Module 2: Portfolio Theory (BUSFIN 4221 - Investments)

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Fall 2016

The Efficient Frontie

Outline

Overview

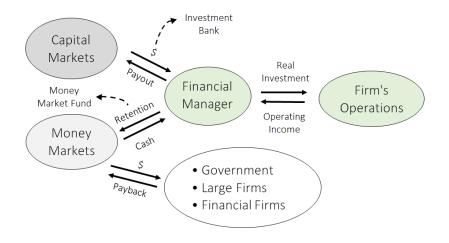
The Statistics of Security Returns

The Efficient Frontier

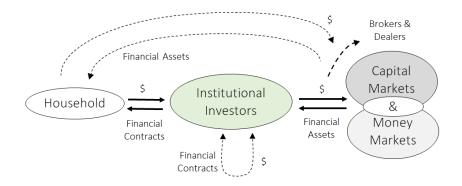
Capital Allocation Line

Index Models

Module 1 - The Demand for Capital



Module 1 - The Supply of Capital

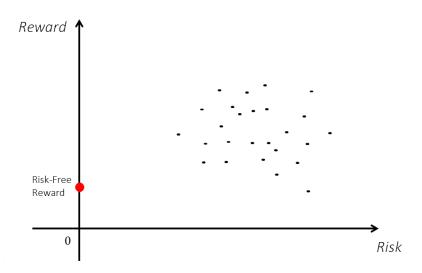


The Efficient Fronti

Module 1 - Investment Principle

$$PV_{t} = \sum_{h=1}^{\infty} \frac{\mathbb{E}_{t} \left[CF_{t+h} \right]}{\left(1 + dr_{t,h} \right)^{h}}$$

This Module: Creating a Portfolio



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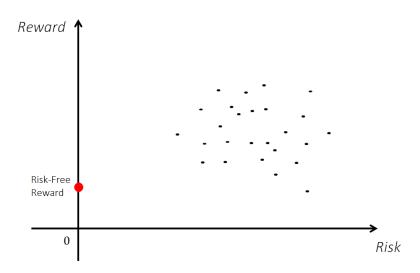
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This Section: Defining Risk and Reward



$$r_{t} = \frac{(P_{t} + CF_{t}) - P_{t-1}}{P_{t-1}}$$
$$= \underbrace{\frac{(P_{t} - P_{t-1})}{P_{t-1}}}_{Capital Gain} + \underbrace{\frac{CF_{t}}{P_{t-1}}}_{Yied}$$

• Arithmetic average return (or simple "average return"):

$$r = \frac{n+a+a+m}{r}$$

Geometric average return:

 $T_{6} = \{(1 + n) \times (1 + n) \times ... \times (1 + n)\}^{2n}$

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• Arithmetic average return (or simple "average return"):

$$\frac{n+n+n+n}{r} = \frac{r}{r}$$

Geometric average return:

 $\overline{r}_6 = \{(1+\alpha) \times (1+\alpha) \times \dots \times (1+\alpha)\}^{1/n}$

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• Arithmetic average return (or simple "average return"):

$$\overline{r} = \frac{r_1 + r_2 + \dots + r_T}{T}$$

Geometric average return:

 $\tilde{r}_6 = \{(1 + \alpha) \times (1 + \alpha) \times ... \times (1 + \alpha)\}^{1/7}$

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$$\overline{\mathbf{r}}_{\mathbf{G}} = \left\{ \left(1 + r_{1}\right) \times \left(1 + r_{2}\right) \times \dots \times \left(1 + r_{T}\right) \right\}^{1/\tau}$$

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Geometric average return:

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Measuring Performance: Annual Returns

- A return of 1% in the previous month is not comparable with a return of 12% in the previous year. We need to fix the time period of different returns to make them comparable
- The effective annual rate, *ear*_t, does that for you:

$1 + ea_t = (1 + r_t)^n$

 n is the number of periods in a year. For instance, n = 1 for annual r_t and n = 12 for monthly r_t

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Measuring Performance: Annual Returns

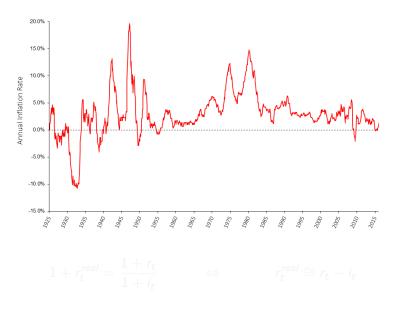
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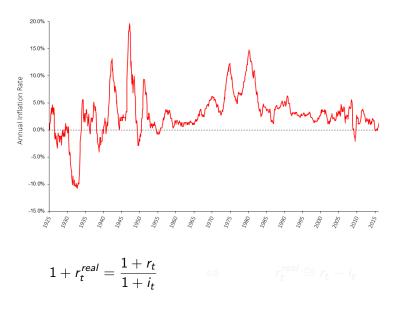
Index Models

Measuring Performance: Inflation Effect



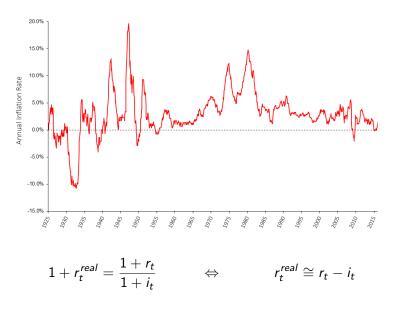
Index Models

Measuring Performance: Inflation Effect



Index Models

Measuring Performance: Inflation Effect



Returns as a Random Variable: Indices

1\$ Invested in January of 1970



$$\mathbb{E}[r_t] = \sum_{s} p(s) \times r(s) = 10\%$$
$$\sigma[r_t] = \sqrt{\sum_{s} p(s) \times \{r(s) - \mathbb{E}[r_t]\}^2} = 16\%$$

Economic Scenario Next Year (<i>s</i>)	p (s)	r (s)	$r(s) - \mathbb{E}[r_t]$
Very High Growth	0.15	30%	20%
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	10%
$Growth = \mathbb{E}\left[\mathit{Growth}\right]$	0.35	10%	0%
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	-15%
Recession	0.05	-40%	-50%

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Recession	0.05	-60%	-70%

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$$\sigma[r_t] = \sqrt{\sum_{s} p(s) \times \{r(s) - \mathbb{E}[r_t]\}^2} = 26\%$$

•
$$\mu = \mathbb{E}[\mathbf{r}_t]$$
 and $\sigma = \sigma[\mathbf{r}_t]$

- Index simulation: I simulate r_t and use it to get future prices
- If r_t are truly normal, then only μ and σ matter (they describe entire distribution). In this case, the only measure of risk is σ
- If $r_{i,t}$ are normal, then so are portfolio returns: $r_{p,t} = w_1 \times r_{1,t} + w_2 \times r_{2,t} + ... + w_N \times r_{N,t}$
- If daily r_t are normal, annual r_t are <u>not</u> normal: horizon matters!

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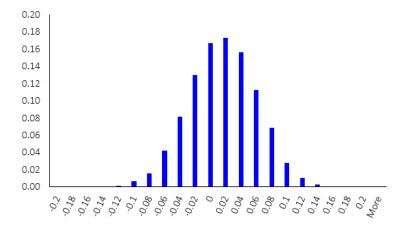
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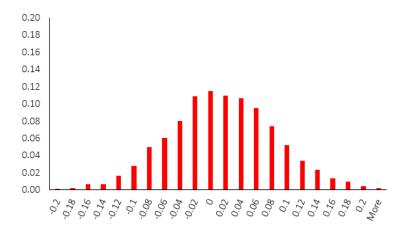
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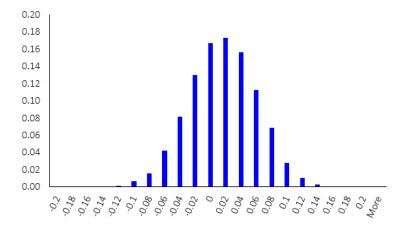
Modeling Returns: $r_t \sim \mathcal{N} (\mu = 0.6\%, \sigma = 4.4\%)$



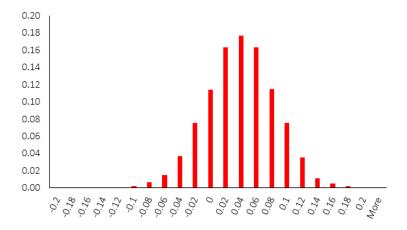
Modeling Returns: $r_t \sim \mathcal{N} (\mu = 0.6\%, \sigma = 7.0\%)$



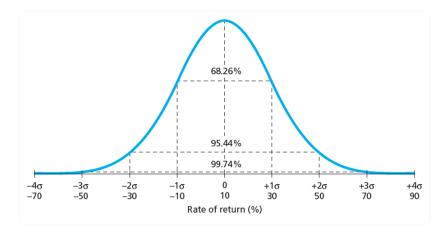
Modeling Returns: $r_t \sim \mathcal{N} (\mu = 0.6\%, \sigma = 4.4\%)$



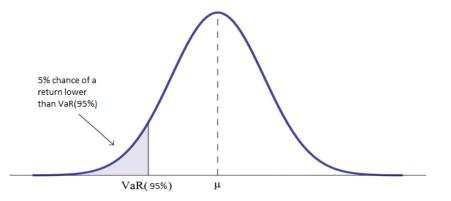
Modeling Returns: $r_t \sim \mathcal{N} (\mu = 3.0\%, \sigma = 4.4\%)$



Modeling Returns: $r_t \sim \mathcal{N} (\mu = 10\%, \sigma = 10\%)$

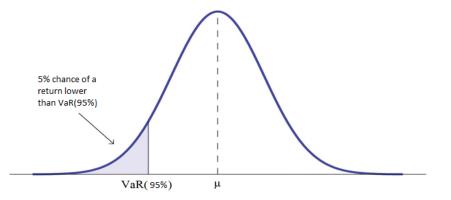


Modeling Returns: Tail Risk for Normal Returns?



