

# Modeling Near-Term Recession Risk in the United States: Evidence from a Regularized Logit Approach

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## Abstract

The aim of this paper is to develop a statistical framework with the purpose to model a near-term recession risk in the United States, using a regularised logistic regression. Based on monthly data from 1990 to 2024, the analysis consisting of a set of financial macroeconomic indicators, like the yield curve spread, labor market conditions, real economic activity and consumer expectations, aims to estimate the probability of a recession within a twelve-month time frame. The dependent variable in the model is a forward-looking binary recession indicator based on the National Bureau of Economic Research (NBER) classification.

To improve the model reliability and mitigate overfitting, L2 regularization is used into the logistic specification. The performance of the model is evaluated using classification metrics like precision, recall, F1 score and the area under the ROC curve (AUC). Instead of using a fixed threshold, the classification boundary is determined by optimizing for the F1 score, resulting with a balanced treatment of false positives and false negatives in a policy-relevant setting.

The results point to a framework with strong predictive performance, with an AUC of around 0.78 and recall above 60% for recession periods. The findings point out the value of combining financial market signals with real-sector and sentiment-based indicators when it comes to evaluating short-term recession risk. In general, this study offers an interpretable and practically applicable approach to recession forecasting, with strong potential to be used in macroeconomic monitoring and risk assessment.

**Keywords:** Recession Probability Modeling, Term Spread, Business Cycle Analysis, Macroeconomic Forecasting, Regularized Logit Model

## 1. Introduction

One of the key issues in the macroeconomic analysis and economics policy is measuring and predicting recession risk. When an economy suffers from recession, it usually leads to a sharp decline in the output, employment, investment, and consumer confidence in a country or region. Which in turn, gives rise to huge economic costs and social costs. As a result, policymakers,

financial institutions and market participants have a keen interest in developing tools and models that help identify the rising risk of recessions sooner rather than later. Increasingly, instead of estimating whether a recession will happen, the academia has been estimating recession probability, producing a more flexible and nuanced basis, resulting in better scope for economic supervision and informed decision making.

One of the most popular methods to forecast business outcomes is logistic regression owing to its simplicity, transparency and appropriate fit for the class of business problems. As opposed to other sophisticated machine learning methods, the logistic regression directly looks at how changes in the explanatory variables affects estimated probabilities of a future recession. Moreover, we can use regularization techniques to strengthen the model stability and improve the predictive performance while limiting the overfitting. Given the above considerations, regularized logit models are especially appealing for policy-oriented applications where robustness and interpretability are important.

Despite predictive analytics-related advancements, it is still difficult to forecast declines in the economy. Business cycles reflect changing relationships between financial, real-sector, and behavioral forces affecting the economy over time. Financial models based solely on one indicator are incomplete and fail to account for additional dimensions of the existing economic conditions. In addition, the use of overly complex models often limits their transparency and practical use. A continuous demand for simple forecasting framework which achieves the goals of predictive accuracy, interpretability and usability will be created.

Forecasting economic downturns remains a challenge despite advances in predictive analytics. The interaction of financial, real-sector, and behavioural factors gradually evolves, causing business cycle fluctuations. Using an overly simple model that relies on one indicator may not capture the full picture of economic conditions. On the other hand, a very complex model may be less transparent and hard to use in practice. Therefore, the need for a parsimonious forecasting framework has gained significance, specifically one that provides a good balance between acceptable predictive accuracy and interpretability and ease of implementation.

The results reveal that the framework may evaluate the near-term recession risk meaningfully and achieve satisfactory predictive performance. The findings reveal that a multitude of financial, macroeconomic as well as sentiment-based indicators are each informative regarding the probability of recession. The study adds valuable insights to the recession forecasting literature. By focusing on transparency, interpretability, and operationalization, it offers a useful tool for assessing the economic risk.

The remaining content of this paper will be as follows. The literature on recession forecasting and probabilities-based economic risk models is reviewed in Section 2. Section 3 goes over the data and variables construction and methodology. The empirical results and predictive performance evaluation are in section 4. In Section 5, we explore the key results of the study, its limitations, and directions for future research.

