

Running head: SUPPLEMENTAL MATERIAL

Supplemental Material

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Appendix A

When y_{it}^T in the Equation (1) of the main text has an AR(1) process, $y_{it}^O - \mu_i$ has a ARMA(1,1) process. To prove this, we introduce a new variable v_{it} , and rewrite $y_{it}^O - \mu_i$ in a ARMA(1,1) form. That is, we replace the function of measurement error e_{it} and shock variable z_{it} by a MA(1) process of v_{it} ,

$$\begin{aligned} (y_{it}^O - \mu_i) - \phi_i(y_{i(t-1)}^O - \mu_i) &= e_{it} - \phi_i e_{i(t-1)} + z_{it} \\ &= v_{it} + \theta_i v_{i(t-1)}. \end{aligned} \quad (1)$$

To simplify the equation, we denote $m_{it} = (y_{it}^O - \mu_i) - \phi_i(y_{i(t-1)}^O - \mu_i)$. Based on the first line of Equation (1), the autocovariance of m_{it} can be calculated based on ϕ_i , e_{it} , and z_{it} ,

$$\begin{aligned} \gamma_{mi}(0) &= \text{var}(e_{it} - \phi_i e_{i(t-1)} + z_{it})^2 \\ &= \sigma_z^2 + (1 + \phi_i^2) \sigma_e^2, \end{aligned} \quad (2)$$

$$\begin{aligned} \gamma_{mi}(1) &= \text{cov}(e_{it} - \phi_i e_{i(t-1)} + z_{it}, e_{i(t+1)} - \phi_i e_{it} + z_{i(t+1)}) \\ &= -\phi_i \sigma_e^2. \end{aligned} \quad (3)$$

On the other hand, based on the second line of Equation (1), m_{it} is also equal to $v_{it} + \theta_i v_{i(t-1)}$, which is a MA(1) process, thus the autocovariance of m_{it} also can be calculated based on v_{it} and θ_i ,

$$\gamma_{mi}(0) = \sigma_{vi}^2(1 + \theta_i^2), \quad (4)$$

$$\gamma_{mi}(1) = \theta_i \sigma_{vi}^2. \quad (5)$$

Solve the Equations (2), (3), (4), and (5), we can calculate the coefficients for the ARMA(1,1) process

$$\begin{aligned} \theta_i &= \frac{\gamma_{mi}(0) - \sqrt{\gamma_{mi}^2(0) - 4\gamma_{mi}^2(1)}}{2\gamma_{mi}(1)}, \\ \sigma_{vi}^2 &= \frac{\gamma_{mi}(1)}{\theta_i}. \end{aligned}$$

Thus the moving average coefficient of individual i (θ_i) and the variance of v_{it} are respectively

$$\theta_i = \frac{\sigma_{zi}^2 + (1 + \phi_i^2)\sigma_e^2 - \sqrt{\sigma_{zi}^4 + \sigma_e^4 + \phi_i^4\sigma_e^4 + 2\sigma_{zi}^2\sigma_e^2 + 2\phi_i^2\sigma_{zi}^2\sigma_e^2 - 2\phi_i^2\sigma_e^4}}{-2\phi_i\sigma_e^2}, \quad (6)$$

$$\sigma_{vi}^2 = \frac{-\phi_i\sigma_e^2}{\theta_i}. \quad (7)$$

As a result, the population autocorrelation at lag h of y_{it}^O is $\rho_{Oyi}(h) = \phi_i^{|h|-1}\rho_{Oyi}(1)$ ($h \geq 2$). And the population variance, covariance at lag 1, and autocorrelation at lag 1 of y_{it}^O for individual i can be expressed by the coefficients for the ARMA(1,1) process (i.e., θ_i , ϕ_i , and σ_{vi}^2) respectively

$$\sigma_{Oyi}^2 = \sigma_{vi}^2 \left[1 + \frac{(\phi_i + \theta_i)^2}{1 - \phi_i^2} \right], \quad (8)$$

$$\gamma_{Oyi}(1) = \sigma_{vi}^2 \left[(\phi_i + \theta_i) + \frac{(\phi_i + \theta_i)^2 \phi_i}{1 - \phi_i^2} \right], \quad (9)$$

$$\rho_{Oyi}(1) = \frac{(\phi_i + \theta_i)(1 + \phi_i\theta_i)}{1 + 2\phi_i\theta_i + \theta_i^2}. \quad (10)$$