 $VaR(95\%) = \mathbb{E}[r_t] - 1.64 \times \sigma[r_t]$

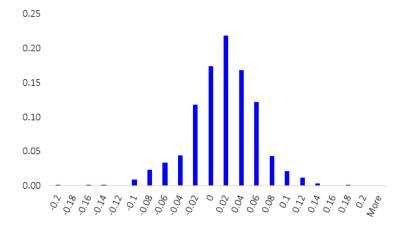
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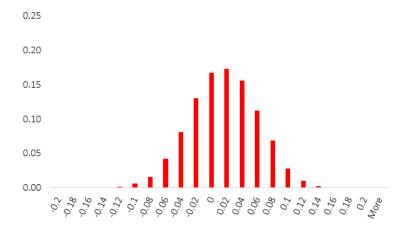
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Modeling Returns: S&P 500



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Modeling Returns: $r_t \sim \mathcal{N}(\mu_{S\&P}, \sigma_{S\&P})$



- If $r_t \sim \mathcal{N}(\mu, \sigma)$, how can we estimate μ and σ from data?
- Recall: $\mu = \mathbb{E}[n] = \sum p(s) \times r(s)$



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• Recall:
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$$\label{eq:alpha} \begin{split} & \theta = \frac{1}{2} \times \sum_{i=1}^{d} \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_{i=1}^{d} (\theta_i - \theta_i)^2 \theta = \sqrt{\frac{1}{2} + 1} \times \sum_$$

• If $r_t \sim \mathcal{N}(\mu, \sigma)$, how can we estimate μ and σ from data?

• Recall:
$$\mu = \mathbb{E}[r_t] = \sum_{s} p(s) \times r(s)$$

 $\sigma = \sigma[r_t] = \sqrt{\sum_{s} p(s) \times \{r(s) - \mathbb{E}[r_t]\}^2}$

$$\hat{\mu} = \frac{1}{T} \times \sum_{t=1}^{T} r_t = \overline{r}$$
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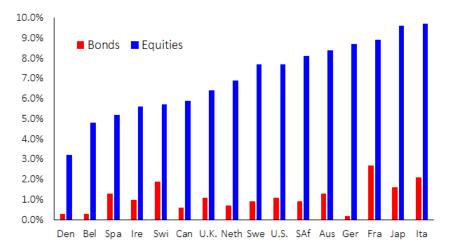
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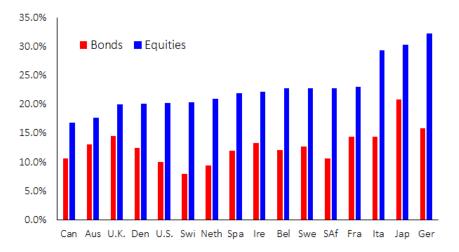
$$\hat{\mu} = \frac{1}{T} \times \sum_{t=1}^{T} \mathbf{r}_t = \overline{\mathbf{r}}$$
$$\hat{\sigma} = \sqrt{\frac{1}{T-1} \times \sum_{t=1}^{T} {\{\mathbf{r}_t - \overline{\mathbf{r}}\}}^2}$$

Data: $(\bar{r} - \bar{r}_{TBill})$ around the World from 1900-2000



Source: Dimson et al (2002) - Triumph of the optimists: 101 years of global investment returns

Data: $\hat{\sigma}[r_t]$ around the World from 1900-2000



Source: Dimson et al (2002) - Triumph of the optimists: 101 years of global investment returns

If asset A daily r_t follow a normal distribution, then:

- a) Asset A monthly r_t also do
- **b)** An increase in $\sigma[r_t]$ implies an increase in the tail risk the asset
- c) Inflation does not matter for the real return on asset A
- d) The geometric average return and the average return are the same
- e) All we need to know about asset A in order to fully understand its daily returns distribution is $\sigma[r_t]$

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- a) Asset A monthly r_t also do
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- c) Inflation does not matter for the real return on asset A
- d) The geometric average return and the average return are the same
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The Efficient Frontier

Capital Allocation Line

Index Models

Outline

Overview

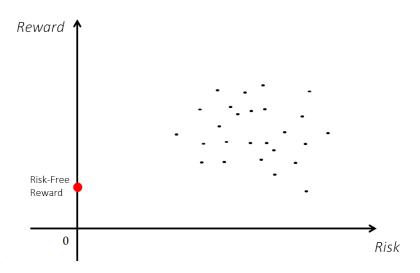
The Statistics of Security Returns

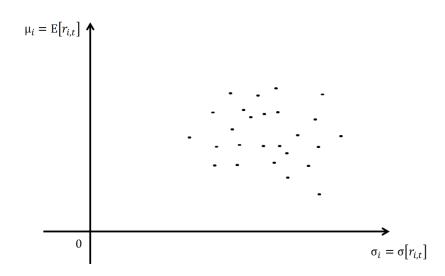
The Efficient Frontier

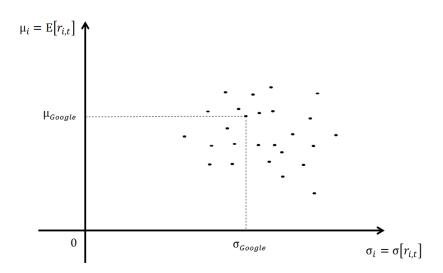
Capital Allocation Line

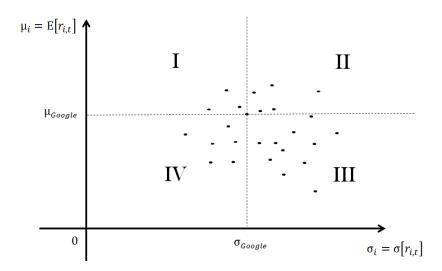
Index Models

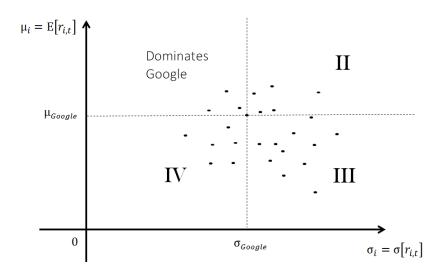
This Section: Find the "Best" Risky Portfolios

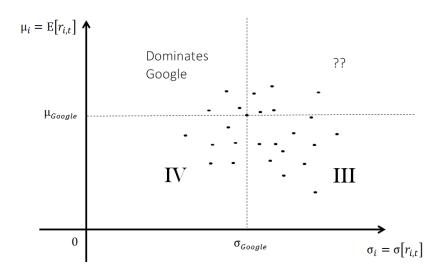


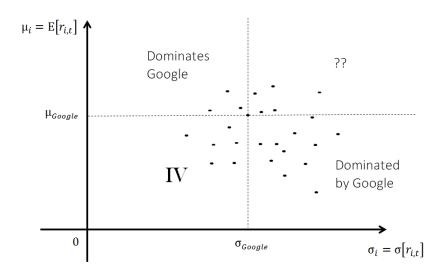


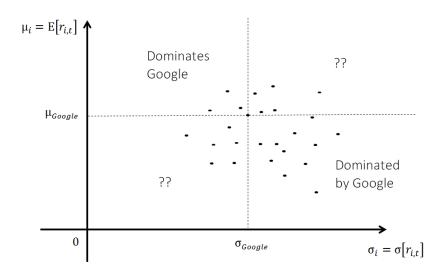












Diversification: Basic Principle

Diversification: Basic Principle



Economic Scenario	p(s)	F	F =	50% - 50%
Next Year (s)	<i>p</i> (3)	r_{Equity}	r _{Gold}	r _{Portfolio}
Very High Growth	0.15	30%	-12%	9%
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	13%
$Growth = \mathbb{E}\left[\textit{Growth}\right]$	0.35	10%	15%	13%
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	20%	8%
Recession	0.05	-40%	25%	-8%
$\mathbb{E}[r_t] =$				
$\sigma[r_t] =$				

Economic Scenario	p(s)	F	F	50% - 50%
Next Year (s)	p(s)	r_{Equity}	r _{Gold}	r _{Portfolio}
Very High Growth	0.15	30%	-12%	9%
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	13%
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$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	20%	8%
Recession	0.05	-40%	25%	-8%
$\mathbb{E}[r_t] =$		10%	10%	
$\sigma\left[r_{t}\right] =$		16%	11%	

Economic Scenario	p(s)	F	F	50% - 50%
Next Year (s)	<i>p</i> (3)	<i>r_{Equity}</i>	r _{Gold}	r _{Portfolio}
Very High Growth	0.15	30%	-12%	9%
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	13%
$Growth = \mathbb{E}\left[\textit{Growth}\right]$	0.35	10%	15%	13%
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	20%	8%
Recession	0.05	-40%	25%	-8%
$\mathbb{E}[r_t] =$		10%	10%	10%
$\sigma\left[r_{t}\right] =$		16%	11%	5%