## **2. Literature review**

The subject of recession forecasting in academic study is of paramount importance in economics both theoretically and practically. It is very important to anticipate the economic downturns for macroeconomic stabilization, financial supervision, and decision-making in both the public and private sectors. For several decades, researchers have produced numerous models and indicators aimed at signalling the presence of heightened recession risk before an economic downturn is observable in mainstream economic data. Out of all the approaches, it is the probabilistic forecasting models that have received much attention, as they give quantitative assessments of recession risk useful for policy analysis and economic surveillance. Within this

literature, financial market indicators especially the term spread (defined as the difference between long and short government interest rates) are widely recognized as important predictors of future economic activity.

Estrella and Hardouvelis (1991) did the preliminary work on the predictive power of the yield curve. Estrella and Mishkin (1996) later extended this work. The studies showed that the difference between long-term and short-term Treasury securities has significant predictive power for US recessions over horizons of up to twelve months. Estrella and Mishkin (1996) utilizing a probabilistic model that the yield curve performs better than the majority of the contemporaneous macroeconomic variables since it is a forward-looking variable and captures expectations about future monetary policy and economic conditions. Evidence from later studies supports the usefulness of the term spread in predicting economic downturns over a variety of time and institutional settings. The term spread is probably the most popular predictor of recessions.

Many researchers believe that the financial crisis does not arise from the financial sector action purely but rather results from the interaction between real sector and behavioral factors along with the financial sector actions. Due to the belief that the origin of financial crisis is quite complex, they try to include non-financial variables to existing financial crisis models and enhance the recession forecasting ability of these existing models. According to Stock and Watson (1989, 2003), a number of measures show promise in tracking cyclical fluctuations. These include industrial production, personal income, and employment conditions. Using dynamic factor models and composite leading indicators, they demonstrated that macroeconomic variables could reveal information about the near-term turning point of business cycles when signals from financial markets are less and/or altered by policy interventions.

Later studies have used multivariate forecasting frameworks that include financial and macroeconomic information. Chauvet and Piger (2008) used a dynamic latent variable model to estimate probability of recession with coincident indicators that include payroll employment, real income and industrial production. A probabilistic business-cycle monitoring system is best to avoid the serious limitations of discrete recession classifications. Wright (2006) found that adding macroeconomic covariates to term spreads in a probit framework improved recession forecasting performance, particularly over short horizons.

In addition to conventional macroeconomic variables, consumer expectations and sentiment measures are becoming important forward-looking indicators of the economy. Ludvigson (2004) pointed out about the role of household expectations in the future consumption behaviour and the business cycle. Consequently, forecasting models for recessions have incorporated measures such as the University of Michigan Consumer Sentiment Index and Conference Board Consumer Confidence Index. The behavioral effects of heightened uncertainty and the evolution of expectations about economic fundamentals (in both the short and medium term) tend to be captured earlier via behavioral measures than are adverse developments in the labor market or production data.

Due to the growing availability of large-scale economic datasets and improvements in computational methods, economists are increasingly interested in machine learning and other non-linear approaches to predicting recessions.

According to Aastveit et al. (2017) study, data-rich forecasting frameworks can uncover sophisticated relationships among economic variables that may not be captured by traditional econometric methods. Machine learning algorithms, including random forests, neural networks and ensemble methods, often show strong out-of-sample predictive performance particularly when the underlying economic relationships are nonlinear or subject to structural change. This means that it will be hard for the model to explain how the predictor variables predict the outcome variable. Due to this restriction, many machine learning models have not been adopted in policy environments that demand transparency and accountability.

Recent methodological advancements have made the logistic regression even more useful with regularization techniques. Regularized logit models include penalties for the coefficient estimates that account for over-fitting causing instability of the model and are used when there is correlation between the explanatory variables or when the sample sizes are not large enough for the complexity of the forecasting problem (Hastie et al., 2009). Researchers find these approaches attractive for practical forecasting application as they enable to achieve an improvement in generalization performance.

Research on real-time performance and forecast reliability of recession forecasting models has illustrated their limitations. Rudebusch and Williams (2009) contend that merely being statistically successful does not guarantee more accurate identification of downturns or fewer false alarms because of data revisions, shifts in the economy and delays in classification of recessions. Thus, models for forecasting should be judged not merely on their accuracy, but on their usefulness for real-time decision-making under uncertainty. This viewpoint has stimulated the utilization of broader performance metrics, such as area under receiver operating characteristic curve (AUC), precision, recall and the F1 score.

