Econometrica Supplementary Material

SUPPLEMENT TO "ROBUST PRIORS IN NONLINEAR PANEL DATA MODELS"

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APPENDIX

This supplementary appendix contains proofs of some results contained in the paper. Specifically, Section S1 provides proofs of Theorem 4 and its corollary, concerning the asymptotic distribution of flexible random effects estimators. Section S1 also proves Theorem 5, its corollary, and Theorem 6 concerning the bias and the asymptotic distribution of estimated marginal effects. Section S2 proves results stated in the paper for the autoregressive and logit models that we use as illustrations. It also contains results for a Poisson counts model as a further example. We keep the same notation as in the paper.

S1. *Proofs on Flexible Random Effects and Policy Parameters*

An Intermediate Lemma to Show Theorem 4

The following lemma gives the first terms of the asymptotic expansion of the score of the concentrated random effects likelihood when N and T go to infinity.

LEMMA S1: *Let us assume that*

(i) $\lim_{\alpha\to\pm\infty}\rho_i(\theta_0,\alpha)\pi_0(\alpha)=0$,

(ii) $\lim_{\alpha\to\pm\infty}\rho_i(\theta_0,\alpha)\pi_0(\alpha)(\ln\widetilde{\pi}_0(\alpha)-\ln\pi_0(\alpha))=0$,

(iii) $\mathbb{E}_{\pi_0}[(\partial/\partial\alpha_i|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)+((\partial\ln\pi_0(\alpha_{i0}))/\partial\alpha_i)\rho_i(\theta_0,\alpha_{i0}))'(\partial/\partial\alpha_i|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)+((\partial\ln\pi_0(\alpha_{i0}))/\partial\alpha_i)\rho_i(\theta_0,\alpha_{i0}))]<\infty$. *Then*

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta))$$
$$=\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\overline{\ell}_i(\theta)+O\left(\frac{\mathcal{K}(\pi_0,\widetilde{\pi}_0)}{T}\right)+o_p\left(\frac{1}{T}\right).$$

Parts (i) and (ii) are limit conditions that are satisfied if the tails of π_0 are thin enough. Condition (iii) requires the existence of some moments. As a particular case, the conditions are satisfied if π_0 has compact support. Lemma S1 will allow us to derive the asymptotic properties of the random effects maximum likelihood (REML) estimator of θ when N and T tend to infinity at the same rate.

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PROOF OF LEMMA S1: We have

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta_0))=\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\overline{\ell}_i(\theta)+\frac{b}{T}+o_p\left(\frac{1}{T}\right),$$

where

$$\begin{aligned}
b &= \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ln\pi(\overline{\alpha}_i(\theta);\widehat{\xi}(\theta_0))+\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)\right)\\
&= \underbrace{\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ln\pi_0(\overline{\alpha}_i(\theta))+\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)\right)}_{A}\\
&\quad+\underbrace{\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\left(\ln\pi(\overline{\alpha}_i(\theta);\widehat{\xi}(\theta_0))-\ln\pi_0(\overline{\alpha}_i(\theta))\right)\right)}_{B}.
\end{aligned}$$

We have

$$\begin{aligned}
A &= \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ln\pi_0(\overline{\alpha}_i(\theta))+\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)\right)\\
&= \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\mathbb{E}_{\pi_0}\left[\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ln\pi_0(\overline{\alpha}_i(\theta))+\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)\right].
\end{aligned}$$

Using that

$$\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\overline{\alpha}_i(\theta)=\rho_i(\theta_0,\alpha_{i0}),$$

we find that

$$\begin{aligned}
&\mathbb{E}_{\pi_0}\left[\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ln\pi_0(\overline{\alpha}_i(\theta))+\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)\right]\\
&\quad=\mathbb{E}_{\pi_0}\left[\rho_i(\theta_0,\alpha_{i0})\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\ln\pi_0(\alpha_i)+\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)\right]\\
&\quad=\int\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}(\rho_i(\theta_0,\alpha_i)\pi_0(\alpha_i))\,d\alpha_{i0}.
\end{aligned}$$

This term is zero as $\rho_i(\theta_0,\alpha)\pi_0(\alpha) \underset{\alpha\to\pm\infty}{\to} 0$. So

$$A = \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial}{\partial\theta}\bigg|_{\theta_0} \ln \pi_0(\overline{\alpha}_i(\theta)) + \frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}} \rho_i(\theta_0,\alpha_i)\right) = 0.$$

Now

$$\begin{aligned}
B &= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial}{\partial\theta}\bigg|_{\theta_0} \left(\ln \pi(\overline{\alpha}_i(\theta);\widehat{\xi}(\theta_0)) - \ln \pi_0(\overline{\alpha}_i(\theta))\right)\right)\\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \rho_i(\theta_0,\alpha_{i0})\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}} \left(\ln \pi(\alpha_i;\widehat{\xi}(\theta_0)) - \ln \pi_0(\alpha_i)\right)\\
&= \underbrace{\operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \rho_i(\theta_0,\alpha_{i0})\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}} \left(\ln \pi(\alpha_i;\widehat{\xi}(\theta_0)) - \ln \widetilde{\pi}_0(\alpha_i)\right)}_{C}\\
&\quad + \underbrace{\operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \rho_i(\theta_0,\alpha_{i0})\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}} \left(\ln \widetilde{\pi}_0(\alpha_i) - \ln \pi_0(\alpha_i)\right)}_{D}.
\end{aligned}$$

Now the proof of Lemma 2 shows that

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\partial \ln \pi(\alpha_{i0};\widehat{\xi}(\theta_0))}{\partial\xi} = O_p\left(\frac{1}{T}\right).$$

So

$$\begin{aligned}
0 &= \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \ln \pi(\alpha_{i0};\widehat{\xi}_0)}{\partial\xi}\\
&\approx \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \ln \pi(\alpha_{i0};\widehat{\xi}(\theta_0))}{\partial\xi} + \frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2 \ln \pi(\alpha_{i0};\widehat{\xi}(\theta_0))}{\partial\xi\,\partial\xi'}(\widehat{\xi}_0 - \widehat{\xi}(\theta_0)).
\end{aligned}$$

It follows that

$$\widehat{\xi}(\theta_0) = \widehat{\xi}_0 + O_p\left(\frac{1}{T}\right)$$

and

$$\begin{aligned}
C &= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \rho_i(\theta_0,\alpha_{i0}) \frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} \left(\ln \pi(\alpha_i;\widehat{\xi}(\theta_0)) - \ln \widetilde{\pi}_0(\alpha_i)\right)\\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \rho_i(\theta_0,\alpha_{i0}) \frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} \left(\ln \pi(\alpha_i;\widehat{\xi}(\theta_0)) - \ln \pi(\alpha_i;\overline{\xi}_0)\right)\\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \rho_i(\theta_0,\alpha_{i0}) \frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} \left(\ln \pi(\alpha_i;\widehat{\xi}(\theta_0)) - \ln \pi(\alpha_i;\widehat{\xi}_0)\right)\\
&= O\left(\frac{1}{T}\right).
\end{aligned}$$

