

Dynamic Allocation or Diversification: A Regime-Based Approach to Multiple Assets

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Peter is head of research at ANNOX, a Danish quant hedge fund. He is performing postdoctoral work on dynamical systems in the department of applied mathematics and computer science at the Technical University of Denmark, in collaboration with Lund University. His research focuses on detection of regime shifts in financial time series, methods for estimating statistical models with time-varying parameters, and development and implementation of dynamic asset-allocation strategies. Prior to joining ANNOX, he completed an industrial PhD at the Technical University of Denmark in collaboration with Danish pension fund Sampension and Lund University. The topic of his dissertation was dynamic asset allocation with a focus on identifying regime shifts in financial time series to build robust portfolios.

Peter is a financial engineer and holds a BS in mathematics and technology and an MS in mathematical modeling and computation with honors from the Technical University of Denmark.

Overview

In **Dynamic Allocation or Diversification: A Regime-Based Approach to Multiple Assets**, published in the 2017 special multi-asset-class issue of *The Journal of Portfolio Management*, **Peter Nystrup, Bo William Hansen, Henrik Olejasz Larsen, Henrik Madsen, and Erik Lindström** investigate a dynamic asset-allocation strategy based on increasing exposure to risky assets during periods of low volatility and decreasing exposure to risky assets during periods of high volatility. The signal to change allocation comes from a regime-switching model based on the MSCI World Index. The strategy uses a “hidden Markov model” to detect changes from a regime of high volatility to low volatility and vice versa.

The authors test their model-driven dynamic strategy over the period from 1997 through 2015. They conclude that their strategy outperforms a benchmark strategy of 60% equities and 40% fixed income. They further conclude that the optimal implementation of their strategy is to overlay it on the benchmark strategy and to apply the dynamic approach to roughly 80% of the total portfolio. Implementing the strategy on 80% of the total portfolio produces the highest Sharpe ratio.

Practical Applications

- **Dynamic asset allocation using a regime-switching model can outperform a basic 60/40 asset allocation.** The regime-switching mechanism provides signals for increasing or decreasing exposures to risky assets.



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Bo is head of investment analysis at Danish pension fund Sampension, where he is responsible for the department's overall input for strategic asset allocation, risk management, and performance analysis. Prior to joining Sampension he worked on risk management and macroeconomic modeling for the Danish Central Bank, Nationalbanken. Bo holds an MA in economics from the University of Aarhus and an MS in commerce from the University of New South Wales.

“The intention is to identify high- and low-volatility regimes in the stock returns using a regime-switching model and let the asset allocation depend on the identified regime.”

—*Dynamic Allocation or Diversification*

- **The regime-switching mechanism is fully automated to produce signals based solely on market data.** It is calibrated and tested based on signals generated over a sample spanning 19 years.
- **The dynamic allocation strategy can be combined with a strategic 60/40 strategy by implementing the dynamic strategy on a specified proportion of total assets.** Implementing the dynamic strategy on 80% of total assets produced the highest Sharpe ratio over the period 1997–2015.

Practical Applications Report

The authors examine a dynamic asset-allocation strategy and compare it to a strategic asset-allocation strategy of 60% equities and 40% fixed income. The dynamic strategy calls for a “risk-on” posture (i.e., increasing exposure to equities) during periods of low volatility. Conversely, it calls for a “risk-off” posture (i.e., decreasing exposure to equities) during periods of low volatility. As shown in the following table, the portfolios comprise 10 assets, with the proportions of each adjusted depending on the state of the market (high or low volatility) and the proportion of total assets deployed in the dynamic strategy.

