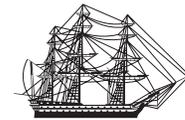


A Primer on Tactical Asset Allocation Strategy Evaluation

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Introduction

Many pension funds, endowment funds, and other institutional investors are concerned that equities—typically their largest asset allocation—will have lower average returns over the next decade. In this environment, many investors have questioned the wisdom of thinking about asset allocation solely in strategic terms and have shown renewed interest in tactical approaches.

Tactical asset allocation (TAA) is a dynamic strategy that actively adjusts a portfolio's strategic asset allocation (SAA) based on short-term market forecasts. Its objective is to systematically exploit inefficiencies or temporary imbalances in equilibrium values among different asset or subasset classes. Over time, strategic long-term target allocations are the most

important determinant of total return for a broadly diversified portfolio. TAA can add value at the margin, if designed with the appropriate rigor to overcome significant risk factors and obstacles unique to the strategy. Our results show that while some TAA strategies have added value, on average TAA strategies have not produced statistically significant excess returns over all time periods.

This raises several important questions for institutional investors: What tools and processes do they need to have in place to make optimal decisions regarding TAA strategies? What are the right questions to ask a prospective manager? What are the critical components of a good model if they choose to run a TAA strategy in-house? This paper provides answers to these questions.

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SAA, TAA, and traditional active strategies juxtaposed

The case for SAA

SAA, or policy asset allocation, is the establishment of a long-term target allocation in major asset classes such as stocks, bonds, and cash based on portfolio objective, risk tolerance, and time horizon. Over time, SAA is the most important determinant of the total return and risk of a broadly diversified portfolio. Studies support empirically the dominance of SAA in determining total return and return variability.¹

The case for TAA

TAA attempts to add value by overweighting those asset classes or subasset classes that are expected to outperform on a relative basis in the near term and underweighting those expected to underperform in the near term. In a TAA model, financial and economic variables (“signals”) are used to predict performance and assign relative short-term asset-class weightings. A TAA model generally consists of stocks, bonds, and U.S. Treasury bills, but it can also include assets such as currencies, commodities, and other alternative investments. A TAA model can decompose to the subasset class level to include growth and value stocks or corporate bonds and Treasury securities. The model may be implemented using only domestic asset classes, or it may be implemented on a global level. While TAA is an active strategy based on systematically timing the market, it can be carried out through security selection or indexed investments.²

Economically, TAA is based on the assumption that relative returns among asset classes will diverge temporarily from equilibrium levels, allowing the opportunity for excess returns from systematic (generally contrarian) strategies. For example, equilibrium spreads between stocks and bonds were well above their long-term ranges before the equity market returned to equilibrium levels in 2000. A well-

designed TAA strategy would have recognized this imbalance and suggested underweighting stocks before the equity market “bubble” burst. Underweighting the equity asset class relative to the strategic allocation would have resulted in value-added for a portfolio.

TAA strategies are different from security-selection strategies in terms of both risks and benefits. It is helpful to understand these differences before implementing a strategy and choosing a manager.

Sources of return

The source of return for a TAA strategy can be illustrated through comparison with other strategies. TAA strategies attempt to add value by timing systematic (or market) risk factors and overweighting those asset classes that are expected to outperform in the near term. A passive indexed strategy also derives return from systematic risk factors. However, with a passive strategy, investors are simply compensated for assuming the market risk resulting from the variation in factors such as interest rates, term-structure shifts, specific business and industry shocks, and unexpected inflation shocks. In other words, passive returns result from beta, and TAA returns attempt to produce alpha through a bet on systematic risk. Like TAA, security-selection strategies attempt to produce alpha, but alpha is a bet on idiosyncratic or firm-specific risk, as opposed to systematic risk. These concepts are illustrated in Figure 1.

TAA versus security-selection strategies

Compared with security-selection strategies, the timing of systematic risk entails different risks and potential benefits. Understanding these differences is critical to the successful implementation of a TAA strategy. The biggest difference is the available opportunity set. Unlike active strategies based on security selection, there are a limited number of assets available for tactical strategies. The number of opportunities is limited by the number of asset or subasset classes

1 For a more detailed discussion of SAA, see The Vanguard Group (2003) and Yesim Tokat (2005).

2 For example, a TAA model may dictate a 10% overweighting in emerging markets. This allocation can be implemented either with an index investment or through security selection.