We also have

$$\begin{aligned}
D &= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \mathbb{E}_{\pi_0}\left[\rho_i(\theta_0,\alpha_{i0}) \frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} (\ln \widetilde{\pi}_0(\alpha_i) - \ln \pi_0(\alpha_i))\right]\\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \int \rho_i(\theta_0,\alpha_{i0})\pi_0(\alpha_{i0})\\
&\quad \times \frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} (\ln \widetilde{\pi}_0(\alpha_i) - \ln \pi_0(\alpha_i))\, d\alpha_{i0}\\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \int \frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} \big(\rho_i(\theta_0,\alpha_i)\pi_0(\alpha_i)\\
&\quad \times (\ln \widetilde{\pi}_0(\alpha_i) - \ln \pi_0(\alpha_i))\big)\, d\alpha_{i0}\\
&\quad - \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \int \left(\frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} \rho_i(\theta_0,\alpha_i)\pi_0(\alpha_i)\right)\\
&\quad \times (\ln \widetilde{\pi}_0(\alpha_{i0}) - \ln \pi_0(\alpha_{i0}))\, d\alpha_{i0}.
\end{aligned}$$

The first term is zero as $\rho_i(\theta_0,\alpha)\pi_0(\alpha)(\ln \widetilde{\pi}_0(\alpha) - \ln \pi_0(\alpha)) \underset{\alpha\to\pm\infty}{\to} 0$. As for the second term, note that, using the Cauchy–Schwarz inequality,

$$\begin{aligned}
&\left|\int \left(\pi_0^{-1/2}\frac{\partial}{\partial \alpha_i}\bigg|_{\alpha_{i0}} \rho_i(\theta_0,\alpha_i)\pi_0(\alpha_i)\right)\left(\pi_0^{1/2}(\ln \widetilde{\pi}_0(\alpha_{i0}) - \ln \pi_0(\alpha_{i0}))\right) d\alpha_{i0}\right|\\
&\leq C^{st}\mathcal{K}(\pi_0,\widetilde{\pi}_0),
\end{aligned}$$

where C^{st} is

$$\left\{\mathbb{E}_{\pi_0}\left[\left(\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)+\frac{\partial\ln\pi_0(\alpha_{i0})}{\partial\alpha_i}\rho_i(\theta_0,\alpha_{i0})\right)'\right.\right.$$
$$\left.\left.\times\left(\frac{\partial}{\partial\alpha_i}\bigg|_{\alpha_{i0}}\rho_i(\theta_0,\alpha_i)+\frac{\partial\ln\pi_0(\alpha_{i0})}{\partial\alpha_i}\rho_i(\theta_0,\alpha_{i0})\right)\right]\right\}^{1/2}<\infty.$$

So

$$B=C+D=O(\mathcal{K}(\pi_0,\widetilde{\pi}_0))+O\left(\frac{1}{T}\right).$$

The lemma follows. *Q.E.D.*

PROOF OF THEOREM 4: An expansion of the score around the truth yields

$$0=\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\widehat{\theta}}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta))$$
$$\approx\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta))+\frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2}{\partial\theta\,\partial\theta'}\bigg|_{\theta_0}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta))(\widehat{\theta}-\theta_0),$$

so

$$\widehat{\theta}-\theta_0\approx\left[-\frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2}{\partial\theta\,\partial\theta'}\bigg|_{\theta_0}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta))\right]^{-1}\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta)).$$

Next, note that, using a Laplace approximation argument, we immediately obtain, when N and T tend to infinity,

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2}{\partial\theta\,\partial\theta'}\bigg|_{\theta_0}\ell_i^{\mathrm{RE}}(\theta,\widehat{\xi}(\theta))=\frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2}{\partial\theta\,\partial\theta'}\bigg|_{\theta_0}\overline{\ell}_i(\theta)+O_p\left(\frac{1}{T}\right).$$

Using this result together with Lemma S1 yields

$$\widehat{\theta}-\theta_0=\left[-\frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2}{\partial\theta\,\partial\theta'}\bigg|_{\theta_0}\overline{\ell}_i(\theta)\right]^{-1}\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\overline{\ell}_i(\theta)$$
$$+O\left(\frac{\mathcal{K}(\pi_0,\widetilde{\pi}_0)}{T}\right)+o_p\left(\frac{1}{T}\right).$$

So, as

$$\sqrt{NT}(\overline{\theta}-\theta_0)=\left[-\frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2}{\partial\theta\,\partial\theta'}\bigg|_{\theta_0}\overline{\ell}_i(\theta)\right]^{-1}\sqrt{NT}\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\overline{\ell}_i(\theta)$$
$$+\,o_p(1),$$

we obtain

$$\sqrt{NT}(\widehat{\theta}-\theta_0)=\sqrt{NT}(\overline{\theta}-\theta_0)+O\left(\sqrt{\frac{N}{T}}\mathcal{K}(\pi_0,\widetilde{\pi}_0)\right)+o_p\left(\sqrt{\frac{N}{T}}\right).$$

The theorem then follows, as $N/T\to C^{st}$. *Q.E.D.*

PROOF OF COROLLARY 3: Theorem 4.2 in Ghosal and van der Vaart (2001) shows that if $K\geq C\log N$ for C large enough, then the convergence rate of the discrete sieve maximum likelihood estimator (MLE) is $(\log N)^{\kappa}N^{-1/2}$ for some $\kappa>0$, where convergence is defined in terms of the Hellinger distance:

$$H(f,g)=\left(\int\left(f^{1/2}(\alpha)-g^{1/2}(\alpha)\right)^2 d\alpha\right)^{1/2}.$$

The result then comes from Theorem 5 in Wong and Shen (1995) that bounds the L^2 Kullback–Leibler loss $\mathcal{K}(\pi_0,\widetilde{\pi}_0)$ by the Hellinger distance $H(\pi_0,\widetilde{\pi}_0)$, under condition (25). *Q.E.D.*

Let us define

$$\widehat{M}_{\mathrm{BFE}}=\int\frac{1}{N}\sum_{i=1}^{N}\underbrace{\left[\frac{\displaystyle\int m_i(\theta,\alpha_i)f_i(\theta,\alpha_i)\pi_i(\alpha_i|\theta)\,d\alpha_i}{\displaystyle\int f_i(\theta,\alpha_i)\pi_i(\alpha_i|\theta)\,d\alpha_i}\right]}_{\widehat{M}_i(\theta)}L^I(\theta)\,d\theta$$
$$\times\frac{1}{\displaystyle\int L^I(\theta)\,d\theta},$$

where

$$L^I(\theta)=\prod_{i=1}^{N}\exp[T\ell_i^I(\theta)]$$

is the integrated likelihood function.

In preparation for the proof of Theorem 5, we need the following lemma that gives the first-order expansion of $\widehat{M}_i(\theta_0)$ when N and T go to infinity.