Ten Indexes and Their Weights in Different Allocations*							
	Index	60/40		Risk-On*		Risk-Off*	
Equity Portion	1. MSCI World (stocks)	25.0%	60%	33.3%	80%	12.5%	30%
	2. MSCI EM (stocks)	5.0%		6.7%		2.5%	
	3. FTSE/EPRA REIT (real estate)	10.0%		13.3%		5.0%	
	4. High-Yield Bonds (credit)	5.0%		6.7%		2.5%	
	5. EM High-Yield Bonds (credit)	5.0%		6.7%		2.5%	
	6. S&P GSCI Crude Oil WTI (commodity)	5.0%		6.7%		2.5%	
	7. S&P GSCI Gold (commodity)	5.0		6.7%		2.5%	
Fixed Income	8. Corporate Bonds Inv Grade (fixed income)	10.0%	40%	5.0%	20%	17.5%	70%
	9. Inflation-Linked Bonds (fixed income)	10.0%		5.0%		17.5%	
	10. JPM Global GBI (fixed income)	20.0%		10.0%		35.0%	

* Assumes that 50% of total assets are deployed in the dynamic asset-allocation strategy while the remainder stay in the 60/40 allocation.



Key Definitions

Asset allocation

Asset allocation is the process of allocating portions of an investor's portfolio to different asset classes to optimize performance based on the investor's objectives, time horizon, and risk appetite. An example of an asset allocation is a "60/40 portfolio" consisting of 60% stocks and 40% bonds.

Strategic asset allocation

In strategic asset allocation, investment managers seek to construct durable, but static, "all-weather" portfolios that optimize efficiently across a range of economic scenarios.

Hidden Markov Model

A hidden Markov model is a statistical model that attempts to detect unobservable states of an underlying system based on other facts that are observable. The underlying system is assumed to follow a Markov process, meaning that its future state does not depend on how it arrived at its current state. For example, the financial markets may be viewed as having two alternative states: low volatility and high volatility. The states are not directly observable, but they can be inferred (to a specified level of certainty) by using observations of asset prices or returns.

DYNAMIC SIGNALS: THE HIDDEN MARKOV MODEL

The signal to switch from a risk-on allocation to a risk-off allocation or vice versa is based on whether the market is in a state of high or low volatility. The state of the market is not directly observable. The strategy calls for inferring it from observable data on the returns of the MSCI World Index. The actual mechanism takes the form of a "hidden Markov model."

The hidden Markov model assumes that the state of the market follows a Markov process, meaning that its future state does not depend on how it arrived at its current state. However, calibration of the model uses the complete time-series data in a way that captures the sequence of observations. By giving more weight to recent observations, the calibration exercise seeks to account for the fact that key model parameters could vary over time.

Part of calibrating the hidden Markov model is selecting a confidence threshold for producing a signal. Using a lower confidence threshold allows for the rapid production of a signal following a regime change (i.e., a shift from low volatility to high volatility or vice versa). However, a lower confidence threshold will produce more false signals. At the chosen calibration, the median delay for detecting a regime change was 25 days.

The authors' final calibration of the hidden Markov model detects 34 regime changes over a period of 18 years. The length of regimes varied from a few weeks to four years.