Economic Scenario	p(s)	F	F a	40% - 60%
Next Year (s)	<i>p</i> (3)	r_{Equity}	r _{Gold}	r _{Portfolio}
Very High Growth	0.15	30%	-12%	5%
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	11%
$Growth = \mathbb{E}\left[\textit{Growth}\right]$	0.35	10%	15%	13%
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	20%	10%
Recession	0.05	-40%	25%	-1%
$\mathbb{E}[r_t] =$		10%	10%	10%
$\sigma\left[r_{t}\right] =$		16%	11%	4%

Economic Scenario	p(s)	F	F	50% - 50%
Next Year (s)	<i>p</i> (3)	<i>r_{Equity}</i>	r _{Gold}	r _{Portfolio}
Very High Growth	0.15	30%	-12%	9%
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	13%
$Growth = \mathbb{E}\left[\textit{Growth}\right]$	0.35	10%	15%	13%
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	20%	8%
Recession	0.05	-40%	25%	-8%
$\mathbb{E}[r_t] =$		10%	10%	10%
$\sigma\left[r_{t}\right] =$		16%	11%	5%

Economic Scenario	p(s)	r	To	50%-50%
Next Year (s)	<i>p</i> (3)	r_{Equity}	r _{Gold}	r Portfolio
Very High Growth	0.15	30%	-7%	12%
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	13%
$Growth = \mathbb{E}\left[\textit{Growth}\right]$	0.35	10%	15%	13%
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	26%	11%
Recession	0.05	-40%	-10%	-25%
$\mathbb{E}[r_t] =$		10%	10%	10%
$\sigma[r_t] =$		16%	11%	8%

Diversification: Covariance & Correlation

Economic Scenario	p(s)	rr	reau	$(\mathbf{r}_{E} - \mathbb{E}[\mathbf{r}_{E}]) \times (\mathbf{r}_{G} - \mathbb{E}[\mathbf{r}_{G}])$
Next Year (s)	P (3)	' Equity	' Gola	
Very High Growth	0.15	30%	-7%	-0.034
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	-0.005
$Growth = \mathbb{E}\left[\mathit{Growth}\right]$	0.35	10%	15%	0.000
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	26%	-0.024
Recession	0.05	-40%	-10%	0.100
$\mathbb{E}[r_t] =$		10%	10%	
$\sigma[r_t] =$		16%	11%	

$$Cov[r_E, r_G] = \sum_{s} p(s) \times \{r_E(s) - \mathbb{E}[r_E]\} \times \{r_G(s) - \mathbb{E}[r_G]\}$$
$$\rho[r_E, r_G] = \frac{Cov[r_E, r_G]}{\sigma[r_E] \times \sigma[r_G]} = -0.34$$

Diversification: Covariance & Correlation

Economic Scenario	p(s)		To U	$(r_E - \mathbb{E}[r_E]) \times (r_G - \mathbb{E}[r_G])$
Next Year (s)	<i>p</i> (3)	' Equity	Gold	$(I_E - \mathbb{E}[I_E]) \times (I_C - \mathbb{E}[I_C])$
Very High Growth	0.15	30%	-7%	-0.034
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	-0.005
$Growth = \mathbb{E}\left[\mathit{Growth}\right]$	0.35	10%	15%	0.000
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	26%	-0.024
Recession	0.05	-40%	-10%	0.100
$\mathbb{E}[r_t] =$		10%	10%	
$\sigma[r_t] =$		16%	11%	

$$Cov[r_E, r_G] = \sum_{s} p(s) \times \{r_E(s) - \mathbb{E}[r_E]\} \times \{r_G(s) - \mathbb{E}[r_G]\}$$
$$\rho[r_E, r_G] = \frac{Cov[r_E, r_G]}{\sigma[r_E] \times \sigma[r_G]} = -0.34$$

Diversification: Covariance & Correlation

Economic Scenario	p(s)		To U	$(r_E - \mathbb{E}[r_E]) \times (r_G - \mathbb{E}[r_G])$
Next Year (s)	<i>p</i> (3)	' Equity	Gold	$(IE - \mathbb{E}[IE]) \times (IC - \mathbb{E}[IC])$
Very High Growth	0.15	30%	-7%	-0.034
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	-0.005
$Growth = \mathbb{E}\left[\mathit{Growth}\right]$	0.35	10%	15%	0.000
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	26%	-0.024
Recession	0.05	-40%	-10%	0.100
$\mathbb{E}\left[r_{t} ight] =$		10%	10%	
$\sigma[r_t] =$		16%	11%	

$$Cov[r_E, r_G] = \sum_{s} p(s) \times \{r_E(s) - \mathbb{E}[r_E]\} \times \{r_G(s) - \mathbb{E}[r_G]\}$$
$$\rho[r_E, r_G] = \frac{Cov[r_E, r_G]}{\sigma[r_E] \times \sigma[r_G]} = -0.34$$

Diversification: Covariance & Correlation

Economic Scenario	p(s)		To U	$(r_E - \mathbb{E}[r_E]) \times (r_G - \mathbb{E}[r_G])$
Next Year (s)	<i>p</i> (3)	' Equity	Gold	$(IE = \mathbb{E}[IE]) \land (IG = \mathbb{E}[IG])$
Very High Growth	0.15	30%	-7%	-0.034
$Growth > \mathbb{E}\left[\textit{Growth}\right]$	0.25	20%	5%	-0.005
$Growth = \mathbb{E}\left[\mathit{Growth}\right]$	0.35	10%	15%	0.000
$Growth < \mathbb{E}\left[\textit{Growth}\right]$	0.2	-5%	26%	-0.024
Recession	0.05	-40%	-10%	0.100
$\mathbb{E}[r_t] =$		10%	10%	
$\sigma[r_t] =$		16%	11%	

$$Cov[r_E, r_G] = \sum_{s} p(s) \times \{r_E(s) - \mathbb{E}[r_E]\} \times \{r_G(s) - \mathbb{E}[r_G]\}$$
$$\rho[r_E, r_G] = \frac{Cov[r_E, r_G]}{\sigma[r_E] \times \sigma[r_G]} = -0.34$$

- Consider the portfolio $r_p = w_A \cdot r_A + w_B \cdot r_B$
- Portfolio expected return, $\mathbb{E}[r_p]$, is given by:

$\mathbb{E}\left[\eta_{0}\right] = w_{0} \cdot \mathbb{E}\left[\eta_{0}\right] + w_{0} \cdot \mathbb{E}\left[\eta_{0}\right]$

• Portfolio variance, $\sigma^2 [r_p] = \sigma_p^2$, is given by:

$\sigma_{i}^{2}=\sigma_{i}^{2}+\sigma_{i}^{2}+\sigma_{i}^{2}+2-\sigma_{i}+2-\sigma_$

= m_{0}^{2} + m_{0}^{2} + m_{0}^{2} + 2 + m_{0} + m_{0} + m_{0} + p [15, 16]

- Consider the portfolio $r_p = w_A \cdot r_A + w_B \cdot r_B$
- Portfolio expected return, $\mathbb{E}[r_p]$, is given by:

$$\mathbb{E}\left[r_{\rho}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{B} \cdot \mathbb{E}\left[r_{B}\right]$$

• Portfolio variance, $\sigma^2 [r_p] = \sigma_p^2$, is given by:

 $[a_1,a_2] = a_2 + a_3 + a_4 + a_5 + a_5 + a_6 + a_6$

- Consider the portfolio $r_p = w_A \cdot r_A + w_B \cdot r_B$
- Portfolio expected return, $\mathbb{E}[r_p]$, is given by:

$$\mathbb{E}[r_{\rho}] = w_{A} \cdot \mathbb{E}[r_{A}] + w_{B} \cdot \mathbb{E}[r_{B}]$$

• Portfolio variance, $\sigma^2[r_p] = \sigma_p^2$, is given by:

$$\sigma_p^2 = w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot Cov[r_A, r_B]$$

 $= w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_A \cdot \sigma_B \cdot \rho [r_A, r_B]$

- Consider the portfolio $r_p = w_A \cdot r_A + w_B \cdot r_B$
- Portfolio expected return, $\mathbb{E}[r_p]$, is given by:

$$\mathbb{E}\left[r_{\rho}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{B} \cdot \mathbb{E}\left[r_{B}\right]$$

• Portfolio variance, $\sigma^2 [r_p] = \sigma_p^2$, is given by:

$$\sigma_p^2 = w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot Cov [r_A, r_B]$$

 $= w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_A \cdot \sigma_B \cdot \rho [r_A, r_B]$

- Consider the portfolio $r_p = w_A \cdot r_A + w_B \cdot r_B$
- Portfolio expected return, $\mathbb{E}[r_p]$, is given by:

$$\mathbb{E}\left[r_{\rho}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{B} \cdot \mathbb{E}\left[r_{B}\right]$$