LEMMA S2: *When T tends to infinity*,

$$\begin{aligned}\widehat{M}_i(\theta_0) &= m_i(\theta_0, \alpha_{i0}) + m_i^{\alpha_i}(\theta_0, \alpha_{i0})\big[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0, \alpha_{i0}))\big]^{-1} v_i(\theta_0, \alpha_{i0}) \\ &\quad + \frac{1}{T\pi_i(\alpha_{i0}|\theta_0)} \frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} \big[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0, \alpha))\big]^{-1} \\ &\quad \times \pi_i(\alpha|\theta_0) m_i^{\alpha_i}(\theta_0, \alpha) + o_p\left(\frac{1}{T}\right).\end{aligned}$$

PROOF: Using a second-order Laplace expansion (e.g., Tierney, Kass, and Kadane (1989, eq. 2.6)) we obtain

$$\begin{aligned}\widehat{M}_i(\theta_0) &= m_i(\theta_0, \widehat{\alpha}_i(\theta_0)) + \frac{H^{-1}}{T} \frac{\partial \ln \pi_i(\alpha_{i0}|\theta_0)}{\partial \alpha_{i0}} m_i^{\alpha_i}(\theta_0, \alpha_{i0}) \\ &\quad + \frac{H^{-1}}{2T} m_i^{\alpha_i\alpha_i}(\theta_0, \alpha_{i0}) - \frac{H^{-2}H_2}{2T} m_i^{\alpha_i}(\theta_0, \alpha_{i0}) + O_p\left(\frac{1}{T^2}\right),\end{aligned}$$

where $H(\alpha) = \mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0, \alpha))$, $H = H(\alpha_{i0})$, and $H_2 = \mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i\alpha_i}(\theta_0, \alpha_{i0}))$.

Now, expanding $m_i(\theta_0, \widehat{\alpha}_i(\theta_0))$ and the score identity $v_i(\theta_0, \widehat{\alpha}_i(\theta_0)) = 0$ around α_{i0} yields

$$\begin{aligned}m_i(\theta_0, \widehat{\alpha}_i(\theta_0)) &= m_i(\theta_0, \alpha_{i0}) + m_i^{\alpha_i}(\theta_0, \alpha_{i0})[\widehat{\alpha}_i(\theta_0) - \alpha_{i0}] \\ &\quad + \frac{1}{2} m_i^{\alpha_i\alpha_i}(\theta_0, \alpha_{i0})[\widehat{\alpha}_i(\theta_0) - \alpha_{i0}]^2 + o_p\left(\frac{1}{T}\right) \\ &= m_i(\theta_0, \alpha_{i0}) + m_i^{\alpha_i}(\theta_0, \alpha_{i0}) H^{-1} v_i(\theta_0, \alpha_{i0}) \\ &\quad - \frac{H^{-3}H_2}{2} m_i^{\alpha_i}(\theta_0, \alpha_{i0}) v_i^2(\theta_0, \alpha_{i0}) \\ &\quad + \frac{1}{2} m_i^{\alpha_i\alpha_i}(\theta_0, \alpha_{i0}) H^{-2} v_i^2(\theta_0, \alpha_{i0}) + o_p\left(\frac{1}{T}\right).\end{aligned}$$

Next, information equality at the truth yields

$$T v_i^2(\theta_0, \alpha_{i0}) = H + o_p(1).$$

Also, note that

$$\frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} H(\alpha) = H_2.$$

So

$$\begin{aligned}
\widehat{M}_i(\theta_0) &= m_i(\theta_0, \alpha_{i0}) + m_i^{\alpha_i}(\theta_0, \alpha_{i0}) H^{-1} v_i(\theta_0, \alpha_{i0}) \\
&\quad - \frac{H^{-2}}{T}\left(\frac{\partial}{\partial \alpha}\bigg|_{\alpha_{i0}} H(\alpha)\right) m_i^{\alpha_i}(\theta_0, \alpha_{i0}) \\
&\quad + \frac{H^{-1}}{T} \frac{\partial \ln \pi_i(\alpha_{i0}|\theta_0)}{\partial \alpha_{i0}} m_i^{\alpha_i}(\theta_0, \alpha_{i0}) + \frac{H^{-1}}{T} m_i^{\alpha_i \alpha_i}(\theta_0, \alpha_{i0}) \\
&\quad + o_p\left(\frac{1}{T}\right) \\
&= m_i(\theta_0, \alpha_{i0}) + m_i^{\alpha_i}(\theta_0, \alpha_{i0}) H^{-1} v_i(\theta_0, \alpha_{i0}) \\
&\quad + \frac{1}{T}\left(\frac{\partial}{\partial \alpha}\bigg|_{\alpha_{i0}} H(\alpha)^{-1}\right) m_i^{\alpha_i}(\theta_0, \alpha_{i0}) \\
&\quad + \frac{H^{-1}}{T \pi_i(\alpha_{i0}|\theta_0)} \frac{\partial}{\partial \alpha}\bigg|_{\alpha_{i0}} \pi_i(\alpha|\theta_0) m_i^{\alpha_i}(\theta_0, \alpha) + o_p\left(\frac{1}{T}\right) \\
&= m_i(\theta_0, \alpha_{i0}) + m_i^{\alpha_i}(\theta_0, \alpha_{i0}) H^{-1} v_i(\theta_0, \alpha_{i0}) \\
&\quad + \frac{1}{T \pi_i(\alpha_{i0}|\theta_0)} \frac{\partial}{\partial \alpha}\bigg|_{\alpha_{i0}} H(\alpha)^{-1} \pi_i(\alpha|\theta_0) m_i^{\alpha_i}(\theta_0, \alpha) \\
&\quad + o_p\left(\frac{1}{T}\right).
\end{aligned}$$

Q.E.D.

PROOF OF THEOREM 5: Given Lemma S2, using a large-NT approximation we obtain

$$\begin{aligned}
\widehat{M}_{\mathrm{BFE}} &= \int \left\{\frac{1}{N}\sum_{i=1}^N \widehat{M}_i(\theta)\right\} L^I(\theta)\, d\theta \times \frac{1}{\int L^I(\theta)\, d\theta} \\
&= \frac{1}{N}\sum_{i=1}^N \widehat{M}_i(\widehat{\theta}) + O_p\left(\frac{1}{NT}\right),
\end{aligned}$$

where $\widehat{\theta}$ is the mode of the integrated likelihood, $\widehat{\theta} = \arg\max_\theta L^I(\theta)$. Note that the approximation comes from

$$L^I(\theta) = \prod_{i=1}^N \exp[T \ell_i^I(\theta)] = \exp\left(NT \frac{1}{N}\sum_{i=1}^N \ell_i^I(\theta)\right),$$

with $\ell_i^I(\theta) = \frac{1}{T}\ln \int \exp[T\ell_i(\theta, \alpha_i)]\pi_i(\alpha_i|\theta)\, d\alpha_i$, so $\frac{1}{N}\sum_{i=1}^N \ell_i^I(\theta) = O_p(1)$.