Figure 1. Sources of return

	Systematic risk	Idiosyncratic risk
Beta	Indexing: compensation for assuming systematic risk	
Alpha	TAA: alpha from timing systematic risk factors	Traditional active: alpha from security selection

that managers can over- or underweight. In contrast, active strategies based on security selection have the entire universe of public companies as potential opportunities to add value. There are typically between 3 and 20 assets in a TAA strategy, compared with 100 to several thousand in an active strategy based on security selection (Grinold and Kahn, 2000). Another difference is that signal predictability is generally very low with TAA strategies, and it is questionable whether strategies are exploitable in out-of-sample periods. The combination of these two factors—low predictability and a limited number of possible bets—makes TAA particularly challenging.

On the other hand, there are two primary benefits to using TAA strategies versus traditional active strategies. One benefit relative to security-selection strategies is that a tactical strategy can, in some cases, be implemented with lower transaction costs. With other active strategies, trading individual securities typically involves significant transaction costs, while tactical shifts in major asset classes can be carried out with liquid futures contracts on an index, resulting in very low transaction costs. Note that tactical subasset allocation or global strategies may not share this benefit. Liquid futures contracts on an index may simply not be widely available for these styles, segments, or markets. The other primary benefit is that TAA strategies can result in more independent bets. Unlike the correlations among individual securities, correlations among asset classes are low, by definition. Low correlation facilitates independent bets and reduces the chance that two

bets in one strategy will effectively cancel each other out. Note that tactical subasset allocation (among equity styles or bond segments) does not share this benefit because of the generally high correlation among subasset classes.

Real-world application: evaluating a TAA strategy

Although the successful implementation of a TAA strategy is often portrayed as simple, it is actually very difficult. As mentioned earlier, predictability is low and opportunity sets are limited. As a result, investors must be careful in selecting managers or strategies. They should understand a strategy's information signals; for example, how a manager determines over- and underweightings and what makes the strategy durable. It is important to use appropriate qualitative and quantitative performance-measurement criteria and to identify strategies with relatively low costs. Some best practices for selecting or developing a TAA strategy follow.

- Understand how a forecast is created.** Success with a TAA strategy is largely dependent on constructing a good model. The first step in developing an overall TAA model is to forecast excess returns by constructing models that attempt to predict asset-class returns using a set of explanatory variables or signals. Running tests over a sample period will help to reveal the strength of the signals and the overall explanatory power of a model. Models may have varying predictive strengths during different periods. As a result, multiple predictive models are typically required to consistently add value. Models should also be dynamic, that is, they should change with structural changes or other factors that permanently affect signal strength. The textbox on page 4 summarizes the commonly used TAA signals, their rationale, and the time periods over which they are expected to add value.

Understanding the commonly used TAA signals

Investors should understand the rationale behind commonly used TAA signals and the time periods over which such signals are expected to add value so they can judge the skill of a manager and be comfortable with the types of bets made in their portfolios.

- *The “Fed model” signals:* This involves a model that compares earnings yields (the inverse of the price/earnings [P/E] ratio) to nominal bond yields to determine the relative attractiveness of equities over bonds. The underlying notion is that stocks and bonds compete for the same dollars and the higher-returning asset class should be overweighted in the portfolio. Clifford Asness (2003) detailed several drawbacks to this approach.
- *Business cycle/macroeconomic signals:* These signals attempt to find value-added by timing the business-cycle-related variation in market risk premiums and firms’ earnings. Widely used signals include the term spread (the yield differential between long- and short-term bonds), the credit spread (the yield differential between high- and low-credit-rated corporate bonds), “unexpected inflation,” and industrial production. Business-cycle variables tend to add value over intermediate time horizons.
- *Fundamental-valuation signals:* One approach involves using fundamental firm-valuation metrics, such as dividend yield, book/market ratio, and P/E ratio, to determine relative valuation. Another approach is to use top-down or bottom-up cash-flow valuation methods (Damodaran, 2002). An example of the latter would be to use the dividend discount model to reverse engineer the required rate of return from market prices and projected dividend growth rates. Fundamental-valuation signals tend to add value over intermediate time horizons.
- *Momentum signals:* These signals attempt to add value by following the short-term momentum in markets. Typical momentum signals include technical indicators, earnings growth, and changes in trading volumes. Momentum signals can be at odds with fundamental or business-cycle signals at times, such as during the technology stock bubble of the late 1990s. However, when momentum signals are appropriately combined with fundamental or business-cycle signals, they can produce complementary short-term value-added.
- *Sentiment signals:* These signals attempt to add value through a contrarian strategy that looks for extreme levels of sentiment, such as consumer confidence and margin borrowing, to identify deviations from equilibrium returns. Sentiment signals tend to add value over intermediate time horizons.

