

Foreword

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- Stephen Boyd and Lieven Vandenberghe, *Convex Optimization*, Cambridge University Press, 2004.

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 - the assumptions on the probability space underlying the models; one should in particular be familiar with Markovianity.
 - the optimization requirements (convexity assumptions needed for first order conditions to be not only necessary but also sufficient, dynamic programming requirements)
- The continuous time setup in particular would require a lot of additional material to become self contained.

The static model

Timing

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 - x : particular outcome; \tilde{x} : random variable

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- I'll assume there are N risky assets ($i = 1, \dots, N$) and potentially cash (the riskless asset), which will then have index 0
- The set of assets will be denoted by \mathcal{I} , with either $\mathcal{I} = (1, \dots, N)$ (no riskless asset) or $\mathcal{I} = (0, \dots, N)$ (with a riskless asset)

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- The rate of return of cash is usually denoted r^f ; it is known as of date 0

Investment and returns

$t = 0$		$t = 1$
ϕ	\rightarrow	$\tilde{R}\phi$
ϕ	\rightarrow	$(1 + \tilde{r})\phi$

Table 1: From investment to payoff

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 - wealth shares $(\pi_i)_{i \in \mathcal{I}}$, with $\pi_i = \phi_i / w_0$

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$$\sum_{i \in \mathcal{I}} \pi_i = 1$$

Borrowing

- Borrowing is best understood as a negative position in cash:

$t = 0$	$t = 1$
$\phi = -d$	$\rightarrow -d(1 + r^f)$

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- portfolio rate of return:

$$\tilde{r}_p = \frac{\tilde{W}}{w_0} = \sum_{i \in \mathcal{I}} \pi_i \tilde{r}_i$$

(since $\sum_{i \in \mathcal{I}} \pi_i = 1$)

The space of excess returns

- In the presence of a riskless asset, it is convenient to introduce excess returns versus the riskless rate:

$$\begin{aligned}\tilde{r}_p &= \sum_{i \in \mathcal{I}} \pi_i \tilde{r}_i \\ &= r^f + \sum_{i=1}^N \pi_i (\tilde{r}_i - r^f)\end{aligned}$$

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- The choice variables are initially $(\pi_i)_{i \in \mathcal{I}}$, under the constraint $\sum_{i \in \mathcal{I}} \pi_i = 1$. In the excess return space, the choice variables are $(\pi_i)_{i=1}^N$ to which no budget constraint applies since it is enforced by $\pi_0 = 1 - \sum_{i=1}^N \pi_i$.

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 - the utility function embodies attitudes towards risk of the decision maker

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- Reminder: an arbitrage is a way to generate a strictly positive pay-off without committing any funds
- The existence of a solution to a portfolio optimization problem thus guarantees the existence of a stochastic discount factor (see below). We will see this principle in action in the case of mean-variance efficiency.

Arbitrage, the law of one price and SDF

- A stochastic discount factor is a random variable \tilde{m} such that for any pay-off \tilde{x} , the market price can be recovered:

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- In the presence of a risk free asset, this implies:

$$E[\tilde{R}] - r^f = -r^f \text{cov}(\tilde{m}, \tilde{R}),$$

which describes the structure of risk premia across assets as a result of the covariances with the SDF.

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- Multiplicative certainty equivalent: for a centered distribution $\tilde{\varepsilon}_m$ and an initial level of wealth w , find $\pi_m(w, \tilde{\varepsilon}_m)$ such that:

$$u(w(1 - \pi_m)) = E[u(w(1 + \tilde{\varepsilon}_m))].$$

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- relative risk aversion: $\rho(w) = \rho$

CRRA utility functions - fig 1

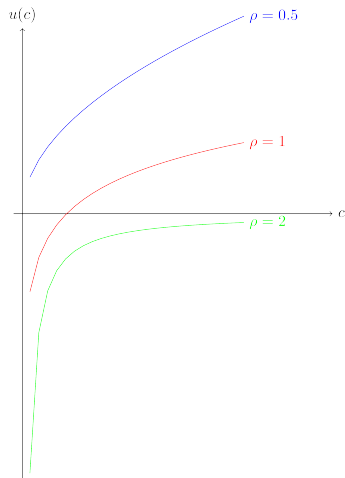


Figure 1: CRRA utility functions

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- For example, CRRA models require $\tilde{R} \geq 0$ i.e. $\tilde{r} \geq 1$. This assumption is sometimes called 'limited liability': the owner of an asset cannot end up having to transfer cash to the issuer.
- This is a problem mainly for discrete time models

