A Note on Additional Materials for
Macro-Finance Decoupling: Robust Evaluations of
Macro Asset Pricing Models

Xu Cheng∗, Winston Wei Dou†, Zhipeng Liao‡

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Abstract
This note contains additional technical details of Cheng, Dou, and Liao (2021). Section A provides the proofs of several lemmas on the asymptotic convergence of the random components in the test statistic $\mathcal{T}$ and the conditional critical value $c_{\alpha}(\hat{d})$. Section B verifies the bounded Lipschitz properties of the test statistic and the conditional critical value, which are used to show their weak convergence in large samples. Section C includes some auxiliary lemmas. Section D derives the Euler equations that serve as the asset pricing moment conditions in the disaster risk model and the long-run risk model. Section E considers the long-run risk model and shows that the Gaussian limit is an innocuous assumption. Section F provides derivations for the time-varying disaster risk model in the empirical application of the paper. Section G contains an additional robustness check for the simulation results in the paper.

∗Department of Economics, University of Pennsylvania; Email: xucheng@econ.upenn.edu.
†Finance Department, The Wharton School, University of Pennsylvania; Email: wdou@wharton.upenn.edu.
‡Department of Economics, University of California, Los Angeles; Email: zhipeng.liao@econ.ucla.edu.
A Proofs for Asymptotic Convergence

This section provides the proofs of Lemmas SA1, SA2, SA6 and SA7 in the Supplemental Appendix to Cheng, Dou, and Liao (2021) under their Assumptions 1, 2, 3 and 4. The proofs of Lemmas SA3, SA4 and SA5 in the Supplemental Appendix to Cheng, Dou, and Liao (2021) are in Sections B and C of this appendix. Throughout this note, we use $\lambda_{\min}(A)$ to denote the minimal eigenvalue of a real symmetric matrix $A$, and $\| \cdot \|$ denotes the matrix Frobenius norm.

Proof of Lemma SA1. (a) Define $C_{1,n} \equiv \sup_{\theta \in \Theta} | \bar{g}(\theta)'(\hat{\Omega}(\theta))^{-1}\bar{g}(\theta) - G(\theta)'(\Omega(\theta))^{-1}G(\theta)|$ where $G(\theta) \equiv \mathbb{E}[\bar{g}(\theta)]$. Then by Assumptions 1(i, iii), 2(i) and 3(iii),

\[
C_{1,n} = o_p(1),
\]  
(A.1)

uniformly over $\mathbb{P} \in \mathcal{P}_0$. Consider any $\varepsilon > 0$. By the definition of $\hat{\theta}$ and $\theta_0$,

\[
\sup_{\mathbb{P} \in \mathcal{P}_0} \mathbb{P} \left( \| \hat{\theta} - \theta_0 \| \geq \varepsilon \right) 
\leq \sup_{\mathbb{P} \in \mathcal{P}_0} \mathbb{P} \left( \min_{\theta \in B_\varepsilon(\theta_0)} \bar{g}(\theta)'(\hat{\Omega}(\theta))^{-1}\bar{g}(\theta) \leq \bar{g}(\theta_0)'(\hat{\Omega}(\theta_0))^{-1}\bar{g}(\theta_0) \right) 
\leq \sup_{\mathbb{P} \in \mathcal{P}_0} \mathbb{P} \left( \min_{\theta \in B_\varepsilon(\theta_0)} G(\theta)'(\Omega(\theta))^{-1}G(\theta) \leq 2C_{1,n} \right) \leq \sup_{\mathbb{P} \in \mathcal{P}_0} \mathbb{P} \left( c_\lambda^{-1} \delta_\varepsilon^2 \leq 2C_{1,n} \right),
\]  
(A.2)

where the second inequality is by the definition of $C_{1,n}$ and the third inequality is by Assumption 3. Combining the results in (A.1) and (A.2), we deduce that

\[
\lim_{n \to \infty} \sup_{\mathbb{P} \in \mathcal{P}_0} \mathbb{P} \left( \| \hat{\theta} - \theta_0 \| \geq \varepsilon \right) = 0 \text{ for any } \varepsilon > 0.
\]  
(A.3)

Let $C_{2,n} \equiv \sup_{\theta \in \Theta} \| q(\theta) - Q(\theta) \|$. Then by Assumption 1(ii),

\[
C_{2,n} = o_p(1) \text{ uniformly over } \mathbb{P} \in \mathcal{P}.
\]  
(A.4)

Applying the first order expansion, we get

\[
g(\hat{\theta}) = g(\theta_0) + q(\hat{\theta})n^{1/2}(\hat{\theta} - \theta_0),
\]  
(A.5)

where $\tilde{\theta}$ is the mean value between $\theta_0$ and $\hat{\theta}$ and it may vary across rows. By Assumption 1(ii), the consistency of $\hat{\theta}$ and (A.4),

\[
q(\tilde{\theta}) = Q(\tilde{\theta}) + o_p(1) = Q + o_p(1) = O_p(1), \text{ uniformly over } \mathbb{P} \in \mathcal{P}_0.
\]  
(A.6)
Similarly, we can show that
\[ q(\hat{\theta}) = Q(\hat{\theta}) + o_p(1) = Q + o_p(1) = O_p(1), \]
uniformly over \( \mathbb{P} \in \mathcal{P}_0 \). \hfill (A.7)

By Assumption 2(i, ii) and the consistency of \( \hat{\theta} \),
\[ \hat{\Omega} \equiv \hat{\Omega}(\hat{\theta}) = \Omega + o_p(1) \]
uniformly over \( \mathbb{P} \in \mathcal{P}_0 \). Applying the chain rule, we get the first order condition of \( \hat{\theta} \):
\[ 0_{d_\theta \times 1} = 2q(\hat{\theta})'\hat{\Omega}^{-1}g(\hat{\theta}) - \left( n^{-1/2}g(\hat{\theta})'\hat{\Omega}^{-1}\frac{\partial \hat{\Omega}(\hat{\theta})}{\partial \theta_j} \hat{\Omega}^{-1}g(\hat{\theta}) \right)_{j=1,\ldots,d_\theta}, \] \hfill (A.9)

where \( (a_j)_{j=1,\ldots,d_\theta} \equiv (a_1,\ldots,a_{d_\theta})' \) for any real numbers \( a_1,\ldots,a_{d_\theta} \). By Assumptions 1(i, iii), 2(iv) and 3(iii), the consistency of \( \hat{\theta} \), (A.5), (A.6), (A.7) and (A.8),
\[ 0_{d_\theta \times 1} = q(\hat{\theta})'\hat{\Omega}^{-1}g(\hat{\theta}) - q(\hat{\theta})'\hat{\Omega}^{-1}g(\theta_0) + q(\hat{\theta})'\hat{\Omega}^{-1}q(\hat{\theta})n^{1/2}(\hat{\theta} - \theta_0) \
= Q'\Omega^{-1}g(\theta_0) + (Q'\Omega^{-1}Q + o_p(1)) n^{1/2}(\hat{\theta} - \theta_0) + o_p(1) \] \hfill (A.10)

uniformly over \( \mathbb{P} \in \mathcal{P}_0 \). Similarly, we can show that for \( j = 1,\ldots,d_\theta \),
\[ n^{-1/2}g(\hat{\theta})'\hat{\Omega}^{-1}\frac{\partial \hat{\Omega}(\hat{\theta})}{\partial \theta_j} \hat{\Omega}^{-1}g(\hat{\theta}) = n^{1/2}(\hat{\theta} - \theta_0) o_p(1) + o_p(1) \] \hfill (A.11)

Combining the results in (A.9), (A.10), (A.11), and applying Assumptions 1(iii) and 3(iii), we deduce that
\[ n^{1/2}(\hat{\theta} - \theta_0) = -(Q'\Omega^{-1}Q)^{-1} Q'\Omega^{-1}g(\theta_0) + o_p(1) = O_p(1) \] \hfill (A.12)

uniformly over \( \mathbb{P} \in \mathcal{P}_0 \), which proves the first claim of the lemma.

(b) This claim follows by Assumptions 1 and 3(iii), (A.5), (A.6) and (A.12).

(c) This claim has been proved in (A.7).

(d) By Assumptions 2(iv) and 3(iii), and (A.8),
\[ \lim_{n \to \infty} \inf_{\mathbb{P} \in \mathcal{P}_0} \mathbb{P} \left( K^{-1} \leq \lambda_{\min}(\hat{\Omega}) \leq \lambda_{\max}(\hat{\Omega}) \leq K \right) = 1. \] \hfill (A.13)

By Assumptions 1(iii) and 3(iii), (A.7) and (A.8), we have
\[ q(\hat{\theta})'\hat{\Omega}^{-1}q(\hat{\theta}) = Q'\Omega^{-1}Q + o_p(1) \] \hfill (A.14)
which together with Assumption 3(iii) implies that
\[
\lim_{n \to \infty} \inf_{P \in P_0} \mathbb{P} \left( K^{-1} \leq \lambda_{\min}(q(\hat{\theta})'\hat{\Omega}^{-1}q(\hat{\theta})) \leq \lambda_{\max}(q(\hat{\theta})'\hat{\Omega}^{-1}q(\hat{\theta})) \leq K \right) = 1. \tag{A.15}
\]

Let \( \|\cdot\|_S \) denote the matrix operator norm. By Exercise 7.2.18 in Horn and Johnson (1990),
\[
\left\| \hat{\Omega}^{1/2} - \Omega^{1/2} \right\|_S \leq \left\| \hat{\Omega} - \Omega \right\| \left\| \Omega^{-1} \right\|_S, \tag{A.16}
\]
which together with Assumption 3(iii) and (A.8) implies that
\[
\left\| \hat{\Omega}^{1/2} - \Omega^{1/2} \right\|_S = o_p(1) \text{ uniformly over } P \in P_0. \tag{A.17}
\]
By (A.17) and the relation between the operator norm and the Frobenius norm,
\[
\left\| \hat{\Omega}^{1/2} - \Omega^{1/2} \right\| = o_p(1) \text{ uniformly over } P \in P_0. \tag{A.18}
\]
By Assumptions 1(iii) and 3(iii), (A.7) and (A.18),
\[
\hat{\Omega}^{-1/2}q(\hat{\theta}) = \Omega^{-1/2}Q + o_p(1) = O_p(1) \tag{A.19}
\]
uniformly over \( P \in P_0 \). The claim in the lemma follows by (A.14), (A.15) and (A.19).

(e) By Assumption 2(i, ii) and the consistency of \( \hat{\theta} \),
\[
\sup_{\theta \in \Theta} \left\| \hat{\Omega}(\theta, \hat{\theta}) - \Omega(\theta, \theta_0) \right\| = o_p(1) \text{ uniformly over } P \in P_0. \tag{A.20}
\]
By (A.13) and (A.20),
\[
\sup_{\theta \in \Theta} \left\| (\hat{\Omega}(\theta, \hat{\theta}) - \Omega(\theta, \theta_0))\Omega^{-1} \right\| \leq (\lambda_{\min}(\hat{\Omega}))^{-1} \sup_{\theta \in \Theta} \left\| \Omega(\theta, \hat{\theta}) - \Omega(\theta, \theta_0) \right\| = o_p(1) \tag{A.21}
\]
uniformly over \( P \in P_0 \), where the inequality is by the Cauchy-Schwarz inequality. Similarly,
\[
\sup_{\theta \in \Theta} \left\| \Omega(\theta, \theta_0)(\hat{\Omega}^{-1} - \Omega^{-1}) \right\| = \sup_{\theta \in \Theta} \left\| \Omega(\theta, \theta_0)\hat{\Omega}^{-1}(\hat{\Omega} - \Omega)\Omega^{-1} \right\| 
\leq (\lambda_{\min}(\hat{\Omega})\lambda_{\min}(\Omega))^{-1} \sup_{\theta, \tilde{\theta} \in \Theta} \left\| \Omega(\theta, \tilde{\theta}) \right\| \left\| \hat{\Omega} - \Omega \right\| = o_p(1) \tag{A.22}
\]
uniformly over \( P \in P_0 \), where the inequality is by the Cauchy-Schwarz inequality, and the last equality is by Assumptions 2(iv) and 3(iii), (A.8) and (A.13). Collecting the results in (A.21) and
(A.22), we deduce that
\[
\sup_{\theta \in \Theta} \left\| \hat{V}(\theta) - V(\theta) \right\| 
\leq \sup_{\theta \in \Theta} \left\| (\hat{\Omega}(\theta, \hat{\theta}) - \Omega(\theta, \theta_0)) \hat{\Omega}^{-1} \right\| 
+ \sup_{\theta \in \Theta} \left\| \Omega(\theta, \theta_0) (\hat{\Omega}^{-1} - \Omega^{-1}) \right\| = o_p(1)
\] (A.23)
uniformly over \( \mathbb{P} \in \mathcal{P}_0 \). By Assumptions 2(iv) and 3(iii),
\[
\sup_{\theta \in \Theta} \left\| V(\theta) \right\| \leq \sup_{\theta \in \Theta} \left\| S_0 \Omega(\theta, \theta_0) (\Omega)^{-1} \right\| \leq (\lambda_{\min}(\Omega))^{-1} \sup_{\theta \in \Theta} \left\| \Omega(\theta, \theta_0) \right\| \leq \epsilon^{-1} C_\Omega
\] (A.24)
which finishes the proof.

Proof of Lemma SA2. To link \( \hat{\xi} \) and \( \xi^* \), we first define
\[
\tilde{\xi} \equiv (\tilde{v}', \tilde{m}(\cdot)', \text{vec}(V(\cdot))', \text{vech}(\Omega)', \text{vech}(\Omega_0(\cdot))', \text{vech}(M)'', \cdot)
\] (A.25)
where \( \tilde{v} \equiv \Omega^{1/2} \Omega^{-1/2} g(\theta_0) \) and \( \tilde{m}(\cdot) \equiv g_0(\cdot) - V(\cdot) \tilde{v} \). The difference between \( \tilde{\xi} \) and \( \xi^* \) lie in the first two elements, where \( \tilde{v} \) and \( \tilde{m}(\cdot) \) in \( \tilde{\xi} \) involve the empirical process \( g(\cdot) \), but \( \Omega^{1/2} M \nu^* \) and \( m^*(\cdot) \) in \( \xi^* \) involve the limiting Gaussian process \( \psi(\cdot) \). Under Assumption 1(i), \( g(\cdot) - \mathbb{E}[g(\cdot)] \) weakly converges to \( \psi(\cdot) \), which is equivalent to
\[
\lim_{n \to \infty} \sup_{\mathbb{P} \in \mathcal{P}_0} \sup_{f \in BL_1} \left\| \mathbb{E}[f(g) - \mathbb{E}[g]] - \mathbb{E}[f(\psi)] \right\| = 0.
\] (A.26)
Furthermore, Assumptions 1(iii), 2(iv) and 3(iii) imply that \( \tilde{v} \) and \( \tilde{m}(\cdot) \) are bounded and Lipschitz in \( g(\cdot) \), which together with (A.26) implies that
\[
\lim_{n \to \infty} \sup_{\mathbb{P} \in \mathcal{P}_0} \sup_{f \in BL_1} \left\| \mathbb{E}[f(\tilde{\xi})] - \mathbb{E}[f(\xi^*)] \right\| = 0.
\] (A.27)
Next, note that the difference between \( \tilde{\xi} \) and \( \tilde{\xi} \) is that \( \hat{V}(\theta), \hat{\Omega} \) and \( \hat{M} \) in \( \tilde{\xi} \) are replaced by their probability limits in Lemma SA1(c, d, e) of Cheng, Dou, and Liao (2021). Thus, we have \( \hat{\xi} = \tilde{\xi} + o_p(1) \) uniformly over \( \mathbb{P} \in \mathcal{P}_0 \) following Lemma SA1(c, d, e) in Cheng, Dou, and Liao (2021), which implies
\[
\lim_{n \to \infty} \sup_{\mathbb{P} \in \mathcal{P}_0} \sup_{f \in BL_1} \left\| \mathbb{E}[f(\hat{\xi})] - \mathbb{E}[f(\tilde{\xi})] \right\| = 0.
\] (A.28)
The desirable result follows from (A.27), (A.28), and the triangle inequality.

