

Information:

- Me

- You

- The course

- The website *WRITTEN* →
- Exams *ORAL*

- Lesson: from 2pm to 4pm

- Tutor: Luigi Barbieri

Structure:

- 1) Introduction to portfolio construction
 - 2) Analysis of financial markets
 - 3) Strategic Asset Allocation
 - 4) Tactical Asset Allocation / market timing
 - 5) Product Selection
-

- 1) Introduction to portfolio construction
- Ex-ante stage*) A) *Investor Profile* *RISK TOLERANCE* → *TOLERATED LOSS*
- HOLDING PERIOD*

HP/Risk Tol	low	medi um	medi um-high	high
1 yr				
3 yrs				
5 yrs				
10 yrs				
+10 yrs				

True Portfolio Construction:

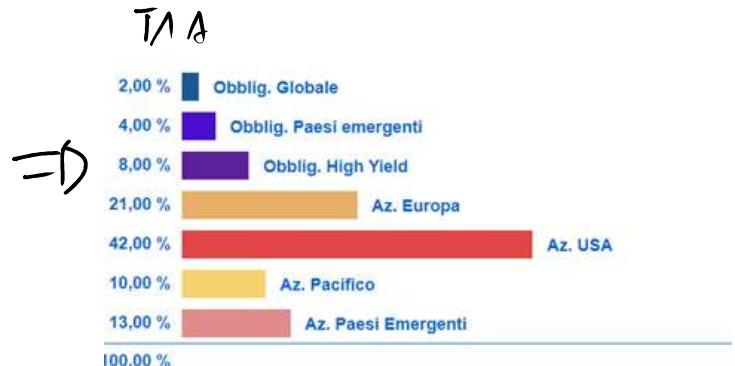
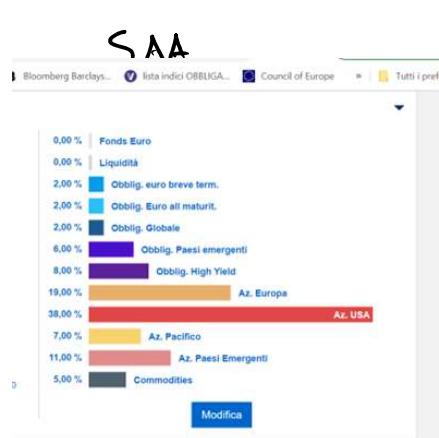
B) Strategic Asset Allocation (SAA): It is a mix of asset classes (financial markets) that is expected to be maintained **on average** "in the long run"



Strategic Committee
Analysts
Quant
→
- forecasts in the long run
- Optimization Models

⇒

C) Tactical Asset Allocation (TAA): A "short term" adjustment from the SAA, where based on tactical view, asset classes with + views area overweighted and asset classes with negative view are underweighted.



⇒

D) Product Selection → Product must confirm the asset allocation

DIRECTLY in stock - bond
INDIRECTLY via FUNDS

Nuova scheda						
Riavvia per aggiornare						
Posta Elettronica C...	YouTube	Maps	email bocconi	per Datastream onl...	Unire PDF	Bloomberg Barclays...
					V lista indici OBBLIGA...	Council of Europe
						Tutti i preferiti
Obblig. High Yield		8,00 %	8,00 %	80.000,00 €	80.000,00 €	0,00 €
BNY Mellon Gbl S-D HY Bd USD G Acc	IE00BZ1LHJ42	★★★★★	8,00 %	80.000,00 €		
Az. Europa		19,00 %	19,00 %	190.000,00 €	190.000,00 €	0,00 €
iShares STOXX Europe 50 UCITS ETF EUR Dis	IE0008470928	★★★★★	12,46 %	124.560,65 €		
White Fleet IV DIVAS EuroZ Value I EUR C	LU1975716835	★★★★★	6,54 %	65.439,35 €		
Az. USA		38,00 %	38,00 %	380.000,00 €	380.000,00 €	0,00 €
UBS ETF S&P 500 ESG USD A-acc	IE00BHXMH11	★★★★★	15,00 %	150.000,01 €		
SPDR S&P 500 ESG Leaders UCITS ETF Acc	IE00B4GPZ28	★★★★★	8,00 %	79.999,98 €		
Invesco Markets plc S&P 500 ESG Acc	IE00BKS7L097	★★★★★	15,00 %	150.000,01 €		
Az. Pacifico		7,00 %	7,00 %	70.000,00 €	70.000,00 €	0,00 €
iShares MSCI Japan USD H ETF Acc	IE00BCLWRG39	★★★★★	7,00 %	70.000,00 €		
Az. Paesi Emergenti		11,00 %	11,00 %	110.000,00 €	110.000,00 €	0,00 €
BSF Em Mkts Equity Strat Fd A2 USD Acc	LU1289970086	★★★★★	5,42 %	54.229,41 €		
Redwheel Next Generation EM Eq Fd B USD	LU1965309757	★★★★★	5,58 %	55.770,59 €		
Commodities		5,00 %	5,00 %	50.000,00 €	50.000,00 €	0,00 €

Ex-post → Monitoring of the portfolio

Measure the Return
Measure the Risk

Performance Attribution : 10% ↴
 ↴ SAA 12%
 ↴ TAA -1%
 ↴ PRODUCT SOCIET -1%

2) Analysis of Financial Market

- 2.1) Selection of asset classes
- 2.2) Market Index/Benchmark
- 2.3) Statistical indicators to capture ret/risk

2.1) Selection of asset classes

Think Global

No overlapping

Money Mkt in €	€ Bond Mkt Short Term	€ Bond Mkt	Global Bond Dev Mkts	Global Corp Bond High Yield	Em Mkts Bond Mkt	Equ. Europe	Equ. North America	Equ. Pacific	Equ. Em Mkts	OPORTUNIT.

- Hedge Funds
- Certifites
- Commodities
- Crypto

- Thematic Funds
- Real Estate
- Infrastructure
- Private Equity/Private Debt
- Arts

2.2) Market Index/Benchmark

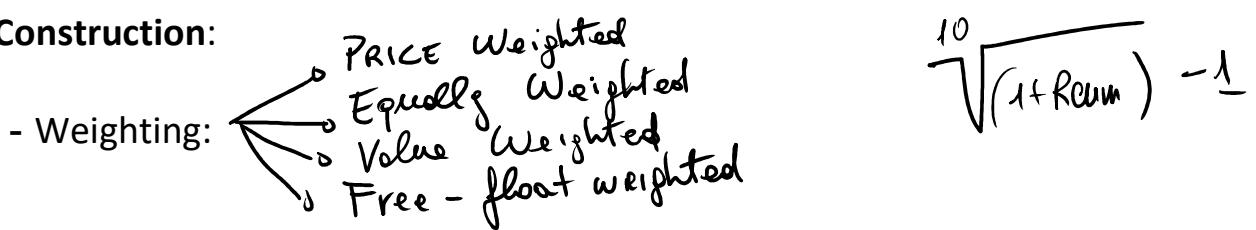
US EQUITY MKT \rightarrow Identify MKT INDEX

- \rightarrow Definition: basket of stock/bonds which composition is a good proxy of the composition of the market

Properties:

- 1) **Representativeness:** (derived by the definition) the basket composition must represent well the composition of the market
- 2) **Replicability:** An index must be easily replicated by an asset manager
- 3) **Transparency/Objectivisness:**

Construction:



- Cash Flow Management

<https://www.msci.com/end-of-day-data-search>

<https://www.msci.com/constituents>

2.3) Statistical indicators to capture ret/risk

Return \rightarrow Average Return $\bar{R} = \frac{1}{T} \sum_{i=1}^T R_i$

= media(B3:B25)
= average(B3:B25)

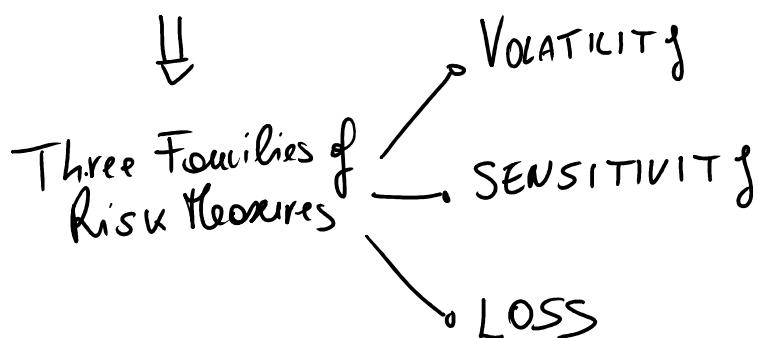
Av. Ret of a Portfolio $\bar{R}_{PORT} = \sum_{i=1}^N w_i \cdot \bar{R}_i$

$$\bar{R}_{PORT} = [w_1 \ w_2 \ \dots \ w_N] \times \begin{bmatrix} \bar{R}_1 \\ \bar{R}_2 \\ \vdots \\ \bar{R}_N \end{bmatrix}$$

Statistical indicators able to capture RISK

List of Risk parameters:

- Standard deviation
- Value at Risk
- Expected Shortfall (Condition VaR)
- Beta
- Modified Duration
- Semi-standard deviation
- Down Side Risk
- Tracking Error Volatility
- Maximum drawdown



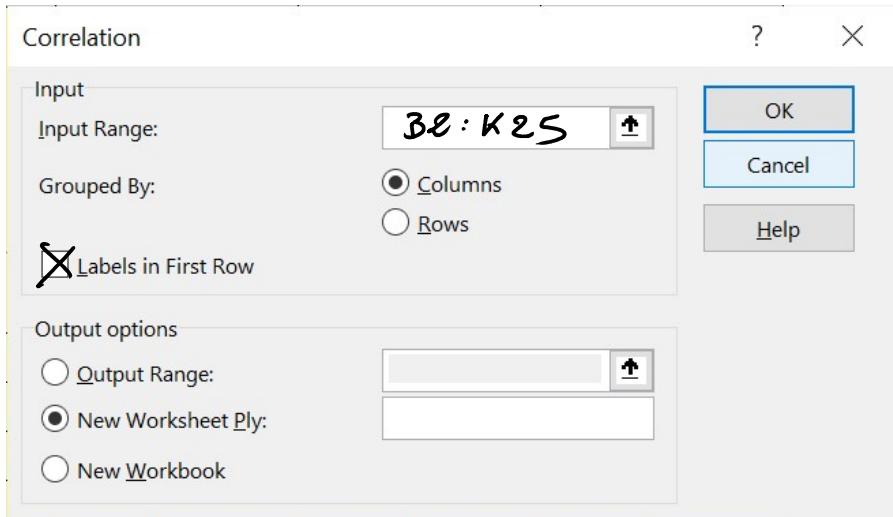
Standard Deviation $\rightarrow \sigma$

σ simple Asset Class $\rightarrow \sigma = \sqrt{\sum_{i=1}^T \frac{(R_i - \bar{R})^2}{T-1}}$

=stdev(time series)

SIGMA annual	1,96%	2,70%	6,24%	8,32%	15,57%	10,55%	18,77%	18,85%	17,71%	26,57%
	Money Mkt in €	€ Bond Mkt Short Term	€ Bond Mkt	Global Bond Dev Mkts	Global Corp Bond High Yield	Em Mkts Bond Mkt	Equ. Europe	Equ. North America	Equ. Pacific	Equ. Em Mkts
Portfolio	3,00%	12,00%	15,00%	12,00%	3,00%	5,00%	11,00%	30,00%	3,00%	6,00%

$\sigma_{PORT} = \sqrt{\sum_{i=1}^N w_i \cdot \sigma_i}$
 $P_{A;B} = \frac{\text{Cov}(A;B)}{\sigma_A \cdot \sigma_B} = \frac{\sum_{i=1}^N (R_i - \bar{R}_A) \cdot (R_i - \bar{R}_B)}{N-1}$
 $\rho_{A;B} = \frac{N \cdot P}{\sum_{i=1}^N (R_i - \bar{R}_A) \cdot (R_i - \bar{R}_B)}$



	Bofa ML Euro 0-1 yr	Bofa ML Bond Euro 1-3 Y	Bofa ML Bond. Euro	Bofa ML Bond. Global	ML Global HY	Bofa ML Bond Emerging	MSCI Europe	MSCI North America	MSCI Pacific	MSCI Emerging Markets
Bofa ML Euro 0-1 yr	1,00									
Bofa ML Bond Euro 1-3 Y	0,84	1,00								
Bofa ML Bond. Euro	0,40	0,76	1,00							
Bofa ML Bond. Global	0,24	0,29	0,57	1,00						
ML Global HY	-0,23	-0,05	0,08	0,01	1,00					
Bofa ML Bond Emerging	0,02	0,17	0,52	0,68	0,56	1,00				
MSCI Europe	-0,42	-0,29	-0,06	-0,28	0,71	0,37	1,00			
MSCI North America	-0,60	-0,38	0,03	0,03	0,69	0,51	0,87	1,00		
MSCI Pacific	-0,52	-0,34	-0,02	-0,11	0,65	0,45	0,87	0,84	1,00	
MSCI Emerging Markets	-0,17	-0,07	0,03	-0,23	0,78	0,41	0,78	0,64	0,79	1,00

Why the low correlations of this market results?

Why the low correlations of this
ordine are don't provide high DIVERS. BENEFITS?