A good forecasting model must include economically meaningful signals and have a research process that correctly identifies meaningful signals:

- *Economically meaningful signals.* Economically meaningful signals are those with rational, intuitive explanations for their expected predictive power. For example, the term spread, as an indicator of the business cycle, is intuitive and rational. Typically, the yield curve is positively sloped, meaning that long-term interest rates are higher than short-term ones. According to the term structure of interest rates, a positively sloped yield curve is compensation for the higher risk of locking in longer-term bonds and the uncertainty of inflation (and therefore the direction of interest rates) in the future. Investor expectations about the future economic environment affect the amount of this risk compensation and, therefore, the shape of the yield curve. Since market risk premiums and firms' cash flows are linked with the future economic environment and the business cycle, a TAA strategy may benefit from systematically following a term-spread indicator.
- *Absence of data mining.* In addition, the manager should be able to confirm that he or she did not "mine the data," the process of rerunning the model with modified signals until a desired result is reached and presenting only those results for the sample period. Data mining, while producing impressive results, runs the risk that the model will not work in real time. Out-of-sample tests of the strategy, such as in other time periods or countries, can help to confirm that the strategy's success is not simply the result of fitting the model to explain one historical period.

- *Rational decision process.* Finally, like the signals themselves, the decision process for determining what signals are included and how they are combined should be economically reasonable. Consider a forecast that relies on a high R-squared to determine whether a signal is predictive and should be included. Despite a high R-squared, an economic rationale may suggest that the signal should not be used. A simple example of this is the "Super Bowl effect," which predicts that the value of the Standard & Poor's 500 Index will increase if an old National Football League team wins the Super Bowl or decline if an old American Football League team wins (example from Clifford Asness [1996]). The explanatory power of the team wins can be quite strong, but of course, there is no plausible rationale for a predictive relationship between football games and equity returns.

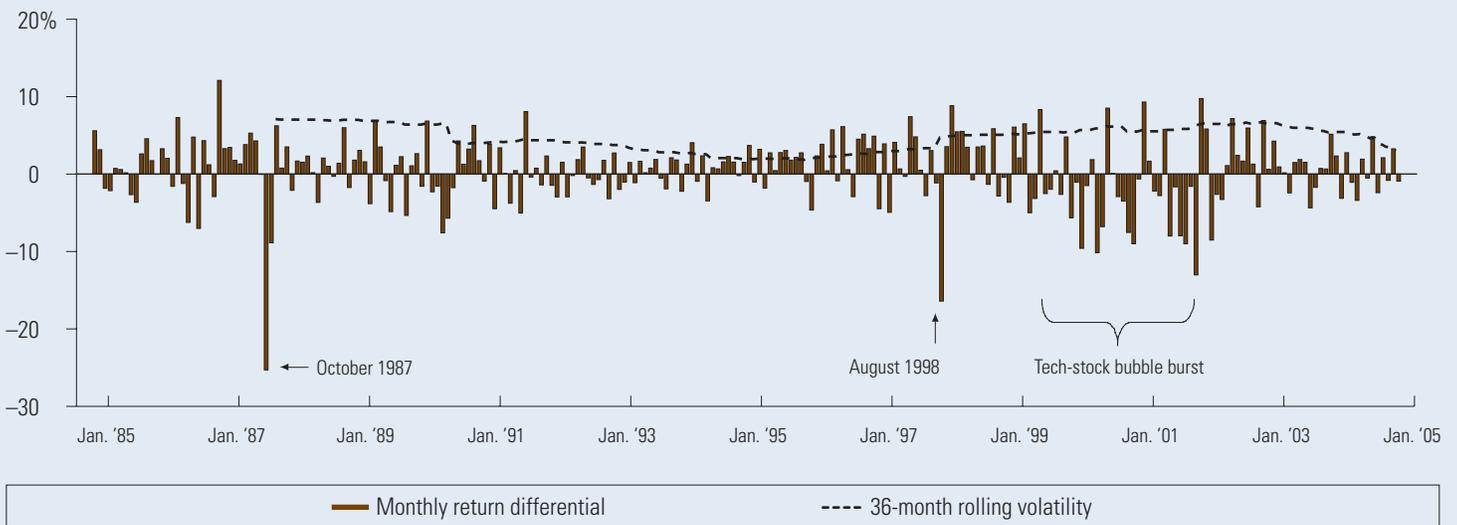
A good model will have a method for ensuring that the selection and testing process is economically reasonable. An example of this is the Bayesian method. Bayesian probability calculations involve assumptions based on economic theory or intuition, which are combined with what is learned from the data (Campbell and Thompson, 2005). For the model, the approach might be to assume that the prospective equity risk premium is positively related to dividend yield, for example. This would mean constraining the forecast model so any results where the relationship between the dividend yield and the equity risk premium was negative would be disregarded. This approach provides a qualitative, rational overlay to the statistical-measurement process. It allows the model to disregard those results that strongly conflict with economic intuition.