• Portfolio variance, $\sigma^2 [r_p] = \sigma_p^2$, is given by:

$$\sigma_{p}^{2} = w_{A}^{2} \cdot \sigma_{A}^{2} + w_{B}^{2} \cdot \sigma_{B}^{2} + 2 \cdot w_{A} \cdot w_{B} \cdot Cov [r_{A}, r_{B}]$$

$$= w_{A}^{2} \cdot \sigma_{A}^{2} + w_{B}^{2} \cdot \sigma_{B}^{2} + 2 \cdot w_{A} \cdot w_{B} \cdot \sigma_{A} \cdot \sigma_{B} \cdot \rho [r_{A}, r_{B}]$$

• When do we have diversification: $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$?

```
• Suppose \rho[r_A, r_B] = 1, then:
```

• Any $\rho[r_A, r_B] < 1$ produces $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$

- When do we have diversification: $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$?
- Suppose $\rho[\mathbf{r}_A, \mathbf{r}_B] = 1$, then:

 $\sigma_{\rho}^{2} = w_{A}^{2} \cdot \sigma_{A}^{2} + w_{B}^{2} \cdot \sigma_{B}^{2} + 2 \cdot w_{A} \cdot w_{B} \cdot \sigma_{A} \cdot \sigma_{B} \cdot 1$ $= (w_{A} \cdot \sigma_{A} + w_{B} \cdot \sigma_{B})^{2}$ \downarrow

 $\sigma_p = w_A \cdot \sigma_A + w_B \cdot \sigma_B$

• Any $\rho[r_A, r_B] < 1$ produces $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$

- When do we have diversification: $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$?
- Suppose $\rho[\mathbf{r}_A, \mathbf{r}_B] = 1$, then:

$$\sigma_p^2 = w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_A \cdot \sigma_B \cdot 1$$

$$= (w_A \cdot \sigma_A + w_B \cdot \sigma_B)^2$$
$$\downarrow$$
$$\sigma_p = w_A \cdot \sigma_A + w_B \cdot \sigma_B$$

• Any $\rho[r_A, r_B] < 1$ produces $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$

- When do we have diversification: $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$?
- Suppose $\rho[\mathbf{r}_A, \mathbf{r}_B] = 1$, then:

$$\sigma_{\rho}^{2} = w_{A}^{2} \cdot \sigma_{A}^{2} + w_{B}^{2} \cdot \sigma_{B}^{2} + 2 \cdot w_{A} \cdot w_{B} \cdot \sigma_{A} \cdot \sigma_{B} \cdot 1$$

$$= (w_A \cdot \sigma_A + w_B \cdot \sigma_B)^2$$

$$\downarrow$$

$$\sigma_a = w_A \cdot \sigma_A + w_B \cdot \sigma_B$$

• Any $\rho[\mathbf{r}_A, \mathbf{r}_B] < 1$ produces $\sigma_p < \mathbf{w}_A \cdot \sigma_A + \mathbf{w}_B \cdot \sigma_B$

- When do we have diversification: $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$?
- Suppose $\rho[\mathbf{r}_A, \mathbf{r}_B] = 1$, then:

$$\sigma_p^2 = w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_A \cdot \sigma_B \cdot 1$$

$$= (w_A \cdot \sigma_A + w_B \cdot \sigma_B)^2$$
$$\Downarrow$$

 $\sigma_{p} = \mathbf{w}_{A} \cdot \sigma_{A} + \mathbf{w}_{B} \cdot \sigma_{B}$

• Any $\rho[\mathbf{r}_A, \mathbf{r}_B] < 1$ produces $\sigma_p < \mathbf{w}_A \cdot \sigma_A + \mathbf{w}_B \cdot \sigma_B$

- When do we have diversification: $\sigma_p < w_A \cdot \sigma_A + w_B \cdot \sigma_B$?
- Suppose $\rho[\mathbf{r}_A, \mathbf{r}_B] = 1$, then:

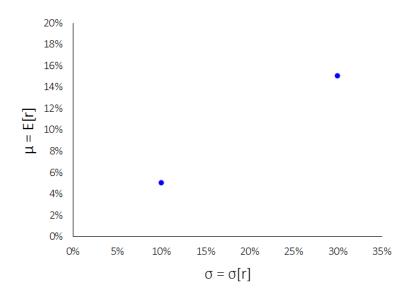
$$\sigma_p^2 = w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_A \cdot \sigma_B \cdot 1$$

$$= (w_A \cdot \sigma_A + w_B \cdot \sigma_B)^2$$
$$\Downarrow$$

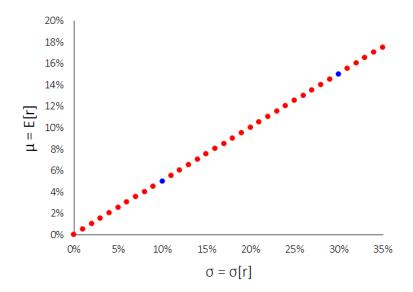
 $\sigma_{p} = w_{A} \cdot \sigma_{A} + w_{B} \cdot \sigma_{B}$

• Any $\rho[\mathbf{r}_{A}, \mathbf{r}_{B}] < 1$ produces $\sigma_{p} < \mathbf{w}_{A} \cdot \sigma_{A} + \mathbf{w}_{B} \cdot \sigma_{B}$

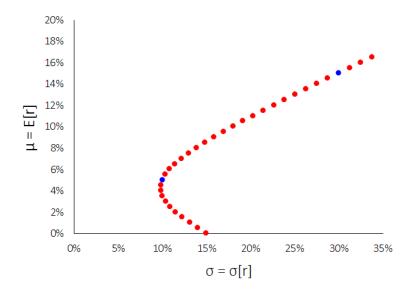
Diversification: Two Risky Assets



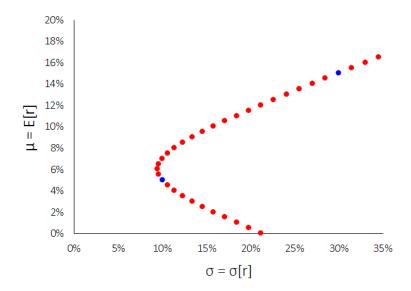
Diversification: Two Risky Assets ($\rho = 1.0$)



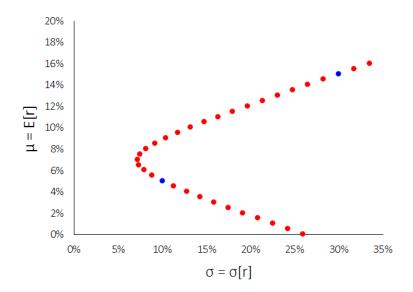
Diversification: Two Risky Assets ($\rho = 0.5$)



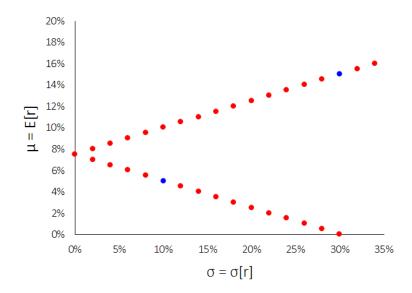
Diversification: Two Risky Assets ($\rho = 0.0$)



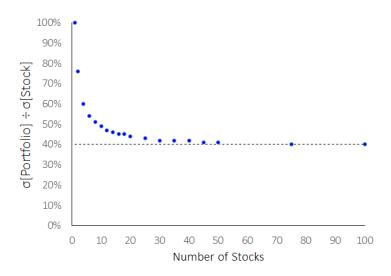
Diversification: Two Risky Assets ($\rho = -0.5$)

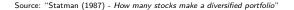


Diversification: Two Risky Assets ($\rho = -1.0$)

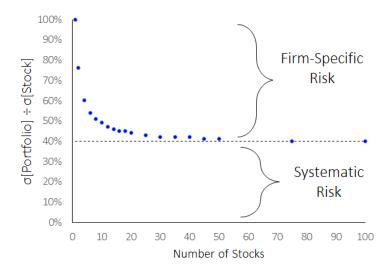


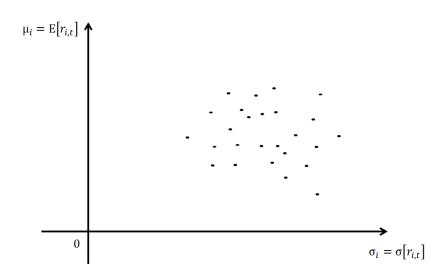
Diversification: Systematic \times Firm-Specific Risk

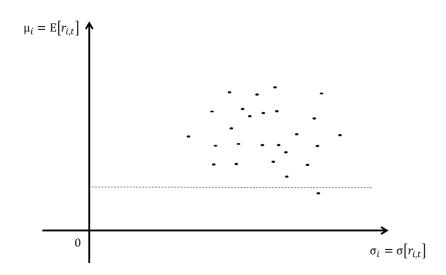


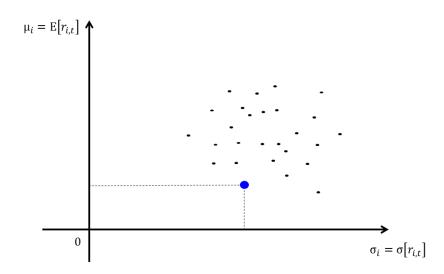


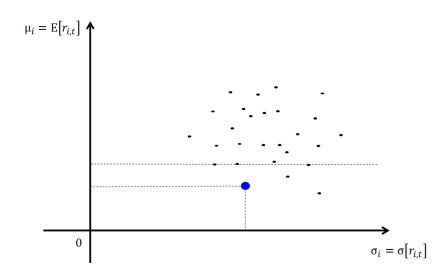
Diversification: Systematic \times Firm-Specific Risk

