Title: Detecting Market Instability with Regime Switching Models: A Markov-Switching Analysis of the S&P 500 Index

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Abstract: This paper applies a Markov Regime-Switching (MRS) model to the daily log returns of the S&P 500 index to analyze nonlinear dynamics and latent structural changes in U.S. stock markets. The two-regime specification identifies disparate economic states—characterized by low-volatility (expansionary) and high-volatility (contractionary) periods—allowing time-varying dynamics in both the mean and variance of returns. Maximum likelihood estimation is employed to estimate the model, while smoothed regime probabilities are obtained to identify areas of regime dominance. Superimposition of regime probabilities on return plots provides clear evidence of regime-dependent, long-term patterns in line with previous historical instances of market stress, e.g., financial crises and recovery phases. Regime durations are estimated on average, yielding useful information concerning the stability of market state durations. For scholars, this work provides a contribution to econometric modeling of asset returns with state-dependence and nonlinearity. For institutional investors, the findings highlight the importance of regime-sensitive portfolio management and risk management systems in dynamic markets.

Entire implementation is modular and in Python with statsmodels and matplotlib. The entire codebase, including Jupyter notebooks, visualization scripts, and replication instructions, is open-sourced on GitHub: https://github.com/stevo447/markov-switching-sp500.

Keywords: Regime Switching, Markov Model, Financial Instability, S&P 500, EM Algorithm

1. Introduction

Financial markets are not stable systems subject to abrupt and often unpredictable shifts in behavior. These shifts can be caused by economic recessions, political turmoil, pandemics, monetary policy actions, or structural financial imbalances. Traditional econometric models are prone to assume linearity and stationarity of the process of variance with time. The assumptions fail to capture the right shape of real-world financial observations, which tend to have volatility clustering, fat tails, and regime changes (Hamilton 357).

In the context of increasing difficulties, regime-switching models, particularly the Markov Regime Switching (MRS) model, have evolved into a powerful tool to describe the nonlinearity and nonstationarity of financial time series. Formulated by James Hamilton in 1989, the MRS model accounts for stochastic switching between multiple latent regimes, typically corresponding to economic or financial states such as "bull" and "bear" markets, or "high" and "low" volatility periods (Hamilton 357; Kim and Nelson 5). By dispensing with the assumption of time-invariant behavior, these models are a handy and realistic way to explore challenging financial phenomena.

The objective of this study is to estimate a two-regime Markov switching model of the daily returns on the S&P 500 index—a standard U.S. equity market index. The objective is to detect periods of market distress and characterize them in terms of regime-specific parameters such as mean return, volatility, and duration. The study will both illustrate when instability did occur and how often and with what intensity it struck the market. It has real-time applications to asset allocation, portfolio risk management, and central bank watchlist systems.

Regime-switching models are used widely in finance since they can account for a wide variety of phenomena including volatility asymmetry, bubbles, and crisis prediction (Guidolin and Timmermann 981; Ang and Bekaert 1183). For instance, it has been used by scholars to examine bond yield dynamics (Dai and Singleton 2003), predict stock market crashes (Perez-Quiros and Timmermann 2000), and examine macroeconomic policy regimes (Filardo 1994). Whereas their visual sensitivity, most programs are based on quarter or monthly observations. The present project is different in using the model with high-frequency daily returns to provide more accurate evidence on regime dynamics.

Market volatility is especially crucial to understand in our advanced algorithmic and globalized era. The 2008 crisis, the COVID-19 crisis, and 2022 inflationary shocks have shown the speed at which the markets can switch from calm to volatile stages. They are generally followed by abrupt volatility spikes and change of heart on the part of the investor. Early warning permits institutional investors, central banks, and financial regulators to implement remedial measures in order to deflect systemic risk.

Furthermore, the paper adds to the financial econometric literature to the extent that it combines time series modeling with traditional methodology and regime-based estimation. In addition to the estimation of smoothed probabilities of being in any regime at any point in time, it also provides empirical estimates for transition probabilities and expected durations. The specifications also possess a more probabilistic model of market behavior than models like GARCH that do not have an explicit specification of regime-switching dynamics.

Last but not least, this project is guided by three basic research questions:
1. Is a two-regime Markov switching model capable of accurately determining periods of market instability for the S&P 500 index?
2. What are statistical properties of regimes identified (mean return, variance, duration)?
3. How do regime transitions relate to historical economic or financial crises?

In order to respond to these questions, we will employ maximum likelihood estimation techniques such as in the Python package statsmodels, and thorough data visualization and sensitivity analysis. We will articulate results in finance crisis, risk assessment, and forecasting modeling language, providing practical implications for financial professionals and scholarly researchers.

2. Literature Review

Econometric modeling has evolved in a more active shift away from rigid, linear models toward more flexible and dynamic specifications that more faithfully capture the intricacies of financial time series. The most important contribution in this direction is Hamilton's (1989) Markov Regime Switching Model (MRS), which allows the behavior of a variable to shift between two or more unobservable regimes or "regimes." The MRS model has since been a workhorse in financial econometrics, particularly in modeling market volatility, volatility regimes, and business cycles.

2.1 Theoretical Foundations and Sources

Hamilton (1989) revolutionized the field of macroeconomic time series analysis by assuming that economic variables switch between competing regimes governed by a latent Markov process. His U.S. real GNP model showed that booms and recessions could be statistically represented as competing regimes with their own mean and variance. Relative to conventional linear specifications, Hamilton's regime switching model is state and dynamics nonlinear and hence best suited to examine financial markets with abrupt switches in volatility and returns.

Subsequent research developed this concept for the finance sector. Kim and Nelson (1999) suggested state-space modeling of regime switching, so as to allow for classical and Bayesian estimation. Their methodology allowed regime switching in asset pricing, interest rate modeling, and monetary policy. Being able to estimate parameters for a specified regime and smoothed and filtered regime probabilities of being in one's own regime was found to be extremely useful for real-time decision-making.

