

Analysis and Forecast of Leading Sector Rotation in the US Stock Market for 2026

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Abstract:

Sector rotation is central to equity allocation because relative industry performance changes with macro conditions, volatility, and investor risk appetite. This study examines the U.S. equity market with monthly data from January 2007 to December 2025 and models the joint dynamics of market variables and five clustered sector groups through a three-state MSIH(3)-VAR(1) framework. The sample combines the S&P 500, VIX, unemployment, credit spreads, an economic growth factor, and industry return clusters constructed from 49 Fama-French industries. Results show that the bull market regime dominates the sample, has the longest average duration, and is associated with lower volatility and stronger technology performance, whereas bear states are shorter and defensive sectors remain relatively resilient. Out-of-sample forecasts for January 2023 to March 2026 achieve high regime consistency but much weaker sector hit rates, implying that macro regimes explain broad market environments better than high-frequency leadership shifts. The findings support regime-switching models as useful tools for strategic allocation, risk monitoring, and structured discussion of sector rotation.

Keywords: Sector rotation; Markov-switching VAR; Regime forecasting; Macroeconomic indicators

1. Introduction

Sector rotation is a persistent feature of equity markets because industries do not react in the same way to changes in growth, inflation, liquidity, and investor sentiment. In the U.S. stock market, technology, cyclical, material, defensive, and financial sectors often outperform at different moments even when the overall index appears broadly stable. This matters because asset allocation decisions are rarely made

only at the market level; investors also need to decide where opportunities and risks are building inside the market. The key difficulty is that sector leadership can change without an obvious break in the aggregate index, and the drivers of those shifts are usually non-linear. Short-term news, valuation pressure, and policy expectations interact with slower macroeconomic variables, making it hard for a simple linear model to explain when rotation is structural and when it is only noise. For this reason, identifying market states

and identifying likely leading sectors are both important and empirically challenging tasks [1,2].

Existing studies provide two main reasons for using a regime-based framework. First, the business-cycle literature argues that expansions, recoveries, and downturns are not smooth deviations around one average path but distinct states with different persistence and transmission mechanisms [3]. Second, MS-VAR research shows that model specification affects interpretation, and filtering, smoothing, and estimation procedures make state identification operational in practice [4,5,6]. Applied studies further confirm that regime dependence appears in financial risk, stock-market volume-volatility transmission, and broader macro-financial dynamics [7,8]. Related recent Chinese studies report similar nonlinear state dependence in bond-yield term structures and macroeconomic growth persistence [9,10]. At the same time, behavioral evidence suggests that sector leadership is also influenced by sentiment and investor behavior, so monthly winners are harder to predict than broad market environments [11]. This literature implies that regime models may be more suitable for identifying the environment that shapes sector rotation than for mechanically calling every short-term leader.

Against this background, the paper applies a three-state MSIH(3)-VAR(1) model to test whether market states can explain sector rotation and support the April 2026 to April 2027 forecast. Section 2 introduces the data, Section 3 presents the model, Section 4 reports the empirical results, Section 5 discusses the forecasts, and Section 6 concludes.

2. Data and Preprocessing

2.1 Market Variables

The data regarding the monthly closing prices of the S&P 500, covering the time from April 2006 to March 2026, are taken from Yahoo Finance. Serving as an alternative for the overall U.S. stock market, the S&P 500 acts as the foundational structure for studying sector rotation and leadership in the market.

The monthly data for the VIX Volatility Index, sourced from the Federal Reserve's Economic Data Database (FRED), has a coverage period from March 2006 to March 2026. The VIX, used as a substitute for market fright, effectively mirrors market expectations about future lack of clarity.

From the real-time pricing mechanism of implied volatility in S&P 500 index options, the methodology behind its construction is derived, and it captures investors' collective hopes regarding short-term market risk.

2.2 Macroeconomic Variables

The monthly unemployment rate (UNRATE) data, acquired from the U.S. Bureau of Labor Statistics, covers the time frame from January 2006 to February 2026. As a core indicator of the labor market, the unemployment rate is crucial for identifying economic slowdowns and changes in sector leadership [1].

