Seminario Finanzas
Asset Allocation

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Índice general

Se pueden encontrar los scripts empleados en este repositorio de GitHub y también en el anexo correspondiente para su consulta y réplica. Para correr el Problem Set 1 es necesaria la función naiveMV.m y para el Problem Set 2 se necesita, además de la anterior función, las funciones clayton.m y simuN.m. Estas dos últimas han sido modificadas respecto a las originales para hacerlo con 2 variables en lugar de 3.

Todos los cálculos los he realizado con Matlab y se pueden comprobar en la sección correspondiente de cada script.

1 Mean Variance Investing

Let be the following sample expected return vector,μ, and the sample covariance matrix, Ω, obtained from 3 time series of yearly stock returns (denoted as 1, 2, and 3):

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{pmatrix} = \begin{pmatrix} 0.25 \\ 0.09 \\ 0.05 \end{pmatrix} ; \quad \Omega = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{pmatrix} = \begin{pmatrix} 0.7 & 0.1 & -0.06 \\ 0.1 & 0.5 & -0.1 \\ -0.06 & -0.1 & 0.1 \end{pmatrix}$$

answer the following questions:

a) Compute the efficient frontier (EF) by allowing short-selling. Which stocks in the EF do increase when increasing μ_p? Make a graphic for each single stock weight in the EF by using a grid of values for μ_p (just start with the expected return of gmv).

   A continuación presento un gráfico donde están representadas las fronteras eficientes tanto con las ventas a corto permitidas (línea roja) como no permitidas (línea azul). Aunque en el gráfico no se distingan, la EF que permite short-selling está ligeramente por encima de la que no, algo que esperaríamos, pues las ventas a corto nos amplían la frontera de posibilidades de inversión y nos facilita la diversificación, reduciendo el riesgo por rentabilidad. Los tres puntos marcados son cada uno de los stocks que componen el portfolio eficiente.

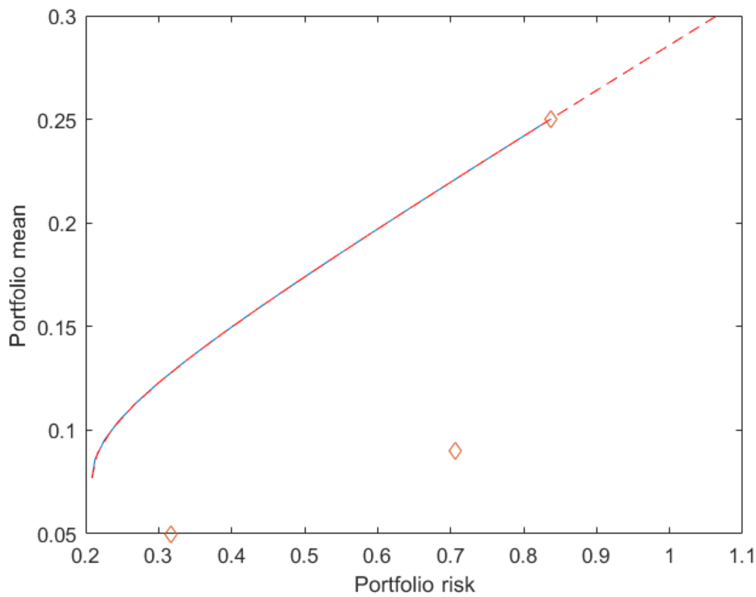

Figura 1: Frontera eficiente con y sin short-selling

En la siguiente imagen podemos observar que sólo el precio del primer activo es creciente con μ_p:

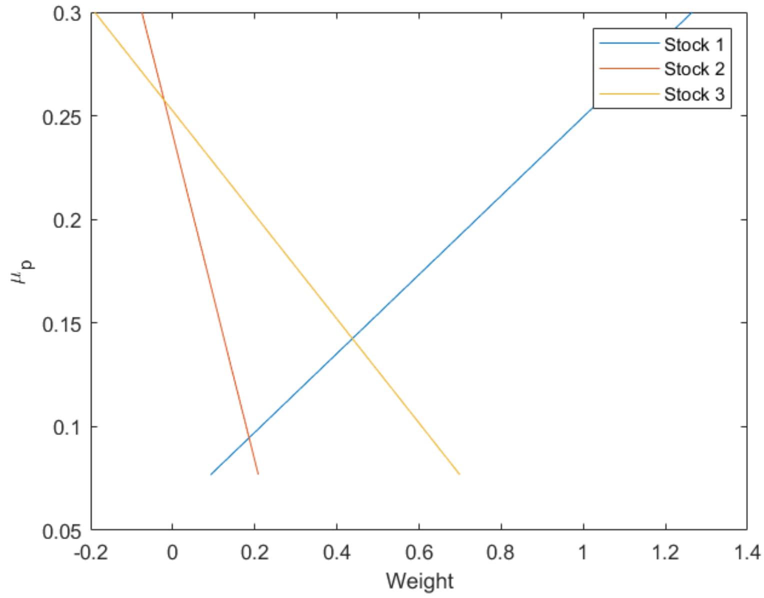

Figura 2: Ponderaciones de los activos según μ_p

b) Consider an investor with a quadratic expected utility function. Assume that you invest all your wealth into three different portfolios such that each follows a certain target. One portfolio is for 'retirement' with $b = 0.5$, another is for 'education' of children with $b = 0.3$ and finally, the last portfolio is for 'bequest' with $b = 0.1$. The total investor's wealth is shared across the different portfolios in the following way: 60% in the portfolio for retirement, 25% in the portfolio for education, and finally the remaining 15% in the portfolio for bequest. Compute the optimal portfolio composition, mean and risk for each target portfolio and the mixed portfolio (i.e., the one containing the three target portfolios). Are the three target portfolios efficient? Does the 'mixed portfolio' belong to the PF? In case of being the 'mixed portfolio' in the PF, then try to obtain this portfolio as a combination of portfolios gmv and d.

Los cálculos se pueden encontrar en la sección h del script, donde $Wstar$ son los pesos de cada portfolio óptimo según el grado de aversión siendo muP y $sigP$ la media y desviación típica de cada uno mientras que $aux, muMixed$ y $sigMixed$ hacen referencia a la mezcla de portfolios según indica el enunciado.

	b = 0.5	b = 0.3	b = 0.1	Mixed
S_1	57.26%	89.27%	249.34%	94.07%
S_2	9.23%	1.50%	-37.20%	0.33%
S_3	33.51%	9.23%	-112.14%	5.59%
μ	0.1682	0.2291	0.5338	0.2383
σ	0.4757	0.7425	2.1479	0.7836

Cuadro 1: Resultados

Podemos comprobar que cuanto más disminuye la aversión al riesgo. más se invierte en S_1, que recordemos que era el único activo creciente con μ_p. Dado que los portfolios calculados son óptimos, también serán eficientes y como cualquier combinación lineal de portfolios eficientes es un portfolio eficiente, podemos decir el portfolio mixto también es eficiente, es decir, estos cuatro portfolios son eficientes. Gráficamente comprobamos que todos los portfolios están sobre la EF:

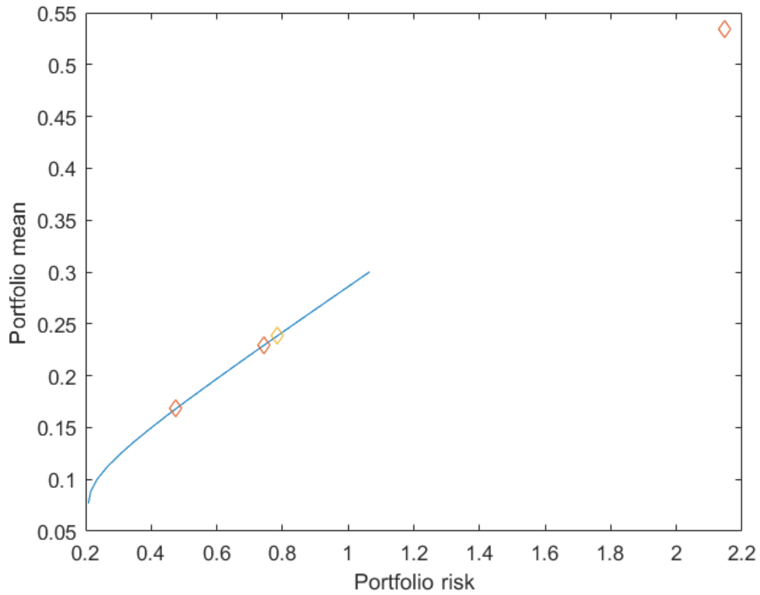

Figura 3: Frontera eficiente y portfolios

Para comprobar que nuestro portfolio mixto se puede expresar como combinación lineal del portfolio gmv y de máximo ratio de Sharpe, aplicamos la siguiente fórmula para que nos de cada peso:

$$w_{p,i} = w_{gmv,i} + \frac{A(C\mu_p - A)(w_{d,i} - w_{gmv,i})}{D}$$

Ahora si multiplicamos los pesos obtenidos por el vector μ de rendimientos iniciales, obtendríamos que (en nuestro script) $mupi = muMixed$ y $Wpi = Wmixed$, es decir, que hemos replicado el porftolio mixto como una combinación del portfolio de mínima varianza global y el de máximo ratio de Sharpe.

