Dynamic Allocation Based On Market Regime

**Monica Whiteside**

Zephyr Analytics

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# Abstract

This paper presents a comprehensive methodology for identifying and forecasting latent financial market regimes using Hidden Markov Models (HMMs). Our approach begins with the construction of a feature set that captures both momentum and volatility across multiple time horizons, two factors widely recognized in the literature for their predictive capacity in market behavior (Jegadeesh & Titman, 1993; Corsi, 2009). The HMM is configured with multivariate Gaussian emissions to model these features, allowing the system to infer unobserved market states over time. Following state inference, regime sequences are evaluated for stability using transition metrics to ensure robust classification. Forecasting is performed by propagating the inferred state through the model’s transition dynamics, yielding a probabilistic outlook over a forward horizon.

To enhance the practical utility of these regime classifications, we perform hierarchical clustering on recent regime sequences across assets, revealing groups of assets that behave similarly under market conditions. These clusters are used to structure the portfolio construction process, where we aggregate forecasted regime probabilities and apply category-based weight adjustments to form a diversified and regime-aware portfolio. This multi-layered approach is grounded in prior research on regime-switching models (Hamilton, 1989; Ang & Bekaert, 2002) and has been demonstrated to outperform static asset allocation strategies, particularly in non-stationary market environments (Maheu & McCurdy, 2000; Guidolin & Timmermann, 2007).

By integrating statistical modeling, stability diagnostics, forecast propagation, and cluster-based asset grouping, this framework provides a comprehensive tool for understanding and acting on market regimes. The result is a principled, interpretable system for allocation decisions that adapts to the evolving dynamics of financial markets.

# Introduction

Financial markets are inherently dynamic, driven by a confluence of economic forces, behavioral patterns, and structural changes that evolve over time. Traditional asset pricing models often assume stationarity or linear relationships that fail to capture the abrupt shifts and persistent trends observed in empirical market data. In response to these limitations, regime-switching models—particularly Hidden Markov Models (HMMs)—have emerged as powerful tools for modeling the latent structure of financial time series.

This paper introduces a comprehensive methodology for identifying and forecasting latent financial market regimes using HMMs applied to engineered features that reflect momentum and volatility across multiple time horizons. These features are selected for their strong empirical and theoretical foundations in capturing market dynamics, as shown in the works of Jegadeesh and Titman (1993) and Corsi (2009). By treating market regimes as unobservable states and price-derived features as observable emissions, the HMM provides a probabilistic framework for detecting structural changes in the financial environment.

Our approach extends beyond static regime classification by incorporating forward-looking forecasts, cluster-based regime similarity analysis, and a disciplined portfolio construction mechanism. We first infer regime sequences across assets using a Gaussian HMM, followed by hierarchical clustering of recent state sequences to detect cross-sectional behavioral similarities. These clusters serve as the foundation for aggregating regime forecasts and assigning asset weights in a regime-aware portfolio. To manage downside risk and ensure robustness, we implement rule-based filters based on directional confidence, structural validation, and technical confirmation.

The contributions of this study are threefold. First, we propose a scalable HMM-based regime detection pipeline tailored to financial markets, with built-in diagnostics for state stability and interpretability. Second, we introduce a method for clustering assets by regime behavior, enabling structured diversification and enhanced allocation discipline. Third, we demonstrate that integrating regime forecasts into portfolio construction improves performance over static or naively diversified strategies, particularly in non-stationary or turbulent market conditions.

By combining theoretical rigor with practical implementation, this paper aims to advance the use of probabilistic regime modeling in financial decision-making. The framework is designed to be modular, interpretable, and adaptable to various asset classes, offering a robust foundation for dynamic asset allocation in the presence of latent market structure.

# Literature Review

The empirical modeling of financial markets has long acknowledged the presence of structural shifts and time-varying dynamics that challenge the assumptions of linear, stationary models. In response, researchers have turned to regime-switching frameworks—most notably Hidden Markov Models (HMMs)—to capture unobservable state transitions that manifest through observable financial indicators such as returns and volatility.

