# Risk components and the market model: a pedagogical note

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Teaching modern finance involves familiarizing the student with terms like total risk, systematic risk, unique risk, beta, and  $R^2$ . Although each of these concepts may be relatively easy to communicate and digest one by one, it is harder to see their internal links. Using the logic of the market model, this note offers a simple framework for presenting the basic risk concepts in an integrated way.

### I. INTRODUCTION

Students of modern finance are familiar with the market model, they know how to estimate its parameters, and they can distinguish between total risk, systematic risk, and unsystematic risk. However, although each of these concepts is easy to understand one by one, it is less straightforward to discover their internal relationship. As existing finance literature does not offer such a unified framework, the purpose of this note is to present an easily accessible structure using very familiar building blocks.

According to the market model, the return on asset j is:

$$r_i = \alpha_i + \beta_i r_{\rm m} + \varepsilon_i$$

 $r_{\rm m}$  is the market return,  $\alpha_j$  is the expected return when  $r_{\rm m}$  is zero,  $\beta_j$  is the market sensitivity of asset j, and  $\varepsilon_j$  is an error term with zero expectation. When  $\varepsilon_j$  and  $r_{\rm m}$  are independent (homoskedastic), the return of asset j has a variance of:

$$\sigma_j^2 = \beta_j^2 \sigma_{\rm m}^2 + \sigma_{\varepsilon j}^2 \tag{1}$$

A fundamental result from portfolio theory is that asset j contributes to the risk of an efficient portfolio primarily through the first term in Equation 1, as the second term tends to disappear through diversification (Fama, 1976, pp. 245–256). Thus, if risk is defined in terms of variance,  $\sigma_{\rm m}^2$  is called the market portfolio's risk (volatility),  $\sigma_j^2$  is the total risk (volatility) of asset j,  $\beta_j^2 \sigma_{\rm m}^2$  is the asset's systematic (non-diversifiable) risk, and  $\sigma_{\epsilon j}^2$  is its unique (diversifiable) risk.

An alternative to the variance-based approach in Equation 1 was introduced by Ben-Horim and Levy (1980), defining the risk components of the market model in terms of standard deviations:

market portfolio risk = 
$$\sigma_{\rm m}$$
 Total risk =  $\sigma_{\rm j}$   
systematic risk =  $\beta_{\rm j}\sigma_{\rm m}$  unique risk =  $\sigma_{\rm j} - \beta_{\rm j}\sigma_{\rm m}$  (2)

This definition has two advantages. First, unlike the variance-based approach in Equation 1, Equation 2 can account for the fact that assets with a negative beta contribute negatively to (i.e. reduce) portfolio risk. Second, in terms of pricing-relevant risk, the asset's expected return in the CAPM is determined by  $\beta_j \sigma_m$  from Equation 2 rather than  $\beta_j^2 \sigma_m^2$  from Equation 1.

When the market model is estimated empirically by OLS, the estimate of the asset's beta is:

$$\beta_j = \frac{\sigma_{jm}}{\sigma_{-}^2} \tag{3}$$

where  $\sigma_{jm}$  is the covariance between the returns of asset j and the market portfolio.<sup>1</sup> Finally, the regression's goodness of fit is given by the coefficient of determination:

$$R_j^2 = \frac{\beta_j^2 \sigma_{\rm m}^2}{\sigma_j^2} \tag{4}$$

Section 2 of this note uses one equation, scatterplots, and a simple graph to relate the risk components in Equations 1, 2 and 3 to each other and to the empirical fit of the market model in Equation 4. Section 3, explains why  $R_j^2$  cannot be used in the traditional way to evaluate

<sup>&</sup>lt;sup>1</sup> For expositional simplicity, we do not distinguish between sample estimates and true population parameters.

the empirical quality of risk components from the market model. The fourth section summarizes the major points.

