

## Lecture 7. The Capital Asset Pricing Model

### 1. Market Equilibrium

risk-averse  
non-satiation

미 솔.

정보이론적 X, information  
free

Assume that (a) everyone is a mean-variance optimizer, (b) all investors have the same estimates of means, variances, and covariances of asset returns, (c) there is a unique risk-free rate of borrowing and lending, and (d) there are no transaction costs.

value, price 따라 가지는  
price = value (efficient).

- In the assumption, all investors have the same efficient frontier and, in turn, select the same risky portfolio, denoted by  $M$ , as an optimal risky portfolio. In equilibrium, it shows that the portfolio  $M$  must equal a **market portfolio** which contains shares of every stock in proportion to that stock's representation in the entire market.

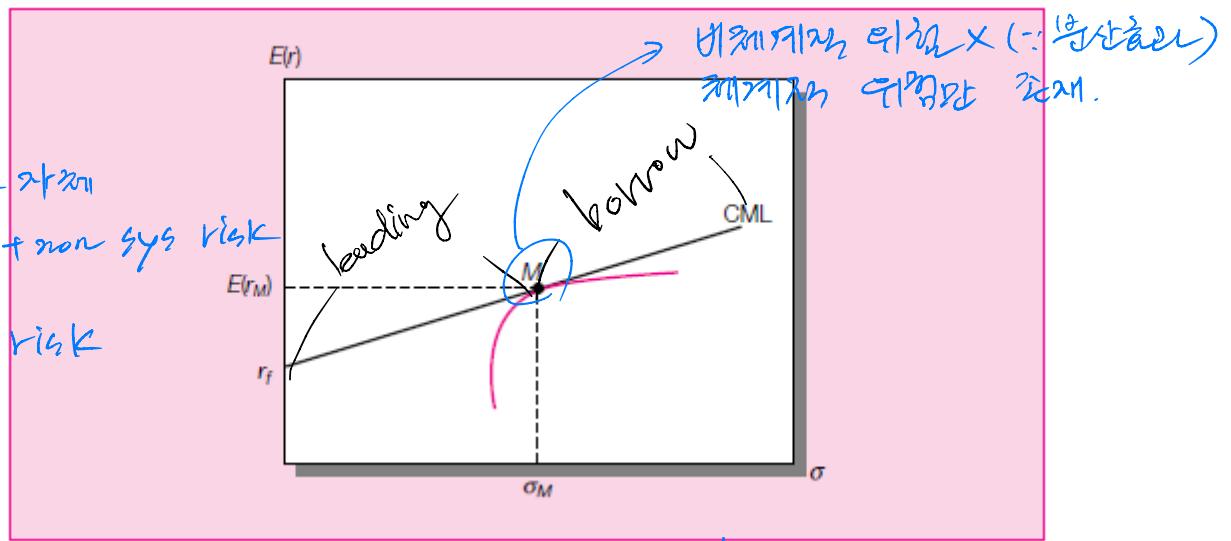
In equilibrium where the market portfolio  $M$  is an optimal risky portfolio, it shows,

$$E[r_p] = r_f + S_p \cdot \delta_p$$

$$E[r_p] = r_f + \left( \frac{E[r_M] - r_f}{\sigma_M} \right) \sigma_p. \quad E[\delta_p] = r_f + S_M \cdot \delta_p$$

So, the efficient set consists of a single straight line, emanating from the risk-free rate and passing through the **market portfolio**. This line is called the **capital market line (CML)**.

- The CML illustrates that the expected return of an efficient portfolio is linearly, positively related to its standard deviation; i.e., as the standard deviation increases, the expected return increases.



### 2. The Capital Asset Pricing Model

The **capital asset pricing model (CAPM)** relates the expected return of an *individual asset* to its **systematic risk**.

**Theorem 1.** If the market portfolio  $M$  is efficient, the expected return  $E[r_i]$  of an asset  $i$  satisfies

Asset  $i$  ∈

Risk-premium

$$E[r_i] - r_f = \beta_i(E[r_M] - r_f),$$

↓

1

$$r_i = r_f + \beta_i(r_M - r_f) + \varepsilon_i$$

error

with  $E(\varepsilon_i) = 0$  -  
 $\text{cov}(r_M, \varepsilon_i) = 0$

In eq

(  
CAL  
CMV)



)

$$\begin{aligned} \text{Var}(r_i) &= \text{Var}(\beta_i r_M + \varepsilon_i) \\ &= \beta_i^2 \text{Var}(r_M) + \text{Var}(\varepsilon_i) \end{aligned}$$

sys      nonsys  
• ( market error )<sup>x</sup>

$$E[r_i] - r_f = \beta_i (E[r_M] - r_f)$$

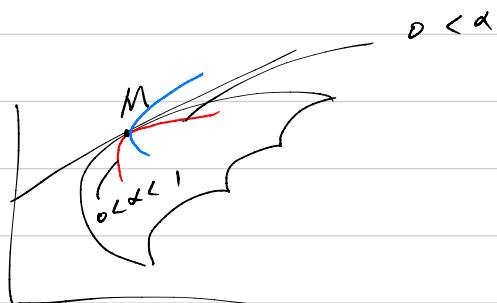
$$\Rightarrow r_i = r_f + \beta_i (r_M - r_f) + \varepsilon_i$$

with  $E[\varepsilon_i] = 0$ ,  $\text{Cov}(r_M, \varepsilon_i) = 0$

$$\Rightarrow \text{Var}[r_i] = \underbrace{\beta_i^2 \text{Var}[r_M]}_{\text{systematic}} + \underbrace{\text{Var}[\varepsilon_i]}_{\text{non-systematic}}$$

$$E[RP_i] = \beta_i E[RP_M]$$

$$RP_i = \alpha + \beta RP_M + \varepsilon_i$$



where

$$\beta_i = \frac{\text{Cov}[r_i, r_M]}{\text{Var}[r_M]} = \frac{\sigma_{iM}}{\sigma_M^2}$$

This relation is referred to as the **CAPM**.

