

Ex 4.4 Proofs: Since $\Sigma \sim IW_m(\Psi, n)$ and $W \sim W_m(\Sigma, n)$

We have $\pi(\Sigma|W) \propto \pi(\Sigma)f(W|\Sigma)$

$$\begin{aligned}
 &= \frac{(\det \Psi)^{\frac{m}{2}} (\det(\Sigma))^{-\frac{n_0+m+1}{2}} e^{-\frac{1}{2}\text{tr}(\Psi\Sigma^{-1})}}{2^{\frac{mn_0}{2}} \Gamma_m\left(\frac{n_0}{2}\right)} * \frac{\det(W)^{\frac{n-m-1}{2}} e^{-\frac{1}{2}\text{tr}(\Sigma^{-1}W)}}{[2^m \det(\Sigma)]^{\frac{n}{2}} \Gamma_m\left(\frac{n}{2}\right)} \\
 &= \frac{(\det \Psi)^{\frac{m}{2}} \det(W)^{\frac{n-m-1}{2}} (\det(\Sigma))^{-\frac{n+n_0+m+1}{2}} \exp\left\{-\frac{1}{2}\text{tr}((\Psi+W)\Sigma^{-1})\right\}}{\Gamma_m\left(\frac{n_0}{2}\right) \Gamma_m\left(\frac{n}{2}\right)} * \frac{1}{2^{\frac{m(n+n_0)}{2}}} \\
 &\propto \frac{(\det(W + \Psi))^{\frac{m}{2}} (\det(\Sigma))^{-\frac{n+n_0+m+1}{2}} \exp\left\{-\frac{1}{2}\text{tr}((\Psi+W)\Sigma^{-1})\right\}}{2^{\frac{m(n+n_0)}{2}} \Gamma_m\left(\frac{n+n_0}{2}\right)} \\
 &\sim IW_m(W + \Psi, n + n_0)
 \end{aligned}$$

Ex 4.5 Proofs: Since $\pi(\beta|\gamma) \sim N\left(z, \frac{V}{2\gamma}\right)$ and $\pi(\gamma) \sim \text{gamma}(g, \lambda)$

We have $\pi(\beta, \gamma|(X, Y)) \propto f((X, Y)|\beta, \gamma) * \pi(\beta, \gamma) = f((X, Y)|\beta, \gamma) * \pi(\beta|\gamma) * \pi(\gamma)$

$$= \left(\frac{\gamma}{\pi}\right)^{\frac{n}{2}} e^{-\gamma(Y-X\beta)^T(Y-X\beta)} * (2\pi)^{-\frac{p}{2}} \left(\det\left(\frac{V}{2\gamma}\right)\right)^{-\frac{1}{2}} e^{-\gamma(\beta-z)^T V^{-1}(\beta-z)} * \frac{\lambda^g \gamma^{g-1} e^{-\lambda\gamma}}{\Gamma(g)}$$

Since $(\beta - \beta_n)^T V_n^{-1}(\beta - \beta_n) + \frac{1}{a_n}$

$$= \beta^T V^{-1} \beta + (X\beta)^T X\beta - z^T V^{-1} \beta - Y^T (X\beta) - \beta^T V^{-1} z - (X\beta)^T Y + \beta_n^T V_n^{-1} \beta_n + \frac{1}{a_n}$$

$$= (Y - X\beta)^T (Y - X\beta) + (\beta - z)^T V^{-1}(\beta - z) - z^T V^{-1} z - Y^T Y + \beta_n^T V_n^{-1} \beta_n + \frac{1}{a_n}$$

$$= (Y - X\beta)^T (Y - X\beta) + (\beta - z)^T V^{-1}(\beta - z) + \lambda$$

$$\pi(\beta, \gamma|(X, Y)) = 2^{-\frac{p}{2}} \pi^{-\frac{n+p}{2}} \left(\det\left(\frac{V_n}{2\gamma}\right)\right)^{-\frac{1}{2}} e^{-\gamma(\beta-\beta_n)^T V_n^{-1}(\beta-\beta_n)} * \frac{\lambda^g \gamma^{g+\frac{n}{2}-1} e^{-\frac{\gamma}{a_n}}}{\Gamma(g)}$$