Esistono σ_{PORT}

$$\sigma_{PORT} \rightarrow 2 AC \quad \left\{ \begin{array}{l} w_1 \sigma_1 \rho_{12} \\ w_2 \sigma_2 \end{array} \right.$$

$$\sigma_{PORT} = \sqrt{(w_1 \cdot \sigma_1)^2 + (w_2 \cdot \sigma_2)^2 + 2 \cdot w_1 \cdot w_2 \cdot \underbrace{\sigma_1 \cdot \sigma_2 \cdot \rho_{12}}_{COV_{12}}}$$

$$\rho_{12}=1 \Rightarrow \sigma_{PORT} = w_1 \sigma_1 + w_2 \sigma_2$$

$$\rho_{12}=-1 \Rightarrow \sigma_{PORT} = |w_1 \sigma_1 - w_2 \sigma_2|$$

$$\sigma_{PORT} \rightarrow 3 AC \quad \left\{ \begin{array}{l} w_1 \sigma_1 \rho_{12} \\ w_2 \sigma_2 \rho_{13} \\ w_3 \sigma_3 \rho_{23} \end{array} \right.$$

$$\sigma_{PORT} = \sqrt{(w_1 \sigma_1)^2 + (w_2 \sigma_2)^2 + (w_3 \sigma_3)^2 + 2w_1 \cdot w_2 \cdot \sigma_1 \cdot \sigma_2 \cdot \rho_{12} + 2 \cdot w_1 \cdot w_3 \cdot \sigma_1 \cdot \sigma_3 \cdot \rho_{13} + 2 \cdot w_2 \cdot w_3 \cdot \sigma_2 \cdot \sigma_3 \cdot \rho_{23}}$$

$\sim \dots \sim \left\{ \begin{array}{l} w_1 \sigma_1 \rho_{12} \\ w_2 \sigma_2 \rho_{13} \\ w_3 \sigma_3 \end{array} \right\} \frac{N \cdot (N-1)}{2}$

$$\sigma_{\text{PORT}} \text{ with } N \text{ A.G.} \left\{ \begin{array}{c} w_1 \\ w_2 \\ \vdots \\ w_N \end{array} \right. \left\{ \begin{array}{c} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_N \end{array} \right. \left\{ \begin{array}{c} \rho_{12} \\ \rho_{13} \\ \vdots \\ \rho_{N-1,N} \end{array} \right. \left\{ \frac{N \cdot (N-1)}{2} \right\}$$

$$\sigma_{\text{PORT}} = \sqrt{\sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_i \cdot \sigma_j \cdot \rho_{ij}}$$

Matrices

$$\sigma_{\text{PORT}} = \sqrt{[w_1 \ w_2 \ \dots \ w_N] \times \begin{bmatrix} \sigma_{11} & & \\ & \sigma_{22} & \\ & & \ddots & \sigma_{NN} \end{bmatrix} \times \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix}}$$

$$\sigma_{\text{PORT}} = \sqrt{[w_1 \sigma_1 \ w_2 \sigma_2 \ \dots \ w_N \sigma_N] \times \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \end{bmatrix} \times \begin{bmatrix} w_1 \sigma_1 \\ w_2 \sigma_2 \\ \vdots \\ w_N \sigma_N \end{bmatrix}}$$

Calculation :

=SQRT(MMULT(MMULT(B30:K30;B33:K42);TRANSPOSE(B30:K30)))

The effect of Hedging on Equity and Bond market

Hedging in Equity \rightarrow S&P 500 USA

Hedging in Government Bond Market I.G.

Risk es Potential Loss $\rightarrow V@R$

Parametric Approach → Pearson Distribution

$$Var(\%) = \bar{R} - K \cdot \sigma$$

↓

$$99\% \rightarrow K=2,386$$
$$98\% \rightarrow K=2,05$$
$$95\% \rightarrow K=1,645$$

In Matlab®

close all
clear all

```
[DATASET LABELS]=xlsread('File_excel.xlsx','Time Series','B2:K25')  
ANN_RET=mean(DATASET)
```

```
figure(1)  
barh(ANN_RET)  
title('Average Annual Returns')  
ylabel('Markets')  
xlabel('Average Returns')  
set(gca,'YTickLabel',LABELS)  
grid on
```

```
WEIGHTS=xlsread('FILE_EXCEL','Time Series','B29:K29')  
figure(2)  
pie(WEIGHTS)  
title('Portfoglio Weights')  
LEGEND=legend(LABELS,'Location','SouthOutside')
```

```
AV_RET_PORT=WEIGHTS*ANN_RET'
```

```
figure(3)  
plot(DATASET(:,1))  
hold on  
plot(DATASET(:,4),'r')  
hold on  
plot(DATASET(:,6),'g')  
hold on  
plot(DATASET(:,7),'y')
```

```

hold off
grid on
title('Volatility')
ylabel('Annual return')
xlabel('Time')
LEGEND= legend([LABELS(1,1) LABELS(1,4) LABELS(1,6)
LABELS(1,7)],'Location','SouthOutside')

SIGMA=std(DATASET)
figure(4)
subplot(1,2,1)
barh(SIGMA,'r')
title('Standard Deviations')
ylabel('Markets')
xlabel('Standard Deviations')
set(gca,'YTickLabel',LABELS)
grid on
subplot(1,2,2)
scatter(SIGMA,ANN_RET,'filled')
title('Risk-Return')
ylabel('Av Ret')
xlabel('Standard Deviation')
grid on

figure(5)
subplot(2,2,1)
scatter(DATASET(:,7),DATASET(:,8))
title('Corr MSCI Europe - MSCI NA')
ylabel('MSCI North America')
xlabel('Msci Europe')
grid on
lsline
subplot(2,2,2)
scatter(DATASET(:,7),DATASET(:,10))
title('Corr MSCI Europe - MSCI EM')
ylabel('MSCI EM')
xlabel('Msci Europe')
grid on
lsline
subplot(2,2,3)
scatter(DATASET(:,7),DATASET(:,5))
title('Corr MSCI Europe - Global HY Corp')
ylabel('Global HY Corp')
xlabel('Msci Europe')
grid on
lsline

```

```
subplot(2,2,4)
scatter(DATASET(:,7),DATASET(:,3))
title('Corr MSCI Europe - Bond Area €')
ylabel('Bond € Area')
xlabel('Msci Europe')
grid on
lsline
```

```
CORRELATIONS=corr(DATASET)
COVARIANCES=cov(DATASET)
```

```
SIGMA_PORT=sqrt(WEIGHTS*COVARIANCES*WEIGHTS')
```

```
K1=norminv([0.95])
K2=norminv([0.99])
VAR_95=ANN_RET-K1.*SIGMA
VAR_99=ANN_RET-K2.*SIGMA
AGGR_VAR=[VAR_95' VAR_99']
figure(6)
barh([AGGR_VAR])
title('VaR (conf lev=95% & 99%)')
ylabel('Mkts')
xlabel('VaR')
set(gca,'YTickLabel',LABELS)
legenda= legend({'VaR 95%', 'VaR 99%'},'Location','SouthOutside')
grid on
```

```
%%%%%%%%%%%%%
%
%THE END
%%%%%%%%%%%%%
```

Strategic Asset Allocation (SAA)

Step 1: Naive Portfolio Formation Rule

Question 1: "Assume that you don't have expectation about markets behaviours in the next 5 years (No Strategic Views), which is the right SAA?"

Golden Rule 1: Without views the SAA should be fully consistent with the global market composition: in other words the strategic solution must be **MARKET NEUTRAL**

Question 2: "Look to this Strategic Solution. Does an average investor consider this portfolio **REASONABLE**" 

Asset Classes	SAA Neutral HBA
Money Mkt in €	3%
€ Bond Mkt Short Term	5%
€ Bond Mkt	10%
Global Bond Dev Mkts	39% 
Global Corp Bond High Yield	3%
Em Mkts Bond Mkt	5%
Equ. Europe	6%
Equ. North America	19% 
Equ. Pacific	3%
Equ. Em Mkts	5%
Opportunities	2%

Golden Rule 2: Given that the market neutral solution is likely to be labelled as unreasonable because of the Home Bias, it can be useful to adjust the market neutrality in order to promote reasonability of the strategic solution.

Golden Rule 3: If (and only if) you have views (with good confidence), you are justified to diverge from the mkt neutrality (HBA)

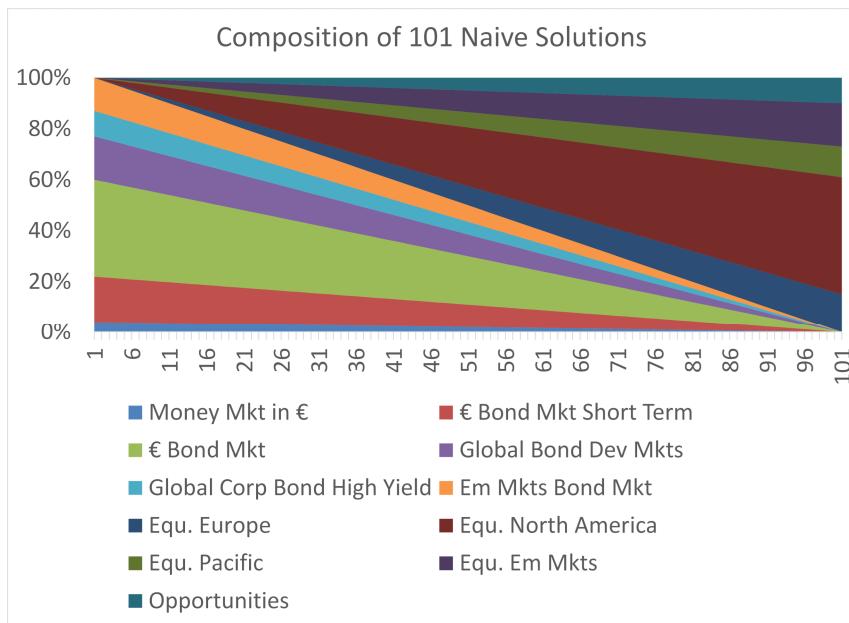
SAA Neutral HBA	SAA Naive
1%	1%
7%	6%
14%	13%
8%	6%
2%	4%
3%	5%
13%	10%
34%	30%
6%	8%
8%	11%
3%	7%

Weights	naive	neutral HBA	
35,0%	4%	4%	Money Mkt in €
	18%	20%	€ Bond Mkt Short Term
	38%	40%	€ Bond Mkt
	17%	23%	Global Bond Dev Mkts
	10%	5%	Global Corp Bond High Yield
	13%	8%	Em Mkts Bond Mkt
65,0%	15%	20%	Equ. Europe
	46%	53%	Equ. North America
	12%	9%	Equ. Pacific
	17%	13%	Equ. Em Mkts
	10%	5%	Opportunities

Long run views

view	confidence
stable	medium
stable dollar \$	medium
credit spread reduction	high
-	medium
-	medium
+	medium
+	medium
sentiment:	
++	high

↙



- Well diversified
- Able to incorporate Market Neutrality and Home bias
- **Naive solution are "good" solution, NEVER OPTIMAL**

↓
If we want to move from a good to an optimal solution,
we need a quantitative approach

If we want a quantitative approach

Modern Portfolio Theory

Markowitz model

Markowitz's "Portfolio Selection": A Fifty-Year Retrospective

Mark Rubinstein

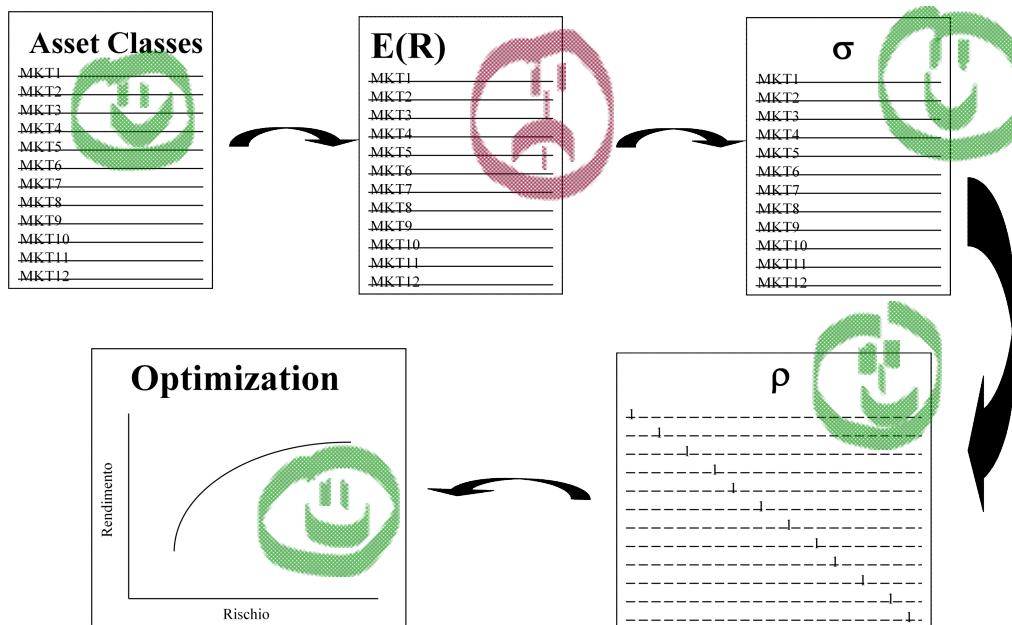
The Journal of Finance, Vol. 57, No. 3. (Jun., 2002), pp. 1041-1045.

