda'}{s'})$. So following similar arguments as in (1), $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$.

(b) If $\sigma_u^2 + \sigma_v^2 \neq \sigma_u'^2 + \sigma_v'^2$, similar arguments in (a) give $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$.

(3) $\sigma_v^2 \neq \sigma_v^{2'}$, and $\frac{\sigma_u^2}{\sigma_v^2} \neq \frac{\sigma_u^{2'}}{\sigma_v^{2'}}$. We again consider three subcases:

- (a) $\sigma_u^2 + \sigma_v^2 = \sigma_u^{2'} + \sigma_v^{2'}$. So $\frac{\lambda}{s} \neq \frac{\lambda'}{s'}$, and $1 - \Phi((y - \eta)\frac{\lambda}{s}) \neq 1 - \Phi((y - \eta')\frac{\lambda'}{s'})$. So as in (2)(a), $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$.
- (b) $\sigma_u^2 + \sigma_v^2 \neq \sigma_u^{2'} + \sigma_v^{2'}$ and $\frac{\lambda}{s} = \frac{\lambda'}{s'}$. Since $1 - \Phi((y - \eta)\frac{\lambda}{s}) \neq 1 - \Phi((y - \eta')\frac{\lambda'}{s'})$, $\frac{2}{\sqrt{\sigma_u^2 + \sigma_v^2}}\phi\left(\frac{y - \eta}{\sqrt{\sigma_u^2 + \sigma_v^2}}\right) \neq \frac{2}{\sqrt{\sigma_u^{2'} + \sigma_v^{2'}}}\phi\left(\frac{y - \eta'}{\sqrt{\sigma_u^{2'} + \sigma_v^{2'}}}\right)$. $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$ as in (1).
- (c) $\sigma_u^2 + \sigma_v^2 \neq \sigma_u^{2'} + \sigma_v^{2'}$ and $\frac{\lambda}{s} \neq \frac{\lambda'}{s'}$, $f_\varepsilon(y - \eta; \theta) \neq f_\varepsilon(y - \eta'; \theta')$ similarly.

PA1.2 : $\tilde{I}_\theta(\theta, \eta) > 0$ for all $\theta \in \Theta$ and $\eta \in \mathcal{H}$. The Fisher information for the parametric submodel $\alpha_\theta(x)$

is

$$\begin{aligned} \mathcal{I}_0\left(\frac{\partial}{\partial\theta}\alpha_{\theta_0}(x)\right) &= E\left(\frac{\partial}{\partial\theta}f_\varepsilon(y - g_0(x); \theta_0) + \frac{d_F}{dg}f_\varepsilon(y - g_0(x); \theta_0)\frac{\partial}{\partial\theta}\alpha_{\theta_0}(x)\right)\left(\frac{\partial}{\partial\theta}f_\varepsilon(y - g_0(x); \theta_0)\right. \\ &\quad \left.+ \frac{d_F}{dg}f_\varepsilon(y - g_0(x); \theta_0)\frac{\partial}{\partial\theta}\alpha_{\theta_0}(x)\right)' \end{aligned}$$

When we use the least favorable direction,

$$\begin{aligned} \mathcal{I}_0\left(\frac{\partial}{\partial\theta}\alpha_{\theta_0}(x)^*\right) &= E\left(\frac{\partial}{\partial\theta}f_\varepsilon(y - g_0(x); \theta_0)\frac{\partial}{\partial\theta}f_\varepsilon(y - g_0(x); \theta_0)\right) \\ &\quad - E\left\{\frac{E(\frac{d_F}{dg}f_\varepsilon(y - g_0(x); \theta_0)\frac{\partial}{\partial\theta}f_\varepsilon(y - g_0(x); \theta_0)|x)E(\frac{d_F}{dg}f_\varepsilon(y - g_0(x); \theta_0)\frac{\partial}{\partial\theta}f_\varepsilon(y - g_0(x); \theta_0)|x)}{E((\frac{d_F}{dg}f_\varepsilon(y - g_0(x); \theta_0))^2|x)}\right\} \end{aligned}$$

$$\begin{aligned} \tilde{I}_\theta(\theta, \eta) &= E\left(\frac{\partial}{\partial\theta}f_\varepsilon(y - \eta; \theta)\frac{\partial}{\partial\theta}f_\varepsilon(y - \eta; \theta)\right) \\ &\quad - \frac{E(\frac{\partial}{\partial\eta}f_\varepsilon(y - \eta; \theta)\frac{\partial}{\partial\theta}f_\varepsilon(y - \eta; \theta))E(\frac{\partial}{\partial\eta}f_\varepsilon(y - \eta; \theta)\frac{\partial}{\partial\theta}f_\varepsilon(y - \eta; \theta))}{E((\frac{\partial}{\partial\eta}f_\varepsilon(y - \eta; \theta))^2)} \end{aligned}$$

where $\frac{\partial}{\partial\theta}\alpha_\theta = -\frac{E(\frac{d_F}{dg}f_\varepsilon(y - \eta; \theta)\frac{\partial}{\partial\theta}f_\varepsilon(y - \eta; \theta))}{E((\frac{d_F}{dg}f_\varepsilon(y - \eta; \theta))^2)}$. Since $\tilde{I}_\theta(\theta, \eta)$ is in a quadratic form, we only need to show

$\frac{\partial}{\partial\theta}f_\varepsilon(y - \eta; \theta) + \frac{d_F}{dg}f_\varepsilon(y - \eta; \theta)\frac{\partial}{\partial\theta}\alpha_\theta \neq 0$. Let w, w_1, I, I_1, C_1, C_2 be as in the verification of A5.4 and $I_2 = \int \frac{\sqrt{2}}{1 - erf(\frac{\lambda e}{s\sqrt{2}})}exp(-e^2(\frac{\lambda^2}{s^2} + \frac{1}{2\sigma^2}))de$. Also, $\alpha'_{\sigma_u^2} = C_1(\frac{1}{s^2} + (\frac{\lambda}{s})^2 I_2)^{-1}$, $\alpha'_{\sigma_v^2} = C_2(\frac{1}{s^2} + (\frac{\lambda}{s})^2 I_2)^{-1}$. If