c) Suppose that the return for the risk-free asset with return r=4%. Obtain the tangency portfolio, denoted as e, in the PF (corresponding to the three risky assets allowing short-selling), its mean and risk. Finally, obtain and represent the capital allocation line (CAL). Does a portfolio containing 50% in the risk-free asset, 15% in stock 1, 20% in stock 2 and 15% in stock 3 belong to the CAL?

A continuación dejo los resultados y, más abajo, la CAL representada gráficamente.

	S_1	S_2	S_3	μ	σ
Portfolio tangente (e)	37.63%	13.98%	45.39%	0.1309	0.3278

Cuadro 2: Portfolio tangente con un activo libre de riesgo

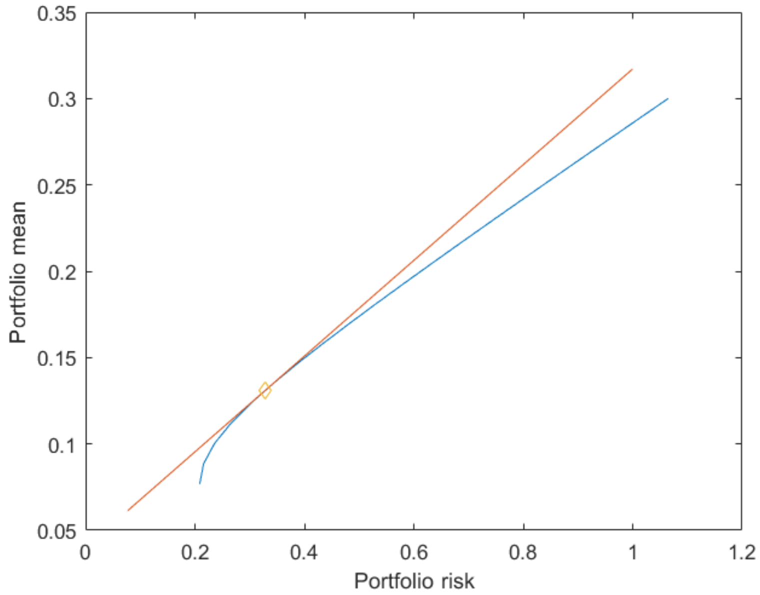

Figura 4: CAL y portfolio tangente

Para comprobar que dicho portfolio se encuentra en la CAL, primero hallamos el rendimiento de dicho portfolio ($\mu_{\text{test}} = 0.083$) y calculamos alfa tal que $\alpha = \frac{\mu_{\text{test}} - rf}{\mu_e - rf} = 0.4733$. Multiplicando alfa por los pesos del portfolio tangente comprobamos que los pesos requeridos no coinciden con los del enunciado ($S_1 = 17.81\%, S_2 = 6.62\%$ y $S_3 = 22.9\%$) y por tanto el portfolio propuesto no pertenece a la CAL.

d) By using Matlab, try to compute the EF already obtained in section a but now only long positions in stocks are allowed.

Hecho en el apartado a).

2 Copulas[1]

Let r_1 and r_2 denote random variables for the returns of two stocks having the following joint density:

$$f(r_1, r_2) = \begin{cases} \alpha + \beta r_1 + \gamma r_2, \; -1 \leq r_1 \leq 2, & -2 \leq r_2 \leq 2.5 \\ 0, & \text{otherwise} \end{cases}$$

where $\alpha = 0.0642, \beta = 0.0049, \gamma = 0.0296$.

a) Obtain by Monte Carlo 100,000 simulated independent $U(0,1)$ draws of (u, v). Given the following copulas, obtain as an output 100,000 dependent $U(0,1)$ draws of (u, w). Since the first draw u is the same under the two cases, we next show how w is obtained according to different copulas:

i) Copula 1: $w = u^{-\theta-1} \left[u^{-\theta} + v^{-\theta} - 1\right]^{-(\theta+1)/\theta}, \quad \theta > 0$

ii) Copula 2: w is from a Gaussian copula with correlation coefficient $\rho \in [-1, 1]$

Make a plot of points (u, v) from each copula. Consider the following parameter values:

[1]Como trabajamos con variables aleatorias hemos establecido la semilla rng(1585) para su replicación.