Near the end of his reign in 14 AD, the Roman emperor Augustus could boast that he had found Rome a city of brick and left it a city of marble. Markowitz can boast that he found the field of finance awash in the imprecision of English and left it with the scientific precision and insight made possible only by mathematics.

Presents by Markowitz:

- a. Investors love Return and hate Risk
- b. Capture risk via standard deviation
- c. First to talk about correlation and he was the first to measure correctly the diversification effect
- d. First to show that a portfolio can be the output of an optimization - *optimization with the method of the CRITICAL LINE*

Steps of the Markowitz Model (1952):



Opinion of Markowitz about the estimation of E° , sigma and correlations...

THE JOURNAL OF FINANCE

Vol. VII, No. 1, March 1952

PRINTED IN U.S.A.

PORTFOLIO SELECTION*

HARRY MARKOWITZ

To use the $E-V$ rule in the selection of securities we must have procedures for finding reasonable μ_i and σ_{ij} . These procedures, I believe, should combine statistical techniques and the judgment of practical men. My feeling is that the statistical computations should be used to arrive at a tentative set of μ_i and σ_{ij} . Judgment should then be used in increasing or decreasing some of these μ_i and σ_{ij} on the basis of factors or nuances not taken into account by the formal computations. Using this revised set of μ_i and σ_{ij} , the set of efficient E, V combinations could be computed, the investor could select the combination he preferred, and the portfolio which gave rise to this E, V combination could be found.

One suggestion as to tentative μ_i, σ_{ij} is to use the observed μ_i, σ_{ij} for some period of the past. I believe that better methods, which take into account more information, can be found. I believe that what is needed is essentially a "probabilistic" reformulation of security analysis. I will not pursue this subject here, for this is "another story." It is a story of which I have read only the first page of the first chapter.

FOUNDATIONS OF PORTFOLIO THEORY

Nobel Lecture, December 7, 1990

by

HARRY M. MARKOWITZ

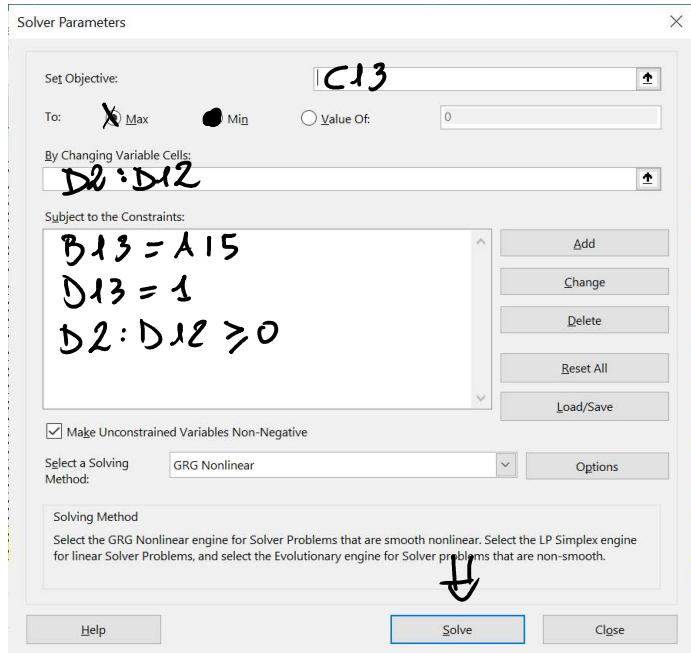
Finally, I would like to add a comment concerning portfolio theory as a part of the microeconomics of action under uncertainty. It has not always been considered so. For example, when I defended my dissertation as a student in the Economics Department of the University of Chicago, Professor Milton Friedman argued that portfolio theory was not Economics, and that they could not award me a Ph.D. degree in Economics for a dissertation which was not in Economics. I assume that he was only half serious, since they did award me the degree without long debate. As to the merits of his arguments, at this point I am quite willing to concede: at the time I defended my dissertation, portfolio theory was not part of Economics. But now it is.

OPTIMIZATION BY MARKOWITZ (1952)

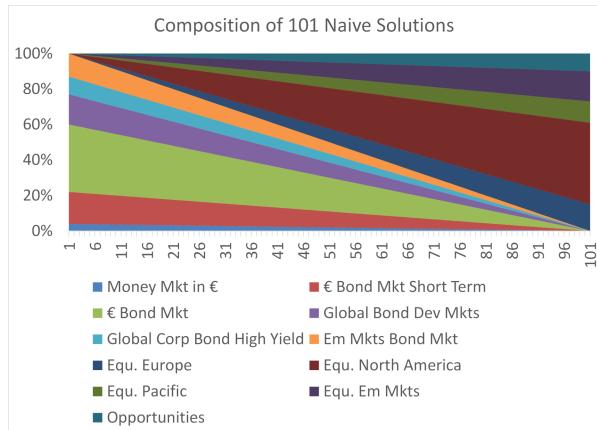
$$\min_{\mathbf{w}} \sigma_{\text{port}}$$

Constraints:

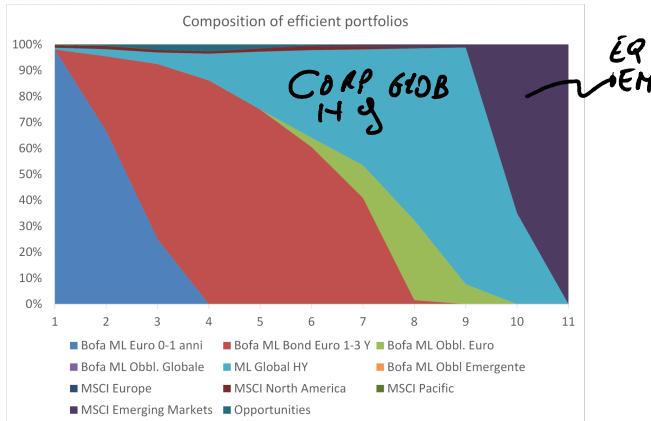
vv
Constraints:
 $E(R)_{\text{PORT}} = R^*$
 $\sum_{i=1}^n w_i = 1$
 $w_i \geq 0$



Naïve



Markowitz



clear all

close all

% Inputs trasferred on Matlab

[EXP_RET_LABELS]=xlsread('File_excel','Mark opt','A2:B12')

COVARIANCE=xlsread('File_excel.xlsx','Mark opt','H2:R12')

```

[RISKPORT RETPORT,
WEIGHTS]=portopt(EXP_RET,COVARIANCE,101)
figure(1)
subplot(2,1,1)
scatter(RISKPORT, RETPORT, 'filled', 'r')
title('Efficient Frontier')
ylabel('E(R)')
xlabel('Sigma')
grid on
subplot(2,1,2)
area(WEIGHTS)
title('Composition of Efficient Portfolios')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
xlim([1 101]);
% Naive Frontier
EQUITY_PORTION=[0:0.01:1]
NAIVE_QUALITATIVE_WEIGHTS=xlsread('File_excel.xlsx','Naive
Strategy','F2:F12')
NAIVE_PORTFOLIOS_COMPOSITION=zeros(101,11);
for i=1:101
    NAIVE_PORTFOLIOS_COMPOSITION(i,:)=[((1-
EQUITY_PORTION(i,1))*NAIVE_QUALITATIVE_WEIGHTS(1:6,1))'
((EQUITY_PORTION(i,1))*NAIVE_QUALITATIVE_WEIGHTS(7:end,1))'];
end

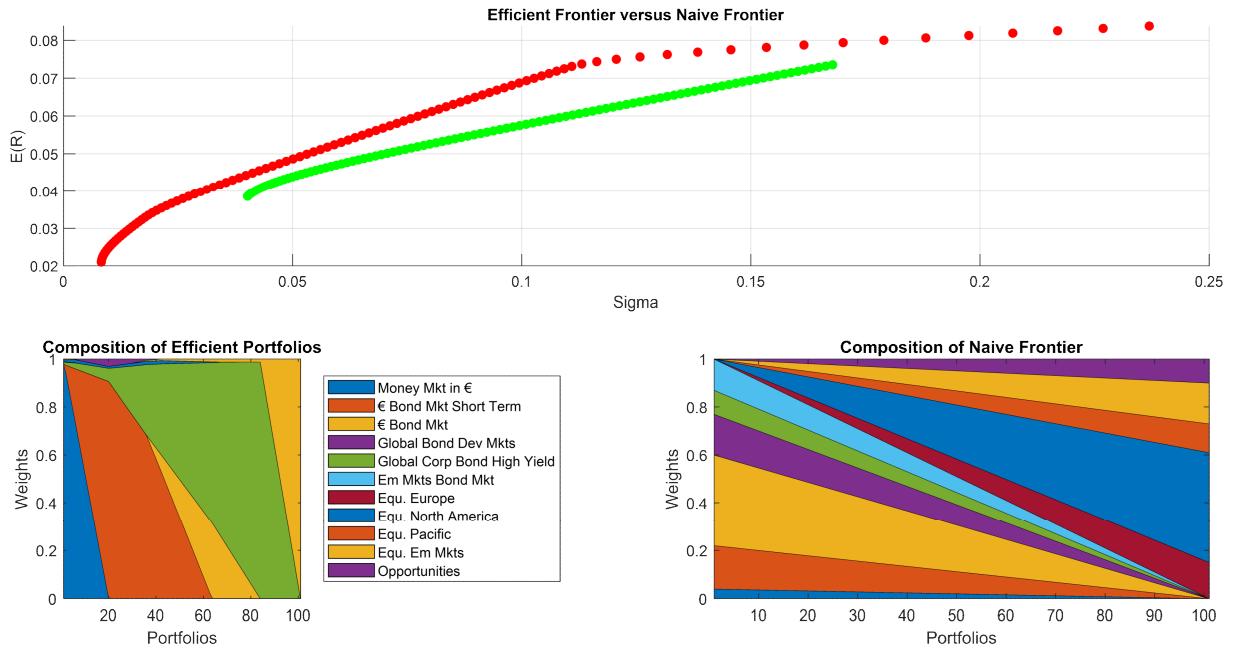
EXP_RET_NAIVE=(EXP_RET*NAIVE_PORTFOLIOS_COMPOSITION)'
SIGMA_NAIVE=zeros(101,1);
for j=1:101
    SIGMA_NAIVE(j,1)=sqrt(NAIVE_PORTFOLIOS_COMPOSITION(j,:)*CO
VARIANCE*NAIVE_PORTFOLIOS_COMPOSITION(j,:));
end
figure(2)
subplot(2,2,[1 2])
scatter(RISKPORT, RETPORT, 'filled', 'r')
hold on
scatter(SIGMA_NAIVE, EXP_RET_NAIVE, 'filled', 'g')

```

```

title('Efficient Frontier versus Naive Frontier')
ylabel('E(R)')
xlabel('Sigma')
grid on
hold off
subplot(2,2,3)
area(WEIGHTS)
title('Composition of Efficient Portfolios')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
xlim([1 101]);
subplot(2,2,4)
area(NAIVE_PORTFOLIOS_COMPOSITION)
title('Composition of Naive Frontier')
ylabel('Weights')
xlabel('Portfolios')
%legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
xlim([1 101]);

```



Potential practical problems of the Markowitz Approach:

- 1) Markowitz solutions have unreasonable composition (concentrated, hugely concentrated on "marginal players", not consistent with market neutrality or home bias);
- 2) Markowitz solution are "not stable";

% Strategic Committe ALFA

```
LABELS={'Money Mkt €';'Eq. Europe';'Equ. North America'}
EXP_RET1=[0.005; 0.07; 0.074]
SIGMA=[0.01; 0.2; 0.2]
CORR=[1 0 0; 0 1 0.94; 0 0.94 1]
COV=corr2cov(SIGMA, CORR)
[RISK1 REND1 W1]=portopt(EXP_RET1,COV,100)
```

```
figure(1)
subplot(2,1,1)
area(W1)
title('Composition of Efficient Portfolios AM Bank ALFA')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
```

```

xlim([1 100]);
% Strategic Committe BETA
EXP_RET2=[0.005; 0.074; 0.07]
[RISK2 REND2 W2]=portopt(EXP_RET2,COV,100)

```

```

subplot(2,1,2)
area(W2)
title('Composition of Efficient Portfolios AM Bank BETA 2')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
xlim([1 100]);

```

- 3) The model assumes that inputs are True, in other words analysts area assumed to be clairuioant
- 4) Because of the concentration markowitz solution are not only "Expected Return maximiser", but also "estimation error maximiser"

 FRANKFURTHER - PHILIPS - SEARCE

(1981): "Since estimation errors are so large portfolios selected according to the Markowitz criterior are likely no more efficient than a well diversified portfolio"

MARKOWITZ

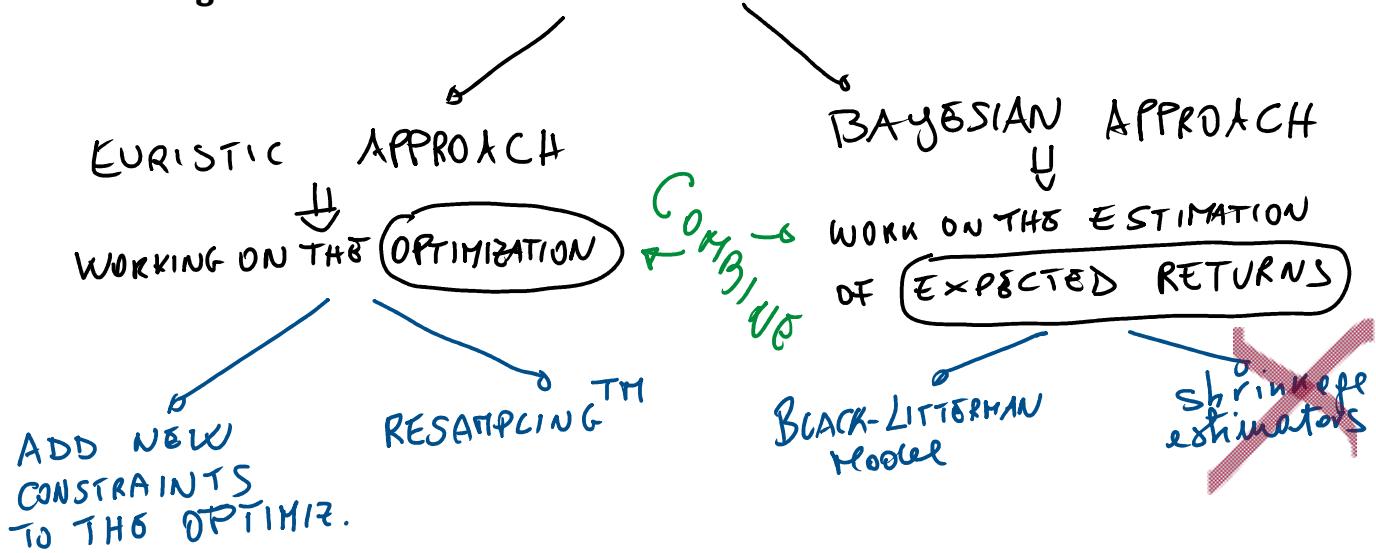


NAIVE





"Putting Markowitz At Work" → PURPOSE: INCREASE DIVERSIFICATION



First Beristic Approach
↳ Additional Constraints to Markowitz Optim.