$e = y - \eta$ then,

$$\begin{aligned} &\frac{\partial}{\partial\sigma_u^2}f_\varepsilon(y - \eta; \theta) + \frac{d_F}{dg}f_\varepsilon(y - \eta; \theta)\frac{\partial}{\partial\sigma_u^2}\alpha_\theta \\ &= -\frac{1}{2s^2} + \frac{e^2}{2s^4} - [1 - \Phi(\frac{\lambda e}{s})]^{-1}\phi(\frac{\lambda e}{s})ew + [\frac{e}{s^2} + [1 - \Phi(\frac{\lambda e}{s})]^{-1}\phi(\frac{\lambda e}{s})(\frac{\lambda}{s})]C_1(\frac{1}{s^2} + (\frac{\lambda}{s})^2 I_2)^{-1} \neq 0 \end{aligned}$$

since it is linear combination of constant, quadratic function of e , $[1 - \Phi(\frac{\lambda e}{s})]^{-1}\phi(\frac{\lambda e}{s})$ and $[1 - \Phi(\frac{\lambda e}{s})]^{-1}\phi(\frac{\lambda e}{s})e$.

Note $\frac{\phi(x)}{\Phi(x)}$ is convex, asymptotes to $-x$ as $x \rightarrow -\infty$ and to zero as $x \rightarrow \infty$. $\frac{\phi(x)x}{\Phi(x)}$ is nonlinear, with

nonlinear second order derivative.

$$\begin{aligned} &\frac{\partial}{\partial\sigma_v^2}f_\varepsilon(y - \eta; \theta) + \frac{d_F}{dg}f_\varepsilon(y - \eta; \theta)\frac{\partial}{\partial\sigma_v^2}\alpha_\theta \\ &= -\frac{1}{2s^2} + \frac{e^2}{2s^4} - [1 - \Phi(\frac{\lambda e}{s})]^{-1}\phi(\frac{\lambda e}{s})ew_1 + [\frac{e}{s^2} + [1 - \Phi(\frac{\lambda e}{s})]^{-1}\phi(\frac{\lambda e}{s})(\frac{\lambda}{s})]C_2(\frac{1}{s^2} + (\frac{\lambda}{s})^2 I_2)^{-1} \neq 0 \text{ similarly.} \end{aligned}$$

PA2 : For $r, s = 0, 1, 2, 3, 4$ and $r + s \leq 4$, $\frac{\partial^{r+s}}{\partial \theta_p^r \partial \eta^s} \log f_\varepsilon(y - \eta; \theta)$ exists for $p = 1, \dots, P$ and

$$E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| \frac{\partial^{r+s}}{\partial \theta_p^r \partial \eta^s} \log f_\varepsilon(y - \eta; \theta) \right|^2 \right) < \infty.$$

Consider $r + s = 0$.

$$\begin{aligned} E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| \frac{\partial^{r+s}}{\partial \theta_p^r \partial \eta^s} \log f_\varepsilon(y - \eta; \theta) \right|^2 \right) &= E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} |\log f_\varepsilon(y - \eta; \theta)|^2 \right) \\ &= E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| \frac{1}{2} \log\left(\frac{2}{\pi}\right) - \frac{1}{2} \log(\sigma_u^2 + \sigma_v^2) - \frac{1}{2} \frac{e^2}{\sigma_u^2 + \sigma_v^2} + \log(\Phi(-\frac{\lambda e}{s})) \right|^2 \right) < \infty. \end{aligned}$$

Since $\sigma_u^2, \sigma_v^2 > 0$, $E(\sup_{\theta \in \Theta} |-\frac{1}{2} \log(\sigma_u^2 + \sigma_v^2)|^2) < \infty$.

$E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| -\frac{1}{2} \frac{e^2}{\sigma_u^2 + \sigma_v^2} \right|^2 \right) < \infty$ since $E \sup_{\eta \in \mathcal{H}} |e|^4 \leq E y^4 + \sup_{\eta \in \mathcal{H}} \eta^4 \leq E(g_0(x))^4 + E\epsilon^4 + c < \infty$ as $g_0(x) \in \mathcal{H}$,

a compact subset of $\mathfrak{R}$. Here $\epsilon = y - g_0(x)$ and $E\epsilon^i < \infty$ for any finite positive integer i . By Taylor

expansion of $\log(\Phi(-\frac{\lambda e}{s}))$ around $e = 0$, for δ between 0 and 1,

$$\begin{aligned} |\log(\Phi(-\frac{\lambda e}{s}))| &\leq |\log(\Phi(0)) + \frac{\phi(-\frac{\lambda \delta e}{s})}{\Phi(-\frac{\lambda \delta e}{s})} (-\frac{\lambda e}{s})| \leq |\log(\Phi(0))| + \frac{\phi(-\frac{\lambda \delta e}{s})}{\Phi(-\frac{\lambda \delta e}{s})} |-\frac{\lambda e}{s}| \\ &\leq |\log(\Phi(0))| + c(1 + \delta|e| \frac{\lambda}{s}) \frac{\lambda}{s} |e| \leq c + c|e| + c|e|^2 \end{aligned}$$

since $\frac{\phi(x)}{\Phi(x)}$ is convex, asymptotes to $-x$ as $x \rightarrow -\infty$ and to zero as $x \rightarrow \infty$, so $\frac{\phi(x)}{\Phi(x)} < c(1 + |x|)$. So

