Predicting Recessions Using U.S. Treasury Yield Data (1981-2005 / 2005-2025)

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Data Science 325
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Date: 5/2/2025

Introduction/Abstract

The U.S. Treasury yield curve has long been viewed as a key indicator of economic health, especially for predicting upcoming recessions. Historically, when the yield curve inverts—meaning short-term interest rates rise above long-term rates—it has often signaled a recession ahead. Because of this, economists and policymakers closely monitor changes in the yield curve to gauge market confidence and the risk of economic slowdowns.

Given the ongoing need for better recession prediction tools, our project explores whether the yield curve, combined with other important economic indicators, can more accurately forecast U.S. recessions within 3-month and 12-month windows. We expected that adding factors like the unemployment rate and industrial production index to the traditional yield spread would strengthen the predictions.

The goal of this project is to build a model that predicts U.S. recessions using macroeconomic and financial data. In particular, we focused on forecasting recessions up to twelve months in advance, which could help policymakers and investors take early action. We used historical data from 1981 to 2005—including treasury yield spreads, unemployment rates, and industrial production—and trained a logistic regression model to identify upcoming recession periods. Our approach prioritizes early warnings over perfect precision by setting a low probability threshold, which reflects the real-world risk of missing early recession signals.

Methods

Data Sources and Structure

We collected and merged multiple economic datasets from the Federal Reserve, including:

- Treasury Yield Rates (e.g., 10-year, 2-year, 3-month),
- Unemployment Rate (UNRATE),
- Industrial Production Index (INDPRO),
- NBER Recession Indicator (USREC).

We engineered features such as yield spreads (10-year minus 3-month, 10-year minus 2-year) and the first differences of yield curves to capture interest rate dynamics. The target variable is a binary label indicating whether a recession will occur 3 or 12 months into the future (look_ahead = 3) / (look_ahead = 12), created by forward-shifting the USREC indicator.

After preprocessing, including missing value handling and standardization with StandardScaler, we split the data into features (X) and target (y) for modeling.

Feature Engineering

To capture yield curve dynamics, we created two critical spread variables:

- 10-Year minus 3-Month Yield Spread
- 10-Year minus 2-Year Yield Spread

These spreads are widely cited in economic literature as signals of yield curve inversion. We also computed the first differences of each Treasury yield maturity to highlight month-over-month rate changes. The macroeconomic variables, UNRATE and INDPRO, were included directly as features.

Target Definition and Preprocessing

Our target variable aimed to predict whether a recession would occur 3 or 12 months ahead. To create this, we shifted the recession indicator forward by 3/12 months. Missing values resulting from differencing and shifting were addressed using backward fill to preserve data integrity.

We scaled the features using a standard scaler for the logistic regression model, though tree-based models were left unscaled due to their robustness to feature scaling.

Modeling Process

We ran three classification models, but we ended up choosing Logistic RegressionCV, as it performed better.

- Logistic Regression (LogisticRegressionCV): A baseline linear model effective for binary classification.
- Decision Tree Classifier: Able to model non-linear relationships and interpret feature splits visually.
- Random Forest Classifier: An ensemble method to improve robustness and mitigate overfitting risk.

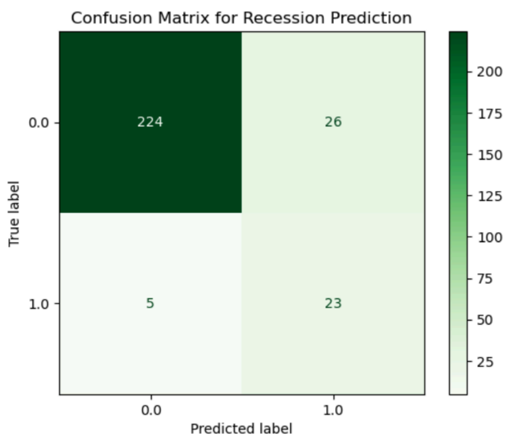
Validation and Testing

We trained a LogisticRegressionCV model on the full dataset from 1981–2005 using all available features. A probability threshold of 0.1 was used to convert predicted probabilities into binary classifications, allowing for greater sensitivity to potential recessions. After fitting the model, we evaluated its performance using a confusion matrix and classification report, focusing on recall to measure how well the model captures actual recessions. The trained model outputs were also stored alongside the original data to visualize the predicted recession probabilities and compare them against actual historical outcomes.