Appendix B

Since $ISD_i^2 = S^2(y_{it}^T + e_{it})$, the reliability of ISD^2 is

$$\rho_{ISD^2}^2 = \left(\frac{\text{cov}(S^2(y_{it}^T + e_{it}), \sigma_i^2)}{\sqrt{\text{var}(S^2(y_{it}^T + e_{it}))\text{var}(\sigma_i^2)}} \right)^2. \quad (11)$$

The numerator is

$$\begin{aligned} (\text{cov}(S^2(y_{it}^T + e_{it}), \sigma_i^2))^2 &= (E[S^2(y_{it}^T + e_{it})\sigma_i^2] - E(S^2(y_{it}^T + e_{it}))E(\sigma_i^2))^2 \\ &= (E[E(S^2(y_{it}^T + e_{it})\sigma_i^2 | i)] - E(S^2(y_{it}^T + e_{it}) | i)E(\sigma_i^2))^2 \\ &= (E[\sigma^2(y_{it}^T + e_{it})\sigma_i^2] - E(\sigma^2(y_{it}^T + e_{it}))E(\sigma_i^2))^2 \\ &= (\text{cov}(\sigma^2(y_{it}^T + e_{it}), \sigma_i^2))^2 \\ &= (\text{var}(\sigma_i^2))^2. \end{aligned}$$

Therefore we can rewrite Equation (11) as

$$\rho_{ISD^2}^2 = \frac{\text{var}(\sigma_i^2)}{\text{var}(S^2(y_{it}^T + e_{it}))}. \quad (12)$$

The denominator is complex. The step by step derivation is as follows,

$$\text{var} \left(S^2(y_{it}^T + e_{it}) \right) = E \left(S^4(y_{it}^T + e_{it}) \right) - E^2 \left(S^2(y_{it}^T + e_{it}) \right). \quad (13)$$

It is easy to obtain $E^2 \left(S^2(y_{it}^T + e_{it}) \right) = \left(E(\sigma_i^2) + \sigma_e^2 \right)^2$, and then we solve $S^4(y_{it}^T + e_{it})$,

$$\begin{aligned} S^4(y_{it}^T + e_{it}) &= \left(\frac{\sum_{t=1}^T (y_{it}^T + e_{it} - (\bar{y}_{it}^T + \bar{e}_{it}))^2}{T-1} \right)^2 \\ &= \frac{\left[T \sum_{t=1}^T (y_{it}^T + e_{it})^2 \right]^2 - 2T \left(\sum_{t=1}^T (y_{it}^T + e_{it})^2 \right) \left(\sum_{t=1}^T (y_{it}^T + e_{it}) \right)^2 + \left(\sum_{t=1}^T (y_{it}^T + e_{it}) \right)^4}{T^2(T-1)^2} \\ &= \frac{T^2 \sum_{t1=1}^T \sum_{t2=1}^T (y_{it1}^T + e_{it1})^2 (y_{it2}^T + e_{it2})^2 - 2T \left(\sum_{t1=1}^T (y_{it1}^T + e_{it1})^2 \right) \sum_{t2=1}^T (y_{it2}^T + e_{it2}) (y_{it3}^T + e_{it3})}{T^2(T-1)^2} \\ &\quad + \frac{\sum_{t1=1}^T \sum_{t2=1}^T \sum_{t3=1}^T \sum_{t4=1}^T (y_{it1}^T + e_{it1}) (y_{it2}^T + e_{it2}) (y_{it3}^T + e_{it3}) (y_{it4}^T + e_{it4})}{T^2(T-1)^2}. \end{aligned} \quad (14)$$