$E \sup_{\theta \in \Theta, \eta \in \mathcal{H}} |\log(\Phi(-\frac{\lambda e}{s}))|^2 < c + E \sup_{\eta \in \mathcal{H}} |y - \eta|^2 + E \sup_{\eta \in \mathcal{H}} |y - \eta|^4 < \infty$. For $r + s = 1$,

$$\begin{aligned} E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| \frac{\partial}{\partial \sigma_u^2} \log f_\varepsilon(y - \eta; \theta) \right|^2 \right) &= E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| -\frac{1}{\sigma_u^2 + \sigma_v^2} + \frac{1}{2} \frac{e^2}{(\sigma_u^2 + \sigma_v^2)^2} - [\Phi(-\frac{\lambda e}{s})]^{-1} \phi(-\frac{\lambda e}{s}) w e \right|^2 \right) < \infty \\ E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| \frac{\partial}{\partial \sigma_v^2} \log f_\varepsilon(y - \eta; \theta) \right|^2 \right) &= E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| -\frac{1}{\sigma_u^2 + \sigma_v^2} + \frac{1}{2} \frac{e^2}{(\sigma_u^2 + \sigma_v^2)^2} - [\Phi(-\frac{\lambda e}{s})]^{-1} \phi(-\frac{\lambda e}{s}) w_1 e \right|^2 \right) < \infty \\ E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| \frac{\partial}{\partial \eta} \log f_\varepsilon(y - \eta; \theta) \right|^2 \right) &= E \left(\sup_{\theta \in \Theta, \eta \in \mathcal{H}} \left| \frac{1}{2} \frac{e}{\sigma_u^2 + \sigma_v^2} - [\Phi(-\frac{\lambda e}{s})]^{-1} \phi(-\frac{\lambda e}{s}) \frac{\lambda}{s} \right|^2 \right) < \infty \end{aligned}$$

Above are true since the term $|[\Phi(-\frac{\lambda e}{s})]^{-i} \phi^i(-\frac{\lambda e}{s}) e^j| \leq c(1 + \frac{\lambda}{s} |e|^i) |e|^j \leq c|e|^j + c|e|^{i+j}$ and by consequence

$|[\Phi(-\frac{\lambda e}{s})]^{-i} \phi^i(-\frac{\lambda e}{s}) e^j|^2 \leq c|e|^{2j} + c|e|^{2(i+j)}$. For $(i, j) = (1, 1)$ and $(1, 0)$, we only need $E \sup_{\theta \in \Theta, \eta \in \mathcal{H}} |e|^4 < \infty$,

which is true since $\mathcal{H}$ is a compact subset of $\mathfrak{R}$ and $E|e|^4 < \infty$. For $r + s = 2, 3$ and 4, the partial derivatives and bounded moments are obtained in a similar fashion.

PA3 : This condition has been verified in Lemma 2 in Martins-Filho and Yao (2011).

PB : 1. $\sup_{x \in G} f_x(x) < C$; 2. $\sup_{x \in G} f_x^{(1)}(x) < C$; 3. $\sup_{x \in G} f_x^{(2)}(x) < C$; 4. $\inf_{x \in G} f_x(x) > 0$; 5. $\sup_{x \in G, \theta \in \Theta} \left| \frac{\partial}{\partial x} \alpha_\theta(x) \right| < C$.

PB1-4 are all conditions on the marginal density of x . PB5 is implied by the fact that $\frac{\partial}{\partial x} \alpha_\theta(x)$ is continuous at $x \in G$ and $\theta \in \Theta$. G and Θ are all compact sets.

PC : $\int \sup_{x \in G} \left| \frac{\partial}{\partial x} \left(\frac{\partial^{s_1+s_2+r}}{\partial \theta_k^{s_1} \partial \theta_j^{s_2} \partial \eta^r} \log f_\varepsilon(y - \alpha_\theta(x); \theta) f_\varepsilon(y - g_0(x); \theta) \right) \right| dy < C$, with $s_1, s_2, r \geq 0$, where $(s_1, s_2, r) = (0, 0, 1), (1, 0, 1), (0, 1, 1), (1, 1, 1)$.

Consider the case $(s_1, s_2, r) = (0, 0, 1)$.

$$\begin{aligned} & \int \sup_{x \in G} \left| \frac{\partial}{\partial x} \left(\frac{\partial}{\partial \eta} \log f_\varepsilon(y - \alpha_\theta(x); \theta) f_\varepsilon(y - g_0(x); \theta) \right) \right| dy \\ & \leq \int \sup_{x \in G} \left| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \alpha_\theta(x); \theta) f_\varepsilon(y - g_0(x); \theta) \frac{\partial}{\partial x} \alpha_\theta(x) \right| dy \\ & + \int \sup_{x \in G} \left| \frac{\partial}{\partial \eta} \log f_\varepsilon(y - \alpha_\theta(x); \theta) \frac{\partial}{\partial x} f_\varepsilon(y - g_0(x); \theta) \right| dy = I_1 + I_2 \end{aligned}$$

$$I_1 \leq \sup_{x \in G, \theta \in \Theta} \left| \frac{\partial}{\partial x} \alpha_\theta(x) \right| \underbrace{\int \sup_{x \in G} \left| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \alpha_\theta(x); \theta) f_\varepsilon(y - g_0(x); \theta) \right| dy}_{I_{11}}. \text{ Since } \sup_{x \in G, \theta \in \Theta} \left| \frac{\partial}{\partial x} \alpha_\theta(x) \right| < \infty,$$

and for s_0^2 and λ_0 , $I_{11} \leq \int \sup_{\eta \in \mathcal{H}} \left| -\frac{1}{s^2} - \Phi^{-2}\left(-\frac{\lambda}{s}e\right)\phi^2\left(-\frac{\lambda}{s}e\right)\left(\frac{\lambda}{s}\right)^2 + \Phi^{-1}\left(-\frac{\lambda}{s}e\right)\phi\left(-\frac{\lambda}{s}e\right)e\left(\frac{\lambda}{s}\right)^3 \right| \sup_{\eta \in \mathcal{H}} \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \Phi\left(-\frac{\lambda_0}{s_0}e\right) dy < \infty$, since all terms involve only σ_u^2 or σ_v^2 are bounded, $\Phi(\cdot) \leq 1$ and the term

$$\begin{aligned} & \int \sup_{\eta \in \mathcal{H}} \Phi^{-i}\left(-\frac{\lambda}{s}e\right)\phi^i\left(-\frac{\lambda}{s}e\right)e^j \sup_{\eta \in \mathcal{H}} \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \Phi\left(-\frac{\lambda_0}{s_0}e\right) dy \\ & \leq \int \sup_{\eta \in \mathcal{H}} c[1 + \frac{\lambda}{s}|y - \eta|^i|y - \eta|^j \sup_{\eta \in \mathcal{H}} \phi\left(\frac{e}{s_0}\right) dy \leq \int \sup_{\eta \in \mathcal{H}} c[|y - \eta|^j + |y - \eta|^{i+j}] \sup_{\eta \in \mathcal{H}} \phi\left(\frac{e}{s_0}\right) dy < \infty \end{aligned}$$

We divide the area of integration for y into three cases: $I = \{y \leq \eta_L\}$, so $\sup_{\eta \in \mathcal{H}} \phi\left(\frac{e}{s_0}\right) = \phi\left(\frac{y - \eta_L}{s_0}\right)$ on I .