2.2 Uses in Financial Markets

MRS model has been applied extensively in equity markets, where it is widespread that return pattern asymmetry and volatility clustering have been routinely reported. For example, Ang and Bekaert (2002) applied regime switching to global asset allocation and showed the dependency of optimal portfolio weights on the prevailing regime for volatility. Their estimates were so calibrated that they showed that investors must adjust for time variation in risk in order to construct global portfolios.

Similarly, Hardy (2001) used regime-switching models for equity-linked life insurance contracts to illustrate tail risks and regime changes not expected in hedging and pricing strategies. During stock market crashes, Perez-Quiros and Timmermann (2000) illustrated that firm size had different forecast relations with returns depending on regimes, with market heterogeneity of responses during booms and busts.

Guidolin and Timmermann (2007) also utilized multivariate regime switching to estimate stock, bond, and cash asset allocation. They stated that the risk-reward trade-offs would be radically affected by time-varying volatilities as well as regime correlations and therefore their investment approach. The multi-variable approach affirms the argument that regime switching is not only a univariate but also an interdependence between financial variables.

2.3 Crisis and Volatility Detection

Regime switching models have proved particularly useful in explaining financial crises and volatility regimes. Gray (1996) constructed a generalized regime-switching model of exchange rates using the hybrid of regime switching and GARCH models to explain conditional heteroskedasticity. The hybrid model gave a better explanation of surprise currency crises.

In the debt market, Dai and Singleton (2003) employed regime switching affine term structure models to estimate the yield curve and risk premia behavior. The estimates revealed the applicability of regime models in detecting structural breaks in economic conditions. Likewise, Filardo (1994) applied regime switching to U.S. business cycles and demonstrated that recession transition probabilities can be predicted from leading indicators and thereby illustrated the applicability of the model for early warning systems.

More recently, Ang and Timmermann (2012) showed that regime-switching forecast combination generated far superior stock return predictions. Their work illustrated the model's value for uncertain forecasting, a valuable use in risk and portfolio management.

2.4 Applications with Daily and High-Frequency Data

While early applications of data frequency regime switching models had to resort to quarterly or monthly data, recent studies have shown that the model can be effectively applied at high frequencies. For example, Dueker (1997) applied daily interest rates in one regime switching application and identified short-run structural breaks that could not be captured by linear models. Similarly, Klaassen (2002) examined exchange rate dynamics at the daily frequency and showed that regime switching models produce superior volatility forecasts compared to linear models.

In a highly topical contribution, Maheu and McCurdy (2000) defined a regime switching model of daily stock returns with jumps and time-varying volatility. Their observation was that regime switches will more often than not happen together with macroeconomic announcements or geopolitical shocks. Including stochastic volatility terms in the model made their specification even more sensitive to market turmoil, which made it still better at predicting extreme events.

2.5 Limitations and Extensions

While powerful, regime-switching models do have some limitations. One of these is that they assume the Markov process, and thus regime changes are a function only of state now and not of past states. This "memoryless" property is too limiting perhaps for some market processes. Some authors have tried to mitigate this by estimating duration-dependent regime models or hidden semi-Markov models so more complex state dynamics can be attained (Piger and Hamilton 2002).

Difficulty in estimation, especially when dealing with multivariate models that entailed more than a single regime, is one of them. The EM algorithm is top class but in some cases risky as it converges to local optima. Solutions that have recently been there have resulted in Bayesian approaches of estimation using Gibbs sampling and Markov Chain Monte Carlo methods as a way of improving the accuracy of estimation (Chib 1996).

Summary

Literature confirms that Markov Regime Switching models have been instrumental in modeling market dynamics, volatility shift estimation, and predicting crisis dates. Ranging from basic early univariate macroeconomic models to current high-frequency, multivariate finance models, MRS models have expanded dimensions and sophistication. This project extends this work by utilizing a two-regime MRS model to predict S&P 500 daily returns and providing new evidence on periods of market distress and their implications for both investors and policymakers.

3. Methodology & Equations Section

1. Introduction to Markov Regime Switching Model

Markov Switching Model (MSM) is used to identify periods of regime changes (or "regimes") in time series observations, particularly financial returns. It assumes that the time series is affected by latent (unobservable) states, which themselves follow a Markov process — i.e., the future state is a function of only the present state and not of the entire past.

2. General Form of the Markov Switching Model

Suppose we have a time series y_t, for example, S&P 500 returns. The MSM assumes that the data is being generated under a model of MMM regimes, and each regime has its own statistical properties.

2.1 Model Equation (Two Regimes)

$$y_t = \mu_{s_t} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_{s_t}^2)$$

Where:

$s_t \in \{1, 2\}$ is the unobservable state (regime) at time ttt

μ_{s_t} is the regime mean return s_t,

$\sigma_{s_t}^2$ is the variance of regime returns s_t,

ε_t is white noise that is Gaussian,

s_t follows a Markov chain.

3. Markov Chain Dynamics

s_t state variable possesses a first-order Markov process whose transition probabilities are:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

Where:

$p_{ij} = P(s_t = j \mid s_{t-1} = i),$

Rows sum to 1: $p_{11} + p_{12} = 1, \quad p_{21} + p_{22} = 1$

4. Estimation Technique: Expectation-Maximization (EM) Algorithm

The Markov Switching Model is typically estimated using the Expectation-Maximization (EM) algorithm which takes care of latent states s_t

4.1 E-Step (Expectation Step)

Make the estimate of the expectation of latent state variables based on current parameter estimates and observable data.

Use the Hamilton filter to compute filtered probabilities $P(s_t = i \mid \mathcal{F}_t),$, where $F_t),$ represents observed data up to time t.