Copula 1: $\theta = 2, 10$;   Copula 2: $\rho = -0.7, 0.6$

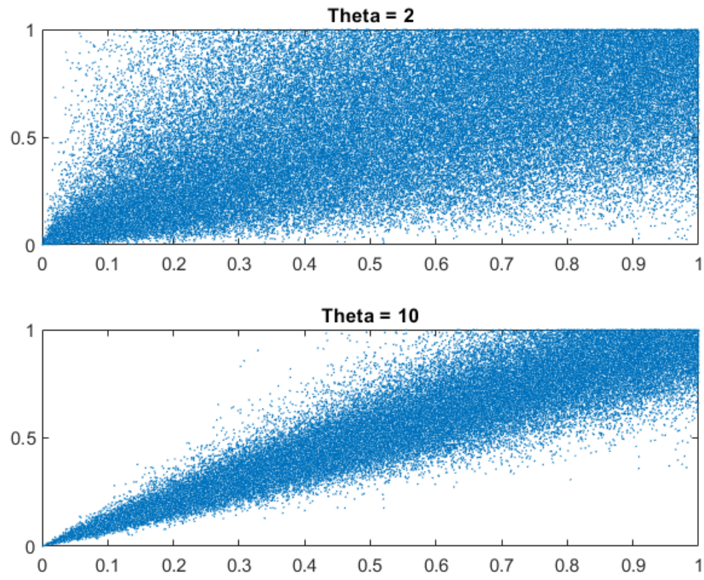

Figura 5: Cópula de Clayton

Vemos que cuanta mayor dependencia (mayor θ), menor dispersión encontramos.

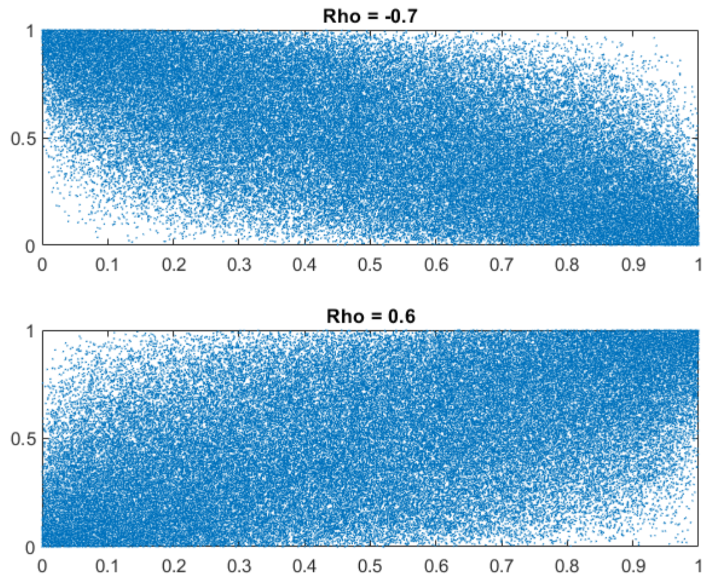

Figura 6: Cópula gaussiana

b) Given each copula and the different parameter values, compute both the mean and standard deviation for the return portfolio A containing 25% of stock 1 and 75% of stock 2. Obtain also the simulated quantiles at 1%, 5%, 95% and 99%. Finally, obtain the correlation matrix corresponding to portfolio A under the four cases.

	μ	σ	$q_{1\%}$	$q_{5\%}$	$q_{95\%}$	$q_{99\%}$
Clayton ($\theta = 2$)	0.8255	0.9939	-1.5162	-1.0445	2.1346	2.2755
Clayton ($\theta = 10$)	0.8264	1.0374	-1.5212	-1.0706	2.2168	2.3179
Gauss($\rho = -0.7$)	0.8266	0.7009	-0.8549	-0.5040	1.7148	1.8854
Gauss($\rho = 0.6$)	0.8258	0.9690	-1.4217	-0.9557	2.1734	2.3166