$II = \{\eta_L < y \leq \eta_U\}$, so $\sup_{\eta \in \mathcal{H}} \phi\left(\frac{e}{s_0}\right) \leq \frac{1}{\sqrt{2\pi}}$ on II . $III = \{\eta_U < y\}$, so $\sup_{\eta \in \mathcal{H}} \phi\left(\frac{e}{s_0}\right) = \phi\left(\frac{y - \eta_U}{s_0}\right)$ on III .

$$\int \sup_{\eta \in \mathcal{H}} C|y - \eta|^j \sup_{\eta \in \mathcal{H}} \phi\left(\frac{e}{s_0}\right) dy \leq C \int_I [|y|^j + |\eta|^j] \phi\left(\frac{y - \eta_L}{s_0}\right) dy + C \int_{II} [|y|^j + |\eta|^j] \frac{1}{\sqrt{2\pi}} dy + C \int_{III} [|y|^j + |\eta|^j] \phi\left(\frac{y - \eta_U}{s_0}\right) dy < \infty.$$

Similarly $\int \sup_{\eta \in \mathcal{H}} C|y - \eta|^{i+j} \sup_{\eta \in \mathcal{H}} \phi\left(\frac{e}{s_0}\right) dy \leq C$, hence $I_1 < \infty$.

$$I_2 \leq \underbrace{\sup_{x \in G} |g'_0(x)|}_{< \infty} \underbrace{\int \sup_{\eta \in \mathcal{H}} \left| \frac{\partial}{\partial \eta} \log f_\varepsilon(y - \eta; \theta) \right| \sup_{\eta \in \mathcal{H}} \left| \frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta) \right| dy}_{I_{21}} < \infty, \text{ as}$$

$$I_{21} \leq \int \sup_{\eta \in \mathcal{H}} \left| \frac{e}{s^2} + \Phi^{-1}\left(-\frac{\lambda}{s}e\right)\phi\left(-\frac{\lambda}{s}e\right)\frac{\lambda}{s} \right| \sup_{\eta \in \mathcal{H}} \left| \frac{2}{s_0} \phi^{-1}\left(-\frac{e}{s_0}\right) \Phi\left(-\frac{\lambda_0}{s_0}e\right) \frac{|e|}{s_0^2} + \frac{2}{s_0} \phi^{-1}\left(-\frac{e}{s_0}\right) \phi\left(-\frac{\lambda_0}{s_0}e\right) \frac{\lambda_0}{s_0} \right| dy < \infty, \text{ since}$$

all terms involving only σ_u^2 or σ_v^2 are bounded, $\Phi(\cdot) \leq 1$ and $\phi(\cdot) \leq \frac{1}{\sqrt{2\pi}}$. Using arguments similar to

those used for I_1 , the terms

$$S_1(y) = \int \sup_{\eta \in \mathcal{H}} \Phi^{-i}\left(-\frac{\lambda}{s}e\right)\phi^i\left(-\frac{\lambda}{s}e\right)e^j \sup_{\eta \in \mathcal{H}} \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \Phi\left(-\frac{\lambda_0}{s_0}e\right) \frac{|e|}{s_0^2} dy < \infty \text{ and}$$

$$S_2(y) = \int \sup_{\eta \in \mathcal{H}} \Phi^{-i}\left(-\frac{\lambda}{s}e\right)\phi^i\left(-\frac{\lambda}{s}e\right)e^j \sup_{\eta \in \mathcal{H}} \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \phi\left(-\frac{\lambda_0}{s_0}e\right) \frac{\lambda_0}{s_0} dy < \infty.$$

Verification of PC when $(s_1, s_2, r) = (1, 0, 1), (0, 1, 1), (1, 1, 1)$ follows in an analogous manner.

PD : $\sup_{x \in G, \theta \in \Theta, \eta \in \mathcal{H}} \left| \int \frac{\partial^{s_1+s_2+r}}{\partial \theta_k^{s_1} \partial \theta_j^{s_2} \partial \eta^r} \log f_\varepsilon(y - \eta; \theta) \frac{\partial^j}{\partial x^j} f_\varepsilon(y - g_0(x); \theta) dy \right| < C$ with $s_1, s_2, r \geq 0$, for $j=0$,

$s_1 + s_2 + r \leq 4$, and $(s_1, s_2, r) = (0, 0, 5)$; for $j=1$, $(s_1, s_2, r) = (0, 0, 1), (1, 0, 2), (0, 1, 2), (1, 0, 3), (0, 1, 3)$,

(0,0,4), (0,0,3), (1,1,2), (1,1,3), (0,1,4), (1,0,4), (0,0,5) and for $j=2$, $(s_1, s_2, r) = (0,0,1), (0,0,2), (0,0,3), (1,0,1), (0,1,1), (1,0,2), (0,1,2), (1,0,3), (0,1,3), (0,0,4), (1,1,1), (1,1,2), (1,1,3), (0,1,4), (1,0,4), (0,0,5)$.

