Recession Prediction

"Forecasts usually tell us more about the forecaster than of the future."
Warren Buffett

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ABSTRACT

This paper investigates the predictive power of the yield curve, focusing on its ability to forecast recessions. Utilizing data from the Federal Reserve Economic Data (FRED) spanning from 1962 to 2019, we employ logistic regression models and Principal Component Analysis (PCA) to examine the relationship between various Treasury spreads and economic downturns. Our findings reveal that the spread between long-term and short-term Treasury rates, particularly the 10-year to 1-year and 10-year to 3-year spreads and the difference between 10-year Treasury Yield and the Federal Funds Rate, are strong indicators of future recessions. The study also highlights the limitations of including short-term spreads, which introduced noise and reduced model accuracy. PCA proved effective in crafting significant components from the data in terms of prediction capability. The results affirm the yield curve's relevance as a recession predictor, and suggest that combining multiple spreads with dimensionality reduction techniques can improve forecasting accuracy.

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INTRODUCTION

Recession prediction is always a hot topic. Throughout its history, the US has experienced significant recessions, which has led to a wealth of literature on predicting recessions. One of the most discussed methods in the literature for predicting recessions is the analysis of the yield curve, particularly the relationship between short-term and long-term interest rates. The yield curve has been extensively studied for its ability to signal upcoming economic slowdowns, and numerous empirical studies have validated its predictive power.

The logic behind it is simple: in normal economic conditions, the yield curve slopes upward, indicating higher yields for long-term bonds compared to short-term bonds. However, during times of anticipated economic slowdown, market participants expect future interest rates to be lower due to either economic contraction or stimulative policy actions. This expectation leads to a decrease in long-term yields while short-term yields remain relatively stable, resulting in a flattening or inversion of the yield curve. This inversion is interpreted as a signal that the probability of a future recession is increasing.

Recent developments have cast doubt on the predictive ability of the yield curve slope. According to a report by Scott Ward from U.S. News & World Report, the current yield curve inversion, which occurred on July 5, 2022, has prompted concerns about a potential recession. Despite this, current economic data shows resilience: U.S. GDP growth was estimated at 2.5% in 2023, up from 1.9% in 2022. The U.S. economy is considered stronger than pre-COVID levels, with sustained demand across various sectors. The Congressional Budget Office expects the deficit to grow from 5.3% of GDP in 2023 to 6.1% in 2024 and 2025. While the inverted yield curve remains a good recession indicator, the current strong economic indicators and government spending could delay or mitigate the anticipated downturn, suggesting a more complex economic outlook than historical patterns alone would predict. Given the credibility of the yield curve as a recession predictor is more questionable than it ever was, we have decided it is of crucial importance to test the historical performance of the yield curve using insightful methods, namely Principal Component Analysis (PCA) and logistic regression.

LITERATURE REVIEW

Studies since the 1980s have consistently shown that the yield curve is a reliable predictor of recessions. Before each of the last six recessions, short-term interest rates rose above long-term rates, producing what is known as a yield curve inversion. Estrella and Mishkin (1996) demonstrated that the spread between the ten-year Treasury note and the three-month Treasury bill is particularly effective. In the literature, the most common spread used is between the ten-year and three-month Treasury rates. However, other spreads, such as the ten-year and two-year rates, can also be effective. In our analysis, we used several spreads to examine their predictive power: 10-Year Treasury Yield Minus Federal Funds Rate, 10-Year Treasury Yield Minus 1-Year Treasury Yield, 10-Year Treasury Yield Minus 3-Year Treasury Yield, 1-Year Treasury Yield Minus Federal Funds Rate, 6-Month Treasury Bill Minus Federal Funds Rate, and 3-Month Treasury Bill Minus Federal Funds Rate.

Estrella and Mishkin's (1996) probit model showed that a narrowing or negative yield spread significantly increases the probability of a recession within the next four quarters. Plus, the yield curve's predictive power is robust across different time periods and economic contexts. Estrella and Mishkin (1996) found that the yield curve accurately predicted recessions in the United States and several European countries, including Germany, France, Italy, and the United Kingdom.

In the world of conventional statistics, the importance attributed to out-of-sample performance is minimal. However, Mishkin and Estrella (1996) emphasize the significance of out-of-sample evaluation in evaluating predictive models. Their analysis showed that the yield curve's predictive power holds up well even when applied to data beyond the estimation period, providing a realistic assessment of its effectiveness in real-world forecasting. Therefore, we also tried to keep our test data as extensive as possible.

Furthermore, Estrella and Trubin (2006) use a probit model to estimate the probability of a recession based on the yield curve spread. Their analysis, using data from 1959 to 2005, shows that the yield curve's predictive power is strong when the spread between the ten-year and three-month Treasury rates turns negative. The model translates the yield curve spread into a probability of recession one year ahead, demonstrating a high correlation with actual recessions. In this context, we position our estimators, i.e., spread rates, as recession predictors located between one and two years before the probable recession, allowing data to lag in three-month intervals.

Estrella and Trubin (2006) indicate that the yield curve has provided accurate recession predictions, with the probability of recession rising significantly as the yield spread turns negative. For instance, a spread of -2.40 percentage points corresponds to a 90 percent probability of recession. Moreover, the yield curve's predictive power is compared with other financial and macroeconomic indicators, such as stock prices and leading economic indicators. While these variables have some forecasting ability, the yield curve consistently outperforms them, especially for longer forecast horizons.

Luca Benzoni, Olena Chyruk, and David Kelley (2018) state in their paper that the literature has examined various measures of the yield curve slope or term spread. Academic studies often use the difference between the yield on the ten-year Treasury note, reflecting long-term investor views, and the three-month Treasury bill rate, a close substitute for the federal funds rate targeted by the Federal Open Market Committee (FOMC). Therefore, we found it appropriate to utilize the spread between the federal funds rate using differences 10-years to 1 year, 6-months and 3-months.