### II. BETA, CORRELATION, AND VOLATILITY

The correlation coefficient between the return on asset j and the market portfolio is  $\rho_j = (\sigma_{jm}/\sigma_j) - \sigma_m$ . Using this definition and the standard deviation-based risk components in Equation 2, Expression 3 can be transformed into a simple relationship between beta, the correlation coefficient, total risk, and market portfolio risk:

$$\beta_j = \rho_j \frac{\sigma_j}{\sigma_{\rm m}} \tag{5}$$

Empirically, negative correlations between market returns and asset returns are virtually non-existent. Thus, for expositional clarity, we only consider a non-negative  $\rho_j$ , which implies a non-negative  $\beta_j$  from Equation (5). This means the correlation coefficient  $\rho_j$  and the coefficient of determination  $R_j^2$  have the same extreme values of 0 and 1, are monotone transformations of each other, and will be equivalent in terms of all our conclusions.<sup>2</sup>

Expression 5 offers several useful insights. To start with the most familiar cases, a *deterministic* asset return is defined by  $\sigma_j = 0$  (no total risk in Equation 2), which implies  $\beta_j = 0$  by Equation 5. This is plot 1 in Fig. 1, where the dots are the empirical observations and the broken line is the fitted regression (the two are inseparable in this case).

Second,  $\beta_j = 0$  may also hold for stochastic asset returns  $(\sigma_j > 0$ , i.e. positive total risk), provided  $\rho_j = 0$ . In such

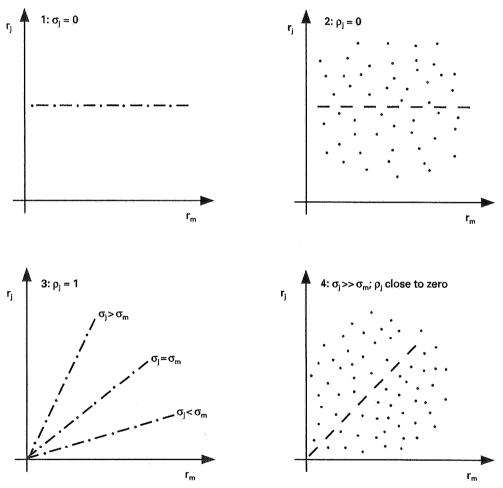


Fig. 1. Scatterplots of market return  $(r_m)$  versus asset returns  $(r_j)$ . The dots represent empirical observations, and the broken lines are OLS regression lines (characteristic lines). The total risk of asset j is  $\sigma_j$ , market portfolio risk is  $\sigma_m$ , and  $\rho_j$  is the coefficient of correlation between the return on asset j and the market portfolio return

<sup>&</sup>lt;sup>2</sup> In fact, when  $\beta_j$  is non-negative,  $R_j = \rho_j$ , and Equation 5 is just the square root of Equation 4 solved for  $\beta_j$ .

a case, the asset has no systematic risk, i.e.  $\beta_j \sigma_m = 0$  in Equation 2. The diffuse scatter in the second plot reflects this case, where asset returns fluctuate independently of market movements. In Equation 1 or 2, the asset's total risk equals its unique risk, which disappears in a well-diversified portfolio. Under CAPM pricing,  $\rho_j = 0$  implies a riskless expected return regardless of whether total risk is high or low.

Third, the case of no unique risk is defined by  $\sigma_j = \beta_j \sigma_m$  in Equation 2, corresponding to  $\sigma_j^2 = \beta_j^2 \sigma_m^2$  and hence  $\sigma_{ej}^2 = 0$  in Equation 1. This means  $\rho_j = 1$  from Equation 5. Such an asset contributes to an efficient portfolio's risk by its full volatility, as no part of total risk is washed out by diversification. Plot 3 in Fig. 1 illustrates that when all the asset's risk is systematic, every combination of asset return and market return falls exactly on the regression line.

However, note that although the asset correlates perfectly with market returns,  $\beta_j$  may still differ from 1. Clearly, with  $\rho_j=1$  in Equation 5,  $\beta_j$  equals 1 if and only if the asset and the market has the same volatility, i.e.  $\sigma_j=\sigma_{\rm m}$ . When the asset is more (less) volatile than the market,  $\beta_j$  will be larger (smaller) than one, even if the asset return responds strictly proportionally to market movements. For instance, given perfect correlation,  $\sigma_j=20\%$  and  $\sigma_{\rm m}=10\%$  implies a  $\beta_j$  of 2. Conversely, when the market is twice as volatile as the asset,  $\beta_j=0.5$ .

Notice also that because  $\rho_j = 1$  means  $\beta_j = \sigma_j/\sigma_m$ , the CAPM predicts that expected return is proportional to the asset's total risk. That is, the asset is priced like an efficient portfolio along the capital market line. Whenever  $\rho_j < 1$ , some part of  $\sigma_j$  is not reflected in  $\beta_j$ , and the asset will be priced below the capital market line.