For $j = 0$ we need to show $\sup_{x \in G, \theta \in \Theta, \eta \in \mathcal{H}} \left| E \left(\frac{\partial^{s_1+s_2+r}}{\partial \theta_k^{s_1} \partial \theta_j^{s_2} \partial \eta^r} \log f_\varepsilon(y - \eta; \theta) | x \right) \right| < C$. Consider specifically the case where $s_1 = 2, s_2 = r = 0$.

$$\begin{aligned} E \left(\frac{\partial^2}{\partial (\sigma_u^2)^2} \log f_\varepsilon(y - \eta; \theta) | x \right) &= \frac{1}{2s^4} - \frac{E(e^2|x)}{s^6} - w^2 E(\Phi^{-2}(-\frac{\lambda}{s}e)\phi^2(-\frac{\lambda}{s}e)e^2|x) \\ &\quad + \frac{w}{2s^4} E(\Phi^{-1}(-\frac{\lambda}{s}e)\phi(-\frac{\lambda}{s}e)e^3|x) - \frac{\partial w}{\partial \sigma_u^2} E(\Phi^{-1}(-\frac{\lambda}{s}e)\phi(-\frac{\lambda}{s}e)e|x) \end{aligned}$$

Again, all terms involving only σ_u^2 or σ_v^2 are bounded. The typical term in the remaining terms are for $i + j \leq 2$,

$$\begin{aligned} &E(\Phi^{-i}(-\frac{\lambda}{s}e)\phi^i(-\frac{\lambda}{s}e)e^j|x) \\ &\leq CE([1 + \frac{\lambda}{s}|y - \eta|^i|y - \eta|^j|x] \leq E(|y - \eta|^j + C|y - \eta|^{i+j}|x) \leq cE(|y - \eta|^{i+j}|x) \\ &\leq CE|y|^{i+j}|x| + c \text{ since } \eta \in \mathcal{H} \\ &\leq CE(|g_0(x) + \epsilon|^{i+j}|x) \leq C + CE|\epsilon|^{i+j} < \infty \text{ since } g_0(x) \in \mathcal{H} \text{ and } \epsilon \text{ is independent of } x. \end{aligned}$$

Hence, $\sup_{x \in G, \theta \in \Theta, \eta \in \mathcal{H}} |E(\frac{\partial^2}{\partial (\sigma_u^2)^2} \log f_\varepsilon(y - \eta; \theta) | x)| < \infty$. The other terms can be shown to be bounded in a similar fashion. Now consider the case where $j = 1$ and $(s_1, s_2, r) = (0, 0, 2)$. Then,

$$\begin{aligned} &\sup_{x \in G, \theta \in \Theta, \eta \in \mathcal{H}} \left| \int \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) \frac{\partial}{\partial x} f_\varepsilon(y - g_0(x); \theta_0) dy \right| \\ &\leq \sup_{x \in G} |g'_0(x)| \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \int \left| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) \right| \sup_{\eta \in \mathcal{H}} \left| \frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta_0) \right| dy \\ &\leq C \sup_{\theta \in \Theta} \int \sup_{\eta \in \mathcal{H}} \left| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) \right| \sup_{\eta \in \mathcal{H}} \left| \frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta_0) \right| dy < \infty \text{ as in } S_1(y) \text{ and } S_2(y) \text{ in the verification of PC.} \end{aligned}$$

The other cases for $j = 1$ can be shown to be bounded in a similar fashion. For $j = 2$, consider specifically the case $(s_1, s_2, r) = (0, 0, 2)$. Then

$$\begin{aligned} &\sup_{x \in G, \theta \in \Theta, \eta \in \mathcal{H}} \left| \int \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) \frac{\partial^2}{\partial x^2} f_\varepsilon(y - g_0(x); \theta_0) dy \right| \\ &\leq \sup_{\theta \in \Theta, \eta \in \mathcal{H}} \int \left| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) \right| \left[\sup_{\eta \in \mathcal{H}} \left| \frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta_0) \right| \sup_{x \in G} |g_0^{(2)}(x)| + \left[\sup_{\eta \in \mathcal{H}} \left| \frac{\partial^2}{\partial \eta^2} f_\varepsilon(y - \eta; \theta_0) \right| \sup_{x \in G} |g'_0(x)|^2 \right] dy \right. \\ &\leq \sup_{\theta \in \Theta} \int \sup_{\eta \in \mathcal{H}} \left| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) \right| \sup_{\eta \in \mathcal{H}} \left| \frac{\partial}{\partial \eta} f_\varepsilon(y - \eta; \theta_0) \right| dy \sup_{x \in G} |g_0^{(2)}(x)| \\ &\quad \left. + \sup_{\theta \in \Theta} \int \sup_{\eta \in \mathcal{H}} \left| \frac{\partial^2}{\partial \eta^2} \log f_\varepsilon(y - \eta; \theta) \right| \sup_{\eta \in \mathcal{H}} \left| \frac{\partial^2}{\partial \eta^2} f_\varepsilon(y - \eta; \theta_0) \right| dy \sup_{x \in G} |g'_0(x)|^2 = I_1 + I_2. \end{aligned}$$

$I_1 < \infty$ is shown when $j = 1$.

$$\begin{aligned} I_2 &< C \sup_{\theta \in \Theta} \int \sup_{\eta \in \mathcal{H}} \left| -\frac{1}{s^2} - \Phi^{-2}(-\frac{\lambda}{s}e)\phi^2(-\frac{\lambda}{s}e)(\frac{\lambda}{s})^2 + \Phi^{-1}(-\frac{\lambda}{s}e)\phi(-\frac{\lambda}{s}e)e(\frac{\lambda}{s})^3 \right| \\ &\quad \times \sup_{\eta \in \mathcal{H}} \left| \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \frac{(y - g_0(x))^2}{s_0^4} \Phi\left(-\frac{\lambda_0}{s_0}(y - g_0(x))\right) + \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \phi\left(-\frac{\lambda_0}{s_0}(y - g_0(x))\right) \left(\frac{\lambda_0}{s_0}\right)^2 \right. \\ &\quad \left. + \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \phi\left(-\frac{\lambda_0}{s_0}(y - g_0(x))\right) \left(\frac{\lambda_0}{s_0}\right) \frac{y - g_0(x)}{s_0^2} + \frac{2}{s_0} \phi\left(\frac{e}{s_0}\right) \phi\left(-\frac{\lambda_0}{s_0}(y - g_0(x))\right) \left(\frac{\lambda_0}{s_0}\right)^2 \frac{y - g_0(x)}{s_0^2} \right| dy \end{aligned}$$

Using arguments similar to those in verifying PC we obtain $I_2 < \infty$. The other cases for $j = 2$ can be shown in a similar fashion.