Results

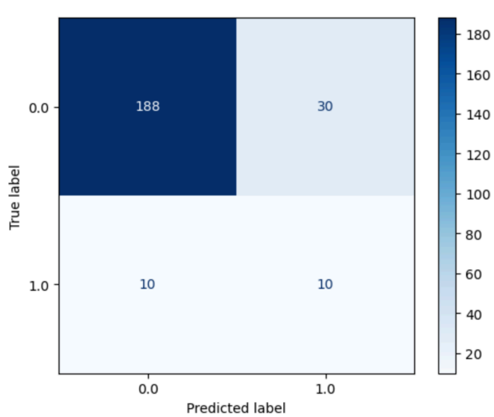
We built a logistic regression model to predict recessions three months in advance (look_ahead = 3) using economic indicators. To improve sensitivity, we set a low threshold of 0.1, making the model more likely to flag potential downturns. During training, it performed well, achieving 90% accuracy and 82% recall (Figure 1), though with some false positives, an expected trade-off with early warnings.

Figure 1: *The confusion matrix for recession prediction for 1981-2005 3-month look-ahead (Logistic Regression CV Model) Training set*



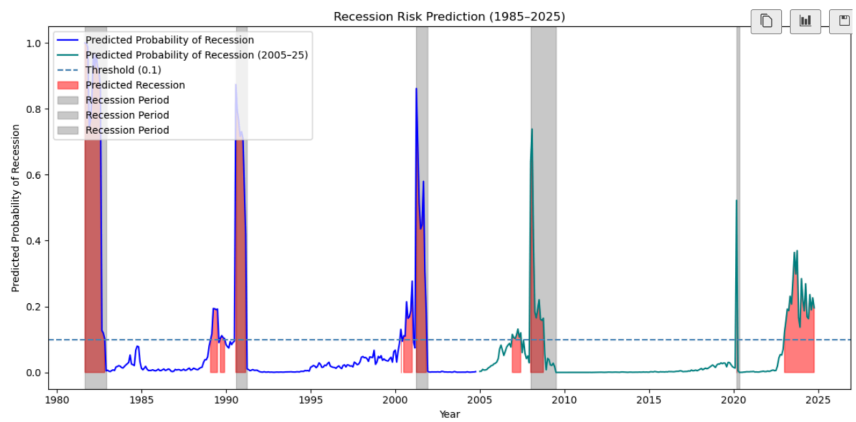
On 2025 test data, accuracy remained solid at 86.7%, but recall dropped to 50% and precision to 25% (Figure 2), showing reduced ability to detect recessions and more false alarms—common in time-series forecasting due to shifting economic patterns. Still, the model's use of leading indicators makes it valuable for early detection, even with occasional over-predictions.

Figure 2: *The confusion matrix for recession prediction for 2005-2025 3-month look-ahead (Logistic Regression CV Model) Testing set*



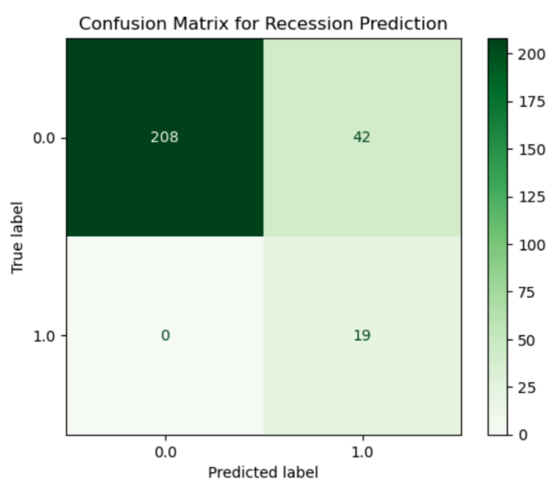
The probability plot (Figure 3) shows the model's predicted recession risk over time. The blue and teal lines represent training and testing periods, respectively, while red areas mark predicted recessions. Spikes align well with major events like the 2008 financial crisis, the 2020 COVID recession, and recent risk signals in 2023–2025. This visual reinforces the model's ability to flag early recession warnings, validating our choice to prioritize caution over precision.

Figure 3: *Recession Prediction 3-month look-ahead 1981-2005 / 2005-2025*



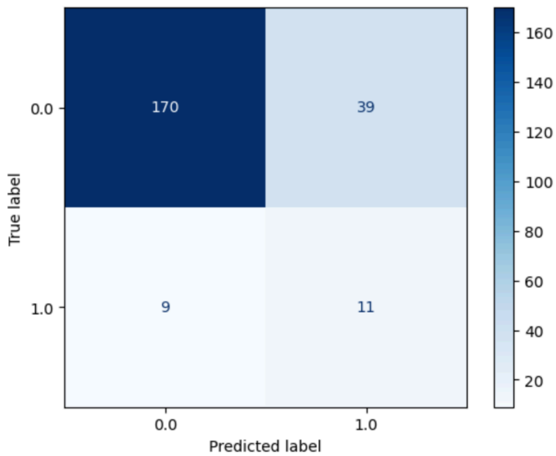
When extending the look-ahead to 12 months, forecasting becomes more challenging as the model must rely on earlier signals. In training (Figure 4), the model achieved perfect recall but generated 42 false positives, lowering precision.

