

The Equal Importance of Asset Allocation and Active Management

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What is the relative importance of asset allocation policy versus active portfolio management in explaining variability in performance? Considerable confusion surrounds both time-series and cross-sectional regressions and the importance of asset allocation. Cross-sectional regressions naturally remove market movements; therefore, the cross-sectional results in the literature are equivalent to analyses of excess market returns even though the regressions were performed on total returns. In contrast, time-series analyses of total returns do not naturally remove market movements. Time-series analyses of excess market returns and cross-sectional analyses of either total or excess market returns, however, are consistent with each other. With market movements removed, asset allocation and active management are equally important in determining portfolio return differences within a peer group. Finally, an examination of period-by-period cross-sectional results reveals why researchers using the same regression technique can get widely different results.

A portfolio's total return can be decomposed into three components: (1) the market return, (2) the asset allocation policy return in excess of the market return, and (3) the return from active portfolio management (see, e.g., Bailey, Richards, and Tierney 2007; Solnik and McLeavey 2003). The "total return" of the portfolio or fund is the return net of all expenses and fees. Our measure of the "market return" is the equally weighted return for a given period for all the funds in the applicable universe. The "asset allocation policy return" refers to the static asset allocation (beta) return of the fund; intuitively, the asset allocation policy return in excess of the market return is the static asset allocation (beta) return less the market return. The "active portfolio management return" refers to the remaining returns from security selection, tactical asset allocation, and fees.

Of the many studies on the importance of asset allocation policy versus active portfolio management, the one most often cited is the seminal work

by Brinson, Hood, and Beebower (BHB 1986). The BHB study used the time-series total returns of a portfolio and did not separate the market returns from the total returns. The BHB study found that asset allocation policy has an explanatory power of more than 90 percent for the total return variations. Several later studies pointed out that this high explanatory power is dominated by market movements embedded in the total returns (see, e.g., Hensel, Ezra, and Ilkiw [HEI] 1991; Ibbotson and Kaplan 2000). In other words, market movements dominate time-series regressions on *total* returns.¹

In studying the *relative* importance of asset allocation policy and active portfolio management within a peer group of portfolios (after removing the overall applicable market return movements), we attempted to answer the question, Why do portfolio returns differ from one another within a peer group? Or, put slightly differently, Is the difference in returns among funds the result of asset allocation policy or active portfolio management? We used both time-series and cross-sectional data to answer these equivalent questions. To remove the dominance of the applicable market returns in the time-series analysis, we used *excess market* returns. We calculated the market returns and asset allocation policy returns for each month for each portfolio and then ran a time-series regression of the portfolio excess market returns against the asset allocation policy excess market returns.² Extending

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and clarifying previous studies by Ibbotson and Kaplan (2000) and Vardharaj and Fabozzi (2007), we also conducted cross-sectional analyses.

Figure 1 plots the decomposition of total return variations under the two different methodologies of BHB (1986) and of HEI (1991) and Ibbotson and Kaplan (2000). It illustrates their *interpretations* of the explanatory power of asset allocation policy for total return variations. The two bars on the left depict the BHB (1986) time-series regression analysis for both equity and balanced funds. In contrast, the two bars on the right describe the argument of HEI (1991) and Ibbotson and Kaplan (2000) that market movements dominate time-series regressions on total returns. These two bars enable a more detailed decomposition of the total return into its three components: (1) the applicable market return, (2) the asset allocation policy return in excess of the market return, and (3) the return from active portfolio management. In our study, we did not focus on the debate surrounding the BHB study;³ our goal was to address the relative importance of asset allocation policy versus active portfolio management (after removing the applicable market returns).

Data

We chose three portfolio peer groups from the Morningstar U.S. mutual fund database: U.S. equity funds, balanced funds, and international

equity funds. We used 10 years of return data (May 1999–April 2009). We removed duplicate share classes and required that each fund have at least five years of return data. The final sample consisted of 4,641 U.S. equity funds, 587 balanced funds, and 400 international equity funds.