5 Asymptotic variance for $\tilde{\theta}$

We derive the exact form of $\mathcal{I}_0$ as the asymptotic variance for $\tilde{\theta}$. In this case the $\mathcal{I}_0$ matrix has (i, j) elements with $i, j = 1, 2$ given by

$$\begin{aligned}\mathcal{I}_{\theta_0}(1, 1) &= \frac{1}{2s_0^4} + w^2 I_1 + \alpha'_{\sigma_u^2} \left(\frac{1}{s_0^2} + (\lambda_0/s_0)^2 I_2 \right) + \frac{1}{s_0^4} \left(\alpha'_{\sigma_u^2} \gamma(\theta_0) + \alpha'_{\sigma_u^2} \frac{\lambda_0}{s_0} \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \frac{s_0^2}{\lambda_0^2 + 1} \right) \\ &- \frac{1}{s_0^2} \alpha'_{\sigma_u^2} \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \left(\frac{\lambda_0}{s_0} + 2w \frac{s_0^2}{\lambda_0^2 + 1} \right) - 2\alpha'_{\sigma_u^2} \frac{\lambda_0}{s_0} w I \\ &+ \frac{1}{s_0^6} \alpha'_{\sigma_u^2} \left(-3\sigma_{v0}^2 \sqrt{2/\pi\sigma_{u0}^2} - \frac{(2\sigma_{u0}^2)^{3/2}}{\sqrt{\pi}} \right)\end{aligned}$$

$$\begin{aligned}\mathcal{I}_{\theta_0}(1, 2) = \mathcal{I}_{\theta_0}(2, 1) &= \frac{1}{2s_0^4} + ww_1 I_1 + \alpha'_{\sigma_u^2} \alpha'_{\sigma_v^2} \left(\frac{1}{s_0^2} + (\lambda_0/s_0)^2 I_2 \right) + \frac{1}{2s_0^4} \left((\alpha'_{\sigma_u^2} + \alpha'_{\sigma_v^2}) (\gamma(\theta_0) \right. \\ &+ \left. \frac{\lambda_0}{s_0} \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \frac{s_0^2}{\lambda_0^2 + 1} \right) \\ &- \frac{1}{s_0^2} \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \left(\frac{\lambda_0}{2s_0} (\alpha'_{\sigma_u^2} + \alpha'_{\sigma_v^2}) + (w\alpha'_{\sigma_v^2} + w_1\alpha'_{\sigma_u^2}) \frac{s_0^2}{\lambda_0^2 + 1} \right) - (w\alpha'_{\sigma_v^2} + w_1\alpha'_{\sigma_u^2}) \frac{\lambda_0}{s_0} I \\ &+ \frac{1}{2s_0^6} (\alpha'_{\sigma_u^2} + \alpha'_{\sigma_v^2}) \left(-3\sigma_{v0}^2 \sqrt{2/\pi\sigma_{u0}^2} - \frac{(2\sigma_{u0}^2)^{3/2}}{\sqrt{\pi}} \right)\end{aligned}$$

$$\begin{aligned}\mathcal{I}_{\theta_0}(2, 2) &= \frac{1}{2s_0^4} + w_1^2 I_1 + \alpha'_{\sigma_v^2} \left(\frac{1}{s_0^2} + (\lambda_0/s_0)^2 I_2 \right) + \frac{1}{s_0^4} \left(\alpha'_{\sigma_v^2} \gamma(\theta_0) + \alpha'_{\sigma_v^2} \frac{\lambda_0}{s_0} \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \frac{s_0^2}{\lambda_0^2 + 1} \right) \\ &- \frac{1}{s_0^2} \alpha'_{\sigma_v^2} \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \left(\frac{\lambda_0}{s_0} + 2w_1 \frac{s_0^2}{\lambda_0^2 + 1} \right) - 2\alpha'_{\sigma_v^2} \frac{\lambda_0}{s_0} w_1 I \\ &+ \frac{1}{s_0^6} \alpha'_{\sigma_v^2} \left(-3\sigma_{v0}^2 \sqrt{2/\pi\sigma_{u0}^2} - \frac{(2\sigma_{u0}^2)^{3/2}}{\sqrt{\pi}} \right)\end{aligned}$$

When $\theta = \theta_0$, let's define $w = \frac{1}{2\lambda_0 s_0^3}$, $w_1 = -\frac{1}{2\lambda_0} \frac{(\sigma_{u0}^2 + 2\sigma_{v0}^2)\sigma_{u0}^2}{(\sigma_{v0}^2)^2 s_0^3}$, $I = \int \frac{e^{-\frac{\sqrt{2}}{s_0 \pi^{3/2}}}}{1 - \text{erf}(e \frac{\lambda_0}{s_0 \sqrt{2}})} \exp(-e^2(\frac{\lambda_0^2}{s_0^2} + \frac{1}{2s_0^2})) de$, $I_1 = \int \frac{e^{-\frac{\sqrt{2}}{s_0 \pi^{3/2}}}}{1 - \text{erf}(e \frac{\lambda_0}{s_0 \sqrt{2}})} \exp(-e^2(\frac{\lambda_0^2}{s_0^2} + \frac{1}{2s_0^2})) de$, $I_2 = \int \frac{\frac{\sqrt{2}}{s_0 \pi^{3/2}}}{1 - \text{erf}(e \frac{\lambda_0}{s_0 \sqrt{2}})} \exp(-e^2(\frac{\lambda_0^2}{s_0^2} + \frac{1}{2s_0^2})) de$, $C_1 = \frac{\gamma(\theta_0)}{s_0^4} + \frac{\lambda_0}{s_0} w I - (\frac{\lambda_0}{s_0})^2 w \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \frac{s_0^2}{\lambda_0^2 + 1} + w \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}}$, $C_2 = \frac{\gamma(\theta_0)}{s_0^4} + \frac{\lambda_0}{s_0} w_1 I - (\frac{\lambda_0}{s_0})^2 w_1 \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}} \frac{s_0^2}{\lambda_0^2 + 1} + w_1 \sqrt{\frac{2}{\pi(\lambda_0^2 + 1)}}$ where erf is the Gaussian error function. Then $\alpha'_{\sigma_u^2} = C_1(\frac{1}{s_0^2} + (\frac{\lambda_0}{s_0})^2 I_2)^{-1}$, $\alpha'_{\sigma_v^2} = C_2(\frac{1}{s_0^2} + (\frac{\lambda_0}{s_0})^2 I_2)^{-1}$.