So

$$\widehat{M}_{\text{BFE}} = \frac{1}{N}\sum_{i=1}^{N}\widehat{M}_i(\theta_0) + \left[\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\widehat{M}_i(\theta)\right](\widehat{\theta}-\theta_0) + o_p\left(\frac{1}{T}\right).$$

Then

$$\operatorname*{plim}_{N\to\infty}\widehat{\theta} = \theta_0 + \frac{B}{T} + o\left(\frac{1}{T}\right)$$

and

$$\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0}\widehat{M}_i(\theta) = \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0} m_i(\theta,\alpha_{i0}) + o(1).$$

So

$$\operatorname*{plim}_{N\to\infty}\widehat{M}_{\text{BFE}} = \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\widehat{M}_i(\theta_0) + \left[\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial\theta}\bigg|_{\theta_0} m_i(\theta,\alpha_{i0})\right]\frac{B}{T} + o\left(\frac{1}{T}\right).$$

Last, Lemma S2 implies, using that $\mathbb{E}_{\theta_0,\alpha_{i0}}(v_i(\theta_0,\alpha_{i0})) = 0$,

$$\begin{aligned}\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\widehat{M}_i(\theta_0) &= \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\mathbb{E}_{\theta_0,\alpha_{i0}}(\widehat{M}_i(\theta_0)) \\ &= \operatorname*{plim}_{N\to\infty} M + \frac{\widetilde{B}_M}{T} + o\left(\frac{1}{T}\right),\end{aligned}$$

with

$$\widetilde{B}_M = \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\pi_i(\alpha_{i0}|\theta_0)}\frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}}\left[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0,\alpha))\right]^{-1} \times \pi_i(\alpha|\theta_0) m_i^{\alpha_i}(\theta_0,\alpha). \qquad \textit{Q.E.D.}$$

PROOF OF COROLLARY 4: Let $\pi_i(\cdot;\xi)$ be a random effects specification. We assume

(i) $\lim_{\alpha\to\pm\infty}\{\mathbb{E}_{\theta_0,\alpha_{i0}}[-v_i^{\alpha_i}(\theta_0,\alpha)]\}^{-1} m_i^{\alpha_i}(\theta_0,\alpha)\pi_0(\alpha) = 0$,

(ii) $\lim_{\alpha\to\pm\infty}\{\mathbb{E}_{\theta_0,\alpha_{i0}}[-v_i^{\alpha_i}(\theta_0,\alpha)]\}^{-1} m_i^{\alpha_i}(\theta_0,\alpha)\pi_0(\alpha)(\ln\widetilde{\pi}_0(\alpha) - \ln\pi_0(\alpha)) = 0$,

(iii) $\mathbb{E}_{\pi_0}((\frac{\partial}{\partial\alpha}|_{\alpha_{i0}}\{\mathbb{E}_{\theta_0,\alpha}[-v_i^{\alpha_i}(\theta_0,\alpha)]\}^{-1} m_i^{\alpha_i}(\theta_0,\alpha) + (\partial\ln\pi_0(\alpha_{i0}))/\partial\alpha_i \times \{\mathbb{E}_{\theta_0,\alpha}(-v_i^{\alpha_i})\}^{-1} m_i^{\alpha_i})^2) < \infty$.

These conditions are very similar to those of Lemma S1, and impose restrictions on the tails of π_0 and $\widetilde{\pi}_0$. As before, they are clearly satisfied if π_0 is compactly supported. Note that in condition (iii) we have left the dependence on true parameter values implicit to simplify the notation.

It follows from Theorem 4 that $B = O(\mathcal{K}(\pi_0, \widetilde{\pi}_0))$. Moreover,

$$\begin{aligned}
\widetilde{B}_M &\equiv \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \frac{1}{\pi_i(\alpha_{i0}; \widehat{\xi}(\widehat{\theta}))} \frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} \big[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0,\alpha))\big]^{-1} \\
&\quad \times \pi_i(\alpha; \widehat{\xi}(\widehat{\theta})) m_i^{\alpha_i}(\theta_0,\alpha) \\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \mathbb{E}_{\pi_0}\bigg(\frac{1}{\widetilde{\pi}_0(\alpha_{i0})} \frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} \big[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0,\alpha))\big]^{-1} \\
&\quad \times \widetilde{\pi}_0(\alpha) m_i^{\alpha_i}(\theta_0,\alpha)\bigg) + o(1) \\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \int \frac{\pi_0(\alpha_{i0})}{\widetilde{\pi}_0(\alpha_{i0})} \frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} \big[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0,\alpha))\big]^{-1} \\
&\quad \times \widetilde{\pi}_0(\alpha) m_i^{\alpha_i}(\theta_0,\alpha)\, d\alpha_{i0} + o(1) \\
&= \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \int \frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} \big[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0,\alpha))\big]^{-1} \\
&\quad \times \pi_0(\alpha) m_i^{\alpha_i}(\theta_0,\alpha)\, d\alpha_{i0} + o(1) \\
&\quad + \operatorname*{plim}_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \int \pi_0(\alpha_{i0}) \big[\mathbb{E}_{\theta_0,\alpha_{i0}}(-v_i^{\alpha_i}(\theta_0,\alpha_{i0}))\big]^{-1} \\
&\quad \times m_i^{\alpha_i}(\theta_0,\alpha_{i0}) \frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} \bigg(\ln \frac{\widetilde{\pi}_0(\alpha)}{\pi_0(\alpha)}\bigg)\, d\alpha_{i0}.
\end{aligned}$$

Conditions (i) and (ii) of the corollary imply, as in the proof of Theorem 4, that

$$\begin{aligned}
\widetilde{B}_M &= \operatorname*{plim}_{N\to\infty} -\frac{1}{N}\sum_{i=1}^{N} \int \bigg(\frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}} \pi_0(\alpha) \big[\mathbb{E}_{\theta_0,\alpha}(-v_i^{\alpha_i}(\theta_0,\alpha))\big]^{-1} m_i^{\alpha_i}(\theta_0,\alpha)\bigg) \\
&\quad \times \ln \frac{\widetilde{\pi}_0(\alpha_{i0})}{\pi_0(\alpha_{i0})}\, d\alpha_{i0} + o(1).
\end{aligned}$$

Last, the Cauchy–Schwarz inequality implies

$$\frac{1}{N}\sum_{i=1}^{N}\int\left(\frac{\partial}{\partial\alpha}\bigg|_{\alpha_{i0}}\pi_0(\alpha)\big[\mathbb{E}_{\theta_0,\alpha}(-v_i^{\alpha_i}(\theta_0,\alpha))\big]^{-1}m_i^{\alpha_i}(\theta_0,\alpha)\right)$$
$$\times\ln\frac{\widetilde{\pi}_0(\alpha_{i0})}{\pi_0(\alpha_{i0})}\,d\alpha_{i0}=O(\mathcal{K}(\pi_0,\widetilde{\pi}_0)),$$

provided that condition (iii) above holds. *Q.E.D.*

PROOF OF THEOREM 6: We have

$$\begin{aligned}\operatorname*{plim}_{N\to\infty}\widehat{M}_{\mathrm{RE}}&=\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\int m_i(\widehat{\theta},\alpha_i)\pi_i(\alpha_i;\widehat{\xi}(\widehat{\theta}))\,d\alpha_i\\&=\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\int m_i(\theta_0,\alpha_i)\pi_i(\alpha_i;\widehat{\xi}(\theta_0))\,d\alpha_i+O\left(\frac{1}{T}\right),\end{aligned}$$

as $\widehat{\theta}$ is large-T consistent even if $\pi_i(\cdot;\xi)$ is misspecified. Next, using that

$$\widehat{\xi}(\theta_0)=\widehat{\xi}_0+O_p\left(\frac{1}{T}\right),$$

we obtain

$$\begin{aligned}\operatorname*{plim}_{N\to\infty}\widehat{M}_{\mathrm{RE}}&=\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\int m_i(\theta_0,\alpha_i)\pi_i(\alpha_i;\widehat{\xi}_0)\,d\alpha_i+O\left(\frac{1}{T}\right)\\&=\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\int m_i(\theta_0,\alpha_i)\pi_i(\alpha_i;\overline{\xi}_0)\,d\alpha_i+O\left(\frac{1}{T}\right)\\&=\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\int m_i(\theta_0,\alpha_i)\widetilde{\pi}_0(\alpha_i)\,d\alpha_i+O\left(\frac{1}{T}\right).\end{aligned}$$

Q.E.D.