Because y_{it}^T is a Gaussian process, when $|\phi_i| < 1$, it is a strictly stationary Gaussian process. All of the

multivariate functions for y_{it}^T 's agree with their counterparts for any number of time lags shifted (e.g.,

$E \left((y_{i1}^T)^2 (y_{i2}^T)^2 \right) = E \left((y_{i2}^T)^2 (y_{i3}^T)^2 \right)$). And y_{it}^T has the same moments as a random variable in a normal

distribution, but y_{it}^T is not independently distributed (i.e., $E \left((y_{it}^T)^2 \mid i \right) = \sigma_i^2 = \frac{\sigma_{zi}^2}{1-\phi_i^2}$, $E((y_{it}^T)^3 \mid i) = 0$,

$E \left((y_{it}^T)^4 \mid i \right) = 3\sigma_i^4 = 3 \left(\frac{\sigma_{zi}^2}{1-\phi_i^2} \right)^2$). The expectation of the first numerator component of $S^4(y_{it}^T + e_{it})$ is

$$\begin{aligned} T^2 E \left[\sum_{t1=1}^T \sum_{t2=1}^T (y_{it1}^T + e_{it1})^2 (y_{it2}^T + e_{it2})^2 \right] &= T^2 E \left[\sum_{t1=1}^T \sum_{t2=1}^T (y_{it1}^T)^2 (y_{it2}^T)^2 + \sum_{t1=1}^T \sum_{t2=1}^T e_{it1}^2 e_{it2}^2 \right. \\ &\quad \left. + 4 \sum_{t1=1}^T \sum_{t2=1}^T y_{it1}^T y_{it2}^T e_{it1} e_{it2} + 2 \sum_{t1=1}^T \sum_{t2=1}^T (y_{it1}^T)^2 e_{it2}^2 \right] \\ &= T^2 E \left(\sum_{t1=1}^T \sum_{t2=1}^T (y_{it1}^T)^2 (y_{it2}^T)^2 \right) + (T^4 + 2T^3) \sigma_e^4 \\ &\quad + (4T^3 + 2T^4) \sigma_e^2 E \left(\sigma_i^2 \right), \end{aligned} \quad (15)$$

where

$$\begin{aligned}
E \left(\sum_{t=1}^T \sum_{i=1}^T (y_{it1}^T)^2 (y_{it2}^T)^2 \right) &= TE \left((y_{it}^T)^4 \right) + 2(T-1)E \left((y_{it1}^T)^2 (y_{it2}^T)^2 \right) + 2(T-2)E \left((y_{it1}^T)^2 (y_{it3}^T)^2 \right) \\
&\quad + \dots + 2E \left((y_{it1}^T)^2 (y_{itT}^T)^2 \right) \\
&= 3TE (\sigma_i^4) + 6E \left(\sigma_i^4 \left(\frac{(T-1)\phi_i^2 - \phi_i^{2T}}{1-\phi_i^2} - \frac{\phi_i^4(1-\phi_i^{2(T-2)})}{(1-\phi_i^2)^2} \right) \right) \\
&\quad + 2E \left(\sigma_i^4 \left(\frac{(1-\phi_i^2)T(T-1)}{2(1-\phi_i)^2} + \frac{(T-1)\phi_i^2 - \phi_i^{2T}}{(1-\phi_i)^2} - \frac{\phi_i^4(1-\phi_i^{2(T-2)})}{(1-\phi_i^2)^2} \right. \right. \\
&\quad \left. \left. - \frac{(2(T-1)\phi_i - \phi_i^T)}{1-\phi_i} - \frac{2\phi_i^2(1-\phi_i^{T-2})}{(1-\phi_i)^2} \right) \right) \\
\text{when } \sigma_i^2 \text{ is independent of } \phi_i &= 3TE (\sigma_i^4) + 6E (\sigma_i^4) E \left(\frac{(T-1)\phi_i^2 - \phi_i^{2T}}{1-\phi_i^2} - \frac{\phi_i^4(1-\phi_i^{2(T-2)})}{(1-\phi_i^2)^2} \right) \\
&\quad + 2E (\sigma_i^4) E \left(\frac{(1-\phi_i^2)T(T-1)}{2(1-\phi_i)^2} + \frac{(T-1)\phi_i^2 - \phi_i^{2T}}{(1-\phi_i)^2} - \frac{\phi_i^4(1-\phi_i^{2(T-2)})}{(1-\phi_i^2)(1-\phi_i)^2} \right. \\
&\quad \left. - \frac{(1-\phi_i^2)(2(T-1)\phi_i - \phi_i^T)}{(1-\phi_i)^3} - \frac{2\phi_i^2(1-\phi_i^2)(1-\phi_i^{T-2})}{(1-\phi_i)^4} \right). \tag{16}
\end{aligned}$$