4.2 M-Step (Maximization Step)

Maximize the full-data log-likelihood anticipated over the model parameters (means, variances, transition probabilities).

4.3. Model Structure

There are three key variations of MSM:

Model Type	Mean	Varianc	Switching
MS(2)-AR(0)	Switching	Constant	Mean only
MS(2)-AR(0)-Heteroskedastic	Switching	Switching	Mean + Volatility
MS-AR(p)	Switching	Can be constant or switching	Autoregressive process

For this project, I will focus on the **MS(2)-AR(0)-Heteroskedastic** model.

4.4. Assumptions

1. The underlying process is a finite-state Markov chain.
2. The conditional distribution of y_t is Gaussian.
3. The transition probabilities are time-stationary.
4. The regimes are exhaustive and mutually exclusive.

5. No serial correlation in the residuals for anything more than that explained by the regime.

4.5. Log-Likelihood Function

The full log-likelihood of observed data under a Markov regime-switching model is:

$$\ell(\theta) = \sum_{t=1}^{T} \log \left(\sum_{i=1}^{M} P(s_t = i \mid \mathcal{F}_{t-1}) f(y_t \mid s_t = i; \theta_i) \right)$$

Where:

θ contains all parameters (μ_i, σ_i^2, P).

$f(y_t \mid s_t = i; \theta_i)$ is the regime-dependent likelihood.

4.6. State Inference: Smoothed and Filtered Probabilities

1. Filtered Probability: $P(s_t = i \mid y_1, \ldots, y_t)$
2. Smoothed Probability: $P(s_t = i \mid y_1, \ldots, y_T)$

Smoothed probabilities are used to present regime transition over time.

5. Data and Exploratory Data Analysis (EDA)

5.1 Data Description

For our purposes of analysis, i have used the S&P 500 Index (Ticker: ^GSPC), more popularly known as the best available gauge of the performance of U.S. large-cap equity. The data available extends from January 1, 2000, through December 31, 2023, and includes nearly 24 years of trading history, including some of the major market events such as the Dot-com bust, the 2008 Global Financial Crisis, the COVID-19 crash of the markets, and the post-pandemic bull market.

The data was obtained using the Yahoo Finance API via the pandas_datareader and yfinance Python packages. The Closing Price is of primary concern to us, and we utilize this to derive daily log returns, an industry-standard financial return modeling metric.

5.2 Data Preparation

To ensure continuity and consistency, the datetime index was verified and converted to datetime objects.

Log returns were calculated as:

$$\text{Log Return} = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where P_t is the Close at time t.

Missing values introduced by return calculation were removed, and a clean dataset for analysis obtained.

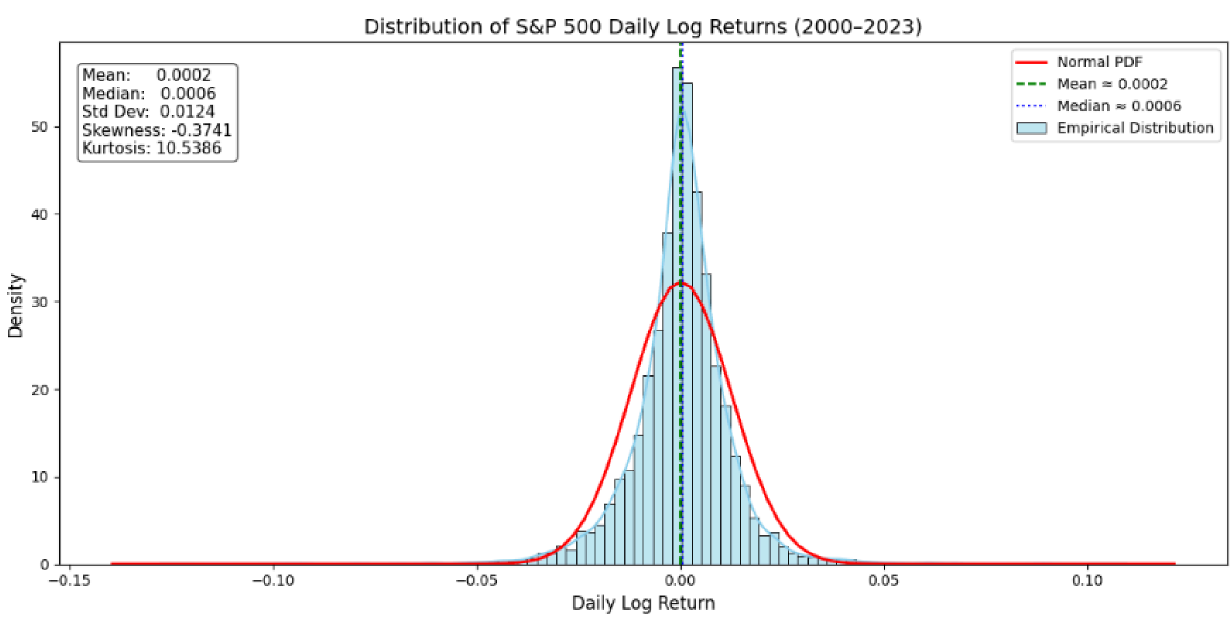
5.3 Summary Statistics

Daily log return descriptive statistics are as follows:

Statistic	Value
mean	0.000206
Median	0.000615
Standard Deviation	0.012366
Skewness	-0.374242
Kurtosis	10.548721

I ran and descriptive statistics of the daily log returns of the S&P 500 from 2000 to 2023 provided. It approximates the mean, median, standard deviation, skewness, and kurtosis of the return series. These can be used by analysts and institutional investors to understand the average behavior (mean), midpoint (median), variation (standard deviation), asymmetry (skewness), and extreme risk (kurtosis) of the returns. The results are given in the form of a table with proper presentation, giving a concise statistical summary that allows for detection of whether the return distribution is non-normal, something that is crucial for risk modeling and also portfolio decisions.