* First kind of constraints → ABSOLUTE CONSTRAINTS

$$\min_{\mathbf{w}} \sigma_{\text{PORT}}$$

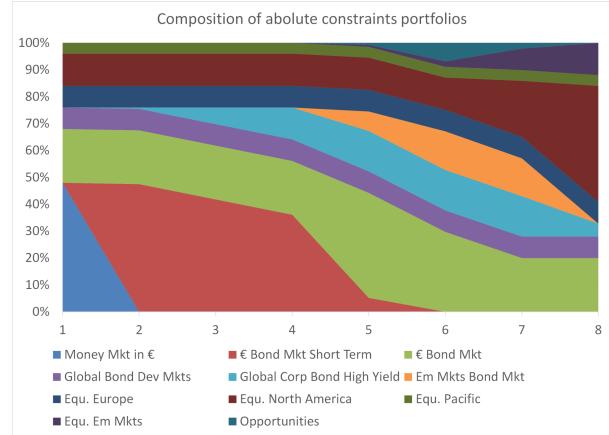
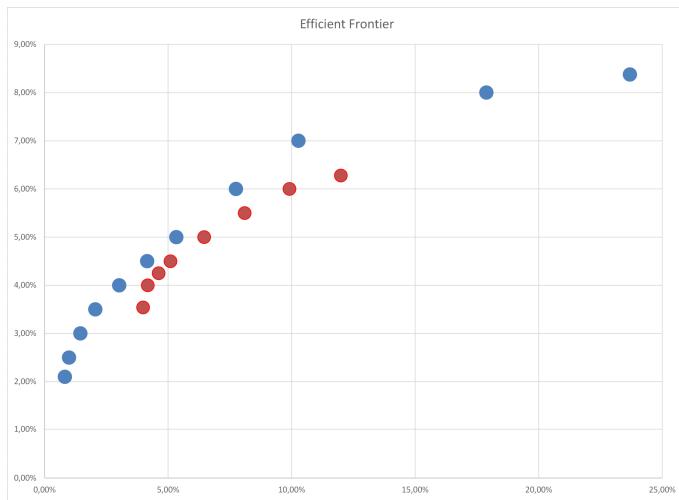
Constraints:

$$E(R)_{\text{PORT}} = R^*$$

$$\sum_{i=1}^N w_i = 1$$

$$w_i \geq 0$$

$$\left. \begin{array}{l} w_i \geq h_i \\ w_i \leq k_i \end{array} \right\} \text{ABSOLUTE CONSTRAINTS}$$



Absolute Constraints with Matlab:

```
clear
```

```
close all
```

```
% Inputs transferred on Matlab
```

```
[EXP_RET LABELS]=xlsread('FILE_EXCEL.xlsx','Mark abs','A2:B12')
```

```
COVARIANCE=xlsread('FILE_EXCEL.xlsx','Mark abs','H2:R12')
```

```
[RISKPORT2 RETPORT2,
```

```
WEIGHTS2]=portopt(EXP_RET,COVARIANCE,100)
```

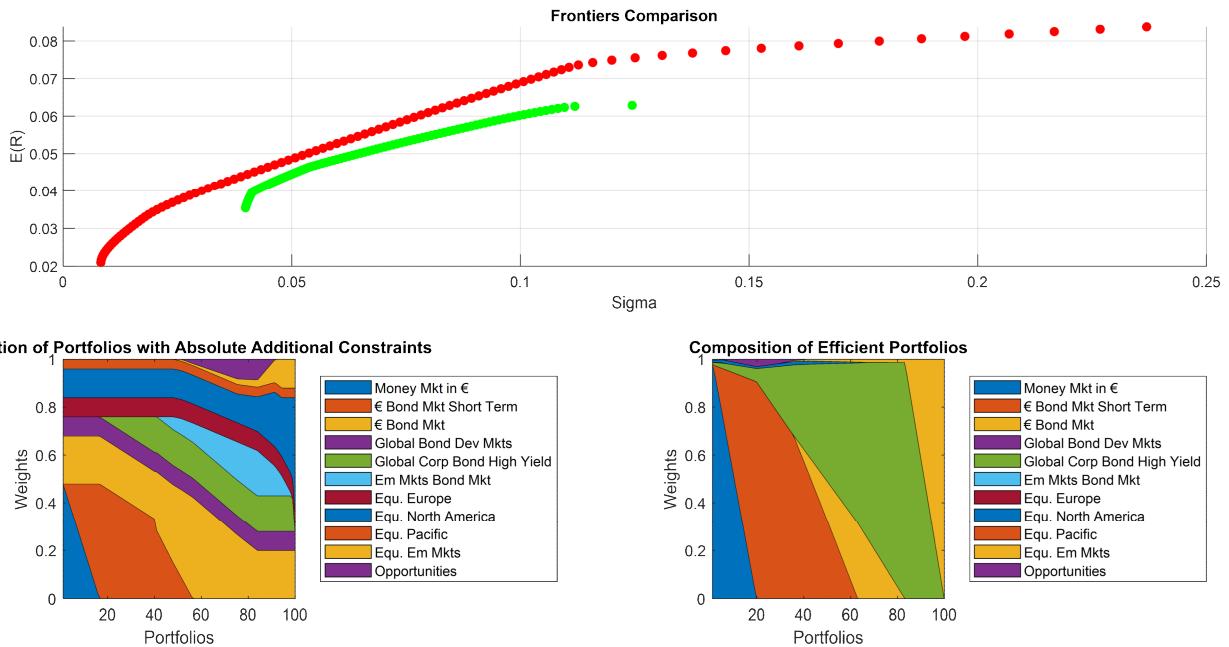
```
AssetMin=xlsread('FILE_EXCEL.xlsx','Mark abs','V2:V12')
```

```

AssetMax=xlsread('FILE_EXCEL.xlsx','Mark abs','W2:W12')
[Aa, ba] = pcalims(AssetMin, AssetMax);
p = Portfolio;
p = setAssetMoments(p, EXP_RET, COVARIANCE);
p = setDefaultConstraints(p); % implement default constraints
first
p = addInequality(p, Aa, ba); % implement bound constraints
here
WEIGHTS = estimateFrontier(p, 100);
[RISKPORT, RETPORT] = estimatePortMoments(p, WEIGHTS);
disp([RISKPORT, RETPORT]);

figure(1)
subplot(2,2,[1 2])
scatter(RISKPORT, RETPORT, 'filled', 'g')
hold on
scatter(RISKPORT2, RETPORT2, 'filled', 'r')
title('Frontiers Comparison')
ylabel('E(R)')
xlabel('Sigma')
grid on
subplot(2,2,3)
area(WEIGHTS)
title('Composition of Portfolios with Absolute Additional Constraints')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
xlim([1 100]);
subplot(2,2,4)
area(WEIGHTS2)
title('Composition of Efficient Portfolios')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
xlim([1 100]);

```



A better way to set constraints
 ↳ from Absolute to Relative constraints....
 ↓
 INFRA - GROUP

$$\min_w \sigma_{\text{PORT}}$$

Constraints:

$$E(R)_{\text{PORT}} = R^*$$

$$\sum_{i=1}^N w_i = 1$$

$$w_i \geq 0$$

$$\frac{w_i}{\sum_{\substack{\text{SANE} \\ \text{GROUP}}} w} \geq h_i$$

$$\sum_{\substack{w_i \\ \text{same group}}} \geq \pi_i$$

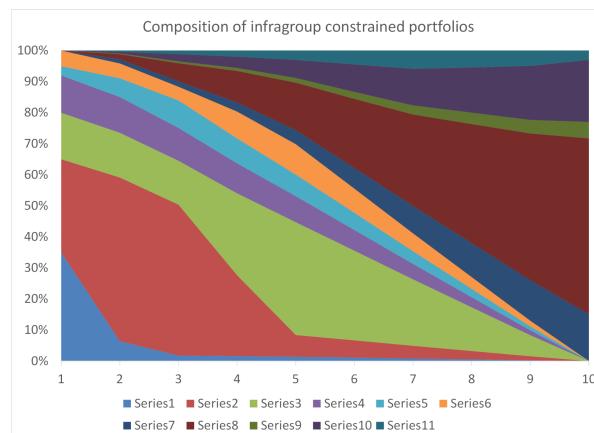
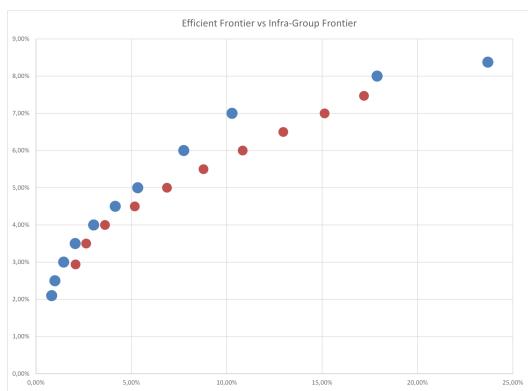
$$\frac{w_i}{\sum_{\substack{w_j \\ \text{same group}}}} \leq K_i$$

EUROPEAN
EQU. MKT

$$H_i \quad \begin{matrix} \text{MKT NEUTR} \\ \downarrow \\ \text{HBA} \\ \downarrow \\ \text{lot.} \end{matrix} \quad K_i$$

Asset Class	min	MKT NEUTR HBA	MAX
Money Mkt in €	2%	4,0%	35%
€ Bond Mkt Short Term	10%	20,0%	55%
€ Bond Mkt	15%	40,0%	65%
Global Bond Dev Mkts	12%	23,0%	28%
Global Corp Bond High Yield	3%	5,0%	10%
Em Mkts Bond Mkt	5%	8,0%	14%
Equ. Europe	15%	20,0%	32%
Equ. North America	35%	53,0%	60%
Equ. Pacific	5%	9,0%	15%
Equ. Em Mkts	6%	13,0%	20%
Opportunities	3%	5,0%	10%

Excel:



clear

close all

%data from the excell file

[EXP_RET LABELS]=xlsread('File_excel.xlsx','Mark Infra Optim','A2:B12');

COV=xlsread('File_excel.xlsx','Mark Infra Optim','H2:R12');

LB1=xlsread('File_excel.xlsx','Mark Infra Optim','U2:U12');

UB1=xlsread('File_excel.xlsx','Mark Infra Optim','W2:W12');

```

%setting P and the constraints for positive weights
P=Portfolio;
P=Portfolio('AssetMean',
EXP_RET,'AssetCovar',COV,'Assetlist',LABELS,'LowerBudget', 1,
'UpperBudget', 1);
LB=-zeros(1,length(EXP_RET));
b=-eye(length(EXP_RET));
P = setInequality(P,b,LB);

POSITION = eye(length(EXP_RET))
GROUP = [1 1 1 1 1 1 0 0 0 0 0;1 1 1 1 1 1 0 0 0 0 0;1 1 1 1 1 1 0
0 0 0;1 1 1 1 1 1 0 0 0 0;1 1 1 1 1 1 0 0 0 0;1 1 1 1 1 1 0 0
0 0;0 0 0 0 0 0 1 1 1 1;0 0 0 0 0 0 1 1 1 1;0 0 0 0 0 0 1 1 1 1
1;0 0 0 0 0 0 1 1 1 1;0 0 0 0 0 0 1 1 1 1]
P = setGroupRatio(P, POSITION, GROUP, LB1, UB1);

```

PORTRWEIGHT=estimateFrontier(P,100)

[RISK_INFRA, EXP_RET_INFRA] = estimatePortMoments(P,
PORTRWEIGHT);

% Standard Optimization
[RISKPORT, RETPORT, WEIGHTS]=portopt(EXP_RET,COV,100)

