

Supplementary Document  
for  
**VALUE AT RISK FOR INTEGRATED RETURNS  
AND ITS APPLICATIONS TO EQUITY PORTFOLIOS**

Hwai-Chung Ho<sup>a,b</sup>, Hung-Yin Chen<sup>a</sup>, and Henghsiu Tsai<sup>a</sup>

<sup>a</sup>Academia Sinica and <sup>b</sup>National Taiwan University

**Supplementary Material**

## S1 Proof of Theorem 1

**Proof of Theorem 1.** Let  $\mathcal{V}_T$  denote the  $\sigma$ -field generated by  $\{v_{i,t} : 1 \leq i \leq m, 1 \leq t \leq T\}$ . Because  $U_t = (u_{1,t}, \dots, u_{m,t})'$  is an iid vector independent from  $\mathcal{V}_T$  and

$$\sum_{i,j=1}^m w_i w_j \left( \sum_{t=1}^T v_{i,t} v_{j,t} E u_{i,t} u_{j,t} \right) / T \longrightarrow \sigma^2$$

with probability one by the law of large numbers,

$$\begin{aligned} & P \left( T^{-1/2} \sum_{t=1}^T (\tilde{r}_t - \tilde{\mu}) \leq x \right) \\ &= E \left\{ P \left( T^{-1/2} \sum_{t=1}^T \left( \sum_{i=1}^m w_i v_{i,t} u_{i,t} \right) \leq x \mid \mathcal{V}_T \right) \right\} \\ &\longrightarrow E \{ \Phi(x/\sigma) \} = \Phi(x/\sigma). \end{aligned}$$

Then (8) follows. To prove (9), rewrite  $\sqrt{T}(\hat{\sigma}_T^2 - \sigma^2)$  as

$$\begin{aligned} \sqrt{T}(\hat{\sigma}_T^2 - \sigma^2) &= T^{-1/2} \sum_{t=1}^T [(\tilde{r}_t - \tilde{\mu})^2 - \sigma^2] + \sqrt{T}(\hat{\mu}_T - \tilde{\mu})^2 \\ &\quad - 2(\hat{\mu}_T - \tilde{\mu})T^{-1/2} \sum_{t=1}^T (\tilde{r}_t - \tilde{\mu}) \\ &= T^{-1/2} \sum_{t=1}^T [(\tilde{r}_t - \tilde{\mu})^2 - \sigma^2] + O_p(T^{-1/2}) \\ &\equiv C_T + O_p(T^{-1/2}) \end{aligned}$$

For a given  $M$ , we approximate  $C_T$  by

$$C_{T,M} = T^{-1/2} \sum_{t=1}^T \left[ \left( \sum_{i=1}^m w_i e^{Z_{i,t,M}} u_{i,t} \right)^2 - \sigma_M^2 \right],$$

where  $Z_{i,t,M} = \mu_{z,i} + \sum_{s=0}^M A_{s,i} \eta_{t-s}$  with  $A_{s,i} = (A_{i,1}^{(s)}, \dots, A_{i,m}^{(s)})'$  and  $\eta_t = (\eta_{1,t}, \dots, \eta_{m,t})'$  (cf. Equation (6)) and  $\sigma_M^2 = E(\sum_{i=1}^m w_i e^{Z_{i,t,M}} u_{i,t})^2$ . Since  $\sum_{i=1}^m w_i e^{Z_{i,t,M}} u_{i,t}$  is a  $m$ -dependent sequence,  $C_{T,M}$  is asymptotically normal. Following the same  $m$ -dependence argument used in proving Theorem-(i) of Ho (2006), we can show that the central limit theorem for  $C_T$  holds, which implies (9) and that the asymptotic variance  $g^2$  is the limit of  $Var(C_{T,M})$  (see also Ho and Hsing (1997)). To derive the explicit form of  $g^2$  under the normal assumption, we note that because  $\{U_t\}$  is an i.i.d. normal vector and is independent of  $\{Z_t\}$ ,

$$\begin{aligned} Var(C_T) &= Var \left( \frac{1}{\sqrt{T}} \sum_{t=1}^T \left\{ \sum_{i,j=1}^m w_i w_j e^{Z_{i,t} + Z_{j,t}} (u_{i,t} u_{j,t} - \sigma_{U,ij}) \right\} \right) \\ &\quad + Var \left( \frac{1}{\sqrt{T}} \sum_{t=1}^T \left\{ \sum_{i,j=1}^m w_i w_j e^{Z_{i,t} + Z_{j,t}} \sigma_{U,ij} - \sigma^2 \right\} \right) \\ &\equiv D_{T,1} + D_{T,2} \end{aligned}$$