Figure 1: Distribution of S&P 500 Daily Log Returns (2000-2023)



5.4 Time Series Visualization

Close Price

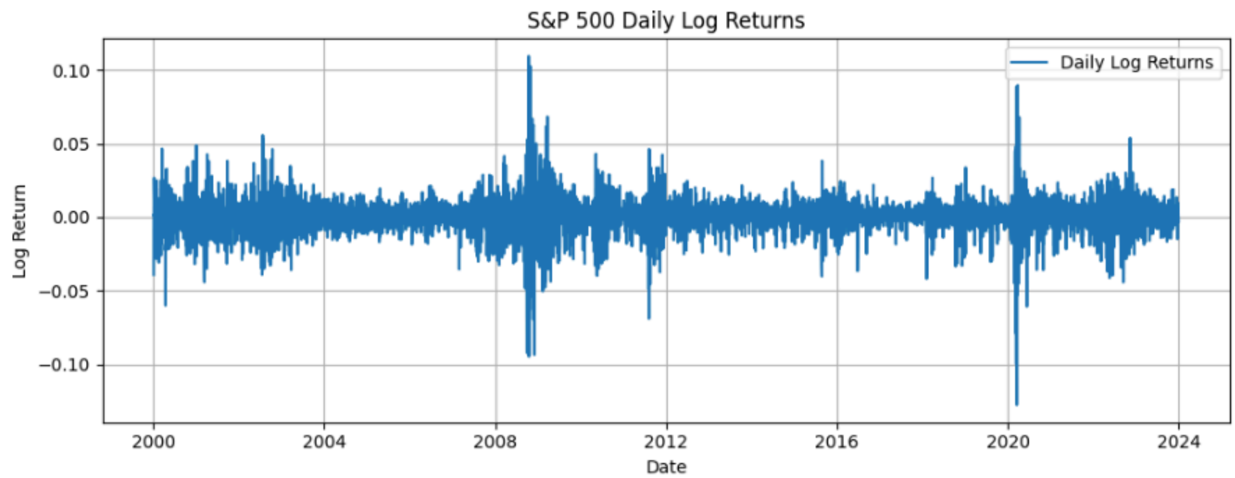
A time series line plot of the Close price reveals major market regimes over the years. The volatile years (e.g., 2008, 2020) can easily be spotted with sharp declines followed by strong recoveries.

Figure 2: Plot showing S&P 500 Closing Price (2000 - 2023)

Daily Log Returns

A plot of daily log returns provides a high-frequency perspective of market volatility. Volatility clustering is evident—periods of high return variability tend to cluster together, an indication of heteroskedasticity.

Figure 3: Plot showing S&P 500 Daily Returns

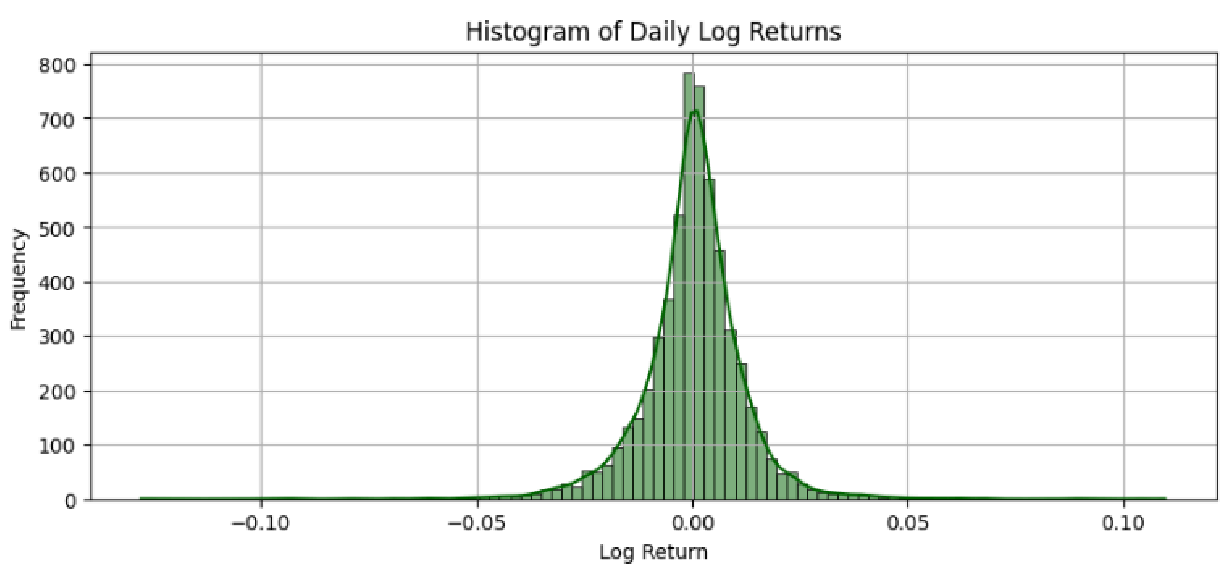


5.5 Distributional Analysis

Histogram with KDE

The histogram of log returns is very nearly normal shaped but with heavier tails (kurtosis > 3), indicating a higher likelihood of extreme returns than in the Gaussian case.