Furthermore, increases in unemployment are more likely to favor defensive sectors over cyclical sectors. The basic data for credit spreads comes from the Federal Reserve's Economic Data Database (FRED), covering the period that goes from January 2006 to March 2026. As a proxy for market risk pricing and financial frictions, credit spreads directly reflect corporate financing costs and risk premiums. They also provide advance information about shifts in the market environment and sector preference [1]. The year-over-year growth rates of the U.S. real gross domestic product (GDPC1) and the industrial production index (INDPRO) are used to synthesize the economic growth factor through principal component analysis. The U.S. Bureau of Economic Analysis provides the quarterly data called GDPC1. The Federal Reserve gives out INDPRO as monthly-based data. The author used quadratic interpolation to convert quarterly GDP data into a monthly series for the purpose of data harmonization.

The synthesis process is presented in the following way: First, calculate the growth rates of the two sequences from one year to the next. Next, standardize the data values. The formula is:

$$X_{i,t}^{\text{std}} = \frac{X_{i,t} - \mu_i}{\sigma_i}, i = 1, 2, \quad (1)$$

and it indicates respectively the mean and standard deviation of the i -th sequence. Standardization eliminates differences in units, ensuring that subsequent principal component analysis is uninfluenced by variable scales. Two standardized sequences were organized by the author in chronological sequence to form a matrix.

After performing principal component analysis on this matrix, two principal component load vectors were obtained. The first principal component can explain the maximum variance in the original variables [12]. Therefore, it is adopted as the synthetic basis for the economic growth factor. The formula is:

$$\text{Factor}_t = \text{load}_1 \times X_{1,t}^{\text{std}} + \text{load}_2 \times X_{2,t}^{\text{std}} \quad (2)$$

The composite economic growth index is subject to the lag in the release of GDP data. The available data covers the period from January 2007 to December 2025. The economic growth factor comprehensively reflects the synergistic variations in actual output and industrial production. It serves to characterize cyclical fluctuations in the

macroeconomy.

2.3 Industry Data and Clustering

The industry returns data is sourced from the Kenneth French database, covering the period from January 2006 to January 2026 and encompassing 49 industries [13]. The authors performed K-means clustering on the return series of 49 industries to reduce the dimensions of the model and

improve the accuracy of the predictions. The clustering process adopts the Pearson correlation coefficient as a distance metric, focused on similarity in yield trends rather than amplitudes. The elbow method determined that the optimal number of clusters is 5. The 49 industries were grouped into five major categories: Tech, CycConsum, Financials, Materials and Defensive (see Table 1). The classification result aligns closely with the Morningstar Super-Sector classification.

Table 1. Basic industry groups

Number	Name	Sector codes included
1	CycConsum	Autos, Hshld, Clths, Rtail, Meals, Toys, Fun, Books, Guns, Aero, Ships, Trans, Boxes, FabPr
2	Tech	Hardw, Softw, Chips, LabEq, BusSv, PerSv, Telem
3	Materials	Mines, Gold, Coal, Oil, Steel
4	Defensive	Food, Soda, Beer, Smoke, Drugs, MedEq, Hlth
5	Financials	Banks, Insur, REst, Fin, Util, Agric, Other

Align the S&P 500 returns, unemployment rate, credit spreads, economic growth factors, and the VIX with the five major index categories by date. The final sample period was set from January 2007 to December 2025.

3. MS-VAR Model

3.1 Model Specification

The author employed a three-state Markov-chain-based vector autoregressive model (MSIH(3)-VAR(1)) to analyze the rotation patterns of leading sectors in the U.S. stock market. The form of MSIH-VAR model is

$$Y_t = \nu(S_t) + A_1(S_t)Y_{t-1} + \Sigma(S_t)\epsilon_t, \epsilon_t \sim N(0, I) \quad (3)$$

The endogenous variable vector Y_t has 10 dimensions.

The Unobserved regime variable $S_t \in \{1, 2, 3\}$ denotes three market regimes: State 1 (Bull Market): The economy is experiencing high growth and low volatility, with cyclical sectors dominating. State 2 (Sideways Market): The economic is experiencing a slowdown and heightened volatility, with sectors performing unevenly. Phase 3 (Bear Market): The economy is contracting with high volatility, and defensive sectors dominate.