Similar to Vardharaj and Fabozzi (2007), we estimated the asset allocation policy return for each fund by using return-based style analysis (see Sharpe 1992). For the U.S. equity mutual funds, we used seven size and style factors: Russell Top 200 Growth Index, Russell Top 200 Value Index, Russell Midcap Growth Index, Russell Midcap Value Index, Russell 2000 Growth Index, Russell 2000 Value Index, and cash. For the balanced funds, we used 11 stock and bond benchmarks.⁴ For the international funds, we used eight factors.⁵ For each peer group, we experimented with other sets of asset classes, all of which led to results that are consistent with the results presented here.

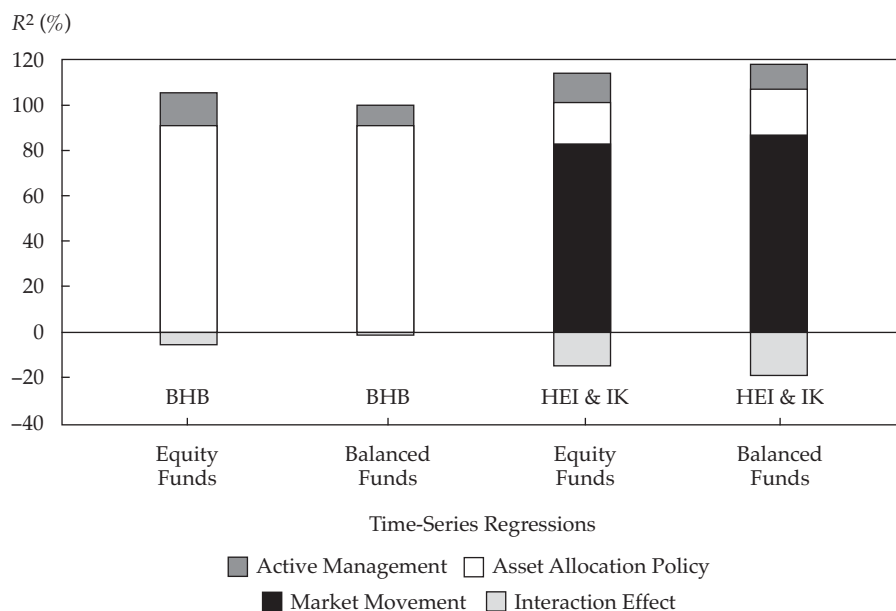
Methodology

Although the mathematics of our study is unsophisticated, the nature of the discussion requires clearly defined notation.

$R_{i,t}$ = fund total return for fund i in period t

$P_{i,t}$ = policy total return for fund i in period t

Figure 1. Decomposition of Time-Series Total Return Variations, May 1999–April 2009



Note: IK stands for Ibbotson and Kaplan (2000).

- M_t = market return (e.g., equally weighted return for a peer group) in period t
 $R_{i,t} - M_t$ = excess market fund return for fund i in period t
 $P_{i,t} - M_t$ = excess market asset allocation policy return for fund i in period t
 $R_{i,t} - P_{i,t}$ = active management or active return for fund i in period t

Time-Series Analysis. In previous time-series studies, total returns were used in the following regression formula to estimate the explanatory power of asset allocation policy:

$$R_{i,t} = b_0 + b_1 P_{i,t} + \varepsilon_{i,t}. \quad (1)$$

The two regression variables are fund total return ($R_{i,t}$) and policy total return ($P_{i,t}$), b_0 and b_1 are the regression coefficients, and $\varepsilon_{i,t}$ is the residual return (the difference between the realized fund return and the predicted fund return). Appendix A shows the definition of the coefficient of determination (R^2), which measures the explanatory power of the model.

As discussed earlier, one problem with the time-series analysis of total returns is that the results are dominated by overall market movement. To further analyze the relative importance of asset allocation policy and active management within a peer group, a more applicable approach is to use excess market returns instead of total returns as the regression variables for the time series. Thus, the regression equation for excess market returns is

$$R_{i,t} - M_t = b_0 + b_1 (P_{i,t} - M_t) + \varepsilon_{i,t}. \quad (2)$$

When carrying out a time-series analysis of excess market return, Equation 1 is very different from Equation 2 because the market return (M_t) varies over time. We refer to Equation 2 as the "excess market return time-series regression."