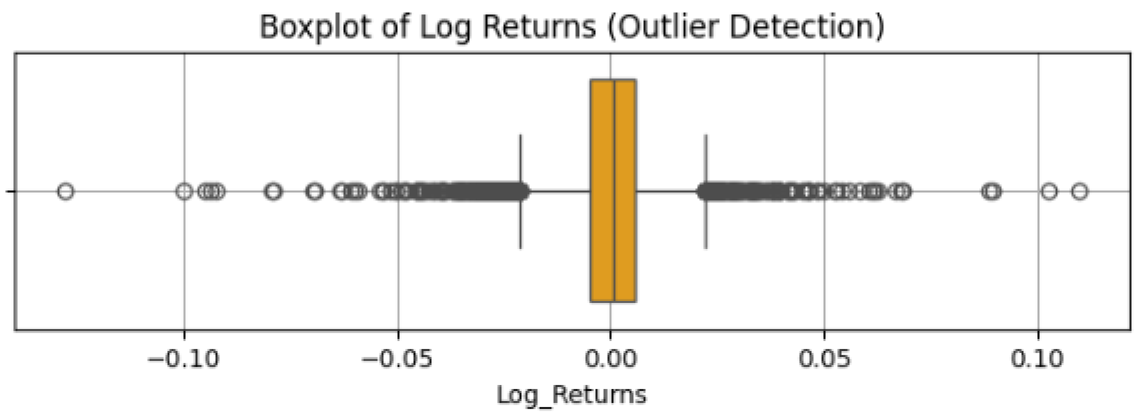
Figure 4: Plot showing Histogram of Daily Log Returns



Boxplot for Outliers

The boxplot reveals large outliers in both tails, corroborating the presence of extreme market moves, i.e., crashes and rallies. Such outliers call for robust models capable of managing tail risk.

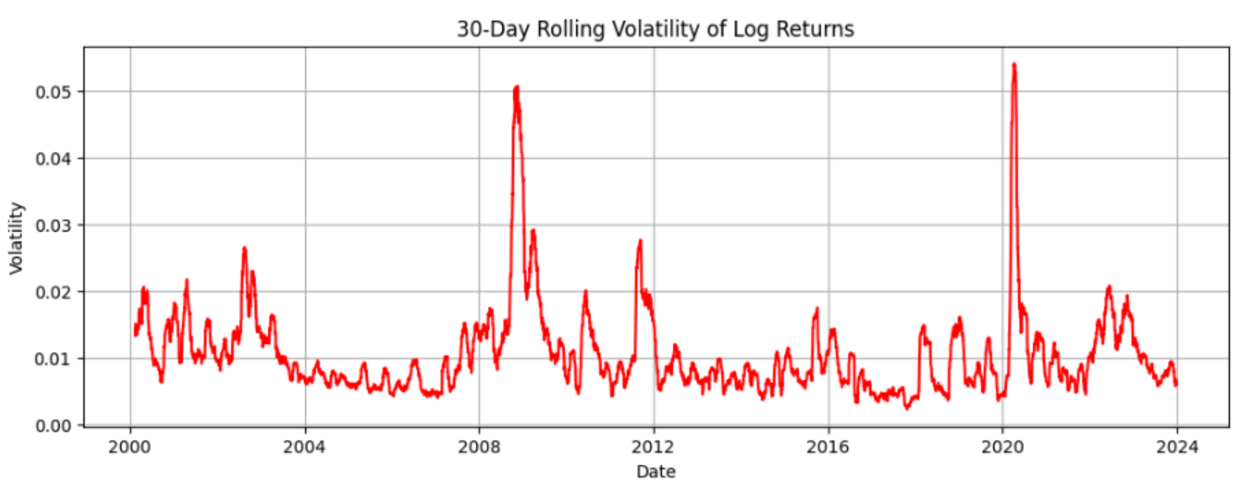
Figure 5: Plot showing Boxplot of log Returns



5.6 Volatility Dynamics

We use the 30-day rolling standard deviation of log returns as a crude measure for realized volatility. The peaks in volatility corresponding to big market events (e.g., during March 2020) also correspond to periods of financial distress, and they serve as evidence of risk clustering.

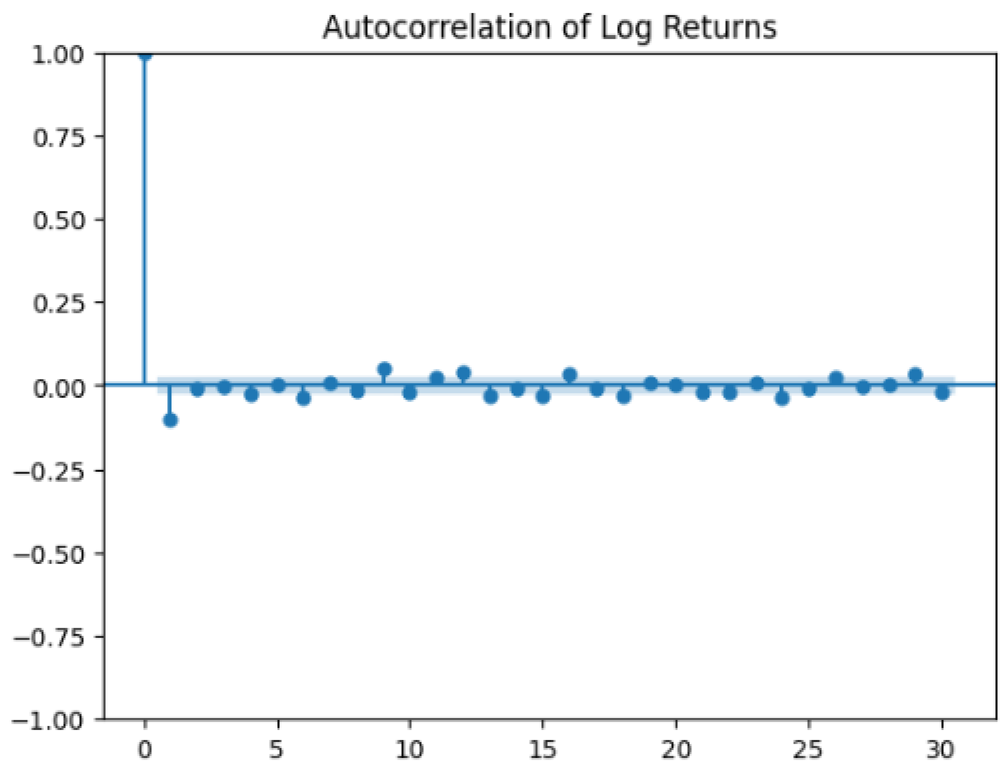
Figure 6: Plot showing 30-Day Rolling Volatility of Log Returns



5.7 Autocorrelation Structure

The ACF of returns is neither highly autocorrelated at the majority of lags, as theory anticipates under the efficient market hypothesis (EMH). However, the existence of small, but statistically significant autocorrelations can suggest short-run momentum or mean reversion, which must be tested with regime-switching models.