Cuadro 3: Performance del porftolio según la cópula empleada

Y la matriz de correlaciones:

$$\Gamma = \begin{pmatrix} 1.0000 & 0.9147 & 0.0431 & 0.9605 \\ 0.9147 & 1.0000 & -0.3178 & 0.8189 \\ 0.0431 & -0.3178 & 1.0000 & 0.1843 \\ 0.9605 & 0.8189 & 0.1843 & 1.0000 \end{pmatrix}$$

c) Consider the following portfolios:

- P1: (50% stock 1, 50% stock 2) with copula 1 where $\theta = 2$.
- P2: (20% stock 1, 80% stock 2) with copula 2 where $\rho = -0.7$.
- P3: (70% stock 1, 30% stock 2) with copula 1 where $\theta = 10$.
- P4: (15% stock 1, 85% stock 2) with copula 2 where $\rho = 0.6$.

Compute the correlation matrix of the four portfolios. Build the efficient frontier (allowing short selling) given the four portfolios. What is the composition of the portfolio with minimum global variance? What is the simulated VaR (quantile) of this portfolio at levels 1% and 5% .

La matriz de correlaciones es la siguiente:

$$\Gamma = \begin{pmatrix} 1.0000 & 0.9414 & -0.1889 & 0.8925 \\ 0.9414 & 1.0000 & -0.4762 & 0.7134 \\ -0.1889 & -0.4762 & 1.0000 & 0.1971 \\ 0.8925 & 0.7134 & 0.1971 & 1.0000 \end{pmatrix}$$

En esta matriz el orden del P2 y el P3 se ha invertido, es decir, $a_{21} = 0.9414$ es la correlación entre P1 y P3 mientras que $a_{31} = -0.1889$ es la correlación entre P1 y P2, ya que en Matlab he trabajado con ese orden de cópulas. Por otro lado, la representación de las fronteras eficientes, junto con la localización de cada portfolio estudiado, se muestra a continuación:

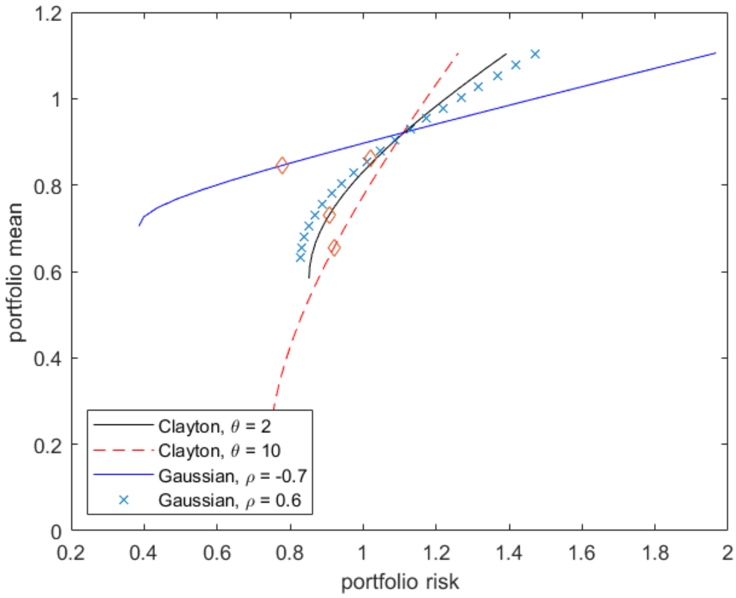

Figura 7: Fronteras eficientes

y los resultados de computar los diferentes portfolios de mínima varianza global:

	μ	σ	$q_{1\%}$	$q_{5\%}$	S_1	S_2
P1 ($\theta = 2$)	0.5838	0.8518	-1.0216	-0.8267	89.09%	10.91%
P2 ($\rho = -0.7$)	0.7051	0.3857	-0.2013	0.0959	57.08%	42.92%
P3 ($\theta = 10$)	0.1333	0.7386	-1.0374	-0.7775	207.70%	-107.70%
P4 ($\rho = 0.6$)	0.6310	0.8287	-1.0175	-0.7352	77.45%	22.55%

Cuadro 4: Portfolio de mínima varianza global según la cópula empleada

Vemos que los valores obtenidos se corresponden con la gráfica representada.

