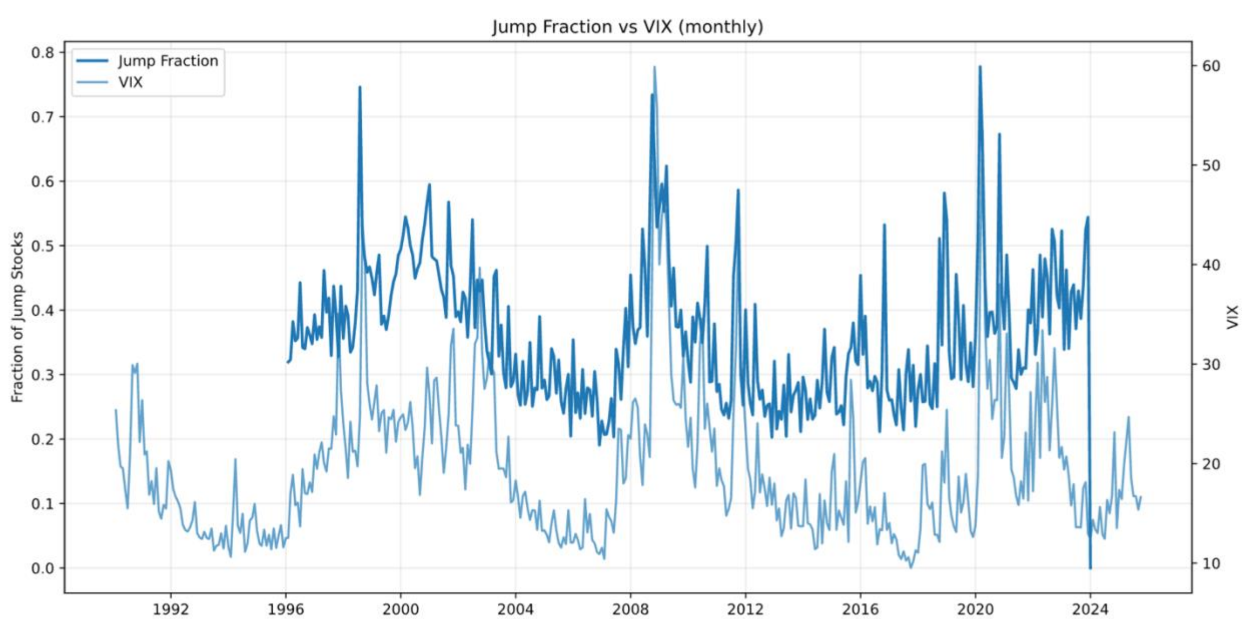
Predicting Stock Return Jumps

Introduction

This report investigates the prediction of extreme stock return jumps using firm-level characteristics and macroeconomic indicators. A “jump” is defined as a one-month return exceeding 10% in absolute value. I examine the time-series behavior of jump frequencies, explore relationships with macro variables (Unemployment, CPI, Industrial Production, and VIX), and evaluate predictive models ranging from logistic regressions with regularization to tree-based methods. The analysis uses CRSP monthly stock data supplemented with FRED macroeconomic series.

Jump Frequency and Macro Indicators

I first compute the fraction of stocks experiencing jumps in each month. This jump share is plotted against macroeconomic indicators, especially the VIX.



Observations:

- Jump frequency spikes during crisis periods such as the dot-com crash, the 2008 financial crisis, and the COVID-19 shock.
- The VIX rises in near-lockstep with the jump share, making it a strong contemporaneous indicator of jump risk.
- Unemployment and Industrial Production lag more, aligning with economic downturns but not offering clear short-term predictive signals.
- CPI changes appear weakly related to jump risk.

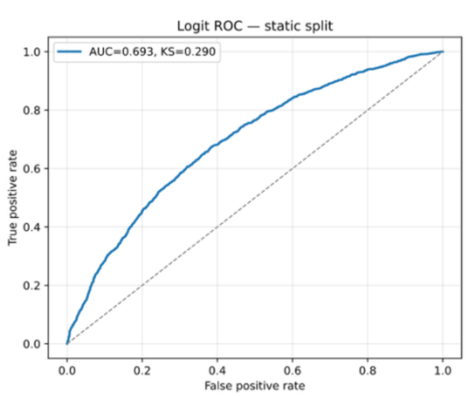
Conclusion: among the indicators, the VIX shows the most potential as a near-term precursor of high jump likelihood .