$$\propto (2\pi)^{-\frac{p}{2}} \left(\det\left(\frac{V_n}{2\gamma}\right)\right)^{-\frac{1}{2}} e^{-\gamma(\beta-\beta_n)^T V_n^{-1}(\beta-\beta_n)} * \frac{(1/a_n)^{g+\frac{n}{2}} \gamma^{g+\frac{n}{2}-1} e^{-\frac{\gamma}{a_n}}}{\Gamma\left(g + \frac{n}{2}\right)}$$

$$= g(\beta|\gamma) * h(\gamma) \text{ Where } g(\beta|\gamma) \sim N\left(\beta_n, \frac{V_n}{2\gamma}\right), h(\gamma) \sim \text{gamma}\left(g + \frac{n}{2}, \frac{1}{a_n}\right)$$

Hence $\pi(\beta|\gamma|(X, Y)) \sim N\left(\beta_n, \frac{V_n}{2\gamma}\right)$, $\pi(\gamma|(X, Y)) \sim \text{gamma}\left(g + \frac{n}{2}, \frac{1}{a_n}\right)$

Ex 2.7 Solutions:

(a) Sample covariance matrix $\hat{V} = \begin{pmatrix} 0.2587 & 0.0758 & 0.0624 \\ 0.0758 & 0.3776 & 0.2367 \\ 0.0624 & 0.2367 & 0.3954 \end{pmatrix} * 10^{-3}$

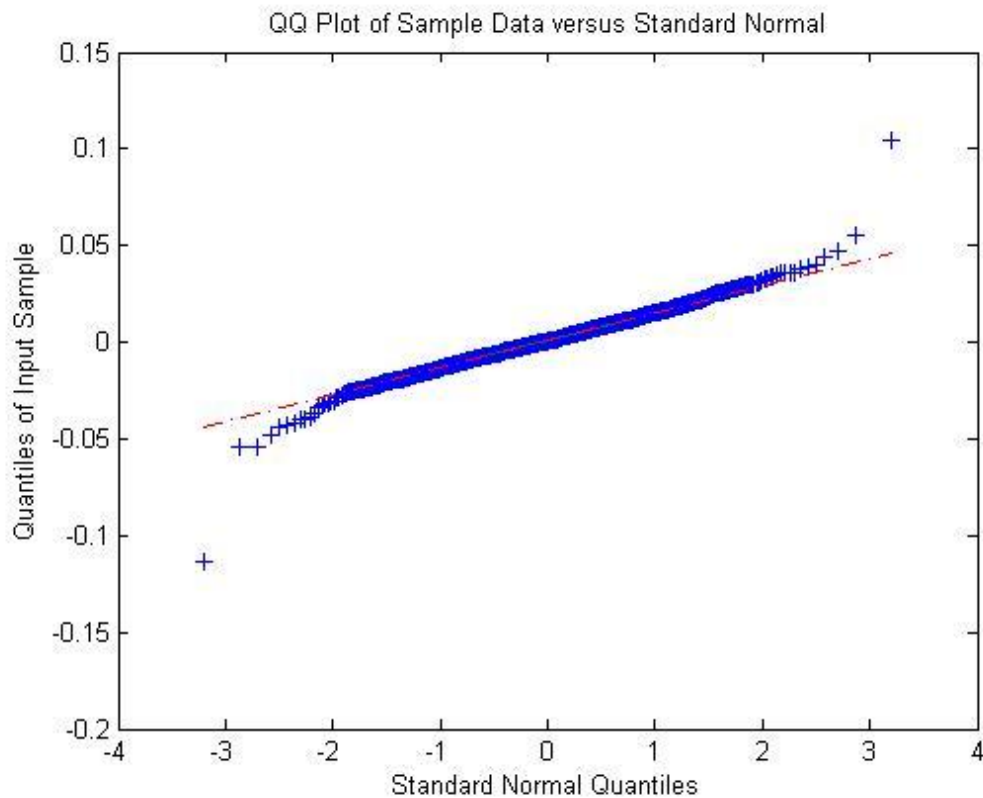
(b) From exercise 2.6(b), we have $\frac{\sqrt{n}(\hat{\rho}-\rho)}{1-\rho^2} \sim N(0,1)$