A Código de Matlab

A.1 Problem Set 1

```
%% Cleaning
clear('all')
clc
close('all')

%% Initial parameters
muR = [0.25;
       0.09;
       0.05];
covR = [ 0.7,   0.1, -0.06;
          0.1,   0.5, -0.1;
         -0.06, -0.1,  0.1];
l = ones(length(muR),1);
MuMax = max(muR);
Nw = 20;
sigR = diag(diag(sqrt(covR)));
corrR = sigR \ covR / sigR; % corrR = corrcov(covR)

% %% PCTR
% eq_w = l/length(muR); % Equally weighted
% alt_w = [0.2;
%          0.6;
%          0.2];        % alternative pportfolio
%
% eqw_sdev = sqrt(eq_w' * covR * eq_w);
% eqw_MCTR = (covR * eq_w) / eqw_sdev;
% eqw_PCTR = eq_w .* eqw_MCTR / eqw_sdev;
%
% alt_sdev = sqrt(alt_w' * covR * alt_w);
% alt_MCTR = (covR * alt_w) / alt_sdev;
% alt_PCTR = eq_w .* alt_MCTR / alt_sdev;

%% Section e) and m): EF with and without short-selling
invcov = inv(covR);

m1 = invcov*l;    %vector of order nx1
m2 = invcov*muR;  %vector of order nx1

A = l'*m2;        %real number
B = muR'*m2;      %real number (positive)
C = l'*m1;        %real number (positive)
D = B*C-A^2;      %real number (positive)

g = (1/D)*(B*m1-A*m2);  %vector of order nx1
h = (1/D)*(C*m2-A*m1);  %vector of order nx1

%Min variance EF portfolio (portfolio mvp)

Wmvp = (1/C)*m1;       %weight of mvp
Mumvp = A/C;           %mean of mvp
Sigmvp = sqrt(1/C);    %sig of mvp

%Build EF under short position

```

```
q = 1.2;
MuMax1 = q*MuMax;
mup = linspace(Mumvp,MuMax1,Nw);

Wshort = zeros(Nw,length(muR));
muShort = zeros(Nw,1);
sigShort = zeros(Nw,1);

for i=1:Nw
    w = g + h*mup(i); %column vector of order length(muR)
    Wshort(i,:) = w';
    muShort(i) = w'*muR;
    sigShort(i) = sqrt(w'*covR*w);
end

[PRisk, PRoR, PWts] = NaiveMV(muR, covR, Nw);

WmvpLo = PWts(1,:)';        % Weight of mvp (Long)
MumvpLo = PRoR(1);          % Mean of mvp (Long)
SigmvpLo = PRisk(1);        % Sig of mvp (Long)

% Portfolio comparison: Long vs Short

compaP = [WmvpLo, Wmvp]
compaMV = [MumvpLo, Mumvp; SigmvpLo, SigmvpLo]

% Plotting

figure(1);
plot(PRisk,PRoR) % Long
hold on
plot(sigShort, muShort, 'r--') % Short selling is allowed
hold on
plot(diag(sigR),muR,'d')
xlabel('Portfolio risk')
ylabel('Portfolio mean')

figure(2);
plot(Wshort(:,1), muShort, Wshort(:,2), muShort, Wshort(:,3), muShort)
xlabel('Weight')
ylabel('\mu_p')
legend('Stock 1', 'Stock 2', 'Stock 3')

%% Section h): quadratic expected utility function

Wd = m2/A;
b = [0.5; 0.3; 0.1];
Wstar = zeros(3);
muP = zeros(1,3);
sigP = zeros(1,3);

for i = 1:3
    Wstar(:,i) = Wmvp + A * (Wd - Wmvp) / b(i);
    muP(i) = Wstar(:,i)'*muR;
    sigP(i) = sqrt(Wstar(:,i)' * covR * Wstar(:,i));
end

Wmixed = [0.6, 0.25, 0.15];
```

```
muMixed = Wmixed * muP';
aux = sum(Wmixed .* Wstar, 2);
sigMixed = sqrt(aux' * covR * aux);

% Proof that all of them are efficient (in the PF):
figure(3);
plot(sigShort, muShort) % Short selling is allowed
hold on
plot(sigP,muP,'d', sigMixed,muMixed,'d')
xlabel('Portfolio risk')
ylabel('Portfolio mean')

for i = 1:3
    Wpi(i) = Wmvp(i) + A * (C * muMixed - A) * (Wd(i) - Wmvp(i)) / D;
end

mupi = Wpi * muR; % mupi is equal to muMixed.

%% Section i): risk-free asset:

rf = 0.04;
We = invcov * (muR - rf)/ (l'*invcov * (muR - rf));
muE = We' * muR;
sigE = sqrt(We' * covR * We);

sigCAL = linspace(Mumvp,1,Nw);
muCAL = rf + (muE - rf) * sigCAL/sigE ;

figure(4);
plot(sigShort, muShort) % Short selling is allowed
hold on
plot(sigCAL, muCAL)
hold on
plot(sigE,muE,'d')
xlabel('Portfolio risk')
ylabel('Portfolio mean')

WtestCAL = [0.15, 0.2, 0.15];
muTestCAL = WtestCAL * muR + (1 - sum(WtestCAL)) * rf;
alpha = (muTestCAL - rf)/(muE - rf);
test = alpha * We;
```