- *Understand how asset-class over- and underweightings are determined and controlled.* Another factor to evaluate is a model's asset-weighting optimization process. First, over- or underweightings should be proportional to the combined strength of the model's information signals. If a strategy recommends a large overweighting in a particular asset class, the manager should be able to demonstrate the model's strong predictive power in that regard. Investors should avoid a manager who makes big bets based on weak signals. Second, over- or underweightings should be made with the appropriate constraints on deviation. Constraints can be based on ad hoc decision rules. For example, if the projected equity risk premium is greater than 10%, then a manager should overweight equities by 15%. Or if optimization is used to determine asset-class weightings, constraints can be implemented with models that "tame" the optimizer. Traditional mean-variance approaches are highly sensitive to expected returns and often result in very large weightings in particular asset classes. The Black-Litterman Model (Black and Litterman, 1992) is an example of a model that corrects for these extreme results. This model *starts* with equilibrium expected returns and then moves away from them based on the volatility and correlations of each asset class and the degree of confidence in each forecasting model. The results of the model tend to be less extreme than traditional mean-variance approaches.
- *Consider the durability of value-added.* Evaluate performance to determine what makes a strategy durable and how the back-tested performance compares with the real-time record. The following checks on a model help to determine this:
 - *Review the manager's historical asset allocation relative to the benchmark.* This process is critical to determine if the model's excess returns are simply a result of bias

toward the historically higher-returning asset class, such as a strategic overweighting in equities, or of predictive power (Lee, 1998). The manager's historical allocations should not be largely different from the benchmark's for long periods. TAA involves short-term over- or underweightings to capture mispricings. For instance, a longer-term overweighting in equities would likely produce an excess return relative to the benchmark, but the source of the return would simply be the equity risk premium.

- *Review significant events.* It is important to review a model's test results during periods marked by significant events—those that cause large divergences among asset-class returns—such as the October 1987 U.S. stock market crash or the August 1998 Russian debt-default crisis. If stock and bond returns are very close, the relative benefit of an overweighting in either asset class is small. If their returns diverge, there are greater opportunities for bets to pay off and, of course, larger opportunities for loss. As shown in Figure 2, historically there have been very few events that caused returns to diverge significantly. However, it was these events that highlighted the success or failure of a strategy. When the volatility of the equity risk premium is high, there are more opportunities to add value, which can result in higher excess returns (Arnott and Miller, 1997; Lee, 1998).
- *Examine a model's results in different periods.* Reviewing a model's results in many different periods can help reveal whether the model is likely to be enduring. A manager's back testing may show excess returns, but these may be the result of data mining, that is, running tests again and again until excess returns emerge. Out-of-sample results, those not presented by the manager, highlight any signal degradation. Signals may weaken over

Figure 2. Monthly return differentials and the volatility of the equity risk premium, January 1985–January 2005



Note: Equities are represented by the S&P 500 Index; bonds are represented by the Lehman Government/Credit Bond Index.

Sources: Standard & Poor's and Lehman Brothers; authors' calculations.

time. Also, it is not uncommon for a signal to produce significant excess returns in one period but not another.

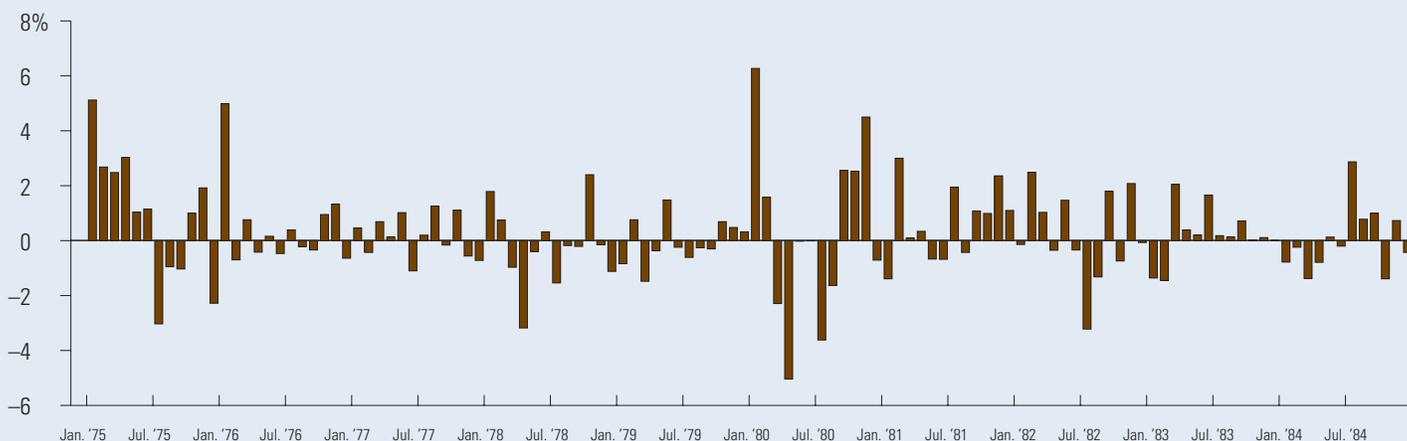
For example, Figure 3 reports the monthly excess returns of a strategy based on one-month lagged values of the following business cycle/macroeconomic variables: term spread, credit spread, inflation, percentage change in oil prices, and equity return.³ During the testing (in-sample) period from 1975 to 1984, the strategy generated an average monthly excess return, or alpha, of 28 basis points, with a t-statistic of 1.82, indicating a good consistency of excess returns relative to a static SAA policy portfolio.⁴