Cross-Sectional Analysis. Unlike time-series regressions, in which the results are highly dependent on the type of return used (total return or excess market return), cross-sectional regressions on total returns are equivalent to cross-sectional regressions on excess market returns.⁶ Cross-sectional regressions naturally remove the applicable market movement from the peer group, essentially resulting in the same analysis as using excess market returns. We reiterate this point because in most studies on this topic, researchers performed cross-sectional regressions on total returns and failed to recognize the natural removal of the applicable market movement.⁷

For single-period cross-sectional regressions, Equation 1 is intrinsically identical to Equation 2 because the market return (M_t) is a constant in the single period (no matter how long the period is) that is inherent in a cross-sectional regression. This point is critical in correctly interpreting the cross-sectional regression results. Because the market movement is naturally removed during the cross-sectional analysis, the resulting R^2 is an indication of the relative importance of detailed asset allocation versus active management after removing market movement. Furthermore, because the market movement is naturally removed in the cross-sectional analysis, to interpret the typical low R^2 from a cross-sectional analysis as a statement regarding the *overall* or *total* importance of asset allocation or as a basis for deciding how much market exposure to take is incorrect. Appendix A provides an additional analysis to demonstrate that cross-sectional regression naturally removes market movement.

Results

We present our results in three areas: a time-series regression on total returns, a time-series analysis of excess market returns, and a month-by-month cross-sectional analysis.

Time-Series Regression on Total Returns.

For a complete picture of total return time-series regression analysis, the total return can be divided into its three components—(1) the return related to the overall market, (2) the return related to asset allocation policy deviation from the applicable market, and (3) the return related to active portfolio management in the form of tactical asset allocation or security selection:

$$R_{i,t} = M_t + (P_{i,t} - M_t) + (R_{i,t} - P_{i,t}). \quad (3)$$

Table 1 shows the average time-series R^2 s of the three components in Equation 3 for all the funds in a given fund universe. It shows the three components' average contributions to the total return variations for each fund universe. The detailed methodology is described in Appendix A.

For all three fund universes, two important observations emerge from Table 1. First, the market movement component accounts for about 80 percent of the total return variations and dominates both detailed asset allocation policy differences and active portfolio management. In other words, market movement dominates time-series regressions on total returns. This observation is consistent with such previous studies as HEI (1991) and Ibbotson and Kaplan (2000).

Table 1. Decomposition of Time-Series Total Return Variations in Terms of Average R^2 s, May 1999–April 2009

Average R^2	U.S. Equity Funds	Balanced Funds	International Funds
Market movement: $R_{i,t}$ vs. M_t	83%	88%	74%
Detailed asset allocation policy: $R_{i,t}$ vs. $P_{i,t} - M_t$	18	20	19
Active management: $R_{i,t}$ vs. $R_{i,t} - P_{i,t}$	15	10	26
Interaction effect	<u>-16</u>	<u>-18</u>	<u>-19</u>
Total	100%	100%	100%

Second, we found that excess market asset allocation policy return and active portfolio management have an equal level of explanatory power, with each accounting for around 20 percent. The interaction effect is a balancing term and makes the three return components' R^2 s add up to 100 percent. The negative interaction effect comes from the negative covariance between the total return and a residual term, as shown in Appendix A. We then focused on the second observation and investigated the contributions to return variations from both excess market asset allocation policy and active portfolio management after removing market movement. To our knowledge, the literature contains no record of this kind of time-series analysis of excess market returns.

Time-Series Analysis of Excess Market Returns. As discussed earlier, a time series of portfolio excess market returns regressed against policy excess market returns explicitly removes the overall market movement seen in the total return regression and, therefore, is more relevant for identifying the explanatory power of asset allocation within a particular peer group or universe of funds. We decomposed fund excess market return into policy excess market return and active return— $R_{i,t} - M_t = (P_{i,t} - M_t) + (R_{i,t} - P_{i,t})$ —and then regressed the fund excess market returns on the corresponding policy excess market returns and active returns over time. That is, we regressed 120 months of $R_{i,t} - M_t$ on 120 months of $P_{i,t} - M_t$ (policy excess market return) and then on 120 months of $R_{i,t} - P_{i,t}$ (active return) for each fund. **Table 2** summarizes the decomposition of excess market return variations for the three peer groups, again in terms of average R^2 s.