A.2 Problem Set 2

```matlab
%% Cleaning
clear('all')
clc
close('all')

%% Inputs
rng(1585); % For replication
N = 1e5; % Number of simulations
U = rand(N,2); % Indep. U(0,1) random matrix of order (N,2)

%% Section a)
% Clayton
theta1 = 2;  % Small dependence relationship
theta2 = 10; % Greater dependence relationship

w1_clay = clayton(theta1,U);
w2_clay = clayton(theta2,U);

% Gaussian
rho1 = -0.7;
corr1 = [1, rho1;
         rho1, 1];
rho2 = 0.6;
corr2 = [1, rho2;
         rho2, 1];
w1_gauss = simuN(corr1,U);
w2_gauss = simuN(corr2,U);

% Plotting

figure(1);
subplot(2,1,1)
plot(w1_clay(:,1), w1_clay(:,2), 'o','MarkerSize',0.5)
title('Theta = 2')

subplot(2,1,2)
plot(w2_clay(:,1), w2_clay(:,2), 'o','MarkerSize',0.5)
title('Theta = 10')

figure(2);
subplot(2,1,1)
plot(w1_gauss(:,1), w1_gauss(:,2), 'o','MarkerSize',0.5)
title('Rho = -0.7')

subplot(2,1,2)
plot(w2_gauss(:,1), w2_gauss(:,2), 'o','MarkerSize',0.5)
title('Rho = 0.6')

%% Section b)
%Parameters of the bivariate pdf given by (I)
%f(r1,r2) = alfa + beta*r1 + gamma*r2

alfa = 0.0642;
beta = 0.0049;
gamma = 0.0296;