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 - intuition suggests people accept greater dollar risk as their wealth rises

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- I assume that there is no labor come
- $\boldsymbol{\pi} = (\pi_i)_{i \in \mathcal{I}}$

$$\begin{aligned} \max_{\boldsymbol{\pi}} \quad & E[-\exp(-\alpha \tilde{w})] \\ \text{s.t.} \quad & \tilde{w} = w_0 \sum_{i \in \mathcal{I}} \pi_i \tilde{R}_i \\ & \sum_{i \in \mathcal{I}} \pi_i = 1 \end{aligned}$$

CARA normal case (1)

- The random variable \tilde{w} is normally distributed. In this case, we know that:

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- Given that the function $u(\cdot)$ is increasing, the program consists in maximizing the certainty equivalent $E[\tilde{w}] - (\alpha/2)V[\tilde{w}]$, which reads, mean wealth minus the variance of wealth weighted by one half absolute risk aversion.

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- The maximized criterion is thus:

$$E\left[\sum_{i \in \mathcal{I}} \pi_i \tilde{r}_i\right] - (\alpha w_0^2 / 2) V\left[\sum_{i \in \mathcal{I}} \pi_i \tilde{r}_i\right].$$

CARA normal case (3)

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 - if this was not the case, optimal portfolio composition would be independent on the wealth level; this would imply that the investor take more dollar risk at higher wealth levels; in the CARA case, the appetite for dollar risk is independent of the level of wealth; thus the correction.

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 - preferences induced by utility functions will not, in general, correspond to mean-variance; additional assumptions are needed.
 - when the distribution of portfolio returns is characterized by mean and variance, all utility functions naturally lead to mean variance preferences (see elliptic distributions).
 - in the presence of stochastic labour income, mean variance needs to be amended

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- In the presence of normally distributed stochastic labor income, the optimal programme is:

$$\begin{aligned} \max_{\pi} \quad & E[-\exp(-\alpha \tilde{w})] \\ \text{s.t.} \quad & \tilde{w} = \tilde{y} + \sum_{i \in \mathcal{I}} \theta_i \tilde{x}_i \\ & \sum_{i \in \mathcal{I}} \theta_i p_i = w_0 \end{aligned}$$

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- It is this time more convenient to take as control variables the quantities: $(\theta_i)_{i \in \mathcal{I}}$.

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- As before, we need to maximize the certainty equivalent: $E[\tilde{w}] - (\alpha/2)V[\tilde{w}]$. This is equivalent to maximizing:

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- We can decompose the variance term as:

$$V[\tilde{y}] + V\left[\sum_{i \in \mathcal{I}} \theta_i \tilde{x}_i\right] + 2\text{Cov}\left(\sum_{i \in \mathcal{I}} \theta_i \tilde{x}_i, \tilde{y}\right).$$

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 - $\text{Cov}(\tilde{x}, \tilde{y})$ is the $N \times 1$ vector where each entry measures the covariance of a financial instrument with labour income
 - $E[\tilde{x}]$ is the $N \times 1$ vector of the expected pay-offs of the financial instruments.

CARA normal case (7)

- The first order condition leads to, in matrix notation:

$$\theta = V[\tilde{x}]^{-1} \left(-\text{Cov}(\tilde{x}, \tilde{y}) + \frac{1}{\alpha} E[\tilde{x}] \right).$$

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- Remember that $1/\alpha$ is risk tolerance.
- The structure of the solution is as follows: the optimal portfolio consists of a hedging portfolio (which tries to replicate income variability using financial assets) and a speculative portfolio which has the same structure as in the case without labour income. The latter portfolio receives a weight equal to risk tolerance.

Mean variance without a riskfree asset (1)

- The program: it consists in minimizing portfolio variance for a given level of expected returns

$$\min_{\boldsymbol{\pi}} V \left[\sum_{i=1}^N \pi_i \tilde{r}_i \right] = \boldsymbol{\pi}' \boldsymbol{\Sigma} \boldsymbol{\pi}$$

$$\text{s.t. } \sum_{i=1}^N \pi_i = \boldsymbol{\pi}' \mathbf{e} = 1$$

$$E \left[\sum_{i=1}^N \pi_i \tilde{r}_i \right] = \boldsymbol{\pi}' \boldsymbol{\mu} = \mu_p$$

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 - $\boldsymbol{\mu}$ is the vector of expected returns
- We assume $\boldsymbol{\mu} \neq \mathbf{e}$ to avoid degeneracy

Mean variance without a riskfree asset (3)

- Lagrangian for the optimization problem (a factor 1/2 is convenient):

$$\frac{1}{2}\boldsymbol{\pi}'\boldsymbol{\Sigma}\boldsymbol{\pi} - \delta(\boldsymbol{\pi}'\boldsymbol{\mu} - \mu_p) - \gamma(\boldsymbol{\pi}'\mathbf{e} - 1)$$

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where I have introduced the Lagrange multipliers δ and γ .