$$\begin{aligned}\mathcal{I}_{\theta_0}(1, 1) &= E \left(\frac{\partial}{\partial \sigma_u^2} f_\varepsilon(y - g_0(x); \theta_0) + \frac{d_E}{d_g} f_\varepsilon(y - g_0(x); \theta_0) \frac{\partial}{\partial \sigma_u^2} \alpha_{\theta_0}(x) \right)^2 \\ &= E \left(-\frac{1}{s_0^2} + \frac{e^2}{2s_0^4} - \Phi^{-1}(-\frac{\lambda_0}{s_0} e) \phi(-\frac{\lambda_0}{s_0} e) ew + \left[\frac{e}{s_0^2} + \Phi^{-1}(-\frac{\lambda_0}{s_0} e) \phi(-\frac{\lambda_0}{s_0} e) \frac{\lambda_0}{s_0} \right] \frac{\partial}{\partial \sigma_u^2} \alpha_{\theta_0}(x) \right)^2\end{aligned}$$

$$\begin{aligned}\alpha'_{\sigma_u^2} &= \frac{\partial}{\partial \sigma_u^2} \alpha_{\theta_0}(x) = -\frac{E(\frac{\partial^2}{\partial \sigma_u^2 \partial \eta} f_\varepsilon(y - g_0(x); \theta_0) | x)}{E(\frac{\partial^2}{\partial \eta^2} f_\varepsilon(y - g_0(x); \theta_0) | x)} \\ &= -\left[-\frac{1}{s_0^2} - \left(\frac{\lambda_0}{s_0} \right)^2 E(\Phi^{-2}(-\frac{\lambda_0}{s_0} e) \phi^2(-\frac{\lambda_0}{s_0} e) | x) + E(\Phi^{-1}(-\frac{\lambda_0}{s_0} e) \phi(-\frac{\lambda_0}{s_0} e) (\frac{\lambda_0}{s_0})^3 e | x) \right]^{-1} \left[E(-\frac{e}{s_0^4} | x) \right. \\ &+ \left. \left(\frac{\lambda_0}{s_0} \right) w E \Phi^{-2}(-\frac{\lambda_0}{s_0} e) \phi^2(-\frac{\lambda_0}{s_0} e) e | x) - \left(\frac{\lambda_0}{s_0} \right)^2 w E \Phi^{-1}(-\frac{\lambda_0}{s_0} e) \phi(-\frac{\lambda_0}{s_0} e) e^2 | x) + w E \Phi^{-1}(-\frac{\lambda_0}{s_0} e) \phi(-\frac{\lambda_0}{s_0} e) | x) \right] \\ &= \left[\frac{1}{s_0^2} + \left(\frac{\lambda_0}{s_0} \right)^2 I_2 \right]^{-1} C_1\end{aligned}$$

since $E(\Phi^{-1}(-\frac{\lambda_0}{s_0}e)\phi(-\frac{\lambda_0}{s_0}e)(\frac{\lambda_0}{s_0})^3e|x) = 0$, $E(\Phi^{-2}(-\frac{\lambda_0}{s_0}e)\phi^2(-\frac{\lambda_0}{s_0}e)|x) = I_2$, $E(-\frac{e}{s_0^4}|x) = \frac{\gamma\theta_0}{s_0^4}$,
 $E\Phi^{-2}(-\frac{\lambda_0}{s_0}e)\phi^2(-\frac{\lambda_0}{s_0}e)e|x) = I$, $E\Phi^{-1}(-\frac{\lambda_0}{s_0}e)\phi(-\frac{\lambda_0}{s_0}e)e^2|x) = \sqrt{\frac{2}{\pi(\lambda_0^2+1)}}\frac{s_0^2}{\lambda_0^2+1}$, $E\Phi^{-1}(-\frac{\lambda_0}{s_0}e)\phi(-\frac{\lambda_0}{s_0}e)|x) = \sqrt{\frac{2}{\pi(\lambda_0^2+1)}}$. The expression for $\mathcal{I}_{\theta_0}(1,1)$ is obtained with the expression for $\frac{\partial}{\partial\sigma_u^2}\alpha_{\theta_0(x)}$ plugged in, and realize $Ee^2 = s_0^2$, $Ee^4 = 3s_0^4$, $E\Phi^{-1}(-\frac{\lambda_0}{s_0}e)\phi(-\frac{\lambda_0}{s_0}e)e^i|x) = 0$ for $i = 1, 3$.

