Tactical Asset Allocation

Regime Detection:

a Powerful Compass for Forecasting Returns

Research Paper

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Starting Point: The idea for this paper came to me while I was working on a previous project to model government and corporate bond ratings using the Logit model. Drawing on the bond rating categories, one could indeed define classes or regimes within the return distribution and model their probability of occurrence using appropriate macroeconomic factors specific to the market in question. The results are quite interesting and provide an exciting foundation for the classic task of forecasting returns, which is very helpful for tactical portfolio steering an risk management.

Key Words: tactical asset allocation, logit model, market regimes, probability of regimes, confusion matrix, predictive accuracy, balanced accuracy, recall, tail recall, crash, bearish, bullish, boom, S&P 500.

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Abstract

Traditional financial forecasting models primarily aim to predict the exact future return of an asset or market index. In practice, however, short- and medium-term market returns are highly noisy, unstable, and strongly influenced by unexpected macroeconomic, geopolitical, and behavioral factors. As a result, precise point forecasts are often difficult to achieve and may provide limited robustness for practical portfolio-steering. The **multinomial logit model** follows a **probabilistic approach** and is designed as a supplementary analytical tool to simplify the forecasting process by first identifying and structuring the prevailing market environment. By classifying markets into more homogeneous macro-financial regimes, the framework reduces the complexity and instability of return forecasting tasks and creates a more robust foundation for subsequent forecasting techniques and algorithms.

In this context, the **regime model** acts as a **first-stage macro-financial filtering mechanism**. Instead of directly forecasting future returns, the framework estimates the probability that the market currently operates within a specific regime, such **as Crash, Bearish, Bullish, or Boom** environments. By identifying the dominant market state and its underlying drivers, the model provides economically interpretable information about market tendencies, risk conditions, volatility dynamics, liquidity environment or credit-marketbehavior.

This **probabilistic regime classification** creates a significantly more stable and robust foundation for subsequent return forecasting. Once the prevailing market environment has been identified, traditional forecasting models can then be applied within the appropriate regime context. This **two-step framework** substantially improves economic interpretability and allows forecasting models to operate under more homogeneous market conditions. The regime approach offers several important advantages in this integrated modeling framework:

1. financial markets naturally evolve through different market states characterized by changing volatility structures, liquidity conditions, and risk premia. Identifying whether markets operate in a **risk-on or risk-off** environment is often more relevant for portfolio allocation decisions than attempting to predict precise monthly returns directly.
2. regime classification models are generally more robust than classical return forecasting approaches because they focus on broader market dynamics rather than unstable point estimates. This reduces sensitivity to short-term noise and **decreases the risk of overfitting**.

3. the framework provides **strong tail-risk detection** capabilities. Variables such as implied volatility, credit spreads, and liquidity indicators frequently contain early-warning information about systemic market stress. The multinomial Logit model is specifically designed to capture these non-linear transitions between market environments.
4. the probabilistic nature of the model allows decision-makers to quantify uncertainty and evaluate alternative market scenarios. Instead of generating a single deterministic forecast, the framework produces a full probability distribution across multiple regimes, thereby supporting risk management, **scenario analysis, and tactical asset allocation.**
5. the model offers a high degree of **economic interpretability** and integrates naturally with scenario analysis. The contribution of each explanatory factor can be analyzed through attribution techniques, marginal probability effects, and stress simulations. This enables transparent and economically intuitive market analysis while preserving the advantages of classical forcasting techniques in the second m odelling-stage.

The objective of this paper is to show how the multinomial logit approach could provide a smart system for analyzing, interpreting, simulating and forecasting market regimes - not only from a theoretical perspective, but also using concrete, real-world data. In our case study we consider the U.S. S&P 500 equity market and some relevant macroeconomic factors to estimate the probability of Crash, Bearish, Bullish and Boom regimes.

Extending this approach to other market segments provides a comprehensive tool for portfolio management.