Overall, excess market asset allocation policy and active portfolio management have about an equal amount of explanatory power after removing the applicable market effect. For the U.S. equity funds, asset allocation policy excess market return accounts for 48 percent of the excess market return variations for the average equity funds; active portfolio management accounts for 41 percent. The residual 11 percent is a result of the interaction effect. For the balanced funds, policy excess market return and active portfolio management account for 36 percent and 39 percent of the excess market return variations, respectively. The results are very similar for the international funds. Thus, this analysis also indicates that excess market asset allocation policy has about the same explanatory power for excess market return variations as active portfolio management within a peer group.

Month-by-Month Cross-Sectional Analysis.

Cross-sectional regressions are run for a single period, which is typically defined as either one month or one year. We ran the analysis 120 times, once for each of the possible 120 monthly periods.

Again, cross-sectional analysis naturally removes the average applicable market return and attempts to determine the excess market return relationship within a given universe of funds. The cross-sectional sample variance is the excess market return variance whether one uses the total returns or the excess market returns. In other words, the R^2 of the cross-sectional regression between $(R_{i,t} - M_t)$ and $(P_{i,t} - M_t)$ is the same as the R^2 of the cross-sectional regression between $R_{i,t}$ and $P_{i,t}$. Not surprisingly, one would find more variability in the policy excess market return $(P_{i,t} - M_t)$ if one studied an eclectic universe of funds.

Table 2. Decomposition of Time-Series Excess Market Return Variations in Terms of Average R^2 s, May 1999–April 2009

Average R^2	U.S. Equity Funds	Balanced Funds	International Funds
Excess market asset allocation policy: $R_{i,t} - M_t$ vs. $P_{i,t} - M_t$	48%	36%	49%
Active portfolio management: $R_{i,t} - M_t$ vs. $R_{i,t} - P_{i,t}$	41	39	45
Interaction effect	<u>11</u>	<u>25</u>	<u>6</u>
Total	100%	100%	100%

In discussing these period-by-period cross-sectional regression results, we will use the results from the peer group of 4,641 U.S. equity funds as the primary peer group. The other two peer group analyses produced similar results.

Figure 2 and **Figure 3** show the results of the 120 separate cross-sectional analyses for the 120 monthly returns from May 1999 to April 2009. Because we ran the cross-sectional regressions month by month, the horizontal axis has 120 points. For each month, we regressed fund returns ($R_{i,t}$) on their corresponding policy returns ($P_{i,t}$).

In **Figure 2**, the cross-sectional fund dispersion is defined as the standard deviation of cross-sectional fund returns ($R_{i,t}$). It is very volatile. The residual error is the standard deviation of the

regression residual— σ_ϵ in Equation A1 (see Appendix A). Note that the residual error is relatively stable, with 68 percent of the values falling between 1 percent and 2.3 percent. The relatively low and stable residual errors imply that the multifactor model that describes fund returns (i.e., the return-based style analysis used to estimate the funds' policy portfolio) works well.

Figure 3 shows the rolling cross-sectional R^2 s, which range from 0 percent to 90 percent. From Equation A1 (the R^2 formula in Appendix A), we can see that the volatility of the cross-sectional R^2 in **Figure 3** is primarily the result of the volatility of the cross-sectional fund return dispersion in **Figure 2** (σ_y in Equation A1).

Figure 2. Rolling Cross-Sectional Regression Results for U.S. Equity Funds, May 1999–April 2009