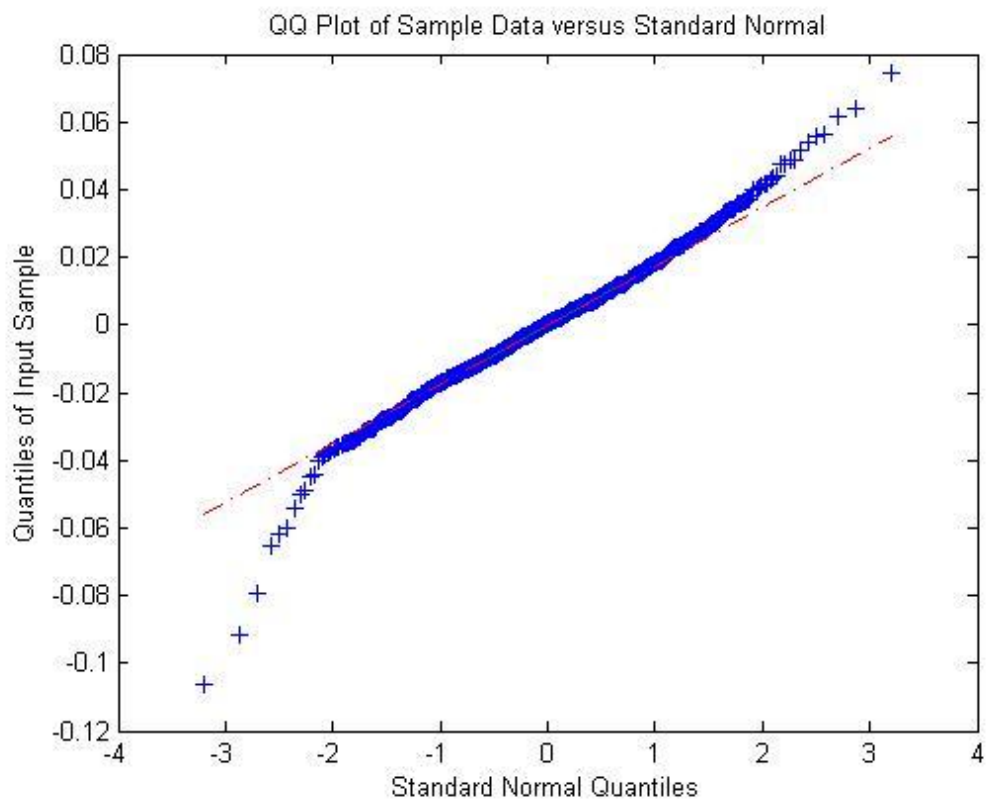
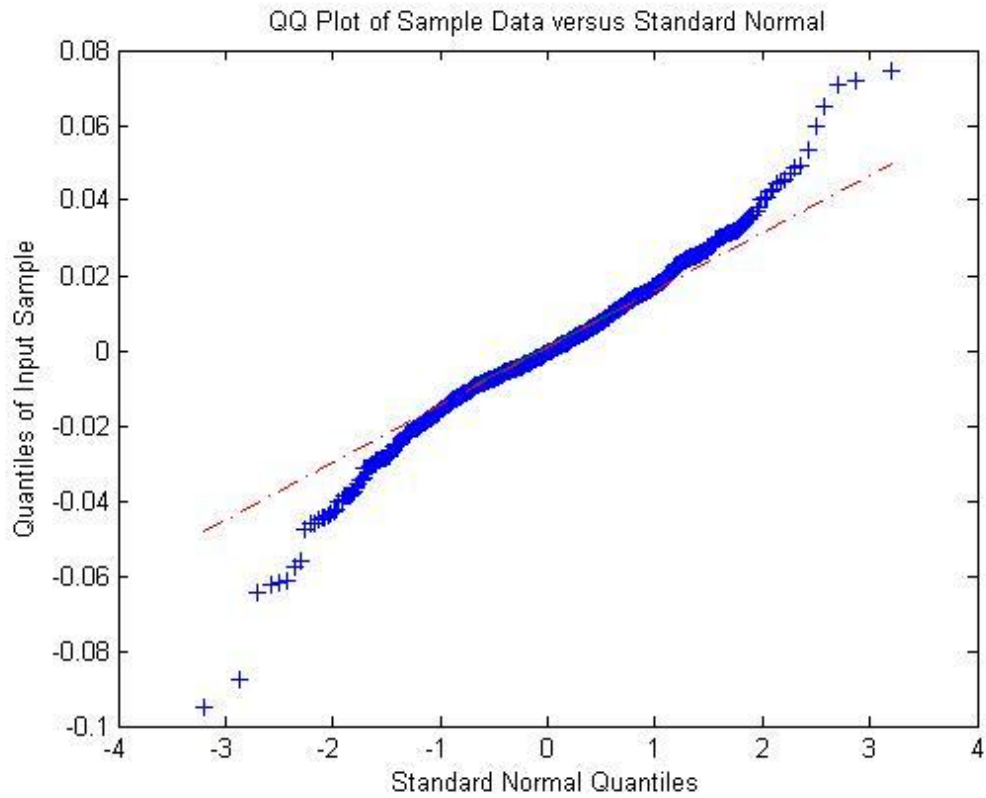
According to Slutsky's Theorem, we have $\frac{\sqrt{n}(\hat{\rho}-\rho)}{1-\hat{\rho}^2} \sim N(0,1)$