Proof of Lemma SA6. Since \( 0 \leq L(v; d^*) \leq v'Mv \) for any \( v \in \mathbb{R}^k \) and \( ut_C(u) \leq C \) for any
\( v \geq 0 \), we have

\[
|L_C(v; d^*) - \mathcal{L}_C(v; d^*)| = \mathcal{L}(v; d^*)t_C(v'Mv)I\{\|v\|^2 > C\} \leq CI\{\|v\|^2 > C\} \tag{A.29}
\]

for any \( v \in \mathbb{R}^k \), which implies that

\[
P\left(|L_C(v^*, d^*)| > \varepsilon\right) \leq P\left(I\{\|v^*\|^2 > C\} > \varepsilon/C\right) \leq P\left(\|v^*\|^2 > C\right). \tag{A.30}
\]

Since \( \|v^*\|^2 \) follows the chi-square distribution with degree of freedom \( k \), there exists a finite constant \( C_\delta \) such that \( P(\|v^*\|^2 > C_\delta) \leq \delta/4 \) which together with (A.30) implies that for any \( C \geq C_\delta \)

\[
P\left(|L_C(v^*, d^*)| > \varepsilon\right) \leq \delta/4. \tag{A.31}
\]

By the union bound of probability and (A.31), we have for any \( C \geq C_\delta \),

\[
P(L_C(v^*, d^*) > c_{\alpha, C}(d^*) + \varepsilon) \leq P(\mathcal{L}_C(v^*, d^*) + |L_C(v^*, d^*) - \mathcal{L}_C(v^*, d^*)| > c_{\alpha, C}(d^*) + \varepsilon)
\leq P(\mathcal{L}_C(v^*, d^*) > c_{\alpha, C}(d^*)) + \delta/4 \leq \alpha + \delta/4, \tag{A.32}
\]

where the last inequality is by the definition of \( c_{\alpha, C}(d^*) \). Since \( R_C(\xi^*) = L_C(v^*, d^*) \) by definition, the claim of the lemma follows from (A.32).

Q.E.D.

Proof of Lemma SA7. (a). Since \( v^* = O_p(1) \), by Assumptions 1(iii), 2(iv) and 3(iii), Lemma SA1(b, d) in Cheng, Dou, and Liao (2021), and (A.18), we have uniformly over \( \mathbb{P} \in \mathcal{P}_0 \),

\[
\hat{\Omega}^{1/2}\hat{M}v^* - g(\hat{\theta}) = \Omega^{1/2}M\Omega^{-1/2}(\Omega^{1/2}v^* - g(\theta_0)) + o_p(1) = O_p(1), \tag{A.33}
\]

which together with Lemma SA1(e) in Cheng, Dou, and Liao (2021) implies that

\[
\sup_{\theta \in \Theta} \left| \hat{\mathcal{V}}(\theta)(\hat{\Omega}^{1/2}\hat{M}v^* - g(\hat{\theta})) \right| = O_p(1) \quad \text{uniformly over } \mathbb{P} \in \mathcal{P}_0. \tag{A.34}
\]

Therefore by the triangle inequality, Assumption 1 and (A.34),

\[
\sup_{\theta \in \Theta} \left| n^{-1/2}(\hat{m}(\theta) + \hat{\mathcal{V}}(\theta)(\hat{\Omega}^{1/2}\hat{M}v^*) - \mathbb{E}[g_0(\theta)]) \right|
\leq \sup_{\theta \in \Theta} \left| n^{-1/2}g_0(\theta) - \mathbb{E}[g_0(\theta)] \right| + \sup_{\theta \in \Theta} \left| n^{-1/2}\hat{\mathcal{V}}(\theta)(\hat{\Omega}^{1/2}\hat{M}v^* - g(\hat{\theta})) \right| = o_p(1) \tag{A.35}
\]

uniformly over \( \mathbb{P} \in \mathcal{P}_0 \). By Assumptions 2(i) and 4, and (A.35), we can apply similar arguments in the proof of (A.3) to deduce that

\[
\hat{\theta}^* = \theta_0 + o_p(1) \tag{A.36}
\]
uniformly over $\mathbb{P} \in \mathcal{P}_0 \cap \mathcal{P}_{00}$. Applying the chain rule, we get the first order condition of $\hat{\theta}^*$: 

$$0_{d_0} = 2 \left( \frac{\partial}{\partial \theta} (\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^*) \right)' (\hat{\Omega}_0^*)^{-1} (\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^*)$$

$$- \left( (\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^*)' (\hat{\Omega}_0^*)^{-1} \frac{\partial \hat{\Omega}_0(\hat{\theta}^*)}{\partial \theta_j} (\hat{\Omega}_0^*)^{-1} (\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^*) \right) = 0_{j=1,\ldots,d_0} $$

(A.37)

where $\hat{\Omega}_0^* = \hat{\Omega}_0^*(\hat{\theta}^*)$ and $\hat{V}_S(\hat{\theta}^*) \equiv \hat{V}(\hat{\theta}^*) \hat{\Omega}^{1/2} \hat{M}$. Using (A.36) and similar arguments for showing (A.5) and (A.6), we obtain

$$g_0(\hat{\theta}^*) = g_0(\theta_0) + n^{1/2}(\hat{\theta}^* - \theta_0)(Q_0 + o_p(1)) = O_p(1) + n^{1/2}(\hat{\theta}^* - \theta_0)O_p(1)$$

(A.38)

uniformly over $\mathbb{P} \in \mathcal{P}_0$. By (A.34) and (A.38),

$$\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^* = g_0(\hat{\theta}^*) + \hat{V}(\hat{\theta}^*)(\hat{\Omega}^{1/2} \hat{M} v^* - g(\hat{\theta})) = O_p(1) + n^{1/2}(\hat{\theta}^* - \theta_0)O_p(1),$$

(A.39)

which together with Assumptions 2 and 3(iii), (A.36) and the Cauchy-Schwarz inequality implies that

$$n^{-1/2}(\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^*)' (\hat{\Omega}_0^*)^{-1} \frac{\partial \hat{\Omega}_0(\hat{\theta}^*)}{\partial \theta_j} (\hat{\Omega}_0^*)^{-1} (\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^*)$$

$$= n^{1/2}(\hat{\theta}^* - \theta_0)o_p(1) + o_p(1), \text{ uniformly over } \mathbb{P} \in \mathcal{P}_0 \cap \mathcal{P}_{00}. $$

(A.40)

By Assumptions 2(iii, iv) and 3(iii),

$$\max_{1 \leq j \leq d_0} \sup_{\theta \in \Theta} \left\| \hat{V}(\theta)/\partial \theta_j \right\| = O_p(1) \text{ uniformly over } \mathbb{P} \in \mathcal{P}_0, $$

(A.41)

which combined with (A.33) implies that

$$\frac{\partial}{\partial \theta'} \hat{V}(\hat{\theta}^*)(\hat{\Omega}^{1/2} \hat{M} v^* - g(\hat{\theta})) = O_p(1)$$

(A.42)

uniformly over $\mathbb{P} \in \mathcal{P}_0 \cap \mathcal{P}_{00}$. By Assumption 1(ii) and (A.36),

$$n^{-1/2} \frac{\partial g_0(\hat{\theta}^*)}{\partial \theta'} = Q_0 + o_p(1) \text{ uniformly over } \mathbb{P} \in \mathcal{P}_0 \cap \mathcal{P}_{00}. $$

(A.43)
Collecting the results in (A.42) and (A.43), we have

\[
\begin{align*}
&n^{-1/2} \frac{\partial}{\partial \theta'} (\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^*) \\
&= n^{-1/2} \frac{\partial}{\partial \theta'} g_0(\hat{\theta}^*) + n^{-1/2} \frac{\partial}{\partial \theta'} \hat{V}(\hat{\theta}^*) (\hat{\Omega}^{1/2} \hat{M} v^* - g(\hat{\theta})) = Q_0 + o_p(1) \quad (A.44)
\end{align*}
\]

uniformly over \( P \in \mathcal{P}_0 \cap \mathcal{P}_{00} \). Applying the first order expansion to get

\[
\begin{align*}
\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^* \\
&= g_0(\hat{\theta}^*) + \hat{V}(\theta_0)(\hat{\Omega}^{1/2} \hat{M} v^* - g(\hat{\theta})) \\
&+ \frac{\partial g_0(\hat{\theta}^*)}{\partial \theta'} (\hat{\theta}^* - \theta_0) + \frac{\partial \hat{V}(\hat{\theta}^*)}{\partial \theta'} (\hat{\Omega}^{1/2} \hat{M} v^* - g(\hat{\theta})) (\hat{\theta}^* - \theta_0) \\
&= g_0(\theta_0) + \hat{V}(\theta_0)(\hat{\Omega}^{1/2} \hat{M} v^* - g(\hat{\theta})) + (Q_0 + o_p(1)) n^{1/2}(\hat{\theta}^* - \theta_0) + o_p(1) \quad (A.45)
\end{align*}
\]

uniformly over \( P \in \mathcal{P}_0 \cap \mathcal{P}_{00} \), where the third equality is by Assumption 1(ii), (A.33), (A.36) and (A.41). By \( V(\theta_0) = S_0 \), Lemma SA1(e) in Cheng, Dou, and Liao (2021) and (A.33),

\[
\hat{V}(\theta_0)(\hat{\Omega}^{1/2} \hat{M} v^* - g(\hat{\theta})) = S_0 \Omega^{1/2} M v^* + o_p(1) \quad (A.46)
\]

uniformly over \( P \in \mathcal{P}_0 \). By (A.45) and (A.46), we have uniformly over \( P \in \mathcal{P}_0 \cap \mathcal{P}_{00} \),

\[
\begin{align*}
\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*) v^* &= (Q_0 + o_p(1)) n^{1/2}(\hat{\theta}^* - \theta_0) \\
&+ Q_0 Q' \Omega^{-1} Q_0^{-1} g(\theta_0) + S_0 \Omega^{1/2} M v^* + o_p(1). \quad (A.47)
\end{align*}
\]

By Assumptions 3(iii) and 4(ii), \( Q_0' \Omega_0^{-1} Q_0 \) is positive definite. Therefore collecting the results in (A.37), (A.40), (A.44), (A.47), and applying Assumption 2(i, ii) and (A.36) to \( \hat{\Omega}_0' \), we obtain

\[
\begin{align*}
n^{1/2}(\hat{\theta}^* - \theta_0) &= -Q_0 Q' \Omega^{-1} Q_0^{-1} g(\theta_0) - Q_0' \Omega_0^{-1} Q_0' \Omega_0^{-1} S_0 \Omega^{1/2} M v^* + o_p(1) \quad (A.48)
\end{align*}
\]

uniformly over \( P \in \mathcal{P}_0 \cap \mathcal{P}_{00} \), which proves part (a) of the lemma.

(b) By (A.48), Assumptions 3(iii) and 4,

\[
\begin{align*}
n^{1/2}(\hat{\theta}^* - \theta_0) &= O_p(1) \quad \text{uniformly over } P \in \mathcal{P}_0 \cap \mathcal{P}_{00}. \quad (A.49)
\end{align*}
\]
By Assumptions 2(iv), 3(iii) and 4, (A.47) and (A.48), we have uniformly over $\mathbb{P} \in \mathcal{P}_0 \cap \mathcal{P}_00$, 

$$
\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*)v^* = -Q_0 \left( Q'_0 \Omega_0^{-1}Q_0 \right)^{-1} Q'_0 \Omega_0^{-1} \mathcal{S} \mathcal{M}^{1/2} Mv^* + \mathcal{S} \mathcal{M}^{-1/2} Mv^* + o_p(1)
$$

$$
= \Omega_0^{-1/2} \mathcal{M}_0 \Omega_0^{-1/2} \mathcal{S} \mathcal{M}^{1/2} Mv^* + o_p(1)
$$

$$
= \Omega_0^{-1/2} \mathcal{M}_0 \Omega_0^{-1/2} \mathcal{S} \mathcal{M}^{1/2} Mv^* + o_p(1) = O_p(1),
$$

(A.50)

where $\mathcal{M}_0 \equiv I_{k_0} - Q'_0 \mathcal{S} \mathcal{M}^{-1/2} Q_0 \left( Q'_0 \Omega_0^{-1}Q_0 \right)^{-1} Q'_0 \Omega_0^{-1/2}$ and the last equality is by $M_0 \Omega_0^{-1/2} Q_0 = 0_{k_0 \times 1}$. By Assumptions 2(i, ii) and 3(iii), (A.36) and (A.50), we deduce that uniformly over $\mathbb{P} \in \mathcal{P}_0 \cap \mathcal{P}_00$,

$$
(\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*)v^*)'(\hat{\Omega}_0^{-1})^{-1}(\hat{m}(\hat{\theta}^*) + \hat{V}_S(\hat{\theta}^*)v^*) = v'^\ast \mathcal{M}_0 v^* + o_p(1),
$$

(A.51)

where $\mathcal{M}_0 \equiv (S_0 \mathcal{M}^{-1/2})' M_0 (S_0 \mathcal{M}^{-1/2})$. Since $v^* = O_p(1)$, Lemma SA1(e) implies that

$$
v'^\ast \mathcal{M}_0 v^* = v'^\ast Mv^* + o_p(1)
$$

(A.52)

uniformly over $\mathbb{P} \in \mathcal{P}_0$, which together with (A.51) finishes the proof.

(c) Since $\mathcal{M} \equiv I_{k} - \Omega^{-1/2} Q (Q' \Omega^{-1} Q)^{-1} Q' \Omega^{-1/2}, M^2 = M$. Moreover,

$$
\mathcal{M}_0^2 = (S_0 \mathcal{M}^{-1/2})' M_0 (S_0 \mathcal{M}^{-1/2})(S_0 \mathcal{M}^{-1/2})' M_0 (S_0 \mathcal{M}^{-1/2}) = \mathcal{M}_0
$$

(A.53)

and

$$
\mathcal{M}_0 M = \mathcal{M}_0 - (S_0 \mathcal{M}^{-1/2})' M_0 (S_0 \mathcal{M}^{-1/2}) \Omega^{-1/2} Q (Q' \Omega^{-1} Q)^{-1} Q' \Omega^{-1/2} = \mathcal{M}_0
$$

(A.54)

where the second equality is by $M_0 \Omega_0^{-1/2} Q_0 = 0_{k_0 \times 1}$. Similarly, $M \mathcal{M}_0 = \mathcal{M}_0$. Therefore, $(M - \mathcal{M}_0)^2 = M^2 - M \mathcal{M}_0 - \mathcal{M}_0 M + \mathcal{M}_0^2 = M - \mathcal{M}_0$ which implies that $M - \mathcal{M}_0$ is an idempotent matrix. The rank of $M - \mathcal{M}_0$ equals the trace of $M - \mathcal{M}_0$ since $M - \mathcal{M}_0$ is idempotent. By the definition of $M$ and $\mathcal{M}_0$,

$$
tr(M) = k - tr(\Omega^{-1/2} Q (Q' \Omega^{-1} Q)^{-1} Q' \Omega^{-1/2}) = k - d_\theta
$$

(A.55)

and

$$
tr(\mathcal{M}_0) = tr((S_0 \mathcal{M}^{-1/2})' M_0 (S_0 \mathcal{M}^{-1/2})) = tr(M_0) = k_0 - d_\theta, \quad (A.56)
$$

which implies that $tr(M - \mathcal{M}_0) = k - k_0 = k_1$. Therefore, $M - \mathcal{M}_0$ is an idempotent matrix with rank $k_1$ which together with $v^* \sim N(0, I_k)$ proves the claim (c).