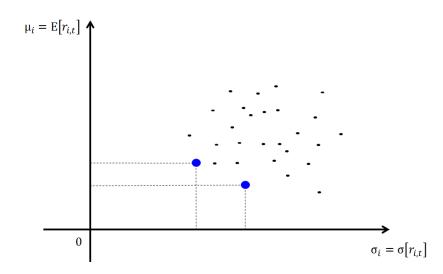


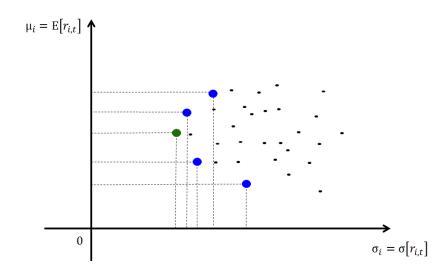


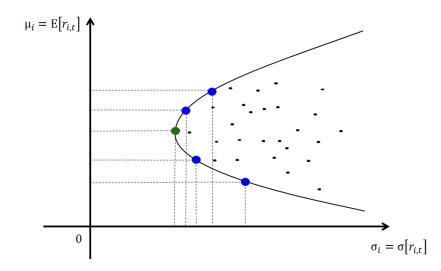


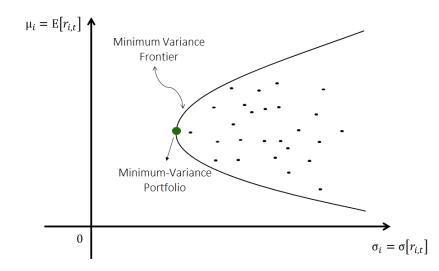


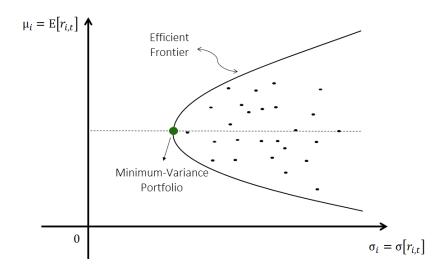












Which of the following is false regarding the Efficient Frontier?

- a) It relies on estimates of risk, $\sigma[r_t]$, reward, $\mathbb{E}[r_t]$, and covariances for multiple assets
- b) Any portfolio formed by first selecting a target $\mathbb{E}[r_t]$ and then choosing the portfolio with minimum risk among the ones with such target $\mathbb{E}[r_t]$ is an efficient portfolio
- c) It restricts the set of potential portfolios an investor should choose from if he measures risk by $\sigma[r_t]$ and reward by $\mathbb{E}[r_t]$
- d) It depends heavily on the power of diversification
- e) With only two assets, the more negatively correlated they are the better is the efficient frontier investors can form using them

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Capital Allocation Line

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Outline

Overview

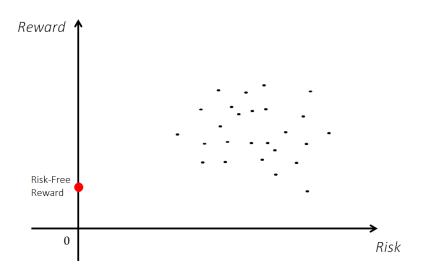
The Statistics of Security Returns

The Efficient Frontier

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This Section: Adding Risk Free Asset



Combining Risky Asset with Risk-Free Asset

• Recall that for $r_p = w_A \cdot r_A + w_B \cdot r_B$ we have:

 $\mathbb{E}[r_{\rho}] = w_{A} \cdot \mathbb{E}[r_{A}] + w_{B} \cdot \mathbb{E}[r_{B}]$

 $\sigma_{p}^{2} = w_{A}^{2} \cdot \sigma_{A}^{2} + w_{B}^{2} \cdot \sigma_{B}^{2} + 2 \cdot w_{A} \cdot w_{B} \cdot \sigma_{A} \cdot \sigma_{B} \cdot \rho \left[r_{A}, r_{B} \right]$

• This means that $r_p = w_A \cdot r_A + w_f \cdot r_f$ satisfies:

 $\mathbb{E}\left[r_{0}\right] = w_{0} \cdot \mathbb{E}\left[r_{0}\right] + w_{0} \cdot r_{0}$

 $\sigma_{p}^{2} = w_{h}^{2} \cdot \sigma_{h}^{2} \implies \sigma_{p} = w_{h} \cdot \sigma_{h} + w_{r} \cdot 0$

Combining Risky Asset with Risk-Free Asset

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 $\sigma_p = m_{0}^{2} \cdot \sigma_{p}^{2} \longrightarrow \sigma_p = m_{0} \cdot \sigma_{n} + m_{0} \cdot 0$

Combining Risky Asset with Risk-Free Asset

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 $\mathbb{E}\left[r_{\rho}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{B} \cdot \mathbb{E}\left[r_{B}\right]$

 $\sigma_{p}^{2} = w_{A}^{2} \cdot \sigma_{A}^{2} + w_{B}^{2} \cdot \sigma_{B}^{2} + 2 \cdot w_{A} \cdot w_{B} \cdot \sigma_{A} \cdot \sigma_{B} \cdot \rho \left[r_{A}, r_{B} \right]$

• This means that $r_p = w_A \cdot r_A + w_f \cdot r_f$ satisfies:

 $\mathbb{E}\left[r_{A}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{C} \cdot r_{C}$

 $\sigma_{p}^{2} = w_{h}^{2} \cdot \sigma_{h}^{2} \implies \sigma_{p} = w_{h} \cdot \sigma_{h} + w_{t} \cdot 0$

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$$\mathbb{E}[r_{\rho}] = w_{A} \cdot \mathbb{E}[r_{A}] + w_{B} \cdot \mathbb{E}[r_{B}]$$

$$\sigma_p^2 = w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_A \cdot \sigma_B \cdot \rho [r_A, r_B]$$

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$$\mathbb{E}\left[r_{\rho}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{f} \cdot r_{f}$$

$$\sigma_{\rho}^{2} = w_{A}^{2} \cdot \sigma_{A}^{2} \implies \sigma_{\rho} = w_{A} \cdot \sigma_{A} + w_{\ell} \cdot 0$$

• Recall that for $r_p = w_A \cdot r_A + w_B \cdot r_B$ we have:

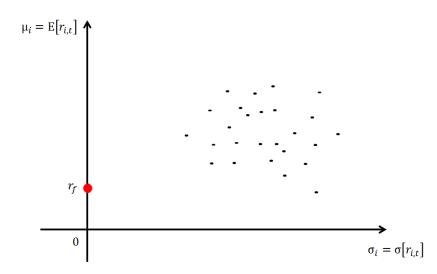
$$\mathbb{E}\left[r_{\rho}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{B} \cdot \mathbb{E}\left[r_{B}\right]$$

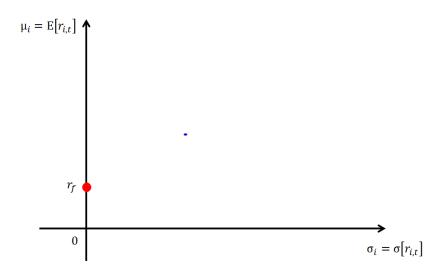
$$\sigma_p^2 = w_A^2 \cdot \sigma_A^2 + w_B^2 \cdot \sigma_B^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_A \cdot \sigma_B \cdot \rho [r_A, r_B]$$

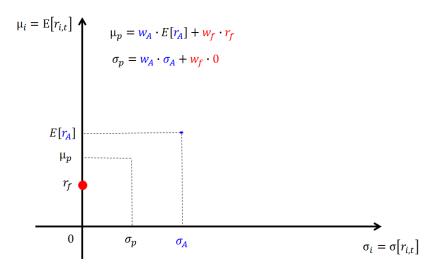
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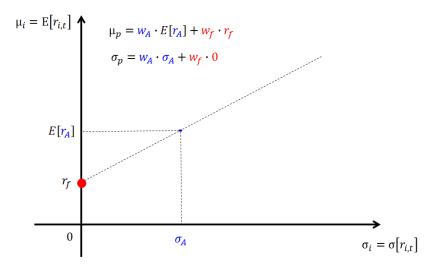
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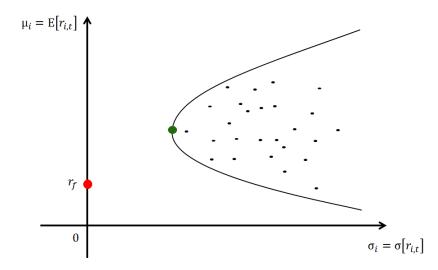




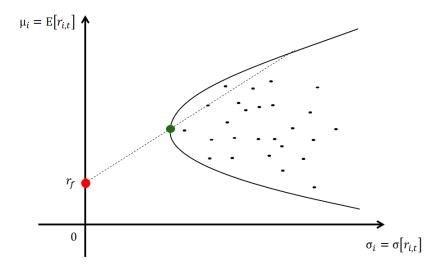




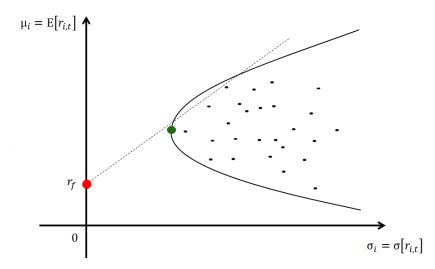
$\sigma[r_t] \times \mathbb{E}[r_t]$: Capital Allocation Line