```

```
%Conditional sampling
%Conditional distribution from bivar. distrib. = F(r1|r2)

% Marginal cumulative distribution of r2: G(r2)
% G(r2) = G0 + G1*r2 + G2*r2^2

G0 = 0.2222;
G1 = 0.2;
G2 = 0.0444;

% Marginal pdf of r2 = g(r2)
% g(r2) = g00 + g11*r2
% r2 belongs to [-2,2.5]

g00 = 0.2;
g11 = 0.0889;

r2 = zeros(N,4); % draws from r2
r1 = zeros(N,4); % draws from r1

d = alfa -0.5*beta;

copu(:,:,1) = w1_clay;
copu(:,:,2) = w2_clay;
copu(:,:,3) = w1_gauss;
copu(:,:,4) = w2_gauss;

for i=1:N
    for j = 1:4
        G0_aux = G0 - copu(i,2,j);
        A = [G2 G1 G0_aux];
        R = roots(A);

        if R(1) < -2
            r2(i,j) = R(2);
        elseif R(1) > 2.5
            r2(i,j) = R(2);
        else
            r2(i,j) = R(1);
        end
    end
end

% r1 by conditional sampling
% r1 belongs to [-1,2]


for i=1:N
    for j = 1:4
        c1 = 1/(g00 + g11*r2(i,j));
        c2 = d + gamma*r2(i,j);
        c3 = alfa + gamma*r2(i,j);
        c4 = 0.5*beta;
        c5 = c2 - U(i,1)/c1;
        B = [c4 c3 c5];
        R = roots(B);
        if R(1) < -1
            r1(i,j) = R(2);
```

```
        elseif R(1) > 2
            r1(i,j) = R(2);
        else
            r1(i,j) = R(1);
        end
    end
end

wa = 0.25; % Weight stock 1

RpA = wa*r1 + (1 - wa)*r2;
%correA = corrcoef(r1, r2)
correA = corrcoef(RpA)
mRpMCA = mean(RpA)  %mean
stdRpMCA = std(RpA) %std

VaR1A = quantile(RpA,0.01) % quantile(1%)
VaR5A = quantile(RpA,0.05) % quantile(5%)
VaR95A = quantile(RpA,0.95) % quantile(95%)
VaR99A = quantile(RpA,0.99) % quantile(99%)

%% Section c)
wpx = [0.5, 0.7, 0.2, 0.15]; % Weights for each portfolio
Rpx = zeros(N, length(wpx));
for i = 1:length(wpx)
    Rpx(:,i) = wpx(i) * r1(:,i) + (1 - wpx(i)) * r2(:,i);
end

correx = corrcoef(Rpx)

% Build Efficient Frontiers (EFs) (short positions allowed)

Nw = 20;

muR = zeros(2, length(Rpx(1,:)));
covR = zeros(2,2,length(Rpx(1,:)));
invcov = zeros(2,2,length(Rpx(1,:)));
l = ones(2,1);
m1 = zeros(2, length(Rpx(1,:)));
m2 = zeros(2, length(Rpx(1,:)));
A = zeros(1, length(Rpx(1,:)));
B = zeros(1, length(Rpx(1,:)));
C = zeros(1, length(Rpx(1,:)));
D = zeros(1, length(Rpx(1,:)));
g = zeros(2, length(Rpx(1,:)));
h = zeros(2, length(Rpx(1,:)));
Wmvp = zeros(2, length(Rpx(1,:)));
Mumvp = zeros(1, length(Rpx(1,:)));
Sigmvp = zeros(1, length(Rpx(1,:)));
Wshort = zeros(Nw,2,length(Rpx(1,:)));
muShort = zeros(Nw,length(Rpx(1,:)));
sigShort = zeros(Nw,length(Rpx(1,:)));

for i = 1:length(Rpx(1,:))
    muR(:,i) = [mean(r1(:,i)); mean(r2(:,i))];
    covR(:,:,i) = cov(r1(:,i), r2(:,i));
    invcov(:,:,i) = inv(covR(:,:,i));
    m1(:,i) = invcov(:,:,i)*l;    %vector of order nx1
```

```
    m2(:,i) = invcov(:,:,i)*muR(:,i);  %vector of order nx1

    A(i) = l'*m2(:,i);         %real number
    B(i) = muR(:,i)'*m2(:,i);      %real number (positive)
    C(i) = l'*m1(:,i);         %real number (positive)
    D(i) = B(i)*C(i)-A(i)^2;      %real number (positive)

    g(:,i) = (1/D(i))*(B(i)*m1(:,i)-A(i)*m2(:,i));  %vector of order nx1
    h(:,i) = (1/D(i))*(C(i)*m2(:,i)-A(i)*m1(:,i));  %vector of order nx1

    %Min variance EF portfolio (portfolio mvp)

    Wmvp(:,i) = (1/C(i))*m1(:,i);       %weight of mvp
    Mumvp(i) = A(i)/C(i);            %mean of mvp
    Sigmvp(i) = sqrt(1/C(i));    %sig of mvp

    %Build EF under short position

    q = 1.2;
    MuMax1(i) = q*max(muR(:,i));
    mup(i,:) = linspace(Mumvp(i), MuMax1(i), Nw);

    for j=1:Nw
        w = g(:,i) + h(:,i)*mup(i,j); %column vector of order length(muR)
        Wshort(j,:,i) = w';
        muShort(j,i) = w'*muR(:,i);
        sigShort(j,i) = sqrt(w'*covR(:,:,i)*w);
    end
end

%Plotting

figure(3);
plot(sigShort(:,1), muShort(:,1),'k')    %Clayton copula
%title('Clayton, \theta = 2')
hold on
plot(sigShort(:,2), muShort(:,2),'r--')  %Clayton copula
%title('Clayton, \theta = 10')
hold on
plot(sigShort(:,3), muShort(:,3),'b')    %Gaussian copula
%title ('Gaussian, \rho = -0.7')
hold on
plot(sigShort(:,4), muShort(:,4),'x')    %Gaussian copula
%title ('Gaussian, \rho = 0.6')
hold on
plot(std(Rpx),mean(Rpx),'d')
legend('Clayton, \theta = 2', 'Clayton, \theta = 10', ...
'Gaussian, \rho = -0.7', 'Gaussian, \rho = 0.6','Location','southwest')
xlabel('portfolio risk')
ylabel('portfolio mean')

newR = zeros(N,4);
for i = 1:length(wpx)
    newR(:,i) = Wmvp(1,i) * r1(:,i) + Wmvp(2,i) * r2(:,i);
end

VaR1 = quantile(newR,0.01) % quantile(1%)
VaR5 = quantile(newR,0.05) % quantile(5%)
```