The state transition obeys a first-order Markov chain. The transition probability matrix is a 3×3 matrix, $P = [p_{ij}]$

, where $(P = [p_{ij}])$, $(p_{ij} = Pr(S_t = j | S_{t-1} = i))$. Re-

gime-dependent coefficients comprise: S_t : the regime-dependent intercept vector; $A_1(S_t)$: a 10×10 autoregressive

coefficient matrix; and $\Sigma(S_t)$: the regime-dependent covariance matrix.

Recent regime-switching research shows that state-transition models capture the nonlinear characteristics of economic time series and can be estimated in ways that accommodate endogenous switching [4,6]. The author adopted the MSIH-VAR framework to comprehensively characterize the abrupt nature of sector rotation. This model distinguishes between sector-specific return differences and variations in market volatility structure. It is better suited to the present research objective than simpler MSI-VAR or MSM-VAR settings [4].

3.2 Estimation, Implementation, and Classification

The model was estimated using the Expectation-Maximization (EM) algorithm, which was implemented through the MS_Regress MATLAB toolbox developed by Perlin [5]. The toolbox supports multiple Markov-switching specifications and parameter settings that are suitable for MS-VAR estimation [4,5]. The lag order was determined jointly by the AIC and BIC criteria to avoid overparameterization.

The author categorizes the three states based on the smoothed probability and the mean of state. Economic implications for each state are subsequently interpreted using the S&P 500 return, the VIX, and the mean returns of the five major sectors.

Table 2. Regime Characteristics

State	Regime Frequency	Average Duration (months)	Average SP500(%)	Average VIX	Economic and Sector Characteristics
Bull Market (Expansionary Regime)	0.7573	6.7600	1.4600	17.3300	Higher growth factor, lower volatility; Tech & Business Services outperform.
Sideways Market (High-Volatility Recovery Regime)	0.0993	3.1800	5.9100	28.8700	VIX and unemployment rise; Basic Materials & Energy show the strongest resilience.
Bear Market (Downturn Regime)	0.1434	1.2900	-7.4800	30.3900	SP500 and most sectors negative; Defensive Consumer & Healthcare relatively resilient

Table 2 indicates the bull market associated with higher market returns and lower volatility. The sideways market corresponds to higher volatility and stronger rebound resilience. The bear market reflects pronounced negative returns and pronounced risk-averse characteristics. Segmentation by market conditions aligns with the premise that market environments influence sector rankings [1,2].

3.3 Transition Probabilities and Regime Persistence

The Transition Probability Matrix is given by

$$P = \begin{bmatrix} 0.8521 & 0.0070 & 0.1409 \\ 0.2621 & 0.6852 & 0.0527 \\ 0.5840 & 0.1884 & 0.2276 \end{bmatrix} \quad (4)$$

The results imply that, more frequently within the sample, the U.S. equity market is in an expansionary phase. A short - term shock state seems to be getting closer for the bear market. The probability of a shift from a bear market to an expansionary market is greater than the probability of the bear market staying the same. Expansionary markets are reached by bear markets more often than bear markets remain in place, showing that market downturns typically do not represent extended spells of inaction. Contrarily, they are like rebalancing processes that come after short - term amendments.

Such asymmetric structures possess direct implications for asset allocation. When the persistent differences in market

conditions are overlooked, there is a chance of mistaking short - term pressures for long - term trends. In the event of neglecting the rebound attributes of bear markets, the perceived duration of risk conditions can be inflated. Similar asymmetric regime features have also been discussed in recent MS-VAR studies of financial risk transmission [8].

The average duration corresponds to the probability of transition. An extended bull market implies its persistence as the dominant environment in the sample, rather than a short-term noise event. The shorter duration of bear markets suggests they are more closely associated with a regime dominated by shocks.

4. Out-of-Sample Forecasts and Sector Rotation Analysis

4.1 Out-of-Sample Forecasts: January 2023 – March 2026

The author classifies out-of-sample forecasting into two dimensions. The first-dimension concerns whether the predicted state can replicate the overall market environment identified during the in-sample period. The second dimension concerns the alignment between the leading sector derived from the predicted state and the actual leading sector for that month.