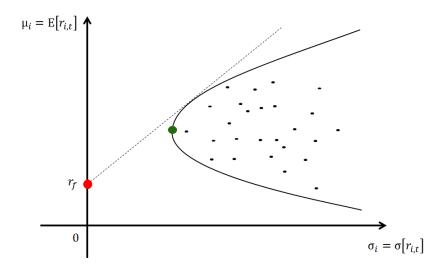


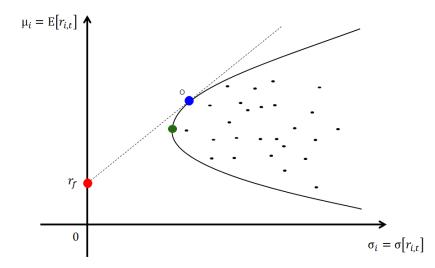
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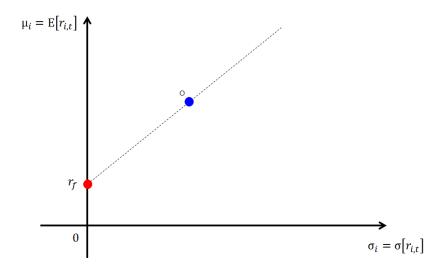


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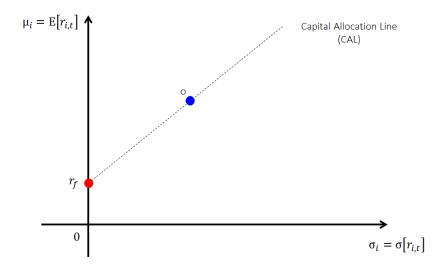




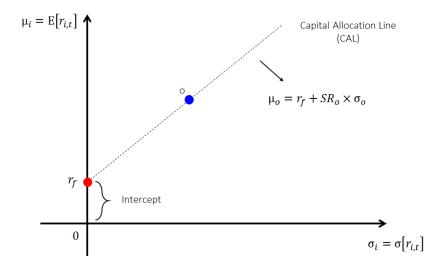




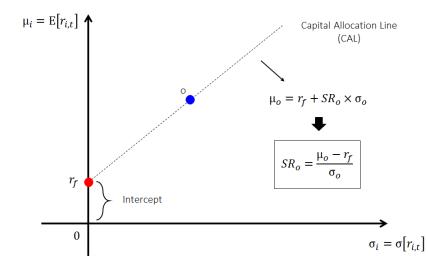
$\sigma[r_t] \times \mathbb{E}[r_t]$: Capital Allocation Line



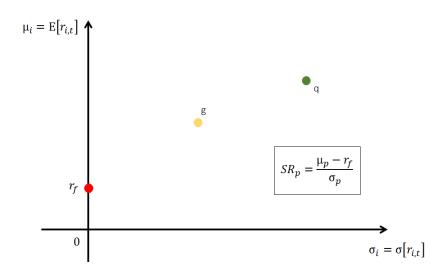
$\sigma[r_t] \times \mathbb{E}[r_t]$: Sharpe Ratio



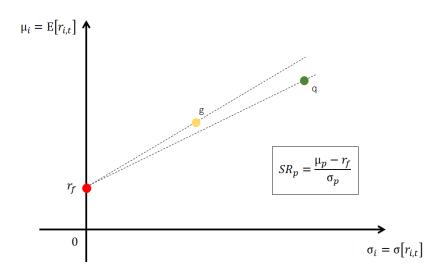
$\sigma[r_t] \times \mathbb{E}[r_t]$: Sharpe Ratio



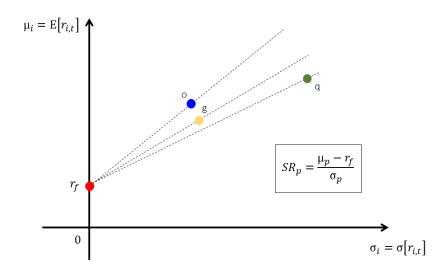
 $\sigma[r_t] \times \mathbb{E}[r_t]$: Portfolio Comparison using Sharpe Ratio



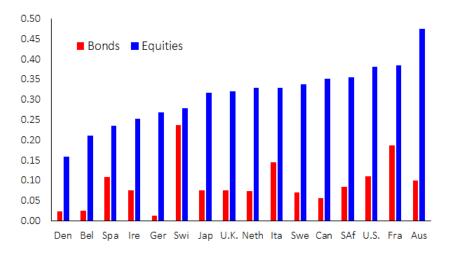
$\sigma[r_t] \times \mathbb{E}[r_t]$: Portfolio Comparison using Sharpe Ratio



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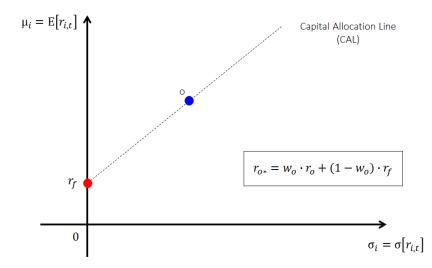


Sharpe Ratios around the World from 1900-2000

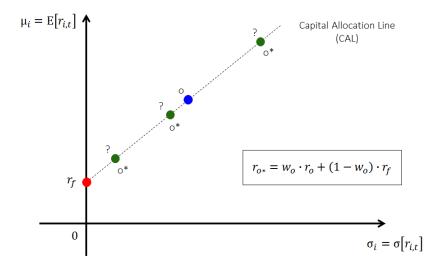


Source: Dimson et al (2002) - Triumph of the optimists: 101 years of global investment returns

$\sigma[r_t] \times \mathbb{E}[r_t]$: Complete Portfolio o^*



$\sigma[r_t] \times \mathbb{E}[r_t]$: Complete Portfolio o^*



• Recall that for $r_p = w_A \cdot r_A + w_B \cdot r_B$ we have:

 $\mathbb{E}[r_{\rho}] = w_{A} \cdot \mathbb{E}[r_{A}] + w_{B} \cdot \mathbb{E}[r_{B}]$

 $\sigma_{p}^{2} = w_{A}^{2} \cdot \sigma_{A}^{2} + w_{B}^{2} \cdot \sigma_{B}^{2} + 2 \cdot w_{A} \cdot w_{B} \cdot \sigma_{A} \cdot \sigma_{B} \cdot \rho \left[r_{A}, r_{B} \right]$

• This means that $r_{o*} = w_o \cdot r_o + (1 - w_o) \cdot r_f$ satisfies:

 $\mathbb{E}\left[\tau_{oe}\right] = w_o \circ \mathbb{E}\left[\tau_o\right] + (1 - w_o) \circ \tau_c$

 $a_{o}^2 = w_0^2 \cdot a_{o}^2 \implies \cdots \mid a_{o'} = w_o \cdot a_{o'} = w_o$

• Recall that for $r_p = w_A \cdot r_A + w_B \cdot r_B$ we have:

 $\mathbb{E}[r_{\rho}] = w_{A} \cdot \mathbb{E}[r_{A}] + w_{B} \cdot \mathbb{E}[r_{B}]$

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$$\eta \in [0, \eta] \cong [0, \eta] \cong [0, \eta] \cong [0, \eta]$$

$$a_{g^*}^2 = w_0^2 \cdot a_{g^*}^2 \implies a_{g^*}^2 = w_0 \cdot a_{g^*}^2$$

• Recall that for $r_p = w_A \cdot r_A + w_B \cdot r_B$ we have:

 $\mathbb{E}\left[r_{\rho}\right] = w_{A} \cdot \mathbb{E}\left[r_{A}\right] + w_{B} \cdot \mathbb{E}\left[r_{B}\right]$

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• This means that $r_{o*} = w_o \cdot r_o + (1 - w_o) \cdot r_f$ satisfies:

 $\mathbb{E}\left[r_{os}\right] = w_o \cdot \mathbb{E}\left[r_o\right] + (1 - w_o) \cdot r_c$

 $\sigma_{g^2}^2 = m_0^2 \cdot \sigma_{g^2}^2 \implies \sigma_{g^2} = m_0 \cdot \sigma_{g^2}$

• Recall that for $r_p = w_A \cdot r_A + w_B \cdot r_B$ we have:

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$$\mathbb{E}[r_{o*}] = w_o \cdot \mathbb{E}[r_o] + (1 - w_o) \cdot r_f$$

$$\sigma_{o^*}^2 = w_o^2 \cdot \sigma_o^2 \quad \Longrightarrow \quad \sigma_{o^*} = w_o \cdot \sigma_o$$

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$$\mathbb{E}\left[r_{o*}\right] = w_o \cdot \mathbb{E}\left[r_o\right] + \left(1 - w_o\right) \cdot r_f$$

$$\sigma_{o^*}^2 = w_o^2 \cdot \sigma_o^2 \quad \Longrightarrow \quad \sigma_{o^*} = w_o \cdot \sigma_o$$

• Investors happiness depends on $\sigma_{o^*} = \sigma[r_{o^*}]$ and $\mu_{o^*} = \mathbb{E}[r_{o^*}]$