Model Evaluation

I estimated several classification models to predict whether a stock will jump in the following month. Models are trained on 1996–2017 data and tested on 2018–2023. Out-of-sample performance is assessed by the Area Under the ROC Curve (AUC) and the Kolmogorov–Smirnov (KS) statistic.

Logistic Regression

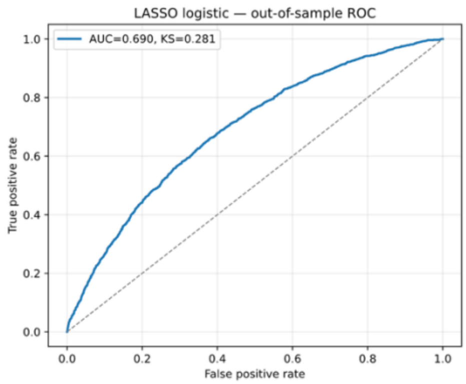
A baseline logistic regression provides a reference point.



- AUC = 0.693, KS = 0.290
- Performance is modest but significantly better than random guessing

LASSO Logistic

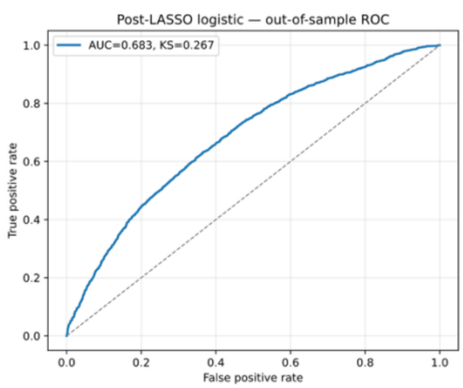
Apply an L1 penalty to select predictive features.



- AUC = 0.690, KS = 0.281
- Sparsity yields interpretability but sacrifices little predictive power

Post-LASSO Logistic

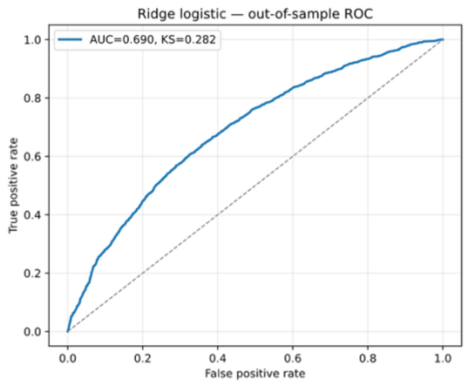
Refit a standard logistic on variables selected by LASSO.



- AUC = 0.683, KS = 0.267
- Slight decline in predictive accuracy relative to baseline

Ridge Logistic

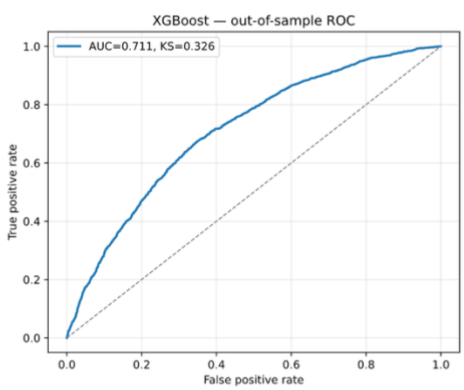
An L2-penalized logistic regression controls for multicollinearity.



- AUC = 0.690, KS = 0.282
- Results nearly identical to LASSO, highlighting robustness

XGBoost

Finally, evaluated a boosted tree model.



- AUC = 0.711, KS = 0.326
- Outperforms logistic models, indicating nonlinear interactions and threshold effects matter for jump prediction

Comparative Summary

- Logistic-based models (plain, LASSO, Ridge, Post-LASSO) achieve AUCs around 0.68–0.69
- XGBoost improves performance to 0.71 AUC, the best among tested models
- The KS statistic similarly favors XGBoost (0.326 vs ~0.28 for logistic)
- This suggests machine learning approaches capture nonlinearities and higher-order interactions that logistic regressions miss

Conclusion

The analysis confirms that stock return jumps cluster around macroeconomic crises and correlate strongly with volatility indices like the VIX. While logistic regression provides a transparent baseline, its predictive power is limited. Regularization does not significantly improve accuracy. In contrast, tree-based ensemble methods like XGBoost deliver stronger out-of-sample performance, making them a promising tool for forecasting extreme stock returns.

Future work could extend the feature set to include option-implied measures, sentiment indices, or more granular firm fundamentals, and test more advanced models such as neural networks or random forests.