Table 3. Forecasts: January 2023 – March 2026

Year	Forecasted Regime	Forecasted Leading Sector	Regime consistency rate	Sector Prediction Hit Rate
2023	Bull Market (Expansionary Regime):12	Materials:11, Defensive:1	0.9167	0.2500
2024	Bull Market (Expansionary Regime):12	Defensive :1, Materials:4	0.9167	0.2500

2025	Bull Market (Expansionary Regime):12	Defensive:12	0.7500	0.1667
2026Q1	Bull Market (Expansionary Regime):3	Defensive :3	1.0000	--

Table 3 illustrates the superior performance of the MSI-H(3)-VAR(1) model for state forecasting. It consistently identifies the bull market throughout the entire window. Subsequent smoothing results on the extended sample generally support the conclusion that states achieved a consistency rate of 87.18%. This result indicates that fluc-

tuations caused by inflation, interest rates, and geopolitical factors failed to induce sustained state reversals within the modeled information set, which is consistent with the idea that regime recognition is less sensitive to short-run noise than high-frequency market turning points [4].

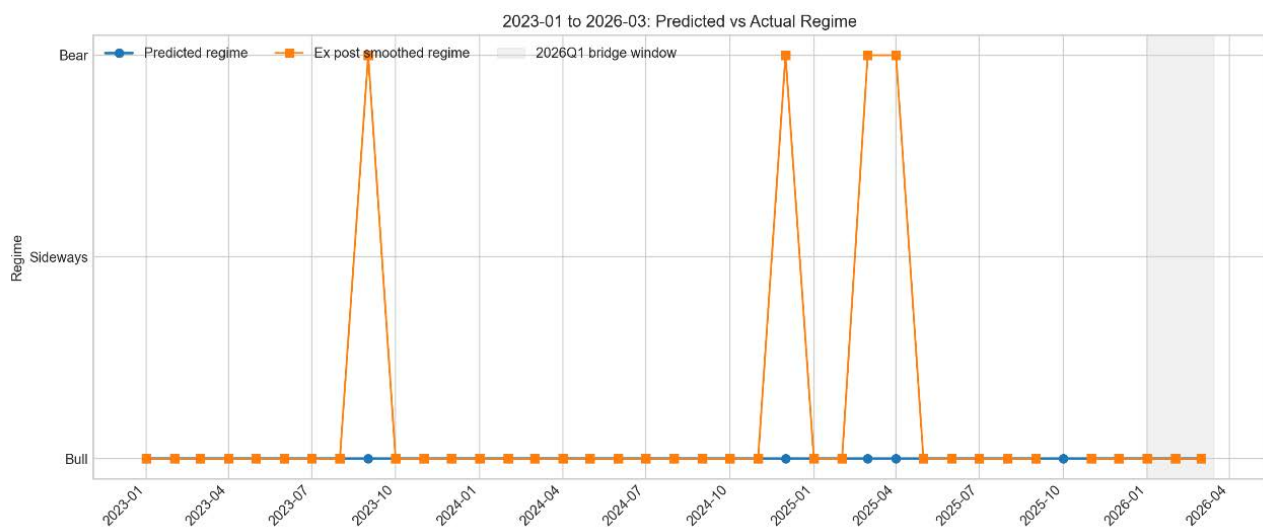


Fig. 1 Forecasted vs. Smoothed Regimes: January 2023 – March 2026

Figure 1 indicates changes in the predicted state, and the post-smoothing state generally follows the same trend.

Relatively smooth state trajectories imply state variables primarily carry low-frequency environmental information.

