The full code are available at:
magentahttps://github.com/theanishk/ml$_{p}roject$

Predicting Economic Recessions Using a Panel Based Machine Learning Framework

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Abstract

Recessions spread more quickly across countries today than at any earlier point in time, driven by strong trade links, global supply chains, cross border credit flows, and synchronized investor sentiment. Standard recession prediction studies focus on single country models, often missing these cross country interactions. This project builds a panel based machine learning system that combines a consistent set of domestic indicators with global macro financial variables for twenty eight OECD economies from 1995 to 2023. We create a Macro Financial Composite Index using principal components to capture the common movements in real activity, financial markets, prices, credit, and external factors. We then use this enriched structure to predict recessions six months ahead. The results show that while nonlinear models provide small gains in ranking recessions through AUC, cost sensitive evaluation reveals that Random Forest delivers the most effective early warning signals when the economic cost of missed recessions is incorporated. The study demonstrates how integrating panel information, global risk variables, and asymmetric loss can significantly improve practical recession warning systems.

1 Introduction

Modern economies are deeply interconnected. Shocks that originate in one country often spread rapidly to others. Events such as the Global Financial Crisis, the Eurozone debt crisis, and the pandemic recession illustrate how disturbances propagate through financial linkages, supply chains, credit markets, and investor expectations. This growing interdependence means that countries rarely face downturns in isolation.

Despite this, most recession forecasting research remains centered on the single country approach. These models treat each economy as independent, relying on domestic predictors such as the yield curve, inflation, credit spreads, or industrial production. This approach misses two important realities. First, many downturns are driven by broad global shocks. Second, domestic recessions often arise from external developments rather than purely internal weaknesses.

To address this gap, we build a unified panel based machine learning model that uses data from multiple countries at once. This approach allows the model to learn both cross sectional patterns and time dynamics that are shared across economies. Our contributions are as follows.

1. We construct a harmonized monthly panel of twenty eight OECD economies covering 1995 to 2023.
2. We create a Macro Financial Composite Index (MFCI) to summarize the joint movements of key macro financial variables.
3. We frame recession prediction as a six month ahead classification problem and incorporate both global risk indicators and domestic features.
4. We evaluate models not only through statistical accuracy but through a cost sensitive framework motivated by the higher cost of missed crises.

2 Data

We assemble a monthly macro financial panel from 1995 to 2023. The dataset includes indicators that capture real activity, prices, financial market behavior, monetary policy, credit conditions, and global economic risk. Data sources include the OECD Main Economic Indicators, the BIS credit database, and the Federal Reserve Economic Data (FRED).

Table 1: Macro financial indicators used in the modelling dataset

Indicator	Economic meaning
Real activity	
Industrial production index	Level of real output
Industrial production growth	Year on year change in production
Prices and inflation	
Consumer price index	Price level
Inflation (year on year)	Annual change in consumer prices
Inflation (month on month)	Monthly change in consumer prices
Interest rates and yield curve	
Short term interest rate	Money market or policy rate
Long term government yield	Ten year government bond rate
Yield curve slope	Difference between long and short rates
Real short term interest rate	Short rate adjusted for inflation
Financial markets	
Equity market return	Monthly domestic stock market return
Real equity return	Equity return adjusted for inflation
Credit and external sector	
Private credit	Credit to private nonfinancial sector
Real effective exchange rate	Competitiveness adjusted exchange rate
Global and United States conditions	
United States policy rate	Federal Funds Rate
United States industrial production	Measure of United States real activity
Global oil price	Brent crude price
United States yield curve slope	Ten year minus two year yield spread
VIX index	Global market volatility indicator

Macro Financial Indicators

The panel includes twenty eight OECD economies. The remaining ten OECD members were excluded because of missing indicators, inconsistent historical coverage, or lack of reliable macro financial data for constructing both the MFCI and the recession label.

The Macro Financial Composite Index

To summarize joint movements in macro financial indicators, we construct a country level MFCI using principal component analysis. The indicators are grouped into four conceptual blocks: real economy, prices and monetary conditions, financial markets, and credit and external conditions.

