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Detecting Trend and Regime Changes

Mark Lee, Min Li, Dawn Lu, Qinyan Wu
Team 5

Background and Methodology

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Background

- Understanding market shifts is critical for effective asset allocation
- Regime changes signal transitions between different economic and market conditions
- The objective is to segment time series data by trends and identify the significant change points

Data and Methodology

- We are detecting changes in trends in S&P 500
- External factors
  - GDP
  - Unemployment rate
  - CPI
  - Interest rate
  - VIX
  - Treasury yield
- Methodology
  - Change point detection algorithms
  - Markov switching regression model

Detect Trend and Change Point

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Overview

We tried to use the argrelextrema function for peak and valley detection for identifying significant changes or turning points in time series data.

We tuned the hyperparameter –“order”.Higher order values yield broader changes, lower values capture finer details.

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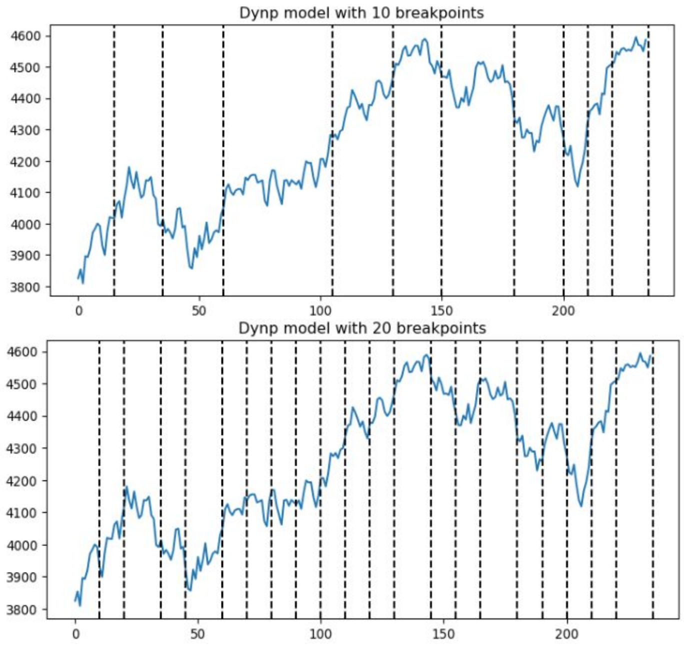
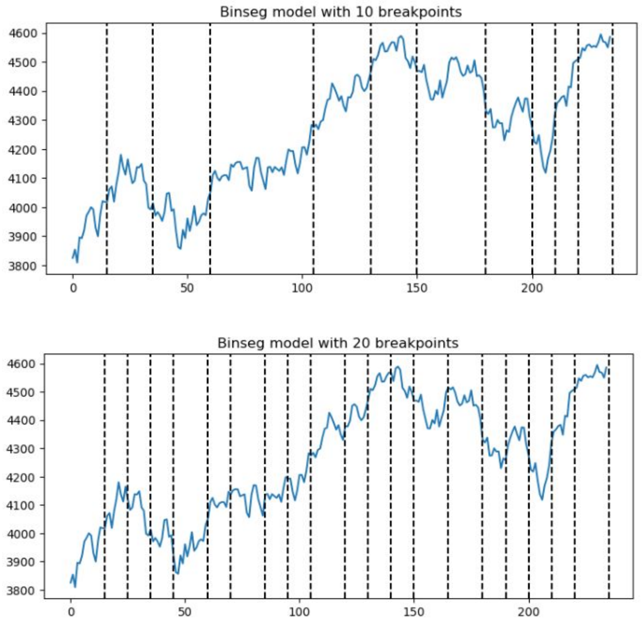
Dynamic Programming

Dynamic Programming works by systematically examining all possible segmentations of a given signal to find the exact minimum of the sum of costs associated with each segmentation. However, one important requirement for using DynP is that the user must specify the number of change points in advance.



Binary Segmentation

It looks for a single change point in the entire signal. Once it finds that point, it splits the signal into two parts and repeats the process for each of those parts. This keeps going until no more change points are found or a specified stopping criterion is met. It makes decisions based on the best immediate choice without considering the overall impact on the final result.



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Markov Switching Regression Model

We applied a Markov Regime Switching Model to S&P 500 data, complemented by economic and market indicators, to detect and analyze market regime changes. The objective was to understand the transitions between high and low volatility states in the market and the influence of economic factors.

Data Preparation

We gathered S&P 500 data from 2000 to 2023 and some quarterly and monthly indicators data. We combined all data by filling quarterly and monthly data gaps to match the daily S&P 500 return to create a unified dataset for analysis.