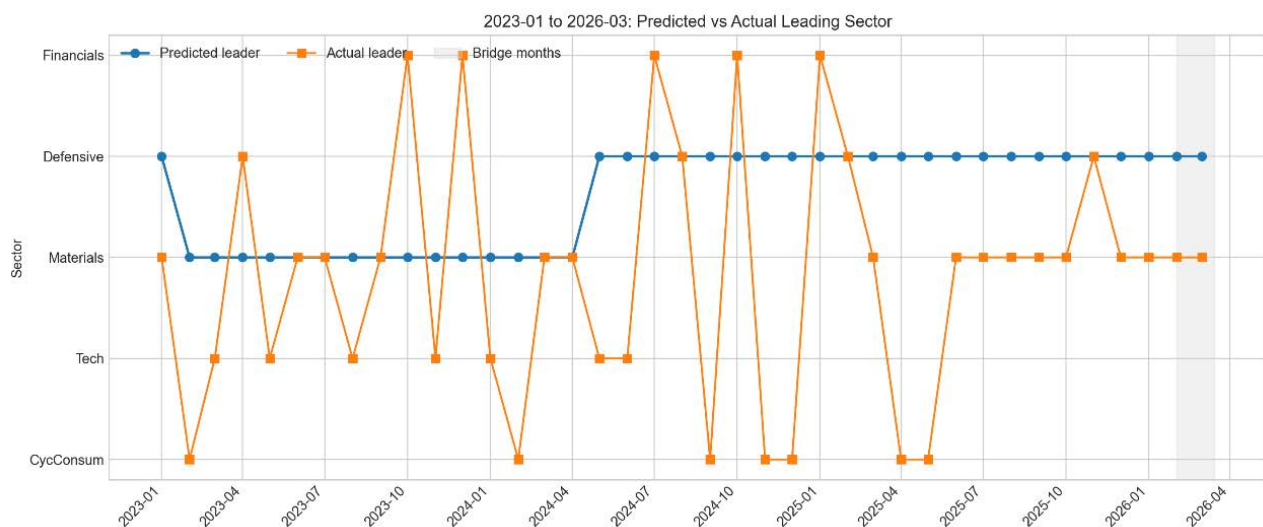


Fig. 2 Forecasted vs. Actual Leading Sectors: January 2023 – March 2026

Figure 2 displays that prediction stability did not translate into high-accuracy predictions of the dominant sector.

The sector hit rate was only 21.62%. Monthly rankings of leading sectors were influenced by factors such as events,

valuations, and trading congestion [11]. The three-state environmental model therefore struggled to fully capture these high-frequency fluctuations.

4.2 Conditional Forecasts: April 2026 – April 2027

Table 4. Forecasts for the Coming Year: April 2026 – April 2027

Year	Forecasted Regime	Forecasted Leading Sector
2026-04~2026-12	Bull Market (Expansionary Regime)	Materials
2027-01	Bull Market (Expansionary Regime)	Materials
2027-02~2027-04	Bull Market (Expansionary Regime)	CycConsum

Table 4 presents the forecast results for the period from April 2026 to April 2027. It maintains the expansionary judgment from the previous phase, simultaneously shifting the focus of internal rotation back to basic materials and energy. By early 2027, the rotation will further shift toward cyclical consumer goods and industrials.

By combining Tables 3 and 4, a clearer internal rotation sequence emerges from the model. The focus will be on the resource sector in 2023, shift to the defensive sector from 2024 through March 2026, return to the resource sector after April 2026, and subsequently transition to the cyclical sector.

Market performance reflects a reallocation of assets within a high-interest-rate environment rather than a fundamental shift in the overall market conditions. The model consistently maintained an expansionary market judgment across the entire forecast period. It indicates sustained relative stability in the macroeconomic environment. Meanwhile, sector rotation represents structural rebalancing within this stable framework based on interest rate sensitivity, earnings certainty, and valuation levels.

1. Conclusion

This study uses a three-state MSIH(3)-VAR(1) framework to connect market returns, macroeconomic variables, and clustered sector returns, then extends the information set through March 2026 to produce a conditional forecast for April 2026 to April 2027. The forecast indicates that the aggregate market environment remains expansionary, but the internal leadership pattern does not stay fixed. Instead, the projected path shifts from renewed strength in basic materials and energy to a later rotation toward cyclical consumer and industrial groups in early 2027. This projected sequence suggests that the coming year is more likely to feature internal reallocation under a still-stable macro regime than a broad reversal of market state. In that sense, the model is most useful as a medium-horizon environment and rotation framework rather than as a high-frequency rule for picking the single best-performing sector each month. Its main value lies in organizing the direction of rotation and the structural logic behind the forecast.

The forecast should nevertheless be read as a conditional scenario rather than a fixed terminal result, because the bridge-window construction means the tail months remain sensitive to later data updates and to possible changes in transition behavior. Even with that limitation, the April 2026 to April 2027 projection offers meaningful guidance for strategic allocation by clarifying that future opportunity may come less from a new aggregate bull-bear switch than from the sequencing of sector leadership inside an expansionary regime.

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