Expanding on the extensive U.S.-based literature, a growing body of international literature is examining whether recession forecasting models can be made more robust across institutional and macroeconomic conditions. For instance, Chinn and Kucko (2015) examined a set of advanced economies and concluded that the term spread and other financial indicators often retain their predictive power, although sizeable variations occur due to monetary policy frameworks, inflation regimes and structures of financial markets.

Likewise, Moneta (2005) found mixed evidence concerning the predictive content of the yield spreads for the euro area, which could be the result of varying financial intermediation mechanisms in the euro area and national economies, as well as differences in monetary transmission channels that may impact the informational contribution of conventional indicators of recessions. The findings suggest that predictions offered by economic indicators are context-specific and may change between countries and time periods.

Another significant theme in forecasting literature has to do with economic relationships instability over time. The research paper by Giannone, Reichlin and Small (2008) shows that real-time forecasting performance is affected by data revisions, model re-specification and by the economy itself. We have been facing such issues over the last twenty years as the economic structure and behaviour have changed. For instance, the association between unemployment and inflation has weakened compared to before, while the indicators capturing consumer sentiment have become far more sensitive to political and social events. Such changes indicate that recession forecasting models should be flexible enough to accommodate changes in the economy but should not lose interpretability and usefulness.

Certain studies indicate that a single-equation forecasting model may not exist that accurately predicts business cycle upward and downward movements. Due to the interdependence and continuously evolving character of macroeconomic activity, various other approaches have also been introduced such as VAR, dynamic factor and regime-switching models. Hamilton's Markov-switching model (1989) is one of the first models that fit the bill. It is a model that identifies unobservable business cycle regimes and nonlinear transitions from expansions to recessions. Models of this nature often yield a more robust depiction of economic dynamics than similar binary classification models. When compared, such models may typically require relatively more involved estimation procedures, larger datasets, and greater technical expertise. Further, they are often less transparent and policy-implementable. At the same time, machine learning and artificial intelligence have made a new set of tools available for recession forecasting.

According to a study by Ahmed et al. (2010), neural network models can outperform traditional econometric methods if large amounts of macro-financial data are available and if there are more nonlinearities. Various machine learning algorithms random forests, the gradient boosting

method, and support vector machine have recently been utilized to make predictions to predict recessions. Nevertheless, these methods often face challenges related to interpretability, model transparency, and the risk of overfitting, especially when forecasting relatively rare events such as recessions. To address these concerns, recent research has increasingly explored hybrid approaches that combine the interpretability of traditional statistical models with the flexibility of machine learning techniques. Examples include generalized additive models (GAMs), penalized regression methods, and logistic regression models augmented with interaction effects or nonlinear transformations. These approaches seek to improve predictive performance while preserving the transparency necessary for policy analysis and economic decision-making.

The literature has also increasingly emphasized the importance of communicability and operational feasibility in economic forecasting models. Orphanides (2003) and Blanchard et al. (2010) argue that the effectiveness of model-based recommendations often depends not only on statistical accuracy but also on the ability of policymakers to understand, evaluate, and implement those recommendations in real time. Data revisions, model complexity, and institutional constraints can all reduce the practical value of highly sophisticated forecasting systems. Consequently, there is a continuing need for models that balance predictive performance with transparency and interpretability. Logistic regression is especially appealing in this respect as it offers a clear probability estimate, is relatively simple to model, and is robust.

Finally, an expanding and enriched body of research on the introduction of recession probability models into the regulatory and policy frameworks. Edge and Meisenzahl (2011) discuss macroeconomic risk indicators for financial stability monitoring and the regulatory policy. Similarly, Claessens and Kose (2018) explain how early-warning systems can assist macroprudential and fiscal policy decisions. Taken together, these studies prove that academic foresight models, when they are interpretable and empirically grounded, can become valuable applied tools for economic monitoring and the design of economic policy. The aim of the present study is to contribute to the academic literature on recession forecasting and to the development of systems designed to monitor economic risk. We aim to use transparent predictors and probability-based decision rules. Also, we plan to combine a regularized logistic regression framework with these techniques.