1 The mathematical model

The purpose of the multinomial Logit model is to estimate the probability that a given market belongs to a specific market regime at time t. Instead of forecasting exact returns, the model classifies the market into one of several discrete regimes: $R_t \in [1,2, \dots K]$ and estimates the corresponding conditional probabilities using regression techniques on a set of selected explanatory factors P_k = P(R_t = k / $X_{1 \le i \le n}$).

1.1 Model Specification

In the multinomial Logit framework, one market regime is automatically selected as the reference regime in order to ensure model identification and avoid perfect multicollinearity. All remaining regime probabilities are estimated relative to this reference category. In the present implementation, we use the last regime category as the reference regime. The probability of the reference regime is therefore not estimated directly, but instead calculated implicitly as the remaining probability required for all regime probabilities to sum to one.

Theorem:

We suppose we deal with n possible regimes. The probability for regime k for: k = 1,…,n−1 is given by:

$$p_k = P(R_t = k \ / \ X_t) = \frac{\exp(\beta_k X_t)}{1 + \sum_{i=1}^{n-1} \exp(\beta_i X_t)}$$

Proof:

The multinomial Logit probability formula is obtained by combining relative log-odds equations with the probability constraint that all regime probabilities must sum to one. Each coefficient β measures the marginal impact of a factor on the log-odds of a regime. For example: β_(Y,Crash) > 0 implies that an increase in Y raises the probability of the Crash regime.

Step 1: Linear regression and relative Log-Odds representation: $log \frac{P(R_t=k \ / \ X_t)}{P(R_t=n \ / \ X_t)}$ = $\beta_k X_t$

Step 2: Exponentiation: $\frac{P(R_t=k \ / \ X_t)}{P(R_t=n \ / \ X_t)}$ = $\exp(\beta_k X_t)$

Step 3: Rearranging: $P(R_t = k \ / \ X_t)$= $P(R_t = n \ / \ X_t) \exp(\beta_k X_t)$

Step 4: Probability Sum Constraint: $\sum_{k=1}^{n} p_k = 1$ ==> $\sum_{k=1}^{n-1} P(R_t = k \ / \ X_t) + P(R_t = n \ / \ X_t) = 1$

Step 5: Substitution: $\sum_{k=1}^{n-1} P(R_t = n \ / \ X_t) \exp(\beta_k X_t) + P(R_t = n \ / \ X_t) = 1$

Step 6: Factorization: $P(R_t = n \ / \ X_t) * (1 + \sum_{k=1}^{n-1} P(R_t = n \ / \ X_t) \exp(\beta_k X_t)) = 1$

Step 7: Reference Regime Probabiliy: $P(R_t = n \ / \ X_t) = \frac{1}{1+\sum_{i=1}^{n-1} \exp(\beta_i X_t)}$

Step 8:Finally, we deduce the Probability Formula: $P(R_t = k \ / \ X_t) = \frac{\exp(\beta_k X_t)}{1+\sum_{i=1}^{n-1} \exp(\beta_i X_t)}$

1.2 Model Parameter Estimation

The model parameters β are estimated using Maximum Likelihood Estimation (MLE):

$$L(\beta) = \prod_{t=1}^{T} \prod_{k=1}^{n} P(R_t = k/X_t)^{I(R_t=k)}$$

The Function $I(R_t = k)$ is the Indicator[1] function and the Vector β is the solution of the log-likelihood optimization problem:

$$\hat{\beta} = max_{\beta} \sum_{t=1}^{T} \sum_{k=1}^{n} I(R_t = k) \log(P\big(R_t = k/(X_t)\big)$$

1.3 Regime Prediction

For each observation t, the model produces a vector of probabilities $\hat{P}_t = [P_1, P_2, \dots, P_K]'$. The predicted regime is obtained via:

$$\widehat{R_t} = argmax_k P(R_t = k/X_t\ )$$

This means that predicted regime corresponds to the maximal probability of occurrence. Nevertheless, it is advisable to analyze the distribution of all probabilities to determine whether there are dominant regimes compared to the others.