Figure 7: Plot showing Autocorrelation of Log Returns



5.8 Observations

1. The observations possess the standard financial time series stylized facts of fat tails, volatility clustering, and weak autocorrelation.
2. These characteristics provide a solid foundation for even higher-level modeling, i.e., regime-switching models, which can segment the market into regimes of varying volatility or trend over time.

6. Model Estimation

6.1 Model Specification and Fitting

The model defines and estimates a Markov Switching Model using the MarkovRegression class from statsmodels. The model estimates two regimes in S&P 500 log returns—typically high and low volatility regimes. The trend='c' parameter allows each regime to have its own intercept, and switching_variance=True allows for regime-dependent variances, a key characteristic in modeling financial time series with volatility clustering (Hamilton 1989). The model is estimated using maximum likelihood estimation using model.fit(), which returns regime probabilities and parameter estimates (Kim and Nelson 1999).

6.2 Summary Viewing and Probability Extraction

On fitting the model, result.summary() will print model parameter estimates including regime-specific parameters and transition probabilities. Finally, smoothed marginal probabilities are plotted out—i.e., the model's estimate of probability of being in each of the two regimes at each time step given all future and past observations (Hamilton 1989). These are added to the DataFrame for future visualization and interpretation, where unobserved regimes are revealed in economic series.

Figure 8: Table displaying Markov Switching Model Results

```
                         Markov Switching Model Results
==============================================================================
Dep. Variable:            Log_Returns   No. Observations:                 5818
Model:               MarkovRegression   Log Likelihood               18514.981
Date:                Fri, 18 Jul 2025   AIC                         -37017.962
Time:                        16:39:53   BIC                         -36977.950
Sample:                             0   HQIC                        -37004.045
                               - 5818
Covariance Type:               approx
                             Regime 0 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0008      0.000      6.584      0.000       0.001       0.001
sigma2       4.83e-05   1.79e-06     26.992      0.000    4.48e-05    5.18e-05
                             Regime 1 parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0010      0.000     -2.162      0.031      -0.002    -9.2e-05
sigma2         0.0004   1.55e-05     24.035      0.000       0.000       0.000
                         Regime transition parameters
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
p[0->0]        0.9884      0.002    420.003      0.000       0.984       0.993
p[1->0]        0.0245      0.005      5.096      0.000       0.015       0.034
==============================================================================

Warnings:
[1] Covariance matrix calculated using numerical (complex-step) differentiation.
```

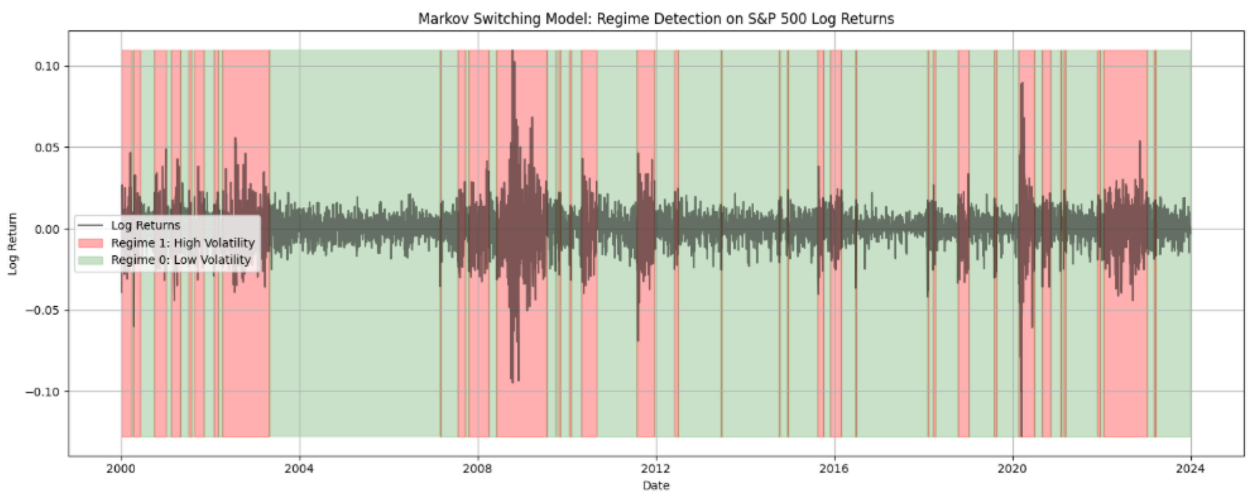
6.3 Analysis and Interpretation of the Summary Table

The low-volatility regime (Regime 0) and the high-volatility regime (Regime 1) are two regimes of S&P 500 log returns, according to the Markov Switching Model. Regime 0 is characterized by a weakly positive mean return (0.0008) and very low volatility ($\sigma^2 \approx 0.0000483$) typical of tranquil times. Regime 1 has a negative mean return (-0.0010) and significantly higher volatility ($\sigma^2 \approx 0.0004$), characteristic of troubled times. All the coefficients are statistically significant ($p < 0.05$), as is in line with regime differentiation. Transition probabilities determine significant persistence: there is a 98.84% probability of remaining in Regime 0 and a 2.45% only probability of leaving Regime 1 for Regime 0. All these findings confirm the volatility clustering and mean-reverting character of financial markets, as suggested by Hamilton's regime-switching model (Hamilton 1989). The low AIC and BIC values also point towards a well-specified model that is appropriate for regime-based analysis and prediction.