### **3. Data collection and research methodology**

The empirical assessment uses publicly available macroeconomic and financial data extracted from Federal Reserve Economic Data (FRED). The sample period is of January 1990 – December 2024 consisting of monthly observations. The aforementioned period consists of a series of phases of the U.S. business cycle, including a recession in the early 1990s, the downturn in 2001 that coincided with the collapse of the dot-com bubble, the Global Financial Crisis of 2007–2009, the COVID-19 recession in 2020, and recovery. Thus, the dataset covers a broad distribution of economic conditions, monetary policy stances, and financial market environments, making it appropriate to the modelling of recession risk.

The model used in the study is parsimonious as it is based on fewer theoretically motivated and empirically validated indicators. The analysis makes use of only four variables rather than a large set of predictors. These 4 variables together summarize important dimensions of the economy and recession risk. They are financial market expectations, labor market conditions, real economic activity and consumer sentiment. The indicators chosen are closely monitored by policy makers, researchers and market participants, and are available in near real time, making them suitable for practical forecasting.

The explanatory variables included in the model are the term spread, the civilian unemployment rate, the industrial production index, and the University of Michigan Consumer Sentiment Index.

Together, these variables provide information on both forward-looking expectations and current economic conditions, allowing the model to assess recession risk from multiple perspectives.

The primary financial indicator used in the analysis is the term spread, calculated as the difference between the 10-year Treasury Constant Maturity Rate (GS10) and the 2-year Treasury Constant Maturity Rate (GS2):

$$Term\ Spread_t = GS10_t - GS2_t$$

The term spread is commonly used as a measure of the slope of the yield curve and has been extensively studied as a leading indicator of future economic activity (Estrella & Hardouvelis, 1991; Estrella & Mishkin, 1996). A narrowing or inversion of the spread is generally interpreted as a signal of weakening economic expectations and increasing recession risk. The economic logic is that investors anticipating a slowdown expect the central bank to cut interest rates, which drives long-term rates lower than short-term ones. Yield spread data is available daily but aggregated monthly for consistency with other macroeconomic series.

Unemployment Rate (UNRATE) - The unemployment rate reflects the degree of slack in the labor market and is a central coincident indicator of macroeconomic conditions. Rising unemployment often signals declining aggregate demand and reduced business confidence. While the unemployment rate typically lags the business cycle, sharp upward movements may occur early enough to serve as warning signs, especially when combined with forward-looking indicators like the yield curve.

Industrial production index (INDPRO) – The industrial production index captures real output in the manufacturing, mining and utilities sectors. As a measure of real economic activity, the commodity price level is quick to respond to supply-side shocks, inventory changes, and shifts in the global demand level. A slowdown or decline in industrial production has preceded all past recessions in the early months. In fact, this is particularly true for manufacturing-led recessions. The value of this variable is consistent with the structure of the vintage business cycles model (Stock & Watson, 1989) and the vintage recession model.

Consumer Sentiment (UMCSENT) – Consumer expectations play a vital role in shaping household spending, investment plans, and demand-side. This research uses University of Michigan Consumer Sentiment Index (UMCSENT) as a proxy for behavioural responses to macroeconomic signals. According to de' Vries 2021, present excess control opportunities and investment needs across countries and across Euro Area countries have significant impacts on sentiment above perceptions. In addition, the inclusion of this variable recognizes the rising role of expectations in contemporary macroeconomic theory.

Recession Indicator (USREC) - The target variable in this study is constructed using the NBER Recession Indicator (USREC), which is a binary variable equal to 1 during official recession months and 0 otherwise. To turn this historical classification into a forward-looking prediction task, the binary target is shifted 12 months ahead and smoothed using a rolling 3-month maximum, so that the model learns to predict the presence of any recession within a future 12-month window:

$$Recession\_Next\_12M_t = \max(USREC_{t+12}, USREC_{t+13}, USREC_{t+14})$$

The yield spread shows the greatest variability during pre-recession periods, consistent with its role as a financial leading indicator. Unemployment and industrial production display smoother, cyclical movements, while consumer sentiment exhibits both trend and shock-driven volatility. Descriptive statistics for the preprocessed dataset are presented in Table 1.