Each variable is transformed to achieve stationarity, standardized, and combined into a vector for each country. We then extract the first principal component which captures the largest share of common variation. This component is interpreted as the underlying macro financial cycle.

To smooth short term noise, we apply a three month centered moving average. The resulting index is standardized again to allow comparisons across countries. For countries such as the United States and Germany, the first principal component explains roughly one quarter to one third of the total variation in the dataset.

We also extract a global factor by performing PCA on the set of all country level MFCIs. The first global factor explains about one third of the cross country variation and aligns closely with periods of global financial stress.

3 Machine Learning Model

The second part of the study focuses on predicting whether a recession will occur six months ahead. We define a recession using industrial production. A country is considered to be in recession when its year on year industrial production growth is negative and also lower than the previous month. This captures both contraction and declining momentum.

To predict this recession label, we use the information available at time t and shift the target variable by six months.

The feature set includes the MFCI, global risk indicators, monetary variables, and lagged versions of key indicators at one, three, and six months. To account for cross country heterogeneity, we include the long run mean of each feature for each country, allowing the models to distinguish between structural and cyclical signals.

We evaluate the following models: Panel Logistic Regression, Decision Tree, Random Forest, XGBoost, LightGBM, Support Vector Machine with radial basis function, and a neural network.

Because the data has time dependence, we use a chronological train test split. The training period runs from 1999 to 2015 and the testing period from 2016 to 2023.

4 Results and Discussion

Comparative Model Performance

The models show moderate predictive power, with AUC values near 0.60 for the strongest performers. XGBoost achieves the highest AUC (0.602) followed closely by Panel Logistic

Regression (0.593). This suggests that while some nonlinear effects are present, the core predictive structure is still largely linear.

At the default threshold of 0.50, however, the nonlinear models are extremely conservative. XGBoost and Random Forest record very low recall values, missing almost all recession months. Logistic Regression, in contrast, identifies a much larger fraction of recessions but with lower precision.

Table 2: Model performance summary at default threshold

Model	AUC	Precision	Recall	F1 Score
XGBoost	0.602	0.400	0.012	0.024
Panel Logistic Regression	0.593	0.280	0.733	0.406
Random Forest	0.584	0.333	0.036	0.066
SVM RBF	0.569	0.286	0.318	0.301
LightGBM	0.561	0.316	0.221	0.260
Decision Tree	0.555	0.251	0.779	0.380
Neural Network	0.523	0.000	0.000	0.000

Cost Sensitive Evaluation

Economic policymakers care more about false negatives than false positives. Missing a recession carries a much higher cost than issuing a false warning. To capture this reality, we use a ten to one cost ratio, meaning a missed recession is ten times more costly than a false alarm.

Under this framework, the optimal decision thresholds fall between 0.020 and 0.170 for all models. This shows that the standard threshold of 0.50 is not appropriate in a risk management context.

Table 3: Cost optimized results under ten to one loss ratio

Model	Optimal Threshold	Minimum Total Cost
Random Forest	0.170	1651
Panel Logistic Regression	0.120	1659
XGBoost	0.030	1660
SVM RBF	0.020	1668

Random Forest emerges as the most effective model when cost is taken into account. It misses only two recession months in the test period while maintaining fewer false alarms than XGBoost. This result highlights that AUC alone is not a sufficient metric when the practical goal is early warning. By adjusting the threshold, Random Forest provides the best balance between sensitivity and economic cost.

5 Conclusion

This study builds a panel based machine learning framework for predicting recessions six months in advance. By combining domestic indicators, global macro financial variables, and a new Macro Financial Composite Index, we capture both local and international components of economic downturns. While nonlinear models offer small improvements in ranking performance, cost sensitive evaluation shows that Random Forest is the most effective tool for early warning systems. The findings emphasize the importance of panel information, global risk variables, and asymmetric loss in designing practical recession warning frameworks.