*Proof.* Consider a portfolio consisting of a portion  $\alpha$  invested in asset  $i$  and a portion  $1 - \alpha$  invested in the market portfolio. Then, the portfolio return is given by

$$r_\alpha = \alpha r_i + (1 - \alpha) r_M, \quad E[r_\alpha] = E[\alpha r_i + (1 - \alpha) r_M] \\ = \alpha \mu_i + (1 - \alpha) \mu_M$$

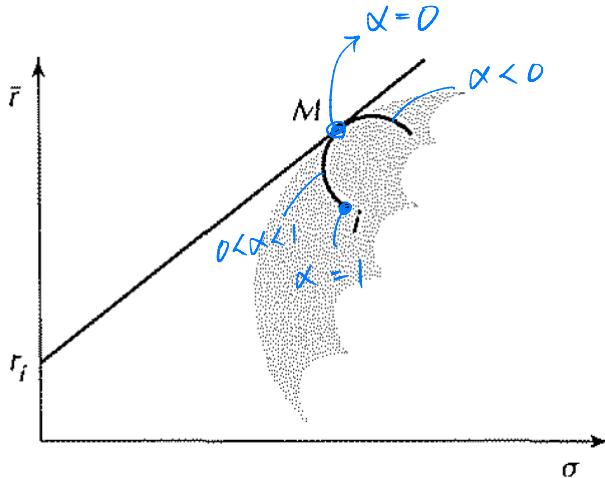
implying

$$\mu_\alpha = \alpha \mu_i + (1 - \alpha) \mu_M$$

$$\sigma_\alpha = (\alpha^2 \sigma_i^2 + 2\alpha(1 - \alpha)\sigma_{iM} + (1 - \alpha)^2 \sigma_M^2)^{1/2}.$$

$$\text{Var}[r_\alpha] = \alpha^2 \sigma_i^2 + 2\alpha(1 - \alpha)\sigma_{iM} + (1 - \alpha)^2 \sigma_M^2$$

As  $\alpha$  varies, one traces out  $\mu_\alpha$  and  $\sigma_\alpha$  in the mean-standard deviation diagram as follows:



When  $\alpha = 0$ , the curve must be tangent to the capital market line at  $M$ . This means that the slope of the curve is equal to the slope of the capital market line at the point  $M$ :

$$\left. \frac{d\mu_\alpha}{d\sigma_\alpha} \right|_{\alpha=0} = \frac{E[r_M] - r_f}{\sigma_M}.$$

Since first-derivatives of  $\mu_\alpha$  and  $\sigma_\alpha$  with respect to  $\alpha$  are given by

$$\begin{aligned} \frac{d\mu_\alpha}{d\alpha} &= \mu_i - \mu_M \\ \frac{d\sigma_\alpha}{d\alpha} &= \frac{\alpha \sigma_i^2 + (1 - 2\alpha)\sigma_{iM} - (1 - \alpha)\sigma_M^2}{(\alpha^2 \sigma_i^2 + 2\alpha(1 - \alpha)\sigma_{iM} + (1 - \alpha)^2 \sigma_M^2)^{1/2}}, \end{aligned}$$

$$\frac{\underline{M_i - M_m}}{\underline{6m - 6m^2}} = \frac{\underline{M_m - r_f}}{\underline{6m}}$$

$$\frac{\underline{M_i - M_m}}{\underline{6m - 6m^2}} = \frac{\underline{M_m - r_f}}{\underline{6m^2}}$$

$$(M_m - r_f)(6m - 6m^2) = 6m^2(M_i - M_m).$$

$$\underline{M_m 6m - M_m 6m^2} - r_f 6m + r_f 6m^2 = \underline{6m^2 M_i} - \underline{6m^2 M_m}$$

$$6m(M_m - r_f) = 6m^2(M_i - r_f)$$

$$E[r_i] - r_f = \frac{6m}{6m^2} (E[r_m] - r_f)$$

one obtains

$$\begin{aligned}\frac{d\mu_\alpha}{d\alpha} \Big|_{\alpha=0} &= \mu_i - \mu_M \\ \frac{d\sigma_\alpha}{d\alpha} \Big|_{\alpha=0} &= \frac{\sigma_{iM} - \sigma_M^2}{\sigma_M}.\end{aligned}$$

$$\frac{\mu_i - \mu_M}{\sigma_{iM} - \sigma_M^2} = \frac{\mu_M - r_f}{\sigma_M}$$

$$\mu_i - \mu_M = \frac{(\mu_M - r_f)}{\sigma_M} \quad (6)$$

Then, it shows

$$\frac{d\mu_\alpha}{d\sigma_\alpha} \Big|_{\alpha=0} = \frac{d\mu_\alpha/d\alpha}{d\sigma_\alpha/d\alpha} \Big|_{\alpha=0} = \frac{\mu_i - \mu_M}{(\sigma_{iM} - \sigma_M^2)/\sigma_M}.$$

Letting (1) equal to the slope of the CML at the point  $M$  leads to

$$\frac{\mu_i - \mu_M}{(\sigma_{iM} - \sigma_M^2)/\sigma_M} = \frac{\mu_M - r_f}{\sigma_M}$$

or

$$E[r_i] - r_f = \frac{\sigma_{iM}}{\sigma_M^2} (E[r_M] - r_f).$$

*Ex ante  
prediction. (1)  
Market portfolio  
vs.  
Asset portfolio  
→ Science.*

□

- The value  $E[r_i] - r_f$  represents the expected excess rate of return of asset  $i$ . The value  $E[r_M] - r_f$  represents the expected excess rate of return of the market portfolio. In the CAPM, the expected excess return of asset  $i$  is proportional to the expected excess return of the market portfolio, and the proportionality factor is  $\beta_i$ .

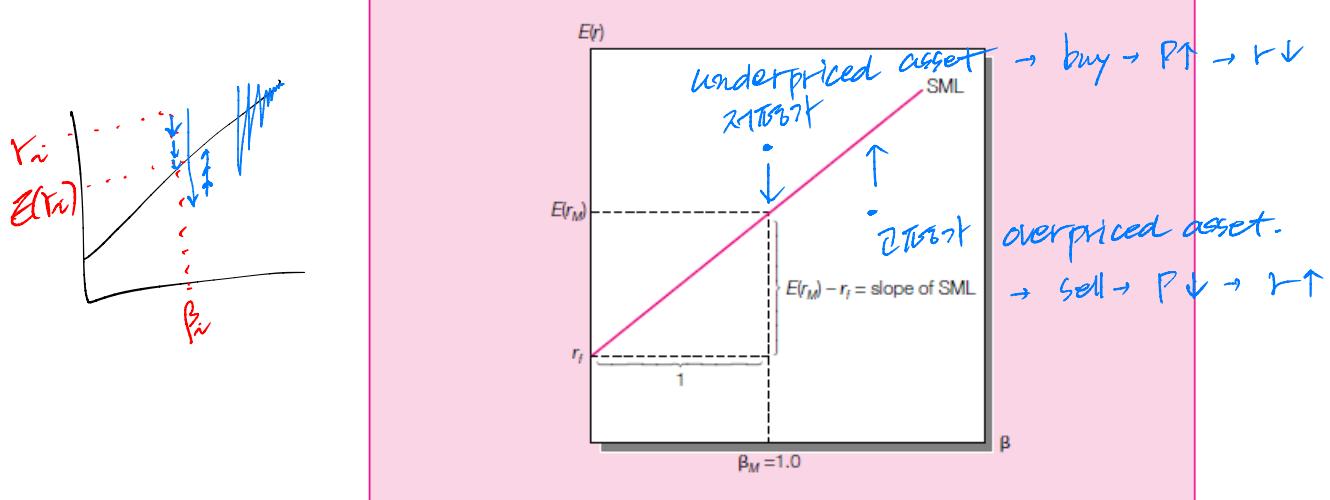
*Remark 2.* In the CAPM,  $\beta_i$  is a measure of the systematic risk of asset  $i$ , and the expected excess return of an asset is directly proportional to its covariance with the market. For instance, suppose  $\beta_i = 0$ , or equivalently,  $\sigma_{iM} = 0$ . Then,  $E[r_i] = r_f$ , no matter how big  $\sigma_i$  is; i.e., there is no necessary compensation for the risk measured with the standard deviation of the asset. This is because the risk associated with an asset that is uncorrelated with the market can be fully diversified away. In sum, the CAPM changes our concept of the risk of an asset from that of  $\sigma_i$  to that of  $\beta_i$ .

