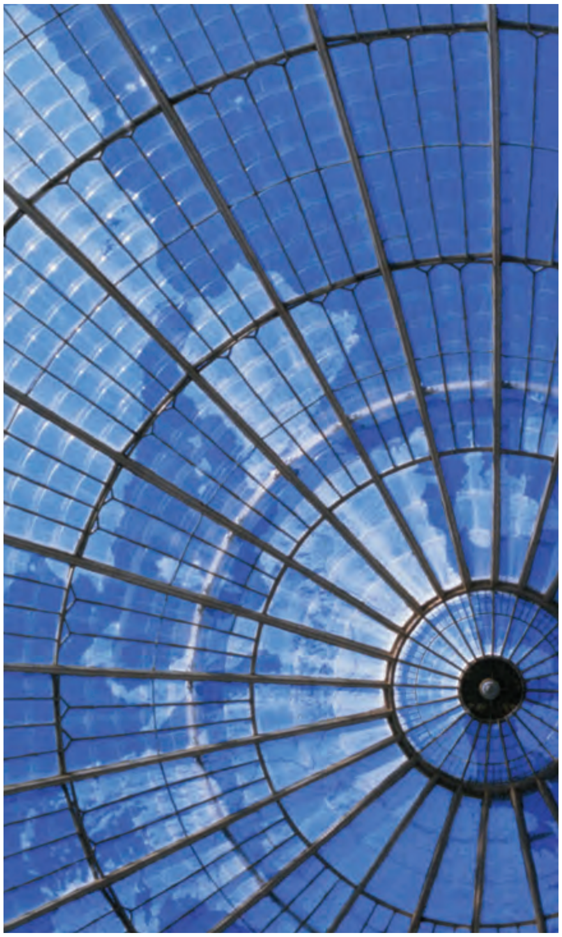

Great Expectations: Regime-Based Asset Allocation Seeks Higher Return, Lower Drawdowns

By

BNY Mellon Investment Strategy and Solutions Group[1]

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ASSET MANAGEMENT

Executive Summary

Research from BNY Mellon's Investment Strategy and Solutions Group (ISSG) has found that dynamically adjusting asset class exposures as growth and inflation *expectations* shift has the potential to significantly improve risk-adjusted returns for asset allocation strategies. Analysis of capital market returns from 1988 to 2011 showed that the ISSG's regime-based portfolio would have achieved nearly a doubling of the Sharpe ratio compared with that of a typical institutional portfolio.[2] Moreover, the ISSG's regime-based approach has the potential to provide meaningful downside protection during periods of extreme market stress, such as the bursting of the technology bubble from 2000-2002 and the global financial crisis from 2007-2009, suggesting its potential risk management utility.

The group's work highlights the potential benefits of moving away from static strategic asset allocation strategies to more opportunistic approaches that incorporate macroeconomic indicators into asset class weightings. Unlike previous research on regime-based or risk-based asset allocation, the ISSG has broken new ground on three levels. First, they developed a more granular understanding of complicated patterns of macroeconomic regimes and their effects on asset prices, especially during transition periods. More significantly, they have pointed to the importance of shifts in growth and inflation *expectations* rather than just levels for signaling regime changes. Finally, they used these insights to develop a probabilistic model to analyze growth and inflation expectations data with a view toward predicting the probability of regime changes and adjusting exposures accordingly.[3]

The following discussion specifies how the group defined macroeconomic regimes and their effects on asset class performance by analyzing 40 years of market and economic data. Against this more detailed understanding of regimes and their transitions, the team describes how it used inflation and growth expectations data to develop their model. They compare the performance of a typical institutional portfolio against that of their regime-based portfolio over the last 23 years and document the improved risk and return results for the regime-based portfolio.[4] Stress-testing their model, they look at how the regime-based portfolio would have performed in two periods of extreme market duress.

1 The Investment Strategy and Solutions Group is part of The Bank of New York Mellon, a principal banking subsidiary of BNY Mellon.
2 The typical institutional portfolio is based on Greenwich Associates data, as explained in the disclosure section. The reason for the time period chosen is explained in footnote 4. See p. 16 for performance comparison.
3 No investment strategy can predict or guarantee performance.
4 To mitigate small-sample bias that could arise from too narrow a data field, the ISSG allowed for the maximum sample for estimation prior to conducting the out-of-sample exercise for prediction. This resulted in an initial in-sample estimation period from February 1973 to February 1988 and out-of-sample period of February 29, 1988 to August 31, 2011. Data adequacy and test size and power properties were also additional parameters that dictated their sample selection process.

Having described how the ISSG model works, the team addresses different ways investors might consider implementing a regime-based asset allocation approach. These include a full-fledged implementation of an asset allocation structure that would dynamically weight asset classes based on macroeconomic views. By contrast, a partial implementation would maintain strategic portfolio weights across traditional asset classes but make shifts within specific asset classes to reflect macroeconomic views. They also weigh up the costs and benefits of adjusting asset class exposures by rebalancing or using synthetic overlays.

While the importance of asset allocation decisions on investment returns has long been documented,[5] the ISSG believes the current environment of modest expected market returns and heightened volatility requires a fresh look at asset allocation approaches. The financial crisis taught painful lessons about the limits of traditional diversification and the need to achieve a deeper understanding of the macroeconomic influences on asset class performance and correlations. The ISSG believes an asset allocation approach that is mindful of and responsive to portfolio risk factors across regimes has the potential to achieve investors' long-term return objectives while better protecting portfolios against devastating drawdowns.

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5 Gary P. Brinson, L. Randolph Hood and Gilbert L. Beebower, "Determinants of Portfolio Performance," The Financial Analysts Journal, July/August 1986.

Let No Crisis Go to Waste: Rethinking Asset Allocation Approaches

Heavy losses incurred by institutional investors during the global financial crisis of 2007-2009 have prompted a rethinking of traditional asset allocation practices. More recent market turmoil, driven by concerns over high levels of sovereign debt and flagging GDP growth, once again highlighted the intimate connection between macroeconomic conditions and asset class performance. As investors revisited assumptions about traditional asset allocation practices, diversification and asset class correlations, our goal was to help them integrate macroeconomic influences on asset class behaviors into their asset allocation strategies. Our belief was that an asset allocation structure that could dynamically overweight assets that behaved well in certain environments and underweight those that performed badly might contain greater upside potential, while protecting against significant drawdowns.

To understand the latest asset allocation challenges, we think it is helpful to remember how investor thinking has evolved. For many years, investors tended to hold equities, fixed income and cash according to their return requirements and risk tolerances. However, during the multi-decade bull market that began in the early 1980s, many investors began abandoning cash allocations as a "drag on performance." Cash allocations were increasingly replaced by a new category of uncorrelated assets lumped together as "alternatives," whether it was real estate, private equity, or hedge funds. Investors were drawn to alternatives' potential to deliver a higher expected rate of return within the same volatility target for the overall portfolio. This putative "free lunch" was based on the historical low correlation of alternatives to traditional asset classes. Notions of optimal diversification changed, as more investors turned to alternatives in lieu of cash allocations. A new asset allocation framework emerged based on three standard buckets of stocks, bonds, and alternatives. The illiquidity of many alternative asset classes was regarded as acceptable compensation for institutional investors with long-term investment horizons.

The global financial crisis changed that view, as many investors learned painful lessons about liquidity and the limits of diversification when it is needed most. The crisis has engendered a new respect for tail risk and prompted widespread soul-searching about liquidity, diversification and asset class correlations. It has not, however, significantly dampened the return expectations of many institutional investors confronted with ongoing pension fund deficits and other investment challenges.

Instead, investors are increasingly looking for ways to improve their asset allocation approaches to address tail risk and the instability of asset class correlations, without sacrificing return expectations. The goal is to understand the underlying forces that drive asset class performance and risk in order to enhance return, minimize drawdown risk and avoid reverting to low-yielding cash allocations.

This has led to a number of asset allocation frameworks that define regimes in different ways. One approach is to categorize asset classes according to their behavior across different growth and inflation regimes. According to this taxonomy, assets are organized into risk buckets consisting of growth assets, inflation-sensitive assets, and deflation-sensitive assets. Subsets of traditional asset classes can fall into multiple risk buckets depending on the underlying instrument's sensitivity to growth and inflation. For example, some types of fixed income can be categorized as growth (high yield bonds), inflation-sensitive (Treasury Inflation Protected Securities), and deflation-sensitive (U.S. Treasuries) assets. Generally speaking, these three risk buckets correspond to macroeconomic regimes that can be described much like Goldilocks' three bowls of porridge: Too Hot (inflation), Too Cold (deflation), and Just Right (growth).