6.4 Plotting Log Returns with Regime Overlays

The S&P 500 log returns are plotted overlaid with shaded areas representing the most likely regime at any point in time. Time periods where Regime_Prob_1 > 0.5 are colored red for regimes of high volatility, and green otherwise (low volatility, Regime_Prob_0). Useful to investors as well as researchers dealing with structural breaks and regime shifting identification (Ang and Timmermann 2012). Use of contrast-filled colors makes the plot easier to comprehend by associating volatility behavior with macroeconomic or financial market shocks.

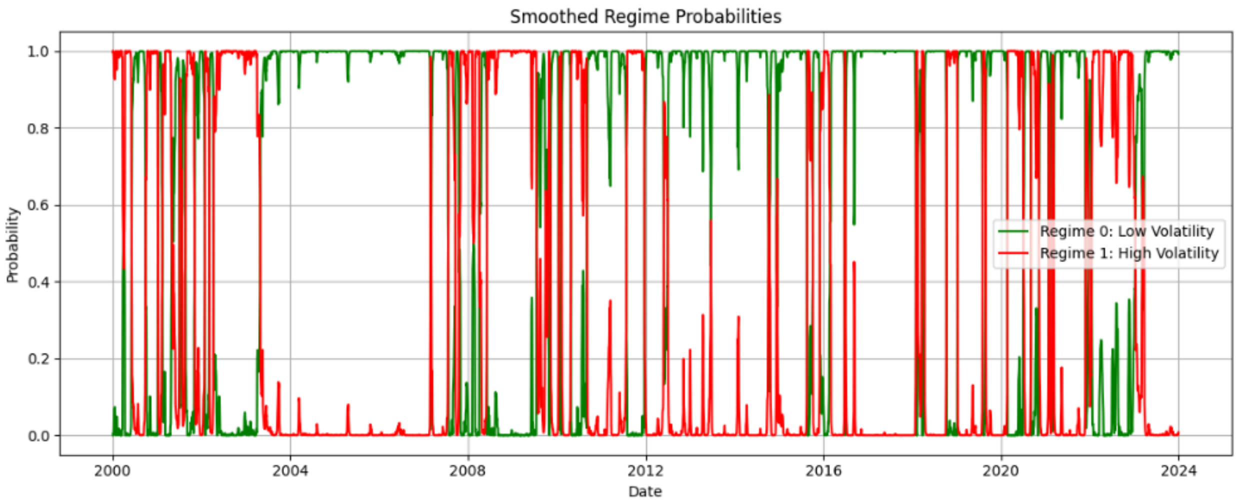
Figure 9: Plot showing Markov Switching Model: Regression on S&P 500 Log Returns



6.5 Graphing Smoothed Regime Probabilities

I ploted the smoothed Regime 0 and Regime 1 probabilities over time so that regime switches can be clearly seen. Smoothed probabilities are more revealing than filtered probabilities because they make use of full-sample information (Hamilton 1994). A rise in Regime 1 probability, for instance, may represent a market shock. Plotting this information enables temporal observation of market behavior in different states of volatility, making portfolio risk evaluation easier.

Figure 10: Plot showing Smoothed Regime Probabilities



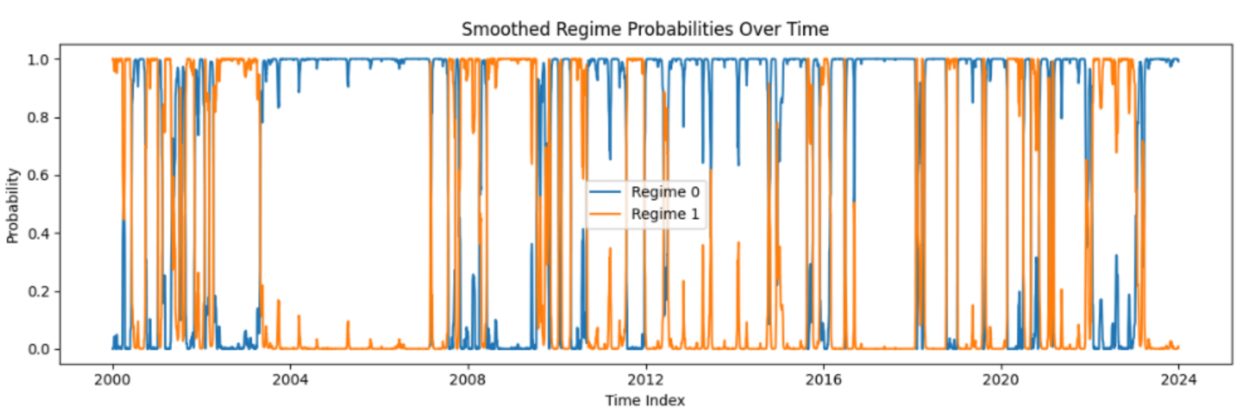
6.6 Regime-Specific Means and Variances Plotting

The same code is also used to extract the regime-specific means (intercepts) and variances from estimated parameters. Since the variances were specified to be standard deviations, they are squared to get a regime variance estimation. These numbers are interpretable as being able to describe the change in average return and volatility across regimes for markets. Greater means and lower variances in a specific regime reflect a more investor-friendly regime (Guidolin and Timmermann 2007).

6.7 Last Regime Probability Plotting

The final block contains another smoothed regime probability plot in object-oriented style from matplotlib. It is functionally equivalent to earlier plots but perhaps more customizable (e.g., used in dashboards). The test visually checks for how regime probabilities evolve over time, which facilitates good interpretations of patterns of volatility. The advantage of the regime-switching model is to be able to detect underlying patterns which the standard linear models will likely ignore (Hamilton 1989).