Q.E.D.
B Proofs for Bounded Lipschitz Conditions

This section contains the proofs of Lemmas SA4 and SA5 in Cheng, Dou, and Liao (2021) under their Assumptions 2 and 3, and some auxiliary results used to show them.

Lemma B1. Consider $\xi \equiv (x',d')'$ where $d$ satisfies Assumptions 2 and 3. Then we have for any given $C > 0$:
(i) $R(\xi)$ is bounded and Lipschitz in $\xi$ on the set $\{\xi : R(\xi) \geq 0 \text{ and } x' \Omega_d^{-1} x \leq C\}$;
(ii) $L(v; d)$ is bounded and Lipschitz in $d$ on the set $\{(v, d) : L(v; d) \geq 0 \text{ and } \|v\| \leq C\}$.

Proof of Lemma B1. (i) Let $\{S_\xi : \xi \in \mathbb{R}\}$ be the set of all $\xi$ satisfying $R(\xi) \geq 0$ and $x' \Omega_d^{-1} x \leq C$. By the definition of $R(\xi)$, $R(\xi) \leq x' \Omega_d^{-1} x \leq C$ for any $\xi \in S_\xi$, which shows that $R(\xi)$ is bounded on $S_\xi$. Next, we want to show that for any $\xi_1, \xi_2 \in S_\xi$,

$$|R(\xi_1) - R(\xi_2)| \leq C_R \|\xi_1 - \xi_2\|_s$$

(B.57)

for some constant fixed $C_R$. By the triangle inequality,

$$|R(\xi_1) - R(\xi_2)| \leq R(\xi_1) + R(\xi_2) \leq x' \Omega_d^{-1} x_1 + x' \Omega_d^{-1} x_2 = 2C,$$

(B.58)

which implies that the claimed result holds with a Lipschitz constant $C_R = 2$ if $\|\xi_1 - \xi_2\|_s > C$.

Thus, it is only necessary to consider the case that $\|\xi_1 - \xi_2\|_s \leq C$.

Define $A_j(\theta) \equiv m_{d_j}(\theta) + V_{d_j}(\theta)x_j$ for $j = 1, 2$. Consider any $\xi_1, \xi_2 \in S_\xi$, by the triangle inequality,

$$|R(\xi_1) - R(\xi_2)| \leq \left| x_1 \Omega_d^{-1} x_1 - x_2 \Omega_d^{-1} x_2 \right| + \left| \min_{\theta \in \Theta} A_1(\theta)'(\Omega_{0,d,1}(\theta))^{-1}A_1(\theta) - \min_{\theta \in \Theta} A_2(\theta)'(\Omega_{0,d,2}(\theta))^{-1}A_2(\theta) \right|. \quad \text{(B.59)}$$

By the triangle inequality, the Cauchy-Schwarz inequality, $x_1 \Omega_d^{-1} x_1 \leq C$ and $x_2 \Omega_d^{-1} x_2 \leq C$,

$$\left| x_1 \Omega_d^{-1} x_1 - x_2 \Omega_d^{-1} x_2 \right| \leq \left| (x_1 - x_2)' \Omega_d^{-1} (x_1 - x_2) \right| + \left| x_2 \Omega_d^{-1} (x_1 - x_2) \right| + \left| x_2 \Omega_d^{-1} (x_1 - x_2) \right|$$

$$\leq \left[ \frac{(x_1 \Omega_d^{-1} x_1)^{1/2}}{\lambda_{\min}(\Omega_{d,1})^{1/2}} + \frac{(x_2 \Omega_d^{-1} x_2)^{1/2}}{\lambda_{\min}(\Omega_{d,2})^{1/2}} \right] \|x_1 - x_2\|$$

$$+ \left[ \frac{(x_1 \Omega_d^{-1} x_1)^{1/2}}{\lambda_{\min}(\Omega_{d,1}) \lambda_{\min}(\Omega_{d,2})^{1/2}} \|\Omega_{d,1} - \Omega_{d,2}\| \right]$$

$$\leq 2c^{1/2} \|x_1 - x_2\| + c^{1/2} \|\Omega_{d,1} - \Omega_{d,2}\| \leq C_1 \|\xi_1 - \xi_2\|_s$$

(B.60)

for some fixed constant $C_1$.  

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Let $\theta_j$ denote the minimizer of $A_j(\theta)'(\Omega_{0,d,j}(\theta))^{-1}A_j(\theta)$ for $j = 1, 2$. By the triangle inequality, we have

$$\left| \min_{\theta \in \Theta} A_1(\theta)'(\Omega_{0,d,1}(\theta))^{-1}A_1(\theta) - \min_{\theta \in \Theta} A_2(\theta)'(\Omega_{0,d,2}(\theta))^{-1}A_2(\theta) \right|$$

$$\leq \max_{\{\theta_1, \theta_2\}} \left| A_1(\theta)'(\Omega_{0,d,1}(\theta))^{-1}A_1(\theta) - A_2(\theta)'(\Omega_{0,d,2}(\theta))^{-1}A_2(\theta) \right|$$

$$\leq \max_{\{\theta_1, \theta_2\}} \left| (A_1(\theta) - A_2(\theta))'(\Omega_{0,d,1}(\theta))^{-1}A_1(\theta) \right|$$

$$\leq \max_{\{\theta_1, \theta_2\}} \left| A_2(\theta)'(\Omega_{0,d,1}(\theta))^{-1}(A_1(\theta) - A_2(\theta)) \right|$$

$$\leq \max_{\{\theta_1, \theta_2\}} \left| A_2(\theta)'((\Omega_{0,d,1}(\theta))^{-1} - (\Omega_{0,d,2}(\theta))^{-1})A_2(\theta) \right|. \tag{B.61}$$

We next investigate the three terms after the second inequality of (B.61) one by one. By the triangle inequality and the Cauchy-Schwarz inequality,

$$\max_{\{\theta_1, \theta_2\}} \|A_1(\theta) - A_2(\theta)\|$$

$$\leq \sup_{\theta \in \Theta} \|m_{d,1}(\theta) - m_{d,2}(\theta)\| + \|x_1\| \sup_{\theta \in \Theta} \|V_{d,1}(\theta) - V_{d,2}(\theta)\| + \sup_{\theta \in \Theta} \|V_{d,2}(\theta)\| \|x_1 - x_2\|$$

$$\leq \|\xi_1 - \xi_2\| + \lambda \max(\Omega_{d,1})(x_1'\Omega_{d,1}^{-1}x_1)^{1/2} \|\xi_1 - \xi_2\| + C_V \|\xi_1 - \xi_2\|, \tag{B.62}$$

where $C_V \equiv \lambda^{-1}C_\Omega$ and the second inequality is by the definition of $\|\xi_1 - \xi_2\|$ and $\sup_{\theta \in \Theta} \|V_{d,2}(\theta)\| \leq \lambda^{-1}C_\Omega$ (which is proved in Lemma SA1 of Cheng, Dou, and Liao (2021)). Therefore, by Assumption 2(iv) and (B.62),

$$\max_{\{\theta_1, \theta_2\}} \|A_1(\theta) - A_2(\theta)\| \leq (1 + (CC_\Omega)^{1/2} + C_V) \|\xi_1 - \xi_2\|, \tag{B.63}$$

which together with the triangle inequality, Assumption 2(iv) and $\|\xi_1 - \xi_2\| \leq C$ implies that

$$\max_{\{\theta_1, \theta_2\}} \|A_1(\theta)\| \leq \|A_1(\theta_1)\| + \|A_1(\theta_2)\|$$

$$\leq \|A_1(\theta_1)\| + \|A_2(\theta_2)\| + \|A_1(\theta_2) - A_2(\theta_2)\|$$

$$\leq C_\Omega^{1/2} \left( (A_1(\theta)'(\Omega_{d,1,0}(\theta))^{-1}A_1(\theta))^{1/2} + (A_2(\theta)'(\Omega_{d,2,0}(\theta))^{-1}A_2(\theta))^{1/2} \right)$$

$$+ (1 + (CC_\Omega)^{1/2} + C_V) \|\xi_1 - \xi_2\|$$

$$\leq 2(C_\Omega C)^{1/2} + (1 + (CC_\Omega)^{1/2} + C_V)C. \tag{B.64}$$

By the same arguments, the inequality in (B.64) applies to $\max_{\{\theta_1, \theta_2\}} \|A_2(\theta)\|$. By the Cauchy-
Schwarz inequality, Assumption 3(iii), (B.63) and (B.64),

$$\max_{\{\theta_1, \theta_2\}} \left| (A_1(\theta) - A_2(\theta))' (\Omega_{d,1,0}(\theta))^{-1} A_1(\theta) \right|$$

$$\leq (\lambda_{\min}(\Omega_{0,d,1}(\theta)))^{-1} \max_{\{\theta_1, \theta_2\}} \|A_1(\theta) - A_2(\theta)\| \max_{\{\theta_1, \theta_2\}} \|A_1(\theta)\| \leq C_2 \|\xi_1 - \xi_2\|_s$$  \hspace{1cm} (B.65)

for some constant fixed $C_2$. Similarly, we can show that

$$\max_{\{\theta_1, \theta_2\}} \left| A_2(\theta)' (\Omega_{0,d,1}(\theta))^{-1} (A_1(\theta) - A_2(\theta)) \right| \leq C_2 \|\xi_1 - \xi_2\|_s.$$  \hspace{1cm} (B.66)

By the Cauchy-Schwarz inequality, Assumption 3(iii) and (B.64),

$$\max_{\{\theta_1, \theta_2\}} \left| A_2(\theta)'((\Omega_{0,d,1}(\theta))^{-1} - (\Omega_{0,d,2}(\theta))^{-1}) A_2(\theta) \right|$$

$$\leq \frac{\max_{\{\theta_1, \theta_2\}} \|A_2(\theta)\|^2 \|\Omega_{0,d,1}(\theta) - \Omega_{0,d,2}(\theta)\|}{(\inf_{\theta \in \Theta} \lambda_{\min}(\Omega_{0,d,1}(\theta))) \inf_{\theta \in \Theta} \lambda_{\min}(\Omega_{0,d,2}(\theta))} \leq C_3 \sup_{\theta \in \Theta} \|\Omega_{0,d,1}(\theta) - \Omega_{0,d,2}(\theta)\|$$  \hspace{1cm} (B.67)

for some constant $C_3$. Collecting the results in (B.61), (B.65), (B.66) and (B.67), we get

$$\left| \min_{\theta \in \Theta} A_1(\theta)'(\Omega_{0,d,1}(\theta))^{-1} A_1(\theta) - \min_{\theta \in \Theta} A_2(\theta)'(\Omega_{0,d,2}(\theta))^{-1} A_2(\theta) \right| \leq (2C_2 + C_3) \|\xi_1 - \xi_2\|_s,$$  \hspace{1cm} (B.68)

which together with (B.59) and (B.60) implies that the lipschitz constant is $C_R = C_1 + 2C_2 + C_3$.

(ii) Note that under the condition $L(v; d) \geq 0$ and $\|v\| \leq C$, we have $0 \leq L(v; d) \leq v'M_d v \leq C^2$.

To show $L(v; d)$ is Lipschitz in $d$, we write

$$L(v; d) \equiv v'M_d v - \min_{\theta \in \Theta} (m_d(\theta) + V_{d,S}(\theta)v)'(\Omega_{d,0}(\theta))^{-1} (m_d(\theta) + V_{d,S}(\theta)v),$$  \hspace{1cm} (B.69)

where $V_{d,S}(\cdot) \equiv V_d(\cdot) \Omega_d^{1/2} M_d$. This functional form is analogous to $R(\xi)$, with $\Omega_d$ and $V_d(\cdot)$ in $R(\xi)$ replaced by $M_d$ and $V_{d,S}(\cdot)$, respectively. Given that $V_{d,S}(\cdot)$ is Lipschitz in $d$ (established in Lemma C4 below) and $\sup_{\theta \in \Theta} \|V_{d,S}(\theta)\| \leq C_1^{1/2} C_V$ (by Assumptions 2(iv) and 3(iii)), showing $L(v; d)$ is Lipschitz in $d$ is analogous to showing $R(\xi)$ is Lipschitz in $\xi$. The only difference is that $M_d$ is not a full rank matrix, unlike $\Omega_d$, which is the reason that we have to bound $\|v\|$ directly instead of bounding $v'M_d v$. Because (B.60) in the proof of part (i) uses the full rank condition of $\Omega_d$, we replace (B.60) with the following argument to show $v'M_d v$ is Lipschitz in $M_d$. Given $\|v\| \leq C$, we have

$$|v'M_{d,1} v - v'M_{d,2} v| = |v'(M_{d,1} - M_{d,2}) v| \leq \|v\|^2 \|M_{d,1} - M_{d,2}\| \leq C^2 \|M_{d,1} - M_{d,2}\|$$  \hspace{1cm} (B.70)

because $M_{d,1}$ and $M_{d,2}$ are both idempotent. The rest of the proof is analogous to those in the
proof of Lemma B1(i) and hence is omitted. 

\textbf{Proof of Lemma SA4.} The truncation function $t_C(u)$ satisfies the following properties: (i) for any $u \in \mathbb{R}^+$, $0 \leq t_C(u) \leq 1$ and $ut_C(u) \leq u$; (ii) for any $u_1$, $u_2 \in \mathbb{R}$, $|t_C(u_1) - t_C(u_2)| \leq C^{-1} |u_1 - u_2|$, which implies that $t_C(u)$ is Lipschitz. Therefore,

$$0 \leq R_C(\xi) \leq (x'\Omega_d^{-1}x) t_C(x'\Omega_d^{-1}x) \leq C$$

(B.71)

which means that $R_C(\xi)$ is bounded.

Next, we show that $R_C(\xi)$ is Lipschitz in $\xi$. That is for any $\xi_j$ with $R(\xi_j) \geq 0$ ($j = 1, 2$),

$$|R_C(\xi_1) - R_C(\xi_2)| \leq C_{R} \|\xi_1 - \xi_2\|_s,$$

(B.72)

where $C_R$ is a finite constant. Without loss of generality, we assume that $x_2'\Omega_{d,2}^{-1}x_2 \leq x_1'\Omega_{d,1}^{-1}x_1$.

By the triangle inequality,

$$|R_C(\xi_1) - R_C(\xi_2)| \leq \left| (R(\xi_1) - R(\xi_2))t_C(x_1'\Omega_{d,1}^{-1}x_1) \right| + \left| (t_C(x_1'\Omega_{d,1}^{-1}x_1) - t_C(x_2'\Omega_{d,2}^{-1}x_2))R(\xi_2) \right|.$$  

(B.73)

We have (B.72) holds with $C_R = C_{R_1} + C_{R_2}$ if we can show that

$$\left| (R(\xi_1) - R(\xi_2))t_C(x_1'\Omega_{d,1}^{-1}x_1) \right| \leq C_{R_1} \|\xi_1 - \xi_2\|_s$$

(B.74)

and

$$\left| (t_C(x_1'\Omega_{d,1}^{-1}x_1) - t_C(x_2'\Omega_{d,2}^{-1}x_2))R(\xi_2) \right| \leq C_{R_2} \|\xi_1 - \xi_2\|_s$$

(B.75)

for some finite constants $C_{R_1}$ and $C_{R_2}$.