Date	Close	Volume	GDP	Unemployment_Rate	CPI	Interest_Rate	VIX	Treasury_Yield	Return
2000-01-04	1399.420044	1009000000	10002.179	4.0	169.300	5.45	27.010000	6.485	-0.038345
2000-01-05	1402.109985	1085500000	10002.179	4.0	169.300	5.45	26.410000	6.599	0.001922
2000-01-06	1403.449951	1092300000	10002.179	4.0	169.300	5.45	25.730000	6.549	0.000956
2000-01-07	1441.469971	1225200000	10002.179	4.0	169.300	5.45	21.719999	6.504	0.027090
2000-01-10	1457.599976	1064800000	10002.179	4.0	169.300	5.45	21.709999	6.558	0.011190
...	...	...	...	...	...	...	...	...	...
2023-03-27	3977.530029	4233540000	26813.601	3.5	301.808	4.65	20.600000	3.528	0.001647
2023-03-28	3971.270020	4014600000	26813.601	3.5	301.808	4.65	19.969999	3.564	-0.001574
2023-03-29	4027.810059	4145250000	26813.601	3.5	301.808	4.65	19.120001	3.566	0.014237
2023-03-30	4050.830078	3930860000	26813.601	3.5	301.808	4.65	19.020000	3.551	0.005715
2023-03-31	4109.310059	4525120000	26813.601	3.5	301.808	4.65	18.700001	3.494	0.014437

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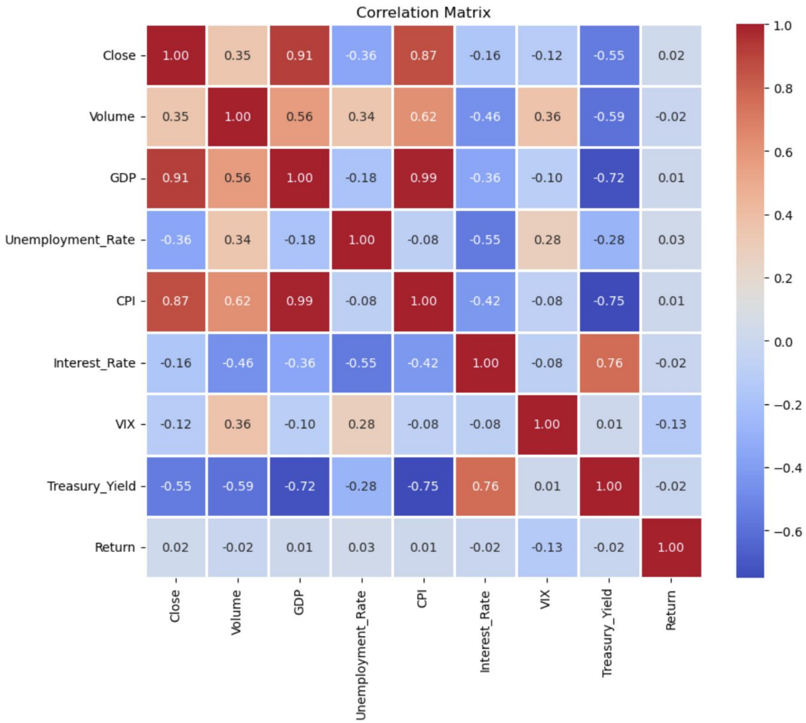
Exploratory Data Analysis

We plotted line graphs for return and each indicator over time to observe trends. We also created a correlation matrix to see how different data points relate because correlations will affect the model performance. Additionally, we printed descriptive statistics to understand the data's basic features like average, range, and variability.



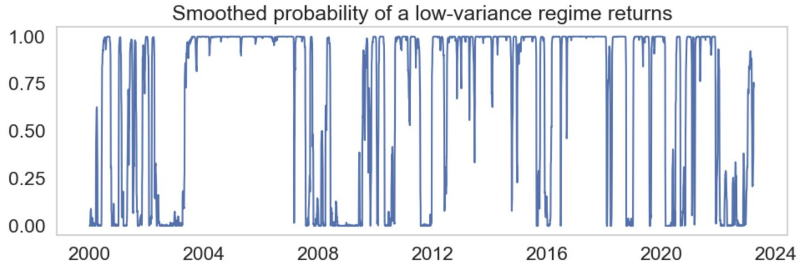
Model Implementation

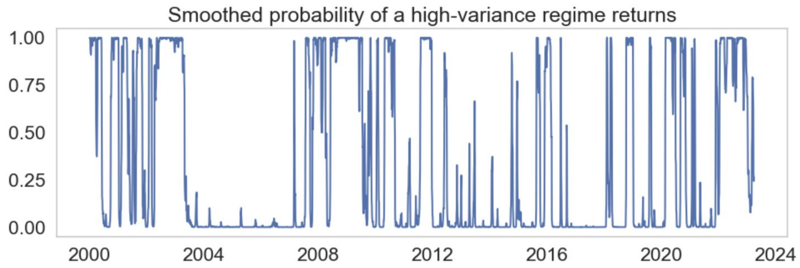
We enhanced the Markov Regime Switching Model by including external factors like the unemployment rate. We plotted graphs showing low and high-variance regime probabilities and the historical S&P 500 regimes.