- The necessary and sufficient first order condition (positive definite quadratic problem) is:

$$\boldsymbol{\Sigma}\boldsymbol{\pi} = \delta\boldsymbol{\mu} + \gamma\mathbf{e},$$

or, assuming the covariance matrix is invertible:

$$\boldsymbol{\pi} = \delta\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} + \gamma\boldsymbol{\Sigma}^{-1}\mathbf{e}.$$

Mean variance without a riskfree asset (4)

- Injecting this into the constraints leads to a system for the Lagrange multipliers:

$$\delta \boldsymbol{\mu}' \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu} + \gamma \boldsymbol{\mu}' \boldsymbol{\Sigma}^{-1} \mathbf{e} = \mu_p,$$

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- reminder:

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad - bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$$

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- It is useful to introduce two specific portfolios:

$$\boldsymbol{\pi}_1 = \frac{1}{\mathbf{e}' \Sigma^{-1} \mathbf{e}} \Sigma^{-1} \mathbf{e},$$

$$\boldsymbol{\pi}_\mu = \frac{1}{\mathbf{e}' \Sigma^{-1} \boldsymbol{\mu}} \Sigma^{-1} \boldsymbol{\mu}.$$

Mean variance without a riskfree asset (5)

- We can write :

$$\begin{aligned}\pi &= (\delta \mathbf{e}' \Sigma^{-1} \boldsymbol{\mu}) \pi_{\mu} + (\gamma \mathbf{e}' \Sigma^{-1} \mathbf{e}) \pi_1 \\ &= \lambda \pi_{\mu} + (1 - \lambda) \pi_1\end{aligned}$$

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- Thus, any optimal portfolio is a combination of the two portfolios we singled out:
 - π_1 is the minimum variance portfolio
 - π_{μ} is another portfolio as soon as $\boldsymbol{\mu} \neq \mathbf{e}$

Mean variance without a riskfree asset (6)

- $A = \boldsymbol{\mu}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}$, $B = \boldsymbol{\mu}'\boldsymbol{\Sigma}^{-1}\mathbf{e}$, $C = \mathbf{e}'\boldsymbol{\Sigma}^{-1}\mathbf{e}$.

$$\lambda = \frac{BC\mu_p - B^2}{AC - B^2},$$

$$\sigma_p^2 = \frac{A - 2B\mu_p + C\mu_p^2}{AC - B^2}.$$

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- Check this
- The efficient frontier (in the standard deviation mean space) is the subset of non dominated portfolios in the set:

$$\{(\sigma_p, \mu_p), \mu_p \geq \mu_1\}$$

where $\mu_1 = \boldsymbol{\pi}'_1\boldsymbol{\mu}$.

Mean variance without a riskfree asset (7) - fig 2

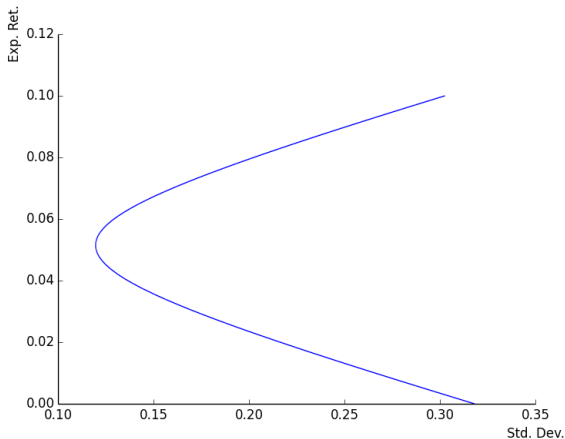


Figure 2: Efficient Frontier (without a risk free asset)

Mean variance with a riskfree asset (1)

- It is convenient in this case to use the notation $\boldsymbol{\pi}$ to denote the vector of positions on the risky assets (see the slide on the space of excess returns). The cash position is thus:

$$\pi_0 = 1 - \mathbf{e}'\boldsymbol{\pi}.$$

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- The vector π is unconstrained. The optimization problem can be written:

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Mean variance with a riskfree asset (2)

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- From $(\boldsymbol{\mu} - r^f \mathbf{e})' \boldsymbol{\pi} = \mu_p - r^f$, we get the value of δ and then the value of $\boldsymbol{\pi}$:

$$\boldsymbol{\pi} = \frac{\mu_p - r^f}{(\boldsymbol{\mu} - r^f \mathbf{e})' \Sigma^{-1} (\boldsymbol{\mu} - r^f \mathbf{e})} \Sigma^{-1} (\boldsymbol{\mu} - r^f \mathbf{e}).$$

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$$\pi = \frac{\mu_p - r^f}{(\mu - r^f \mathbf{e})' \Sigma^{-1} (\mu - r^f \mathbf{e})} \Sigma^{-1} (\mu - r^f \mathbf{e}).$$

- The standard deviation of the portfolio is:

$$\frac{|\mu_p - r^f|}{\sqrt{(\mu - r^f \mathbf{e})' \Sigma^{-1} (\mu - r^f \mathbf{e})}}.$$

Mean variance with a riskfree asset (3)

- The tangency portfolio is:

$$\pi_* = \frac{1}{\mathbf{e}'\Sigma^{-1}(\boldsymbol{\mu} - r^f\mathbf{e})}\Sigma^{-1}(\boldsymbol{\mu} - r^f\mathbf{e}).$$

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- It is a portfolio fully invested in risky assets which is on the overall efficient frontier. It is thus also on the risky asset efficient frontier.

Mean variance with a riskfree asset (4) - fig 3

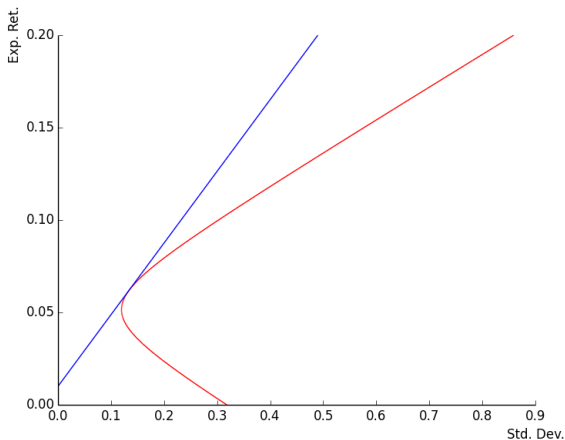


Figure 3: Efficient Frontier (with risk free asset)

Mean variance with a riskfree asset (5) - fig4

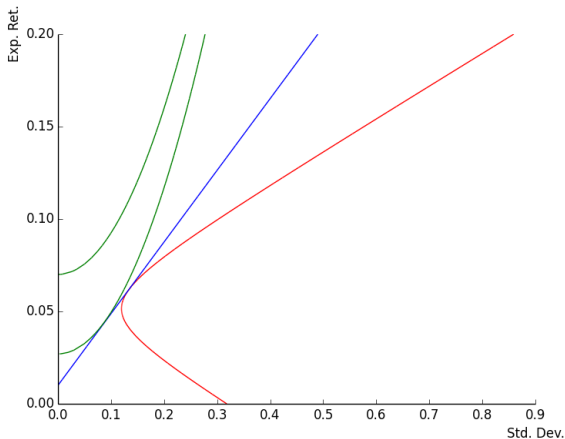


Figure 4: Efficient Frontier (with risk free asset): iso-utility curve

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 - $\text{sharpe}(\pi_*) = 0.39$

Data for the graphs (2)

- The graphs shown assume positive Sharpe ratios for the underlying assets. This is the 'normal' situation. It ensures that the efficient frontier (with a riskfree asset!) is upward sloping.

A different description of the efficient frontier (1)

- Maximize the expected return penalized for portfolio variance ($\rho > 0$):

$$\max_{\pi} r^f + \pi'(\mu - r^f) - \frac{\rho}{2}\pi'\Sigma\pi$$

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- Exercise: recover the lagrange multipliers of the traditional approach
- The criteria are given by quadratic utility functions, indexed by ρ

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- We will remember that:

$$\rho \hat{\pi} = \frac{\mu_* - r^f}{\text{var}(\pi_*)},$$

which is therefore independent of the risk aversion level of the investor. This will play a role in the derivation of the CAPM.