We first consider (B.74). First, note that it holds trivially if $x_1'\Omega_{d,1}^{-1}x_1 > 2C$ because, in this case, $t_C(x_1'\Omega_{d,1}^{-1}x_1) = 0$. Second, given $x_2'\Omega_{d,2}^{-1}x_2 \leq x_1'\Omega_{d,1}^{-1}x_1 \leq 2C$, we deduce that

$$\left| (R(\xi_1) - R(\xi_2))t_C(x_1'\Omega_{d,1}^{-1}x_1) \right| \leq |R(\xi_1) - R(\xi_2)| \leq C_{R_1} \|\xi_1 - \xi_2\|_s,$$

(B.76)

where the first inequality is by property (i) of $t_C(u)$, and the second inequality is by Lemma B1(i).

Next, we show (B.75). First, note that it holds trivially if $2C < x_2'\Omega_{d,2}^{-1}x_2$. In this case,

$$t_C(x_1'\Omega_{d,1}^{-1}x_1) = t_C(x_2'\Omega_{d,2}^{-1}x_2) = 0$$

(B.77)

following the definition of $t_C(u)$. Second, given $x_2'\Omega_{d,2}^{-1}x_2 \leq 2C$, we have

$$\left| (t_C(x_1'\Omega_{d,1}^{-1}x_1) - t_C(x_2'\Omega_{d,2}^{-1}x_2))R(\xi_2) \right| \leq |R(\xi_2)| \leq x_2'\Omega_{d,2}^{-1}x_2 \leq 2C.$$

(B.78)
Thus, (B.75) holds with $C_{R_2} = 1$ if $\|\xi_1 - \xi_2\|_s > 2C$. Third, it remains to consider the case where $x_2' \Omega_{d,2}^{-1} x_2 \leq 2C$ and $\|\xi_1 - \xi_2\|_s \leq 2C$. In this case, Lemma C3 in the Section C implies that $x_1' \Omega_{d,1}^{-1} x_1 \leq C^*$ for some finite constant $C^*$. In this case,

$$\left| (t_C(x_1' \Omega_{d,1}^{-1} x_1) - t_C(x_2' \Omega_{d,2}^{-1} x_2)) R(\xi) \right| \leq t_C(x_1' \Omega_{d,1}^{-1} x_1 - t_C(x_2' \Omega_{d,2}^{-1} x_2) | x_2' \Omega_{d,2}^{-1} x_2 | \leq 2C \left| x_1' \Omega_{d,1}^{-1} x_1 - x_2' \Omega_{d,2}^{-1} x_2 \right|$$

(B.79)

using $0 \leq R(\xi) \leq x_2' \Omega_{d,2}^{-1} x_2 \leq 2C$ and $|t_C(x_1) - t_C(x_2)| \leq C^{-1} |x_1 - x_2|$ which follows from property (ii) of $t_C(x)$. Then we can show $|x_1' \Omega_{d,1}^{-1} x_1 - x_2' \Omega_{d,2}^{-1} x_2| \leq C_{R_2} \|\xi_1 - \xi_2\|_S$ for some constant $C_{R_2}$ by the same arguments that show (B.60) but with $x_1' \Omega_{d,1}^{-1} x_1 \leq 2C$ replaced by $x_1' \Omega_{d,1}^{-1} x_1 \leq C^*$. Q.E.D.

**Lemma B2.** Given $L(v; d) \geq 0$, $\overline{T}_C(v; d)$ is bounded and Lipschitz in $d$.

**Proof of Lemma B2.** The proof is analogous to that of Lemma SA4 with the truncation function $t_C(x' \Omega_{d}^{-1} x)$ replaced by $t_C(v' M_d v) I\{\|v\|^2 \leq C\}$ and Lemma B1(i) replaced by Lemma B1(ii), and hence is omitted. Q.E.D.

**Proof of Lemma SA5.** Since $0 \leq L(v; d) \leq v' M_d v$ for any $v \in \mathbb{R}^k$ and $ut_C(u) \leq C$ for any $u \geq 0$, we have

$$\overline{T}_C(v; d) = L(v; d) t_C(v' M_d v) I\{\|v\|^2 \leq C\} \leq L(v; d) t_C(v' M_d v) \leq C,$$

(B.80)

which implies that $c_{\alpha, C}(d)$ is bounded. For any $v$, any $d_1$ and $d_2$, by Lemma B2 there exists a finite constant $C_L$ such that

$$|\overline{T}_C(v; d_1) - \overline{T}_C(v; d_2)| \leq C_L \|d_1 - d_2\|_s.$$ 

(B.81)

Since $\overline{T}_C(v; d_1) \geq \overline{T}_C(v; d_2) - C_L \|d_1 - d_2\|_s$ for any $v$ and $P^* (\overline{T}_C(v^*; d_1) > c_{\alpha, C}(d_1)) \leq \alpha$, we have $P (\overline{T}_C(v^*; d_2) > c_{\alpha, C}(d_1) + C_L \|d_1 - d_2\|_s) \leq \alpha$, which implies that

$$c_{\alpha, C}(d_2) \leq c_{\alpha, C}(d_1) + C_L \|d_1 - d_2\|_s.$$ 

(B.82)

Similarly, we also have

$$c_{\alpha, C}(d_1) \leq c_{\alpha, C}(d_2) + C_L \|d_1 - d_2\|_s.$$ 

(B.83)

Combining (B.82) and (B.83), we get

$$|c_{\alpha, C}(d_1) - c_{\alpha, C}(d_2)| \leq C_L \|d_1 - d_2\|_s,$$

(B.84)

which shows the claim of the lemma. Q.E.D.
C Additional Auxiliary Lemmas

This section contains the proof of Lemma SA3 in Cheng, Dou, and Liao (2021) and some other auxiliary results.

Proof of Lemma SA3. For any square matrices $A_1$ and $A_2$, let $\text{diag}(A_1, A_2)$ denote the block diagonal matrix created by aligning the input matrices $A_1$ and $A_2$ along the diagonal. Since $\hat{\theta} \in \Theta$ is the minimizer of $g(\theta)'(\hat{\Omega}(\theta))^{-1}g(\theta)$,

$$ T \geq g(\hat{\theta})'\hat{\Omega}^{-1}g(\hat{\theta}) - g(\hat{\theta})'\hat{\Omega}_0^{-1}g(\hat{\theta}) = g(\hat{\theta})' \left(\hat{\Omega}^{-1} - \text{diag}(\hat{\Omega}_0^{-1}, 0_{k_1 \times k_1})\right) g(\hat{\theta}) $$

(C.85)

Let $\hat{\Omega}_{0,1}$ denote the upper-right $k_0 \times k_1$ submatrix of $\hat{\Omega}$ and $\hat{\Omega}_{1,0} \equiv \hat{\Omega}_{0,1}$. Since $\hat{\Omega}$ is positive definite,

$$ \hat{\Omega}(\hat{\Omega}^{-1} - \text{diag}(\hat{\Omega}_0^{-1}, 0_{k_1 \times k_1}))\hat{\Omega} = \text{diag}(0_{k_0 \times k_0}, \hat{\Omega}_1 - \hat{\Omega}_{1,0}\hat{\Omega}_0^{-1}\hat{\Omega}_{0,1}) $$

(C.86)

is a positive semi-definite matrix, which together with (C.85) proves the first claim of the lemma.

To prove the second claim, we first notice that $\hat{m}(\hat{\theta}) = g_0(\hat{\theta}) - \hat{V}(\hat{\theta})g(\hat{\theta}) = 0_{k_0 \times 1}$ which implies that for any $v \in \mathbb{R}^k$

$$ L(v; \hat{d}) \geq v'\hat{M}v - v'\hat{V}_S(\hat{\theta})'\hat{\Omega}_0^{-1}\hat{V}_S(\hat{\theta})v, $$

(C.87)

where $\hat{V}_S(\theta) \equiv S_0\hat{\Omega}^{1/2}\hat{M}$. Therefore

$$ L(x; \hat{d}) \geq v'\hat{M}\hat{\Omega}^{1/2} \left(\hat{\Omega}^{-1} - \text{diag}(\hat{\Omega}_0^{-1}, 0_{k_1 \times k_1})\right)\hat{\Omega}^{1/2}\hat{M}v \geq 0, $$

(C.88)

where the second inequality holds since the matrix in (C.86) is positive semi-definite. Q.E.D.

Lemma C3. For any $\xi_1$ and $\xi_2$ with $x_2'\Omega_{d,2}^{-1}x_2 \leq C$ and $\|\xi_1 - \xi_2\|_s \leq C$, where $C$ is a finite constant, we have $\xi_1\Omega_{d,1}^{-1}\xi_1 \leq C^*$ for some finite constant $C^*$, which depends the constant $C$ of the lemma, $C_{\Omega}$ and $c_\lambda$ in Assumptions 2(iv) and 3(iii) respectively.

Proof of Lemma C3. Since $\Omega_{d,1}^{-1}$ is symmetric and positive definite under Assumption 3(iii),

$$ x_1\Omega_{d,1}^{-1}x_1 \leq 2x_2\Omega_{d,1}^{-1}x_2 + 2(x_1 - x_2)'\Omega_{d,1}^{-1}(x_1 - x_2) $$

$$ = 2x_2\Omega_{d,2}^{-1}x_2 + 2x_2'(\Omega_{d,1}^{-1} - \Omega_{d,2}^{-1})x_2 + 2(x_1 - x_2)'\Omega_{d,1}^{-1}(x_1 - x_2) $$

$$ \leq 2C + 2x_2'(\Omega_{d,1}^{-1} - \Omega_{d,2}^{-1})x_2 + 2(x_1 - x_2)'\Omega_{d,1}^{-1}(x_1 - x_2), $$

(C.89)

where the second inequality is by $x_2'\Omega_{d,2}^{-1}x_2 \leq C$ as assumed in the lemma. By Assumption 3(iii) and $\|\xi_1 - \xi_2\|_s \leq C$,

$$ (x_1 - x_2)'\Omega_{d,1}^{-1}(x_1 - x_2) \leq (\lambda_{\min}(\Omega_{d,1}))^{-1}\|x_1 - x_2\|^2 \leq C^2c_\lambda^{-1}. $$

(C.90)
Similarly, by Assumption 3(iii) and $\|\xi_1 - \xi_2\|_s \leq C$,
\[
\left|x'(\Omega^{-1}_{d,1} - \Omega^{-1}_{d,2})x_2\right|^2 = \left|x'(\Omega_{d,1}^{-1} - \Omega_{d,2}^{-1})\Omega_{d,2}^{-1}x_2\right|^2 \\
\leq \frac{\lambda_{\max}(\Omega_{d,1})(x'\Omega_{d,1}^{-1}x_2)^2}{\lambda_{\min}(\Omega_{d,1})}\|\Omega_{d,1} - \Omega_{d,2}\|^2 \\
\leq C^4 c_\lambda^{-3} C_\Omega, \tag{C.91}
\]
where the last inequality is by $x'\Omega_{d,2}^{-1}x_2 \leq C$, Assumption 3(iii) and $\|\xi_1 - \xi_2\|_s \leq C$. The claim of the lemma follows from (C.89)-(C.91). \textit{Q.E.D.}

**Lemma C4.** For any $\xi_1$ and $\xi_2$, define $V_{d,s,j}(\theta) \equiv V_{d,j}(\theta) \Omega_{d,j}^{1/2} M_{d,j}$ for $j = 1, 2$. Then we have
\[
\sup_{\theta \in \Theta} \|V_{d,s,1}(\theta) - V_{d,s,2}(\theta)\| \leq C_\Omega^{1/2} (1 + c_\lambda^{-1} C_\Omega^{1/2} + c_\lambda^{-1} C_\Omega) \|\xi_1 - \xi_2\|_s, \tag{C.92}
\]
where $C_\Omega$ and $c_\lambda$ are in Assumptions 2(iv) and 3(iii) respectively.

**Proof of Lemma C4.** By definition,
\[
V_{d,s,1}(\theta) - V_{d,s,2}(\theta) = [V_{d,1}(\theta) - V_{d,2}(\theta)] \Omega_{d,1}^{1/2} M_{d,1} \\
+ V_{d,2}(\theta) (\Omega_{d,1}^{1/2} - \Omega_{d,2}^{1/2}) M_{d,1} + V_{d,2}(\theta) \Omega_{d,2}^{1/2} (M_{d,1} - M_{d,2}). \tag{C.93}
\]
By the properties of $\Omega_{d,j}$ and $M_{d,j}$,
\[
\sup_{\theta \in \Theta} \left\|V_{d,1}(\theta) - V_{d,2}(\theta)\right\| \Omega_{d,1}^{1/2} M_{d,1} \leq C_\Omega^{1/2} \sup_{\theta \in \Theta} \left\|V_{d,1}(\theta) - V_{d,2}(\theta)\right\|. \tag{C.94}
\]
By the properties of $V_{d,j}(\theta)$ and $M_{d,j}$, and Exercise 7.2.18 in Horn and Johnson (1990),
\[
\sup_{\theta \in \Theta} \left\|V_{d,2}(\theta) (\Omega_{d,1}^{1/2} - \Omega_{d,2}^{1/2}) M_{d,1}\right\| \leq \sup_{\theta \in \Theta} \left\|V_{d,2}(\theta)\right\| \left\|\Omega_{d,1}^{1/2} - \Omega_{d,2}^{1/2}\right\|_S \\
\leq c_\lambda^{-1} C_\Omega \left\|\Omega_{d,2}^{-1}\right\|_S \|\Omega_{d,1} - \Omega_{d,2}\| \leq c_\lambda^{-2} C_\Omega \|\Omega_{d,1} - \Omega_{d,2}\|. \tag{C.95}
\]
Similarly,
\[
\sup_{\theta \in \Theta} \left\|V_{d,2}(\theta) \Omega_{d,2}^{1/2} (M_{d,1} - M_{d,2})\right\| \leq c_\lambda^{-1} C_\Omega^{3/2} \|M_{d,1} - M_{d,2}\|. \tag{C.96}
\]
The desirable result follows by (C.94)-(C.96) and the triangle inequality. \textit{Q.E.D.}
D Derivations of Asset Pricing Moments in Examples

D.1 Solution of the Disaster Risk Model

The dividend-price ratio is constant in the equilibrium, denoted by $C/P$. The stock return is

$$R_t = (C_t + P_t)/P_{t-1} = (C/P + 1)C_t/C_{t-1} = (C/P + 1)e^{\sigma z_t - \zeta_t}. \tag{D.1}$$

Thus, the expected log stock return is

$$E_{t-1} [\ln R_t] = \ln(C/P + 1) - p (v + 1/\alpha). \tag{D.2}$$

The equilibrium dividend-price ratio is characterized by

$$P/C = E_{t-1} \left[ e^{-\delta} (C_t/C_{t-1})^{-\gamma} (P_t/C_t + 1)C_t/C_{t-1} \right]$$

$$= (P/C + 1)e^{-\delta}E_{t-1} \left[ (C_t/C_{t-1})^{1-\gamma} \right]$$

$$= (P/C + 1)e^{-\delta + \frac{1}{2}(1-\gamma)^2 \sigma^2} \left[ 1 - p + pe^{-(1-\gamma)v} \frac{\alpha}{\alpha - \gamma + 1} \right]. \tag{D.3}$$