Appendix

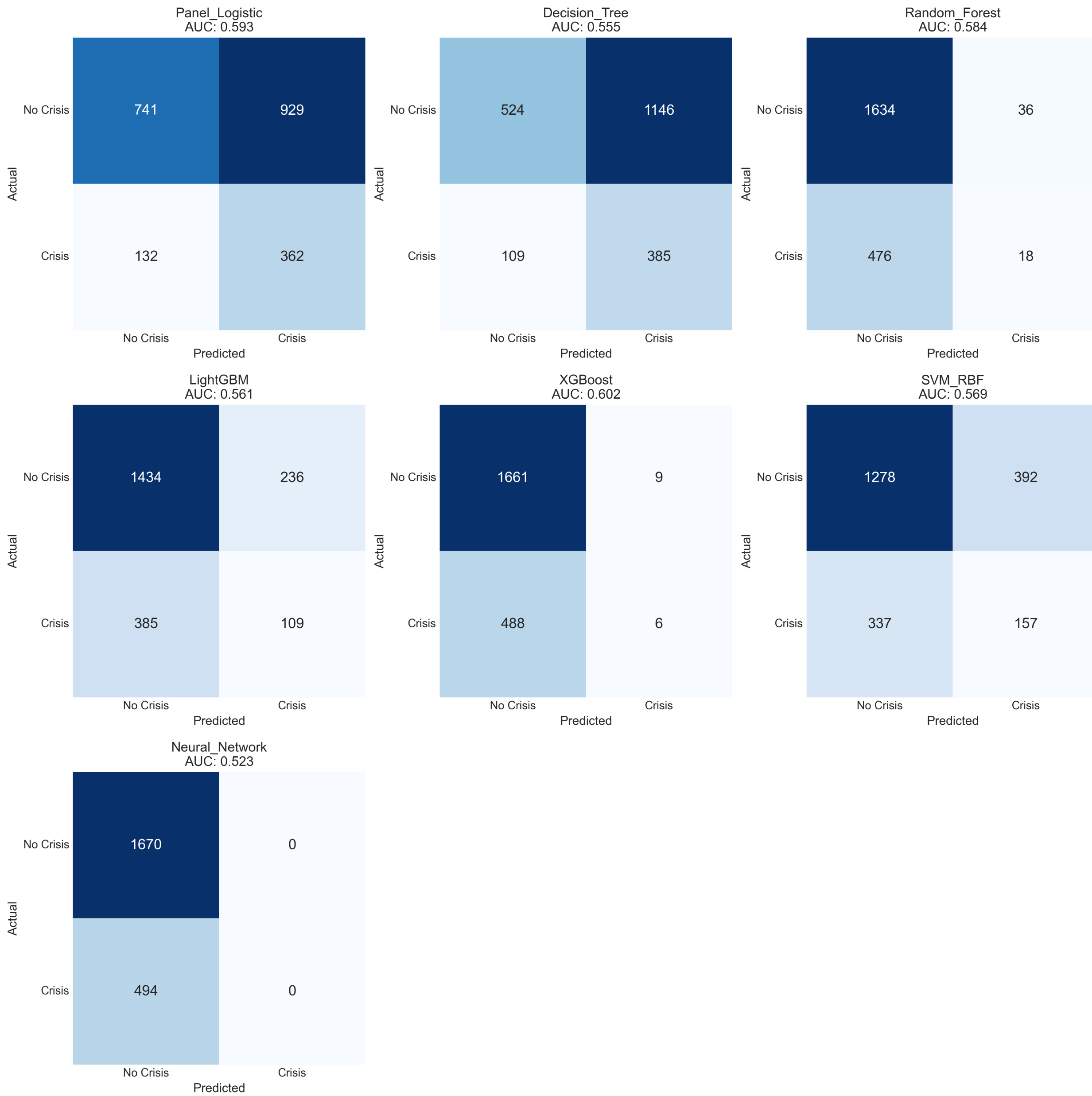

Figure 1: Confusion Matrix