% Naive Frontier
EQUITY_PORTION=[0:0.01:1]'
NAIVE_QUALITATIVE_WEIGHTS=xlsread('File_excel.xlsx','Naive
Strategy','F2:F12')
NAIVE_PORTFOLIOS_COMPOSITION=zeros(101,11);
for i=1:101
NAIVE_PORTFOLIOS_COMPOSITION(i,:)=[((1-
EQUITY_PORTION(i,1))*NAIVE_QUALITATIVE_WEIGHTS(1:6,1)
)'

```
((EQUITY_PORTION(i,1))*NAIVE_QUALITATIVE_WEIGHTS(7:end,1))';
end
```

```
EXP_RET_NAIVE=(EXP_RET'*NAIVE_PORTFOLIOS_COMPOSITION)';
SIGMA_NAIVE=zeros(101,1);
for j=1:101
SIGMA_NAIVE(j,1)=sqrt(NAIVE_PORTFOLIOS_COMPOSITION(j,:)*COV*NAIVE_PORTFOLIOS_COMPOSITION(j,:));
end
```

```
figure(1)
subplot(2,2,[1 2])
scatter(RISK_INFRA, EXP_RET_INFRA, 'o', 'r')
hold on
scatter(RISKPORT, RETPORT, 'o', 'b')
%hold on
%scatter(SIGMA_NAIVE, EXP_RET_NAIVE, 'o', 'g')
hold off
title('Infra Group Frontier versus Efficient Frontier')
ylabel('E(R)')
xlabel('Sigma')
grid on
subplot(2,2,3)
area(PORT_WEIGHT)
title('Composition of Infr-Group Portfolios')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
```

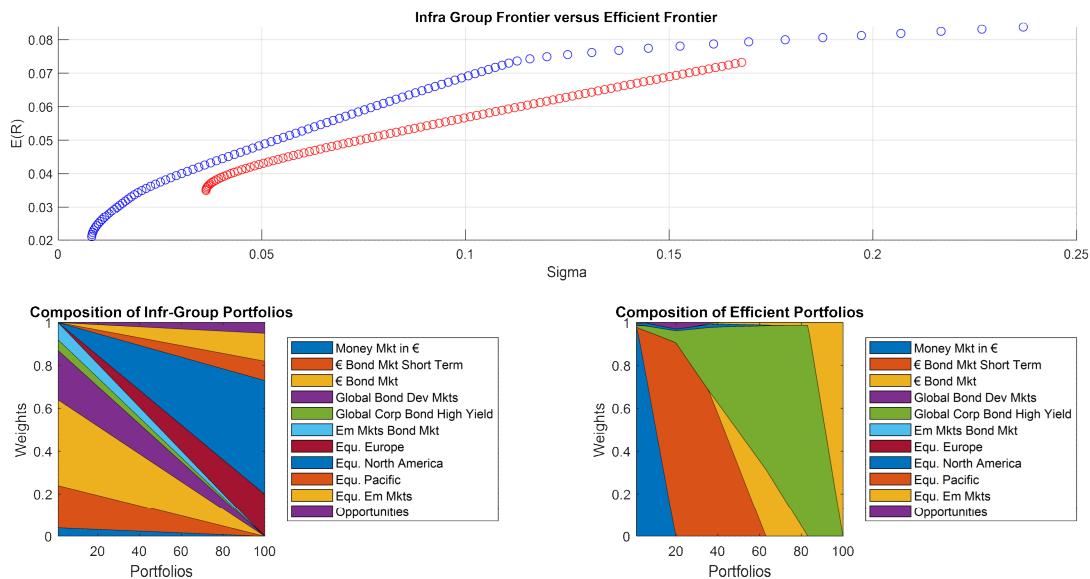
```

xlim([1 100]);
subplot(2,2,4)
area(WEIGHTS)
title('Composition of Efficient Portfolios')
ylabel('Weights')
xlabel('Portfolios')
legenda= legend(LABELS,'Location','EastOutside')
ylim([0 1]);
xlim([1 100]);

```

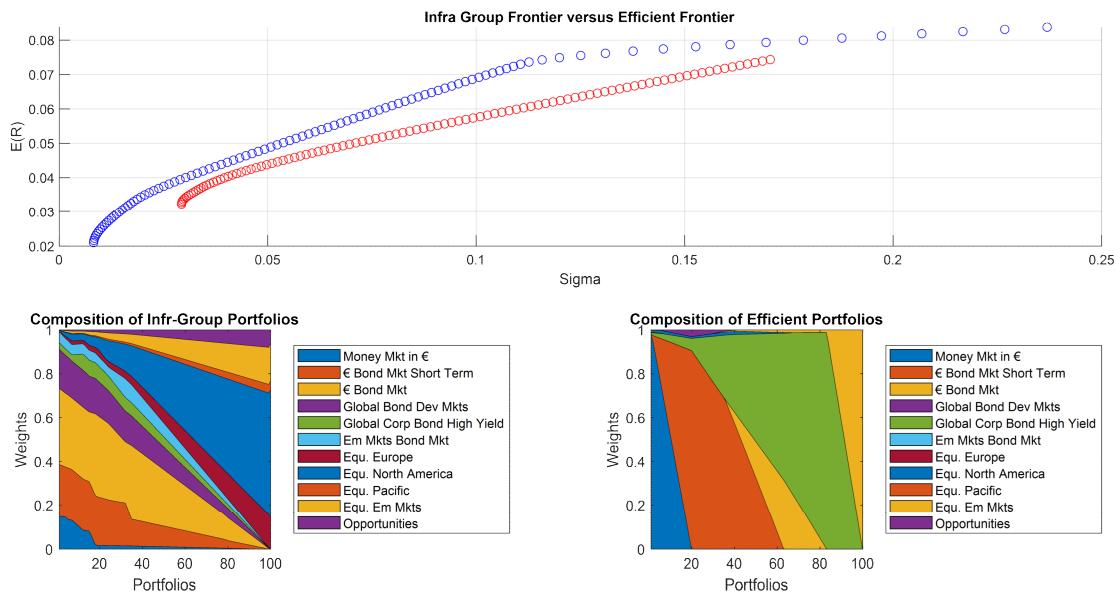
Confidence → Ø

Asset Class	<i>min</i>	MKT NEUTR HBA	<i>MAX</i>
Money Mkt in €	4%	4,0%	4%
€ Bond Mkt Short Term	20%	20,0%	20%
€ Bond Mkt	40%	40,0%	40%
Global Bond Dev Mkts	23%	23,0%	23%
Global Corp Bond High Yield	5%	5,0%	5%
Em Mkts Bond Mkt	8%	8,0%	8%
Equ. Europe	20%	20,0%	20%
Equ. North America	53%	53,0%	53%
Equ. Pacific	9%	9,0%	9%
Equ. Em Mkts	13%	13,0%	13%
Opportunities	5%	5,0%	5%



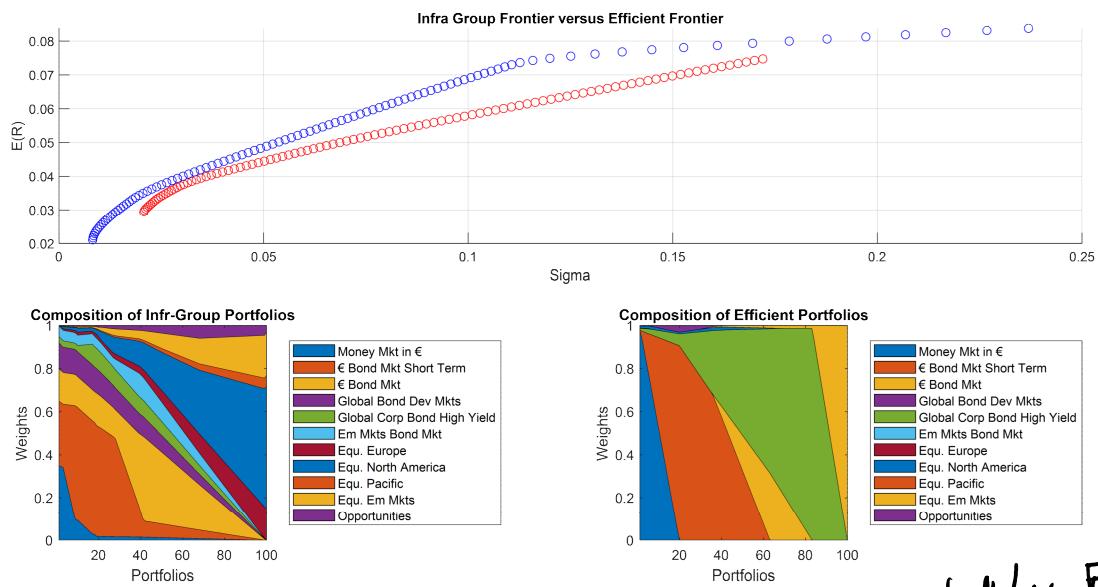
Confidence → SMALL

Asset Class	<i>min</i>	MKT NEUTR HBA	<i>MAX</i>
Money Mkt in €	2%	4,0%	15%
€ Bond Mkt Short Term	15%	20,0%	25%
€ Bond Mkt	35%	40,0%	45%
Global Bond Dev Mkts	18%	23,0%	29%
Global Corp Bond High Yield	3%	5,0%	8%
Em Mkts Bond Mkt	5%	8,0%	11%
Equ. Europe	15%	20,0%	25%
Equ. North America	47%	53,0%	58%
Equ. Pacific	4%	9,0%	13%
Equ. Em Mkts	9%	13,0%	17%
Opportunities	3%	5,0%	8%

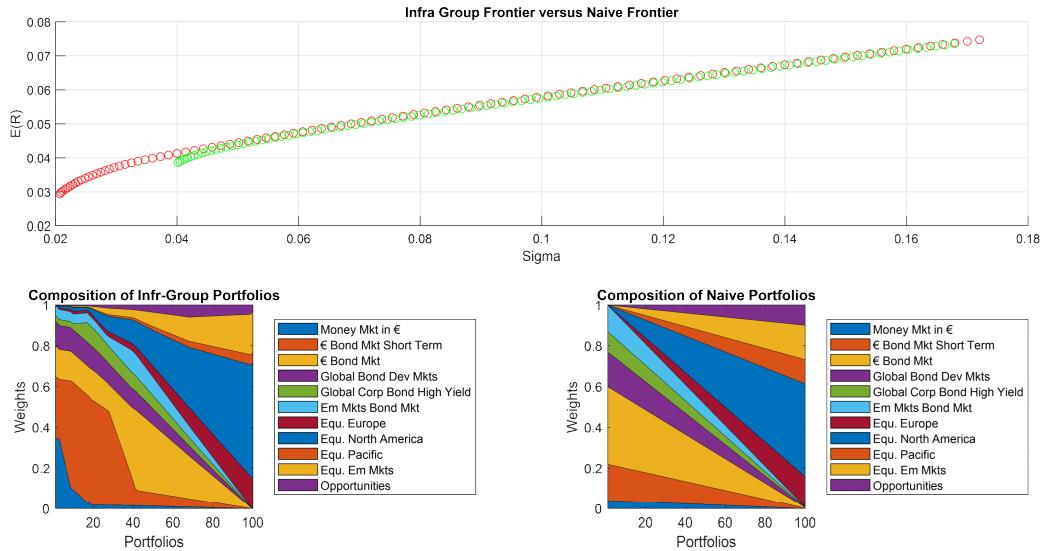


Confidence → Good

min	MKT NEUTR HBA	MAX
2%	4,0%	35%
10%	20,0%	55%
15%	40,0%	65%
12%	23,0%	28%
3%	5,0%	10%
5%	8,0%	14%
15%	20,0%	32%
35%	53,0%	60%
5%	9,0%	15%
6%	13,0%	20%
3%	5,0%	10%



A comparison between Infra Group Frontier and Noise Frontier



Resampling \rightarrow (by Michaud) \rightarrow Markowitz Opt. + Monte Carlo Simulation

Extra-argument 3: A deeper analysis of Resampling (4/7)

What do we need in order to simulate?

- Forecasts ($\Rightarrow E(R), \sigma, \rho$) \rightarrow Exp
- Confidence on estimations \rightarrow
- Random process that is able to make R_{rand} deviations from the expectation.