Despite this, the strategy's successful historical performance was not durable in subsequent periods. Figure 4 shows that this strategy consistently detracted an average of 19 basis points from the benchmark's performance from 1985 through 1994, while it added 29 basis points from 1995 to 2004. It is important to understand why the value-added from the strategy was not consistently repeatable. The nonexistence of significant events, changes in the macroeconomic environment, weakening of the signals, or just bad luck are possible reasons that should be explored. A robust strategy should produce significant excess returns whether it is applied to in-sample or out-of-sample periods.

3 We first created a time-series regression model using economically meaningful standard signals that best characterized the historical equity returns over the previous rolling 60-month window. Based on this model, we forecasted the next month's expected equity return and calculated the expected equity risk premium, which is the expected equity return minus the 10-year Treasury bond's yield. Compared with a 50% stocks/50% bonds benchmark, the portfolio had over- or underweightings using ad hoc decision rules based on the standard error of the historical equity risk premium from 1926 to 1969. For instance, when the expected annualized equity premium was between 10.11% and 11.76%, there was a 15% increase in the equity allocation. Then we moved the clock forward one month and repeated the regression analysis, forecasting, and portfolio reallocation.

4 The t-statistic (the arithmetic average return divided by the standard error of the arithmetic average) tests the hypothesis that mean alpha is different from zero if the variable of interest follows a normal distribution or the sample size is large, in accordance with the Central Limit Theorem. Standard error is volatility divided by the square root of the number of observations minus 1.

Figure 3. Using business cycle/macroeconomic variables: in sample, 1975–1984



Benchmark: 50% MSCI US Broad Market Index, 50% Lehman Long U.S. Treasury Bond Index.

Note: The forecast was generated by using one-month lagged values of term spread, credit spread, inflation, percentage change in oil prices, and equity return.

Sources: Federal Reserve Bank of St. Louis FRED Database, Morgan Stanley Capital International, and Lehman Brothers; authors' calculations.

In Sample, 1975–1984	100% MSCI US	TAA Strategy	50%/50% Benchmark
Monthly mean return	1.09%	1.14%	0.86%
Monthly standard deviation	4.16	3.59	3.18

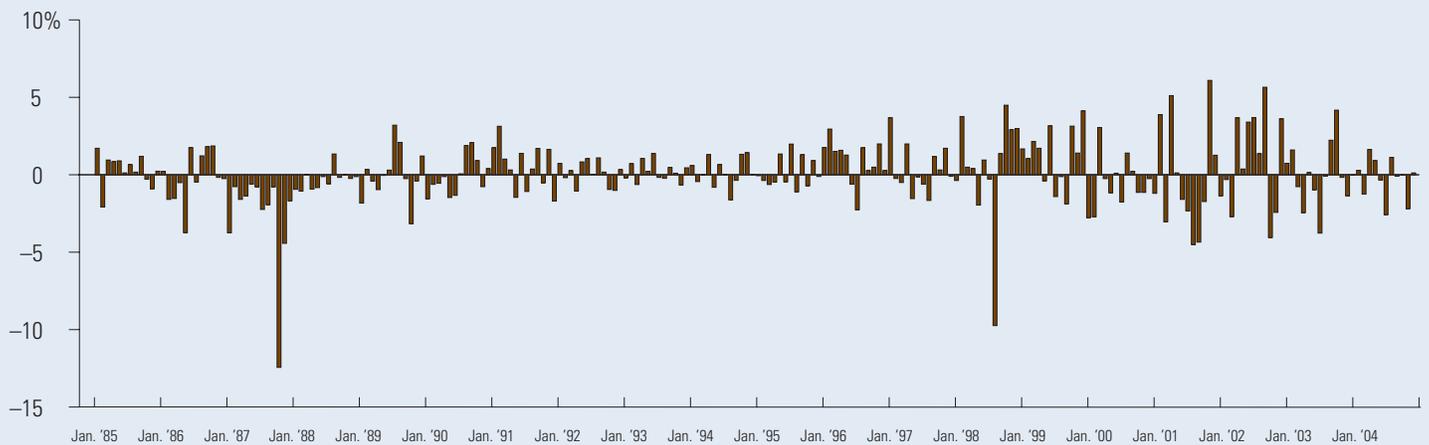
In Sample, 1975–1984	
Monthly mean excess return	0.28%
T-statistic	1.82