for All Models

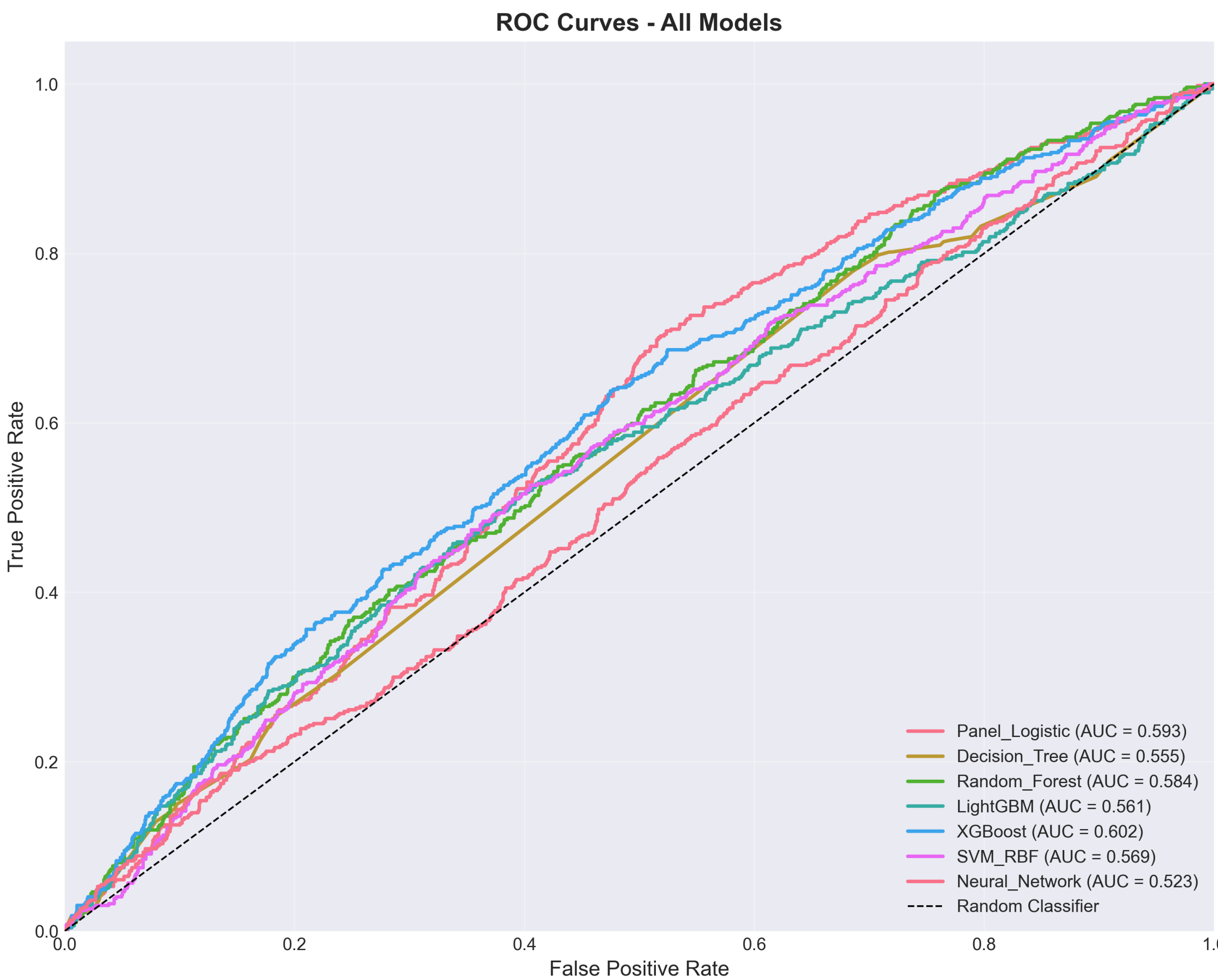

Figure 2: ROC Curves