As a result, the term $\ln(C/P + 1)$ in (D.1) equals to

$$\ln(C/P + 1) = \delta - \frac{1}{2}(1-\gamma)^2 \sigma^2 - \ln \left[ 1 - p + pe^{-(1-\gamma)v} \frac{\alpha}{\alpha - \gamma + 1} \right]$$

$$\approx \delta - \frac{1}{2}(1-\gamma)^2 \sigma^2 + p - pe^{-(1-\gamma)v} \frac{\alpha}{\alpha - \gamma + 1}. \tag{D.4}$$

Define the log return as $r_t \equiv \ln R_t$. Equations (D.4) and (D.2) imply the following relation:

$$E_{t-1} [r_t] \approx \delta - \frac{1}{2}(1-\gamma)^2 \sigma^2 - p (v + 1/\alpha) + p - pe^{(1-\gamma)v} \frac{\alpha}{\alpha - \gamma + 1}. \tag{D.5}$$

The equilibrium risk-free rate satisfies that

$$R_f = E_{t-1} \left[ e^{-\delta} (C_t/C_{t-1})^{-\gamma} \right]^{-1} = e^{\delta - \frac{1}{2} \gamma^2 \sigma^2} \left[ 1 - p + pe^{\gamma v} \frac{\alpha}{\alpha - \gamma} \right]^{-1}. \tag{D.6}$$

Define the log risk-free rate as $r_f \equiv \ln R_f$. Thus, the log risk-free rate satisfies

$$r_f = \delta - \frac{1}{2} \gamma^2 \sigma^2 - \ln \left[ 1 - p + pe^{\gamma v} \frac{\alpha}{\alpha - \gamma} \right]$$

$$\approx \delta - \frac{1}{2} \gamma^2 \sigma^2 + p - pe^{\gamma v} \frac{\alpha}{\alpha - \gamma}. \tag{D.7}$$
The excess log return, defined as $r^e_t \equiv r_t - r_f$, is

$$E_{t-1}[r^e_t] = \gamma \sigma^2 - \frac{1}{2} \sigma^2 - p(\bar{v} + 1/\alpha) + p\alpha \left[ \frac{e^{\gamma \bar{v}}}{\alpha - \gamma} - \frac{e^{(\gamma-1)\bar{v}}}{\alpha - \gamma + 1} \right].$$  \tag{D.8}

The excess log return $r^e_t$ has the same conditional exposure to the shocks as the log return $r_t$ since the log risk-free rate $r_f$ has zero exposure to the shocks. Therefore, the excess log return in the equilibrium can be represented as follows:

$$r^e_t = \gamma \sigma^2 - \frac{1}{2} \sigma^2 - p(\bar{v} + 1/\alpha) + p\alpha \left[ \frac{e^{\gamma \bar{v}}}{\alpha - \gamma} - \frac{e^{(\gamma-1)\bar{v}}}{\alpha - \gamma + 1} \right] + \varepsilon^e_{t,t},$$  \tag{D.9}

where $\varepsilon^e_{t,t} \equiv \sigma \varepsilon_t - [x_t(\bar{v} + J_t) - p(\bar{v} + 1/\alpha)] + \sigma_t \varepsilon_{t,t}$. The shock of the consumption growth is $\varepsilon_t$, the jump shock of the consumption growth is $-[x_t(\bar{v} + J_t) - p(\bar{v} + 1/\alpha)]$, and the shock of the measurement error is $\varepsilon_{t,t}$. The measurement error $\varepsilon_{t,t}$ is i.i.d. standard normal and is independent of other shocks.

### D.2 Solution of the Long-Run Risk Model

The stochastic discount factor (SDF) can be expressed as follows:

$$M_t = \delta^\vartheta \left( \frac{C_t}{C_{t-1}} \right)^{-\vartheta/\psi} R_{c,t}^{\vartheta-1}, \quad \text{with } \vartheta \equiv \frac{1 - \gamma}{1 - 1/\psi},$$  \tag{D.10}

where $R_{c,t}$ is the return on the consumption claim. The log SDF can be written as

$$m_t = \vartheta \log \delta - \frac{\vartheta}{\psi} \Delta c_t + (\vartheta - 1) r_t.$$  \tag{D.11}

The state variable in the simplest long-run risk model is $x_t$. To turn the system into an affine model, we first exploit the Campbell-Shiller log-linearization approximation:

$$r_t = \kappa_0 + \kappa_1 z_t + \Delta c_t - z_{t-1},$$  \tag{D.12}

where $z_{t-1} = \ln(W_{t-1}/C_{t-1})$ is the log wealth-consumption ratio and wealth is the “price” of consumption claims. The log-linearization constants are determined by long-run steady state:

$$\kappa_0 = \ln(1 + e^\overline{z}) - \kappa_1 \overline{z} \quad \text{and} \quad \kappa_1 = \frac{e^\overline{z}}{1 + e^\overline{z}},$$  \tag{D.13}

where $\overline{z}$ is the mean of the log price-consumption ratio. Given the log-linearization approximation
(D.12) – (D.13), we can search the equilibrium characterized by

\[ z_t = A_0 + A_1 x_t, \quad (D.14) \]

where the constants \( A_0 \) and \( A_1 \) are to be determined by the equilibrium conditions.

Thus, the log return on consumption claim can be written as

\[ r_t = \kappa_0 + \kappa_1 (A_0 + A_1 x_t) + \Delta c_t - (A_0 + A_1 x_{t-1}). \quad (D.15) \]

Therefore, the log SDF can be re-written in terms of state variables and exogenous shocks

\[ m_t = \Gamma_0 + \Gamma_1 x_{t-1} - \lambda_c \sigma_c \epsilon_{c,t} - \lambda_x \phi \epsilon_{x,t}, \quad (D.16) \]

where predictive coefficients are

\[ \Gamma_0 = \ln \delta \quad \text{and} \quad \Gamma_1 = -\psi^{-1}, \quad (D.17) \]

and the market price of risk coefficients are

\[ \lambda_c = \gamma \quad \text{and} \quad \lambda_x = (\gamma - \psi^{-1}) \frac{\kappa_1 \phi}{1 - \kappa_1 \rho}, \quad (D.18) \]

The coefficients \( A_j \)'s are determined by the equilibrium condition (i.e., the Euler equation for the price of consumption claim) as follows:

\[ 1 = E_{t-1} [M_t R_{c,t}] = E_{t-1} [e^{m_t + r_t}], \quad (D.19) \]

where \( E_{t-1}[:]\) denote the expectation given the information at time \( t - 1 \). It leads to the equilibrium conditions:

\[ A_0 = \frac{1}{1 - \kappa_1} (\ln \delta + \kappa_0) \quad \text{and} \quad A_1 = \frac{1 - \psi^{-1}}{1 - \kappa_1 \rho} \phi. \quad (D.20) \]

The long-run mean \( \bar{z} \) is also determined endogenously in the equilibrium. In the long-run steady state, we have

\[ \bar{z} = A_0. \quad (D.21) \]

We first derive \( \kappa_1 \) in equilibrium. After taking log on the both sides of (D.13) and plugging (D.20) and (D.21) into the equation, we can obtain the following relation:

\[ \ln \kappa_1 = \bar{z} - \ln(1 + e^{\bar{z}}) = \bar{z} - \kappa_0 + \kappa_1 \bar{z} \]

\[ = (1 - \kappa_1) \bar{z} - \kappa_0 = \ln \delta. \quad (D.22) \]
Thus, the equilibrium log-linearization coefficient is equal to the representative agent’s time preference parameter; that is, \( \kappa_1 = \delta \), in equilibrium.

From (D.15) and (D.20), it follows that

\[
r_t - \mathbb{E}_{t-1} [r_t] = \beta_c \sigma_c \epsilon_{c,t} + \beta_x \epsilon_{x,t},
\]

(D.23)

where the betas are

\[
\beta_c = 1 \quad \text{and} \quad \beta_x = \kappa_1 A_1.
\]

(D.24)

The Euler equation for the log market return, denoted by \( r_t \), and the risk free rate, denoted by \( r_{f,t-1} \), can be written in one equation

\[
\mathbb{E}_{t-1} [e^{m_t}] = \mathbb{E}_{t-1} [e^{m_t + r_t^e}],
\]

(D.25)

where \( r_t^e \equiv r_t - r_{f,t-1} \) is the excess log return.

The Euler equation (D.25) leads to

\[
\mathbb{E}_{t-1} [r_t^e] = \lambda_c \beta_c \sigma_c^2 + \lambda_x \beta_x - \frac{1}{2} \left( \beta_c^2 \sigma_c^2 + \beta_x^2 \phi^2 \right) = \gamma \sigma_c^2 - \frac{1}{2} \sigma_c^2 + \frac{1}{2} (2 \gamma - \psi^{-1} - 1) (1 - \psi^{-1}) \frac{\kappa_1^2 \phi^2}{(1 - \kappa_1 \rho)^2}
\]

\[
= \gamma \sigma_c^2 - \frac{1}{2} \sigma_c^2 + \frac{1}{2} (2 \gamma - \psi^{-1} - 1) (1 - \psi^{-1}) \frac{\phi^2}{(\delta^{-1} - \rho)^2},
\]

(D.26)

The excess log return \( r_t^e \) has the same conditional exposure to the shocks as the log return \( r_t \) since the log risk-free rate \( r_{f,t-1} \) has zero conditional exposure to the shocks \( \epsilon_{c,t} \) and \( \epsilon_{x,t} \). Therefore, combining (D.20), (D.24), and (D.26), we can obtain that the excess log return in the equilibrium can be represented as follows:

\[
r_t^e = \gamma \sigma_c^2 - \frac{1}{2} \sigma_c^2 + \frac{1}{2} (2 \gamma - \psi^{-1} - 1) (1 - \psi^{-1}) \frac{\phi^2}{(\delta^{-1} - \rho)^2} + \epsilon_{d,t},
\]

(D.27)

where \( \epsilon_{d,t} \equiv \sigma_c \epsilon_{c,t} + (1 - \psi^{-1})(1 - \rho)^{-1} \phi \epsilon_{x,t} + \sigma_r \epsilon_{d,t} \). The shock of the contemporaneous consumption growth is \( \epsilon_{c,t} \), the shock of the low-frequency component is \( \epsilon_{x,t} \), and the shock of the measurement error is \( \epsilon_{d,t} \). The measurement error \( \epsilon_{d,t} \) is i.i.d. standard normal and is independent of other shocks.

E Gaussian Limit in the Long-Run Risk Model

For the long-run risk model, we show that the Gaussian limit for the moment conditions is an innocuous assumption even if \( \rho_n \to 1 \) and \( \phi_n \to 0 \) at any rate, as long as \( \theta_n = (1 - \rho_n) / \phi_n \) is
bounded from above and below by some finite positive constants, where the subscript \( n \) denotes the sample size \( n \).

We start with the first moment condition. The observed process \( \Delta c_t \) satisfies

\[
\Delta c_{t+1} - \rho \Delta c_t = \phi_n \left( \rho_n x_{t-1} + \epsilon_{x,t} \right) + \sigma_c \epsilon_{c,t+1} + \sigma_c \epsilon_{c,t} - \rho \left( \phi_n x_{t-1} + \sigma_c \epsilon_{c,t} \right)
\]

\[
= \phi_n (\rho_n - \rho) x_{t-1} + \phi_n \epsilon_{x,t} + \sigma_c \epsilon_{c,t+1} - \rho \sigma_c \epsilon_{c,t}.
\] (E.1)

Multiply the first difference \( \Delta c_{t+1} - \rho \Delta c_t \) in (E.1) by \( \Delta c_{t-1} = \phi_n x_{t-2} + \sigma_c \epsilon_{c,t-1} \). We obtain

\[
M_{1t} \equiv \Delta c_{t-1} (\Delta c_{t+1} - \rho \Delta c_t) = M_{1a,t} + M_{1b,t} + M_{1c,t} + M_{1d,t} + \mu_1,
\] (E.2)

where

\[
\mu_1 \equiv \mathbb{E} [\Delta c_{t-1} (\Delta c_{t+1} - \rho \Delta c_t)] = \phi_n^2 (\rho_n - \rho) \rho_n \mathbb{E} [x_{t-2}^2],
\]

\[
M_{1a,t} \equiv \phi_n^2 (\rho_n - \rho) \rho_n \left( x_{t-2}^2 - \mathbb{E} [x_{t-2}^2] \right),
\]

\[
M_{1b,t} \equiv \phi_n (\rho_n - \rho) (\sigma_c x_{t-1} \epsilon_{c,t-1} + \phi_n x_{t-2} \epsilon_{x,t-1}),
\]

\[
M_{1c,t} \equiv \phi_n x_{t-2} (\phi_n \epsilon_{x,t} + \sigma_c \epsilon_{c,t+1} - \rho \sigma_c \epsilon_{c,t}),
\]

\[
M_{1d,t} \equiv \sigma_c \epsilon_{c,t-1} (\phi_n \epsilon_{x,t} + \sigma_c \epsilon_{c,t+1} - \rho \sigma_c \epsilon_{c,t}).
\] (E.3)

The moment condition satisfies

\[
M_1 \equiv n^{-1/2} \sum_{t=1}^n (M_{1t} - \mathbb{E} [M_{1t}]) = M_{1a} + M_{1b} + M_{1c} + M_{1d},
\] (E.4)

where \( M_{1j} \equiv n^{-1/2} \sum_{t=1}^n M_{1j,t} \) for \( j = a, b, c, d \).

Below we consider three separate cases: (i) \( \rho_n \) is bounded away from 1; (ii) \( \rho_n \) converges to 1 at the rate slower than \( n^{-1} \), i.e., \( (1 - \rho_n) n \to \infty \); (iii) \( \rho_n \) converges to 1 at the rate \( n^{-1} \) or faster, i.e., \( (1 - \rho_n) n \to c \in [0, \infty) \). In all three cases, \( \theta_n = (1 - \rho_n) / \phi_n \) is bounded below from 0 and above from infinity. Therefore, \( \phi_n \) always converges to 0 at the same rate at which \( \rho_n \) converges to 1.

In case (i), we can apply the central limit theorem (CLT) for weakly dependent triangular arrays and \( M_1 \) has a Gaussian limit.