We now compute  $D_{T,1}$  and  $D_{T,2}$  separately.

$$\begin{aligned} D_{T,1} &= \frac{1}{T} \sum_{t=1}^T E \left\{ \sum_{i,j=1}^m w_i w_j e^{Z_{i,t} + Z_{j,t}} (u_{i,t} u_{j,t} - \sigma_{U,ij}) \right\}^2 \\ &\quad + \frac{1}{T} \sum_{s \neq t} \sum_{i,j=1}^m E \left\{ \sum_{i,j=1}^m w_i w_j e^{Z_{i,t} + Z_{j,t}} (u_{i,t} u_{j,t} - \sigma_{U,ij}) \sum_{k,l=1}^m w_k w_l e^{Z_{k,s} + Z_{l,s}} (u_{k,s} u_{l,s} - \sigma_{U,kl}) \right\} \\ &= \sum_{i,j,k,l=1}^m w_i w_j w_k w_l E \left\{ e^{Z_{i,1} + Z_{j,1} + Z_{k,1} + Z_{l,1}} (u_{i,1} u_{j,1} - \sigma_{U,ij}) (u_{k,1} u_{l,1} - \sigma_{U,kl}) \right\} \\ &= \sum_{i,j,k,l=1}^m w_i w_j w_k w_l (\sigma_{U,ik} \sigma_{U,jl} + \sigma_{U,il} \sigma_{U,jk}) e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_4 \Sigma_Z(i,j,k,l) J_4}. \end{aligned}$$

$$\begin{aligned} D_{T,2} &= Var \left( \sum_{i,j=1}^m w_i w_j e^{Z_{i,1} + Z_{j,1}} \sigma_{U,ij} \right) \\ &\quad + \frac{2}{T} \sum_{1 \leq t < s \leq T} Cov \left( \sum_{i,j=1}^m w_i w_j e^{Z_{i,t} + Z_{j,t}} \sigma_{U,ij}, \sum_{k,l=1}^m w_k w_l e^{Z_{k,s} + Z_{l,s}} \sigma_{U,kl} \right). \end{aligned} \quad (S1.1)$$

The first term of (S1.1) is

$$\begin{aligned}
& \text{Var} \left( \sum_{i,j=1}^m w_i w_j e^{Z_{i,1} + Z_{j,1}} \sigma_{U,ij} \right) \\
&= E \left( \sum_{i,j=1}^m w_i w_j e^{Z_{i,1} + Z_{j,1}} \sigma_{U,ij} \right)^2 - \left( E \sum_{i,j=1}^m w_i w_j e^{Z_{i,1} + Z_{j,1}} \sigma_{U,ij} \right)^2 \\
&= \sum_{i,j,k,l=1}^m w_i w_j w_k w_l e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_4 \Sigma_Z(i,j,k,l) J_4} \sigma_{U,ij} \sigma_{U,kl} \\
&\quad - \sum_{i,j,k,l=1}^m w_i w_j w_k w_l e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_2 \{\Sigma_Z(i,j) + \Sigma_Z(k,l)\} J_2} \sigma_{U,ij} \sigma_{U,kl} \\
&= \sum_{i,j,k,l=1}^m w_i w_j w_k w_l e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_2 \{\Sigma_Z(i,j) + \Sigma_Z(k,l)\} J_2} \sigma_{U,ij} \sigma_{U,kl} (e^{\sigma_{Z,ik} + \sigma_{Z,il} + \sigma_{Z,jk} + \sigma_{Z,jl}} - 1).
\end{aligned}$$

The second term of (S1.1) is

$$\begin{aligned}
& \frac{2}{T} \sum_{1 \leq t < s \leq T} \text{Cov} \left( \sum_{i,j=1}^m w_i w_j e^{Z_{i,t} + Z_{j,t}} \sigma_{U,ij}, \sum_{k,l=1}^m w_k w_l e^{Z_{k,s} + Z_{l,s}} \sigma_{U,kl} \right) \\
&= \frac{2}{T} \sum_{r=1}^{T-1} \sum_{u=1}^r \sum_{i,j,k,l=1}^m w_i w_j w_k w_l \text{Cov} \left( e^{Z_{i,r+1-u} + Z_{j,r+1-u}}, e^{Z_{k,r+1} + Z_{l,r+1}} \right) \sigma_{U,ij} \sigma_{U,kl},
\end{aligned}$$

