Dynamic Allocation Based on Market Regime

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Contents

[Abstract 3](#_Toc201482916)

[Introduction 4](#_Toc201482917)

[Literature Review 5](#_Toc201482918)

[Regime-Switching Models in Financial Markets 5](#_Toc201482919)

[Volatility and Momentum as Informative Features 6](#_Toc201482920)

[Hidden Markov Models and Extensions 7](#_Toc201482921)

[Forecasting, Risk Management, and Implementation 7](#_Toc201482922)

[Algorithm Composition 8](#_Toc201482923)

[Test Portfolio Composition 9](#_Toc201482924)

[Global Macro ETF Portfolio 9](#_Toc201482925)

[Global Macro Stock Portfolio 9](#_Toc201482926)

[Data and Descriptive Statistics 10](#_Toc201482927)

[Data Sources 10](#_Toc201482928)

[Feature Engineering 10](#_Toc201482929)

[Normalization and Dataset Splitting 11](#_Toc201482930)

[Methodology 12](#_Toc201482931)

[Model Architecture 13](#_Toc201482932)

[HMM Model 13](#_Toc201482933)

[Rolling Training Window 14](#_Toc201482934)

[Model Initialization and Training 14](#_Toc201482935)

[State Labeling 15](#_Toc201482936)

[State Inference 15](#_Toc201482937)

[State Forecasting 16](#_Toc201482938)

[Model Tuning 17](#_Toc201482939)

[Risk Management 18](#_Toc201482940)

[Results 18](#_Toc201482941)

[Discussion 18](#_Toc201482942)

[Conclusion 19](#_Toc201482943)

[References 20](#_Toc201482944)

[Appendix A: ETF Indices 22](#_Toc201482945)

# 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 the use of scaled 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 the 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.

Add in risk parity research

Add in Meb Faber’s and Paul Tudor Jone’s work on simple moving average

# Algorithm Composition

The base theory lies in the ability to hedge away all or majority of risk while maintaining exposure above expectations providing greater risk adjusted returns. The starting principles begin with using hierarchical clustering of state sequences over a sixty three day time horizon, sixty days was selected after testing parameters which provided a sharpe ratio of 3.12 over using one hundred and twenty six days which was only able to achieve a 2.42 sharpe ratio this proved that shortening the sequence lookback to have more recency gives the hierarchal clustering better ability to group assets based on the previous quarter rather than the last half year.

Assets that are most similar to each other in sequences are then clustered with upper and lower bound caps on the allowable number of clusters to be decided.

When constructing the portfolio from the clusters this process begins with selecting the top assets based on propagated forward bullish sentiment using the HMM transition matrix and current state probabilities. Sixty three trading days which represents three months of trading data is utilized for the length of sequences that the hierarchical clustering model will cluster with.

Then all the assets within each cluster are weighted based on vanilla risk parity, with returns being discounted to the risk-free rate of return. This was utilized to have a current market effect on the equation of returns as well as improve the explanatory power of returns for the risk parity weighting. Such that each asset is weighted based on risk contribution to the cluster itself. Following this the clusters are then vanilla risk parity weighted among themselves. This process further reduces risk, at the level of assets that are clustered together will have a unit risk among themselves and at the portfolio level each cluster will have unit risk among themselves.

# Test Portfolio Composition

To test the model a diversified mix of assets was necessary to demonstrate asset selection and differentiation by the model. As well as improving risk adjusted returns across the business cycle and overall market regime.

## Global Macro ETF Portfolio

This portfolio was constructed to match that of a global macro portfolio utilizing ETFs for ease of use and asset class representation. Each asset class was broken down by global world region where possible and then further categorized by type. Bonds represent the largest portion of assets with exposure to aggregate, treasuries, corporates, high yield, long duration U.S. treasuries, and cash like instruments. Real assets are represented first by regional real estate, and then commodities broken down into categories of energy, agriculture, industrial metals, and physical gold. Equities are represented first by regional and then into value and growth divisions, and then by global sectors, with the only region not being represented by value and growth division was emerging markets due to a lack of options available.