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- The utility level changes by (first order approximation):

$$\begin{aligned} & \mu_\delta - \rho \text{cov}(r_\delta, r_p) \\ &= \mu_\delta - \rho \frac{\text{cov}(r_\delta, r_p)}{\text{var}(r_p)} \text{var}(r_p), \\ &= \mu_\delta - \rho \beta(\delta, p) \text{var}(r_p), \\ &= \mu_\delta - \rho \hat{\pi} \beta(\delta, r_*) \text{var}(r_*). \end{aligned}$$

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- For long short portfolios which borrow to buy a stock, the condition reads:

$$(r_i - r^f) = (\mu_{*} - r^f)\beta(r_i, r_{*}).$$

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- At this stage, no equilibrium assumption has been made. We are looking at the implications of a portfolio being mean-variance optimal.
- Note that the tangency portfolio can be replaced by any other efficient portfolio in the relationship.

The excess return-beta relationship (1) - fig 5

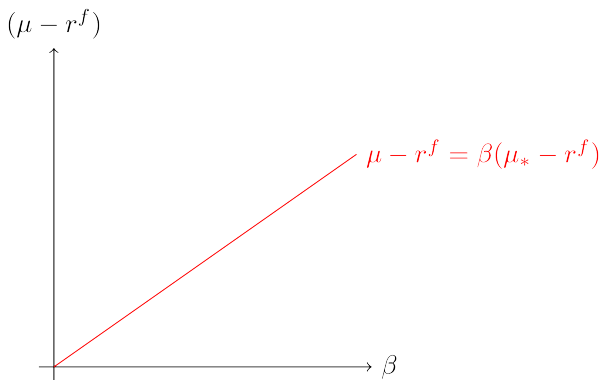


Figure 5: Return/beta relationship

The excess return-beta relationship (2) - fig 6

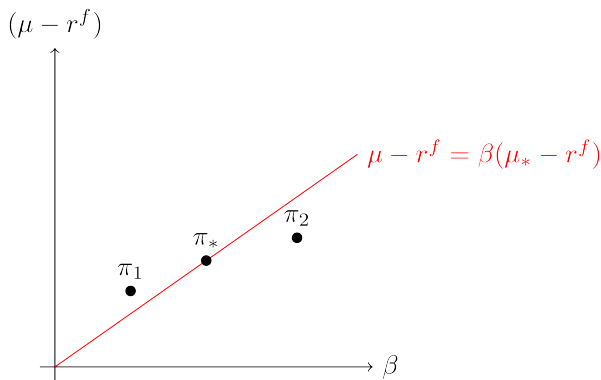


Figure 6: Imperfectly priced portfolios

The two fund theorem and the CAPM

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- This is an instance of the two fund theorem, which also holds in more general contexts
- The risky asset portfolio should be equal to the market portfolio of risky asset, with return r_m . This gives:

$$(r_i - r^f) = (\mu_m - r^f)\beta(r_i, r_m).$$

Conditions for the CAPM to hold

Illustration of the CAPM - fig 7

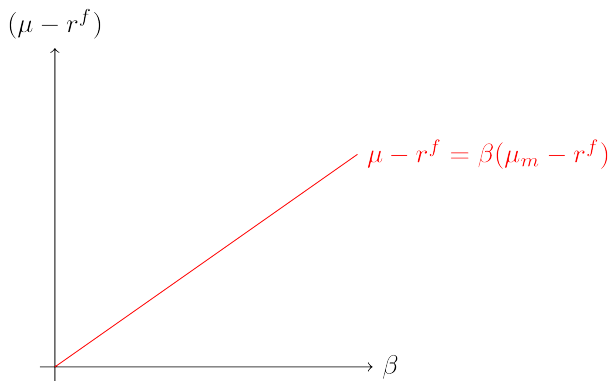


Figure 7:CAPM

The low beta anomaly - fig 8

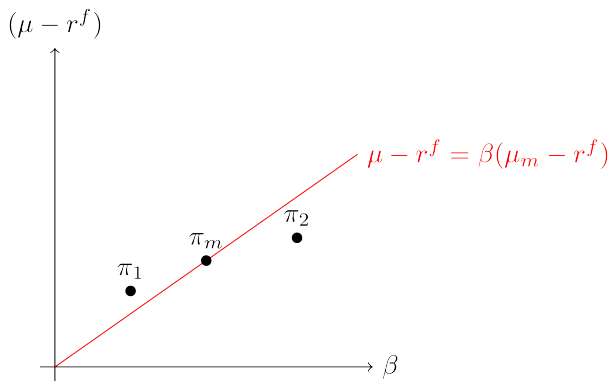


Figure 8: The low beta anomaly

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