Exhibit 1: The Goldilocks Model of Economic Regimes

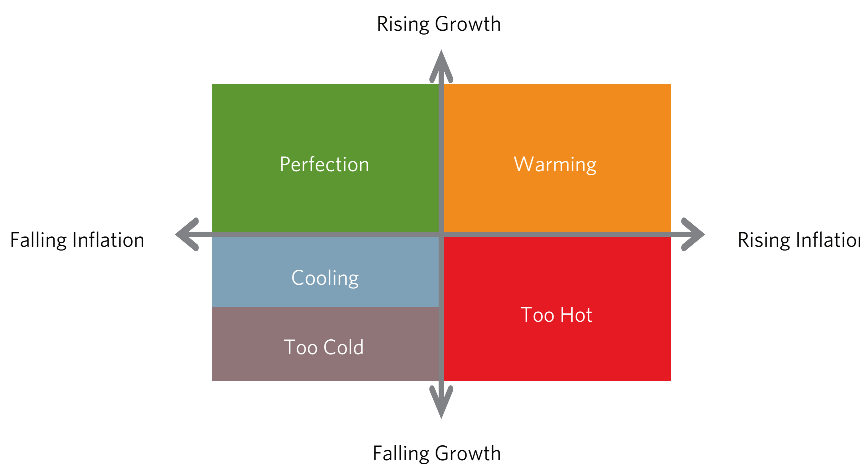
Source: ISSG

However, we believe this basic temperature scale masks important gradations between these three points, which have important implications for asset class performance. Even more misleading, in our view, is the implication, from this scale shown above, that economies heat up and cool down in a sequential, orderly process. On the contrary, our research into over 40 years of U.S. macroeconomic conditions and asset class behavior reveals a far more complex picture of how macroeconomic regimes unfold and the transitions between those regimes.

Mapping Regimes and Their Effects on Asset Prices

We believe the Goldilocks scenario of Too Hot (rising inflation choking off growth), Too Cold (falling inflation and falling growth), and Just Right (positive growth and low inflation, which encompass Warming, Cooling and Perfection subsections) regimes does not adequately capture all of the possible permutations given the two macroeconomic variables of inflation and growth. In our view, there should be a minimum of four regimes to represent the possible combinations of growth and inflation scenarios (rising and falling growth, rising and falling inflation). While four regimes depict the four possible scenarios, we think a fifth scenario, a Too Cold regime, represents a special case of the falling inflation and falling growth regime, when growth contracts sharply as in the case of economic recessions. Admittedly, it would be possible to introduce ever more dissections, but this has to be balanced with a practical need to decipher and identify regimes meaningfully.

Exhibit 2: Three Regimes to Five



Source: ISSG

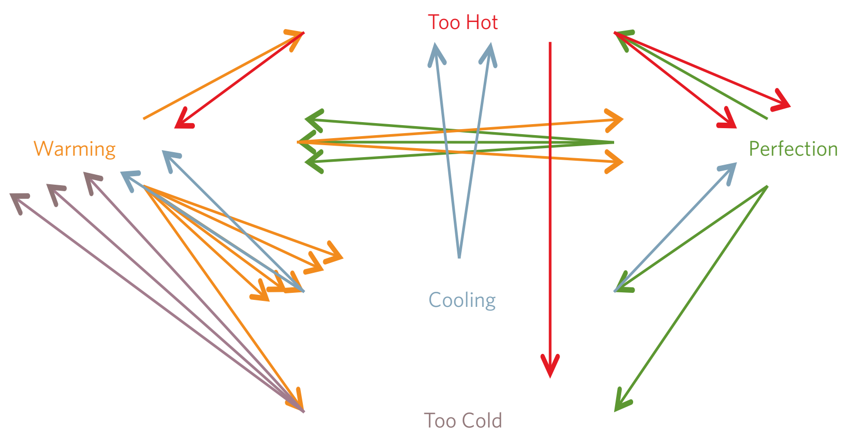
A more nuanced five-bucket framework has profound implications for understanding asset class behavior. By contrast, investors using the basic three-bucket framework might be inclined to allocate away from equities and other growth assets as GDP begins to decline. But historical data show that growth-sensitive assets can still have positive real returns even as GDP is declining (or Cooling) on average. A rules-based, three-bucket system might halt investing in growth assets as GDP begins to decline, despite the fact that there is still positive return potential for them during a Cooling period.

While growth and inflation have clear implications for asset class performance, investors recognize that changes in the price of an asset are driven by expectations about these factors, not simply the changes in level. The current price of an asset reflects an expectation of the inflation rate, real growth rate and risk premium. Changes in the price of an asset are a function of changes in expected inflation, real growth and the risk premium.

These changes in expectations can be measured in aggregate through the use of forecasted inflation and growth rates (holding the risk premium constant). CPI and real GDP data from the Survey of Professional Forecasters compiled and maintained by the Federal Reserve Bank of Philadelphia provide a long history of how real growth and inflation expectations have changed over time. As we developed our historical view of economic regimes and their transitions, we focused on changes in inflation and growth expectations as opposed to level changes in order to better align changes in asset prices with macroeconomic shifts.

In addition to tracking macroeconomic regimes according to changes in inflation and growth expectations, we believe it is also important for investors to understand the non-sequential movements across different regimes over time. Investors often think of the economy as ebbing and flowing in a neat, sequential pattern of heating and cooling. The typical picture is that of an economy Warming up, getting Too Hot, and then Cooling until the point of Too Cold. While this image is easy to understand, it does not correspond to actual experience in most macroeconomic cycles. Instead, we found a far more complex pattern of regime transitions.

Exhibit 3: Complex Transitioning Across Macroeconomic Regimes

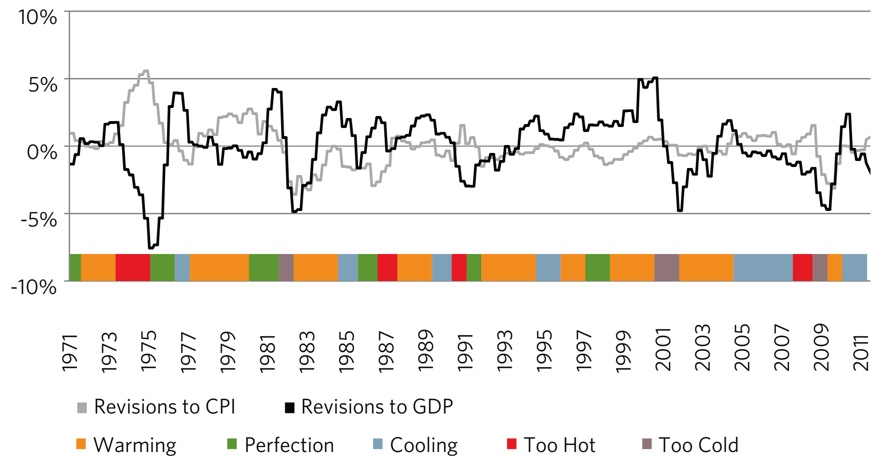


Source: ISSG

In fact, our research shows that a transition from Too Hot to Cooling has not happened in the past 40 years. The Too Hot regime has been succeeded by Perfection (rising growth and falling inflation) two of the four times it was experienced in the last 40 years. This more complex pattern of transitions presents a significant hurdle for investors, as it complicates the challenge of trying to predict the order of macroeconomic regimes. However, it does provide a richer understanding of how the economy can transition through time. Exhibit 4 shows the interaction of the year-over-year revisions[6] to expectations of growth and inflation since 1970. This helps capture a trend in investors' expectations of the macroeconomic environment.