## Global Macro Stock Portfolio

The stock portfolio used for testing has composition when it comes to bonds and real assets, but instead of using regional and sector ETFs individual stocks are utilized in their place. The stock selection criteria is as follows, the portfolio was split evenly across US and non-US stocks, the companies selected needed to have IPO dates at least 20 years ago, and the Market Capitalization needed to be greater than 10 billion. Selection size

# 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.

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 1, 3, 6, and 9 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. For purposes of this model a range between 50% to 80% splitting was implemented to test the ability of the model to inference future states based on the trained model. This structure contributes to ensuring 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.

To initialize the parameters for a state-based model, we began by extracting a subset of features—specifically, Momentum, Volatility, and Short Rates—from the training dataset. These features were used as inputs to a K-means clustering algorithm with a predefined number of clusters (equal to the number of model states), using the k-means++ initialization method and a fixed random seed for reproducibility. The K-means algorithm assigned each data point to a cluster, producing both the cluster labels and the corresponding cluster centroids, which were used as initial state means.

To compute the initial covariance structure, we estimated a diagonal covariance matrix for each state based on the data points assigned to that cluster. For each cluster, if it contained more than one data point, the feature-wise variances were computed across those points and a small constant (1e-4) was added to each variance value to ensure numerical stability and avoid singularities. In cases where a cluster contained only a single point, the global variance across all training data was used instead, with the same constant added.

## Model Architecture

### HMM Model

This framework centers on a Gaussian Hidden Markov Model (HMM), which models observed financial features—such as momentum, volatility, and short-term interest rates—as outputs generated by a latent sequence of discrete market regimes. The model assumes that at each time step, the market occupies one of several hidden regimes, each characterized by a distinct multivariate normal distribution over the observed features.

The HMM operates under two core assumptions. First, the current hidden state (or regime) depends only on the previous state, following a first-order Markov process. Second, the observed features at each time step are conditionally independent of past observations and states, given the current state. This structure enables the HMM to capture both temporal dependencies and cross-sectional patterns in the financial data.

To train the model, it employs the Expectation-Maximization (EM) algorithm, which iteratively estimates the most likely sequence of hidden regimes (via the Forward-Backward algorithm) and optimizes the model parameters—namely, the transition probabilities between regimes and the parameters of the Gaussian emission distributions. Once trained, the model can infer the most probable regime at each time step and forecast future regime probabilities based on observed data.

By mapping each regime to a distinct statistical profile of the features, the HMM provides a probabilistic framework for identifying market conditions such as high-volatility bear markets, low-volatility bull markets, or transitional periods. This regime identification supports downstream tasks such as asset allocation, risk management, and scenario analysis.

### Rolling Training Window

The model uses a rolling training window to continuously adapt to evolving market conditions. After initial testing revealed that financial regimes exhibit structural shifts over time, the team implemented this approach to prevent the model from becoming anchored to outdated patterns. Instead of training the HMM on a fixed historical dataset, the rolling window approach retrains the model on a fixed-length slice of the most recent data at each time step.

This process ensures that the model remains responsive to new information and reflects the most current market dynamics. As each new observation becomes available, the window shifts forward, discarding the oldest data point and incorporating the latest one. This mechanism effectively balances model stability with adaptability, enabling the HMM to adjust its regime definitions and transition probabilities in response to emerging trends, shocks, or structural breaks in the data.

By constantly refreshing the training data, the rolling window helps the model avoid overfitting to past regimes and enhances its ability to detect and respond to regime shifts in real time.

## Model Initialization and Training

To initialize the Gaussian HMM, K-means clustering is applied to the training feature matrix. The resulting cluster 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 the Gaussian HMM model.

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 Labeling

To assign semantic labels to the hidden states identified by the model, a rule-based mapping was employed based on the average momentum associated with each state. Specifically, the time series of inferred states was analyzed from the training data and computed the mean momentum represented by the *Momentum* feature for each unique state. The momentum values were then standardized using z-scores to facilitate a relative comparison across states. The states were ranked according to their z-scored mean returns, and labels were assigned in order of increasing return: *Bearish* to the state with the lowest average momentum, *Neutral* to the intermediate one, and *Bullish* to the state with the highest.