Fourth, it also follows from Equation 5 that the strength of the correlation between asset returns and market portfolio returns (i.e. the size of  $R_j^2$  or  $\rho_j$ , which reflects the concentration of the scatterplot) implies nothing about the size of beta. In particular, Equation 5 shows that a high beta is fully consistent with a low correlation. This happens when the asset's total risk (a large part of which would be unique) is considerably higher than the market portfolio's risk. Plot 4 of Fig. 1 illustrates the case of an asset with high beta (steep regression line), low correlation with the market (small  $\rho_j$ ), and high total risk relative to market portfolio risk  $(\sigma_j \gg \sigma_m)$ . The latter point is reflected in the fact that asset returns are scattered over a considerably larger range than market returns.

This case can be directly related to the typical New York Stock Exchange (NYSE) stock. Based on monthly CRSP data over the period 1926–1990, the average  $\sigma_j/\sigma_m$  is found to be 2.6, ranging from a minimum of 1.5 (in 1929 and 1962) to a maximum of 6.8 (1964). The average  $\sigma_j/\sigma_m$  for 1980–1990 is 2.5. Moreover, as the average beta of all stocks is 1, Expression 5 suggests that with an average  $\sigma_j/\sigma_m$  of 2.5, the average  $\rho_j$  is 0.4 and hence the average  $R_j^2$  is 0.16. Thus, in terms of the standard deviation based definition of risk

components in Equation 2, 40% of a typical NYSE stock's risk is systematic. With the variance-based definition in Equation 1, the fraction becomes 16%.

Figure 2 summarizes the insights from the four scatter-plots. This figure, which is the graphical representation of Expression 5, shows the relationship between  $\rho_j$  and  $\beta_j$  for three different levels of total risk ( $\sigma_{\rm A} < \sigma_{\rm B} < \sigma_{\rm C}$ ). The ratio of total asset risk ( $\sigma_j$ ) to market portfolio risk ( $\sigma_{\rm m}$ ) is thus constant along a given line, but increases with the steepness of a line. For each line, the minimum beta of zero occurs when  $\rho_j=0$ , and the maximum value of  $\beta_j=\sigma_j/\sigma_{\rm m}$  occurs when  $\rho_j=1$ , corresponding to  $R_j^2=1$ . For a given total asset risk and market portfolio risk, beta increases linearly with the correlation coefficient. If  $R_j^2$  is used instead of  $\rho_j$  on the horizontal axis, the three increasing curves would be concave between the same endpoints.

Case 1 ( $\sigma_j = 0$ ) and case 2 ( $\sigma_j > 0$  and  $\rho_j = 0$ ) from Fig. 1 are both represented by the origins in Fig. 1. The third case ( $\rho_j = 1$ ) is illustrated by the assets at the end points A, B, and C. These three assets all have perfect correlation with the market (no unique risk), but different volatility (total risk). Clearly,  $\beta_C > \beta_B > \beta_A$ , but whether these betas are high or low relative to the market beta of one is completely determined by the ratio of the asset's total risk to the market portfolio's risk ( $\sigma_j/\sigma_m$ ).

Case 4 clarifies that high betas are fully compatible with low correlations. This is seen by comparing asset D to asset E, which both have the same, moderate correlation with the

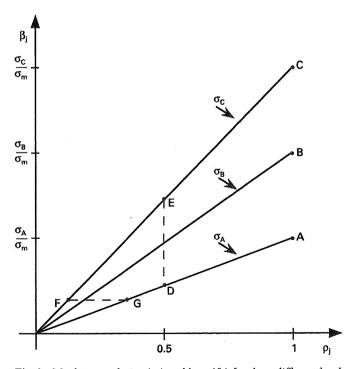


Fig. 2. Market correlation  $(\rho_j)$  and beta  $(\beta_j)$  for three different levels of total risk  $(\sigma_A < \sigma_B < \sigma_C)$ . The risk of the market portfolio is  $\sigma_m$ 

market portfolio (low  $\rho_j$ ). Because asset E has a higher total risk than asset D, the beta of E is almost three times higher.

Notice also that when  $\rho_j$  is large a given difference in total risk between two assets transforms into a higher difference in betas: The total risk difference between E and D equals the difference between C and A. Still, the difference in beta is larger between C and A ( $\rho_j = 1$ ) than between E and D ( $\rho_i = 0.5$ ).