*Market vs systematic risk?  
non-sys → diversifiable.  
large sys risk vol explained well.*

### 3. The Security Market Line

The **security market line (SML)** is a graphical illustration of the CAPM. The SML represents all expected return-beta combinations of the individual stock  $i$ .

$$E(r_i) = r_f + \beta_i (E(r_M) - r_f)$$



- The difference between the actually observed and expected returns is called the asset's *alpha*, denoted by  $\alpha$ :

$$\alpha_i = r_i - E[r_i].$$

underpriced :  $\alpha > 0$   
 overpriced :  $\alpha < 0$ .

Any *fairly-priced* assets will plot exactly on the SML (i.e.,  $\alpha_i = 0$ ). In disequilibrium, *underpriced* assets will plot *above* the SML (i.e.,  $\alpha_i > 0$ ), while *overpriced* assets will plot *below* the SML (i.e.,  $\alpha_i < 0$ ).

**Example 3.** Suppose that  $r_f = 6\%$ ,  $\beta_i = 1.2$ , and  $E[r_M] = 14\%$ . According to the CAPM, then,  $E[r_i]$  should be equal to 15.6%, since

$$E[r_i] = 6 + 1.2(14 - 6) = 15.6\%.$$

If one observes that the actual return  $r_i$  is 17%, then the implied alpha is 1.4% and this asset is a good buy because it is underpriced.

#### 4. Systematic Risk

According to the CAPM, the return of asset  $i$  is written as

$$r_i = r_f + \beta_i(r_M - r_f) + \varepsilon_i$$

where  $\varepsilon_i$  is a random error with  $E[\varepsilon_i] = 0$ ,  $Var[\varepsilon_i] \neq 0$ , and  $Cov[r_M, \varepsilon_i] = 0$ . So, the variance of  $r_i$  is given by

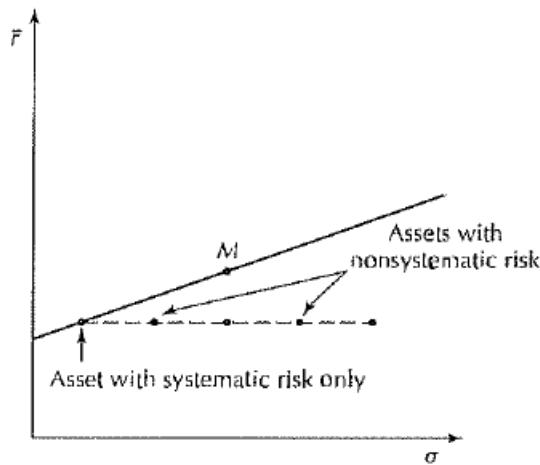
$$\begin{aligned} Var[r_i] &= Var[r_f + \beta_i(r_M - r_f) + \varepsilon_i] \\ &= \beta_i^2 Var[r_M] + Var[\varepsilon_i]. \end{aligned}$$

↗ 시장 위험은 시장 위험.  
 ↗ 이 부분은 시장 위험과 무관한 것.

- $\beta_i^2 Var[r_M]$  is the systematic risk that is associated with the market and thus cannot be reduced by diversification.  $Var[\varepsilon_i]$  is nonsystematic (or idiosyncratic) risk that is uncorrelated with the market

시장 위험은 시장 위험.

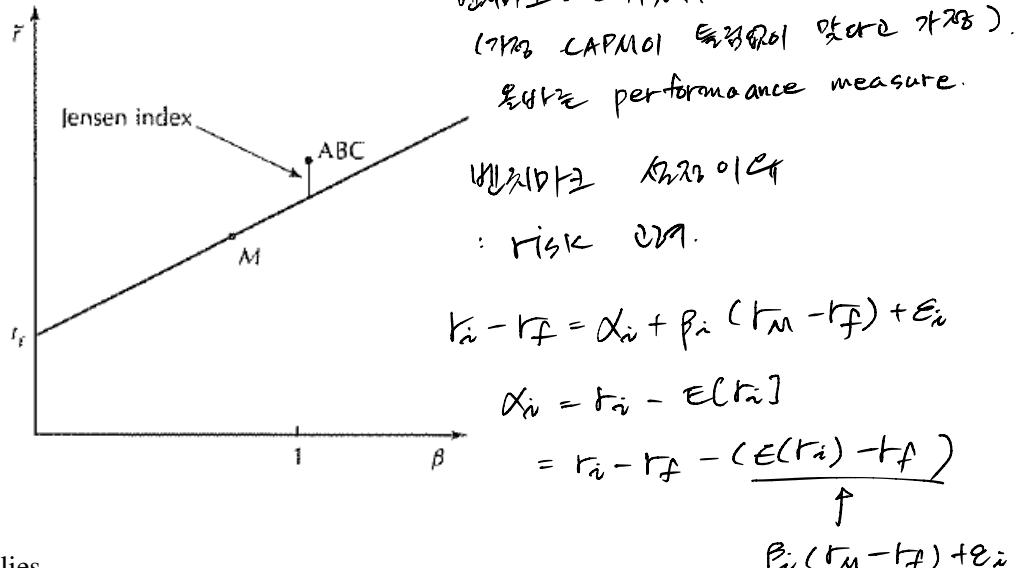
and thus can be diversified away. That is, the variance or standard deviation of the asset measures the *total risk* that consists of the systematic risk and the nonsystematic risk.



## 5. Performance Evaluation

The CAPM is often used to evaluate the performance of an asset (or an investment portfolio). Let  $\alpha_i$  be the alpha of the asset  $i$ :  $\alpha_i = r_i - E[r_i]$ . In a portfolio context,  $\alpha_i$  is called **Jensen's index**.

- When  $\alpha_i$  is positive (or negative), it is said that the asset  $i$  outperformed (or underperformed) relative to the expected return predicted by the CAPM given the asset's beta. In other words, Jensen's index measures the vertical distance between the portfolio return and the point on the SML given the beta value.