This labeling strategy ensures interpretability by aligning statistical properties of the data with economically meaningful labels. A model warmup period was implemented to ensure that all states are present before beginning to train, this ensured that algorithm has all necessary states to complete the next processes.

State Inference  
Once the Hidden Markov Model (HMM) is trained, it is used to infer the most probable sequence of latent regimes (or hidden states) that could have produced the observed data. This step is crucial for understanding how the underlying dynamics evolve over time. The inference is typically performed using the Viterbi algorithm, a dynamic programming technique that computes the single most likely sequence of hidden states given the observed sequence and the trained model parameters (transition probabilities, emission probabilities, and initial state distribution). The Viterbi algorithm operates efficiently by recursively maximizing the likelihood of state paths, avoiding the exponential complexity of brute-force enumeration.

After obtaining this optimal state path, each numerical state index in the sequence is mapped back to its corresponding labeled regime using the state labels learned during training. These labels provide semantic meaning to the inferred states for this model state labels are "bullish," "bearish," or "neutral" market regimes. This mapping enables interpretable analysis of the state dynamics over time, making it possible to examine regime durations, transitions, and their alignment with external events or predictive features.

## State Forecasting

This process involves projecting the future state distribution of a Hidden Markov Model (HMM) over a fixed time horizon, specifically 21 time steps ahead (1 trading month). It begins with the current posterior state probabilities, which represent the likelihood of being in each latent state at the most recent observation. These probabilities are then propagated forward using the model's state transition matrix. By raising the transition matrix to the 21st power, the model simulates the cumulative effect of transitions over that period. The current state probability vector is then multiplied by this powered matrix to produce a forecasted probability distribution across all hidden states. This resulting vector captures the model’s belief about the system’s state composition 21-time steps into the future, reflecting the stochastic evolution governed by the learned transition dynamics.

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.

# Model Tuning

Based on testing the model will need to have its parameters tuned to a time period no shorter than four years’ worth of data to have the best fit. Issues observed were that if tuned over a longer time period than 4 year then the model loses explanatory power for the more recent datapoints as it is trying to fit for the entire period. This is similar to the rolling training window which should be fit based on the entire available time window. Retuning parameters should occur regularly either every quarter or every year, but no more than a year. It is foreseen that most parameters will not change to have the best explanatory power, but it is assumed that certain variables will adjust based on currently changing market dynamics.

As there are cross parameter interactions certain parameters will absolutely need to be tuned together. Specific to clustering “min\_clusters”, “max\_clusters”, and “max\_assets\_per\_cluster” will all need to be tuned together as they have interactions within each other on the overall outcome.

Moving average tuning:

Within the model itself is a tuning pipeline that when run will set a configurable file with the best fit moving average per asset. Upon original testing having a “one size fits all” approach failed to have to the best outcomes and so a better approach was implemented to tune each asset and set a moving average individually.

# Risk Management

Simple Moving Average (SMA)

Risk Parity Weighting Assets

Stop Loss

# Results

Based on a multiple regression analysis of the data these variables demonstrate poor explanatory power for certain types of assets FIGURE REF. Bonds most notable demonstrate

* When adding in other economic variables there were issues with multicollinearity interacting with momentum.
* Non-significant p-values for certain items at times.
* Could adding these macro data items help? Such as TLT and 20+y yield.

Are the findings so far significant enough?

What about correlation selection based on greatest momentum and remove hierarchical clustering? Adding this as an alternative?

# Discussion

Holding constant clustering parameters throughout the initial testing phase showed that even with being a hybrid model of utilizing a simple moving average, momentum based on propagated forward state probabilities, and risk contribution weighting that some systemic market risk is not able to be hedged away.

(Quantify through asset clusters and selection based on market regime.)

The demonstrated the differentiation power that would be expected this was demonstrated through the use of ETFs and individual stocks representing the same breakdown of equities.

The model is able to build a diversified portfolio effectively through clustering based on recency of state sequences.

# 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