6 See appendix for additional information.

Exhibit 4: Revisions to Expectations of Growth and Inflation since 1970



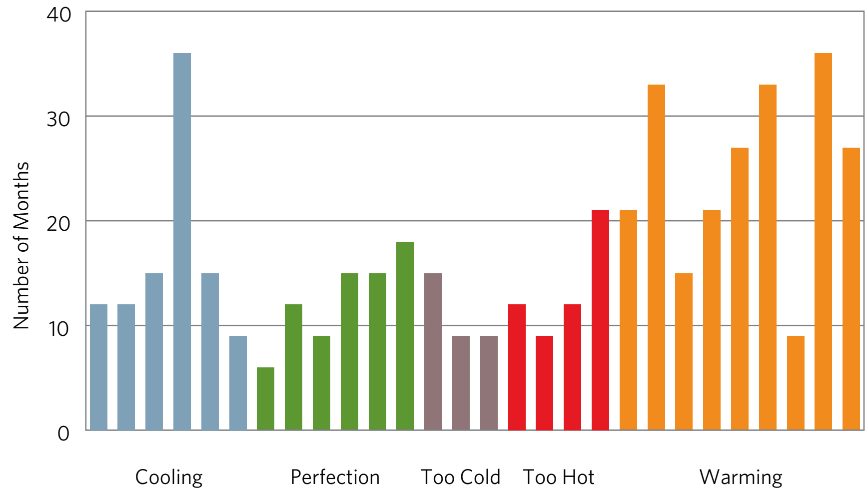
Source: ISSG & Philadelphia Federal Reserve as of 8/31/2011. Please see appendix for index descriptions

While transitions between regimes appear to be quite arbitrary, there are some discernible patterns over the last 40 years. For example, the three Too Cold regimes have been succeeded by Warming. While this experience may not hold true indefinitely, we can understand why this pattern exists. Too Cold regimes are characterized by a drastic decline in growth expectations and decreasing inflation expectations. We know that the U.S. Federal Reserve has historically combated dramatic growth declines by adding substantial stimulus to the economy in the form of lower interest rates. However, that stimulus often comes with rising real prices, a tailwind for increasing inflation expectations and thus setting the stage for a Warming regime.

The second interesting pattern is the propensity of the Warming and Cooling regimes to rotate back and forth. Again, this is intuitive as there can be extended periods of relatively benign economic activity. A third insight from our drill down into regime transitions is that the Perfection regime generally follows periods of high inflation expectations. As such, if inflation expectations are not at a relatively high level, we are unlikely to experience the best scenario for equity-like assets. Investors might use this insight to dampen the return expectations on equity-like instruments and/or allocate capital to assets that perform well in benign or increasing inflation expectation environments.

Another vital consideration for investors is that regime lengths can vary. We found that the Warming and Cooling environments (typically fairly benign) tend to last longer on average, but also exhibit a higher variance in length, while the extremes (Perfection, Too Hot and Too Cold) tend to be shorter and have more consistent duration. For example, Warming regimes averaged a length of 25 months but ranged from 9 months to 36 months. In contrast, the Too Cold regimes had an average length of 11 months and had a tighter range of 9 months to 15 months. The Too Cold regime length is the shortest on average, another example of the Fed interceding to counter the market's dramatically decreasing growth expectations.

Exhibit 5: Regimes Vary in Length



Source: ISSG

Asset prices behave differently according to investor perceptions of the coming economic regimes. U.S. equities have earned a real return of 6.0% since 1970 (see Exhibit 6). More importantly, the anticipated economic regime has had a profound effect on when that 6.0% was earned and lost. For example, equities gained a real return of 14.6% in periods of rising expectations for growth coupled with falling expectations for inflation (Perfection). Contrast this with another scenario, that of falling growth expectations and falling inflation expectations (Too Cold), in which equities returned a negative 21.6%.

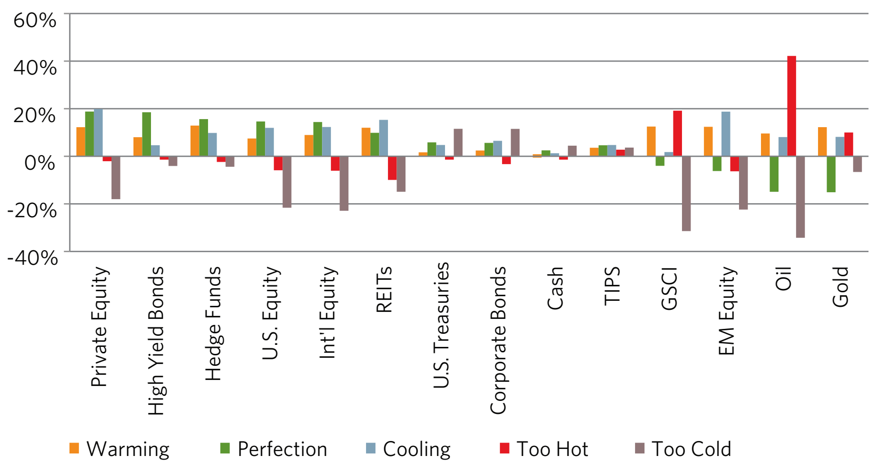
Exhibit 6: Equity Returns Across Regimes (Real, 12/31/69 - 5/31/11)

Regime	Frequency	Real Return	Contribution to Return
Warming	46%	7.5%	3.4%
Perfection	16%	14.6%	2.3%
Cooling	20%	12.0%	2.4%
Too Hot	11%	-5.9%	-0.7%
Too Cold	7%	-21.6%	-1.5%
	100%	**6.0%**	**6.0%**

Source: ISSG, Ibbotson & Bloomberg as of 8/31/2011. Returns calculated using ISSG's regimes. Please see appendix for index descriptions.

In addition to equities, we found that nearly all assets performed in a similarly intuitive fashion. For example, TIPS outperformed nominal bonds in the two scenarios of rising inflation expectations (Warming and Too Hot). Inflation-sensitive assets (such as commodities) performed best in Too Hot regimes, and they performed better in Warming regimes than Cooling. The major exception was emerging markets (EM) equities during Perfection regimes. Intuitively, emerging market equities should benefit from rising growth and falling inflation expectations; however, this was not the case in the data set analyzed. This is most likely due to the short history of emerging market indices and the fact that the Asian currency crisis occurred during one of the two Perfection regimes for which we have high-quality data for EM equities.

Exhibit 7: Asset Class Performance Across Regimes



Source: Refer to Sources for Data within the appendix for time periods. Please see appendix for index descriptions.

Building a Probabilistic Model to Predict Regimes

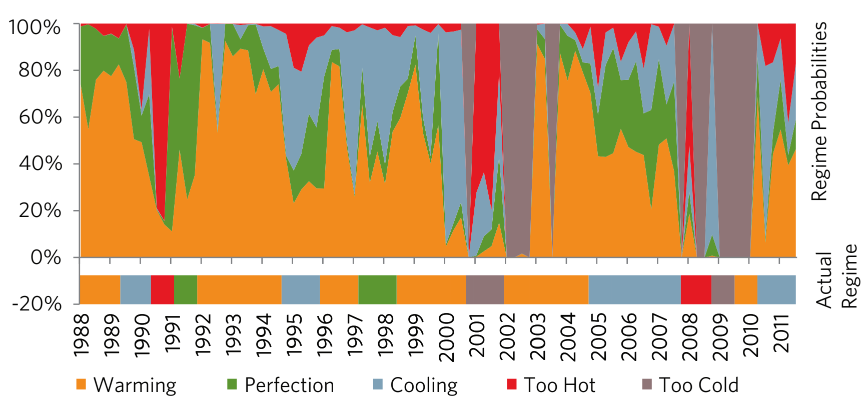
Our detailed investigation into regime durations and transitions over the last 40 years using historical series of revisions to inflation and real GDP expectations provided valuable insights into how macroeconomic regimes unfold over time. We believed we could apply these insights to identify regimes in real time, so that investors might leverage this approach on a prospective basis.

Our goal was to create a model using multinomial logistic regression[7] to help predict regime probabilities by processing new information about changing real GDP and inflation expectations and mapping that to what we already knew about the current economic regime. This would allow us to test for the probability of a certain regime, based on a set of possible variables for growth and inflation data.

The model incorporates the most recent levels and rates of change for the real GDP and inflation expectations revisions series, as well as the regime the economy was experiencing two quarters ago. It then generates a set of probabilities about which regime the economy will "choose" over the next three months. We tested the probability predictions of our model against the actual regimes that occurred based on historical data from 1988 to the end of August 2011.