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Table 1. Descriptive data

|                      | count | mean  | std   | min   | 25%   | 50%   | 75%    | max    |
|----------------------|-------|-------|-------|-------|-------|-------|--------|--------|
| 10Y                  | 420   | 4.25  | 1.97  | 0.62  | 2.57  | 4.15  | 5.76   | 8.89   |
| 2Y                   | 420   | 3.23  | 2.30  | 0.12  | 0.93  | 3.08  | 5.03   | 8.72   |
| Recession            | 420   | 0.09  | 0.28  | 0.00  | 0.00  | 0.00  | 0.00   | 1.00   |
| Unemployment         | 420   | 5.71  | 1.75  | 3.40  | 4.40  | 5.40  | 6.63   | 14.80  |
| IndustrialProduction | 420   | 90.13 | 13.09 | 60.30 | 85.13 | 93.75 | 100.20 | 104.10 |
| ConsumerSentiment    | 420   | 85.22 | 13.34 | 50.00 | 75.07 | 87.90 | 95.03  | 112.00 |
| Yield_Spread         | 420   | 1.02  | 0.92  | -0.93 | 0.23  | 0.96  | 1.80   | 2.83   |
| Recession_Next_12M   | 420   | 0.09  | 0.28  | 0.00  | 0.00  | 0.00  | 0.00   | 1.00   |

The study employs a binary classification model based on logistic regression, a well-established technique in both econometrics and statistical learning. The binary nature of the outcome variable—recession or no recession—makes logistic regression a natural methodological choice. It offers not only predictive power but also interpretability, statistical inference, and comparability with prior literature.

Logistic regression models the probability of a binary outcome as a function of one or more explanatory variables. Formally, the logistic model estimates the conditional probability:

$$P(Y_t = 1|X_t) = \frac{1}{1 + e^{-Z_t}}$$

where:

$Y_t \in \{0,1\}$  is the binary indicator of whether a recession will occur within the next 12 months,

$X_t$  is a vector of explanatory variables at time  $t$ ,

$Z_t = \beta_0 + \beta_1 x_{1t} + \dots + \beta_k x_{kt}$  is the linear combination of features and coefficients.

The logistic function ensures that the estimated probability lies in the interval  $[0,1]$ . The coefficients  $\beta_j$  are estimated using maximum likelihood estimation (MLE), which seeks to find the parameter values that maximize the log-likelihood of the observed data.

In the context of this study, the logistic model takes the form:

$$\log\left(\frac{P(Y_t = 1)}{1 - P(Y_t = 1)}\right) = \beta_0 + \beta_1 Spread_t + \beta_2 Unemp_t + \beta_3 IndProd_t + \beta_4 Sentiment_t$$

The log-odds interpretation directly interprets marginal effect of each variable on the odds of future recession. By exponentiating the coefficients, we derive odds ratios that reflect the effect of the one standard deviation increase in a predictor on the odds of recession.

## 4. Findings and Analysis

In this section we present the empirical findings from our logistic regression model predicting U.S. recession within one year and interpret the results. The analysis will specify the correlation structure, model estimation results and predictive performance. The predictors' statistical behaviour and the model's ability to indicate a future recession risk, are illustrated together.

The correlation matrix outlines the linear relationships of the main features of the model as well as their concurrent as well as forward-looking recession indicators.

There are many important patterns emerging. The high correlation of 10Y and 2Y Treasury yields reflects shared macro-financial determinants of interest rates across the term structure ( $r = 0.918$ ). The high level of collinearity of inflation expectation and the yield curve along with their future output growth potential is unsurprising given that they are derived from the same yield curve. However, their collinearity is reduced in the present model by using their yield spread ( $10Y - 2Y$ ) to allow the model to yield better informed transformations.