S2. *Examples*

This section proves results stated in the paper for the autoregressive and logit models that we use as examples. As an additional example, the section also contains results for a Poisson counts model. For notational simplicity we drop the indices of the expectation terms when they are evaluated at true parameter values.

S2.1. *Dynamic* AR(p)

Let $y_i^0 = (y_{i,1-p}, \dots, y_{i0})'$ be the vector of initial conditions; which we assume is observed. In matrix form, we have

$$y_i = X_i\mu_0 + \alpha_{i0}\iota + \varepsilon_i,$$

where the tth row of X_i is $x_{it}' = (y_{i,t-p}, \dots, y_{i,t-1})$, $\mu_0 = (\mu_{10}, \dots, \mu_{p0})'$, and ι is a $T \times 1$ vector of 1s. The scaled individual log-likelihood is given by

$$\begin{aligned}\ell_i(\mu, \sigma^2, \alpha_i) &= \frac{1}{T}\ln f(y_i|y_i^0, \alpha_i; \mu, \sigma^2)\\ &= -\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(\sigma^2) - \frac{1}{2T}\sum_{t=1}^{T}\frac{(y_{it} - x_{it}'\mu - \alpha_i)^2}{\sigma^2}.\end{aligned}$$

We thus have

$$v_i(\mu, \sigma^2, \alpha_i) = \frac{1}{T}\sum_{t=1}^{T}\frac{(y_{it} - x_{it}'\mu - \alpha_i)}{\sigma^2}$$

and hence

$$\mathbb{E}[-v_i^{\alpha_i}(\mu, \sigma^2, \alpha_i)] = \frac{1}{\sigma^2}.$$

Moreover,

$$\begin{aligned}\mathbb{E}[v_i^2(\mu, \sigma^2, \alpha_i)] &= \frac{1}{T^2\sigma^4}\iota'\mathbb{E}\big((y_i - X_i\mu - \alpha_i\iota)(y_i - X_i\mu - \alpha_i\iota)'\big)\iota,\\ &= \frac{1}{T^2\sigma^4}\iota'\mathbb{E}\big((X_i(\mu_0 - \mu) + (\alpha_{i0} - \alpha_i)\iota + \varepsilon_i)\\ &\qquad \times (X_i(\mu_0 - \mu) + (\alpha_{i0} - \alpha_i)\iota + \varepsilon_i)'\big)\iota.\end{aligned}$$

Note that this expectation depends on the true values of the parameters. Note also that the expectation is taken for i fixed. The same will be true of the variances and covariances that we will consider in this section of the Appendix.

Computation of $\mathbb{E}[v_i^2(\mu, \sigma^2, \alpha_i)]$: One has

$$\mathrm{Var}(\varepsilon_i + X_i(\mu_0 - \mu)) = \mathrm{Var}(\varepsilon_i + [(\mu_0 - \mu)' \otimes I_T]\operatorname{vec} X_i).$$

Let $B(\mu_0, \mu) = (\mu_0 - \mu)' \otimes I_T$. Then

$$\begin{aligned}&\mathrm{Var}(\varepsilon_i + X_i(\mu_0 - \mu))\\ &\quad = \sigma^2 I_T + \mathbb{E}(\varepsilon_i(\operatorname{vec} X_i)')B(\mu_0, \mu)' + B(\mu_0, \mu)\mathbb{E}(\varepsilon_i(\operatorname{vec} X_i)')'\\ &\qquad + B(\mu_0, \mu)\,\mathrm{Var}(\operatorname{vec} X_i)B(\mu_0, \mu)'.\end{aligned}$$

To compute these expressions, we shall write the model as (see Alvarez and Arellano (2004, Appendix A.3))

$$\begin{pmatrix} I_p & 0 \\ B_{Tp} & B_T \end{pmatrix} \begin{pmatrix} y_i^0 \\ y_i \end{pmatrix} = \begin{pmatrix} y_i^0 \\ \alpha_i \iota + \varepsilon_i \end{pmatrix},$$

where

$$(\, B_{Tp} \quad B_T \,) = \begin{pmatrix} -\mu_{p0} & -\mu_{(p-1)0} & \cdots & -\mu_{10} & 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & -\mu_{p0} & \cdots & -\mu_{20} & -\mu_{10} & 1 & 0 & \cdots & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & -\mu_{10} & 1 \end{pmatrix}.$$

Inverting the system yields

$$y_i = \overline{C}_{Tp} y_i^0 + \alpha_i \overline{C}_T \iota + \overline{C}_T \varepsilon_i,$$

where $\overline{C}_T = B_T^{-1}$ and $\overline{C}_{Tp} = -B_T^{-1} B_{Tp}$.

At this stage, it is convenient to introduce the $(T + p) \times (Tp)$ selection matrix such that

$$\operatorname{vec}(X_i) = P' \begin{pmatrix} y_i^0 \\ y_i \end{pmatrix}.$$

Moreover, the matrix $B(\mu_0, \mu)P'$ reads

$$\begin{pmatrix} \mu_{10} - \mu_1 & \mu_{20} - \mu_2 & \cdots & \mu_{p0} - \mu_p & 0 & 0 & \cdots & 0 & 0 \\ 0 & \mu_{10} - \mu_1 & \mu_{20} - \mu_2 & \cdots & \mu_{p0} - \mu_p & 0 & \cdots & 0 & 0 \\ 0 & 0 & \mu_{10} - \mu_1 & \mu_{20} - \mu_2 & \cdots & \mu_{p0} - \mu_p & \cdots & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & \mu_{p0} - \mu_p & 0 \end{pmatrix}.$$

We shall write

$$B(\mu_0, \mu)P' = (\, \overline{A}(\mu_0, \mu) \quad \overline{B}(\mu_0, \mu) \,),$$

where $\overline{A}(\mu_0, \mu)$ is $T \times p$ and $\overline{B}(\mu_0, \mu)$ is $T \times T$. Now

$$\text{(S1)} \qquad \begin{aligned} \operatorname{vec}(X_i) &= P' \begin{pmatrix} y_i^0 \\ y_i \end{pmatrix} \\ &= P' \begin{pmatrix} I_p \\ \overline{C}_{Tp} \end{pmatrix} y_i^0 + \alpha_i P' \begin{pmatrix} 0 \\ \overline{C}_T \iota \end{pmatrix} + P' \begin{pmatrix} 0 \\ \overline{C}_T \varepsilon_i \end{pmatrix}. \end{aligned}$$

It thus follows that

$$\begin{aligned} \mathbb{E}[\varepsilon_i (\operatorname{vec} X_i)'] B(\mu_0, \mu)' &= \sigma_0^2 \begin{pmatrix} 0_p & \overline{C}_T' \end{pmatrix} P B(\mu_0, \mu)' \\ &= \sigma_0^2 \overline{C}_T' \overline{B}(\mu_0, \mu)'. \end{aligned}$$