1.4 Marginal Contribution

The attribution framework improves transparency and makes the model substantially easier to interpret and communicate. It also transforms purely statistical outputs into economically meaningful market narratives. To measure the sensitivity of regime probabilities to changes in explanatory variables, the present model uses finite-difference marginal effects:

$$MC_{j,k} = \frac{P_k\big(X_t + \Delta X_j\big) - P_k(X_t)}{\Delta X_j}$$

Marginal contributions also serve as an important model validation tool. If the dominant explanatory factors are economically plausible, this increases confidence that the model captures genuine market mechanisms rather than statistical noise or overfitting. For example:

- VIX dynamics driving Crash probabilities,
- liquidity improvements supporting Bullish regimes,
- or widening credit spreads may shift the model toward Bearish environments.

are economically intuitive relationships that reinforce the credibility of the framework.

[1] *$I(R_t = k) = 1$ when the regime k occures and zero otherwise.*

2 Model Quality Metrics

This section summarizes the key model quality metrics and the statistical significance framework used to evaluate the multinomial Logit regime model.

2.1 Confusion Matrix

The Confusion Matrix compares the actual observed market regimes with the regimes predicted by the model. Diagonal elements represent correct classifications, while off-diagonal elements indicate classification errors.

2.2 Recall and Tail Recall

Recall measures the model's ability to correctly identify observations belonging to a specific regime. It is particularly important for tail-risk regimes such as Crash or Boom periods.

$Recall_k$ = Correctly Classified (Regime-k) Periods / Total Actual (Regime-k) Periods

Tail Recall measures the average detection quality of extreme market regimes.

$Recall_{Crash}$ = Correctly Classified Crash Periods / Total Actual Crash Regime Periods

$Recall_{Boom}$ = Correctly Classified Boom Periods / Total Actual Boom Regime Periods

Tail Recall = ($Recall_{Crash}$ + $Recall_{Boom}$) / 2

2.3 Prediction Accuracy and Balanced Accuracy

Prediction Accuracy measures the overall percentage of correctly classified observations and provides a simple measure of predictive performance while Balanced Accuracy measures the average classification quality across all market regimes by assigning equal importance to each regime. Prediction Accuracy = Correctly Classified Observations / Total Observations . Balanced Accuracy = Average of all rates of Recall

2.4 Statistical Significance

In addition to predictive performance, the multinomial Logit framework also evaluates the statistical significance[2] of explanatory variables. These metrics help identify which macro-financial variables contribute significantly to regime classification. In regime classification models, statistical significance alone is not sufficient to evaluate model quality. Predictive robustness and regime detection capabilities remain at least equally important. The combination of predictive metrics and economically interpretable coefficients creates a robust and transparent macro-financial regime framework.

$$Sigificance\_Score = \frac{Number\ of\ significant\ coefficients}{Total\ number\ of\ coefficients}$$

[2] *p-Values, Standard erros and t-statistics. In this framework, we consider significant coefficients those with a p-value less than 5%*

3 Implementation and Results

In this section we test the multinomial Logit model for the S&P500 US Equity Market. This framework uses macro-financial and market-stress variables that are economically linked to changes in equity market regimes. The objective is to capture shifts in market sentiment, liquidity conditions, credit risk, and investor risk appetite that influence the behavior of the S&P500.

3.1 Modeling Market Regimes

The S&P 500 regime framework classifies monthly equity market environments into four distinct market regimes based on the empirical distribution of historical S&P 500 returns. The regimes are defined using return quantiles in order to create a probabilistic and economically interpretable classification structure:

Regime	Definition	Characteristic
Regime 1 (Crash)	Returns below the 20% quantile	Severe downside market environment
Regime 2 (Bearish)	Returns between the 20% and 50% quantile	Moderately negative market phases
Regime 3 (Bullish)	Returns between the 50% and 80% quantile	Constructive market conditions
Regime 4 (Boom)	Returns above the 80% quantile	strong expansionary equity market regimes

3.2 Explanatory Factors

Various factors have already been tested in different combinations to explain the statistical structure of the various regimes of the U.S. S&P 500 stock market, and here is a selection of those that have shown the best results. However, there is certainly room to test additional factors that might yield even better results.