## Regime-Switching Models in Financial Markets

The foundational work by Hamilton (1989) introduced Markov-switching models as a means to model business cycles via latent economic states. This approach has since become instrumental in financial time series analysis, enabling models to capture nonlinear dynamics associated with bull and bear markets, volatility clustering, and macroeconomic shifts. Extending this framework, Ang and Bekaert (2002) incorporated regime-switching into international asset allocation models, demonstrating that accounting for regime transitions improves the explanatory power of time-varying risk premia.

Guidolin and Timmermann (2007) further advanced this line of research by applying multivariate regime-switching models to asset allocation. Their findings confirmed that accounting for structural shifts enhances portfolio performance, particularly in environments characterized by economic uncertainty or market stress. These works collectively motivate the use of HMMs in our framework, where market regimes are treated as latent states inferred from engineered financial features.

## Volatility and Momentum as Informative Features

Momentum and volatility are two of the most widely studied empirical phenomena in asset pricing and serve as the backbone of our feature construction. Jegadeesh and Titman (1993) documented the persistence of return momentum, providing evidence that past winners tend to outperform losers in the medium term—a pattern inconsistent with weak-form market efficiency and indicative of latent market structure. Volatility, likewise, has been shown to exhibit long memory and clustering. Ding, Granger, and Engle (1993) found that absolute returns and volatility exhibit autocorrelation across multiple time horizons, suggesting the presence of underlying regimes that govern risk.

To model the persistence and long-range dependence in volatility, Corsi (2009) proposed a heterogeneous autoregressive (HAR) framework. His approach captures realized volatility across multiple time scales and has proven to be both theoretically sound and practically effective. These insights inform our use of multiscale volatility measures, normalized for comparability, to enhance the HMM’s capacity for regime separation.

## Hidden Markov Models and Extensions

While traditional HMMs assume geometric state durations, extensions such as Hidden Semi-Markov Models (HSMMs) have been developed to address more flexible state persistence. Bulla and Bulla (2006) explored HSMMs in the context of financial time series, demonstrating improved modeling of stylized facts such as heavy tails and volatility clustering. Although our implementation focuses on standard Gaussian HMMs, we incorporate stability diagnostics to guard against unrealistic transition frequencies—an indirect response to the duration limitations highlighted in this literature.

From a practical perspective, HMMs have been effectively applied to pattern recognition and financial forecasting. Lo, Mamaysky, and Wang (2000) utilized HMMs to detect technical patterns in price series, validating the use of probabilistic models over rule-based heuristics. Similarly, Maheu and McCurdy (2000) applied HMMs to identify bull and bear markets in asset returns, finding superior performance compared to GARCH-based methods. These studies support the viability of HMMs as a statistical engine for real-world financial modeling.

## Forecasting, Risk Management, and Implementation

The practical utility of regime inference lies in its ability to inform forward-looking portfolio decisions. Mitra and Mitra (2011) emphasized the role of dynamic state-based forecasts in guiding asset allocation under uncertainty. Their work aligns with our use of probabilistic regime forecasts, which are aggregated and filtered to produce robust portfolio weights. Our approach builds on this literature by integrating unsupervised clustering to identify structural commonalities among assets and applying directional risk filters to improve portfolio resilience.

# Data and Descriptive Statistics

This section outlines the structure and characteristics of the data used for training and evaluating the Hidden Markov Model (HMM). The dataset consists of both market-based and macroeconomic inputs, transformed into features designed to capture regime-relevant information such as trend persistence, return volatility, and monetary policy stance.

## Data Sources

The market data comprises daily adjusted closing prices for a selection of exchange-traded funds (ETFs), downloaded using the yfinance Python library. Adjusted prices are used to ensure that dividends, splits, and other corporate actions are reflected in the return series. The sample spans multiple market cycles and includes a diverse set of asset classes to support robust regime modeling.

For the ETF portfolio assets where selected to represent a global macro portfolio ex global currency.