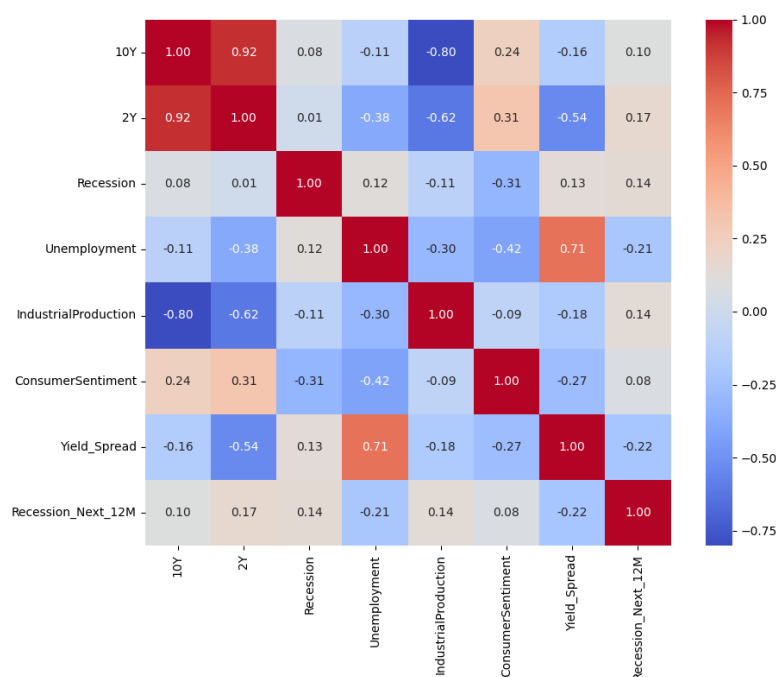


Figure 1. Correlation Matrix

The yield spread has a slight negative association with the recession predictor. Specifically, it indicates ( $r = -0.2154$ ) that when the spread trends downwards (that is, the curve flattens or inverts) a recession is more likely. A considerable amount of literature suggests that the inverted yield curve reliably forecasts economic downturns.

Unemployment tends to have a negative correlation with the yield spread, as well as a positive correlation with future recessions. More specifically, as unemployment rises, the spread flattens as the probability of recession increases. Though its own correlation with the raw recession indicator ( $r = 0.1172$ ) is quite low, it reinforces the case that this is a coincident to lagging indicator. Industrial Production exhibits moderate negative correlations with 10Y and 2Y rates and with unemployment and future likelihood of recession ( $r = 0.1351$ ) Falling output often signals the early stages of a recession, which is consistent with this idea.

The value of consumer sentiment is far away from recession ( $r = -0.3113$ ) as well as unemployment ( $r = -0.4207$ ). This means as the macroeconomic condition deteriorates, consumers sentiment also deteriorates. The connection to the forward recession indicator ( $r = 0.0759$ ) is weaker, but directionally consistent.

To summarize, including these features is justified both theoretically and empirically by the correlation matrix. After the transformations, the features appear not to exhibit a collinearity and each feature captures distinct dimensions of the macroeconomic situation.

The estimated logit regression model unveils that the selected predictors significantly affect the probability of a future recession. The estimated coefficients, standard errors, z-values, p-values, odds ratios, and 95% confidence intervals are summarized in Table 2 below.

Table 2. Regression results

| Feature              | Coeff.  | Std.Err | z       | P> z   | Odds Ratio | [0.025 | 0.975] |
|----------------------|---------|---------|---------|--------|------------|--------|--------|
| Intercept            | -0.6157 | 0.1298  | -4.7446 | 0.0000 | 0.5403     | 0.4189 | 0.6967 |
| Yield_Spread         | -0.6282 | 0.2029  | -3.0965 | 0.0020 | 0.5335     | 0.3585 | 0.7941 |
| Unemployment         | -1.0340 | 0.2853  | -3.6238 | 0.0003 | 0.3556     | 0.2033 | 0.6220 |
| IndustrialProduction | 0.2533  | 0.1436  | 1.7634  | 0.0778 | 1.2882     | 0.9722 | 1.7071 |
| ConsumerSentiment    | -0.3401 | 0.1474  | -2.3073 | 0.0210 | 0.7117     | 0.5332 | 0.9501 |

Yield Spread above is highly statistically significant ( $p = 0.0020$ ) and has an odds ratio of 0.5335. This means that for every standard deviation increase in the yield spread (i.e., a steeper yield curve), the odds of a recession decrease by nearly 47%. This confirms its utility as a leading indicator.

Unemployment shows an even stronger effect, with an odds ratio of 0.3556 and a highly significant p-value ( $p = 0.0003$ ). A one standard deviation increase in unemployment reduces the odds of economic stability, significantly increasing recession probability.

Consumer Sentiment is also a statistically significant predictor ( $p = 0.0210$ ), and its negative coefficient aligns with theory: as sentiment worsens, recession risk increases.

Industrial Production is only marginally significant ( $p = 0.0778$ ), but its positive coefficient is somewhat counterintuitive. It may reflect cyclical noise or residual correlation with other variables, possibly due to revisions in real-time data.