Now we consider case (ii). We assume the initial condition satisfies \( \mathbb{E} [x_0^2] = o(n^{1/2}) \) as in GP. Following Lemma 1 of Giraitis and Phillips (2006) (hereafter GP),

\[
\frac{(1 - \rho_n^2)}{n^{1/2}} \sum_{t=1}^n x_{t-1} \epsilon_{x,t} \to_d N(0,1)
\] (E.5)

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using $\text{Var}(\epsilon_{x,t}) = 1$. We assume the initial condition satisfies $\mathbb{E}[x_0^2] = o(n^{1/2})$ as in GP. Following the proof for Lemma 1 of GP we also have

$$
\frac{(1 - \rho_n^2)^{1/2}}{n^{1/2}} \sum_{t=1}^{n} x_{t-1} \epsilon_{x,t+1} \rightarrow_d N(0,1),
$$

$$
\frac{(1 - \rho_n^2)^{1/2}}{n^{1/2}} \sum_{t=1}^{n} x_{t-1} \epsilon_{c,t+j} \rightarrow_d N(0,\sigma_c^2),
$$

(E.6)

for any $j$ following the independence of $\epsilon_{x,t}$ and $\epsilon_{c,t'}$ for any $t \neq t'$. Following equation (20) in the proof of Lemma 2 of GP,

$$
n^{-1/2} \sum_{t=1}^{n} (x_{t-1}^2 - \mathbb{E}[x_{t-1}^2]) = (1 - \rho_n^2)^{-3/2} 2\rho_n Z_1 + (1 - \rho_n^2)^{-1} Z_2 + Z_3,
$$

(E.7)

where

$$
Z_1 \equiv \frac{(1 - \rho_n^2)^{1/2}}{n^{1/2}} \sum_{t=1}^{n} x_{t-1} \epsilon_{x,t} \rightarrow_d N(0,1),
$$

$$
Z_2 \equiv n^{-1/2} \sum_{t=1}^{n} (\epsilon_{x,t}^2 - 1) \rightarrow_d N(0,\text{Var}^2),
$$

$$
Z_3 \equiv \frac{x_0^2 - \mathbb{E}[x_0^2]}{n^{1/2}} - \frac{x_n^2 - \mathbb{E}[x_n^2]}{n^{1/2} (1 - \rho_n^2)},
$$

(E.8)

where the convergence for $Z_1$ holds by (E.5), the convergence for $Z_2$ follows from the CLT with $\text{Var}^2$ being the variance of $\epsilon_{x,t}^2$. Then, we have $M_{1a} = o_p(1)$ because

$$
\phi_n^2 (1 - \rho_n^2)^{-3/2} 2\rho_n Z_1 = o_p(1),
$$

$$
\phi_n^2 (1 - \rho_n^2)^{-1} Z_2 = o_p(1),
$$

$$
\phi_n^2 Z_3 = o_p(1),
$$

(E.9)

which in turn holds because $\theta_n = (1 - \rho_n) / \phi_n$ is bounded, $x_0^2 = o_p(n^{1/2})$ by the initial condition, and $\phi_n^2 (1 - \rho_n^2)^{-1} n^{-1/2} x_n^2 = o_p(1)$ by Lemma 3 of GP and the Markov inequality.

The other terms satisfy

$$
M_{1b} = \phi_n O_p((1 - \rho_n^2)^{-1/2}) = o_p(1),
$$

$$
M_{1c} = \phi_n O_p((1 - \rho_n^2)^{-1/2}) = o_p(1),
$$

(E.10)

by $\phi_n = O((1 - \rho_n))$, (E.5) and (E.6). Then we can apply the CLT for triangular array of i.i.d. random variables to $M_{1d}$ and the Gaussian limit holds for $M_1$. 

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Finally, we consider the case (iii), where \( n(1 - \rho_{n}) \to c \) for \( c \in [0, \infty) \). Following Phillips (1987),

\[
\sum_{t=1}^{n} x_{t-1}^{2} = O_{p}(1), \quad \sum_{t=1}^{n} x_{t-1} \epsilon_{x,t} = O_{p}(1). \tag{E.11}
\]

We also have

\[
\sum_{t=1}^{n} x_{t-1} \epsilon_{x,t+1} = O_{p}(1) \quad \text{and} \quad \sum_{t=1}^{n} x_{t-1} \epsilon_{c,t+j} = O_{p}(1) \tag{E.12}
\]

for any \( j \), because \( \epsilon_{x,t} \) is i.i.d. with mean zero and it is independent of \( \epsilon_{c,t+j} \), following results for a vector process, see Park and Phillips (1988). Therefore,

\[
M_{1a} = \phi_{n}^{2} \left[ O_{p}(n^{3/2}) - O(n^{1/2}) \right] (1 - \rho_{n}^{2})^{-1} = o_{p}(1),
\]

\[
M_{1b} = \phi_{n} O_{p}(n^{1/2}) = o_{p}(1) \quad \text{and} \quad M_{1c} = \phi_{n} O_{p}(n^{1/2}) = o_{p}(1), \tag{E.13}
\]

because \( \phi_{n} = O(n^{-1}) \). As in case (ii), we can apply the CLT to \( M_{1d} \) to obtain the Gaussian limit for \( M_{1} \).

Next, we consider multiplying the first difference \( \Delta c_{t+1} - \rho \Delta c_{t} \) in (E.1) by \( \Delta c_{t} = \phi_{n} \epsilon_{x,t} + \sigma_{c} \epsilon_{c,t} \).

We obtain

\[
M_{2,t} \equiv \Delta c_{t} (\Delta c_{t+1} - \rho \Delta c_{t}) = M_{2a,t} + M_{2b,t} + M_{2c,t} + M_{2d,t} + \mu_{2}, \tag{E.14}
\]

where

\[
\mu_{2} \equiv \mathbb{E} \left[ \Delta c_{t} (\Delta c_{t+1} - \rho \Delta c_{t}) \right] = \phi_{n}^{2} (\rho_{n} - \rho) \mathbb{E}[x_{t-1}^{2}] - \rho \sigma_{c}^{2},
\]

\[
M_{2a,t} \equiv \phi_{n}^{2} (\rho_{n} - \rho) (x_{t-1}^{2} - \mathbb{E}[x_{t-1}^{2}]),
\]

\[
M_{2b,t} \equiv \phi_{n} (\rho_{n} - \rho) \sigma_{c} x_{t-1} \epsilon_{c,t},
\]

\[
M_{2c,t} \equiv \phi_{n} \epsilon_{x,t} (\phi_{n} \epsilon_{x,t} + \sigma_{c} \epsilon_{c,t+1} - \rho \sigma_{c} \epsilon_{c,t}),
\]

\[
M_{2d,t} \equiv \sigma_{c} \epsilon_{c,t} (\phi_{n} \epsilon_{x,t} + \sigma_{c} \epsilon_{c,t+1} - \rho \sigma_{c} \epsilon_{c,t}). \tag{E.15}
\]

As above, we consider three cases. In case (i) where \( \rho \) is bounded away from 1, we can apply the CLT directly. In case (ii),

\[
M_{2a} = n^{-1/2} \sum_{t=1}^{n} M_{2a,t} = \phi_{n}^{2} (\rho_{n} - \rho) n^{-1/2} \sum_{t=1}^{n} (x_{t-1}^{2} - \mathbb{E}[x_{t-1}^{2}]) = o_{p}(1) \tag{E.16}
\]

following the same arguments for \( M_{1a} \). Similarly, we can show that \( M_{2b} \) and \( M_{2c} \), defined similarly to \( M_{1b} \) and \( M_{1c} \) respectively, are both \( o_{p}(1) \) following the arguments for \( M_{1b} \) and \( M_{1c} \). Finally, the CLT always applies to \( M_{2d} \), the counterpart of \( M_{1d} \). In case (iii), same arguments for \( M_{1a} \) give

\[
M_{2a} = \phi_{n}^{2} \left[ O_{p}(n^{3/2}) - O(n^{1/2}) (1 - \rho_{n}^{2})^{-1} \right] = o_{p}(1). \tag{E.17}
\]
Arguments for $M_{1b}$, $M_{1c}$ and $M_{1d}$ can be used to show the same results hold for their counterparts $M_{2b}$, $M_{2c}$ and $M_{2d}$ respectively.

Finally, the asset pricing moment condition always has a Gaussian limit because it is a location model with an i.i.d. error.

F Additional Materials for the Empirical Application

First, we start with a discussion on the importance of studying the robust evaluation of time-varying disaster risk models. After that, we verify the baseline moment conditions since they do not depend on the model solution. Then, we solve the model and derive the equilibrium relations. Lastly, we verify the asset pricing moment conditions.

Motivation. The time-varying disaster risk model has been one of the most influential frameworks in the literature. For instance, the time-varying disaster risk mechanism has been used to explain important empirical patterns in macroeconomic quantities (e.g., Gourio, 2012, 2013), exchange rates and international capital flows (e.g., Gourio, Siemer, and Verdelhan, 2013; Martin, 2013; Farhi and Gabaix, 2015; Dou and Verdelhan, 2017; Lewis and Liu, 2017), global imbalances (e.g., Gourinchas, Rey, and Govillot, 2017), volatile unemployment flows (e.g., Kilic and Wachter, 2018; Petrosky-Nadeau, Zhang, and Kuehn, 2018), prices of derivatives (e.g., Gabaix, 2012; Farhi and Gabaix, 2015; Seo and Wachter, 2018, 2019), credit spreads (e.g., Gourio, 2013), and term structure of return volatility and risk premia (e.g., Hasler and Marfè, 2016). Tsai and Wachter (2015) and Welch (2016) provide lucid summaries of (time-varying) disaster risk mechanisms.

The feature of information imbalance is ubiquitous in macro asset pricing structural models, especially in time-varying rare-disaster risk models (e.g., Chen, Dou, and Kogan, 2021). However, the literature lacks a robust and efficient way to statistically evaluate these influential models or reliably quantify model uncertainty embedded in these potentially fragile structural models. Using this full-fledged example of the time-varying disaster risk mechanism, we show how to use the real data, the structural asset pricing model, and our robust specification test procedure to construct joint uncertainty sets of average return and volatility for the optimal robust portfolio problem.

Besides robust portfolio problems, data-driven model uncertainty sets are crucial for robustness analysis of structural economic models in other dimensions (e.g., Hansen and Sargent, 2001, 2008, 2020; Cagetti, Hansen, Sargent, and Williams, 2002; Hansen, 2014; Bidder and Dew-Becker, 2016). In particular, model uncertainty is intrinsic to climate change and thus is an essential element in climate economics (e.g., Brock and Hansen, 2019; Barnett, Brock, and Hansen, 2020; Diebold and Rudebusch, 2021). In practice, constructing statistically valid uncertainty sets of structural models is also useful for formal econometric analysis accounting for model misspecifications (e.g., Andrews, Gentzkow, and Shapiro, 2017; Cheng, Liao, and Shi, 2019; Bonhomme and Weidner, 2020; Arm

Although we focus on a real-data application on structural asset pricing models in the paper, we emphasize that the proposed conditional specification test can also be applied to the setting of linear asset pricing models studied by Kan and Zhang (1999), Kleibergen (2009), Beaulieu, Dufour, and Khalaf (2013), Beaulieu, Dufour, and Khalaf (2020), Gospodinov, Kan, and Robotti (2014), Burnside (2015); Kleibergen and Zhan (2015), Kleibergen and Zhan (2020), Anatolyev and Mikusheva (2020), Antoine, Proulx, and Renault (2020), Laurinaityte, Meinerding, Schlag, and Thimme (2020), and Manresa, Penaranda, and Sentana (2020).1 Recently, as a complementary contribution, a growing body of literature has started to apply machine learning techniques to evaluate linear asset pricing models (e.g., Kelly, Pruitt, and Su, 2019; Feng, Giglio, and Xiu, 2020; Giglio and Xiu, 2020).

Verifying the Baseline Moment Conditions. We now verify the baseline moment conditions. The first moment condition is:

\[
E[(\Delta c_t - g_c) + p\mu_1(\alpha)] = E[\sigma_c \varepsilon_{c,t+1} - \zeta_{t+1}] + p\mu_1(\alpha) \\
= -E[x_{t+1}(\psi + J_{t+1})] + p\mu_1(\alpha) \\
= -E[p_t] \mu_1(\alpha) + p\mu_1(\alpha) = 0. \tag{F.1}
\]

The second moment condition can be derived similarly. The third moment condition can also be easily verified as follows:

\[
E[(\Delta c_t - g_c)^2 - \sigma_c^2 - p\mu_2(\alpha)] = E[(\sigma_c \varepsilon_{c,t+1} - \zeta_{t+1})^2 - \sigma_c^2 - p\mu_2(\alpha)] \\
= E[\sigma_c^2 \varepsilon_{c,t+1}^2 + x_{t+1}(\psi + J_{t+1})^2] - \sigma_c^2 - p\mu_2(\alpha) \\
= E[p_t] \mu_2(\alpha) - p\mu_2(\alpha) = 0. \tag{F.2}
\]

1Instead of focusing on the test statistic itself, Lewellen, Nagel, and Shanken (2010), Daniel and Titman (2012), Ahn, Conrad, and Dittmar (2009), and Nagel and Singleton (2011) emphasize and propose new methods for constructing informative test assets to increase the power of testing linear factor models.
The fourth moment condition can be verified in the same way. The fifth moment condition is verified below.

\[
E \left[ \Delta c_{t-1} \left[ \Delta c_{t+1} - \rho \Delta c_t + (1 - \rho)(p\mu_1(\alpha) - g_c) \right] \right] \\
= E \left[ \Delta c_{t-1} \left[ (\sigma_c \varepsilon_{c,t+1} - \zeta_{t+1}) - \rho(\sigma_c \varepsilon_{c,t} - \zeta_t) + (1 - \rho)p\mu_1(\alpha) \right] \right]. \tag{F.3}
\]

The law of iterated expectation further leads to

\[
E \left[ \Delta c_{t-1} \left[ (\sigma_c \varepsilon_{c,t+1} - \zeta_{t+1}) - \rho(\sigma_c \varepsilon_{c,t} - \zeta_t) + (1 - \rho)p\mu_1(\alpha) \right] \right] \\
= -E \left[ \Delta c_{t-1} E_{t-1} \left[ \zeta_{t+1} - \rho \zeta_t - (1 - \rho)p\mu_1(\alpha) \right] \right] \\
= -E \left[ \Delta c_{t-1} E_{t-1} \left[ x_{t+1}(v + J_{t+1}) - \rho x_t(v + J_t) - (1 - \rho)p\mu_1(\alpha) \right] \right]. \tag{F.4}
\]

Applying again the law of iterated expectation leads to

\[
E \left[ \Delta c_{t-1} E_{t-1} \left[ x_{t+1}(v + J_{t+1}) - \rho x_t(v + J_t) - (1 - \rho)p\mu_1(\alpha) \right] \right] \\
= E \left[ \Delta c_{t-1} E_{t-1} \left[ x_{t+1}(v + J_{t+1}) - \rho p_{t-1} \mu_1(\alpha) - (1 - \rho)p\mu_1(\alpha) \right] \right] \\
= E \left[ \Delta c_{t-1} E_{t-1} \left[ p_t - \rho p_{t-1} - (1 - \rho)p \right] \right] \mu_1(\alpha) \\
= E \left[ \Delta c_{t-1} E_{t-1} \left[ \sigma_p p \varepsilon_{p,t} \right] \right] \mu_1(\alpha) = 0. \tag{F.5}
\]

The sixth moment condition can be verified in the same way.

**Model Solution.** We next derive the equilibrium of the model. Because the EIS coefficient is one, the first-order condition of optimal consumption leads to 

\[
C_t = (1 - \delta) W_t. \tag{F.6}
\]

where \( I(p_t) \) is a deterministic function of \( p_t \), capturing the marginal value of net worth. The specification of the dynamics is consistent with the exponential-affine models, and thus, we further conjecture that

\[
I(p_t) = e^{I_0 + I_1 p_t}, \tag{F.7}
\]

with constants \( I_0 \) and \( I_1 \) to be determined by the equilibrium conditions.