We can model investors happiness (called utility function) as:

 $U(\sigma_{\sigma^*},\mu_{\sigma^*}) = \mu_{\sigma^*} - 0.5 \cdot A \cdot \sigma_{\sigma^*}^2$

 $\frac{5n + 5n - 4 - 2.0 - n (n - 1) + n 4 - n m}{n^2} = \dots = \frac{n (n - 1) + n 4 - n m}{n^4}$

• If investors select w_o to maximize their happiness we have:

$$\begin{array}{l} \displaystyle \frac{1}{A \circ \sigma_{0}^{2}} \circ \left(\mu_{0} - \sigma_{0}^{2} \right) \\ \displaystyle \qquad \qquad \displaystyle = \frac{1}{A \circ \sigma_{0}^{2}} \circ \left(\mu_{0} - \sigma_{0}^{2} \right) \\ \displaystyle \qquad \qquad \displaystyle = \frac{1}{A \circ \sigma_{0}} \circ SR_{0} - m_{0} \circ A \circ \sigma_{0} \\ \displaystyle \qquad \qquad \displaystyle = \frac{1}{A \circ \sigma_{0}} \circ SR_{0} - m_{0} \circ A \circ \sigma_{0} \\ \end{array}$$

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$$U(\sigma_{o^*}, \mu_{o^*}) = \mu_{o^*} - 0.5 \cdot A \cdot \sigma_{o^*}^2$$
$$= \underbrace{w_o \cdot \mu_o + (1 - w_o) r_f}_{\mu_{o^*}} - 0.5 \cdot A \cdot \underbrace{w_o^2 \cdot \sigma_o^2}_{\sigma_{o^*}^2}$$

• If investors select w_o to maximize their happiness we have:

$$\begin{array}{l} \displaystyle \frac{1}{2} \left(h_{0} - h \right) \\ \displaystyle = \frac{1}{2} \left(SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} \right) \\ \displaystyle = \frac{1}{2} \left(SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} \right) \\ \displaystyle = \frac{1}{2} \left(SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} \right) \\ \displaystyle = \frac{1}{2} \left(SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} - SR_{0} \right) \\ \displaystyle = \frac{1}{2} \left(SR_{0} - SR_{0} \right) \\ \displaystyle = \frac{1}{2} \left(SR_{0} - SR_{0}$$

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$$U(\sigma_{o^*}, \mu_{o^*}) = \mu_{o^*} - 0.5 \cdot A \cdot \sigma_{o^*}^2$$
$$= \underbrace{w_o \cdot \mu_o + (1 - w_o) r_f}_{\mu_{o^*}} - 0.5 \cdot A \cdot \underbrace{w_o^2 \cdot \sigma_o^2}_{\sigma_{o^*}^2}$$

If investors select w_o to maximize their happiness we have:

$$\begin{array}{l} \displaystyle \frac{1}{A \cdot \sigma_0^2} \left(\mu_0 - \alpha \right) \\ \displaystyle = \frac{1}{A \cdot \sigma_0^2} \left(R_0 - \infty \right) \\ \displaystyle = \frac{1}{A \cdot \sigma_0^2} SR_0 - \infty \left(SR_0 - \infty \right) \\ \end{array}$$

- Investors happiness depends on $\sigma_{o^*} = \sigma[r_{o^*}]$ and $\mu_{o^*} = \mathbb{E}[r_{o^*}]$
- We can model investors happiness (called utility function) as:

$$U(\sigma_{o^*}, \mu_{o^*}) = \mu_{o^*} - 0.5 \cdot A \cdot \sigma_{o^*}^2$$
$$= \underbrace{w_o \cdot \mu_o + (1 - w_o) r_f}_{\mu_{o^*}} - 0.5 \cdot A \cdot \underbrace{w_o^2 \cdot \sigma_o^2}_{\sigma_{o^*}^2}$$

• If investors select w_o to maximize their happiness we have:

$$w_o = \frac{1}{A \cdot \sigma_o^2} \cdot (\mu_o - r_f)$$

- Investors happiness depends on $\sigma_{o^*} = \sigma[r_{o^*}]$ and $\mu_{o^*} = \mathbb{E}[r_{o^*}]$
- We can model investors happiness (called utility function) as:

$$U(\sigma_{o^*}, \mu_{o^*}) = \mu_{o^*} - 0.5 \cdot A \cdot \sigma_{o^*}^2$$
$$= \underbrace{w_o \cdot \mu_o + (1 - w_o) r_f}_{\mu_{o^*}} - 0.5 \cdot A \cdot \underbrace{w_o^2 \cdot \sigma_o^2}_{\sigma_{o^*}^2}$$

• If investors select w_o to maximize their happiness we have:

$$w_{o} = \frac{1}{A \cdot \sigma_{o}^{2}} \cdot (\mu_{o} - r_{f})$$
$$= \frac{1}{A \cdot \sigma_{o}} SR_{o} \implies SR_{o} = w_{o} \cdot A \cdot \sigma_{o}$$

U

Deciding on Complete Portfolio o*

- Investors happiness depends on $\sigma_{o^*} = \sigma[r_{o^*}]$ and $\mu_{o^*} = \mathbb{E}[r_{o^*}]$
- We can model investors happiness (called utility function) as:

$$(\sigma_{o^*}, \mu_{o^*}) = \mu_{o^*} - 0.5 \cdot A \cdot \sigma_{o^*}^2$$
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• If investors select w_o to maximize their happiness we have:

$$w_{o} = \frac{1}{A \cdot \sigma_{o}^{2}} \cdot (\mu_{o} - r_{f})$$
$$= \frac{1}{A \cdot \sigma_{o}} SR_{o} \implies SR_{o} = w_{o} \cdot A \cdot \sigma_{o}$$

The task of forming the "complete portfolio" (called o^*), is separated into two different tasks: (i) finding the "optimal" risky portfolio (called o) and (ii) getting o^* by combining portfolio owith r_f . Which of the following is true regarding this process:

- a) Two investors using the same inputs to step (i) always end up with the same risky portfolio, *o*
- b) Step (ii) is investor specific. However, if two investors have the same risk aversion, they always end up with the same o^*
- c) Portfolio *o* can only be found if we first find the entire efficient frontier
- d) The negative covariance between r_f and o is very important to decide on portfolio o^*
- e) Portfolio *o* is the portfolio with lowest risk among all possible portfolios that exclude the risk-free rate

The task of forming the "complete portfolio" (called o^*), is separated into two different tasks: (i) finding the "optimal" risky portfolio (called o) and (ii) getting o^* by combining portfolio owith r_f . Which of the following is true regarding this process:

- a) Two investors using the same inputs to step (i) always end up with the same risky portfolio, *o*
- b) Step (ii) is investor specific. However, if two investors have the same risk aversion, they always end up with the same o^*
- c) Portfolio *o* can only be found if we first find the entire efficient frontier
- d) The negative covariance between r_f and o is very important to decide on portfolio o^*
- e) Portfolio *o* is the portfolio with lowest risk among all possible portfolios that exclude the risk-free rate

The Efficient Frontie

Outline

Overview

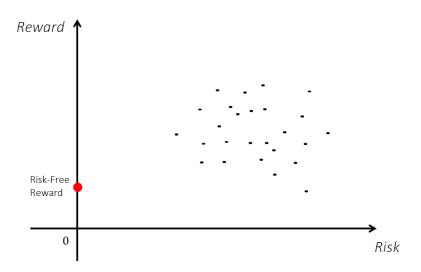
The Statistics of Security Returns

The Efficient Frontier

Capital Allocation Line

Index Models

This Section: Inputs to $\sigma[r_t] \times \mathbb{E}[r_t]$ Framework



$$Cov[r_A, r_B] = \sum_{s} p(s) \times \{r_A(s) - \mathbb{E}[r_A]\} \times \{r_B(s) - \mathbb{E}[r_B]\}$$
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- The number of estimates "explodes" (results are unreliable):
 - $\sigma = M = 50$ securities $\implies 1,225$ covariance estimates (only 100 σ and μ estimates)
 - $\sim N = 500$ securities $\implies 124,750$ covariance estimates

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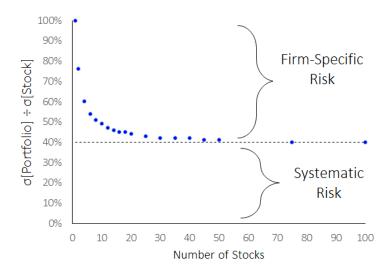
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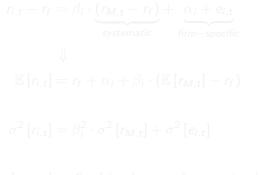
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Systematic \times Firm-Specific Risk

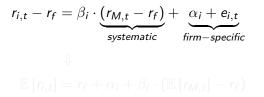


• Decomposing returns into two components:



$$= \beta_A \cdot \beta_B \cdot \sigma^2 \left[r_{M,t} \right]$$

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 $\sigma^{2}[r_{i,t}] = \beta_{i}^{2} \cdot \sigma^{2}[r_{M,t}] + \sigma^{2}[e_{i,t}]$

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• Decomposing returns into two components:

 $r_{i,t} - r_f = \beta_i \cdot \underbrace{(r_{M,t} - r_f)}_{systematic} + \underbrace{\alpha_i + e_{i,t}}_{firm-specific}$ \Downarrow $\mathbb{E}[r_{i,t}] = r_f + \alpha_i + \beta_i \cdot (\mathbb{E}[r_{M,t}] - r_f)$

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- With an index model with N assets, we need:
 - *N* estimates of α_i , β_i and $\sigma[e_{i,t}]$
 - 1 estimate $\mathbb{E}[r_{M,t}]$ and $\sigma^2[r_{M,t}]$
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 - \circ N = 50 securities \rightarrow 1,355 estimates
 - $\sim M = 50$ securities \longrightarrow 152 estimates (with index model)

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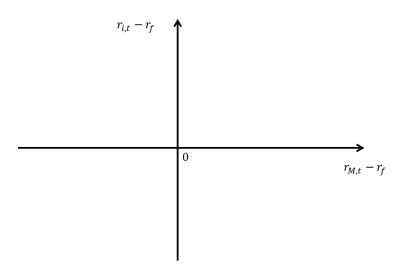
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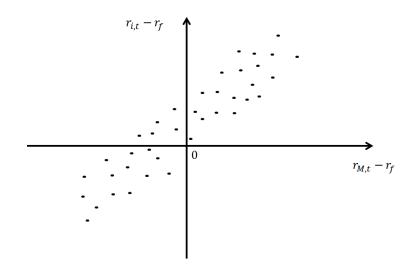
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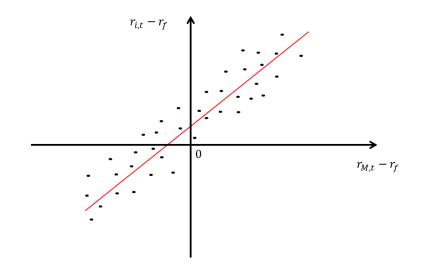
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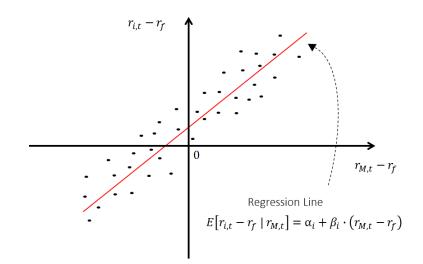
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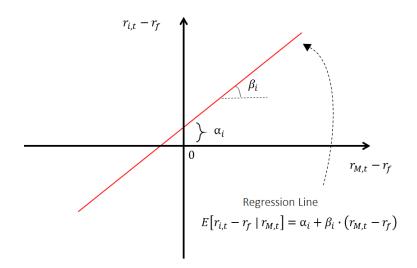




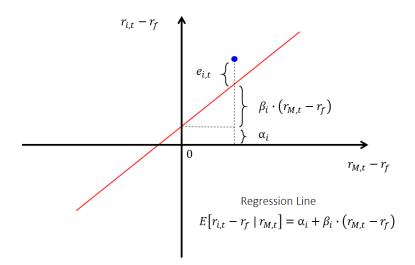




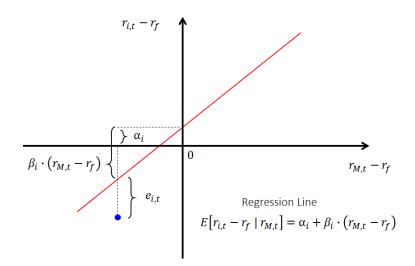
Index Model as a Regression: α_i and β_i



Index Model as a Regression: Decomposing $r_{i,t}$



Index Model as a Regression: Decomposing $r_{i,t}$



Index Models

Index Model: Systematic \times Firm-Specific Risk

• Decomposing risk into two components:

systematic risk

$$= \frac{\beta_i^2 \cdot \sigma^2 [r_{M,t}]}{\beta_i^2 \cdot \sigma^2 [r_{M,t}] + \sigma^2 [e_{i,t}]}$$

Decomposing risk into two components: •

$$\sigma^{2}[r_{i,t}] = \underbrace{\beta_{i}^{2} \cdot \sigma^{2}[r_{M,t}]}_{systematic \ risk} + \underbrace{\sigma^{2}[e_{i,t}]}_{firm-specific \ risk}$$

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• When we form a (equal-weighted) portfolio $r_p = \frac{1}{N} \sum_{i=1}^{N} r_i$:

$$r_{p} - r_{f} = \underbrace{\left(\frac{1}{N}\sum_{i}\alpha_{i}\right)}_{\alpha_{p}} + \underbrace{\left(\frac{1}{N}\sum_{i}\beta_{i}\right)}_{\beta_{p}} \cdot (r_{M} - r_{f}) + \left(\frac{1}{N}\sum_{i}e_{i}\right)$$
$$= \alpha_{p} + \beta_{p} \cdot (r_{M} - r_{f}) + \left(\frac{1}{N}\sum_{i}e_{i}\right)$$
$$\cong \alpha_{p} + \beta_{p} \cdot (r_{M} - r_{f})$$
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$$\sigma^{2} [r_{p}] \cong \beta_{p}^{2} \cdot \sigma^{2} [r_{M}]$$

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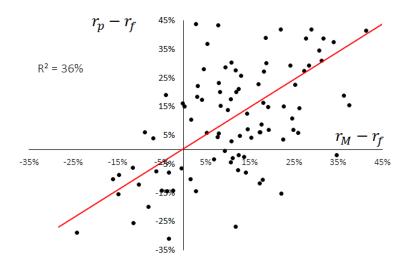
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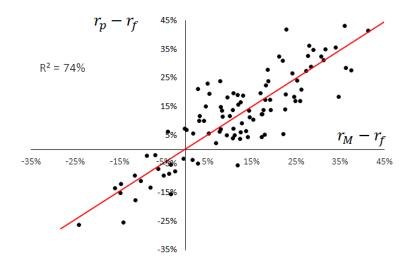
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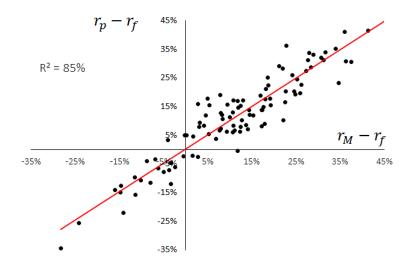
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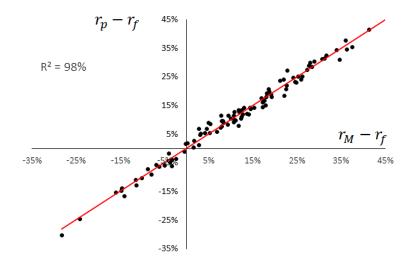
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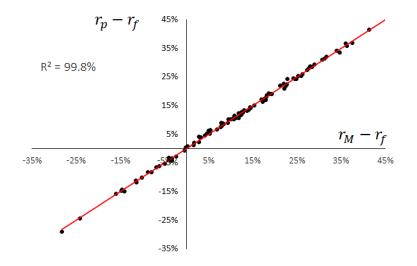


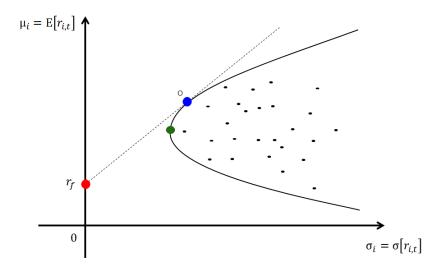
The Efficient Frontie



The Efficient Frontie

N = 1,000





• It turns out that (using the index model):

$$r_{o} = \underbrace{w_{A} \cdot r_{A}}_{Active} + \underbrace{(1 - w_{A}) \cdot r_{M}}_{Passive}$$
$$w_{A}^{0} = \frac{\alpha_{A}/\sigma^{2}[e_{A}]}{(\mathbb{E}[r_{M}] - r_{f})/\sigma_{M}^{2}} \quad and \quad w_{A} = \frac{w_{A}^{0}}{1 + w_{A}^{0} \cdot (1 - \beta)}$$

• Moreover, weight of asset *i* in the active portfolio is:



Index Models

Index Model: Finding the Tangency Portfolio

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• Moreover, weight of asset *i* in the active portfolio is:

$$\frac{\alpha/\sigma^2 \omega}{2} = \frac{\gamma/\sigma^2 \omega}{2} = \frac{1}{2} \frac{1}{\sigma^2} \frac{1}{\sigma^2} \frac{1}{\sigma^2} = \frac{1}{2} \frac{1}{\sigma^2} \frac{1}$$

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You are considering using an index model when estimating inputs for your portfolio optimization problem. All of the followings are advantages of this approach of estimating inputs, except:

- a) It reduces substantially the number of parameters to be estimated
- b) It creates a clear decomposition between systematic and firm-specific risk
- c) It breaks the optimal risky portfolio into a passive portfolio and an active position, which allows you to understand how you are deviating from the given index
- d) It provides you with estimates that rely on a lower number of assumptions about returns
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- Portfolio theory provides you with an extremely useful tool for portfolio formation. However:
 - "Garbage in, garbage out" principle
 - Portfolio Theory is silent about how to estimate $\mathbb{E}[r_t]$ and $\sigma[r_t]$. Forward looking estimates are key (security analysis)
 - Maximum Sharpe Ratio portfolio is very sensitive to model inputs (especially $\mathbb{E}[r_t]$)
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