— *Examine model results over the intermediate term.* Finally, it is important to examine model results over the appropriate time period. Short-term predictability requires very informative signals. There is simply too much noise around short-term returns to find a pattern to determine which asset class will outperform. TAA strategies cannot be expected to work day-to-day or month-to-month. Over the intermediate term, it is more likely that some pattern or cycle related to economic variables, momentum, or change in investor sentiment can be gleaned. Over time, perhaps three-year periods, some pattern may emerge that can be exploited.

- *Use appropriate quantitative and qualitative performance-measurement criteria.* As with any strategy, when evaluating a TAA strategy, it is useful to combine qualitative and quantitative performance-measurement criteria. In terms of quantitative measurement, the two metrics that deserve the most attention are the historical information ratio⁵ and the t-statistic associated with the historical average return. A historical information ratio calculated over five or more years provides an indication of the risk/return trade-off that the strategy has offered and may continue to offer if the historical relationships hold. The t-statistic measures the consistency of the average historical excess return. A t-statistic greater than 2 indicates that the historical excess

5 The information ratio is the ratio of alpha to tracking error, that is, the standard deviation of alpha.

Figure 4. Using business cycle/macroeconomic variables: out of sample, 1985–2004



Benchmark: 50% MSCI US Broad Market Index, 50% Lehman Long U.S. Treasury Bond Index.

Note: The forecast was generated by using one-month lagged values of term spread, credit spread, inflation, percentage change in oil prices, and equity return.

Sources: Federal Reserve Bank of St. Louis FRED Database, Morgan Stanley Capital International, and Lehman Brothers; authors' calculations.

Out of Sample, 1985–2004	100% MSCI US	TAA Strategy	50%/50% Benchmark	Out of Sample, 1985–2004	1985–1994	1995–2004	1985–2004
Monthly mean return	1.03%	1.01%	0.96%	Monthly mean excess return	-0.19%	0.29%	0.05%
Monthly standard deviation	4.53	3.75	2.80	T-statistic	-1.85	1.40	0.40

return has been and probably will continue to be very consistent—most likely due to the skill of the manager and the durability of the strategy—if the historical relationships hold (see the textbox on page 10).

In terms of qualitative criteria, we believe investors should evaluate any manager in terms of four principles—people, philosophy, process, and performance. Questions to ask include:

- How have *all* the manager's strategies or funds performed, not just the ones being touted?
- Who is performing the work? How long has the team been in place?
- What is the manager's approach to investments? Is it easily understood?
- How long has the strategy operated? Does it have at least a three-year track record?

Quantitative criteria help distinguish skill from luck in the *historical* performance of a TAA manager, while the qualitative criteria outlined above help ensure that historical relationships will continue to hold in the future. For example, the information ratio for all the manager's strategies would provide more insight about manager skill than that for the one or two strategies being marketed. Likewise, information about the makeup and tenure of the team producing a particularly high information ratio would be important to determine if the ratio were to be replicable.

More on quantitative performance-measurement criteria

It is essential to combine the use of qualitative criteria for investment-management processes with quantitative performance-evaluation metrics, which can help distinguish skill from luck in historical performance (Molitor, 2004). Some widely used informative metrics are:⁶