VIX Level: The VIX Index measures implied equity market volatility and is commonly interpreted as a proxy for market fear and uncertainty. Higher VIX levels are typically associated with elevated market stress, increased risk aversion, and deteriorating investor sentiment.

VIX Growth: The change in the VIX captures the dynamics of market stress rather than its absolute level. Sudden increases in volatility often occur during regime transitions, market corrections, or liquidity shocks.

High Yield Spread Growth: The High Yield spread measures the risk premium demanded by investors for holding lower-quality corporate debt. Widening spreads typically indicate deteriorating credit conditions and increasing financial stress.

Dollar [3]Index Growth: Changes in the U.S. Dollar Index reflect shifts in global liquidity, monetary conditions, capital flows, and risk sentiment. A strengthening Dollar is frequently associated with tighter financial conditions and risk-off market behavior.

[3] *The US Dollar Index is a benchmark financial metric that measures the relative value of the USD against a specific basket of six major global currencies: the Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona, and Swiss Franc.*

3.3 Modeloutput

The multinimial Logit model estimates the impact of each explanatory factor on the probability of different market regimes relative to the [4]reference regime. Positive coefficients indicate that an increase in the corresponding variable raises the probability of the associated regime relative to the reference category.

The following tables shows the estimated model coefficients and their respective p-values:

Coefficients	Crash	Bearish	Bullish
Intercept	0,53	2,22	1,84
Implied_Volatility_Level	1,56	0,44	-0,39
Implied_Volatility_Growth	3,78	2,69	1,76
High_Yield_Spread_Growth	3,42	2,17	0,91
Dollar_Growth	1,24	0,92	0,89

P-Values	Crash	Bearish	Bullish
Intercept	4,67%	0,00%	0,00%
Implied_Volatility_Level	0,00%	8,30%	15,27%
Implied_Volatility_Growth	0,00%	0,00%	0,00%
High_Yield_Spread_Growth	0,00%	0,00%	0,79%
Dollar_Growth	0,00%	0,00%	0,00%

Global Assessment: The estimated coefficient structure reveals a highly coherent and economically intuitive relationship between macro-financial risk factors and U.S. equity market regimes. The results indicate that the model is not merely statistically functional, but captures economically meaningful market dynamics with a high degree of consistency.

Dynamics of Volatility: Among all explanatory variables, VIX Growth emerges as the most influential and statistically robust factor across all estimated regimes. The coefficients are economically large, consistently positive and associated with extremely small p-values close to zero. This indicates that changes in implied market volatility play a central role in regime transitions and market-state identification. The results strongly suggest that shifts in market stress dynamics are among the primary drivers of equity market regime changes. This finding is highly consistent with financial market theory and empirical evidence from crisis periods.

Dynamics of Credit Market: The High Yield Spread Growth factor also exhibits large positive coefficients combined with very strong statistical significance. This confirms the close relationship between deteriorating credit conditions, tightening financial environments and adverse equity market regimes. The results imply that credit-market stress provides substantial forward-looking information regarding changes in equity market behavior. From a macro-financial perspective, this is particularly important because credit markets frequently react earlier than equity markets during periods of financial deterioration.

Dynamics of Dollar Growth: Dollar Growth is statistically robust across all estimated regimes and exhibits consistently positive coefficients. This finding indicates that changes in global dollar liquidity and financial conditions materially influence S&P 500 regime probabilities. The results support the interpretation that dollar appreciation is associated with tighter financial conditions reduced global liquidity and increased market stress. This reinforces the macro-financial robustness of the regime framework.