The constants \( I_0 \) and \( I_1 \) can be solved by plugging (F.6) and (F.7) into the recursive value function relation. Specifically, it holds that

\[
I_0 + I_1 p_t + \ln C_t = (1 - \delta) \ln C_t + (1 - \gamma)^{-1} \delta \ln E_t \left[ e^{(1-\gamma)(I_0 + I_1 p_{t+1}) C_{t+1}^{1-\gamma}} \right]. \tag{F.8}
\]
The relation above can be rewritten as

\[ I_0 + I_1 p_t = \delta [I_0 + I_1 (1 - \rho)p + I_1 \rho p_t + g_c] + \frac{1}{2} \delta (1 - \gamma) (I_1^2 \sigma_p^2 p^2 + \sigma_c^2) \]

\[ + (1 - \gamma)^{-1} \delta \left[ I_{(p_t \geq 0)p_t} \ell(\alpha, \gamma - 1) - I_{(p_t < 0)p_t} \ell(\alpha, 1 - \gamma) \right] , \tag{F.9} \]

with \( \ell(\alpha, x) \equiv e^{\Delta x \cdot \alpha - x} - 1. \)

Because \( I_{(p_t < 0)p_t} \approx 0 \) under the relevant calibrations, we can rewrite (F.9) as

\[ I_0 + I_1 p_t \approx \delta [I_0 + I_1 (1 - \rho)p + I_1 \rho p_t + g_c] + \frac{1}{2} \delta (1 - \gamma) (I_1^2 \sigma_p^2 p^2 + \sigma_c^2) \]

\[ + (1 - \gamma)^{-1} \delta I_{(p_t \geq 0)p_t} \ell(\alpha, \gamma - 1) . \tag{F.10} \]

By matching the constant term and \( p_t \) term, we obtain that

\[ I_1 \approx \delta I_1 \rho + (1 - \gamma)^{-1} \delta \ell(\alpha, \gamma - 1) \tag{F.11} \]

\[ I_0 \approx \delta I_0 + \delta I_1 (1 - \rho)p + g_c + \frac{1}{2} \delta (1 - \gamma) (I_1^2 \sigma_p^2 p^2 + \sigma_c^2) . \tag{F.12} \]

Equation (F.11) has one root, which is the solution for \( I_1 \) in equilibrium:

\[ I_1 = \frac{\ell(\alpha, \gamma - 1)}{(1 - \gamma)(\delta^{-1} - \rho)} . \tag{F.13} \]

Thus, after plugging (F.13) into (F.12), we can obtain the solution for \( I_0 \) in equilibrium:

\[ I_0 = \frac{\delta}{1 - \delta} \left[ I_1 (1 - \rho)p + g_c + \frac{1}{2} (1 - \gamma)(I_1^2 \sigma_p^2 p^2 + \sigma_c^2) \right] . \tag{F.14} \]

The equilibrium stochastic discount factor (SDF) is

\[ M_{t+1} = \delta \left( \frac{C_{t+1}}{C_t} \right)^{-1} \frac{V_{t+1}^{1-\gamma}}{E_t [V_{t+1}^{1-\gamma}]} . \tag{F.15} \]

Thus, by combining (F.6), (F.7), (F.13), and (F.14), the SDF expression in (F.15) can be rewritten as follows:

\[ M_{t+1} = \delta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \frac{e^{(1-\gamma)(I_0 + I_1 p_{t+1})}}{E_t [e^{(1-\gamma)(I_0 + I_1 p_{t+1})}(C_{t+1}/C_t)^{1-\gamma}]} \]

\[ = \delta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \frac{e^{(1-\gamma)(I_0 + I_1 (1-\rho)p + I_1 \rho p_t + I_1 \sigma_p p_{t+1})}}{E_t [e^{(1-\gamma)(I_0 + I_1 p_{t+1})}(C_{t+1}/C_t)^{1-\gamma}]} . \tag{F.16} \]
Here, the expected value function with power $1 - \gamma$ can be computed as follows:

\[
\mathbb{E}_t \left[ e^{(1-\gamma) (I_{t0} + I_{1,t}^p + 1)} (C_{t+1} / C_t)^{1-\gamma} \right] \\
= \mathbb{E}_t \left[ e^{(1-\gamma) (I_{t0} + I_{1,t} (1 - \rho) p + I_{1,tp} + I_{1,t} \sigma_p \sigma_p \varepsilon_{p,t+1} + g_c + \sigma_c \varepsilon_{c,t+1} + z_{t+1})} \right] \\
= e^{(1-\gamma) (I_{t0} + I_{1,t} (1 - \rho) p + I_{1,tp} + g_c) + \frac{1}{2} (1 - \gamma)^2 (I_{1,t}^2 \sigma_p^2 p^2 + \sigma_c^2) \mathbb{E}_t \left[ e^{-(1-\gamma) z_{t+1}} \right]} \\
= e^{(1-\gamma) (I_{t0} + I_{1,t} (1 - \rho) p + I_{1,tp} + g_c) + \frac{1}{2} (1 - \gamma)^2 (I_{1,t}^2 \sigma_p^2 p^2 + \sigma_c^2) \left[ 1 + p_t \ell(\alpha, \gamma - 1) \right].}
\] (F.17)

After plugging in the equilibrium value function and rearranging the terms, we get the log SDF, denoted by $m_{t+1} \equiv \ln M_{t+1}$ as follows:

\[
m_{t+1} = \ln \delta - \gamma (g_c + \sigma_c \varepsilon_{c,t+1} - \zeta_{t+1}) + (1 - \gamma) I_1 \sigma_p \varepsilon_{p,t+1} - \gamma g_c - \frac{1}{2} (1 - \gamma)^2 (I_{1,t}^2 \sigma_p^2 p^2 + \sigma_c^2) - p_t \ell(\alpha, \gamma - 1).
\] (F.18)

Re-arranging terms leads to

\[
m_{t+1} = \Gamma_0 + \Gamma_1 p_t - \lambda_c \sigma_c \varepsilon_{c,t+1} - \lambda_p \sigma_p \varepsilon_{p,t+1} + \lambda_\zeta \zeta_{t+1},
\] (F.19)

where the predictive coefficients are

\[
\Gamma_0 = \ln \delta - g_c - \frac{1}{2} (1 - \gamma)^2 (I_{1,t}^2 \sigma_p^2 p^2 + \sigma_c^2)
\]
\[
\Gamma_1 = -\ell(\alpha, \gamma - 1),
\] (F.20)

and the loading coefficients are

\[
\lambda_c = \gamma, \quad \lambda_p = (\gamma - 1) I_1, \quad \lambda_\zeta = \gamma.
\] (F.21)

The log risk-free rate, denoted by $r_{f,t} = -\ln \mathbb{E}_t [M_{t+1}]$, is

\[
r_{f,t} = -\ln \mathbb{E}_t [e^{m_{t+1}}] \\
= -\Gamma_0 - \frac{1}{2} (\lambda_c^2 \sigma_c^2 + \lambda_p^2 \sigma_p^2 p^2) - \left[ \Gamma_1 + \ell(\alpha, \lambda_\zeta) \right] p_t \\
= -\ln \delta + g_c - \frac{1}{2} (2 \gamma - 1) \sigma_c^2 - \left[ \ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1) \right] p_t.
\] (F.22)

Using the Campbell-Shiller decomposition and log-linearization approximation, we can represent the log return in terms of log price-dividend ratio and log dividend growth:

\[
r_{m,t+1} = \kappa_{m,0} + \kappa_{m,1} z_{m,t+1} + \Delta d_{t+1} - z_{m,t},
\] (F.23)
where

\[
\kappa_{m,0} = \ln(1 + e^{\overline{z}_m}) - \kappa_{m,1} \overline{z}_m
\]  

(F.24)

and

\[
\kappa_{m,1} = \frac{e^{\overline{z}_m}}{1 + e^{\overline{z}_m}}
\]  

(F.25)

and \(\overline{z}_m\) is long-run mean of market log price-dividend ratio.

Using the log-linearization approximation, we search the equilibrium characterized by

\[
z_{m,t} = A_{m,0} + A_{m,1} p_t,
\]  

(F.26)

where the constants \(A_{m,0}\) and \(A_{m,1}\) can be computed recursively as follows.

Define the period-\(t\) price of the dividend strip paid at the period \(t + n\) as \(H(D_t, p_t, n) = \mathbb{E}_t [M_{t,t+n}D_{t+n}]\) where \(M_{t,t+n} \equiv e^{\sum_{i=1}^{n} m_{t+i}}\). The price function \(H(D_t, p_t, n)\) satisfies the following recursive relations:

\[
H(D_t, p_t, n) = \mathbb{E}_t \left[ e^{\Delta D_{t+1} + \Delta m_{t+1} + A_{n-1} + B_{n-1} p_{t+1}} \right]
\]  

(F.27)

\[
H(D_t, p_t, 0) = D_t
\]  

(F.28)

for arbitrary \(t\) and \(n \geq 1\).

We conjecture that \(H(D_t, p_t, n) = D_t e^{A_n + B_n p_t}\). Then, the recursive relations in (F.27) and (F.28) can be rewritten as follows:

\[
e^{A_n + B_n p_t} = \mathbb{E}_t \left[ e^{\Delta D_{t+1} + \Delta m_{t+1} + A_{n-1} + B_{n-1} p_{t+1}} \right]
\]

\[
= \mathbb{E}_t \left[ e^{\sum_{i=1}^{n} (g_{d,i} + \phi \sigma_{c,i} \epsilon_{c,i} - \phi \zeta_{t+1}) + (\Gamma_0 + \Gamma_1 p_t - \lambda \sigma_{c} \epsilon_{c,t+1} - \lambda \sigma_{p} p_{t+1} + \lambda \zeta_{t+1}) + (A_{n-1} + B_{n-1} p_{t+1})} \right]
\]

\[
= e^{\tilde{A}_n + \tilde{B}_n p_t} \mathbb{E}_t \left[ e^{\sum_{i=1}^{n} (g_{d,i} + \phi \sigma_{c,i} \epsilon_{c,i} - \phi \zeta_{t+1}) + (\Gamma_0 + \Gamma_1 p_t - \lambda \sigma_{c} \epsilon_{c,t+1} - \lambda \sigma_{p} p_{t+1} + \lambda \zeta_{t+1})} \right]
\]

\[
= e^{\tilde{A}_n + \tilde{B}_n p_t + \frac{1}{2} (\phi - \gamma)^2 \sigma_{c}^2 + \frac{1}{2} (B_{n-1} - (\gamma - 1) I) \sigma_{p}^2 \mathbb{E}_t \left[ e^{\sum_{i=1}^{n} (g_{d,i} + \phi \sigma_{c,i} \epsilon_{c,i} - \phi \zeta_{t+1})} \right]}
\]  

(F.29)

where \(\tilde{A}_n = g_{d} + \Gamma_0 + A_{n-1} + B_{n-1} (1 - \rho) p\), and \(\tilde{B}_n = \Gamma_1 + B_{n-1} \rho\).

The moment generating function of \(\zeta_{t+1}\) gives

\[
\ln \mathbb{E}_t \left[ e^{\sum_{i=1}^{n} (g_{d,i} + \phi \sigma_{c,i} \epsilon_{c,i} - \phi \zeta_{t+1})} \right] \approx p_t \ell(\alpha, \gamma - \phi).
\]  

(F.30)
Thus, $A_n$ has the following recursive relation:

$$
A_n = \tilde{A}_n + \frac{1}{2} (\phi - \gamma)^2 \sigma_c^2 + \frac{1}{2} \left[ B_{n-1} - (\gamma - 1) I_1 \right]^2 \sigma_p^2 p^2
$$

$$
= g_d + \Gamma_0 + A_{n-1} + B_{n-1} (1 - \rho) p + \frac{1}{2} (\phi - \gamma)^2 \sigma_c^2 + \frac{1}{2} \left[ B_{n-1} - (\gamma - 1) I_1 \right]^2 \sigma_p^2 p^2
$$

$$
= \ln \delta + (g_d - g_c) - \frac{1}{2} (1 - \gamma)^2 \left( I_1^2 \sigma_p^2 p^2 + \sigma_c^2 \right) + \frac{1}{2} (\phi - \gamma)^2 \sigma_c^2
$$

$$
+ A_{n-1} + B_{n-1} (1 - \rho) p + \frac{1}{2} \left[ B_{n-1} - (\gamma - 1) I_1 \right]^2 \sigma_p^2 p^2, \quad (F.31)
$$

and $B_n$ has the following recursive relation:

$$
B_n = \tilde{B}_n + \ell (\alpha, \gamma - \phi)
$$

$$
= \rho B_{n-1} + \ell (\alpha, \gamma - \phi) - \ell (\alpha, \gamma - 1), \quad (F.32)
$$

with initial values $A_0 = B_0 = 0$.

Therefore, it holds that

$$
B_n = \frac{1 - \rho^n}{1 - \rho} \left[ \ell (\alpha, \gamma - \phi) - \ell (\alpha, \gamma - 1) \right]. \quad (F.33)
$$

Because $\sigma_p^2 p \approx 0$, equation (F.35) can be rewritten as

$$
A_n - A_{n-1} \approx \ln \delta + (g_d - g_c) + \frac{1}{2} (\phi - 1) (\phi + 1 - 2\gamma) \sigma_c^2
$$

$$
+ (1 - \rho^n) \left[ \ell (\alpha, \gamma - \phi) - \ell (\alpha, \gamma - 1) \right] p. \quad (F.34)
$$

Thus, it holds that

$$
A_n = n \ln \bar{\delta} - \frac{1 - \rho^n}{1 - \rho} \left[ \ell (\alpha, \gamma - \phi) - \ell (\alpha, \gamma - 1) \right] p, \quad (F.35)
$$

where $\bar{\delta}$ is referred to as the effective time preference coefficient (Barro, 2009), and the log of the effective time preference coefficient is equal to

$$
\ln \bar{\delta} \equiv \ln \delta + (g_d - g_c) + \frac{1}{2} (\phi - 1) (\phi + 1 - 2\gamma) \sigma_c^2 + [\ell (\alpha, \gamma - \phi) - \ell (\alpha, \gamma - 1)] p. \quad (F.36)
$$

Therefore, the log price-dividend ratio is

$$
z_{m,t} = \ln \left[ \sum_{n=1}^{+\infty} e^{A_n + B_n p t} \right]. \quad (F.37)
$$
According to Taylor expansion in terms of $p_t$ around $p$, it follows that

$$A_{m,0} = \ln \left[ \sum_{n=1}^{+\infty} e^{A_n + B_n p} \right] - A_{m,1} p$$

and

$$A_{m,1} = \frac{\sum_{n=1}^{+\infty} B_n e^{A_n + B_n p}}{\sum_{n=1}^{+\infty} e^{A_n + B_n p}}.$$

(F.38)

And thus, it holds that

$$A_{m,1} = \frac{1}{1 - \rho} \left[ \ell(\alpha, \gamma - \phi) - \ell(\alpha, \gamma - 1) \right] - \sum_{n=1}^{+\infty} \frac{e^{n(\ln \bar{\delta} + \ln \rho)}}{\sum_{n=1}^{+\infty} e^{n \ln \bar{\delta}}} \frac{1}{1 - \rho} \left[ \ell(\alpha, \gamma - \phi) - \ell(\alpha, \gamma - 1) \right]$$

$$= \frac{1}{1 - \rho} \left[ \frac{1 - \rho}{1 - \rho} \right] \left[ \ell(\alpha, \gamma - \phi) - \ell(\alpha, \gamma - 1) \right]$$

$$= \frac{1 - \rho}{(1 - \rho)(1 - \rho \bar{\delta})} \left[ \ell(\alpha, \gamma - \phi) - \ell(\alpha, \gamma - 1) \right]$$

$$= \frac{1 - \rho}{1 - \rho \bar{\delta}} \left[ \ell(\alpha, \gamma - \phi) - \ell(\alpha, \gamma - 1) \right].$$

(F.39)

In principle, the persistence parameter $\rho$ can be infinitely close to 1, and thus, we require the effective time preference coefficient to be less than one (i.e., $\bar{\delta} < 1$).