$$\begin{aligned}\mathcal{I}_{\theta_0}(2,2) &= E\left(\frac{\partial}{\partial\sigma_v^2}f_\varepsilon(y-g_0(x);\theta_0) + \frac{d_F}{dg}f_\varepsilon(y-g_0(x);\theta_0)\frac{\partial}{\partial\sigma_v^2}\alpha_{\theta_0(x)}\right)^2 \\ &= E\left(-\frac{1}{s_0^2} + \frac{e^2}{2s_0^4} - \Phi^{-1}\left(-\frac{\lambda_0}{s_0}e\right)\phi\left(-\frac{\lambda_0}{s_0}e\right)ew_1 + \left[\frac{e}{s_0^2} + \Phi^{-1}\left(-\frac{\lambda_0}{s_0}e\right)\phi\left(-\frac{\lambda_0}{s_0}e\right)\frac{\lambda_0}{s_0}\right]\frac{\partial}{\partial\sigma_v^2}\alpha_{\theta_0(x)}\right)^2 \\ \alpha'_{\sigma_v^2} &= \frac{\partial}{\partial\sigma_v^2}\alpha_{\theta_0(x)} = -\frac{E(\frac{\partial^2}{\partial\sigma_v^2\partial\eta}f_\varepsilon(y-g_0(x);\theta_0)|x)}{E(\frac{\partial^2}{\partial\eta^2}f_\varepsilon(y-g_0(x);\theta_0)|x)} \\ &= -\left[-\frac{1}{s_0^2} - \left(\frac{\lambda_0}{s_0}\right)^2E(\Phi^{-2}(-\frac{\lambda_0}{s_0}e)\phi^2(-\frac{\lambda_0}{s_0}e)|x) + E(\Phi^{-1}(-\frac{\lambda_0}{s_0}e)\phi(-\frac{\lambda_0}{s_0}e)(\frac{\lambda_0}{s_0})^3e|x)]^{-1}\left[E(-\frac{e}{s_0^4}|x) \right. \\ &+ \left. \left(\frac{\lambda_0}{s_0}\right)w_1E\Phi^{-2}(-\frac{\lambda_0}{s_0}e)\phi^2(-\frac{\lambda_0}{s_0}e)e|x) - \left(\frac{\lambda_0}{s_0}\right)^2w_1E\Phi^{-1}(-\frac{\lambda_0}{s_0}e)\phi(-\frac{\lambda_0}{s_0}e)e^2|x) + w_1E\Phi^{-1}(-\frac{\lambda_0}{s_0}e)\phi(-\frac{\lambda_0}{s_0}e)|x)\right] \\ &= \left[\frac{1}{s_0^2} + \left(\frac{\lambda_0}{s_0}\right)^2I_2\right]^{-1}C_2\end{aligned}$$

The expression for $\mathcal{I}_{\theta_0}(2,2)$ is obtained with the expression for $\frac{\partial}{\partial\sigma_v^2}\alpha_{\theta_0(x)}$ plugged in and follow similar arguments as in $\mathcal{I}_{\theta_0}(1,1)$.

$$\begin{aligned}\mathcal{I}_{\theta_0}(1,2) &= \mathcal{I}_{\theta_0}(2,1) \\ &= E\left(\frac{\partial}{\partial\sigma_u^2}f_\varepsilon(y-g_0(x);\theta_0) + \frac{d_F}{dg}f_\varepsilon(y-g_0(x);\theta_0)\frac{\partial}{\partial\sigma_u^2}\alpha_{\theta_0(x)}\right) \\ &\times \left(\frac{\partial}{\partial\sigma_v^2}f_\varepsilon(y-g_0(x);\theta_0) + \frac{d_F}{dg}f_\varepsilon(y-g_0(x);\theta_0)\frac{\partial}{\partial\sigma_v^2}\alpha_{\theta_0(x)}\right) \\ &= E\left(-\frac{1}{s_0^2} + \frac{e^2}{2s_0^4} - \Phi^{-1}\left(-\frac{\lambda_0}{s_0}e\right)\phi\left(-\frac{\lambda_0}{s_0}e\right)ew + \left[\frac{e}{s_0^2} + \Phi^{-1}\left(-\frac{\lambda_0}{s_0}e\right)\phi\left(-\frac{\lambda_0}{s_0}e\right)\frac{\lambda_0}{s_0}\right]\frac{\partial}{\partial\sigma_u^2}\alpha_{\theta_0(x)}\right) \\ &\times \left(-\frac{1}{s_0^2} + \frac{e^2}{2s_0^4} - \Phi^{-1}\left(-\frac{\lambda_0}{s_0}e\right)\phi\left(-\frac{\lambda_0}{s_0}e\right)ew_1 + \left[\frac{e}{s_0^2} + \Phi^{-1}\left(-\frac{\lambda_0}{s_0}e\right)\phi\left(-\frac{\lambda_0}{s_0}e\right)\frac{\lambda_0}{s_0}\right]\frac{\partial}{\partial\sigma_v^2}\alpha_{\theta_0(x)}\right)\end{aligned}$$

The expression for $\mathcal{I}_{\theta_0}(1,2)$ is obtained with the expression for $\frac{\partial}{\partial\sigma_u^2}\alpha_{\theta_0(x)}$ and $\frac{\partial}{\partial\sigma_v^2}\alpha_{\theta_0(x)}$ plugged in and follow similar arguments as in $\mathcal{I}_{\theta_0}(1,1)$ and $\mathcal{I}_{\theta_0}(2,2)$.

References

- [1] Azzalini, A., 1985, A class of distributions which includes the normal ones. Scandinavian Journal of Statistics, 12, 171-178.
- [2] Burrridge, J., 1981, A Note on maximum likelihood estimation for regression models using grouped data. Journal of the Royal Statistical Society, Series B, 43, 41-45.
- [3] Graves, L. M., 1927, Riemann integration and Taylor's Theorem in general analysis. Transactions of the American Mathematical Society, 29,163-177.
- [4] Martins-Filho, C. and F. Yao, 2006, A Note on the use of V and U statistics in nonparametric models of regression. Annals of the Institute of Statistical Mathematics, 58, 389-406

- [5] Martins-Filho, C. and F. Yao, 2007, Nonparametric frontier estimation via local linear regression. *Journal of Econometrics*, 141, 283-319.
- [6] Martins-Filho, C. and F. Yao, 2011, Semiparametric stochastic frontier estimation via profile likelihood. Unpublished manuscript. Available at <http://spot.colorado.edu/~martinsc/Research.html>
- [7] Newey, W. and D. McFadden, 1994, Large sample estimation and hypothesis testing. In: R. F. Engle and D. L. McFadden, (Eds.), *Handbook of Econometrics*, Volume 4. Elsevier Science B.V., Amsterdam.