In order to use this model in real time for predicting regime probabilities, we developed a procedure for re-estimating our model at each quarterly time period using only the data known up to that time period. Using the model that is estimated at any given point in time, we can produce a set of probabilities for the regime that the market will "choose" over the next quarter. It was important to avoid introducing look-ahead bias into the calculations. Using this "expanding window" approach to model estimation, the model would likely get better over time at assigning odds to the current state of the economy as it gathered more and more historical data points over which to estimate.

Exhibit 8: Regime Probabilities Through Time

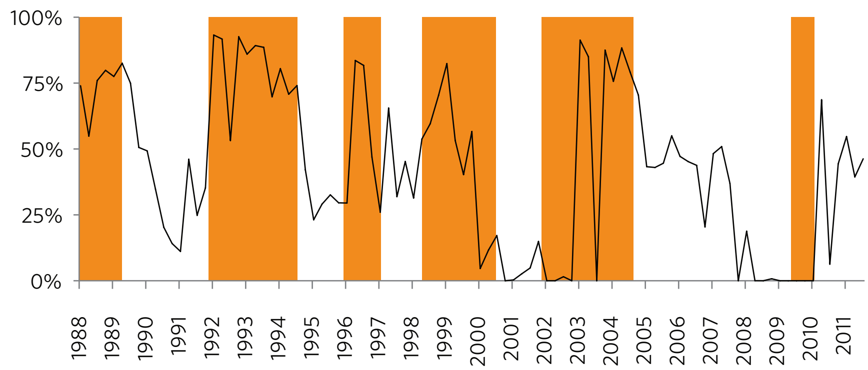


Source: ISSG

7 Multinomial logistic regression models are typically used to predict the probabilities of different possible outcomes of a predefined, dependent variable, given a set of independent variables.

Exhibit 8 shows the times series of the quarterly estimations of the regime probabilities on the top half, as well as the actual regime that was assigned to the quarter based on knowledge of the full time period (on the bottom half). The probability of a Warming regime is much higher on average than that of the other four regimes. Warming regimes prevailed in 48% of the quarters in our testing period from 1988-present (see Exhibit 9).

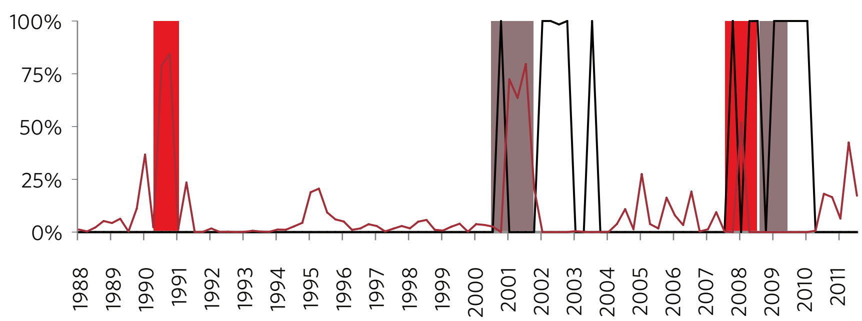
Exhibit 9: Warming Regimes: Probability vs Actual



Source: ISSG

The probabilities of Too Hot and Too Cold regimes are quite close to zero most of the time, though they periodically spike in response to large moves in revisions to the real GDP and CPI expectations data (see Exhibit 10).

Exhibit 10: Too Hot and Too Cold Regimes: Probability vs Actual



Source: ISSG

In general, our model correctly predicted the Too Cold regime as the most probable one at the appropriate times (Exhibit 10). However, as shown, it is sometimes difficult for the model to distinguish between Too Hot and Too Cold regimes, as these are both characterized by falling growth expectations.

Exhibit 11 shows the model's track record in assigning a high probability to the actual successor regime as defined by historical experience. We find that roughly 46% of the time, the regime with the highest model probability matched with the actual regime experienced. If we consider the two most probable regimes, the actual regime was captured about 68% of the time, and 88% of the time the actual regime experienced was one of the three most probable regimes. We believe that this ability to narrow the scope of the probabilities of regimes might allow us to construct portfolios that outperform traditional strategic asset allocations by adjusting to these regime shifts.

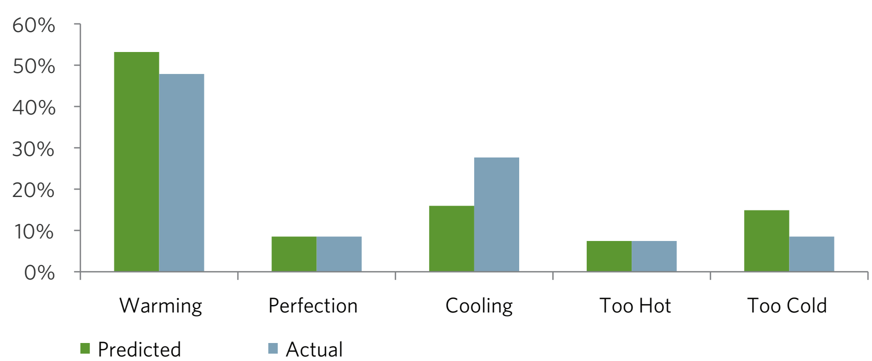
Exhibit 11: Model Predictions vs Actual Regimes Experienced

	Hit Rate	Cumulative
Highest Probability	45.7%	45.7%
2nd Highest	22.3%	68.1%
3rd Highest	20.2%	88.3%
4th Highest	6.4%	94.7%
Lowest	5.3%	100.0%

Source: ISSG

Exhibit 12 shows how often we predicted each of the five regimes to be the most probable regime, versus how often each regime actually occurred during the testing period. This was an important diagnostic for testing the model's probability estimation, since the model should be responsive to incoming data and should assign high probabilities to less likely or "tail" scenarios when warranted. We found our model performed well in this regard. It slightly overestimated the likelihoods of Warming and Too Cold regimes, while underestimating the Cooling regime, but the model assigned high probabilities to current regimes in line with their experienced frequency. This suggested that on average the model would lead to decisions in line with the historical experience of macroeconomic regimes.

Exhibit 12: Highest Probability Regime vs Actual Sample Frequency



Source: ISSG

Better Performance with Regime-Based Asset Allocation

Once we were satisfied with the reliability of our model, we could apply the regime-based asset allocation approach in real time to hypothetical portfolios and compare the performance results with those of typical institutional portfolios. To that end, we translated regime probabilities from our model into our asset allocation decisions.

The goal was to show how the model would dynamically weight six asset classes through time to seek better performance. The asset classes in the simulation were based on data from Greenwich Associates regarding the composition of typical institutional portfolios. We calculated implied weights for the typical institutional portfolio through time for six asset classes: US Equity, International Equity, Emerging Market Equity, REITs, Corporate Bonds, and U.S. Treasuries. At each portfolio formation date, we re-estimated the model and used the resultant probabilities to develop a set of expected returns and a covariance matrix that acted as inputs into our optimization process. We then formed portfolios based on a set of minimal constraints that were held for the subsequent quarter.[8]

As the data from the Survey of Professional Forecasters is released at the end of the second month of each calendar quarter, our portfolio formation dates were the last day of February, May, August, and November of each year.[9] We began by weighting the historical average returns of our six assets for each of the five regimes by the current regime probabilities. In a similar way, we also formed a covariance matrix for optimization by regime probability-weighting historical covariance data. To form expected returns for optimization, we blended these historical returns with reverse-optimized "market-implied" returns using a Black-Litterman-style Bayesian averaging process.[10] These two building blocks formed the basis for our mean-variance optimization. When solving the optimization problem, we applied a minimal set of constraints that we believed were reasonable for a typical institutional investor. We sought to maximize expected returns such that:

- Portfolio weights summed to 100%
- Positions were long-only
- Portfolio expected volatility was less than the institutional portfolios' expected volatility
- The U.S. Equity weighting was less than 75%; REITs weighting was less than 10%; Emerging Market Equity weighting less than 10%; and Corporate Bonds plus U.S. Treasuries were less than 75%. The International Equity weighting had no constraint.