\downarrow

$$\text{Simulation} = \alpha \cdot Exp + (1-\alpha) R_{rand}$$

Univariate MC Simulation \rightarrow Excel

European Equ Mkt	Expectation	Simulation
Exp return	6,00%	5,62%
Sigma	12,72%	18,79%

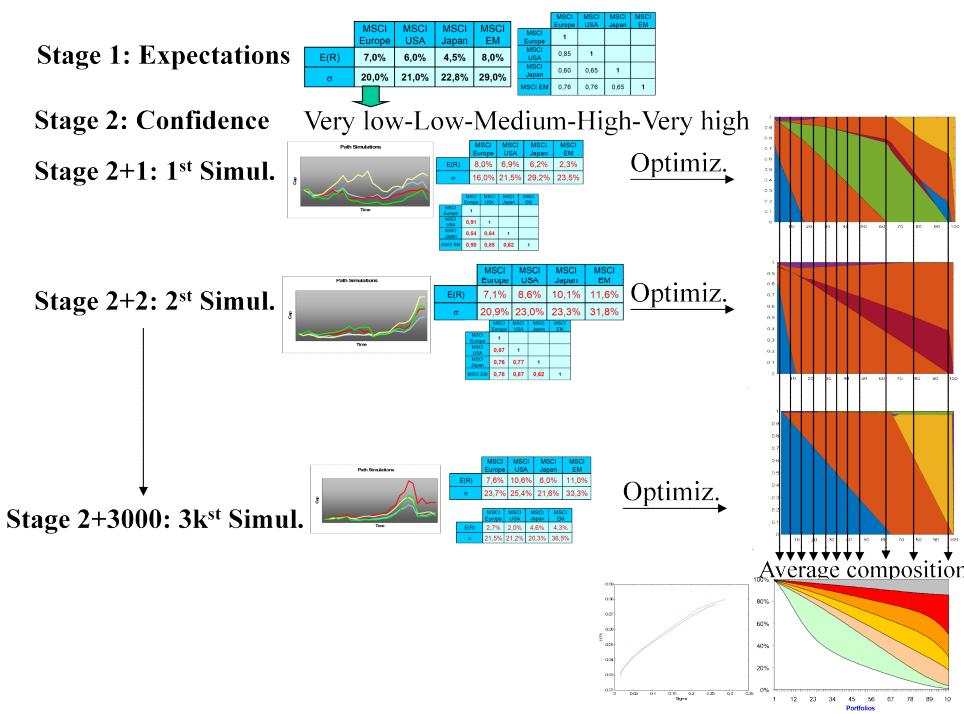
Expectation versus Simulation

rand numb	simul returns
0,4621242	4,79%
0,9983643	43,41%
0,0116022	-22,87%
0,4295233	3,74%
0,3905747	2,47%
0,3329822	0,51%
0,5438641	7,40%
0,3211239	0,09%
0,0755519	-12,26%
0,9644984	28,96%
0,0848392	-11,47%
0,2064946	-4,41%
0,7762947	15,66%

Parameter for \rightarrow Size (number of simulated returns from which I calculate $E(R)_{sim}$ and σ_{sim})

In Practice:

CONFIDENCE:	5-25
LOW	12-15
MEDIUM	25-35
HIGH	40-50



Resampling® on Matlab:

```

clear
close all
% Inputs transferred on Matlab
[EXP_RET LABELS]=xlsread('File_excel.xlsx','Mark opt','A2:B12')
COV=xlsread('File_excel.xlsx','Mark opt','H2:R12')

```

ASSET=11;
SIZE=25;

```
SIM= 1000;
```

```
% frontiera efficiente semplice  
[RISK2,ROR2,WTS2]=portopt(EXP_RET,COV,100);
```

```
STORE_WTS=zeros(100,ASSET,SIM);
```

```
for i = 1:SIM  
i  
SIM_RET= mvnrnd(EXP_RET, COV,SIZE);  
EXP_RET_SIM=mean(SIM_RET);  
COV_SIM=cov(SIM_RET);  
[RISK,ROR,WTS]=portopt(EXP_RET_SIM,COV_SIM,100);  
if i<=25  
figure(1)  
subplot(5,5,i)  
area(WTS)  
ylim([0 1]);  
xlim([1 100]);  
pause  
end  
STORE_WTS(:,:,i)= WTS;  
end
```

```
RESAPL_WEIGHTS=mean(STORE_WTS,3);
```

```
EXP_RET_RESAMPL= RESAPL_WEIGHTS*EXP_RET;  
RISK_RESAMPL = zeros(100,1);  
for i = 1 :100  
RISK_RESAMPL(i,1) =  
sqrt(RESAPL_WEIGHTS(i,:)*COV*RESAPL_WEIGHTS(i,:));  
end
```

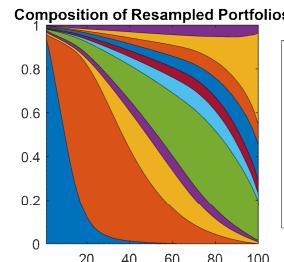
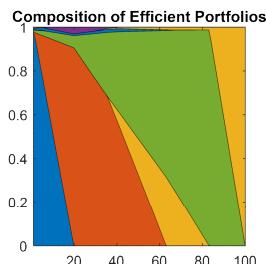
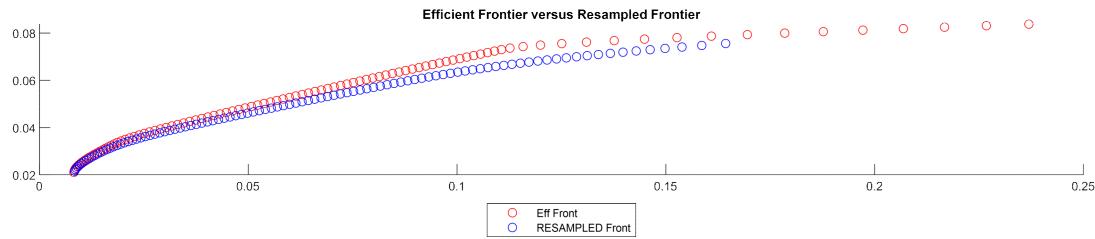
```
figure(2)  
subplot(2,2,[1 2])  
scatter (RISK2,ROR2,'R')  
hold on
```

```

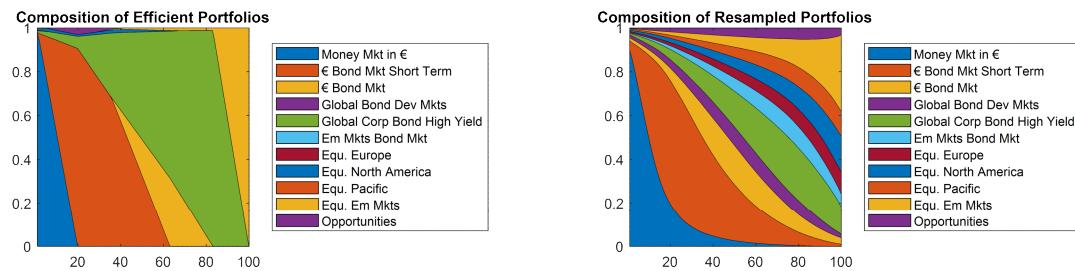
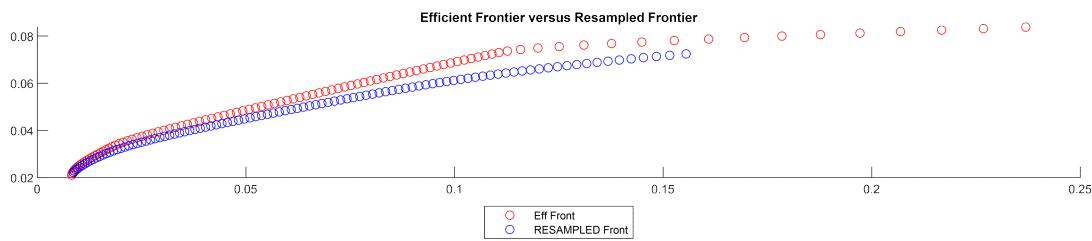
scatter (RISK_RESAMPL,EXP_RET_RESAMPL,'B')
hold off
title('Efficient Frontier versus Resampled Frontier')
legenda= legend({'Eff Front','RESAMPLED
Front'},'Location','SouthOutside')
subplot(2,2,3)
area(WTS2)
legenda= legend(LABELS,'Location','EastOutside')
title('Composition of Efficient Portfolios')
ylim([0 1]);
xlim([1 100]);
subplot(2,2,4)
area(RESAPL_WEIGHTS)
legenda= legend(LABELS,'Location','EastOutside')
title('Composition of Resampled Portfolios')
ylim([0 1]);
xlim([1 100]);

```

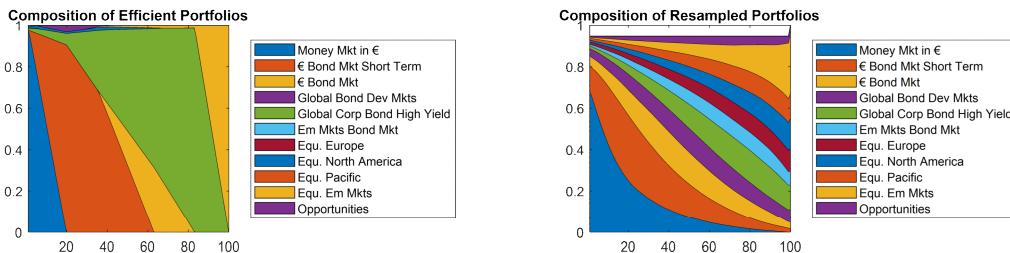
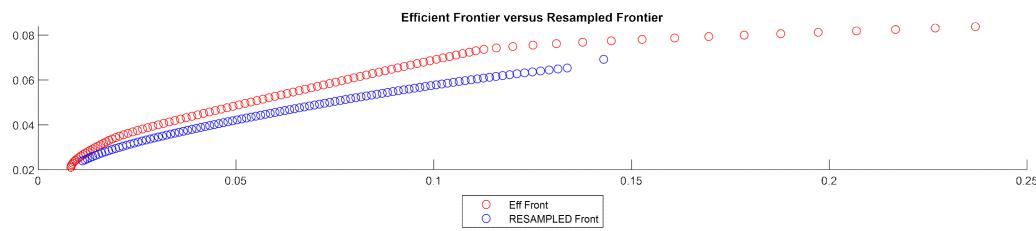
Size = 25 



$S_{12} = 12 \Rightarrow$



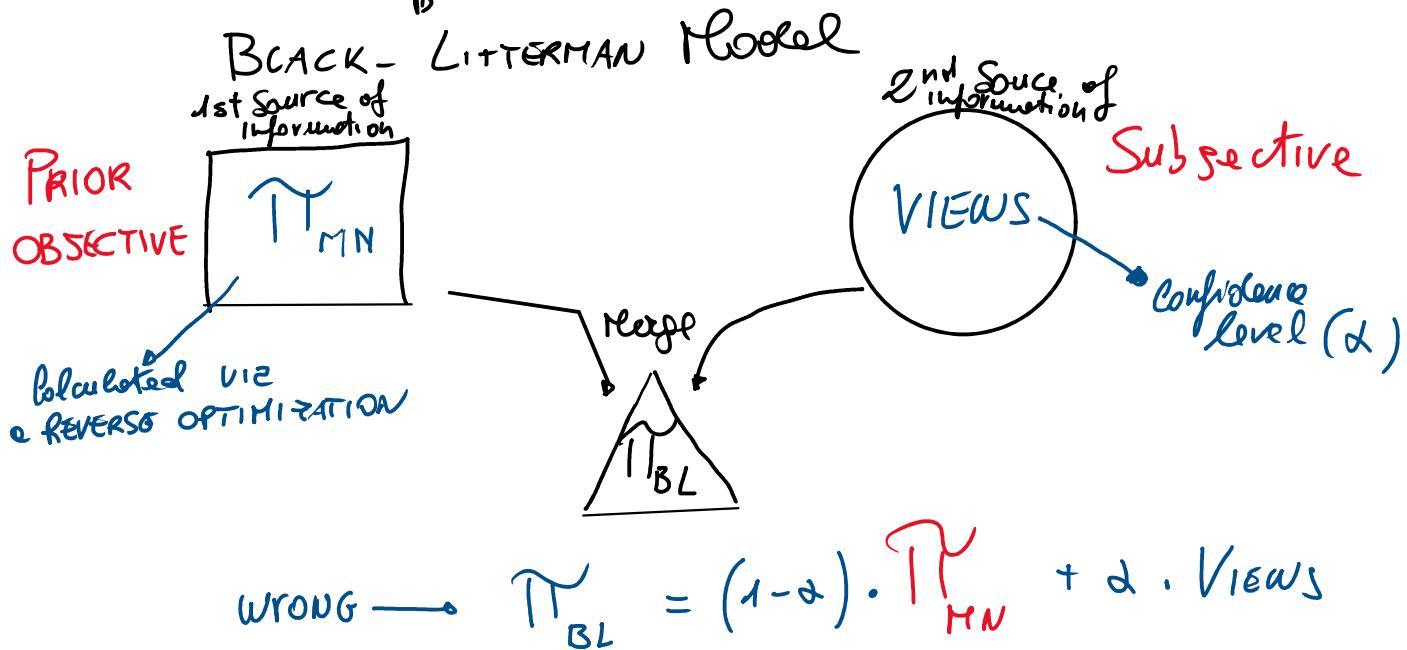
$S_{12} = 10,000$



Bayesian Approaches

Improving Markowitz Optimization
working on - EXPECTED RETURN ESTIMATION

↳ Improving Markowitz Optimization
Working on ----- EXPECTED RETURNS ESTIMATION
(2nd stage)



Analytics of the Black-Litterman Approach

Analytics of the Prior:

4 Ingredients

r_f = risk-free rate

\mathbf{X}_{MN} = column vector of M.N. portfolio composition

Σ = Variance-Covariance Matrix of RETURN of Asset Classes

λ = Lambda \leftarrow risk-aversion coefficient
coefficient of optimism about the future performance
of the MARKET NEUTRAL PORTFOLIO

$$\lambda = \frac{E(R)_{HN} - r_f}{\sigma_{HN}^2}$$

INPUT: r_f , W_{MN} , Σ , λ

Reverse Optimization:

$$\tilde{\pi}_{MN} = r_f + \lambda \cdot \Sigma \cdot W_{MN}$$

Variance - Covariance
Matrix of Asset Classes
EXPECTED RETURN

Prior Information

$$\text{Expected Returns} \sim N(\tilde{\pi}_{MN}; \tilde{\Sigma})$$

$\tilde{\Sigma}$ parameter has the role to
transform the r_f -Cov MATRIX
of Returns in a r_f -Var. MATRIX
of Expected Returns

Property of the Sample Mean

$$\pi \rightarrow \sigma_n^2 \Rightarrow \bar{\pi} \rightarrow \left(\frac{1}{n} \right) \cdot \sigma_n^2$$

$$\tilde{\pi} = \frac{1}{\lambda}$$

Analytics of the 2nd source of information \Rightarrow VIEWS

$\hookrightarrow P, Q, C, \Omega$

$P = \text{Matrix}$ $\begin{cases} \text{n. of rows} \rightarrow \text{n. of views} \\ \text{n. of columns} = \text{n. of asset classes selected} \end{cases}$

$\hookrightarrow P$ shows the asset classes involved in each view

	Money Mkt in €	€ Bond Mkt Short T	€ Bond Mk	Global Bond	Global Corp Bond	Em Mkts	Bond Mk	Equ. Europe	Equ. North America	Equ. Pacific	Equ. Em Mkts	Opportunities	
P	0	0	0	-1	1	0	0	0	0	0	0	0	p1
	0	0	0	0	0	0	0	-1	1	0	0	0	p2

VIEWS
Corporate Global HY will overperform Global Bond
Equity North America will overperform Equity Europe

view
3,5%
1,5%

\cap n \dots n rows = num. of Views

3,50%
1,50%

$Q = \text{Column vector} \rightarrow \text{nº of rows} = \text{numb. of Views}$

Q	3,50%
	1,50%

$\hookrightarrow Q$ shows the Views

$C = \text{Column vector} \rightarrow \text{nº of rows} = \text{numb. of Views}$

confidence
30,0000000000%
30,0000000000%

$\hookrightarrow C$ shows the confidences of the single views

C	30%	c1
	30%	c2

Theory $c_1, c_2, \dots, c_K \in]0; 1[\Rightarrow c_1, c_2, \dots, c_3 \in [15\%; 40\%]$

Views $\sim N(Q; \Omega)$ uncertainty of view
Lever-Cov matrix of the views.