Hence the 95% C.I. for ρ is $\hat{\rho} \pm Z_{0.025} * \frac{1-\hat{\rho}^2}{\sqrt{n}}$

95% C.I. for the correlation coefficient of the returns	
General & Ford	[0.1732, 0.3117]
Ford & Toyota	[0.5665, 0.6585]
Toyota & General	[0.1244, 0.2660]

(c) In part (b), we make an assumption that the weekly log returns are i.i.d multivariate normal. We check the normality assumption with Q-Q plots with each manufacturer.





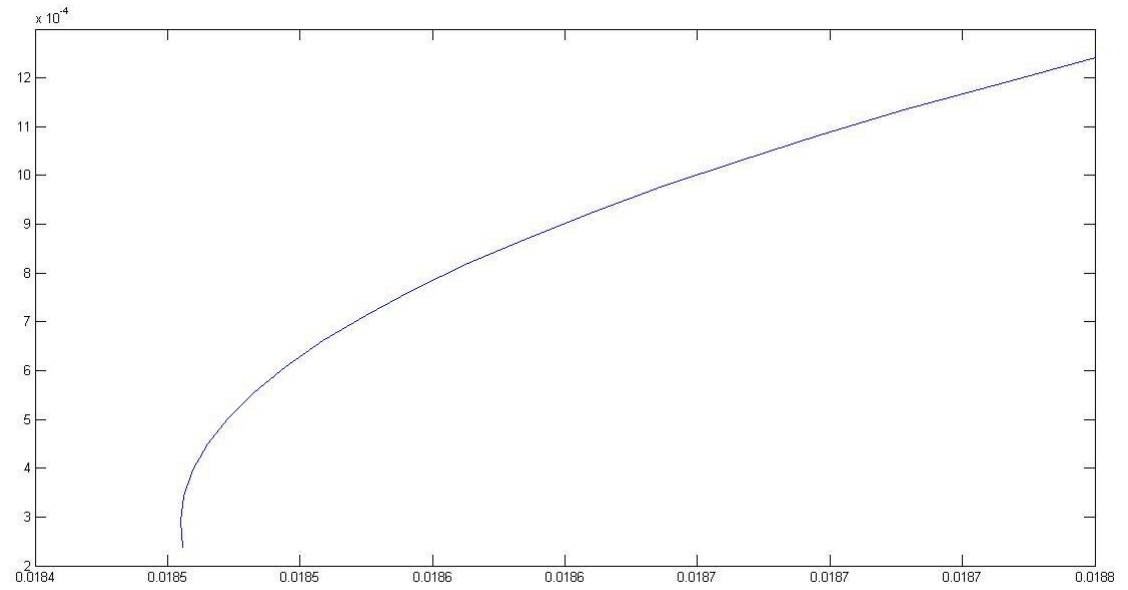
The three Q-Q plots are for General Motors Corp., Ford Motor Corp., and Toyota Motor Corp., respectively. The data are generally normal.