where, by the moment formula of log-normal random variable (see, for example, Taylor 1986, p. 74),

$$\begin{aligned}
& \text{Cov} \left( e^{Z_{i,r+1-u} + Z_{j,r+1-u}}, e^{Z_{k,r+1} + Z_{l,r+1}} \right) \\
&= E \left( e^{Z_{i,r+1-u} + Z_{j,r+1-u} + Z_{k,r+1} + Z_{l,r+1}} \right) - \left( E e^{Z_{i,r+1-u} + Z_{j,r+1-u}} \right) \left( E e^{Z_{k,r+1} + Z_{l,r+1}} \right) \\
&= e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_2 \{\Sigma_Z(i,j) + \Sigma_Z(k,l)\} J_2 + J'_2 \{\Sigma_{Z,\{(i,j),(k,l)\}}(-u)\} J_2} \\
&\quad - \left( e^{J'_2 \mu_z(i,j) + \frac{1}{2} J_2 \Sigma_Z(i,j) J_2} \right) \left( e^{J'_2 \mu_z(k,l) + \frac{1}{2} J_2 \Sigma_Z(k,l) J_2} \right) \\
&= e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_2 \{\Sigma_Z(i,j) + \Sigma_Z(k,l)\} J_2} \left( e^{J'_2 \{\Sigma_{Z,\{(i,j),(k,l)\}}(-u)\} J_2} - 1 \right).
\end{aligned}$$

The second term of (S1.1) then becomes

$$\begin{aligned}
& \frac{2}{T} \sum_{1 \leq t < s \leq T} \text{Cov} \left( \sum_{i,j=1}^m w_i w_j e^{Z_{i,t} + Z_{j,t}} \sigma_{U,ij}, \sum_{k,l=1}^m w_k w_l e^{Z_{k,s} + Z_{l,s}} \sigma_{U,kl} \right) \\
&= \frac{2}{T} \sum_{r=1}^{T-1} \sum_{u=1}^r \sum_{i,j,k,l=1}^m w_i w_j w_k w_l e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_2 \{\Sigma_{Z,ij} + \Sigma_{Z,kl}\} J_2} \times \\
&\quad \times \left( e^{J'_2 \{\Sigma_{Z,\{(i,j),(k,l)\}}(-u)\} J_2} - 1 \right) \sigma_{U,ij} \sigma_{U,kl}
\end{aligned}$$

which converges to

$$2 \sum_{i,j,k,l=1}^m w_i w_j w_k w_l e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_2 \{\Sigma_{Z,ij} + \Sigma_{Z,kl}\} J_2} \sum_{u=1}^{\infty} \left( e^{J'_2 \{\Sigma_{Z,\{(i,j),(k,l)\}}(-u)\} J_2} - 1 \right) \sigma_{U,ij} \sigma_{U,kl}$$

as  $T \rightarrow \infty$  according to the Cesáro mean. Consequently,

$$\begin{aligned} & \lim_{T \rightarrow \infty} \text{Var}(C_T) \\ = & \sum_{i,j,k,l=1}^m w_i w_j w_k w_l (\sigma_{U,ik} \sigma_{U,jl} + \sigma_{U,il} \sigma_{U,jk}) e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_4 \Sigma_Z(i,j,k,l) J_4} \\ & + \sum_{i,j,k,l=1}^m w_i w_j w_k w_l e^{J'_4 \mu_z(i,j,k,l) + \frac{1}{2} J'_2 \{\Sigma_Z(i,j) + \Sigma_Z(k,l)\} J_2} \sigma_{U,ij} \sigma_{U,kl} (e^{\sigma_{Z,ik} + \sigma_{Z,il} + \sigma_{Z,jk} + \sigma_{Z,jl}} - 1) \\ & \times \left\{ 1 + \frac{2}{e^{\sigma_{Z,ik} + \sigma_{Z,il} + \sigma_{Z,jk} + \sigma_{Z,jl}} - 1} \sum_{u=1}^{\infty} (e^{J'_2 \{\Sigma_Z, \{(i,j), (k,l)\} (-u)\} J_2} - 1) \right\}. \end{aligned}$$

The proof is complete.

## S2 Proof of Theorem 2

The following lemma serves as a preparatory step for proving Theorem 2.