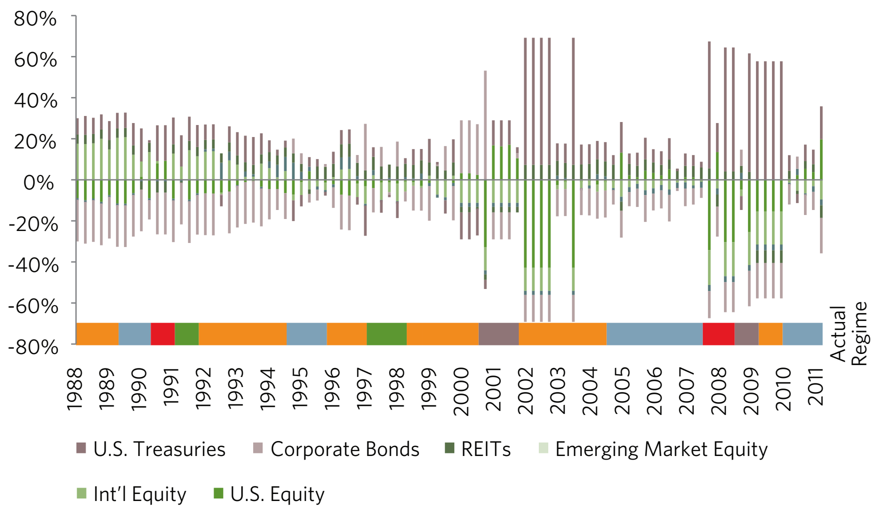
We found that our Regime-Based Asset Allocation model (RBAA) portfolio outperformed the typical institutional portfolio, having both higher annualized

8 See the appendix for additional details.
9 See the appendix for additional details.
10 The Black–Litterman model, developed by Fischer Black and Robert Litterman, starts with market equilibrium expected returns, and then modifies them to take into account the "views" of the investor in a systematic way. Bayesian Inference is a method of statistical inference in which data are used to update prior beliefs about a probability distribution to form a posterior probability estimate.

returns (9.5% vs 7.9%) and lower volatility (8.3% vs 11.5%) for the period from February 1988 to August 2011. The evolving regime probabilities allowed for timely changes in asset allocation that produced better returns during the testing period, both on an absolute and risk-adjusted basis. Our regime-based portfolio had a much higher Sharpe ratio compared with the institutional portfolio (0.67 vs 0.34) (see Exhibit 16).

Averaged over the time period, the RBAA portfolio was slightly underweight equities versus the institutional benchmark, and slightly overweight fixed income. Within equities, our RBAA portfolio had an overweight preference for REITs, and modest underweights to U.S. Equity, International Equity, and Emerging Market Equity. Within fixed income, the RBAA portfolio had a strong preference for U.S. Treasuries over Corporate Bonds, perhaps preferring to seek risk premia in equities as opposed to fixed income.

Exhibit 13: RBAA Over and Underweights vs Institutional Portfolio



Source: ISSG & Greenwich Associates

As can be seen in Exhibit 13, the quarterly allocations among the six asset classes could vary widely from these averages. The RBAA portfolio favored equities during Warming, Cooling, and Perfection periods, and dramatically de-risked when the Too Hot and Too Cold probabilities rose. U.S. Treasuries were normally the favored fixed income asset; however, during Cooling periods the RBAA portfolio often switched to Corporate Bonds.

It is interesting to note that this set of assets does not contain any that are typically expected to outperform during Too Hot periods (such as TIPS and commodities). Including those assets should lead to greater differentiation in the composition of Too Hot and Too Cold portfolios. With the six asset classes used in our sample, the RBAA portfolio has many similarities to a typical risk on/risk off portfolio, in which spiking probabilities for Too Hot and Too Cold regimes function as a signal to insulate the portfolio from equity risk. Exhibit 14 shows that over the full period, the allocation weights to equities and bonds were quite similar, but the RBAA portfolio slightly preferred bonds.

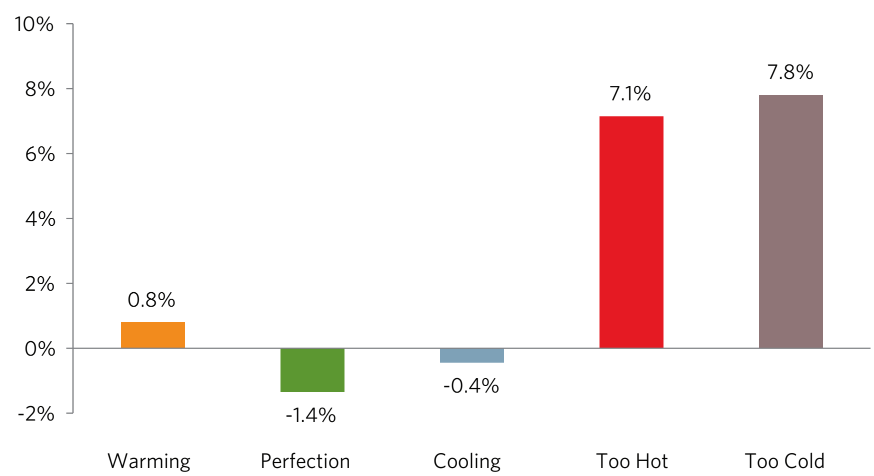
Exhibit 14: Average Weights

	RBAA Portfolio	Inst. Portfolio
Equities	**63%**	**67%**
Bonds	**37%**	**33%**
U.S. Equity	46%	51%
International Equity	8%	10%
Emerging Market Equity	1%	2%
REITS	8%	4%
Corporate Bonds	7%	17%
U.S. Treasuries	29%	17%

Source: ISSG & Greenwich Associates

In Exhibit 15 we see that during the sample period, the excess return deviations of the RBAA portfolio from the institutional portfolio were fairly modest during the Just Right economic regimes – Warming, Cooling, and Perfection. The RBAA portfolio realized the majority of its outperformance during times of stress when Too Hot and Too Cold regimes are predicted as most probable.

Exhibit 15: Excess Returns of RBAA Portfolio by Regime



Source: ISSG & eVestment Alliance

Exhibit 16 shows the performance statistics of the RBAA model portfolio compared with a typical institutional portfolio from February 1988 through to August 2011. The RBAA portfolio had roughly 1.6% better annualized performance, with volatility (annualized risk) that was about 3% less than that of the typical institutional portfolio. This resulted in an almost doubling of the RBAA portfolio's Sharpe ratio compared with that of the institutional portfolio.

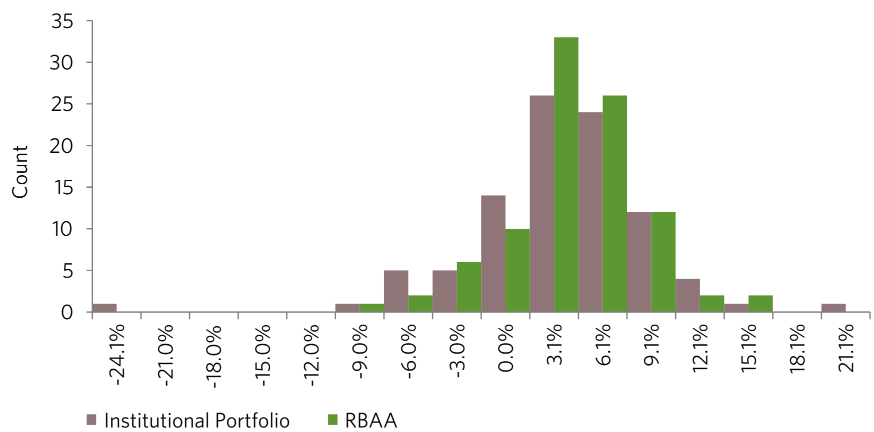
Exhibit 16: RBAA vs Institutional Portfolio Performance (Net of Fees)

	RBAA Portfolio	Inst. Portfolio
Annualized Return	9.5%	7.9%
Annualized Risk	8.3%	11.5%
Risk Free Rate	4.0%	4.0%
Sharpe Ratio	0.67	0.34

Source: ISSG. See appendix for additional information regarding fees.

Interestingly, the distribution of returns for the RBAA portfolio exhibited much more normality than that of the institutional portfolio. The tails of the distribution were truncated as shown in Exhibit 17. Statistically, the RBAA portfolio returns cannot be rejected as normally distributed, while the institutional portfolio is rejected as being normally distributed using the Jarque-Bera test for normality.[11]

Exhibit 17: Histogram: Quarterly Returns



Source: ISSG

11 The Jarque-Bera test, created by Carlos Jarque and Anil Bera, measures whether sample data have skewness and kurtosis that are consistent with a normal distribution.