Matlab code:

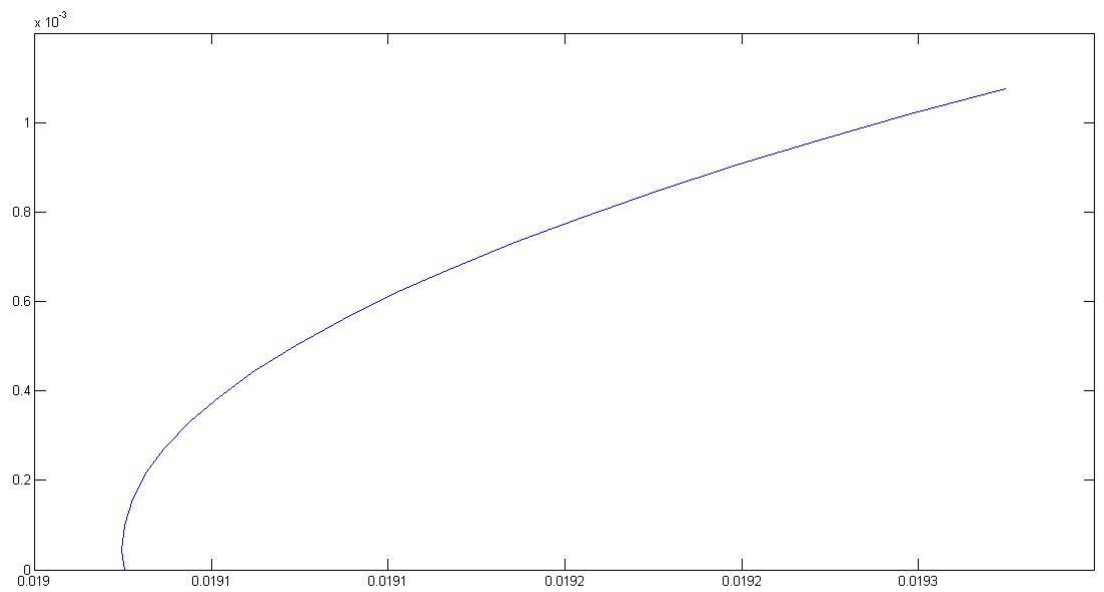
```
load w_logret_3automanu.txt;
Auto = w_logret_3automanu;
Cov = zeros(3);
for i = 1:3
    for j = 1:3
        Cov(i,j)=
(Auto(:,i+1)-mean(Auto(:,i+1)))'*(Auto(:,j+1)-mean(Auto(:,j+1)))/709;
    end;
end;
Corr = zeros(3);
for i = 1:3
    for j = 1:3
        Corr(i,j) = Cov(i,j)/sqrt(Cov(i,i)*Cov(j,j));
    end;
end;
CorrSd = zeros(3);
for i = 1:3
    for j = 1:3
        CorrSd(i,j) = (1-Corr(i,j)^2)/sqrt(709);
    end;
end;
Corr + CorrSd*norminv(0.975,0,1)
Corr - CorrSd*norminv(0.975,0,1)
qqplot(Auto(:,2))
qqplot(Auto(:,3))
qqplot(Auto(:,4))
```