**Lemma.** Let  $\sigma_T^* = (T^{-1} \sum_{t=1}^T \sum_{i,j=1}^m w_i w_j v_{i,t} v_{j,t} \sigma_{U,ij})^{1/2}$ . Then

$$\Delta_T \equiv E[\Phi(A_T/\sigma_T^*) - \Phi(A_T/\sigma)] = o(T^{-1/2}) \quad \text{as } T \rightarrow \infty, \quad (\text{S2.2})$$

where  $\Phi(\cdot)$  stands for the standard normal distribution function.

**Proof of Lemma.** Write  $\sqrt{T}(\Phi(A_T/\sigma_T^*) - \Phi(A_T/\sigma))$  as

$$\sqrt{T}(\Phi(A_T/\sigma_T^*) - \Phi(A_T/\sigma)) = \left\{ \phi(C^*) [\sigma_T^* \sigma (\sigma_T^* + \sigma)]^{-1} \right\} \left\{ \sqrt{T}(\sigma^2 - \sigma_T^{*2}) \right\}, \quad (\text{S2.3})$$

where  $\phi(x) = \Phi'(x)$  and  $C^*$  is a constant lying between  $A_T/\sigma_T^*$  and  $A_T/\sigma$ . Similar to (9), it can be shown that  $E(\sqrt{T}(\sigma^2 - \sigma_T^{*2}))^2 = O(1)$  and  $\sqrt{T}(\sigma^2 - \sigma_T^{*2})$  converges in distribution to a mean-zero normal random variable. Moreover, since  $\sigma_T^* \xrightarrow{p} \sigma$ ,  $A_T$  converges to  $\Phi^{-1}(\alpha)\sigma$ , and  $\sqrt{T}(\Phi(A_T/\sigma_T^*) - \Phi(A_T/\sigma))$  is uniformly integrable due to  $E(\sqrt{T}(\sigma^2 - \sigma_T^{*2}))^2 = O(1)$  (Chung, 2001), it follows that  $\sqrt{T}\Delta_T \rightarrow 0$  as  $T \rightarrow \infty$  (Billingsley, 1971).

**Proof of Theorem 2.** To evaluate the  $\alpha$ -th quantile  $Q_\alpha(T)$ , we first express Equation (11) as

$$\begin{aligned} \alpha &= P\left(\frac{\sum_{t=1}^T \tilde{r}_t - T\mu}{\sqrt{T}\sigma_T^*} < \frac{A_T}{\sigma_T^*}\right) \\ &= E\left\{P\left(\frac{\sum_{t=1}^T \tilde{r}_t - T\mu}{\sqrt{T}\sigma_T^*} < \frac{A_T}{\sigma_T^*} \mid \mathcal{V}_T\right)\right\} \\ &= \Phi\left(\frac{A_T}{\sigma}\right) + E\left[\Phi\left(\frac{A_T}{\sigma_T^*}\right) - \Phi\left(\frac{A_T}{\sigma}\right)\right]. \end{aligned} \quad (\text{S2.4})$$

Then, by applying (S2.2) to the right side of (S2.4),

$$\Phi^{-1}(\alpha + o(T^{-1/2})) = A_T/\sigma,$$

which yields

$$Q_\alpha(T) = S_0 \exp\{\sqrt{T}\sigma\Phi^{-1}(\alpha + o(T^{-1/2})) + T\tilde{\mu}\}.$$

If  $\tilde{\mu}$  is known, since

$$\begin{aligned} & \ln(\hat{Q}_\alpha(T)/Q_\alpha(T)) \\ &= (\hat{\sigma}_T + \sigma)^{-1}\Phi^{-1}(\alpha)\sqrt{T}(\hat{\sigma}_T^2 - \sigma^2) + \Delta_T\sqrt{T}\left(\frac{\alpha\sigma}{\phi(\Phi^{-1}(\alpha^*))}\right) \end{aligned}$$

for some  $\alpha^*$  in  $(\alpha - \Delta_T, \alpha + \Delta_T)$ , then (13) follows from (9). When  $\tilde{\mu}$  is unknown,

$$\begin{aligned} & T^{-1/2} \ln(\hat{Q}_\alpha(T)/Q_\alpha(T)) \\ &= (\hat{\sigma}_T + \sigma)^{-1}\Phi^{-1}(\alpha)(\hat{\sigma}_T^2 - \sigma^2) + \Delta_T\left(\frac{\alpha\sigma}{\phi(\Phi^{-1}(\alpha^*))}\right) + \sqrt{T}(\hat{\mu}_T - \tilde{\mu}) \\ &= \sqrt{T}(\hat{\mu}_T - \tilde{\mu}) + o_p(1), \end{aligned} \tag{S2.5}$$

implying (14).