The intercept term is also significant, which adjusts the baseline probability of recession in the absence of high values of the predictors.

The model strongly demonstrates a solid statistical link between the macro-financial and behavioral indicators and recession risk. By enabling the comparison of coefficient magnitudes, the use of standardized variables confirms the dominance of yield spread and unemployment in the forecasting of any variable.

To convert continuous probability estimates into decisions (recession/no recession), an optimal threshold was chosen that maximizes the precision, as generating false positives in forecasting is costly. The best threshold to use is 0.64, which is above the naïve default of 0.50, because recession events are relatively low in the sample.

The model identifies actual recession in 65% of the cases, which is quite high recall for rare events.

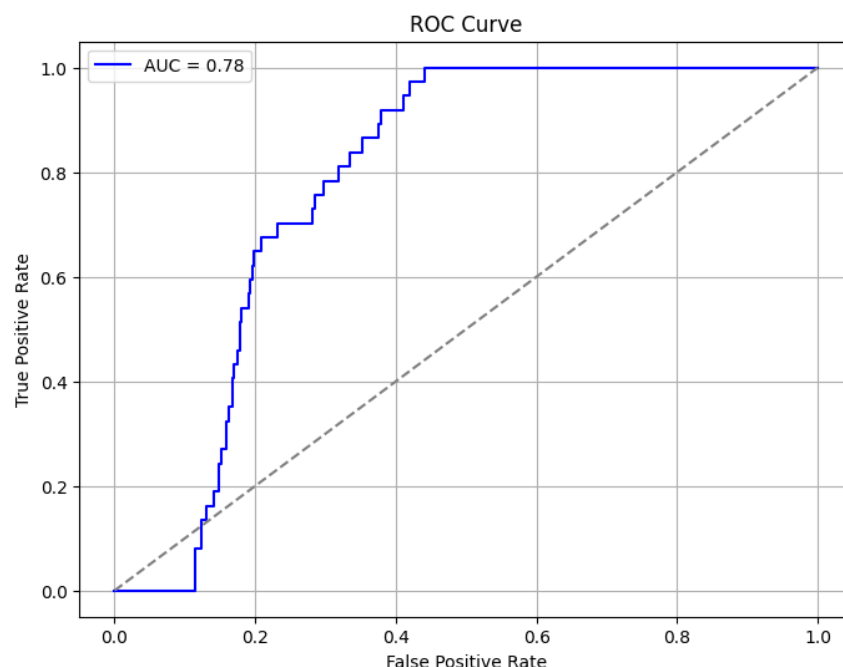


Figure 2. ROC Curve

Nonetheless, the 24% precision suggests that many of these predicted recessions are false alarms. It's reasonable to expect such trade-off with imbalanced classification.

The AUC score equalling 0.78 shows good overall ranking ability. The model gives a higher probability to recession periods than stable ones in almost 8 out of 10 cases.