- *Geometric average alpha.* This is the difference between the geometric average return of the strategy and the geometric average return of the benchmark. It is an AIMR (Association for Investment Management and Research) standard measure of actual historical investment return, which incorporates the effects of compounding returns over time.
- *Arithmetic average alpha and the associated t-statistic.* While the geometric average alpha is a better measure of historical experience, the arithmetic average alpha is a better measure of what an investor can expect in any given period. The consistency of this periodic return expectation can be tested using a metric called the t-statistic.⁷ A t-statistic greater than 2 indicates that the historical alpha has been very consistent. Greater consistency of alpha is generally seen as an indication of the skill of the manager and the durability of the strategy if historical relationships continue to hold. However, this is never a guarantee, as the simulated business cycle/macroeconomic strategies on pages 8 and 9 illustrate.
- *Information ratio.* This is the ratio of alpha to tracking error, that is, the standard deviation of alpha. It is used as an indication of the risk/return trade-off that the strategy has offered and is likely to offer. It is important to note that historical information ratios are rarely predictive of future information ratios (Molitor, 2004). Although monthly average alpha and tracking error are typically annualized to generate an annualized information ratio, the standard scaling practice tends to be flawed for TAA strategies. There is evidence that most TAA alphas are serially correlated and that standard scaling underestimates tracking error and overestimates the information ratio (Lee, 2000). Monthly information ratios are better indicators of the historical risk/return trade-off of a given strategy.
- *Hit ratio.* Hit ratio is the proportion of times that the manager was able to add value. It is calculated as the number of periods with positive alphas divided by the total number of periods. It does not capture the magnitude of gains or losses, so it is not an ideal metric.
- *Skewness.* James D. MacBeth and David C. Emanuel (1993) have suggested that TAA managers produce returns that are more positively skewed than the benchmark return. A positively skewed return distribution will result in a large number of results just below the mean return and several results well above the mean. To the extent that investors prefer the opportunity for large gains, positive skewness of the strategy may be desirable even if the TAA portfolio has the same average return and volatility as the benchmark portfolio.

⁶ If the committee has access to the underlying return forecasts, the following two tests can also be used. The Hendriksson-Merton measure of market-timing ability, which tests the probability of correctly forecasting that one asset class will outperform the other (Weigel, 1991; Philips et al., 1996). The main drawbacks of the Hendriksson-Merton test are that it only tests the sign and not the magnitude of outperformance and that it requires at least 100 monthly observations to have enough power to reject the null hypothesis of no market-timing skill. The Cumby-Modest test refines the Hendriksson-Merton test by taking the magnitude of outperformance into consideration, but it does not explicitly measure the variability of returns (Lee, 2000).

⁷ The t-statistic is used to test the hypothesis that the mean alpha is different from zero if the variable of interest follows normal distribution or the sample size is large, in accordance with the Central Limit Theorem. It is the arithmetic average return divided by the standard error of the arithmetic average. Standard error is volatility divided by the square root of the number of observations minus 1.

Table 1. The gross return performance of 13 U.S. TAA separate accounts, January 1985–December 2005

Metric	Average
Number of months	103.92
Average monthly alpha (%)	0.03
Monthly tracking error (%)	1.39
T-statistic	0.24
Monthly information ratio	0.02

Note: The sample included separate-account products whose processes were reported to be U.S. TAA. The product name or the process description was verified on the provider's website if it was not clear. Benchmarks are as reported by Mobius. If the manager did not report a benchmark, it was assumed to be 60% S&P 500 Index and 40% Lehman Government/Credit Bond Index. Returns are since inception and are arithmetic averages. The results pertain to 13 separate accounts that reported more than 30 monthly returns.

Sources: Standard & Poor's, Lehman Brothers, and Mobius Management Systems; authors' calculations.

- *Consider cost.* As with any investment, cost affects returns and should be evaluated. The higher the implementation and investment-management costs, the higher the threshold for the success of a TAA strategy.

TAA strategies are typically implemented with liquid futures contracts. This can be a benefit relative to security-selection strategies because transaction costs for futures trading in liquid markets are typically lower than those for trading individual securities. However, futures trading for TAA strategies requires expertise to be cost-efficient, particularly when a global TAA is implemented. For example, to maintain the benchmark position, hedging ratios must be accurately calculated. For equities, this is the process of measuring the sensitivity of changes in the futures index to changes in the benchmark. For fixed income securities, the process is more complex. In addition, global TAA and tactical subasset allocation strategies may require trading in illiquid futures markets, resulting in higher costs.

Real-time performance: setting reasonable expectations

The historical performance of TAA separate accounts helps set reasonable return expectations for these strategies. Have TAA strategies historically provided the value-added that institutional investors are looking for? Have most managers implemented rigorous methodology and produced significant excess returns?

From January 1985 to December 2005, our sample of 13 U.S. stock/bond TAA separate accounts added 3 basis points a month of excess return, on average, before taking investment-management fees into account⁸ (see Table 1). However, because of the high tracking error⁹ of 1.39% a month, this value-added was not statistically significant. A t-statistic of 0.24 suggests that the managers, on average, did not show consistent skill in identifying misvaluations. The average standard annualized information ratio¹⁰ of 0.08 is low compared with what can be achieved from the average security-selection strategy.