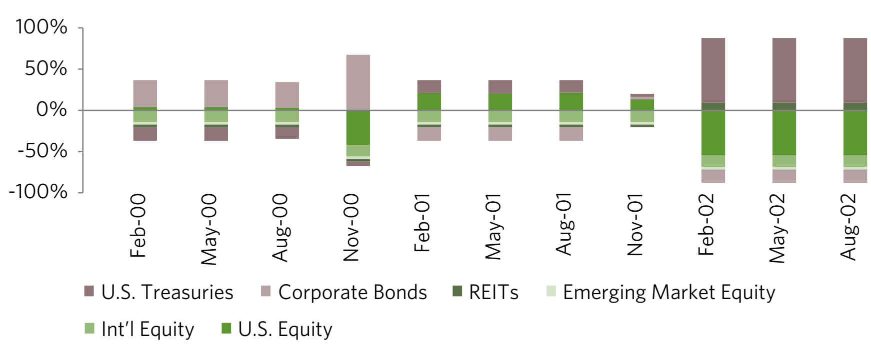
Stress-Testing the Model

To further showcase what we regard as distinctive benefits of applying a regime-based approach to asset allocation, especially during times of market stress, we highlighted our RBAA portfolio results for two particularly challenging periods in the markets, the bursting of the technology bubble in the early part of the 2000s as well as the global financial crisis of 2007-2009. We isolated those crisis periods as those are the points at which a regime-focused investor would hope to outperform relative to a buy-and-hold strategy.

Case Study 1: The Bursting of the Technology Bubble (2/28/00 to 11/30/02)

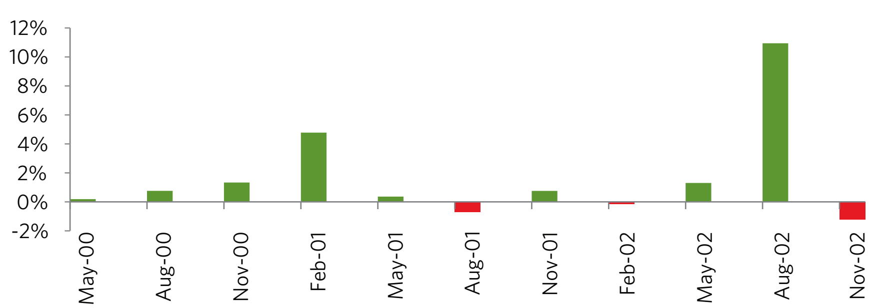
While the results overall were positive (-15.7% holding period return for the institutional portfolio versus 1.7% holding period return for the RBAA portfolio), we believed it was important to determine what drove the higher risk-adjusted returns historically. While the average weights across the regime-based portfolio and the institutional portfolio were quite similar, the dynamic nature of the regime-based portfolio was quite stark. For example, Exhibit 18 illustrates the allocation swings relative to the institutional portfolio for the tech-bubble crisis period. As shown, going into the crisis, the RBAA portfolio held a modest overweight to Corporate Bonds compared to the instititutional portfolio. By November of 2000, the RBAA portfolio increased this overweight position. As the signals became stronger that growth was slowing, a U.S. Treasuries overweight was introduced in February of 2001. A second leg down in the market was captured by investors' expectations and the probability of a second Too Cold scenario increasing under the RBAA model. The model responded and de-risked almost immediately in February of 2002, offering significant protection. Exhibit 19 shows the relative performance of the RBAA portfolio to the institutional portfolio.

Exhibit 18: Relative Asset Class Weights of the RBAA Portfolio vs Institutional Portfolio



Source: ISSG. See appendix for index descriptions

Exhibit 19: Quarterly Excess Return of the RBAA Portfolio vs Institutional Portfolio

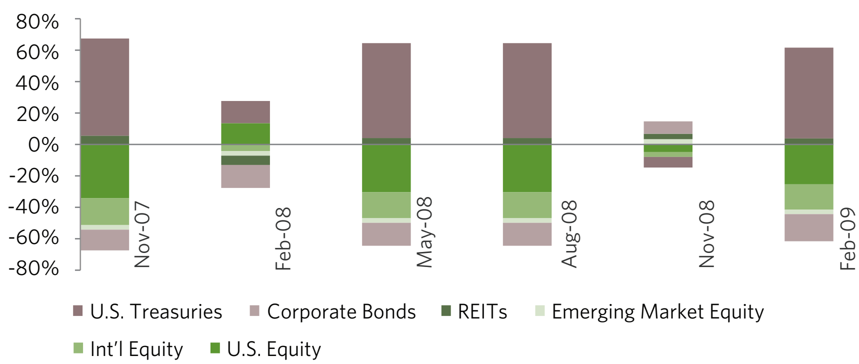


Source: ISSG

Case Study 2: The Financial Crisis (11/30/2007 to 5/31/2009)

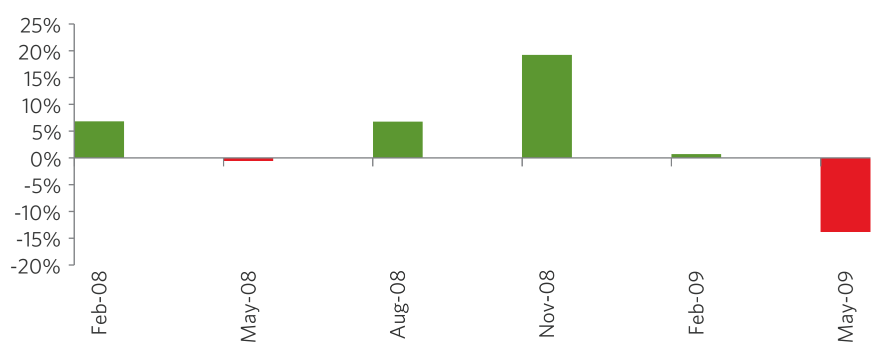
From November 2007 through May of 2009, the RBAA portfolio holding period return was -4.7% while the typical institutional portfolio holding period return was -25.6%. Exhibit 20 shows the relative asset class weights of the RBAA portfolio during that time period. Of the six quarters shown in Exhibit 21, the model had a statistically significant positive contribution to performance only half of the time. However, the protection the model provided in the dramatically down quarters for the institutional portfolio added value. In fact, the RBAA portfolio outperformed the institutional portfolio in all four negative quarters and had positive returns in two of them. However, the RBAA portfolio lagged (although still positive returns) in the quarter ended May 2009. While the RBAA portfolio had a positive result for the full period, it exhibited the characteristic of participation in up markets while protecting in down.

Exhibit 20:
Relative Asset Class Weights of the RBAA Portfolio vs Institutional Portfolio



Source: ISSG. See appendix for index descriptions

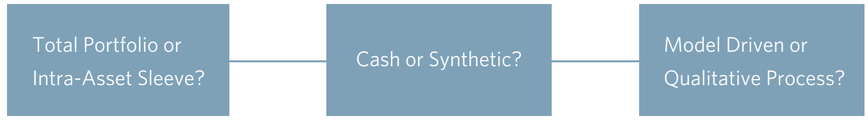
Exhibit 21: Quarterly Excess Return of the RBAA Portfolio vs Institutional Portfolio



Source: ISSG

Implementation Considerations

Exhibit 22: Implementation Questions



Source: ISSG

There are several possible ways to implement a regime-based framework in an institutional portfolio. A full convert to regime-based investing could implement an asset allocation structure that seeks to dynamically weight asset classes based on a view of the macroeconomic state. A partial adopter might choose to maintain strategic portfolio weights across the traditional asset classes (i.e., equity, fixed income, alternatives) but make shifts within asset classes to reflect a view on the macroeconomic state. For example, our research showed that within the equity sleeve, using a sector rotation strategy based on inflation and growth might perform quite well.

Another important implementation decision is whether to dynamically adjust the allocations (total portfolio or intra-asset class) by rebalancing or using a synthetic overlay strategy. In our view, there are pros and cons to each approach.

Investors with highly liquid portfolios consisting of only public securities might consider rebalancing portfolio holdings to the target regime-dependent portfolio. In normal markets, the benefit of rebalancing according to regime may outweigh the explicit transaction costs. However, in non-normal, illiquid markets this might not be possible. Additionally, an investor would need to consider other factors such as realized gains and losses, relationships with managers, or the other implicit costs of rebalancing with physical securities.