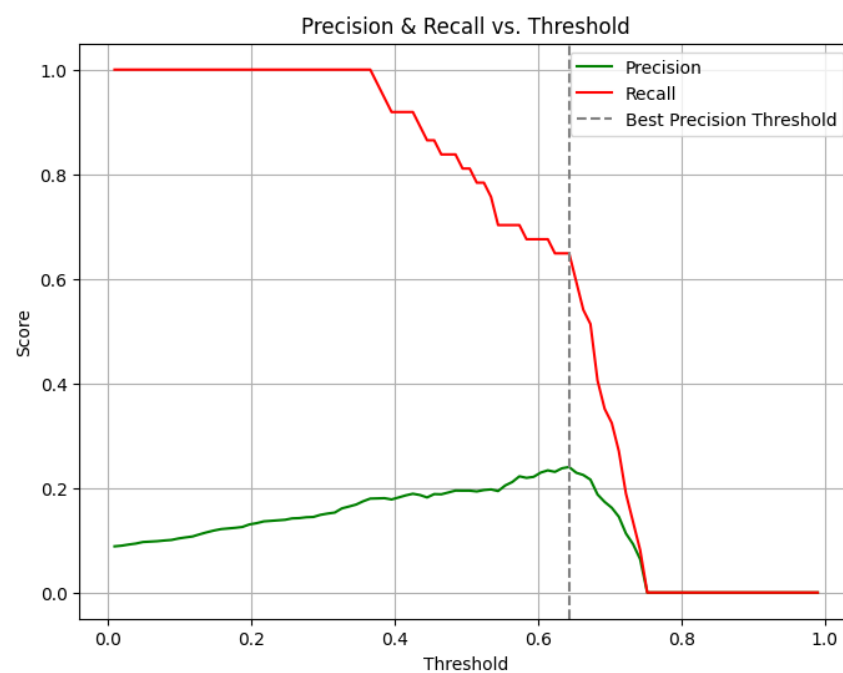


Figure 3. Precision & Recall vs. Threshold

The model is especially helpful as an early warning tool according to these findings. Its effectiveness is primarily in recall, even if precision is more modest. In a policymaking framework,

this compromise is typically viewed as acceptable as false negatives (missed recessions) are generally more costly than false positives.

Although the logistic regression model is statistically and economically significant, there are some limitations to consider.

Logistic regression first imposes a linear link between the log-odds of the dependent variable and the independent variables. This framework, while widely used in practice for binary classification, fails to capture the non-linear interactions or threshold effects found in macro-financial complex phenomena. For example, we may only have reached a recession signal when the yield curve goes deeply negative. And such non-linear thresholds are hard to model in linear ways.

Moreover, even though we find the optimal cut-off for the F1 score, the model has low precision indicating many of the recession warnings are in fact false warnings. This is partly due to the class imbalance in the data: recessions are rare compared to concerning stability periods.

The model depends on a small number of predictors for interpretability and transparency. Although these represent potentially macroeconomic impactful variables, there are many other significant variables (for example, equity market volatility, credit spreads, business investment expectations, or geopolitical risks) that can improve forecasting performance. However, to use such variables you must get access to proprietary or noisy data sources and may obfuscate the model.

To conclude, model uncertainty and economic regime changes are not explicitly taken into consideration. Structural breaks such as the 2008 financial crisis, the COVID-19 pandemic and some new monetary policy measures, can degrade the stability and reliability of predictive models that are trained on data from the past. A model that works well in one decade will probably perform poorly in another if the underlying dynamics change.

## 5. Conclusion

This study developed a regularized logistic regression framework to estimate the probability of a U.S. recession. Specifically, it seeks to determine which of many macroeconomic indicators most help us identify the risk of recession over a one-year horizon.

The analysis uses monthly data from 1990 to 2024 and includes four explanatory variables, namely, the term spread between 10 year and 2 year Treasuries, the civilian unemployment rate, the Industrial Production Index and the University of Michigan Consumer Sentiment Index. The chosen indicators provide complementary perspectives on the risk of recession stemming from financial market, labor market, real economy, and household sentiment information. The dependent variable was made as a forward-looking recession indicator based on the National Bureau of Economic Research (NBER) definition of business cycles allowing the model to forecast real future recessions rather than retroactively identifying recessions.

The model had an AUC of 0.78, meaning it did a good job at distinguishing recessionary periods from other periods. Moreover, using threshold optimization based on the F1 score favored precision to recall, leading to the identification of a sizeable number of future recession episodes without generating too many false-positive signals.

Estimated relationships are largely consistent with economic theory and previous empirical evidence. A narrowing or inverted term spread increased recession probabilities because the market anticipated worse future conditions and recession conditions. In the same vein, increasing unemployment and softer consumer sentiment raised the odds that a downturn would occur sometime in the future. Meanwhile, changes in the industrial production of goods provided useful information about real economic activity. The integration of various dimensions of economic information into a single forecasting approach is advantageous.

There are several limitations to note. Despite its ability to achieve stability of the models and reduce the chances of overfitting, this economic crisis logistic regression is nonetheless a linear modelling approach and therefore, not capable of capturing nonlinear interactions or structural shifts in the economy. This analysis depends on historical data that may be revised and omits potentially informative credit-market, financial volatility, and international economic variables. The predictive performance might change across the monetary policy regimes and during crisis periods.

In summary, we provide a transparent, empirical, and policy-relevant framework for estimating near-term recession risk in the United States, making a contribution to the recession forecasting literature. Using a regularized logistic regression approach with a chosen set of macroeconomic predictors and proper classification exhibits that interpretable models can provide useful information for economic monitoring.

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