For the asset  $i$ , the CAPM implies

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{M,t} - r_{f,t}) + \epsilon_{i,t}$$

or more compactly

$$Z_{i,t} = \alpha_i + \beta_i Z_{M,t} + \epsilon_{i,t}$$

for  $t = 1, \dots, T$ , where  $Z_{i,t} = r_{i,t} - r_{f,t}$ ,  $Z_{M,t} = r_{M,t} - r_{f,t}$ ,  $r_{i,t}$  is the return on asset  $i$  in time  $t$ ,  $r_{M,t}$  is the return on a market index portfolio in time  $t$ ,  $r_{f,t}$  is the return on a risk-free asset in time  $t$ , and  $\epsilon_{i,t} \sim N(0, \sigma_e^2)$ .

- In practice, the market index portfolio is some well diversified portfolio like the S&P 500 index.  $r_{f,t}$  is taken as the T-bill rate to match the investment horizon associated with  $r_{i,t}$ .
- The parameters  $\alpha_i$  and  $\beta_i$  are estimated using the *ordinary least squares (OLS)* estimation which minimizes the sum of squared residuals:

$$\begin{aligned} SSR &= \sum_{t=1}^T \epsilon_{i,t}^2. & Y &= X\beta + \varepsilon & \varepsilon &\sim N(0, \sigma_e^2) \\ &= \sum_{t=1}^T (Z_{i,t} - \alpha_i - \beta_i Z_{M,t})^2. & b &= (X'X)^{-1}X'Y & b &\sim N(\beta, \sigma_b^2 (X'X)^{-1}) \\ && \text{get parameter.} & & \end{aligned}$$

The OLS estimates  $a_i$  and  $b_i$  that minimize  $SSR$  are given by

$$b_i = \frac{\sum_{t=1}^T (Z_{i,t} - \bar{Z}_i)(Z_{M,t} - \bar{Z}_M)}{\sum_{t=1}^T (Z_{M,t} - \bar{Z}_M)^2}$$

and

$$a_i = \bar{Z}_i - b_i \bar{Z}_M$$

where  $\bar{Z}_i = (1/T) \sum_{t=1}^T Z_{i,t}$  and  $\bar{Z}_M = (1/T) \sum_{t=1}^T Z_{M,t}$ .

**Theorem 4.** With *some assumptions*, an appropriate test statistic for testing the null hypothesis  $H_0 : \alpha_i = 0$  versus the alternative hypothesis  $H_1 : \alpha_i \neq 0$  is given by

$$t_\alpha = \frac{a_i}{s.e.(a_i)}$$

where

$$\begin{aligned} s.e.(a_i) &= s \sqrt{\frac{1}{T} + \frac{\bar{r}_M^2}{\sum_{t=1}^T (r_{M,t} - \bar{r}_M)^2}} \\ s &= \sqrt{\frac{\sum_{t=1}^T e_{i,t}^2}{T-2}} \\ e_{i,t} &= Z_{i,t} - a_i - b_i Z_{M,t}. \end{aligned}$$

Under  $H_0$ , it shows

$$t_\alpha \sim t_{T-2}$$

and in turn  $H_0$  is rejected at the 5% significance level if

$$|t| > t_{T-2, 0.025}.$$

Alternatively,  $H_0$  is rejected at the 5% level if the p-value is less than 5%.

**Example 5.** Consider the CAPM regression for Microsoft using monthly return over the periods 4/1986

to 6/2012:

$$Z_{MSFT,t} = \alpha_{MSFT} + \beta_{MSFT} Z_{M,t} + \varepsilon_{MSFT,t}$$

```
> mydat <- read.csv("MSFT.csv", header = T)
> mydat[1:5, ]
  Date      MSFT MKT_RF   RF    SMB   HML
1 4/1/1986  28.57143 -1.31 0.52  2.82 -2.91
2 5/1/1986   0.00000  4.59 0.49 -1.30 -0.11
3 6/2/1986 -11.11111  0.90 0.52 -0.89  1.38
4 7/1/1986   0.00000 -6.49 0.52 -3.43  4.71
5 8/1/1986   0.00000  6.16 0.46 -4.17  3.53
> attach(mydat)
> fit <- lm(I(MSFT-RF) ~ MKT_RF)
> summary(fit)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.5144	0.5041	3.004	0.00288 **
MKT_RF	1.2351	0.1075	11.493	< 2e-16 ***

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.89 on 313 degrees of freedom

Multiple R-squared: 0.2968, Adjusted R-squared: 0.2945

F-statistic: 132.1 on 1 and 313 DF, p-value: < 2.2e-16

*Jensen's index*  
*outperformance*  
 $\alpha > 0$  buy  
 $\alpha < 0$  sell

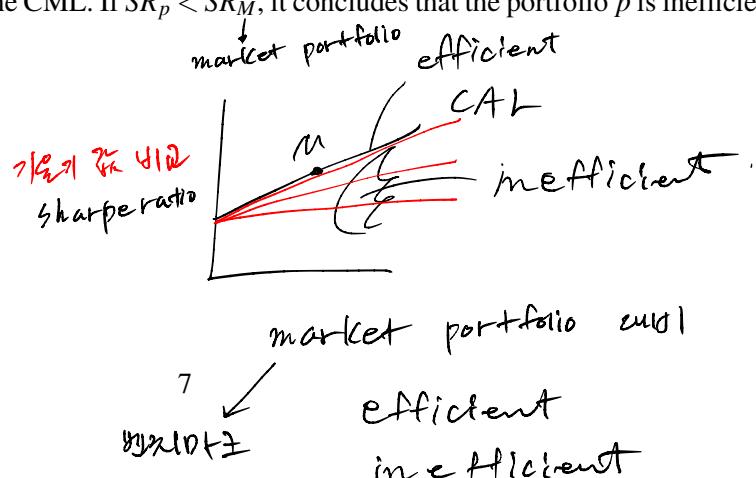
*CAPM → CAPM*

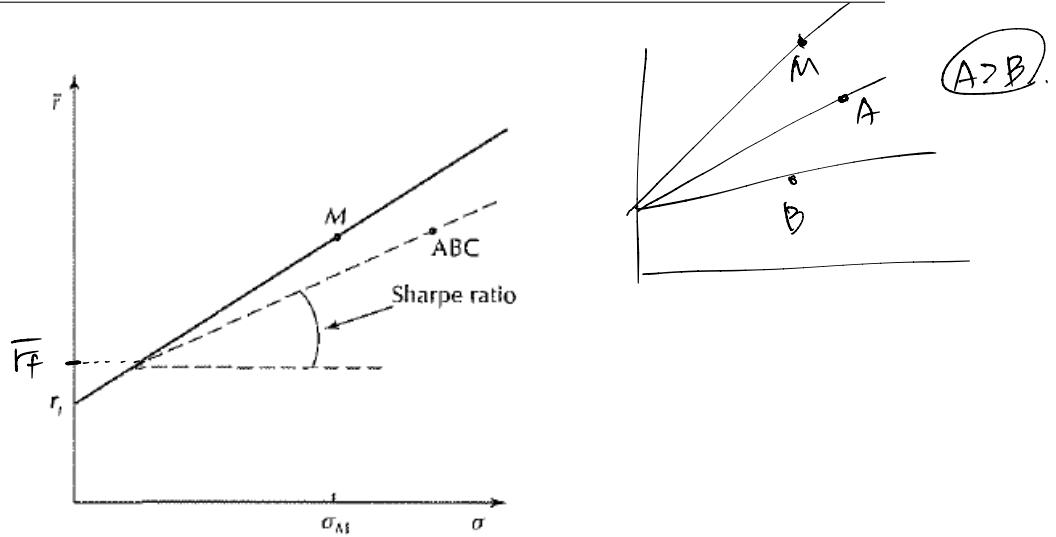
The estimated value for  $\beta_{MSFT}$  is 1.2351, so that Microsoft is judged to be riskier than the market index. The  $p$ -value for  $H_0 : \alpha_{MSFT} = 0$  is less than 0.05, meaning that  $\alpha_i$  is statistically significantly different from zero at the 5% level. If the CAPM is true, the MSFT stock is underpriced.

*Remark 6.* Jensen's index does not tell if the portfolio  $p$  is efficient, or equivalently, on the CML. In order to measure the efficiency, *Sharpe index* of the portfolio  $p$ , denoted by  $SR_p$ , is defined by

$$SR_p = \frac{\bar{r}_p - \bar{r}_f}{s_p} \quad \text{↑ total } SR_M \text{ - market sharpe index.}$$

for  $t = 1, \dots, T$ , where  $\bar{r}_p = (1/T) \sum_{t=1}^T r_{p,t}$ ,  $\bar{r}_f = (1/T) \sum_{t=1}^T r_{f,t}$ ,  $s_p = \sqrt{(T-1)^{-1} \sum_{t=1}^T (r_{p,t} - \bar{r}_p)^2}$ , and  $r_{p,t}$  is the portfolio return in time  $t$ . If the value of  $SR_p$  is equal to the value of  $SR_M$  (i.e., Sharpe index for the market), the portfolio  $p$  lies on the CML. If  $SR_p < SR_M$ , it concludes that the portfolio  $p$  is inefficient.





**Example 7.** Suppose that the portfolio  $p$  has the 10-year record of returns as follows:

$t$	$r_{p,t}$	$r_{M,t}$	$r_{f,t}$	$Z_{p,t}$	$Z_{M,t}$	$(Z_{p,t} - \bar{Z}_p)(Z_{M,t} - \bar{Z}_M)$	$(Z_{M,t} - \bar{Z}_M)^2$
1	14	12	7	7	5	0.96	0.36
2	10	7	7.5	2.5	-0.5	14.21	24.01
3	19	20	7.7	11.3	12.3	46.61	62.41
4	-8	-2	7.5	-15.5	-9.5	290.51	193.21
5	23	12	8.5	14.5	3.5	-8.19	0.81
6	28	23	8	20	15	154.76	112.36
7	20	17	7.3	12.7	9.7	38.69	28.09
8	14	20	7	7	13	13.76	73.96
9	-9	-5	7.5	-16.5	-12.5	370.11	285.61
10	19	16	8	11	8	20.16	12.96
Average	13	12	7.6	5.4	4.4		
Standard Deviation	12.4	9.4				941.58	793.78
Sum							

The value of  $\beta_p$  is estimated as

$$b_p = \frac{\sum_{t=1}^T (Z_{p,t} - \bar{Z}_p)(Z_{M,t} - \bar{Z}_M)}{\sum_{t=1}^T (Z_{M,t} - \bar{Z}_M)^2} = \frac{941.58}{793.78} = 1.19.$$

The value of Jensen's index for the portfolio  $p$  is given by

$$\alpha_p = \bar{Z}_p - b_p \bar{Z}_M = 5.4 - 1.19 \times 4.4 = 0.164 > 0,$$

outperform  
and/or price.

thereby concluding that the portfolio  $p$  outperformed relative to the expected return implied by the CAPM. However, this portfolio is not efficient, since

$$SR_p = \frac{\bar{r}_p - \bar{r}_f}{s_p} = \frac{13 - 7.6}{12.4} = 0.44$$

$$SR_M = \frac{\bar{r}_M - \bar{r}_f}{s_M} = \frac{12 - 7.6}{9.4} = 0.47.$$

CAPM of other stocks  $\rightarrow$  Jensen's

8 : performance estimate.

## 6. Maximum Likelihood Estimation

## MLE

**Definition 8.** The probability density function (pdf) of the *normal distribution* with mean  $\mu$  and variance  $\sigma^2$ , denoted by  $N(\mu, \sigma^2)$ , is given by

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

for  $-\infty < x < \infty$ .

**Definition 9.** If  $X_1, \dots, X_n$  are an *iid* sample from a population with pdf  $f(x|\theta)$ , the *likelihood function* is defined by

$$L(\theta|\tilde{x}) = L(\theta|x_1, x_2, \dots, x_n) = \prod_{i=1}^n f(x_i|\theta). \quad \text{marginal pdf.}$$

**Example 10.** Let  $X_1, \dots, X_n$  be an *iid* sample from  $N(\mu, 1)$ . Then, the likelihood function is

$$\begin{aligned} L(\theta|\tilde{x}) &= \prod_{i=1}^n \frac{1}{(2\pi)^{1/2}} \exp\left(-\frac{(x_i-\mu)^2}{2}\right) \\ &= \frac{1}{(2\pi)^{n/2}} \exp\left(-\frac{1}{2} \sum_{i=1}^n (x_i-\mu)^2\right). \end{aligned}$$

**Definition 11.** For each sample point  $\tilde{x}$ , let  $\hat{\theta}(\tilde{x})$  be a parameter value at which  $L(\theta|\tilde{x})$  attains its maximum as a function of  $\theta$ , with  $\tilde{x}$  held fixed. A *maximum likelihood estimator (MLE)* of the parameter  $\theta$  based on a sample  $\tilde{X} = (X_1, \dots, X_n)$  is  $\hat{\theta}$ .

- If the likelihood function is differentiable in  $\theta$ , the MLE is the value that solves