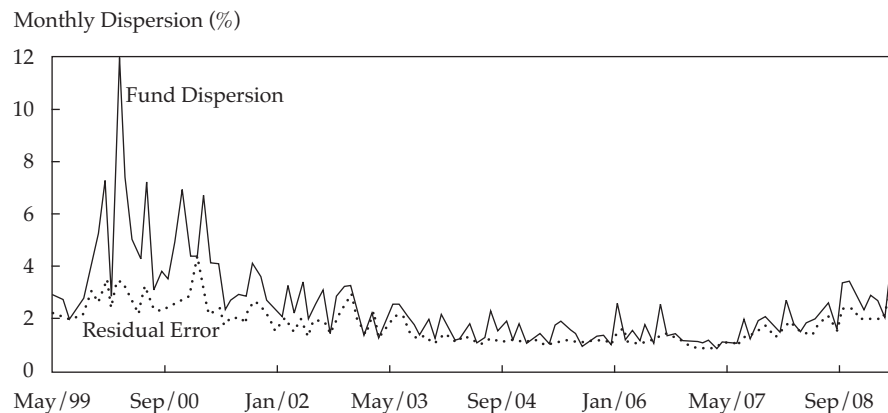
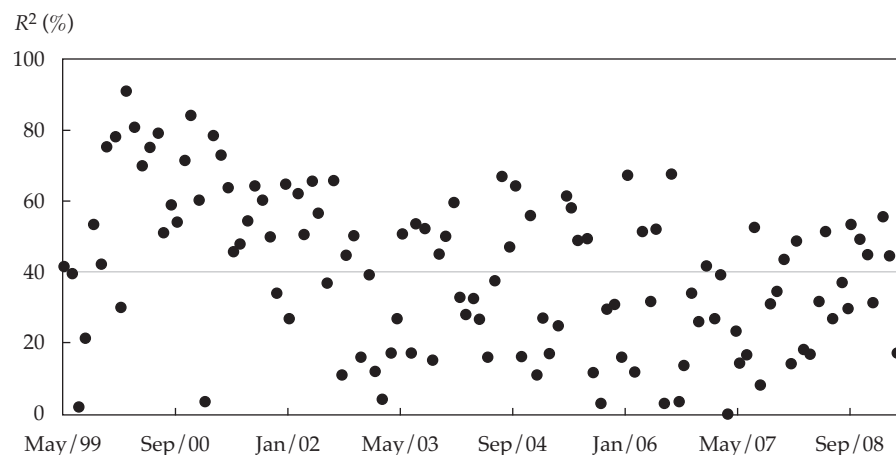


Figure 3. Rolling Cross-Sectional R^2 s for U.S. Equity Funds, May 1999–April 2009



Note: Each point represents a cross-sectional regression for a single month.

A wider cross-sectional return dispersion was observed among both individual stocks and equity mutual funds during the internet bubble from 1999 to 2001. De Silva, Sapra, and Thorley (2001) showed that the wider dispersion in funds was primarily the result of wide individual security return dispersions and had little to do with changes in the range of portfolio manager talent. They believed that the information embedded in cross-sectional fund return dispersion, as well as the information on the market mean return, is useful in performance evaluation. They suggested that active fund return (realized return minus policy return) be adjusted by a period-specific dispersion statistic from the peer group for which the manager is being evaluated.

The wide and varying fund dispersion in Figure 2 demonstrates that analyses performed for different periods can lead to very different results. This finding explains the wide range of cross-sectional results reported in the literature. Period-by-period cross-sectional R^2 s are unstable, leading to the differences in previously reported R^2 s. For example, Vardharaj and Fabozzi (2007) studied a group of large and small U.S. equity funds. They reported that the R^2 ranged from 15 percent for 10-year (1995–2004) compounded cross-sectional fund returns to 72 percent for the 5-year (2000–2004) period. They attributed the variability in R^2 to fund sector or style drift over the 10-year period. But our analysis, which pertains to partially overlapping periods, suggests that the primary reason is the wider dispersion of cross-sectional fund returns and that sector or style drift over the 10-year period is more likely a secondary factor.⁸

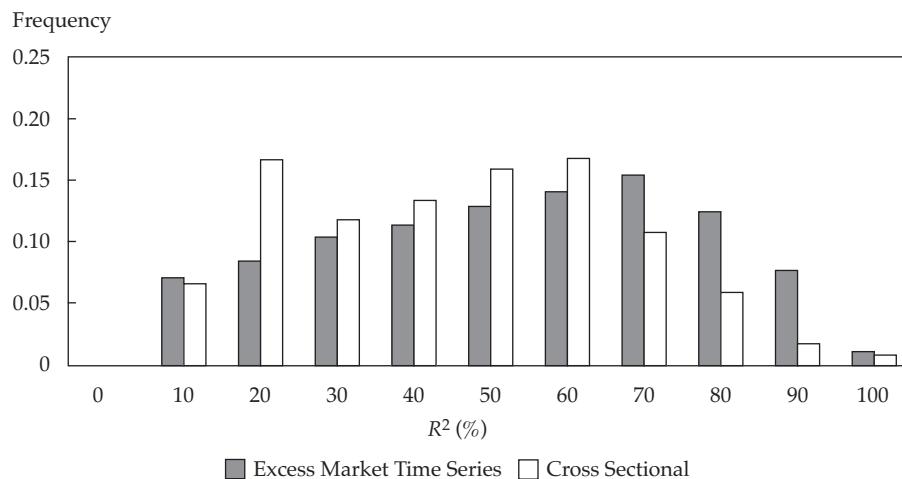
Figure 3 shows that the average of the 120 cross-sectional R^2 s is 40 percent. Thus, on average, the excess market asset allocation policy explains about 40 percent of the cross-sectional excess market return variances for the U.S. equity fund universe. This result is consistent with the time-series analysis of excess market return results reported in Table 2.