For the stock portfolio assets criteria was that the portfolio needed to be split evenly across US and non-US stocks, the company needed to have IPO at least 10 years ago, and the Market Capitalization needed to be greater than 10 billion. Include non-stock assets for further diversification throughout all cycles.

To incorporate macroeconomic context, the Effective Federal Funds Rate (EFFR) is added to the dataset. This short-term interest rate, sourced from the Federal Reserve Economic Data (FRED) under the symbol DFF, serves as a proxy for monetary policy and provides important information about the prevailing economic environment.

## Feature Engineering

The model uses three engineered features:

Momentum: Calculated as the average of compounded returns over multiple time horizons (typically 3, 6, 9, and 12 months). This feature captures medium-term trend strength and is commonly associated with market persistence or reversals.

Volatility: Measured as the standard deviation of daily returns over a rolling window, typically 21 trading days. This captures recent market risk and uncertainty, and helps distinguish between stable and turbulent market phases.

Short-Term Rates: The Effective Fed Funds Rate is included as a third feature to reflect the monetary policy regime. Unlike the market-derived features, this macroeconomic variable is not transformed, allowing its original scale to be preserved for interpretability.

All features are aligned at a daily frequency, forward-filled to handle missing values, and cleaned to remove any invalid entries or extreme gaps.

## Normalization and Dataset Splitting

To ensure stable training of the HMM, the momentum and volatility features are normalized using a z-score transformation, which scales each feature to have zero mean and unit variance. The short-term interest rate is left unscaled so that its real-world magnitude can be interpreted directly in downstream analysis.

The final feature matrix is divided into training and testing sets based on a configurable split ratio. Typically, 80% of the data is reserved for training the model, while the remaining 20% is used for out-of-sample inference and evaluation. This structure ensures that the model is not overfitted to recent trends and can generalize across unseen data.

# Methodology

This section outlines the empirical framework used to identify and forecast latent market regimes using a Hidden Markov Model (HMM). The methodology integrates statistical modeling, engineered financial features, and regime-based inference to create a robust tool for market state classification and forward-looking investment decision-making.

## Model Architecture

The central component of this framework is a Gaussian Hidden Markov Model (HMM), which assumes that observed financial features—momentum, volatility, and short-term interest rates—are generated by a sequence of unobserved, discrete market regimes. Each regime is associated with a multivariate normal distribution over the observed features, while regime transitions follow a first-order Markov process. This structure enables the model to infer hidden states over time and generate probabilistic forecasts of future regime behavior.

## Model Initialization and Training

To initialize the HMM, k-means clustering is applied to the training feature matrix. The resulting centroids are used to seed the mean vectors of the Gaussian emissions, and within-cluster variances provide initial estimates for the covariance matrices. This improves the convergence behavior of the Expectation-Maximization (EM) algorithm used for training.

Model training proceeds using the EM algorithm, which iteratively alternates between:

Expectation Step (E-Step): Estimating the posterior probabilities of latent regimes given the observed features.

Maximization Step (M-Step): Updating the model parameters (transition probabilities, means, and covariances) to maximize the expected likelihood.

Training continues until the change in log-likelihood across iterations falls below a predefined threshold, indicating convergence.

## State Inference and Forecasting

Once trained, the HMM is used to infer the most likely sequence of regimes that generated the observed data. This is done using the Viterbi algorithm, which efficiently computes the optimal hidden state path based on model parameters and the input sequence.

In addition to backward-looking inference, the model also supports forward-looking regime forecasting. Given the last known state, the model propagates regime probabilities forward using the learned transition matrix. This results in a probability distribution over possible future states at a given forecast horizon (e.g., 21 trading days). These regime forecasts serve as the input to the portfolio construction process.

## Regime Labeling

After the HMM is trained and the latent state sequence is inferred, a post-processing step assigns interpretable economic labels—**Bearish**, **Neutral**, and **Bullish**—to the model’s hidden states. This is achieved using the z-score of average momentum returns within each state.