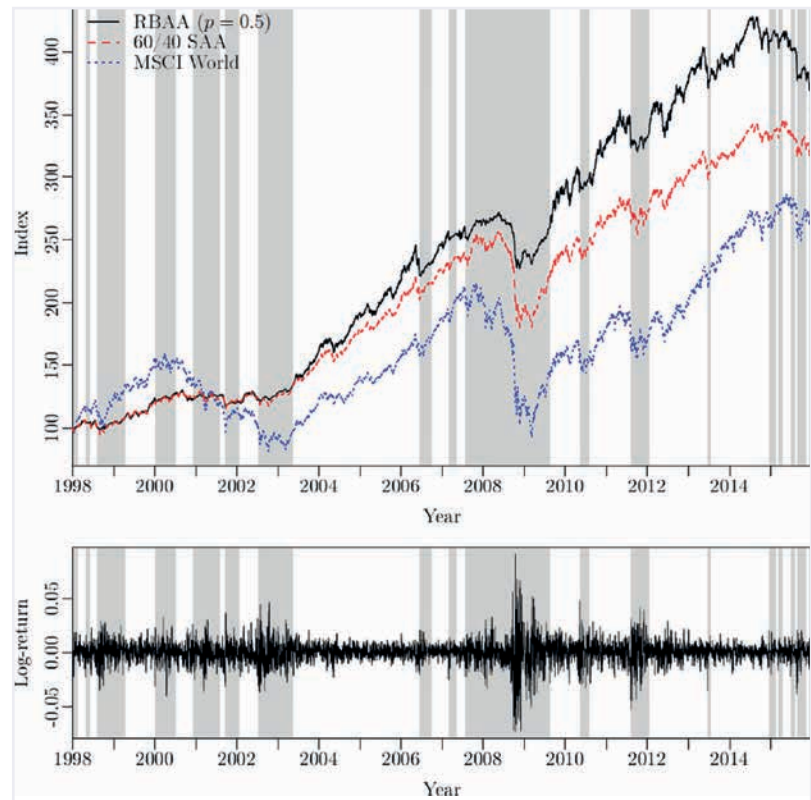
THE RESULTS

The authors tested their strategy of regime-based asset allocation (RBAA) at varying levels of deployment from 0% (corresponding to the basic 60/40 allocation) to 100%. They found that returns increased consistently as the level of deployment increased. By contrast, they found the least variability of returns at approximately 50% deployment. The Sharpe ratio—capturing both the level of returns and variability—was highest at a deployment level of roughly 80%.

BROADER IMPLICATIONS

The authors conclude with the important observation that the advantage of RBAA depends critically on how effectively regime changes can be detected. The familiar caveat that "past performance is not an indicator of future results" seems to hover, unstated. RBAA's ability to outperform from 1998 through 2015 is undoubtedly impressive. However, it relies on the fiction that the

Results of RBAA Strategy at 50% Deployment vs. 60/40 Allocation and MSCI World Index



Note: The legends are sorted according to the index values at the end of 2015; p is the percentage of the portfolio that is allocated to the RBAA strategy. In the shaded, high-volatility periods, the allocation was risk-off.

“The purpose of RBAA is not to predict regime changes or future market movements, but to identify when a regime change has occurred and then benefit from persistence of equilibrium returns, volatilities, and correlations to take advantage of favorable regimes and reduce potential drawdowns.”

—*Dynamic Allocation
or Diversification*

world can be sufficiently described in terms of two states and that the mechanism by which it changes from one state to another is relatively stable. Of course, it is impossible to tell whether those assumptions will be valid over the long run.

The ability to exploit the RBAA strategy also may depend on whether many market participants embrace it as a superior alternative to 60/40. If so, the trade might become crowded, causing its advantages to be squeezed.

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Henrik is a professor of mathematical statistics at the Technical University of Denmark, with a special focus on stochastic dynamical systems. His main research interest is related to analysis and modeling of stochastic dynamical systems. This includes signal processing, time-series analysis, identification, estimation, grey-box modeling, prediction, optimization, and control. The applications are mostly related to energy systems, informatics, environmental systems, bioinformatics, biostatistics, process modeling, and finance.

Henrik has authored or co-authored approximately 500 papers and 12 books. His most recent books are *Time Series Analysis* (Chapman and Hall/CRC, 2008); *Introduction to General and Generalized Linear Models* (Chapman and Hall/CRC, 2010); *Integrating Renewables in Electricity Markets* (Springer, 2013), and *Statistics for Finance* (Chapman and Hall/CRC, 2015). Henrik received a PhD in statistics from the Technical University of Denmark in 1986.



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Erik is a professor at the Centre for Mathematical Sciences at Lund University. He earned his MS in engineering physics in 2000 and his MA in business and economics in 2001, followed by a PhD in mathematical statistics in 2004, all from Lund Institute of Technology (LTH)/Lund University. Erik has a great interest in teaching; he is part of the LTH Pedagogical Academy and was appointed an Excellent Teaching Practitioner (ETP) in 2013.

Erik's research ranges from statistical methodology to financial mathematics and problems related to the energy markets, and he has published extensively in each of these fields. His most recent book is *Statistics for Finance* (Chapman and Hall/CRC, 2015).