Figure 4 summarizes the distributions of R^2 s for the 4,641 U.S. equity funds under two different regression techniques: (1) time-series regressions of fund excess market returns on policy excess market returns and (2) cross-sectional regressions of fund total returns on policy total returns (as noted, this technique is equivalent to cross-sectional regressions of fund excess market returns on policy excess market returns). The frequency in the vertical axis is rescaled for 4,641 time-series regressions and 120 cross-sectional regressions so that the cumulative distribution adds up to 100 percent for both sets of regressions. We can see from the two R^2 distributions that the results are consistent. These results confirm our earlier finding that cross-sectional regression is consistent with excess market time-series regression.

Conclusion

Our study helped identify and alleviate a significant amount of the long-running confusion surrounding the importance of asset allocation. First, by decomposing a portfolio's total return into its three components—(1) the market return, (2) the asset allocation policy return in excess of the market return, and (3) the return from active portfolio

Figure 4. Distribution of R^2 for Cross-Sectional and Excess Market Time-Series Regressions for U.S. Equity Funds, May 1999–April 2009



Note: We ran 120 cross-sectional regressions and 4,641 excess market time-series regressions.

management—we found that market return dominates the other two return components. Taken together, market return and asset allocation policy return in excess of market return dominate active portfolio management. This finding confirms the widely held belief that market return and asset allocation policy return in excess of market return are collectively the dominant determinant of total return variations, but it clarifies the contribution of each.

More importantly, after removing the dominant market return component of total return, we answered the question, Why do portfolio returns differ from one another within a peer group? Our results show that within a peer group, asset allocation policy return in excess of market return and active portfolio management are equally important. Critically, this finding is not the result of a mathematical truth. In contrast to the mathematical identity that in aggregate, active management is a zero-sum game (and thus, asset allocation policy explains 100 percent of aggregate pre-fee returns), the relative importance of both asset allocation policy return in excess of market return and active portfolio management is an empirical result that is highly dependent on the fund, the peer group, and the period being analyzed.

The key insight that ultimately enabled us to conclude that asset allocation policy return in excess of market return and active portfolio management are equally important is the realization that cross-sectional regression on *total* returns is equivalent to cross-sectional regression on *excess market* returns because cross-sectional regression naturally removes market movement from each portfolio. We believe that this critical and subtle fact has not been clearly articulated in the past and has been overlooked by many researchers, especially when interpreting cross-sectional results vis-à-vis the overall importance of asset allocation.

The insight that cross-sectional regression naturally removes market movement leads to the notion that removing market movement from traditional total return time-series regression is necessary should one want to put the time-series and cross-sectional approaches on an equal footing. After putting the two approaches on an equal footing, we found that the values of R^2 for the excess market time-series regressions and the cross-sectional regressions (on either type of return) are consistent.

Finally, by examining period-by-period cross-sectional results and highlighting the sample period sensitivity of cross-sectional results, we explained why different researchers using the same regression technique can get widely different

results. More specifically, cross-sectional fund dispersion variability is the primary cause of the period-by-period cross-sectional R^2 variability.

The authors thank William N. Goetzmann of the Yale School of Management and Paul Kaplan and Alexa Auerbach of Morningstar for their helpful comments.

This article qualifies for 1 CE credit.