$\Omega \rightarrow \text{Matrix} \Rightarrow \text{nº of rows} = \text{nº of columns} = \text{nº of Views}$
 $\hookrightarrow \Omega$ is the variance-covariance matrix of Views

Assumption: Views are ^{STRONG} ϕ correlated

$$\Omega = \begin{bmatrix} \left(\frac{1}{c_1}-1\right) \cdot p_1 \cdot (\tau\Sigma) \cdot p_1^T & 0 & 0 \\ 0 & \left(\frac{1}{c_2}-1\right) \cdot p_2 \cdot (\tau\Sigma) \cdot p_2^T & 0 \\ 0 & 0 & \ddots \\ 0 & 0 & 0 \left(\frac{1}{c_K}-1\right) \cdot p_K \cdot (\tau\Sigma) \cdot p_K^T \end{bmatrix}$$

Prior

$$Exp_{Ret} \sim N(\bar{\pi}_{NN}; \gamma \Sigma)$$

Views

$$\text{Views} \sim N(Q; \Omega)$$

merge!

$$\begin{aligned}
 \tilde{\Pi}_{BL} &= (\tau \Sigma)^{-1} \cdot \Pi_{MN} + (\Omega)^{-1} \cdot Q = \\
 &= \left[(\tau \Sigma)^{-1} + \Omega^{-1} \right] \cdot \left[(\tau \Sigma)^{-1} \cdot \Pi_{MN} + \Omega^{-1} \cdot Q \right]
 \end{aligned}$$

$$\Pi_{BL} = \left[(\tau \Sigma)^{-1} + P^T \cdot \Omega^{-1} \cdot P \right]^{-1} \times \left[(\tau \Sigma)^{-1} \cdot \Pi_{MN} + P^T \cdot \Omega^{-1} \cdot Q \right]$$

Black-Litterman on Matlab

```

clear
close all
SIGMA=xlsread('File_excel.xlsx','BL','D6:N16')
[W_MN LABELS]=xlsread('File_excel.xlsx','BL','A6:B16')

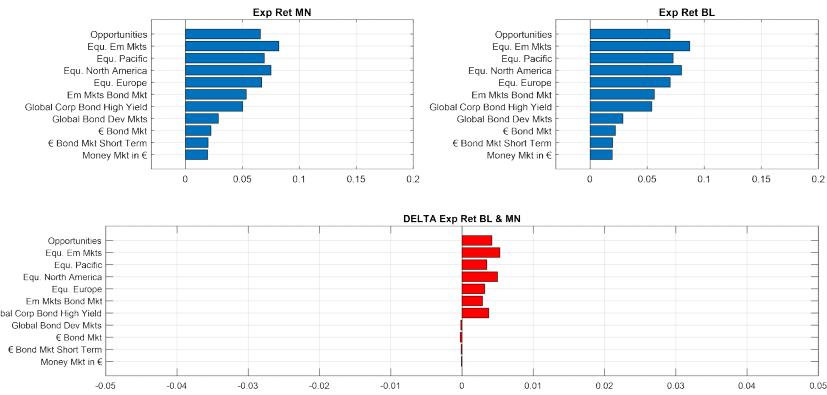
RISK_FREE=0.02
LAMBDA=4.5;
EXP_RET_MN=RISK_FREE+LAMBDA*SIGMA*W_MN
TAU=1/20
TAU_SIGMA=TAU*SIGMA
P=[0 0 0 -1 1 0 0 0 0 0;
   0 0 0 0 0 -1 1 0 0 0];
Q=[0.035;0.015]
C=[0.30; 0.30]
OMEGA=zeros(2,2);
for f=1:2
for g=1:2
if f==g
OMEGA(f,g)=((1/C(f,1)-1)*P(f,:)*(TAU_SIGMA)*P(f,:)');

```

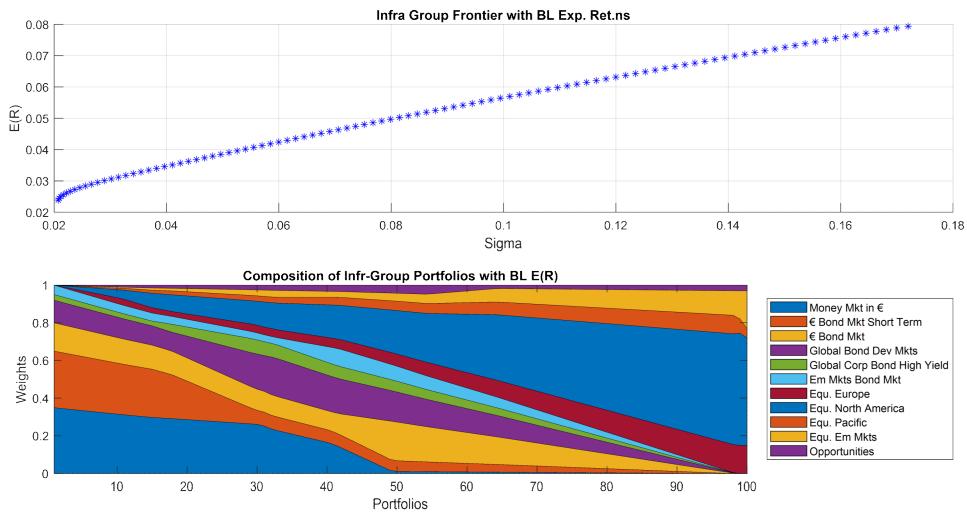
```
end  
end  
end
```

```
REND_BL=inv(inv(TAU_SIGMA)+P'*inv(OMEGA)*P)*(inv(TAU_  
SIGMA)*EXP_RET_MN+P'*inv(OMEGA)*Q)  
GAP=REND_BL-EXP_RET_MN;
```

```
figure(1)  
subplot(2,2,1)  
barh (EXP_RET_MN)  
xlim([-0.03 0.20]);  
set(gca,'YTickLabel',LABELS)  
grid on  
title('Exp Ret MN')  
subplot(2,2,2)  
barh (REND_BL)  
xlim([-0.03 0.20]);  
title('Exp Ret BL')  
set(gca,'YTickLabel',LABELS)  
grid on  
  
subplot(2,2,[3 4])  
barh (GAP,'r')  
title('DELTA Exp Ret BL & MN')  
xlim([-0.05 0.05]);  
set(gca,'YTickLabel',LABELS)  
grid on
```



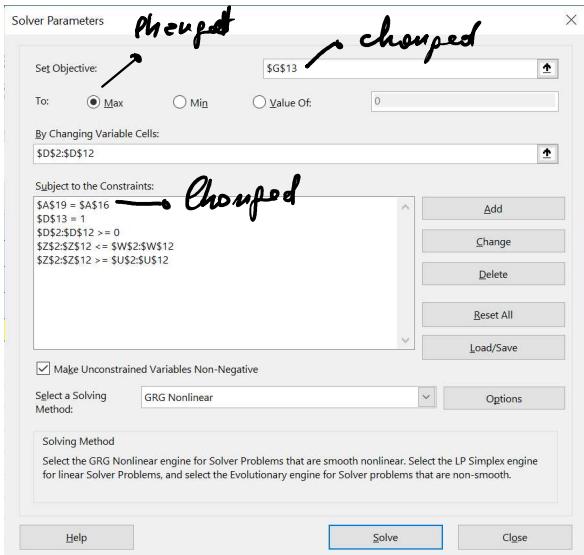
The best is to combine BL & infra-group constrained optimization



Portfolio selection

↳ Identify a subset of SAA that are compliant with the risk tolerance and investment horizon of each prototype of investor

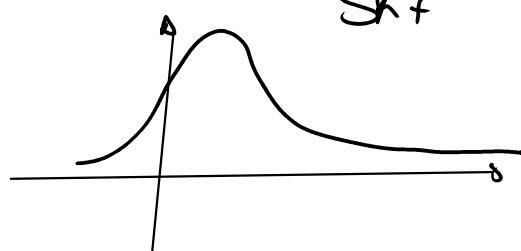
VaR can be a useful tool in order to select SAA's.



ASSET CLASSES	E(r)	BL	σ	Weights
Money Mkt in €	1,93%		0,87%	1,2%
€ Bond Mkt Short Term	1,98%		1,69%	5,9%
€ Bond Mkt	2,28%		4,17%	21,2%
Global Bond Dev Mkts	3,08%		6,92%	16,5%
Global Corp Bond High Yie	5,95%		11,07%	5,9%
Em Mkts Bond Mkt	6,27%		12,72%	8,2%
Equ. Europe	7,94%		17,53%	6,2%
Equ. North America	9,07%		17,80%	24,7%
Equ. Pacific	8,25%		18,56%	4,9%
Equ. Em Mkts	9,92%		23,69%	3,8%
Opportunities	7,87%		15,36%	1,6%
PORTFOLIO	5,63%		8,29%	100,00%
<hr/>				
-8,00% Tolerated Annual Loss				Equ porti lambda=4.5 lambda=5.5
-8,00% VaR 1yr (95%)				

cov	ML Euro 0-1	ML Bond Euro	fa ML Obbl. Et	ML Obbl. Glo
Money Mkt	0,0001	0,0001	0,0001	0,0001
€ Bond Mkt	0,0001	0,0003	0,0005	0,0003
€ Bond Mkt	0,0001	0,0005	0,0017	0,0012
Global Bon	0,0001	0,0003	0,0012	0,0048
Global Cor	-0,0002	-0,0000	0,0004	0,0024
Em Mkts B	-0,0001	0,0001	0,0008	0,0026
Equ. Europ	-0,0003	-0,0004	-0,0004	-0,0023
Equ. North	-0,0004	-0,0006	-0,0003	0,0009
Equ. Pacific	-0,0003	-0,0003	-0,0002	0,0003
Equ. Em M	-0,0003	-0,0005	-0,0004	-0,0019
Opportuniti	-0,0003	-0,0005	-0,0007	-0,0006

Higher Order Moments



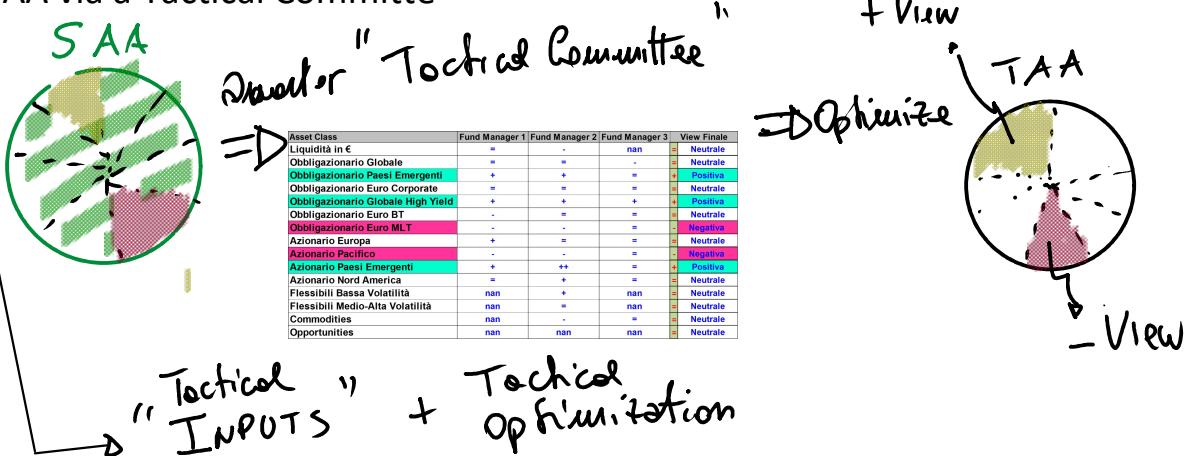
Mean - σ - Sk optimisation

$$\max_{\omega} \left[\alpha \cdot E(r)_{\text{Port}} + (1-\alpha) S_k_{\text{Port}} \right]$$