[4] *In this framework, Crash is reference the regime*

3.4 Quality Check

The following tables show the various quality criteria for the tested model:

Confusion Matrix	Detected Crash	Detected Bearish	Detected Bullish	Detected Boom	Recall
Empirical Crash	**13%**	6%	1%	0%	66%
Empirical Bearish	4%	**14%**	11%	1%	46%
Empirical Bullish	0%	7%	**20%**	3%	66%
Empirical Boom	1%	1%	4%	**13%**	68%

Prediction Accuracy	61%
Signficance Score	83%

Balanced Accuracy	62%
Tail Recall	67%

Global Assessment:

- The empirical results indicate that the multinomial Logit framework achieves a robust and economically meaningful classification of U.S. equity market regimes and demonstrates strong predictive performance across multiple dimensions of model quality, including:
  . overall classification accuracy
  . balanced regime detection
  . tail-risk identification
  . and statistical significance of the explanatory variables.

- The Confusion Matrix shows that the framework successfully identifies both extreme market environments and standard market conditions with a relatively balanced classification structure. Particularly noteworthy is the strong detection capability for Crash regimes, Bullish environments and Boom periods, which are identified with Recall rates about **67%.**

- In addition, the model reaches a Significance Score of **83%,** indicating that a large majority of the estimated coefficients are statistically significant. This substantially increases confidence that the framework captures genuine macro-financial market dynamics rather than statistical noise or overfitting effects.

- Overall, the empirical evidence suggests that the regime-based Logit framework provides statistically robust regime classification, economically interpretable market signals, effective tail-risk detection and practical applicability for portfolio steering and scenario analysis as well.

3.5 Simulation and Analysis

The following scenarios illustrate how the multinomial Logit regime framework can be used to evaluate different macro-financial market environments and their potential impact on S&P 500 regime probabilities.

3.5.1 Scenario 1: Post-Crisis Recovery

VIX Level: **30%** → High Stress Level

VIX Growth: **-5%** → Declining Volatility

HY Spread Growth: **-1%** → Easing Credit Markets

Dollar Growth: **-1.5%** Weaker dollar → More liquidity

Scenario Regime Probabilities

Regime	Probability
Crash	0.18%
Bearish	3.78%
Bullish	10.45%
Boom	85.59%

Attribution: Relative Marginal Contribution

Regime	VIX_Level	VIX_Growth	HY_Spread_Growth	Dollar_Growth
Crash	0.00%	0.00%	0.18%	0.00%
Bearish	0.03%	0.27%	3.30%	0.19%
Bullish	0.35%	2.33%	4.90%	2.86%
Boom	0.36%	9.23%	66.69%	9.31%

The model assigns a dominant probability to the Boom Regime. This result is particularly interesting because it demonstrates that the framework does not react mechanically to elevated volatility levels alone. Instead, the model places greater emphasis on the positive dynamics of market conditions.

The attribution analysis provides additional insight into the drivers of the Boom probability:

- The results clearly indicate that improving credit-market conditions are the dominant driver (66.69% from 85.59%) of the positive regime classification. The strong contribution from High Yield Spread Growth suggests that tightening credit spreads are interpreted as a significant improvement in financial conditions and investor risk appetite.
- Allthough volatility levels remain elevated, the market dynamics indicate that systemic stress is beginning to normalize. The model also reacts positively to declining volatility dynamics and improving dollar liquidity conditions, both of which are typically associated with recovery phases and risk-on market behavior.

Historically, similar dynamics were observed during:

- The recovery phase following the Global Financial Crisis in 2009
- The post-COVID rebound in 2020
- And several liquidity-driven risk-on episodes in recent years

This shows the the model captures not only static market stress levels, but also the transition dynamics between market regimes

3.5.2 Scenario 2: Fragile Transition Regime

VIX Level: **25%** → High Stress Level

VIX Growth: **+2.5%** → Rising Volatility

HY Spread Growth: **-0.5%** → Easing Credit Markets

Dollar Growth: **-0.75%** Weaker dollar → More liquidity

This scenario combines risk-off chraracteristics and residual liquidity support as well. The elevated VIX Level and positive Volatility Growth indicate that the market volatility and investor uncertainty are increasing. On the other hand, improving credit-market conditions and a weakening Dollar continue to provide support for financial markets.