As part of the quest for higher returns, TAA strategies have become popular because most TAA managers predicted and benefited from the bursting of the “tech” bubble in 2000–2002. From April 2000 through December 2005, the average U.S. TAA manager added 8 basis points to the benchmark return each month. However, it is important to note that from January 1996 through March 2000 the average U.S. TAA fund lost 12 basis points a month relative to its benchmark because typical valuation measures did not work, resulting in an underweighting of U.S. equities. Another market correction that U.S. TAA strategies generally timed well was the October 1987 stock market crash, subsequent to which TAA strategies also became popular. It is important to understand and be comfortable with the time-period-dependent and generally contrarian nature of TAA returns.

⁸ We acknowledge that separate-account returns in Mobius are likely overstated because of self-reporting and survivorship bias. The actual aggregate return experience of U.S. TAA separate-account investors may be lower than that reported here. Our sample size is admittedly low. We were unable to report TAA mutual fund results since the Morningstar, Lipper, and University of Chicago Center for Research in Security Prices mutual fund databases do not have an exclusive category for TAA managers and they do not report the precise benchmark that the TAA manager tracks. This makes accurate comparison across TAA strategies unreliable.

⁹ Tracking error is the standard deviation of excess return. It is a measure of the variability and uncertainty around the excess return.

¹⁰ The annualized information ratio is the monthly information ratio times the square root of 12.

Conclusion

As we have highlighted, consistently predicting systematic risk is challenging at many levels. SAA is the critical decision, while a well-designed TAA strategy can add value at the margin. However, successful TAA requires rigorous methodology. Understanding the TAA investment process, using quantitative performance-evaluation metrics to distinguish luck from skill, and minimizing costs are essential to the success of TAA strategies.

References

- Arnett, Robert, and Todd Miller, 1997. Surprise! TAA Can Work in Quiet Markets. *Journal of Investing* 6(3):33–45.
- Asness, Clifford, 2003. Fight the Fed Model. *Journal of Portfolio Management* 30(1):11–24.
- Asness, Clifford, 1996. *Global Tactical Asset Allocation*. New York, N.Y.: The Goldman Sachs Group. (Goldman Sachs September Pension and Endowment Forum.)
- Black, Fischer, and Robert Litterman, 1992. Global Portfolio Optimization. *Financial Analysts Journal* 48(5):28–43.
- Campbell, John Y., and Samuel B. Thompson, 2005. *Predicting the Equity Premium Out of Sample: Can Anything Beat the Historical Average?* Cambridge, Mass.: National Bureau of Economic Research. NBER Working Paper No. 11468.
- Damodaran, Aswath, 2002. *Investment Valuation: Tools and Techniques for Determining the Value of Any Asset*. New York: Wiley. 992 p.
- Grinold, Richard C., and Ronald N. Kahn, 2000. *Active Portfolio Management: A Quantitative Approach for Providing Superior Returns and Controlling Risk*. New York: McGraw-Hill. 596 p.
- Lee, Wai, 1998. Risk and Return Characteristics of TAA Under Imperfect Information. *Journal of Portfolio Management* 25(1):61–70.
- Lee, Wai, 2000. *Theory and Methodology of Tactical Asset Allocation*. Hoboken, N.J.: Wiley. 159 p. (The Frank J. Fabozzi Series.)
- MacBeth, James D., and David C. Emanuel, 1993. Tactical Asset Allocation: Pros and Cons. *Financial Analysts Journal* 49(6):30–43.
- Molitor, Jeffrey S., 2004. *Evaluating Managers: Are We Sending the Right Messages?* Valley Forge, Pa.: Investment Counseling & Research, The Vanguard Group. 11 p.
- Philips, Thomas K., Greg T. Rogers, and Robert E. Capaldi, 1996. Tactical Asset Allocation: 1977–1994. *Journal of Portfolio Management* 23(1):57–64.
- The Vanguard Group, 2003. *Sources of Portfolio Performance: The Enduring Importance of Asset Allocation*. Valley Forge, Pa.: Investment Counseling & Research, The Vanguard Group. 11 p.
- Tokat, Yesim, 2005. *The Asset Allocation Debate: Provocative Questions, Enduring Realities*. Valley Forge, Pa.: Investment Counseling & Research, The Vanguard Group. 11 p.
- Weigel, Eric J., 1991. The Performance of Tactical Asset Allocation. *Financial Analysts Journal* 47(5):63–70.



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