Figure 4: *The confusion matrix for recession prediction for 1981-2005 12-month look-ahead (Logistic Regression CV Model) Training set*



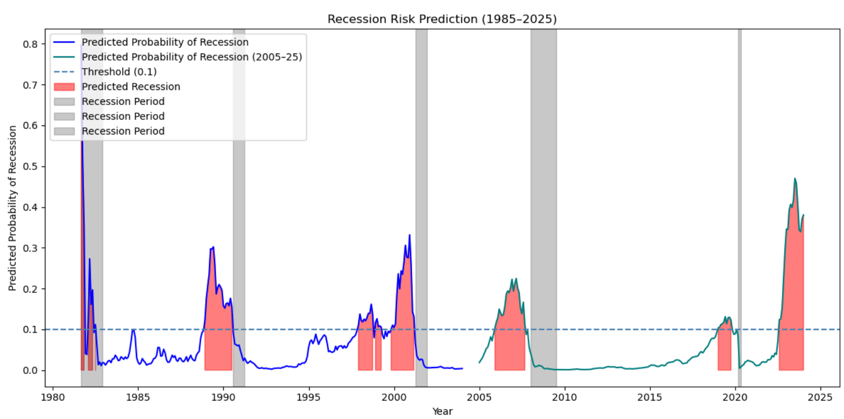
In testing (Figure 5), it correctly identified only 11 of 20 actual recessions and missed 9, while producing 39 false positives.

Figure 5: *The confusion matrix for recession prediction for 2005-2025 12-month look-ahead (Logistic Regression CV Model) Testing set*



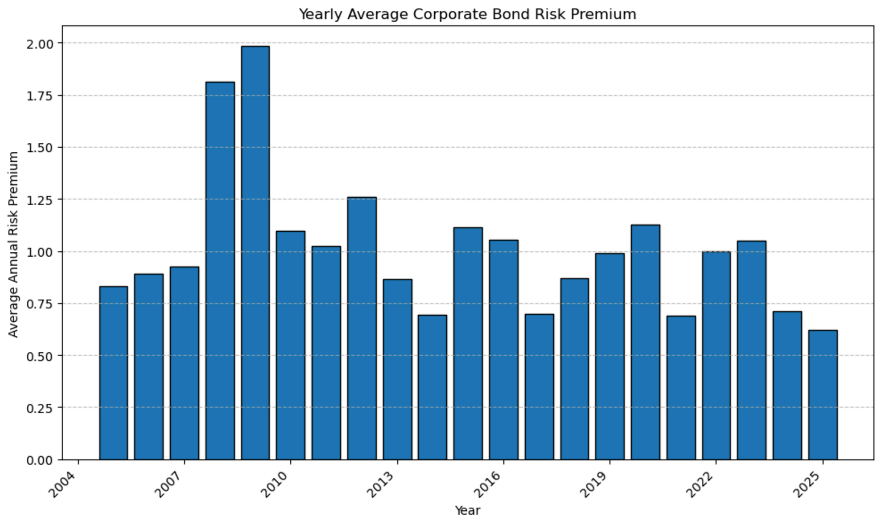
The updated probability plot shows broader, less sharp risk signals. While longer horizons reduce precision and timing accuracy, the model still captures meaningful early warnings, emphasizing the balance between early detection and predictive certainty in long-term forecasting.

Figure 6: *Recession Prediction 12-month look-ahead 1981-2005 / 2005-2025*



Discussions

Figure 7: *Yearly Average Corporate Bond Risk Premium 2005 - 2025*



This bar graph displays the yearly average corporate bond risk premium from 2005 to 2025, a key indicator of perceived credit risk in the economy. Spikes in the premium, especially during 2008–2010 and 2020, align with the global financial crisis and the COVID-19 recession, both of which were accurately flagged by our model's predicted recession probabilities. A smaller increase around 2023–2024 also supports our model's recent elevated risk predictions, reinforcing the value of the risk premium as a leading economic indicator.

Conclusions

Our project shows that the U.S. Treasury yield curve, when combined with the unemployment rate and industrial production index, can be a reliable tool for predicting U.S. recessions. The logistic regression model worked well during training, with strong recall and accuracy, and successfully flagged major recessions like the 2008 financial crisis and the 2020 COVID-19 downturn. However, when we tested the model on new data, its precision dropped. This is a common trade-off—while the model caught early warning signs, it also gave some false alarms, which is expected when the goal is early detection.

One of the main challenges we faced was class imbalance because recessions happen much less often than non-recession periods. To handle this, we lowered the probability threshold to make the model more sensitive and created key features like yield spreads to improve detection of inversion patterns. A key limitation is that the model is trained on past data, so it might not fully catch unexpected types of recessions, like those caused by unique events such as pandemics.

In the future, we suggest trying stronger models like gradient boosting, adding more economic indicators (such as inflation and consumer confidence), and using cost-sensitive learning to better balance recall and precision. Expanding the dataset to include recent years and regularly updating the model will also help keep predictions accurate as the economy changes.

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