Appendix A. Regression Analyses

Coefficient of Determination

The coefficient of determination, R^2 , is defined as the fraction of the total variation that is explained by the univariate regression between dependent variable y and independent variable x . Formally,

$$\begin{aligned} R^2 &= b_1^2 \frac{\sigma_x^2}{\sigma_y^2} \\ &= 1 - \frac{\sigma_\varepsilon^2}{\sigma_y^2}, \end{aligned} \quad (\text{A1})$$

where

- b_1 = the regression's slope coefficient
- σ_x^2 = the variance of x
- σ_y^2 = the variance of y
- σ_ε^2 = the unexplained or residual variance

Variances for Time-Series and Cross-Sectional Regressions

Under the single-factor market model, the fund return for fund i is

$$R_{i,t} = \alpha_{i,t} + \beta_i M_t + \varepsilon_{i,t}, \quad (\text{A2})$$

where

- $\alpha_{i,t}$ = average return to fund i that is not related to the market return in period t
- β_i = the sensitivity of fund i to the return on the market
- M_t = market return in period t
- $\varepsilon_{i,t}$ = an error term

Traditional or Total Return Time-Series Variance. We take a variance operator on Equation A2 to get the time-series variance for fund i :

$$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma_{\varepsilon,i}^2, \quad (\text{A3})$$

where $\sigma_{\varepsilon,i}^2$ is the variance of the residual amount ($\alpha_i + \varepsilon_i$).

The first component is the systematic risk, and the second component is the fund-specific risk. Assuming that the *monthly* standard deviation of the market return is 5 percent and the beta of the fund relative to the market is 0.9, the estimated systematic (i.e., market) risk is

$$\beta_i^2 \sigma_M^2 = 0.9^2 \times 5\%^2 \approx 0.002. \quad (\text{A4})$$

Excess Market Time-Series Variance. On the basis of Equations A2 and A3, we can show that the excess market time-series variance for fund i is

$$\sigma_{i,\text{excess}}^2 = (\beta_i - 1)^2 \sigma_M^2 + \sigma_{\varepsilon_i}^2. \quad (\text{A5})$$

The excess market return variance is typically much less than the total return variance because with total returns, β_i is close to 1 for a typical fund. With excess market returns, $\beta_i - 1$ is typically closer to 0 than it is to 1. This result can be seen by continuing with our example based on commonly observed values and comparing the following estimate with Equation A4:

$$\begin{aligned} (\beta_i - 1)^2 \sigma_M^2 &= (0.9 - 1)^2 \times 5\%^2 \\ &\approx 0.00003. \end{aligned} \quad (\text{A6})$$

Cross-Sectional Variance. We can show that the cross-sectional variance, $\sigma_{\beta,t}^2$, is conditional on a realized market return of M_t . In a given period t , the cross-sectional variance is

$$\sigma_t^2 = \sigma_{\beta,t}^2 M_t^2 + \sigma_{\varepsilon,t}^2, \quad (\text{A7})$$

where $\sigma_{\beta,t}^2$ is the cross-sectional variance of fund betas.

Equation A7 assumes that the fund-specific risk, $\sigma_{\varepsilon,t}^2$, is the same for all the funds (hence, no fund subscript). Assuming that the *monthly* market return and standard deviation of fund betas are 1 percent and 0.3, respectively, an estimate of the first term in Equation A7 is⁹

$$\sigma_{\beta,t}^2 M_t^2 = 0.3^2 \times 1\%^2 \approx 0.00001. \quad (\text{A8})$$

Comparing Equations A4, A6, and A8, we can see that the time-series variance is much higher than both the excess time-series variance and the cross-sectional variance. Note that Equation A5 is comparable to Equation A7, which indicates that excess market time-series and cross-sectional regressions are on the same footing, and that market movement is removed from both.

Return Variations Decomposition

To determine the contributions to total return variations from the three components, we need to modify Equation 3 as follows:

$$\begin{aligned} R_{i,t} &= b_{1M} M_t + b_{1P} (P_{i,t} - M_t) \\ &\quad + b_{1S} (R_{i,t} - P_{i,t}) + \varepsilon_{i,t}, \end{aligned} \quad (\text{A9})$$

where b_{1M} , b_{1P} , and b_{1S} are the univariate regression coefficients between $R_{i,t}$ and M_t , between $R_{i,t}$ and $(P_{i,t} - M_t)$, and between $R_{i,t}$ and $(R_{i,t} - P_{i,t})$, respectively—that is,

$$\begin{aligned} b_{1M} &= \frac{\text{cov}(R_{i,t}, M_t)}{\text{var}(M_t)}, \\ b_{1P} &= \frac{\text{cov}(R_{i,t}, P_{i,t} - M_t)}{\text{var}(P_{i,t} - M_t)}, \text{ and} \\ b_{1S} &= \frac{\text{cov}(R_{i,t}, R_{i,t} - P_{i,t})}{\text{var}(R_{i,t} - P_{i,t})}. \end{aligned} \quad (\text{A10})$$