The expectations of the second and third numerator components of $S^4(y_{it}^T + e_{it})$ can be obtained in the same way. They have much more tedious forms but still functions of σ_i^2 , σ_e^2 , T , and ϕ_i . Especially, when σ_i^2 is independent of ϕ_i , $E(S^4(y_{it}^T + e_{it}))$ is a function of $E(\sigma_i^4)$ (implies $var(\sigma_i^2)$), $E(\sigma_i^2)$, σ_e^2 , T , and distribution of ϕ_i . And σ_e^2 is a function of $E(\sigma_i^2)$, σ_μ^2 , and ρ_y^2 . Because of Equations (12), (13), (14), (15), and (16), overall the reliability of ISD^2 depends on the joint distribution of σ_i^2 and ϕ_i , and values of σ_μ^2 , T , and ρ_y^2 .

Appendix C

The asymptotic distribution for $\hat{\rho}_i(1)$ is given by Shumway & Stoffer (2010),

$$\hat{\rho}_i(1) \sim AN(\rho_{Oyi}(1), \frac{1}{n}w_i).$$

For the time series model in the current study,

$$\begin{aligned}
w_i &= \sum_{u=-\infty}^{\infty} [\rho_{Oyi}(u+1)^2 + \rho_{Oyi}(u-1)\rho_{Oyi}(u+1) + 2\rho_{Oyi}(1)^2\rho_{Oyi}(u)^2 - 4\rho_{Oyi}(1)\rho_{Oyi}(u)\rho_{Oyi}(u+1)] \\
&= 1 + 2\phi_i\rho_{Oyi}(1) + \frac{7\phi_i^2-3}{1-\phi_i^2}\rho_{Oyi}^2(1) - \frac{8\phi_i}{1-\phi_i^2}\rho_{Oyi}^3(1) + \frac{4}{1-\phi_i^2}\rho_{Oyi}^4(1). \tag{17}
\end{aligned}$$

Appendix D

References

Shumway, R. H., & Stoffer, D. S. (2010). *Time series analysis and its applications: With R examples*. New York: Springer Science & Business Media.

Figure Captions

Figure 1. Comparing reliabilities of \bar{y} , ISD , ISD^2 , $\rho(\hat{1})$, and $MSSD$ when $\sigma_\mu^2 = 0.1$

Figure 2. Comparing reliabilities of \bar{y} , ISD , ISD^2 , $\rho(\hat{1})$, and $MSSD$ when $\sigma_\mu^2 = 5$

Figure 3. Comparing reliabilities of \bar{y} , ISD , ISD^2 , $\rho(\hat{1})$, and $MSSD$ when $\sigma_\mu^2 = 10$