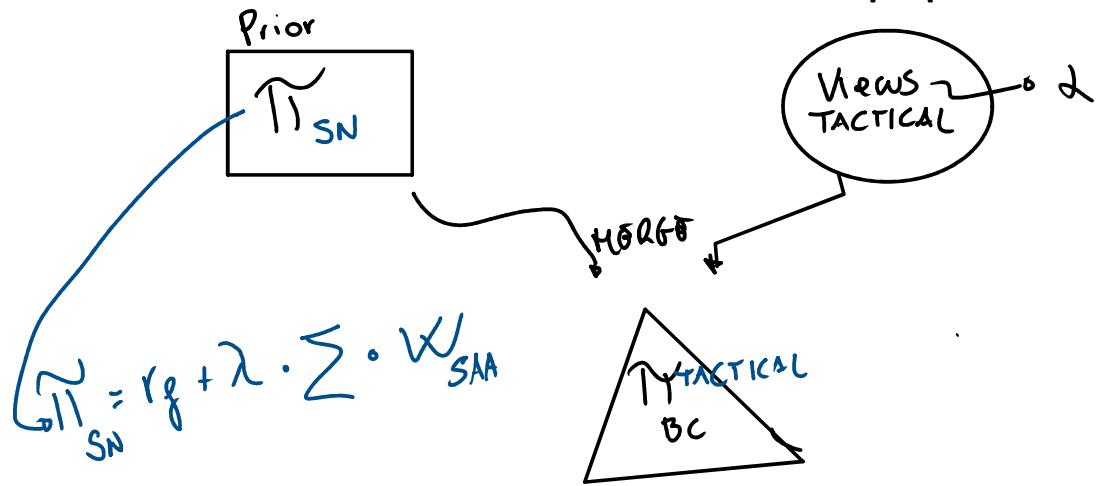
Constraints:



(b) TAA via a Tactical Committee



How to use the Black-Litterman Model for tactical purposes



Example of TACTICAL OPTIMIZATION

$$\max_{w_{TAA}} E(R)_{TAA}$$

Constraints:

$$\sum w_i^{TAA} = 1$$

$$w_i^{TAA} \geq 0 \quad \forall i \in [1; K]$$

$$\sigma_{TAA} \leq \sigma^*$$

$$\sum w_i \geq h_i$$

$$\begin{aligned} w_{TAA} &= w \\ \sum w_{\text{Risky}} &\geq h_i \\ \sum w_{\text{Risky}_j} &\leq k_i \end{aligned}$$

$$\begin{aligned} w_i &\geq LB_i \quad \forall i \in [1:2, \dots, K] \\ w_i &\leq UB_i \\ \text{ReVaR}_{TAA} &\geq \text{ReVaR}^* \end{aligned}$$

ReVaR = Measure the potential underperformance of the TAA versus SAA
The VaR of the position LONG in TAA and SHORT in SAA

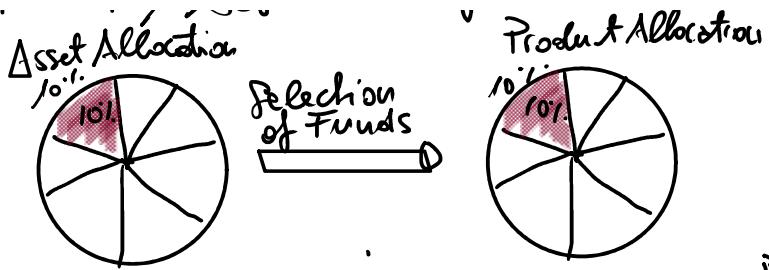
$$\text{ReVaR} = \left[E(R)_1^T \ E(R)_2^T \ \dots \ E(R)_K^T \right] \times \begin{bmatrix} w_1^T - w_s^T \\ w_2^T - w_s^T \\ \vdots \\ w_K^T - w_s^T \end{bmatrix} - K \cdot \sqrt{d^T \times \begin{bmatrix} \text{cov} \\ \text{Matrix} \end{bmatrix} \times d} \times \alpha$$

ASSET CLASSES	Rend att TATTICAL	σ Tact	SAA	TAA	Weights Tact- Weights Strat
Money Mkt in €	0,63%	0,87%	2%	2%	0,00%
€ Bond Mkt Short Term	1,00%	1,56%	22%	22%	0,00%
€ Bond Mkt	2,01%	3,58%	11%	14%	2,60%
Global Bond Dev Mkts	2,50%	7,13%	9%	25%	15,65%
Global Corp Bond High Yiel	-2,50%	11,19%	5%	0%	-5,00%
Em Mkts Bond Mkt	-3,50%	10,01%	6%	2%	-4,00%
Equ. Europe	-3,00%	16,66%	8%	8%	0,00%
Equ. North America	-3,00%	16,37%	20%	17%	-2,60%
Equ. Pacific	-2,80%	17,16%	5%	4%	-0,88%
Equ. Em Mkts	-5,00%	21,90%	8%	6%	-1,77%
Opportunities	-4,00%	16,52%	4%	0%	-4,00%
PORTAFOGLIO	-0,14%	6,49%		100,00%	0,00%

cov	ML Euro 0-1
Bofa ML E	0,0001
Bofa ML B	0,0001
Bofa ML O	0,0001
Bofa ML O	0,0001
ML Global	-0,0002
Bofa ML O	-0,0001
MSCI Euro	-0,0003
MSCI North	-0,0004
MSCI Pacific	-0,0003
MSCI Eme	-0,0003
Opportuniti	-0,0003

SIGMA Threshold	10,00%
RE-VAR (cl=95%)	-3,00%
ReVaR Threshold	-3,00%

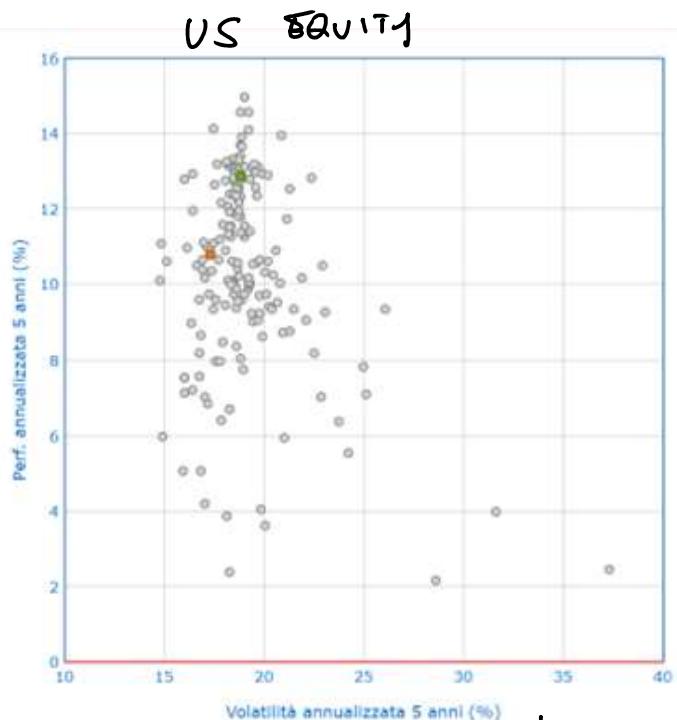
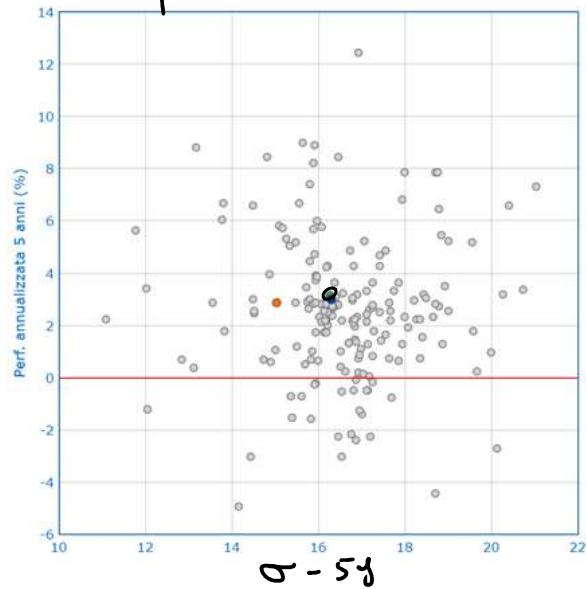




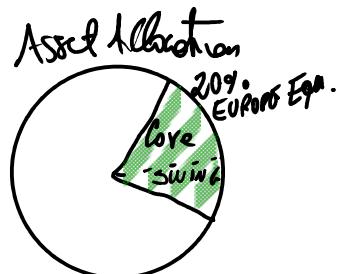
2) Active vs Passive → Efficient Markets → Developed MKTS

For Non Efficient MARKETS → Bond Equity E.M. MKT

Eg. EM. MKTS



b) Core/Blend vs Swing/Satellite



Core/Blend Fund: Cover all the MARKET

Swing/Satellite Fund: focused on 2 "portion" of the Market

- Country
- Size
- Sector
- Style (G/V)

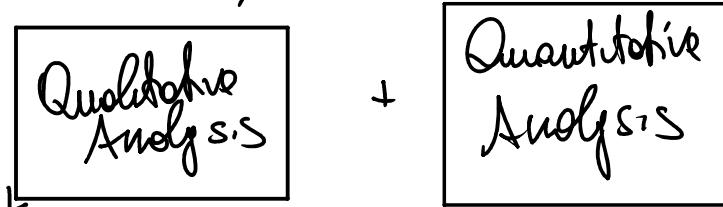
Cover all the market
but are very very ACTIVE

Fund Valuation / Selection

... 1 ...

... 2 ...

Fund Valuation / Selection



- Reputation
- Quality of Asset Mix
- Size Company
- Size of the Fund
- Quality of Risk Management processes

QUANTITATIVE ANALYSIS



- Comparison of homogeneous funds:
European Equity Funds Blend
- Time series: time window of 5 years

	PICTET FUNDS LUX E	JANUS HENDERSON	FUND XXX	INVESCO SUST PAN E	MSCI EUROPA	RISK FREE
--	--------------------	-----------------	----------	--------------------	-------------	-----------

1) Return $\rightarrow \bar{R}_F = \frac{\sum_{i=1}^T R_{F,i}}{T}$

$$\rightarrow \overline{RD_F} = \bar{R}_F - r_f$$

$$\rightarrow \overline{TE}_F = \bar{R}_F - \bar{R}_B$$

$$\rightarrow \text{Cumulative Return}_F = \prod_{i=1}^T (1 + \bar{R}_{F,i}) - 1 \Rightarrow 5 \text{ years}$$

$$\rightarrow \text{Annualised Performance} = \sqrt[5]{(1 + \text{Cumulative Return}_F)} - 1$$

	PICTET FUNDS LUX E	JANUS HENDERSON	FUND XXX	INVESCO SUST PAN E	MSCI EUROPA	RISK FREE
Monthly Av. Return	0,71%	0,91%	1,07%	0,39%	0,79%	-0,01%
Monthly Risk Premium	0,72%	0,92%	1,08%	0,40%		
Average Tracking Error	-0,08%	0,12%	0,28%	-0,40%		
Cumulative Return	43,01%	60,91%	72,63%	19,31%	50,09%	
Annualised Return	7,42%	9,98%	11,54%	3,59%	8,46%	

2) Risk

$$\sigma_F = \sqrt{\frac{\sum_{i=1}^T (R_{F,i} - \bar{R})^2}{T}}$$

DOWNSIDE RISK

$$DSR_F = \sqrt{\frac{\sum_{i=1}^T (R_{F,i} - S)^2}{T}} \quad R_{F,i} \leq S$$

TRACKING ERROR VOLATILITY

$$TEV_F = \sqrt{\frac{\sum_{i=1}^T (\bar{R}_E_i - \bar{R}_E)^2}{T}}$$

3) Risk Adjusted Performance Analysis

$$\text{Ratios} = \frac{\text{Return}}{\text{Risk}}$$

$$\text{Sharpe Ratio} = \frac{\bar{R}_F - r_f}{\sigma_F} = \frac{\bar{RP}_F}{\sigma_F}$$

$$\text{Sortino Ratio} = \frac{\bar{R}_F - r_f}{DSR_F} = \frac{\bar{RP}_F}{DSR_F}$$

$$\text{Information Ratio} = \frac{\bar{R}_F - \bar{R}_B}{TEV_F} = \frac{\bar{TE}_F}{TEV_F}$$

4) Rating \Rightarrow 5 Classes

4) Rating \Rightarrow 5 classes

	BLEND/CORE	BLEND/CORE	SATELLITE/SWING	BLEND/CORE
	PICTET FUNDS LUX EUROPE INDEX R - TOT RETURN IND	JANUS HENDERSON PAN EUROPEAN A2 EUR	BSF EUROPN OPPTYS EXTSN A2 EUR - TOT RETURN IND	INVESCO SUST PAN EUROPN STRUCT EQ E ACC EUR - TOT RETURN IND
ISIN	LU0130731713	LU0201075453	LU0313923228	LU0119753308
Quantalys	5*	5*	5*	2*

THE END