Ex 3.4 Solutions:

(a) $B = 1$

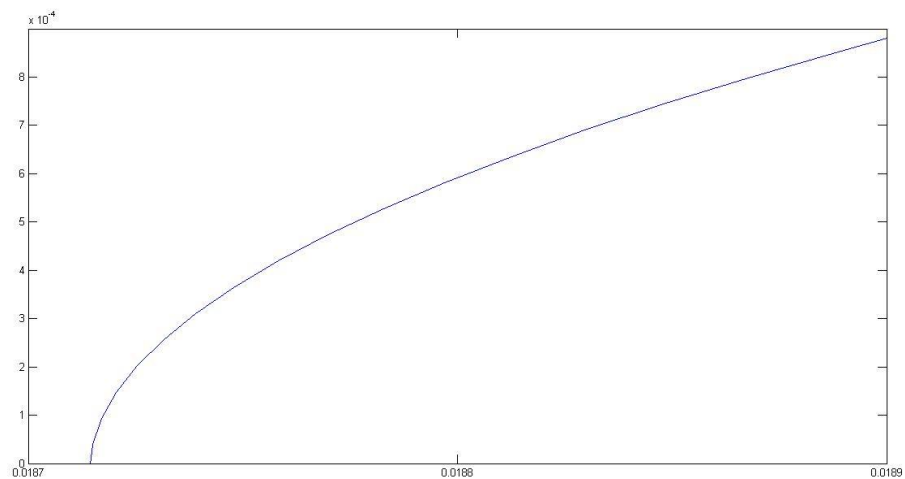


(b) $B = 10$



Since $\bar{w} = \frac{1}{B} \sum_{b=1}^B w_b^*$ is not the efficient portfolio given $\hat{\mu}$ and $\hat{\Sigma}$, the plotted curves are below the estimated efficient frontier based on $\hat{\mu}$ and $\hat{\Sigma}$.

(c) $B = 500$



Matlab code:

```
clear
load d_logret_6stocks.txt;
Stocks = d_logret_6stocks;
Cov = zeros(6);
M = mean(Stocks(:,2:7));
for i = 1:6
    for j = 1:6
        Cov(i,j) =
            (Stocks(:,i+1)-mean(Stocks(:,i+1)))'*(Stocks(:,j+1)-mean(Stocks(:,j+1))) / 64;
    end;
end;
Rep = 500;
N = 64;
W = zeros(20,6);
for i = 1:Rep
    Resample = zeros(N,6);
    for j = 1:N
        for k = 1:6
            Resample(j,k) = Stocks(ceil(N*rand(1,1)),k+1);
        end
    end
    mu = mean(Resample);
    iSigma = inv(cov(Resample));
    ind = ones(1,6);
    B = mu*iSigma*transpose(mu);
    A = ind*iSigma*transpose(mu);
    C = ind*iSigma*transpose(ind);
    D = B*C-A*A;
```

```

    for l = 1:20
        W(l,:) =
W(l,:)+transpose((B*iSigma*transpose(ind)-A*iSigma*transpose(mu)+0.00
01*1*(C*iSigma*transpose(mu)-A*iSigma*transpose(ind)))/D);
    end
end
W = W/Rep;
frontMu = W*M';
frontSd = zeros(1,20);
for l = 1:20
    frontSd(l) = sqrt(W(l,:)*Cov*W(l,:)');
end
plot(frontSd,frontMu)
xlim([1.87, 1.89]/100)
ylim([0, 0.9]/1000)

```