Scenario Regime Probabilities

Regime	Probability
Crash	14.25%
Bearish	51.40%
Bullish	28.42%
Boom	5.93%

Attribution: Relative Marginal Contribution

Regime	VIX_Level	VIX_Growth	HY_Spread_Growth	Dollar_Growth
Crash	0.70%	1.18%	11.74%	0.63%
Bearish	2.04%	7.73%	41.08%	0.55%
Bullish	2.46%	3.49%	22.15%	0.31%
Boom	0.16%	1.33%	3.29%	1.16%

The model assigns the highest probability to the Bearish Regime. Importantly, however, the frameworg does not fully transition into a Crash environment. Instead, the results suggest that themarkert is entering a weaker and more fragile regime characterizes by uncertainty, deteriorating investor sentiment but not yet systemic financial stress. The still meaningful Bullish probability of 28.42% further indicates that supportive liquidity conditions to partially stabilize the market environment.

The attribution analysis indicates that the dominant driver of the Bearish classification is still the credit-market factor. Although High Yield spreads continue to improve slightly, the overall macro-financial environment is no longer sufficiently supportive to sustain a Boom or strong Bullish regime. At the same time, rising volatility dynamics contribute meaningfully to the increase in Bearish probabilities.
The combination of elevated volatility, rising volatility, improving but weakening credit support and still supportive liquidity conditions creates a market structure frequently observed during:

- maturing bull markets
- late-cycle equity expansions
- unstable recovery phases or
- temporary volatility shocks
- periods preceding broader market heavy corrections

This Scenario highlights an important strength of the multinomial Logit framework: the ability to identify nuanced transitional market environments rather than only extrem market states. This produces a more realistic and economically meaningful interpretation of market behavior.

4 Conclusion

The proposed approach represents a conceptual shift away from relying exclusively on precise point forecasts toward a probabilistic understanding of market dynamics and regime transitions. Instead of attempting directly to predict inherently noisy and unstable short-term return movements directly, the model estimates the probability that financial markets are operating within distinct market regimes characterized by different volatility structures, liquidity conditions, credit-market dynamics, and investor risk preferences. This regime-identification process creates a robust and economically interpretable foundation for subsequent forecasting and portfolio management decisions. Once the prevailing market environment has been identified, traditional forecasting models can then be applied within a more homogenous and contextually consistent market regime.

The framework contributes several important capabilities within this integrated modeling architecture:

- probabilistic identification of prevailing market environments
- enhanced robustness and stability across changing macro-financial conditions
- improved detection and monitoring of tail-risk and systemic stress regimes
- deeper economic interpretability of market dynamics and regime transitions
- direct integration of macro-financial scenario analysis and stress testing
- transparent attribution of regime probabilities to underlying explanatory factors
- practical support for portfolio steering, tactical asset allocation, and risk management processes
- creation of a structured macro-financial context for subsequent return forecasting models

This integrated approach allows regime analysis and traditional forecasting techniques to complement each other within a coherent macro-financial decision framework.

In addition, the probabilistic nature of the framework enables decision-makers to evaluate market uncertainty more effectively and to distinguish between gradual regime transitions and abrupt market dislocations.

The model supports an economically intuitive interpretation of financial markets by focusing on the conditional probability structure of market regimes rather than relying exclusively on deterministic return forecasts. In this context, the central question is no longer: “What will next month’s market return be?” but rather: “What type of market environment is the market most likely transitioning toward, and how should portfolio positioning adapt to this evolving regime structure?”

Main References

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