$$\frac{\partial L(\theta|\tilde{x})}{\partial \theta} = 0$$

and satisfies

$$\frac{\partial^2 L(\theta|\tilde{x})}{\partial \theta^2} < 0.$$

monotonous increase.  
orderly est.

*Remark 12.* In most cases, it is easier to work with the natural logarithm of  $L(\theta|\tilde{x})$ , which is known as the *log likelihood*, than it is to work with  $L(\theta|\tilde{x})$  directly; that is, the MLE is the value that solves

$$\frac{\partial \ln L(\theta|\tilde{x})}{\partial \theta} = 0$$

and satisfies

$$\frac{\partial^2 \ln L(\theta|\tilde{x})}{\partial \theta^2} < 0.$$

e<sup>v</sup>

This is possible because the log function is strictly increasing on  $(0, \infty)$ , which implies that the extrema of  $L(\theta|\tilde{x})$  and  $\ln L(\theta|\tilde{x})$  coincide.

**Example 13.** Let  $X_1, \dots, X_n$  be iid  $N(\mu, \sigma^2)$ . Then one obtains that

$$L(\mu, \sigma^2|\tilde{x}) = \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2} \sum_{i=1}^n \frac{(x_i-\mu)^2}{\sigma^2}\right)$$

and

$$\ln L(\mu, \sigma^2 | \tilde{x}) = -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2 - \frac{1}{2} \sum_{i=1}^n \frac{(x_i - \mu)^2}{\sigma^2}.$$

The partial derivatives, with respect to  $\mu$  and  $\sigma^2$ , are

$$\begin{aligned}\frac{\partial \ln L(\mu, \sigma^2 | \tilde{x})}{\partial \mu} &= \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu) \\ \frac{\partial \ln L(\mu, \sigma^2 | \tilde{x})}{\partial \sigma^2} &= -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (x_i - \mu)^2.\end{aligned}$$

OLS

MLE

Letting the derivatives equal to zero, one solves for  $\hat{\mu}$  and  $\hat{\sigma}^2$  as

$$\begin{aligned}\hat{\mu} &= \frac{1}{n} \sum_{i=1}^n x_i \\ \hat{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2.\end{aligned}$$

$E(\hat{\sigma}^2) \neq \sigma^2$   
not unbiased.

## 7. Gibbons, Ross, and Shanken (1989)

### 7.1. The CAPM Test

Define  $Z_t$  as an  $N \times 1$  vector of excess returns for  $N$  assets: i.e.,

$$Z_t = \begin{bmatrix} r_{1,t} - r_{f,t} \\ \vdots \\ r_{N,t} - r_{f,t} \end{bmatrix}.$$

For these  $N$  assets, the CAPM describes  $Z_t$  as

$$Z_t = \alpha + \beta Z_{M,t} + \varepsilon_t,$$

$$Z_{i,t} = \alpha_{i,t} + \beta_{i,t} (r_{M,t} - r_{f,t}) + \varepsilon_{i,t}$$

for  $i = 1, \dots, N$ , where  $Z_{M,t} = r_{M,t} - r_{f,t}$ ,

$$\alpha = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_N \end{bmatrix}, \varepsilon_t = \begin{bmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{N,t} \end{bmatrix}.$$

- The CAPM implies that “all” of the elements of the vector  $\alpha$  are zero. Equivalently speaking, the CAPM holds if

$$H_0 : \alpha_1 = \alpha_2 = \dots = \alpha_N = 0$$

is not rejected. Gibbons, Ross, and Shanken (1989) rely on MLE to test for  $H_0$ .

F-test.

reject the known CAPMo reject.

## 7.2. MLE Estimation

One assumes the followings:

$$\begin{aligned} E[Z_{M,t}] &= \mu_M, \\ Var[Z_{M,t}] &= \sigma_M^2 \\ E[\varepsilon_t] &= 0_{(N \times 1)} \\ Var[\varepsilon_t] &= \Sigma_{(N \times N)} \\ Cov[Z_{M,t}, \varepsilon_t] &= 0_{(N \times 1)}. \end{aligned}$$

Assuming the joint normality of  $Z_t$ , one obtains the probability density function of  $Z_t$  conditional on  $Z_{M,t}$  as

$$\begin{aligned} f(Z_t | Z_{M,t}) &= (2\pi)^{-N/2} |\Sigma|^{-1/2} \\ &\times \exp \left[ -\frac{1}{2} (Z_t - \alpha - \beta Z_{M,t})' \Sigma^{-1} (Z_t - \alpha - \beta Z_{M,t}) \right]. \end{aligned}$$

Assume that each element of  $Z_t$  is *i.i.d.* Then, the likelihood function is given by

$$\begin{aligned} L(\alpha, \beta, \Sigma | \tilde{Z}_t) &= \prod_{t=1}^T f(Z_t | Z_{M,t}) \\ &= \prod_{t=1}^T (2\pi)^{-N/2} |\Sigma|^{-1/2} \\ &\quad \times \exp \left[ -\frac{1}{2} (Z_t - \alpha - \beta Z_{M,t})' \Sigma^{-1} (Z_t - \alpha - \beta Z_{M,t}) \right], \end{aligned}$$

so that the log-likelihood function is

$$\begin{aligned} \ln L(\alpha, \beta, \Sigma | \tilde{Z}_t) &= -\frac{NT}{2} \log(2\pi) - \frac{T}{2} \log |\Sigma| \\ &\quad - \frac{1}{2} \sum_{t=1}^T \frac{1}{2} (Z_t - \alpha - \beta Z_{M,t})' \Sigma^{-1} (Z_t - \alpha - \beta Z_{M,t}). \end{aligned}$$

- The MLE estimates are the values of the parameters which maximize  $\ln L$ . The first-order conditions (FOCs) produce

$$\begin{aligned} \frac{\partial \ln L}{\partial \alpha} &= \Sigma^{-1} \left[ \sum_{t=1}^T (Z_t - \alpha - \beta Z_{M,t}) \right] = 0 \\ \frac{\partial \ln L}{\partial \beta} &= \Sigma^{-1} \left[ \sum_{t=1}^T (Z_t - \alpha - \beta Z_{M,t}) Z_{M,t} \right] = 0 \\ \frac{\partial \ln L}{\partial \Sigma} &= -\frac{T}{2} \Sigma^{-1} + \frac{1}{2} \Sigma^{-1} \left[ \sum_{t=1}^T (Z_t - \alpha - \beta Z_{M,t}) (Z_t - \alpha - \beta Z_{M,t})' \right] \Sigma^{-1} = 0. \end{aligned}$$