Then

$$\begin{aligned} &B(\mu_0, \mu) \operatorname{Var}(\operatorname{vec} X_i) B(\mu_0, \mu)' \\ &\quad = \sigma_0^2 B(\mu_0, \mu) P' \begin{pmatrix} 0 & 0 \\ 0 & \overline{C}_T \overline{C}_T' \end{pmatrix} P B(\mu_0, \mu)' \\ &\quad = \sigma_0^2 \overline{B}(\mu_0, \mu) \overline{C}_T \overline{C}_T' \overline{B}(\mu_0, \mu)'. \end{aligned}$$

Hence

$$\begin{aligned} \operatorname{Var}(\varepsilon_i + X_i(\mu_0 - \mu)) = \sigma_0^2 I_T &+ \sigma_0^2 \overline{C}_T' \overline{B}(\mu_0, \mu)' + \sigma_0^2 \overline{B}(\mu_0, \mu) \overline{C}_T \\ &+ \sigma_0^2 \overline{B}(\mu_0, \mu) \overline{C}_T \overline{C}_T' \overline{B}(\mu_0, \mu)'. \end{aligned}$$

Now

$$\begin{aligned} &\mathbb{E}((X_i(\mu_0 - \mu) + (\alpha_{i0} - \alpha_i)\iota + \varepsilon_i)(X_i(\mu_0 - \mu) + (\alpha_{i0} - \alpha_i)\iota + \varepsilon_i)') \\ &\quad = \operatorname{Var}(\varepsilon_i + X_i(\mu_0 - \mu)) + \mathbb{E}(X_i(\mu_0 - \mu) + (\alpha_{i0} - \alpha_i)\iota + \varepsilon_i) \\ &\qquad \times \mathbb{E}(X_i(\mu_0 - \mu) + (\alpha_{i0} - \alpha_i)\iota + \varepsilon_i)'. \end{aligned}$$

Since

$$\operatorname{vec}(X_i) = P' \begin{pmatrix} I_p \\ \overline{C}_{Tp} \end{pmatrix} y_i^0 + \alpha_{i0} P' \begin{pmatrix} 0 \\ \overline{C}_T \iota \end{pmatrix} + P' \begin{pmatrix} 0 \\ \overline{C}_T \varepsilon_i \end{pmatrix},$$

it follows that

$$\begin{aligned} \mathbb{E}[X_i(\mu_0 - \mu)] &= B(\mu_0, \mu) \mathbb{E}[\operatorname{vec}(X_i)] \\ &= (\overline{A}(\mu_0, \mu) + \overline{B}(\mu_0, \mu) \overline{C}_{Tp}) y_i^0 + \alpha_{i0} \overline{B}(\mu_0, \mu) \overline{C}_T \iota. \end{aligned}$$

The previous results yield

$$
\begin{aligned}
\mathbb{E}[v_i^2(\mu,\sigma^2,\alpha_i)] = \frac{1}{T^2\sigma^4}\iota'\big\{&\sigma_0^2 I_T + \sigma_0^2\overline{C}_T'\overline{B}(\mu_0,\mu)' + \sigma_0^2\overline{B}(\mu_0,\mu)\overline{C}_T \\
&+ \sigma_0^2\overline{B}(\mu_0,\mu)\overline{C}_T\overline{C}_T'\overline{B}(\mu_0,\mu)' \\
&+ \big[(\overline{A}(\mu_0,\mu) + \overline{B}(\mu_0,\mu)\overline{C}_{Tp})y_i^0 \\
&+ \alpha_{i0}\overline{B}(\mu_0,\mu)\overline{C}_T\iota + (\alpha_{i0}-\alpha_i)\iota\big] \\
&\times \big[(\overline{A}(\mu_0,\mu) + \overline{B}(\mu_0,\mu)\overline{C}_{Tp})y_i^0 \\
&+ \alpha_{i0}\overline{B}(\mu_0,\mu)\overline{C}_T\iota + (\alpha_{i0}-\alpha_i)\iota\big]'\big\}\iota.
\end{aligned}
$$

The infeasible robust prior is thus given by

$$
\begin{aligned}
\pi_i^{\mathrm{IR}}(\alpha_i|\mu,\sigma^2) \propto \big(\iota'\big\{&\sigma_0^2 I_T + \sigma_0^2\overline{C}_T'\overline{B}(\mu_0,\mu)' + \sigma_0^2\overline{B}(\mu_0,\mu)\overline{C}_T \\
&+ \sigma_0^2\overline{B}(\mu_0,\mu)\overline{C}_T\overline{C}_T'\overline{B}(\mu_0,\mu)' \\
&+ \big[(\overline{A}(\mu_0,\mu) + \overline{B}(\mu_0,\mu)\overline{C}_{Tp})y_i^0 + \alpha_{i0}\overline{B}(\mu_0,\mu)\overline{C}_T\iota \\
&+ (\alpha_{i0}-\alpha_i)\iota\big] \\
&\times \big[(\overline{A}(\mu_0,\mu) + \overline{B}(\mu_0,\mu)\overline{C}_{Tp})y_i^0 + \alpha_{i0}\overline{B}(\mu_0,\mu)\overline{C}_T\iota \\
&+ (\alpha_{i0}-\alpha_i)\iota\big]'\big\}\iota\big)^{-1/2} \\
\propto (1 + a(\mu-\mu_0) &+ b(\mu-\mu_0,\alpha_i-\alpha_{i0}))^{-1/2},
\end{aligned}
$$

where

$$
a(\mu-\mu_0) = \frac{1}{T}\iota'\{\overline{C}_T'\overline{B}(\mu_0,\mu)' + \overline{B}(\mu_0,\mu)\overline{C}_T\}\iota \tag{S2}
$$

is a linear function of $\mu-\mu_0$ and

$$
\begin{aligned}
b(\mu-\mu_0,\alpha_i-\alpha_{i0}) = \frac{1}{T\sigma_0^2}\iota'\big\{&\sigma_0^2\overline{B}(\mu_0,\mu)\overline{C}_T\overline{C}_T'\overline{B}(\mu_0,\mu)' \\
&+ \big[(\overline{A}(\mu_0,\mu) + \overline{B}(\mu_0,\mu)\overline{C}_{Tp})y_i^0 \\
&+ \alpha_{i0}\overline{B}(\mu_0,\mu)\overline{C}_T\iota + (\alpha_{i0}-\alpha_i)\iota\big] \\
&\times \big[(\overline{A}(\mu_0,\mu) + \overline{B}(\mu_0,\mu)\overline{C}_{Tp})y_i^0 \\
&+ \alpha_{i0}\overline{B}(\mu_0,\mu)\overline{C}_T\iota + (\alpha_{i0}-\alpha_i)\iota\big]'\big\}\iota
\end{aligned} \tag{S3}
$$

is a quadratic function of $\mu-\mu_0$ and $\alpha_i-\alpha_{i0}$.