Finally, for two assets F and G to have the same beta, Equation 5 requires that:

$$\frac{\rho_{\rm F}}{\rho_{\rm G}} = \frac{\sigma_{\rm G}}{\sigma_{\rm F}}$$

For instance, if asset F has half the market correlation of asset G (i.e. four times the  $R_j^2$ ), it must have twice the total risk (as defined by Equation 2) for  $\beta_F$  to equal  $\beta_G$ . Suppose  $\sigma_F = 0.3$  and  $\rho_F = 0.2$ , and that asset G has  $\rho_G = 0.4$ , i.e. twice as strong a market correlation. The betas of F and G will still be equal if the volatility of asset G is just 0.15, i.e. half of  $\sigma_F$ .

This general relationship can be seen by comparing assets F and G in Fig. 2. The higher market correlation of G is neutralized by a correspondingly lower total risk, producing identical betas, i.e.  $(\sigma_F \rho_F)/\sigma_m = (\sigma_G \rho_G)/\sigma_m$ .

## III. R<sup>2</sup> AND THE QUALITY OF RISK ESTIMATES

When linear regression is used to test a theory's predictions, a high  $R_i^2$  is normally desirable, as it reflects a case where the independent variables predict the dependent variables quite well. Correspondingly, a low  $R_i^2$  is considered unattractive, as it signals low predictive power. However, this general guideline for theory evaluation is not valid in our context, where the purpose is not to test a theory, but rather to estimate an asset's risk components as specified by the market model. As seen from Equations 1 and 4,  $R_i^2$  is the fraction of the asset's (variance-based) total risk which is systematic, whereas  $(1 - R_i^2)$  represents the unique part. Therefore, a low  $R_j^2$  simply means that most of the asset's volatility is unique, because the asset's return cannot be well predicted by market movements. Such risk information is as valuable as finding a high  $R_i^2$  for a different asset, which just tells that unique (non-market) risk accounts for only a small part of that asset's volatility. In terms of the right-hand side of Expression 1, the second term dominates total risk in the former case, and the first term dominates in the latter.

A quite different question is how well the market model per se explains cross-sectional differences in asset returns. A low cross-sectional  $R^2$  in a market-wide regression does indeed suggest that systematic risk (market movements) is an unimportant determinant of asset returns. However, this

is a question of relative model performance (e.g. single-factor versus multi-factor models) rather than estimation of risk components within a given model. In terms of Equations 1 or 2, what matters is the statistical significance of the separate risk components of the asset return, not the significance of the market return as a predictor of asset return.

### IV. SUMMARY

This pedagogical note supplements existing literature by integrating well-known risk concepts into a simple framework. We used Equation 5, scatterplots of market returns versus asset returns (Fig. 1), and a graph of correlation versus beta (Fig. 2) to illustrate the essential properties of an asset's risk components as implied by the market model.

Beta is zero whenever the asset's return has either no total risk (volatility) or no correlation with the market returns. Perfect correlation with the market means unsystematic risk is zero, but implies nothing about the asset's beta. In particular, the asset's beta equals the market portfolio's beta of one only if the market portfolio's volatility equals the volatility of the perfectly correlated asset.

An asset's beta is multiplicatively determined by the asset's total risk and its correlation with market returns. Thus, even a low correlation (reflecting that most of the asset's total risk is unique) produces a high beta when the asset is considerably more volatile than the market. Moreover, two assets may have the same beta even though their market correlations differ widely. A high correlation may be neutralized by a correspondingly smaller total risk.

When the market model is used to estimate the risk components of asset returns, the coefficient of determination does not reflect the usefulness of the regression. What matters is the statistical significance of the separate risk components, not how well market returns predict individual asset returns.

### **ACKNOWLEDGEMENTS**

The author acknowledges helpful comments from Øystein Gjerde, from workshop participants at the Norwegian School of Management, and particularly from Dag Michalsen.

### REFERENCES

Ben-Horim, M. and Levy, H. (1980) Total risk, diversifiable risk and nondiversifiable risk: a pedagogical note, *Journal of Financial and Quantitative Analysis*, 15, 289-97.

Fama, E. F. (1976) Foundations of Finance (Basic Books, New York).