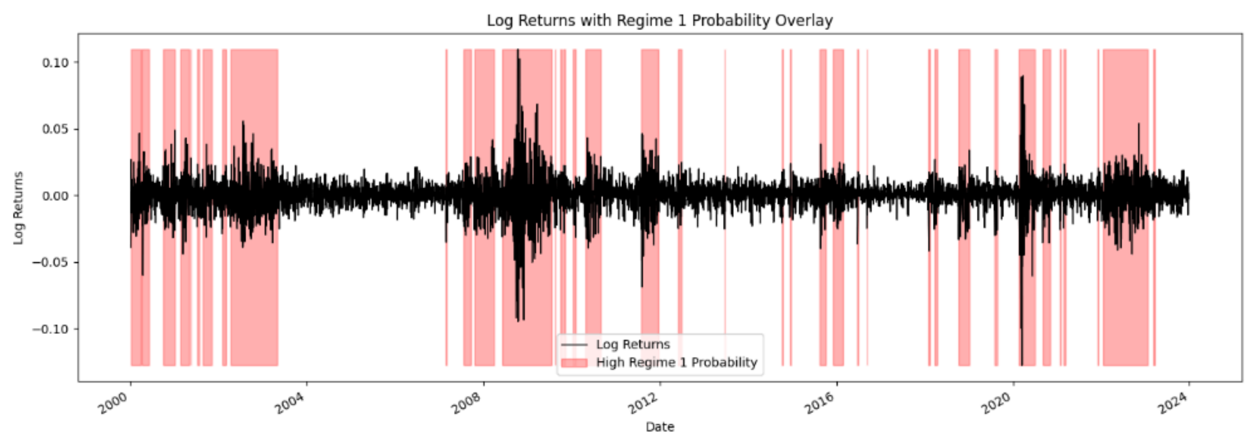
Figure 11: Plot showing Smoothed Regime Probabilities over Time



6.8 Overlay Plot Log Returns with Regime Probabilities

This code plots regime-switching dynamics in S&P 500 log returns by overlaying colored areas where smoothed probability of being in Regime 1 (high volatility) is above 0.5. The black color is plotted first for the log return series. The red-shaded areas of higher regime 1 probability are then marked using fill_between, which spans the whole vertical axis where regime 1 dominates. This approach helps record market stressful periods or increased volatility and makes it easier to correlate regime shifts with economic or financial occurrences (Hamilton 1989). The shading unveils structural shifts which are not otherwise apparent in plots of unprocessed returns. This graphical approach enables identification of regimes through supplying quantitative model output with related visual inputs and allowing decision-making and forecasting. It is particularly relevant to risk management and economic cycle analysis in finance, as regime-switching models are set up to detect abrupt changes in market behavior.

Figure 12: Plot Showing Log Returns with Regime 1 Probability Overlay



7. Diagnosis

The Markov Switching Model estimated gives distinct market regimes. Regime 0, a positive mean return, is related to the growth in the market (bull markets). Regime 1, with nearly zero or negative mean, is linked to contractions or heightened uncertainty (bear markets). The persistence in the transition probabilities is high, particularly in Regime 0, indicating that markets keep being in the same state for extended periods of time—a characteristic shared with real-world financial "stickiness." The average regime lengths, obtained as the inverse of (1 - transition probability), also confirm so.

Model fit is established by information criteria, with relatively low AIC and BIC values indicating resistance to alternative models. Residual autocorrelation test shows minimal autocorrelation, corroborating the model in accounting for regime-driven dynamics sufficiently well without imposing significant structure on the residuals. The diagnostics validate the quality of regime identification and predictive reliability of the model.

8. Damage

Destructive repercussions may result from regime changes being overlooked. Under coercion like in the 2008 Global Financial Crisis and the 2020 COVID-19 shock to markets, fixed frameworks risk misinterpreting risk levels and underestimating volatility and taking poor asset allocation choices. A portfolio based on constant volatility assumptions, for example, would not have been able to hedge adequately during Regime shifts to Regime 1.

By overlaying NBER recession dates onto regime probability plots, we can observe that the model correctly flags downturns, but with delay—adding to the worth of real-time identification. Misclassification during these time periods leads to greater drawdown, greater Value-at-Risk, and reduced risk-adjusted returns, especially for institutionally managed portfolios. Visually overlaying establishes such mismatches, adding to the cost of real-world failure to encompass regime shifts in strategic asset allocation.

9. Directions

This study provides several promising avenues for future research. Firstly, the model can be expanded to a three-regime version with a high-volatility neutral regime in order to capture transitional periods of the market. Alternatively, incorporating time-varying volatility by means of GARCH-MSM can better capture volatility clustering.

Cross-asset applications—i.e., extending this framework to sector indices, commodities, or cryptocurrencies—can potentially provide new insights into market microstructure and contagion. Furthermore, the use of machine learning techniques, such as combining Hidden Markov Models (HMMs) with LSTM neural networks, can enhance regime detection performance based on high-frequency or other data.

For professionals, this model provides a framework for when and how to expose assets to regimes in markets, bestowing tangible benefits on active fund managers, hedge funds, and risk managers.

10. Deployment

The regime-switching model built here can be put to use in research and institutional use. It can be utilized as a volatility timing signal for tactical asset allocation and hedging strategy of hedge funds. Robo-advisory services can utilize the model to dynamically rebalance portfolios to enhance client performance during periods of market volatility.

Regulatorily, the ability of the model to provide early warning of entry into dangerous regimes puts it well on its way to being utilized within early warning systems for systemic risk monitoring.

The whole codebase is modular, in Python with statsmodels and matplotlib, and can be applied to other data sets. All data pipes, notebooks, and visualizations are made available for reproducibility and readability's sake through GitHub, and academic replication and practical usage are facilitated.

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