The AR(1) *Case:* Let us assume that $p = 1$. Then

$$\overline{C}_T = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \mu_{10} & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \mu_{10}^{T-1} & \mu_{10}^{T-2} & \cdots & 1 \end{pmatrix},$$

so that

$$\overline{C}_T \iota = \frac{1}{1-\mu_{10}} \begin{pmatrix} 1-\mu_{10} \\ 1-\mu_{10}^2 \\ \cdots \\ 1-\mu_{10}^T \end{pmatrix}.$$

Moreover,

$$\overline{C}_{Tp} = \begin{pmatrix} \mu_{10} \\ \mu_{10}^2 \\ \cdots \\ \mu_{10}^T \end{pmatrix}$$

and

$$\overline{A}(\mu_0, \mu) = \begin{pmatrix} \mu_{10} - \mu_1 \\ 0 \\ \cdots \\ 0 \end{pmatrix},$$

$$\overline{B}(\mu_0, \mu) = \begin{pmatrix} 0 & 0 & \cdots & 0 & 0 \\ \mu_{10} - \mu_1 & 0 & \cdots & 0 & 0 \\ 0 & \mu_{10} - \mu_1 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & \mu_{10} - \mu_1 & 0 \end{pmatrix}.$$

Hence $\pi_i^{\mathrm{IR}}(\mu_i|\mu, \sigma^2)$ is proportional to

$$\begin{aligned} \Bigg\{ & \sigma_0^2 T + 2\sigma_0^2 \frac{\mu_{10}-\mu_1}{1-\mu_{10}} \cdot \sum_{t=1}^{T-1} (1-\mu_{10}^t) + \sigma_0^2 \left(\frac{\mu_{10}-\mu_1}{1-\mu_{10}}\right)^2 \cdot \sum_{t=1}^{T-1} (1-\mu_{10}^t)^2 \\ & + \Bigg[\left((\mu_{10}-\mu_1) \frac{1-\mu_{10}^T}{1-\mu_{10}} \right) y_i^0 \\ & + \alpha_{i0} \frac{\mu_{10}-\mu_1}{1-\mu_{10}} \cdot \sum_{t=1}^{T-1} (1-\mu_{10}^t) + (\alpha_{i0}-\alpha_i) T \Bigg] \\ & \times \Bigg[\left((\mu_{10}-\mu_1) \frac{1-\mu_{10}^T}{1-\mu_{10}} \right) y_i^0 \\ & + \alpha_{i0} \frac{\mu_{10}-\mu_1}{1-\mu_{10}} \cdot \sum_{t=1}^{T-1} (1-\mu_{10}^t) + (\alpha_{i0}-\alpha_i) T \Bigg]' \Bigg\}^{-1/2}. \end{aligned}$$

We thus obtain

$$\pi_i^{\mathrm{IR}}(\overline{\alpha}_i(\mu,\sigma^2)|\mu,\sigma^2) \propto \left\{T + 2\frac{\mu_{10}-\mu_1}{1-\mu_{10}}\cdot\sum_{t=1}^{T-1}(1-\mu_{10}^t) \right.$$
$$\left. + \left(\frac{\mu_{10}-\mu_1}{1-\mu_{10}}\right)^2 \cdot \sum_{t=1}^{T-1}(1-\mu_{10}^t)^2\right\}^{-1/2}.$$

Hence, for π to reduce bias we need that

$$\left.\frac{\partial \ln \pi(\overline{\alpha}_i(\mu,\sigma^2)|\mu,\sigma^2)}{\partial\mu}\right|_{\mu_{10},\sigma_0^2,\alpha_{i0}} = \frac{1}{T(1-\mu_{10})}\cdot\sum_{t=1}^{T-1}(1-\mu_{10}^t)$$
$$= \frac{1}{T}\sum_{t=1}^{T-1}(T-t)\mu_{10}^{t-1}.$$

Gaussian REML: We have

$$v_i(\mu,\sigma^2,\alpha_i) = \frac{1}{T}\sum_{t=1}^{T}\frac{(y_{it}-x_{it}'\mu-\alpha_i)}{\sigma^2}$$

and hence

$$\mathbb{E}(-v_i^{\alpha_i}(\mu,\sigma^2,\alpha_i)) = \frac{1}{\sigma^2}, \quad \mathbb{E}(-v_i^{\mu}(\mu,\sigma^2,\alpha_i)) = -\frac{1}{T\sigma^2}\sum_{t=1}^{T}x_{it},$$
$$\mathbb{E}(-v_i^{\sigma^2}(\mu,\sigma^2,\alpha_i)) = 0.$$

Dropping for simplicity the derivative with respect to σ^2, we obtain

$$\rho_i(\mu,\alpha_i) = -\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}(x_{it}).$$

Let us define the $p\times(T+p)$ matrix

$$Q = (\, I_p \quad \cdots \quad I_p\,)\,P'.$$

Then as

$$\sum_{t=1}^{T}x_{it} = (\, I_p \quad \cdots \quad I_p\,)\,\mathrm{vec}(X_i),$$

we obtain, using (S1),

$$\rho_i(\mu,\alpha_i) = -\frac{1}{T}\left(Q\left(\frac{I_p}{\overline{C}_{Tp}}\right)y_i^0 + \alpha_i Q\left(\frac{0}{\overline{C}_T\iota}\right)\right),$$

where $\overline{C}_{Tp}$ and $\overline{C}_T$ are functions of μ. Moreover, for a stationary process, the coefficient of α_i is $O(1)$, while the coefficient of y_{i0} is $O(1/T)$. For example, for a stationary AR(1) process, the coefficient of y_{i0} is $-(1+\mu_{10}+\mu_{10}^2+\cdots+\mu_{10}^{T-1})/T = O(1/T)$.

S2.2. *Linear Model With One Endogenous Regressor*

The individual log-likelihood is given by (see, e.g., Hahn (2000))

$$\ell_i(\theta,\alpha_i) = -\frac{1}{2}\ln|\Omega| - \frac{1}{2T}\omega_{11}\sum_{t=1}^T(y_{it}-\theta\alpha_i)^2 - \frac{1}{T}\omega_{12}\sum_{t=1}^T(y_{it}-\theta\alpha_i)(x_{it}\alpha_i) - \frac{1}{2T}\omega_{22}\sum_{t=1}^T(x_{it}-\alpha_i)^2.$$

We thus have

$$v_i(\theta,\alpha_i) = \frac{1}{T}\omega_{11}\theta\sum_{t=1}^T(y_{it}-\theta\alpha_i) + \frac{1}{T}\omega_{12}\sum_{t=1}^T(y_{it}-2\theta\alpha_i+\theta x_{it}) + \frac{1}{T}\omega_{22}\sum_{t=1}^T(x_{it}-\alpha_i).$$

Then

$$\mathbb{E}(-v_i^{\alpha_i}(\theta,\alpha_i)) = \omega_{11}\theta^2 + 2\omega_{12}\theta + \omega_{22}$$

and

$$v_i^\theta(\theta,\alpha_i) = \frac{1}{T}\omega_{11}\sum_{t=1}^T(y_{it}-2\theta\alpha_i) + \frac{1}{T}\omega_{12}\sum_{t=1}^T(-2\alpha_i+x_{it}).$$

Hence, at true values,

$$\mathbb{E}_{\theta_0,\alpha_{i0}}(v_i^\theta(\theta_0,\alpha_{i0})) = -\omega_{11}\theta_0\alpha_{i0} - \omega_{12}\alpha_{i0}.$$

We obtain that

$$\rho_i(\theta,\alpha_i) = \alpha_i\frac{-\omega_{11}\theta-\omega_{12}}{\omega_{11}\theta^2+2\omega_{12}\theta+\omega_{22}}.$$