The primary benefits of adjusting allocations synthetically are speed and cost. Equity and interest rate deriviatives, for example, can be used to adjust a portfolio's equity beta or duration without disrupting the activity of underlying managers. Using derivatives to adjust portfolio exposures may be the only option for portfolios with significant holdings of illiquid investments.

Investors who are able to deploy derivatives for rebalancing face their own unique challenges, though. Investors must be able to accommodate the operational, regulatory and governance challenges of implementing a derivatives program, and sufficient liquidity for collateral must be allocated to the positions. Further, there may be signficant basis risk between an investor's holdings and the derivative instruments with which he is able to adjust his portfolio exposures.

For example, in anticipation of a Warming or Too Hot regime, an investor might want to increase the portfolio's sensitivity (i.e., beta) to inflation and inflation surprises. The investor may already hold an allocation to private real asset investments with an adequate inflation surprise beta, but it is unlikely that he would be able to deploy sufficient private capital in time to raise the portfolio's overall inflation sensitivity. So, to increase the portfolio's allocation to real assets, the investor could turn to derivatives, based on commodity indices. Over a short or medium horizon, these indices might not have the inflation surprise sensivity required due to the tendency of commodity-related assets to, at times, exhibit growth-like characteristics.

In our view, the efficacy of a regime framework for asset allocation will be affected by the active managers within a portfolio. An investor contemplating when to over- or underweight a manager relative to his strategy's strategic weight in the asset allocation structure should be aware of the regimes in which the strategy should be poised to outperform.

Finally, investors should consider the relative benefits of a model-driven process (state probability estimates combined with an optimization process, along the lines of what we developed) versus a qualitative process. Quantitative processes have the advantage of consistency, while avoiding behavioral biases. Qualititative processes might allow investors to retain a larger degree of oversight. We believe there is value from both, and think that a skilled investor with a good model framework by which to frame the issue might offer the best option.

Conclusion

We believe incorporating macroeconomic changes into asset allocation structures in a dynamic way might improve overall performance. Our RBAA portfolio demonstrated the potential for improving risk-adjusted returns over time compared with more static institutional approaches to strategic asset allocation. More importantly, given the devastating losses suffered from the unexpected convergence of asset class correlations during the financial crisis, we believe regime-based asset allocation has the potential to become a powerful risk management tool during times of market stress. At the very least, understanding how changes in growth and inflation can affect specific asset prices and correlations should enable investors to better recognize the potential risks in their portfolios. Amid general expectations of protracted market volatility and uncertainty as the global economy endures historic rebalancing, we believe traditional approaches to strategic asset allocation with limited flexibility to adjust to regime shifts might be at a disadvantage. A new era in financial markets seems to suggest that a more opportunistic approach should be considered.

BNY Mellon's Investment Strategy & Solutions Group would like to thank David Chapman, Director, Risk Management, at Catholic Healthcare Investment Management Company for his extensive collaboration with the regime-based asset allocation research project as well as his thoughtful review of and helpful suggestions for this white paper.

Appendix

To test the goodness of fit for the multinomial logistic regression approach in predicting regimes, we estimate the coefficients of our model using the statistical software package R. As Warming is the most frequent regime, we use this as the baseline or reference category for the model estimation. Thus, coefficients must be estimated for 5 independent variables and an intercept for each of the 4 remaining regimes, for a total of 24 coefficients. Over the full time period, we find that the model is highly statistically significant, with 21 of the 24 estimated coefficients being significant at a 10% or better level, with a model p-value of 2 x 10-16 and a Pseudo- or McFadden R2 of 0.35. Academic literature suggests that a value for this statistic of 0.2 to 0.4 implies strong explanatory power.

RBAA portfolio formation proceeds as follows:

- Using data from Greenwich Associates, we calculate implied weights for a typical institutional portfolio through time for our six asset classes: US Equity, International Equity, Emerging Market Equity, REITs, Corporate Bonds, and US Treasuries. Our data on these allocations begins in 1990 and is updated every five years through 2005, and then every year for 2006-2010. The 1990 weights are applied to 1988 and 1989 as well, and the 2010 weights are used for 2011. We use these weights as our implied "market" portfolio.
- The model was initially estimated based on the period from February 1973 to February 1988, which was the first hypothetical portfolio formation date. At each quarter thereafter, the model coefficients were re-estimated with all of the data that was available up to that point in time. Our testing period began with the first portfolio formation date of February 29, 1988 and ended with the last portfolio formation date of May 31, 2011 (i.e., returns were measured through August 31, 2011).

Historical quarters up to two quarters before the portfolio formation date are grouped by regime. Mean excess returns are calculated for each asset class in each historical regime. A covariance matrix of the excess returns is also calculated for each regime, where the covariances are shrunken with a Bayesian estimation technique toward the covariance with the typical institutional portfolio as defined in the disclosure section. The mean return vectors for each of the five regimes are weighted in accordance with the probabilities from the multinomial logistic regression model to form an expected return "view" for each asset.

$$\mu_{view} = \sum_{i=1}^{5} \mu_i * prob(i)$$

Likewise, the regime covariance matrices are blended according to the probabilities from the multinomial logistic regression model.

$$V_{regime} = \sum_{i=1}^{5} V_i * prob(i)$$

This probability-weighted covariance matrix is in turn blended with the sample covariance matrix for all periods from 1973-portfolio formation date, shrunken to the market portfolio.

$$V_{opt} = .6 * V_{regime} + .4 * V_{sample}$$

Using this covariance matrix, we reverse-optimize a set of market implied expected returns for each of our asset classes using the following formula:

$$\mu_{mkt} = \lambda * V_{opt} * x_{mkt}$$

Where:

$$\mu_{mkt} \coloneqq Market\ Implied\ Expected\ Return$$

$$\lambda{:=} \frac{Market\ Risk\ Premium}{Variance\ Market\ Portfolio}$$

$$V_{opt}{:=} Estimated\ covariance\ matrix\ of\ risky\ assets$$

$$x_{mkt} \coloneqq Market\ or\ Institutional\ Portfolio\ weights$$

We use these reverse-optimized expected returns in conjunction with the regime probability weighted historical excess returns as inputs to a Black-Litterman-style Bayesian estimation of posterior expected returns.

$$\mu_{opt} = \mu_{mkt} + Q * P^T * (P * Q * P^T + \Omega)^{-1}(\mu_{view} - P * \mu_{mkt})$$

Where:

$$\mu_{view} \coloneqq The\ regime\ probability\ weighted\ views$$

$$\mathrm{P} \coloneqq \begin{matrix} An\ NxN\ identity\ matrix\ indicating\ that\ we\ have\ one\ absolute \\ view\ for\ each\ asset\ return \end{matrix}$$

$$\mathrm{Q} \coloneqq \begin{matrix} The\ NxN\ confidence\ matrix\ associated\ with\ the\ reverse \\ optimized\ expected\ returns \end{matrix}$$

Q is a scalar multiple of V_{opt}.

$$\Omega \coloneqq \begin{matrix} The\ NxN\ diagonal\ confidence\ matrix\ associated\ with \\ the\ historical\ return\ views \end{matrix}$$

Ω is a scalar multiple of the diagonal of V_{opt}.

The resultant posterior expected return vector μ_{opt} is used as an input to our optimization process, along with V_{opt} , our expected covariance matrix. We solve a constrained mean-variance optimization problem to choose portfolio weights at each portfolio formation date. We apply a minimal set of constraints that we believe are feasible for the typical institutional investor:

$$\max_x \ \mu^T x$$

$$\text{s.t. } \mathbf{1}^T x = 1$$

$$x(i) \geq 0$$

$$x^T * V_{opt} * x \leq x_{mkt}^T * V_{opt} * x_{mkt}$$

$$x_{S\&P} \leq 0.75,\ x_{REIT} \leq 0.10, x_{EM} \leq 0.10,\ x_{CORP} + x_{TREAS} \leq 0.75$$

Sources for Data and Charts:

Asset Class Name	Index	Start	End
U.S. Equity	S&P 500 Index (Total Return)	12/31/1969	8/31/2011
International Equity	MSCI EAFE (Total Return)	12/31/1970	8/31/2011
Hedge Funds	HFRI Fund Weighted Composite	1/31/1990	8/31/2011
Private Equity	Cambridge Associates Private Equity Returns	3/31/1986	3/31/2011
High Yield Bonds	CSFB High Yield Index	12/31/1985	8/31/2011
REITs	FTSE EPRA/NAREIT U.S Real Estate Equity Index (Total Return)	12/31/1971	8/31/2011
U.S. Treasuries	Barclay Capital US Aggregate Treasury Total Return Index	1/31/1973	8/31/2011
Corporate Bonds	Barclay Capital US Aggregate Investment Grade Corporate Total Return Index	1/31/1973	8/31/2011
Cash 1	Citigroup 3 Month Treasury Bill Local Currency Index	2/28/1978	8/31/2011
Cash 2	St. Louis Federal Reserve Bank3-Month Treasury Bill: Secondary Market Rate	12/31/1971	2/28/1978
TIPS	ISSG TIPS Simulation	1/31/1972	8/31/2011
GSCI	S&P GSCI Total Return Index	1/31/1973	8/31/2011
EM Equity 1	MSCI Emerging Markets Index (Total Return)	12/31/1987	8/31/2011
EM Equity 2	S&P IFC Emerging Markets Data	1/31/1976	12/31/1987
EM Equity 3	Regression based on MSCI EAFE Index	2/28/1973	1/31/1976
Oil 1	Nymex Crude Futures	3/31/1983	08/31/2011
Oil 2	Spot Oil	12/31/1969	3/31/1983
Gold 1	Comex Gold Futures	1/31/1975	08/31/2011
Gold 2	Spot Gold	12/31/1969	01/31/1975
CPI	CPI Urban Consumers (seasonally adjusted)	12/31/1969	7/31/2011
(Real) GDP	US Real GDP (seasonally adjusted)	12/31/1969	6/30/2011
CPI Revisions	Survey of Professional Forecasters / Federal Reserve Bank of Philadelphia	12/31/1969	8/31/2011
GDP Revisions	Survey of Professional Forecasters / Federal Reserve Bank of Philadelphia	12/31/1969	8/31/2011

- S&P 500 Index is considered to be generally representative of the U.S. large capitalization stock market as a whole. It is an unmanaged capitalization-weighted index of 500 commonly traded stocks designed to measure performance of the broad domestic economy through changes in the aggregate market value of those stocks. The index assumes reinvestment of dividends.
- The MSCI EAFE index is widely accepted as a benchmark for international stock performance (excluding the United States and Canada), and measures the performance of the developed stock markets of Europe, Australia, and the Far East (EAFE). The index is an aggregate of 22 individual country indexes that collectively represent many of the major markets of the world. The index series includes only markets, companies, and share classes available to foreign investors. It is designed to maximize float and liquidity, minimize cross-ownership, and accurately reflect the market's total size, industry composition, and size of stock. The index is calculated on a total return with the percentage change in price plus actual coupon income making up the total return. The index is rebalanced monthly.

- HFRI Fund Weighted Composite Index is an equally weighted performance index of fund of hedge funds selected by HFR. The index includes both onshore and offshore fund of funds, which invest across the spectrum of hedge fund strategies. There are no minimum asset sizes or operating history constraints. All underlying funds report returns net of fees and in US dollars. HFR, as a business practice, does not reveal of the names of participant funds.
- Cambridge Associates Private Equity Returns- Please refer to the Proprietary Benchmarks page of the Cambridge Associates website at www.cambridgeassociates.com for additional information.
- The CSFB High Yield Index, compiled by Credit Suisse First Boston, measures high-yield debt securities, which are often referred to as "junk bonds."
- The FTSE EPRA/NAREIT U.S. Real Estate Equity Index Series is designed to provide the most comprehensive assessment of overall industry performance, and includes all tax-qualified real estate investment trusts (REITs) that are listed on the New York Stock Exchange, the American Stock Exchange and the NASDAQ National Market List. The index constituents span the commercial real estate space across the US economy and provide investors with exposure to all investment and property sectors.
- Barclay Capital US Aggregate Treasury Total Return Index is a broad-based benchmark that measures the performance of US Treasury Securities with greater than one year to maturity. The index was launched on January 1, 1973.
- Barclay Capital US Aggregate Investment Grade Corporate Total Return Index is a broad-based benchmark that measures the investment grade, fixed-rate, taxable, corporate bond market. It includes USD-denominated securities publicly issued by U.S. and non-U.S. industrial, utility, and financial issuers that meet specified maturity, liquidity, and quality requirements. Securities in the index roll up to the U.S. Credit and U.S. Aggregate Indices. The index was launched on January 1, 1973.
- The Citigroup 3 Month Treasury Bill Local Currency Index is designed to track the returns of 3 month U.S. Treasury securities
- The St. Louis Federal Reserve Bank 3-Month Treasury Bill: Secondary Market Rate comes from the Board of Governors of the Federal Reserve System's Selected Interest Rates – H.15 report. The value for each month is the average daily rate on 3-Month Treasury Bills for that month.
- TIPS returns were simulated by the ISSG using breakeven inflation rates from the United Kingdom, Ten-Year Treasury Yields, and Survey of Professional Forecasters data from the Federal Reserve Bank of Philadelphia. They are intended to represent hypothetical returns for a constant maturity 10 year TIPS total return index.
- S&P GSCI index is a composite index of commodity sector returns representing an unleveraged, long-only investment in commodity futures that is broadly diversified across the spectrum of commodities. The returns are calculated on a fully collateralized basis with full reinvestment.
- MSCI Emerging Markets Index (EM) is a capitalization-weighted benchmark designed to measure global emerging equity market performance and is calculated on a total return basis with dividends reinvested.
- S&P IFC Emerging Market indices are broad market indicators that measure the widest possible opportunity set of investable stocks in eachemerging market.
- NYMEX Oil is an index blend of several U.S. domestic streams of light sweet crude oil with physical delivery.
- COMEX Gold is an index of 100 troy ounces of gold with physical delivery.
- CPI Urban Consumers (seasonally adjusted) –All Urban program produces monthly data on changes in the prices paid by urban consumers for a representative basket of goods and services.
- GDP measures the final value of goods and services produced in the US economy on a quarterly basis. Chain weighted (Real) GDP measures the value of goods and services at constant dollar prices. This date is compiled by the Bureau of Economic Analysis.
- The Federal Reserve Bank of St. Louis is one of the 12 regional reserve banks in the Fed System.
- The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American

Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990. The forecasted annual CPI inflation and GDP growth are an aggregation of the forecasted values for each of the next four quarters.

- These benchmarks are broad-based indices which are used for comparative purposes only and have been selected as they are well known and are easily recognizable by investors. Comparisons to benchmarks have limitations because benchmarks have volatility and other material characteristics that may differ from the portfolio. For example, investments made for the portfolio may differ significantly in terms of security holdings, industry weightings and asset allocation from those of the benchmark. Accordingly, investment results and volatility of the portfolio may differ from those of the benchmark. Also, the indices noted in this presentation are unmanaged, are not available for direct investment, and are not subject to management fees, transaction costs or other types of expenses that the portfolio may incur. In addition, the performance of the indices reflects reinvestment of dividends and, where applicable, capital gain distributions. Therefore, investors should carefully consider these limitations and differences when evaluating the comparative benchmark data performance. The indices are trademarks and have been licensed for use by The Bank of New York Mellon Corporation (together with its affiliates and subsidiaries) and are used solely herein for comparative purposes. The foregoing index licensers are not affiliated with The Bank of New York Mellon Corporation, do not endorse, sponsor, sell or promote the investment strategies or products mentioned in this presentation and they make no representation regarding advisability of investing in the products and strategies described herein.
- A real return is the return on an investment, less the reduction in its value as a result of inflation.
- The RBAA portfolio and typical institutional portfolio returns are based on simulations using various index returns. Investors cannot invest in an index. Indices are unmanaged, and are not subject to management fees, transaction costs or other types of expenses that a portfolio may incur. As an illustration of these fees, returns are shown net of 50 basis points (bps) on all assets. The following provides a simplified example of the cumulative effect of management fees on investment performance. An annual management fee of 50 bps applied over a five-year period to a $100 million portfolio with an annualized gross return of 10% would produce a 9.5% annual return and reduce the value of the portfolio from $161 million to $157 million.

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Typical institutional portfolio data is based on a survey compiled by Greenwich Associates on average asset allocations for Corporate, Public, and Endowment & Foundation plans covering the period from 1990-2009. The ISSG applied the 1990 weights to 1988 and 1989 as well, and used the 2010 weights for 2011.

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