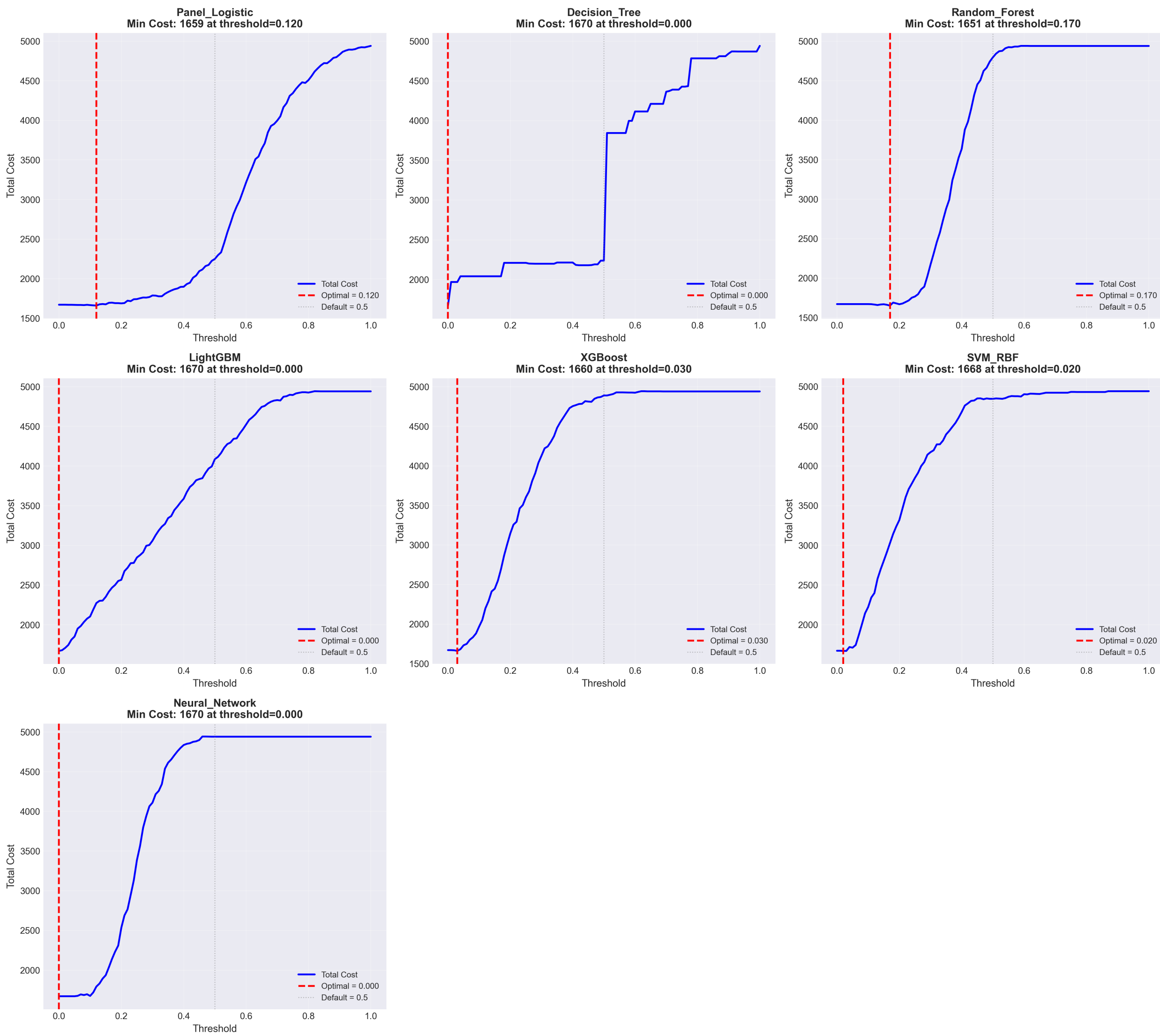

Figure 3: Optimal Threshold for All Models