S2.3. *Poisson Counts*

Let the data consist of T Poisson counts y_{it} with individual means

$$\mathbb{E}_{\theta_0,\alpha_{i0}}(y_{it}) = \alpha_{i0}\exp(x_{it}'\theta_0) \qquad (i=1,\dots,N,\ t=1,\dots,T),$$

where x_{it} are known covariates. The individual log-likelihood is given by

$$\ell_i(\theta,\alpha_i) \propto -\alpha_i \frac{1}{T}\sum_{t=1}^{T}\exp(x_{it}'\theta) + \frac{1}{T}\sum_{t=1}^{T} y_{it}\ln(\alpha_i) + \frac{1}{T}\sum_{t=1}^{T} y_{it}x_{it}'\theta.$$

So

$$v_i(\theta,\alpha_i) = \frac{1}{T\alpha_i}\sum_{t=1}^{T}(y_{it} - \alpha_i\exp(x_{it}'\theta)).$$

Note that it follows that

$$\overline{\alpha}_i(\theta) = \alpha_{i0}\frac{\sum_{t=1}^{T}\exp(x_{it}'\theta_0)}{\sum_{t=1}^{T}\exp(x_{it}'\theta)}. \tag{S4}$$

Moreover,

$$\mathbb{E}(-v_i^{\alpha_i}(\theta,\alpha_i)) = \frac{1}{T\alpha_i^2}\sum_{t=1}^{T}\alpha_{i0}\exp(x_{it}'\theta_0)$$

and

$$\begin{aligned}
&\mathbb{E}(v_i^2(\theta,\alpha_i)) \\
&\quad = \frac{1}{T^2\alpha_i^2}\sum_{t=1}^{T}\mathbb{E}\big((y_{it} - \alpha_i\exp(x_{it}'\theta))^2\big) \\
&\quad = \frac{1}{T^2\alpha_i^2}\sum_{t=1}^{T}\big(\mathbb{E}((y_{it} - \mathbb{E}(y_{it}))^2) + (\mathbb{E}(y_{it}) - \alpha_i\exp(x_{it}'\theta))^2\big) \\
&\quad = \frac{1}{T^2\alpha_i^2}\sum_{t=1}^{T}\alpha_{i0}\exp(x_{it}'\theta_0) + (\alpha_{i0}\exp(x_{it}'\theta_0) - \alpha_i\exp(x_{it}'\theta))^2,
\end{aligned}$$

where we have used that $\mathrm{Var}(y_{it}) = \mathbb{E}(y_{it}) = \alpha_{i0}\exp(x_{it}'\theta_0)$. Hence a consistent estimate of the following quantity is robust:

$$\text{(S5)} \qquad \pi_i^{\mathrm{IR}}(\alpha_i|\theta) \propto \frac{1}{\alpha_i}\left(\sum_{t=1}^{T}\alpha_{i0}\exp(x_{it}'\theta_0) + [\alpha_{i0}\exp(x_{it}'\theta_0) - \alpha_i\exp(x_{it}'\theta)]^2\right)^{-1/2}.$$

Then, by Proposition 1 one can add a quadratic adjustment in $(\theta - \theta_0)$ and $(\alpha_i - \alpha_{i0})$ to the logarithm of π_i^{IR} without altering its bias properties. It follows that

$$\text{(S6)} \qquad \widetilde{\pi}(\alpha_i|\theta) \propto \frac{1}{\alpha_i}$$

is also bias reducing. Note that π_i^{IR} is proper, while $\widetilde{\pi}$ is not.

As in Lancaster (2002), let us consider the reparameterization $\psi_i = \alpha_i \times \sum_{t=1}^{T}\exp(x_{it}'\theta)$. Then it is straightforward to show that $(\partial^2\ell_i(\theta,\psi_i))/(\partial\theta\,\partial\psi_i) = 0$. In this reparameterized model, parameters are fully orthogonal, not just information orthogonal. In particular, the uniform prior is bias reducing. Therefore, in terms of the original reparameterization, the following prior reduces bias:

$$\pi_i(\alpha_i|\theta) \propto \left|\frac{\partial\psi_i(\alpha_i,\theta)}{\partial\alpha_i}\right| = \sum_{t=1}^{T}\exp(x_{it}'\theta).$$

Interestingly, the robust prior and Lancaster's prior are directly as follows:

$$\pi_i^{\mathrm{IR}}(\overline{\alpha}_i(\theta)|\theta) \propto \widetilde{\pi}(\overline{\alpha}_i(\theta)|\theta) = \sum_{t=1}^{T}\exp(x_{it}'\theta) = \pi_i(\alpha_i|\theta).$$

This result follows directly from (S4).

REML: For the Poisson counts model, we have

$$\rho_i(\theta,\alpha_i) = -\alpha_i h(x_i,\theta),$$

where

$$h(x_i,\theta) = \frac{\sum_{t=1}^{T}\exp(x_{it}'\theta)x_{it}}{\sum_{t=1}^{T}\exp(x_{it}'\theta)}.$$

It follows that uncorrelated Gaussian REML is not bias reducing in this model, in general, unless α_{i0} is independent of x_i. Note that if we let α_{i0} and x_i be dependent, then correlated REML (as introduced in Corollary 2) is not robust either.

In addition, note that the local approximation to the robust prior,

$$\widetilde{\pi}(\alpha_i|\theta) = \frac{1}{\alpha_i},$$

is a bias-reducing prior that is independent of θ. However, $\widetilde{\pi}$ is an improper prior, which does not correspond to a random effects specification.

Assume now that π belongs to the $\Gamma(p, r)$ family for some $p > 0$, $r > 0$. We have

$$\pi(\alpha_i; p, r) = \frac{p^r \alpha_i^{r-1} \exp(-p\alpha_i)}{\Gamma(r)}.$$

It is straightforward to check that the left-hand side in equation (21) is equal to

$$\text{(S7)} \qquad \operatorname*{plim}_{N\to\infty} -\frac{1}{N}\sum_{i=1}^{N} \mathbb{E}_{\pi_0}[(\overline{r}(\theta_0) - \overline{p}(\theta_0)\alpha_{i0})h(x_i, \theta_0)].$$

So Gamma REML is not bias reducing, in general, in the Poisson model. Here also, it is bias reducing only under the assumption that α_{i0} and x_i are independent.

S2.4. *Static Logit*

We have

$$v_i(\theta, \alpha_i) = \frac{1}{T}\sum_{t=1}^{T}(y_{it} - c(x_{it}'\theta + \alpha_i)).$$

It follows that

$$\text{(S8)} \qquad \mathbb{E}[-v_i^{\alpha_i}(\theta, \alpha_i)] = \frac{1}{T}\sum_{t=1}^{T} \Lambda(x_{it}'\theta + \alpha_i)(1 - \Lambda(x_{it}'\theta + \alpha_i))$$

and

$$\text{(S9)} \qquad \mathbb{E}[v_i^2(\theta, \alpha_i)] = \mathbb{E}\left(\frac{1}{T}\sum_{t=1}^{T}(y_{it} - \Lambda(x_{it}'\theta + \alpha_i))\right)^2$$

$$= \frac{1}{T^2}\sum_{t=1}^{T} \mathbb{E}\big((y_{it} - \Lambda(x_{it}'\theta + \alpha_i))^2\big),$$

where we have used the fact that observations are independent and identically distributed across T.

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