Finally, we compared the original and extended models using log-likelihood, AIC, and BIC metrics. According to Log-Likelihood and AIC, the model with exogenous variables has better performance.

Model Performance

These graphs show the chances of the S&P 500 being calm or turbulent over time. The top one shows stable times with less price movement. The bottom one shows risky times with bigger price changes. Sharp rises indicate shifts to that market state. They help predict if the market will be smooth or rough.





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Model Performance

This graph shows the S&P 500 closing prices with two colors marking different market regimes. Green dots signal stable times with smaller price moves. Red dots indicate volatile periods with more significant price swings. It helps us see how market conditions change over time.

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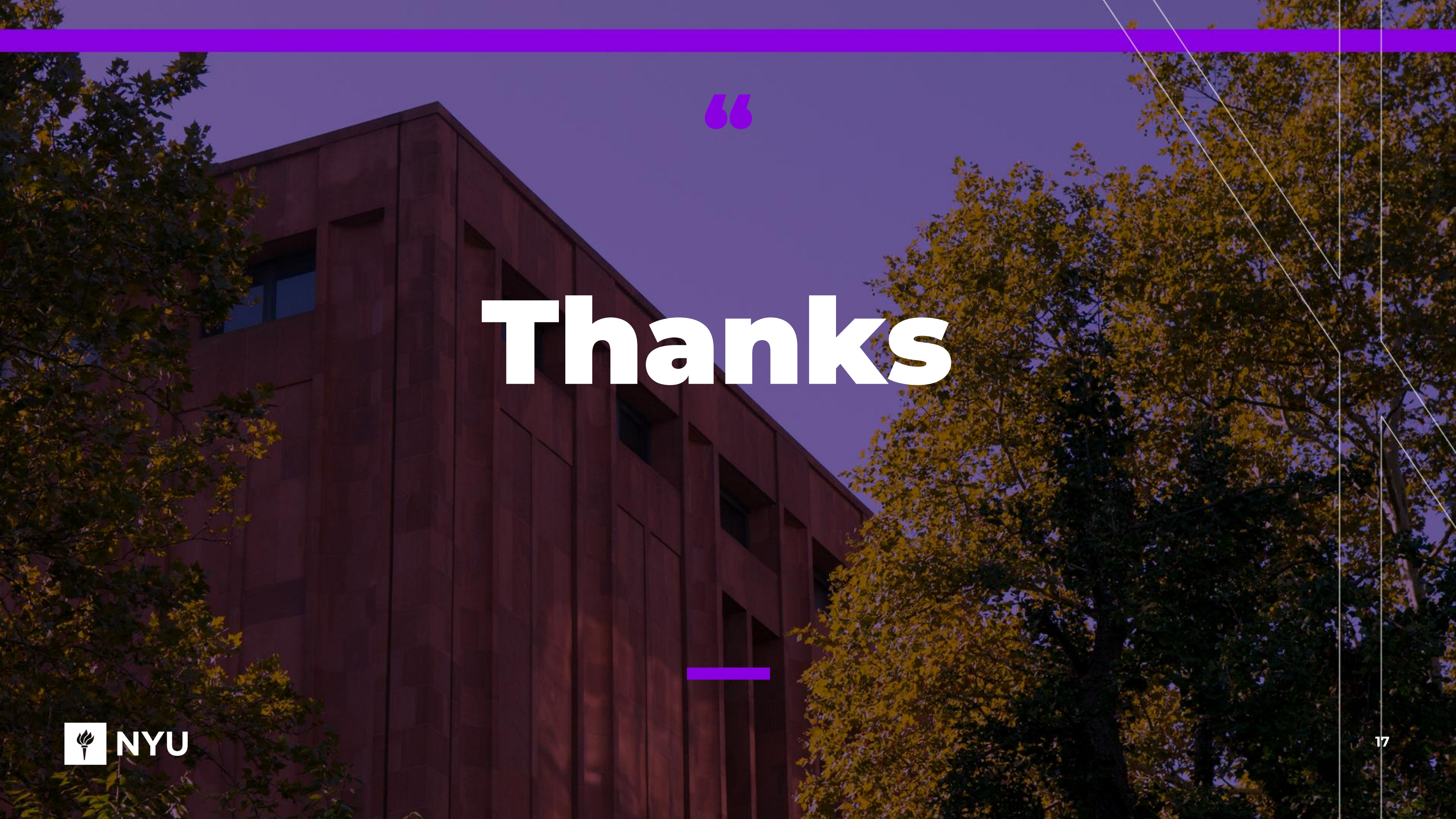
Testing and Refining Model

We predicted market behavior using Mean Squared Error (MSE) for accuracy. We refined our model by increasing the number of regimes and removing the time trend. We then evaluated the refined model by MSE. The MSE of the refined model was 0.000151.



Thanks