Note that Equation A9 is not a standard multiple regression equation. We chose b_{1M} , b_{1P} , and b_{1S} in this particular way because we needed to decompose R^2 into its three components. Taking a covariance with $R_{i,t}$ on both sides of Equation A9, we obtain

$$\begin{aligned} \text{cov}(R_{i,t}, R_{i,t}) &= b_{1M} \text{cov}(M_t, R_{i,t}) \\ &\quad + b_{1P} \text{cov}[(P_{i,t} - M_t), R_{i,t}] \\ &\quad + b_{1S} \text{cov}[(R_{i,t} - P_{i,t}), R_{i,t}] \\ &\quad + \text{cov}(\varepsilon_{i,t}, R_{i,t}). \end{aligned} \quad (\text{A11})$$

Combining Equations A10 and A11 and the first part of Equation A1, we obtain

$$R_M^2 + R_P^2 + R_S^2 + R_\varepsilon^2 = 1, \quad (\text{A12})$$

where R_M^2 , R_P^2 , and R_S^2 are the R^2 s of the univariate regressions between $R_{i,t}$ and M_t , between $R_{i,t}$ and $(P_{i,t} - M_t)$, and between $R_{i,t}$ and $(R_{i,t} - P_{i,t})$, respectively. R_ε^2 is a balancing term and is proportional to the covariance between $\varepsilon_{i,t}$ and $R_{i,t}$; we call it “interaction effect” in Table 1.

The same methodology can be applied to Table 2.

Notes

1. See Ibbotson (forthcoming 2010) for a detailed review.
2. We calculated the market return as the equally weighted return for all the funds in the applicable fund universe (e.g., U.S. equity funds or balanced funds). Dollar-weighted returns produced similar results.
3. For those interested in the debate, see Nuttall (2000).
4. The 11 asset classes are Russell 1000 Growth Index, Russell 1000 Value Index, Russell 2000 Growth Index, Russell 2000 Value Index, FTSE NAREIT Equity Index, MSCI EAFE Index, MSCI Emerging Markets Index, Barclays Capital High Yield Index, Barclays Capital 1–3 Year Government/Credit Index, Barclays Capital Long-Term Government/Credit Index, and cash.
5. The eight factors are S&P 500 Index, MSCI Canada Index, MSCI Japan Index, MSCI AC Asia ex Japan Index, MSCI United Kingdom Index, MSCI Europe ex UK Index, MSCI Emerging Markets Index, and cash.
6. Technically, the intercept of the regression is different, but the remaining regression coefficients and R^2 are the same.
7. This key observation was also made by Solnik and Roulet (2000), who stated that the cross-sectional method looks at relative returns. In our context, the relative return is the excess market return.
8. To verify this finding, we attempted to duplicate the Vardharaj and Fabozzi (2007) results by decomposing the R^2 . Using what we believed to be a similar universe of U.S. equity funds, we calculated the 5-year (2000–2004) and 10-year (1995–2004) annually compounded cross-sectional fund dispersions (8.39 percent and 3.13 percent for the 5-year and 10-year compounded returns, respectively). We estimated the residual dispersion to be 4.44 percent for the five-year compounded return, and thus, the R^2 is about 72 percent ($\approx 1 - 4.44^2/8.39^2$). We estimated the residual dispersion to be 2.88 percent for the 10-year compounded return, and thus, the R^2 is about 15 percent ($\approx 1 - 2.88^2/3.13^2$). The residual dispersions do not differ much (2.88 percent to 4.44 percent), but the fund dispersions differ considerably (3.13 percent to 8.39 percent). Therefore, the wide fund dispersion explains the widely distributed R^2 s in Vardharaj and Fabozzi (2007).
9. For the universe of U.S. equity funds, the cross-sectional beta volatility, $\sigma_{\beta,t}$, is about 0.3, which is estimated from the Morningstar mutual fund database.

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