Solving the FOCs for  $\alpha$ ,  $\beta$ , and  $\Sigma$ , the MLE estimates are given by

$$\begin{aligned}\hat{\alpha} &= \bar{Z} - \hat{\beta}\bar{Z}_M \\ \hat{\beta} &= \frac{\sum_{t=1}^T (Z_t - \bar{Z})(Z_{M,t} - \bar{Z}_M)}{\sum_{t=1}^T (Z_{M,t} - \bar{Z}_M)^2} \\ \hat{\Sigma} &= \frac{1}{T} \sum_{t=1}^T (Z_t - \hat{\alpha} - \hat{\beta}Z_{M,t})(Z_t - \hat{\alpha} - \hat{\beta}Z_{M,t})'\end{aligned}$$

where

$$\bar{Z} = \frac{1}{T} \sum_{t=1}^T Z_t \text{ and } \bar{Z}_M = \frac{1}{T} \sum_{t=1}^T Z_{M,t}.$$

*Remark 14.* Under the *some* conditions, the conditional distributions of the MLE estimates are given by

$$\begin{aligned}\hat{\alpha} &\sim N\left[\alpha, \frac{1}{T} \left(1 + \frac{\bar{Z}_M^2}{\hat{\sigma}_M^2}\right) \Sigma\right] \\ \hat{\beta} &\sim N\left[\beta, \frac{1}{T \hat{\sigma}_M^2} \Sigma\right] \\ T\hat{\Sigma} &\sim W_N[T-2, \Sigma]\end{aligned}$$

$\chi^2$

where

$$\hat{\sigma}_M^2 = \frac{1}{T} \sum_{t=1}^T (Z_{M,t} - \hat{\mu}_M)^2$$

and  $W_N[T-2, \Sigma]$  represents a Wishart distribution with  $(T-2)$  degrees of freedom and variance matrix  $\Sigma$ .

**Theorem 15.** Assume  $\varepsilon_{i,t} \sim i.i.d.N(0, \sigma_\varepsilon^2)$ . Gibbons, Ross, and Shanken (1989) derive a finite-sample F distribution for the null hypothesis  $H_0: \alpha_1 = \dots = \alpha_N = 0$  as

$$\frac{T-N-1}{N} \left(1 + \frac{\bar{Z}_M^2}{\hat{\sigma}_M^2}\right)^{-1} \hat{\alpha}' \hat{\Sigma}^{-1} \hat{\alpha} \sim F_{N, T-N-1}.$$

↗ CAPM 01  
↗ GRS test statistic

This is called the GRS test statistic.

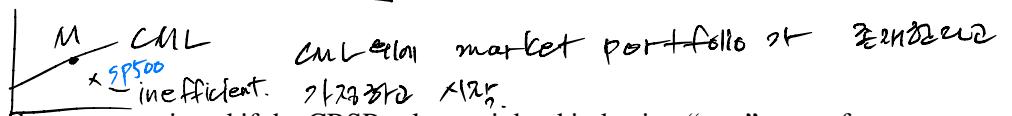
### 7.3. Empirical Results

The GRS test is conducted using monthly returns on ten portfolios from January 1965 through December 1994. Stocks listed on the NYSE and on the AMEX are allocated to the portfolios based on the market value of equity and are value-weighted within the portfolios. The CRSP value-weighted index is used as a proxy for the market portfolio, and the one-month U.S. T-bill return is used for the risk-free return. The results are quoted from Campbell, Lo, and MacKinlay (1997).

Time	GRS statistic	p-value
<b>Panel A. Five-year subperiods</b>		
1/65-12/69	<b>2.038</b>	<b>0.049</b>
1/70-12/74	<b>2.136</b>	<b>0.039</b>
1/75-12/79	1.914	0.066
1/80-12/84	1.224	0.300
1/85-12/89	1.732	0.100
1/90-12/94	1.153	0.344
Overall	<b>77.224</b>	<b>0.004</b> → reject
<b>Panel B. Ten-year subperiods</b>		
1/65-12/74	2.400	0.013
1/75-12/84	<b>2.248</b>	<b>0.020</b>
1/85-12/94	1.900	0.053
Overall	<b>57.690</b>	<b>0.001</b> → reject
<b>Panel C. Thirty-year period</b>		
1/65-12/94	<b>2.159</b>	<b>0.020</b> → reject + CAPM (+)

- The CAPM is dead! For instance, the *p*-value for the overall thirty-year period is 0.020, indicating that  $H_0 : \alpha = 0$  is rejected at the 5% significance level. The five- and ten-year subperiod results also suggest the empirical evidence against the CAPM.

## 8. Roll's Critique



In testing the CAPM, one has not questioned if the CRSP value-weighted index is a “true” proxy for the market portfolio that is actually *unobservable*. For this reason, Roll (1977) emphasizes that tests of the CAPM using the proxy of the true market portfolio only reject the mean-variance efficiency of the proxy and that the CAPM could not be rejected if the true market portfolio is used instead.

- Stambaugh (1982) shows that the CAPM is rejected if the market portfolio is proxied by a stock-based proxy, a stock- and bond-based proxy, or a stock-, bond-, and real-estate-based proxy. Thus, he concludes that the rejection of the CAPM is not sensitive to the different measures of the market portfolio.
- Roll = SP500 if market portfolio is efficient  
(CAPM is true)  
Shanken (1987) estimates an upper bound on the correlation between the proxy and the true market portfolio which is necessary to overrun the rejection of the CAPM. The finding is that if the correlation exceeds 0.7, then the rejection of the CAPM with the market proxy would imply the rejection of the CAPM with the true market portfolio. Therefore, if one believes that the CRSP value-weighted index reasonably approximates the true market portfolio, the empirical evidence against the CAPM remains robust and is free from the Roll’s critique.

## 9. Fama-French Three-factor Model

### 9.1. Empirical Regularities Against the CAPM

The CAPM anomalies are empirical regularities that seem to be inconsistent with the CAPM. Since anomalies are defined relative to a model of “normal” return behaviors, the CAPM anomalies indicate