According to (F.33) and (F.35), it follows that

$$A_{m,0} = \ln \left[ \sum_{n=1}^{\infty} e^{n \ln \bar{\delta}} \right] - A_{m,1} p$$

$$= \ln \left[ \frac{\bar{\delta}}{1 - \bar{\delta}} \right] - A_{m,1} p,$$

(F.40)

and the long-run average log price-dividend ratio is

$$\bar{z}_m = A_{m,0} + A_{m,1} p = \ln \left[ \frac{\bar{\delta}}{1 - \bar{\delta}} \right].$$

(F.41)

Plugging back into (F.25), we obtain that

$$\kappa_{m,1} = \bar{\delta} = \delta e^{(g_d - g_c) + \frac{1}{2} \phi (\phi - 1)(\phi + 1 - 2\gamma) \sigma_c^2 + \ell(\alpha, \gamma - \phi) - \ell(\alpha, \gamma - 1)} p.$$

(F.42)

Because $\sigma_c^2 \approx 0$ and $p \approx 0$, the following approximation works well for relevant parameter regions:

$$\kappa_{m,1} = \bar{\delta} \approx \delta e^{(g_d - g_c)}.$$

(F.43)
According to (F.23) and (F.26), the log market return can be rewritten as

$$r_{m,t+1} - E_t[r_{m,t+1}] = \beta_c \sigma_c \varepsilon_{c,t+1} + \beta_p \sigma_p \varepsilon_{p,t+1} - \beta_\zeta (\zeta_{t+1} - p_t \mu_1(\alpha)),$$  (F.44)

where $\beta_c = \phi$, $\beta_p = \kappa_m A_m$, and $\beta_\zeta = \phi$. The Euler equation for the log market return is

$$1 = E_t[e^{r_{m,t+1} + m_{t+1}}],$$  (F.45)

which leads to

$$E_t[e^{m_{t+1}}] = E_t[e^{r_{m,t+1} - r_f, t + m_{t+1}}].$$  (F.46)

It further leads to

$$e^{E_t[m_{t+1} + \frac{1}{2} [\gamma^2 \sigma_c^2 + \lambda^2 \sigma_p^2 p^2] - \gamma p_t \mu_1(\alpha)] E_t[\gamma \zeta_{t+1}]} = e^{E_t[m_{t+1} + E_t[r_{m,t+1} - r_f, t + m_{t+1} + \frac{1}{2} [\phi(\gamma)^2 \sigma_c^2 + (\beta_p - \lambda p)^2 \sigma_p^2 p^2] - (\gamma - \phi) p_t \mu_1(\alpha)] E_t[\gamma(\gamma - \phi) \zeta_{t+1}]].}$$  (F.47)

Finally, rearranging terms leads to

$$E_t[r_{m,t+1} - r_f, t] = \phi \gamma \sigma_c^2 + \beta_p \lambda p \sigma_p^2 p^2 + [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - \phi) - \phi \mu_1(\alpha)] p_t - \frac{1}{2} (\phi^2 \sigma_c^2 + \beta_p^2 \sigma_p^2 p^2).$$

Now, we derive the yield of the defaultable government bond, denoted by $y_{b,t}$, and we express the log government bond return as follows:

$$r_{b,t+1} = y_{b,t} - x_{b,t+1}(\gamma + J_{t+1}).$$  (F.48)

A default on the government bond occurs with probability $q$ conditional on the occurrence of a disaster. Thus, by definition, it holds that

$$E_t[r_{b,t+1}] = y_{b,t} - p_t q \mu_1(\alpha).$$  (F.49)

According to the Euler equation of the defaultable government bond and the risk-free bond, it holds that

$$E_t[e^{m_{t+1} + r_{b,t+1} - r_f, t}] = E_t[e^{m_{t+1}}].$$  (F.50)
Some calculations show that the following relation approximately holds:

\[
\begin{align*}
\ln \mathbb{E}_t \left[ e^{r_{m,t+1} + r_{b,t+1} - r_{f,t}} \right] &= \Gamma_0 + \Gamma_1 p_t + y_{b,t} - r_{f,t} + \frac{1}{2} \gamma^2 \sigma_c^2 + \frac{1}{2} \lambda^2 p^2 \sigma_p^2 + \ln \mathbb{E}_t \left[ e^{\gamma^2 (x_{t+1} + 1 - x_{b,t+1})} \right] \\
&= \Gamma_0 + \Gamma_1 p_t + y_{b,t} - r_{f,t} + \frac{1}{2} \gamma^2 \sigma_c^2 + \frac{1}{2} \lambda^2 p^2 \sigma_p^2 + [(1 - q) \ell(\alpha, \gamma) + q \ell(\alpha, \gamma - 1)] p_t. \tag{F.51}
\end{align*}
\]

Combining (F.22), (F.50), and (F.52), it follows that

\[
y_{b,t} - r_{f,t} = q [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1)] p_t. \tag{F.52}
\]

Further, putting (F.49) and (F.53) together, we obtain the following relation:

\[
\mathbb{E}_t [r_{b,t+1}] - r_{f,t} = q [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1) - \mu_1(\alpha)] p_t. \tag{F.53}
\]

Therefore, the conditional mean of excess log returns of the market portfolio relative to the defaultable government bill is

\[
\mathbb{E}_t [r_{m,t+1} - r_{b,t+1}] = \phi \gamma \sigma_c^2 + \beta p \lambda \sigma_p^2 + [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - \phi) - \phi \mu_1(\alpha)] p_t \tag{F.54}
\]

and the conditional variance of excess returns of the market portfolio relative to the defaultable government bill is

\[
\mathbb{V}ar_t [r_{m,t+1} - r_{b,t+1}] = \phi^2 \sigma_c^2 + \beta^2 p^2 \sigma_p^2 + (\phi^2 - 2\phi q + q) p_t \mu_2(\alpha) - (\phi - q)^2 p_t^2 \mu_1(\alpha)^2. \tag{F.55}
\]

**Verifying the Asset Pricing Moment Conditions.** Lastly, we verify the asset pricing moment conditions. The first moment condition is the expected log return of defaultable government bills:

\[
\mathbb{E} [r_{b,t}] - \omega_1(\vartheta) = (\mathbb{E} [r_{b,t}] - r_{f,t-1}) + r_{f,t-1} - \omega_1(\vartheta). \tag{F.56}
\]
Plugging (F.22) and (F.54) into the equation above, it follows that

\[ E[r_{b,t} - \omega_1(\vartheta)] = q [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1) - \mu_1(\alpha)] E[p_{t-1}] \]

\[ \quad - \ln \delta + g_c - \frac{1}{2}(2\gamma - 1)\sigma_c^2 - [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1)] E[p_{t-1}] - \omega_1(\vartheta) \]

\[ = - \ln \delta + g_c - \frac{1}{2}(2\gamma - 1)\sigma_c^2 - (1 - q)p [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1)] - qp\mu_1(\alpha) - \omega_1(\vartheta) \]

\[ = - \ln \delta + g_c - \frac{1}{2}(2\gamma - 1)\sigma_c^2 - qp\mu_1(\alpha) - (1 - q)h_1(\vartheta) \frac{p}{\alpha - \gamma} - \omega_1(\vartheta) \]

\[ = 0, \quad \text{(F.57)} \]

where \( h_1(\vartheta) \equiv \alpha \left[ e^{\vartheta \gamma} - e^{(\vartheta - 1)\gamma} \frac{\alpha - \gamma}{\alpha - \gamma + 1} \right] \).

The second asset pricing moment condition is the unconditional variance of the log government bill return:

\[ E[r_{b,t} - \omega_1(\vartheta)]^2 - \omega_2(\vartheta) = \text{Var} \left[ E_{t-1}(r_{b,t}) \right] + E \left[ \text{Var}_{t-1}(r_{b,t}) \right] - \omega_2(\vartheta) \quad \text{(F.58)} \]

Plugging in the equilibrium expressions for \( \text{Var} \left[ E_{t-1}(r_{b,t}) \right] \) and \( E \left[ \text{Var}_{t-1}(r_{b,t}) \right] \), the equation above can further lead to

\[ E[r_{b,t} - \omega_1(\vartheta)]^2 - \omega_2(\vartheta) = \]

\[ = [(1 - q)(\ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1)) + qp\mu_1(\alpha)]^2 \frac{\sigma_p^2 \rho^2}{1 - \rho^2} \]

\[ + qp\mu_2(\alpha) - q^2 p^2 \mu_1(\alpha)^2 \left( 1 + \frac{\sigma_p^2}{1 - \rho^2} \right) - \omega_2(\vartheta). \quad \text{(F.59)} \]

According to the definition of the function \( \omega_2(\vartheta) \) and the equation above, it follows that

\[ E[r_{b,t} - \omega_1(\vartheta)]^2 - \omega_2(\vartheta) = 0. \quad \text{(F.60)} \]

The third asset pricing moment condition is the unconditional mean of the excess log market return relative to the defaultable government bills. The excess log market return is

\[ r_{m,t}^e = \mathbb{E}_{t-1} \left[ r_{m,t}^e \right] + \phi \sigma_c \varepsilon_{c,t} + \beta_p \sigma_p \sqrt{p} \varepsilon_{p,t} \]

\[ - \phi \left[ x_t(\underline{\gamma} + J_t) - p_{t-1}\mu_1(\alpha) \right] + \left[ x_{b,t}(\underline{\gamma} + J_t) - qp_{t-1}\mu_1(\alpha) \right] , \quad \text{(F.61)} \]
Therefore, the unconditional mean of excess log market returns is

$$\mathbb{E}_{t-1}[r^e_{m,t}] = \phi \gamma \sigma_c^2 + \beta_p \lambda_p \sigma_p^2 p^2 + [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - \phi) - \phi \mu_1(\alpha)] p_{t-1}$$

$$- \frac{1}{2} \left( \phi^2 \sigma_c^2 + \beta_p^2 \sigma_p^2 p^2 \right) - q [\ell(\alpha, \gamma) - \ell(\alpha, \gamma - 1) - \mu_1(\alpha)] p_{t-1}. \quad (F.62)$$

The unconditional mean of the conditional variance is

$$\mathbb{E}[r^e_{m,t}] = h_0(\theta) + h_3(\theta) \frac{p}{\alpha - \gamma}, \quad (F.63)$$

where

$$h_0(\theta) = \phi \gamma \sigma_c^2 + \beta_p \lambda_p \sigma_p^2 p^2 - \frac{1}{2} \left( \phi^2 \sigma_c^2 + \beta_p^2 \sigma_p^2 p^2 \right),$$

$$h_3(\theta) = \alpha \left[ (1 - q)e^{\mu \gamma} - e^{\mu(\gamma-\phi)} \frac{\alpha - \gamma}{\alpha - \gamma + \phi} + q e^{\mu(\gamma-1)} \frac{\alpha - \gamma}{\alpha - \gamma + 1} \right] - (\alpha - \gamma)(\phi - q) \mu_1(\alpha).$$

The fourth asset pricing moment condition is the unconditional variance of the excess log market return relative to the defaultable government bills. The unconditional variance has the following decomposition:

$$\mathbb{V}ar[r^e_{m,t+1}] = \mathbb{E}[\mathbb{V}ar_t(r^e_{m,t+1})] + \mathbb{V}ar[\mathbb{E}_t(r^e_{m,t+1})]. \quad (F.64)$$

The unconditional mean of the conditional variance is

$$\mathbb{E}[\mathbb{V}ar_t(r^e_{m,t+1})] = \mathbb{E} [\phi^2 \sigma_c^2 + \beta_p^2 \sigma_p^2 p^2 + p_t(q - 2\phi q + \phi^2) \mu_2(\alpha) - p_t^2(q - \phi)^2 \mu_1(\alpha)^2] \quad (F.65)$$

$$= \phi^2 \sigma_c^2 + \beta_p^2 \sigma_p^2 p^2 + (q - 2\phi q + \phi^2) \mu_2(\alpha) p - (q - \phi)^2 \mu_1(\alpha)^2 \left( \frac{\sigma_p^2 p^2}{1 - \rho^2} + p^2 \right).$$

The unconditional variance of the conditional mean is

$$\mathbb{V}ar[\mathbb{E}_t(r^e_{m,t+1})] = \mathbb{V}ar \left[ ((1 - q)\ell(\alpha, \gamma) - \ell(\alpha, \gamma - \phi) + q \ell(\alpha, \gamma - 1) - (\phi - q) \mu_1(\alpha)) p_t \right]$$

$$= \left[ (1 - q)\ell(\alpha, \gamma) - \ell(\alpha, \gamma - \phi) + q \ell(\alpha, \gamma - 1) - (\phi - q) \mu_1(\alpha) \right]^2 \frac{\sigma_p^2 p^2}{1 - \rho^2}$$

$$= h_3(\theta)^2 \left( \frac{1}{\alpha - \gamma} \frac{\sigma_p^2 p^2}{1 - \rho^2} \right). \quad (F.66)$$

The sixth asset pricing moment condition can be derived as follows, and the fifth asset pricing moment can be derived similarly. The excess log market return in period $t+1$ is

$$r^e_{m,t+1} = h_0(\theta) + h_3(\theta) \frac{p_t}{\alpha - \gamma} + e_{t+1}, \quad (F.67)$$

where $e_{t+1}$ is a random variable such that $\mathbb{E}_t[e_{t+1}] = 0$. Thus, the excess log market return in
period $t + 1$ can further expressed in terms of $p_{t-1}$:

$$r_{m,t+1}^e = h_0(\theta) + h_3(\theta)(\alpha - \gamma)^{-1} [(1 - \rho)p + \rho p_{t-1} + \sigma_p \varepsilon_{p,t}] + \varepsilon_{t+1}$$

$$= h_0(\theta) + h_3(\theta) \frac{p}{\alpha - \gamma} + h_3(\theta)(\alpha - \gamma)^{-1} \rho (p_{t-1} - p) + \tilde{\varepsilon}_t,$$

where $\mathbb{E}_{t-1}[\tilde{\varepsilon}_t] = 0$ with $\tilde{\varepsilon}_t \equiv h_3(\theta)(\alpha - \gamma)\sigma_p \varepsilon_{p,t} + \varepsilon_{t+1}$.

The log price-dividend ratio is

$$z_{m,t} - \bar{z}_m = \frac{1}{1 - \rho \delta} h_2(\theta)(p_t - p).$$

(F.69)

Plugging (F.70) into (F.69), it follows that

$$r_{m,t+1}^e = \omega_3(\theta) + \frac{\rho(1 - \rho \delta)}{\alpha - \gamma} h_2(\theta)^{-1} h_3(\theta)(z_{m,t-1} - \bar{z}_m) + \tilde{\varepsilon}_t.$$

Therefore, according to the definition of $\omega_6(\theta)$ and the equation above, the asset pricing moment condition follows,

$$\mathbb{E}_{t-1} [r_{m,t+1}^e - \omega_6(\theta)(z_{m,t-1} - \bar{z}_m) - \omega_3(\theta)] = 0.$$

(F.71)

G Robustness Check for the Simulation Result

In Figure 1 of the main text, for each model, the true value of $\theta$ and its parameter space are both calibrated based on the asset pricing moment condition, which links the equity premium to the structural parameter $\theta$. Specifically, the true value of $\theta$ is calibrated to match an annual equity premium of 6% and the bounds of the parameter spaces are calibrated to match 3% and 9%. Here we report a figure similar to Figure 1 of the main text, but the parameter spaces for both models are calibrate to match equity premium between 2% and 10%, as robustness checks. Compared to Figure 1 of the main text, this additional figure demonstrates similar patterns. For each test, the level of the local power does slightly vary with the parameter space because the baseline moments are nearly flat.

References


Figure 1: Parameter space calibrated with equity premium between 2% and 10%

Note: Panels A and B plot the rejection probabilities of three different specification tests for the simulation study on the rare-disaster risk and long-run risk model, respectively. In both panels, the solid curve represents the rejection probability of the conditional specification test; the dashed curve represents the rejection probability of the $J$ test; the dotted curve represents the rejection probability of the $C$ test; and the bold solid horizontal line represents the 5% nominal size for all three specification tests.