For each inferred state, the average momentum value is computed based on the observations assigned to that state. These average returns are standardized using z-scores to enable consistent ranking across states. States are then sorted from lowest to highest standardized return, and labels are assigned accordingly:

The state with the lowest z-score is labeled **Bearish**

The middle-ranked state is labeled **Neutral**

The highest is labeled **Bullish**

This process ensures that the latent states correspond to intuitive market conditions based on directional strength.

If fewer than three states are present (e.g., due to model constraints or over-clustering), the function gracefully handles the shortfall by assigning multiple labels to the same state or defaulting all labels to the only available state. This guarantees that all three regime categories are always represented, which is essential for downstream applications like forecast aggregation and portfolio construction.

The result is a robust, rule-based regime labeling system that transforms abstract latent states into interpretable market signals grounded in asset momentum.

Model Validation and Stability Checks

To ensure that the HMM is capturing stable and meaningful regimes, we evaluate its transition stability by calculating the average frequency of state changes. Models that switch too frequently are flagged as unstable and retrained with different initialization. This helps to avoid overfitting to short-term noise and ensures that inferred regimes align with coherent economic behavior.

# Risk Management

To begin the risk management, process a threshold is set based on forecasted future bearish probability anything beyond the threshold was removed from the portfolio.

Assets are first constrained by the cluster they are grouped in with the clusters being ranked on bullish discount basis by subtracting bearish probability from bullish probability. If the difference was less than zero it was replaced with zero. The same constraint was applied to the assets within the cluster. These constraint were utilized for cases where both bullish and bearish sentiment were high and neutral was low to remove error on simply focusing on bullish probability.

# Results

# Discussion

For all portfolios the importance focused on mix of assets having enough assets to create distinct clusters of significance during any overall market regime.

Initial testing began with only two features momentum and volatility. First test of this approach did prove effective at mitigating risk from the portfolio due to the poor quality of the model. An economic indicator of the Effective FED Funds Rate was added to the feature set to test whether a third variable that was not non-market related. Initial tests showed significant improvement over just momentum and volatility as shown in FIGURE REF demonstrating the models ability to overcome issues with shorter unexpected trends instead of longer-term trend based states.

When

# Conclusion

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# Appendix A: ETF Indices

**Equities:**

**Global Regions:**

* US Growth, S&P 900 Growth Index
* US Value, S&P 900 Value Index
* Developed ex US Growth, MSCI EAFE Growth Index
* Developed ex US Value, MSCI EAFE Value Index
* Emerging, FTSE Emerging Markets All Cap China A Inclusion Index

**Global Sectors:**

* Communication Services, S&P Global 1200 Communication Services Index
* Consumer Discretionary, S&P Global 1200 Consumer Discretionary Index
* Consumer Staples, S&P Global 1200 Consumer Staples Index
* Energy, S&P Global 1200 Energy Index
* Financials, S&P Global 1200 Financials Index
* Health Care, S&P Global 1200 Health Care Index
* Industrials, S&P Global 1200 Industrials Index
* Materials, S&P Global 1200 Materials Index
* Information Technology, S&P Global 1200 Information Technology Index
* Utilities, S&P Global 1200 Utilities Index

**Real Assets:**

* Gold, LBMA Gold Price PM
* Commodities, DBIQ Optimum Yield Diversified Commodity Index ER
* US Real Estate, MSCI US Investable Market Real Estate 25/50 Index
* Ex-US Real Estate, S&P Global ex‑U.S. Property Index

**Bonds:**

**Cash:**

* U.S. Treasury short-term maturity index

**US Treasuries:**

* U.S. Treasuries with 1–3 year maturities
* U.S. Treasuries with 3–7 year maturities
* ICE U.S. Treasury 7–10 Year index
* ICE U.S. Treasury 10–20 Year index
* ICE U.S. Treasury 20+ Year index

**Global Bonds:**

* Bloomberg U.S. Aggregate Float Adjusted Index
* Bloomberg Global Aggregate ex‑USD Float Adjusted RIC Capped Index
* J.P. Morgan EMBI Global Core Index