that the CAPM would be *inadequate*.

**The Size Effect** Banz (1981) finds that small-capitalization firms on the NYSE earned higher average returns than is predicted by the CAPM from 1936 - 1975. Put differently, he finds the positive abnormal alpha from

$$(r_{i,t} - r_{f,t}) = \alpha_i + \beta_i(r_{M,t} - r_{f,t}) + \varepsilon_{i,t},$$

where  $r_{i,t}$  is the return on a portfolio of small companies.

$$P = \frac{EPS}{F} + PVGD$$

**The Value Effect** Basu (1977) notes that firms with high earnings-to-price (E/P) ratios earn positive abnormal returns relative to the CAPM. Others find that positive abnormal returns seem to accrue to portfolios of stocks with high dividend yield (D/P) or to stocks with high book-to-market (B/M) values.

**The Momentum Effect** Jegadeesh and Titman (1993) find a momentum effect that recent past winners out-perform recent past losers. That is to say, a zero-cost portfolio taking a long position on winners and taking a short position on losers generates the positive abnormal returns relative to the CAPM.

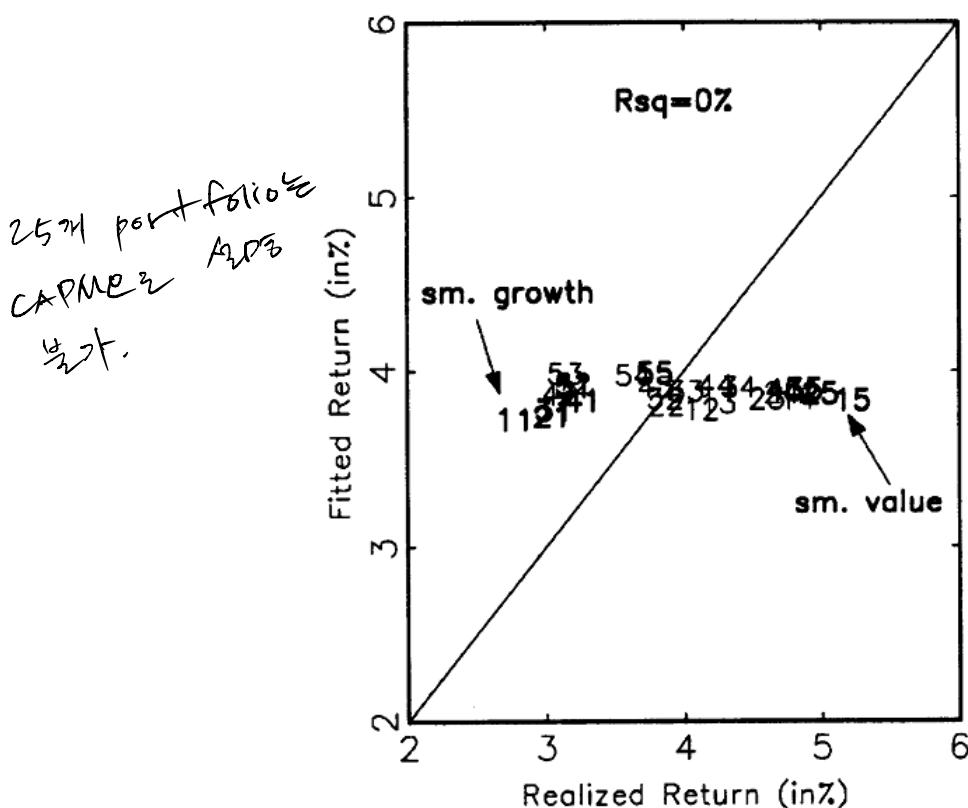
## 9.2. Fama and French (1992)

Fama and French (1992) perform the cross-sectional test to see if *size*, proxied by  $\ln(ME)$ , and *book-to-market*, proxied by  $\ln(B/M)$ , have explanatory power beyond the CAPM  $\beta$ .

<i>Size</i>	<i>Value</i>						
	$\beta$	$\ln(ME)$	$\ln(BE/ME)$	$\ln(A/ME)$	$\ln(A/BE)$	E/P Dummy	E(+)/P
0.15 (0.46)							
	-0.15 (-2.58)						
-0.37 (-1.21)	-0.17 (-3.41)						
		0.50 (5.71)					
			0.50 (5.69)	-0.57 (-5.34)			
					0.57 (2.28)	4.72 (4.57)	
-0.11 (-1.99)	0.35 (4.44)						
-0.11 (-2.06)		0.35 (4.32)	-0.50 (-4.56)				
-0.16 (-3.06)				0.06 (0.38)	2.99 (3.04)		
-0.13 (-2.47)	0.33 (4.46)			-0.14 (-0.90)	0.87 (1.23)		
-0.13 (-2.47)		0.32 (4.28)	-0.46 (-4.45)	-0.08 (-0.56)	1.15 (1.57)		

- *Size explains the cross-section of average stock returns.* The slope from the monthly regressions of returns on size alone is -0.15% (with a  $t$ -statistic of -2.58). This reliable negative relation persists no matter which other explanatory variables are in the regression.
- *Book-to-market explains the cross-section of average stock returns.* The slope from the monthly regressions of returns on  $\ln(\text{BE}/\text{ME})$  alone is 0.50% (with a  $t$ -statistic of 5.71). Book-to-market does not replace size in explaining average returns; i.e., when both  $\ln(\text{ME})$  and  $\ln(\text{BE}/\text{ME})$  are included in the regressions, the average size slope is -0.11% (with a  $t$ -statistic of -1.99) and the book-to-market slope is 0.35% (with a  $t$ -statistic of 4.44).
- *In contrast to the consistent explanatory power of size and book-to-market, the CAPM  $\beta$  does not explain average stock returns.* The slope from the regressions of returns on  $\beta$  alone is 0.15% per month with a  $t$ -statistic of 0.46.

It plots the CAPM fitted expected returns for 25 size and book-to-market sorted portfolios against their realized average returns. If the CAPM might fit perfectly, all the points in this figure would lie along the 45-degree line. The figure shows clearly that few do.



*Remark 16.* Fama and French (1992) conclude that the size and value effects are empirical regularities of cross-sectional asset pricing data. By contrast, they find that the CAPM demonstrates virtually no power to explain the cross section of average returns on assets sorted by size and book-to-market.

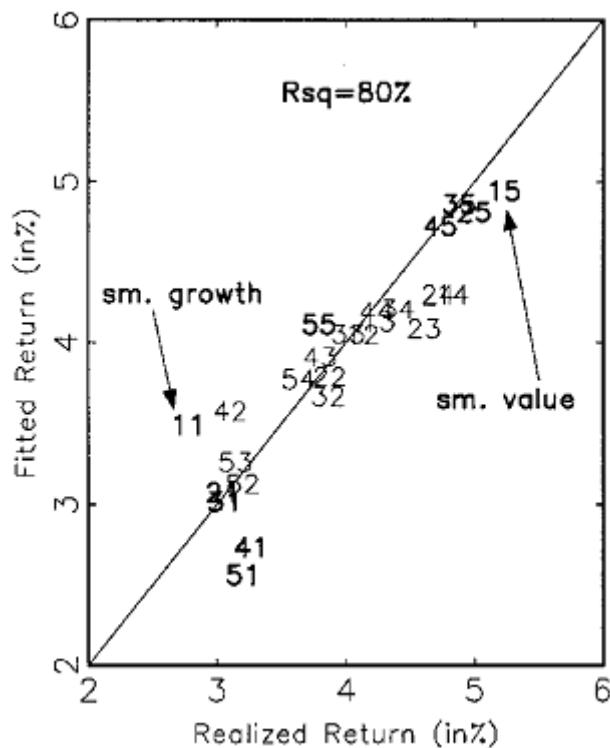
### 9.3. Fama and French (1993)

Fama and French (1993) develop a three-factor model with factors related to *firm size*, *book-to-market*, and the *aggregate stock market*. The cross-sectional variation in expected returns in excess of the risk-free rate of return can be captured by

$$E[r_i] - r_f = \beta_{i,1}E[MKT] + \beta_{i,2}E[SMB] + \beta_{i,3}E[HML],$$

where *MKT* is the return on the market portfolio in excess of the risk-free rate of return, *SMB* is a zero-cost portfolio that is long in small firm stocks and short in large firm stocks, and *HML* is a zero-cost portfolio that is long in high book-to-market stocks and short in low book-to-market stocks.

- Fama and French (1993) demonstrate, in sharp contrast to the CAPM, that the three-factor model successfully explains the cross section of average returns on the portfolios sorted by size and book-to-market.



*Remark 17.* Fama and French (1996) show that the Fama-French three-factor model successfully explains many of the market anomalies, excluding momentum effects.

- momentum ↗ other ↘ ↑ X.