Furthermore, Principal Component Analysis (PCA) is a widely used tool for predicting yield curve movements for various reasons, such as developing trading strategies: forecasting market direction, identifying relative value trade opportunities, and anticipating changes in yield volatility. These predictions can be made through the analysis of principal components (PCs). There is extensive literature on utilizing the PCA method for yield curves. One well-known example is the paper by Litterman and Scheinkman (1991), titled "Common Factors Affecting Bond Returns." They applied PCA to yield curves and identified the first three principal components as level, slope, and curvature, which together explained a significant portion of the variance in bond returns. Thanks to the PCA, we were able to eliminate noise and capture the significant components that explain variability in yield spreads. This approach allowed us to more accurately detect movements in the yield curve.

DATA

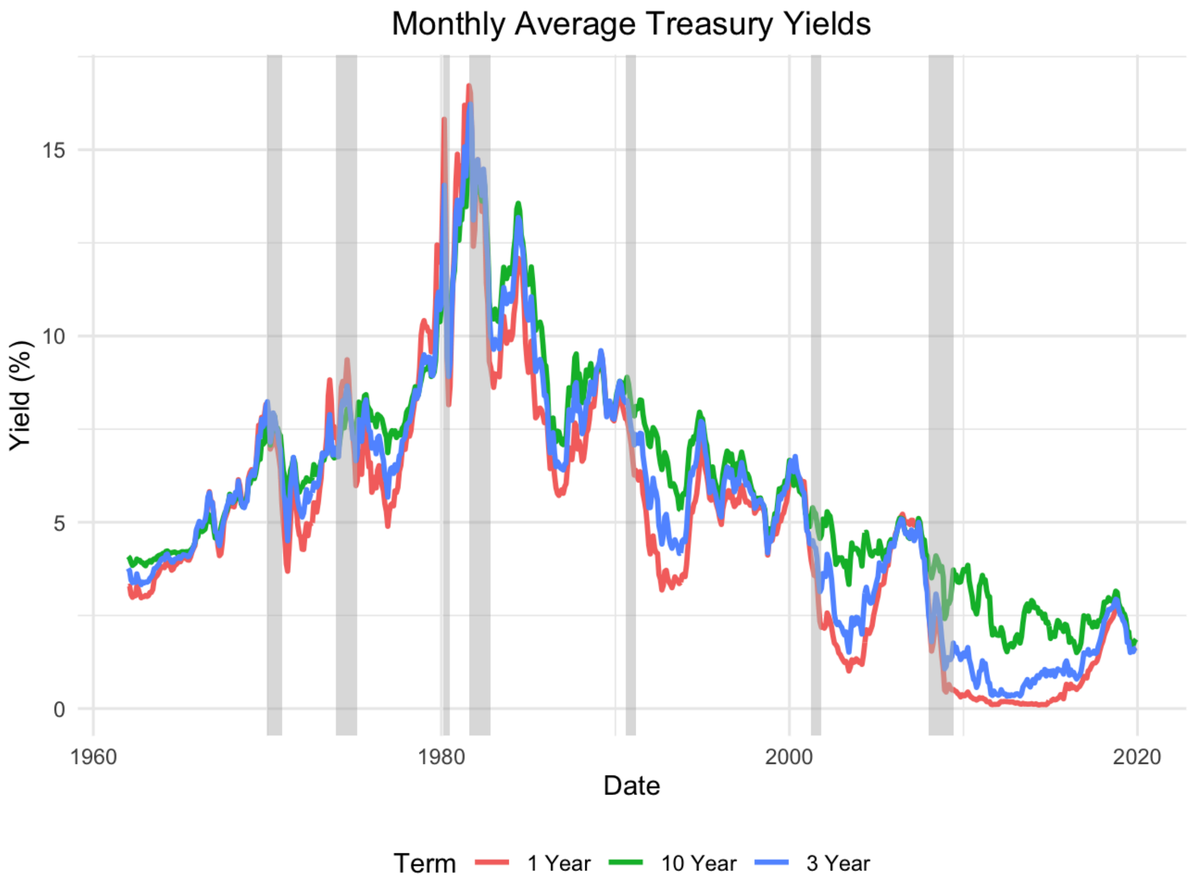
All the data sources are from the Federal Reserve Economic Data (FRED) website, which is managed by the Federal Reserve Bank of St. Louis, which is a widely respected and credible source for economic data and their database compiles data from various reliable sources including government agencies, central banks, and other reputable institutions.

The dataset has been divided into training and testing sets based on the following time periods: January 1962 to December 1998 for the training set, and January 1999 to December 2019 for the testing set. The year 2020 has been excluded from the analysis due to the extraordinary economic conditions caused by the COVID-19 pandemic, which could introduce patterns not representative of typical economic cycles. This division ensures that the model is trained on historical data and tested on more recent data, allowing for a robust evaluation of its predictive performance.

First, the recession data is obtained from NBER-based Recession Indicators from the Federal Reserve Bank of St. Louis. This time series uses dummy variables (values of 1 or 0) to represent periods of economic expansion and recession in the US, as determined by the National Bureau of Economic Research (NBER). The data is not seasonally adjusted and is recorded monthly. A value of 1 indicates a recession, while a value of 0 indicates an expansion. The vertical gray bars in Graph 1 below represent periods of economic recession.

The market yield on U.S. Treasury securities at a 1/3/10-year constant maturity are quoted on an investment basis, represented in percentage values and not seasonally adjusted. The data is updated monthly and represents an average for the month.

GRAPH 1



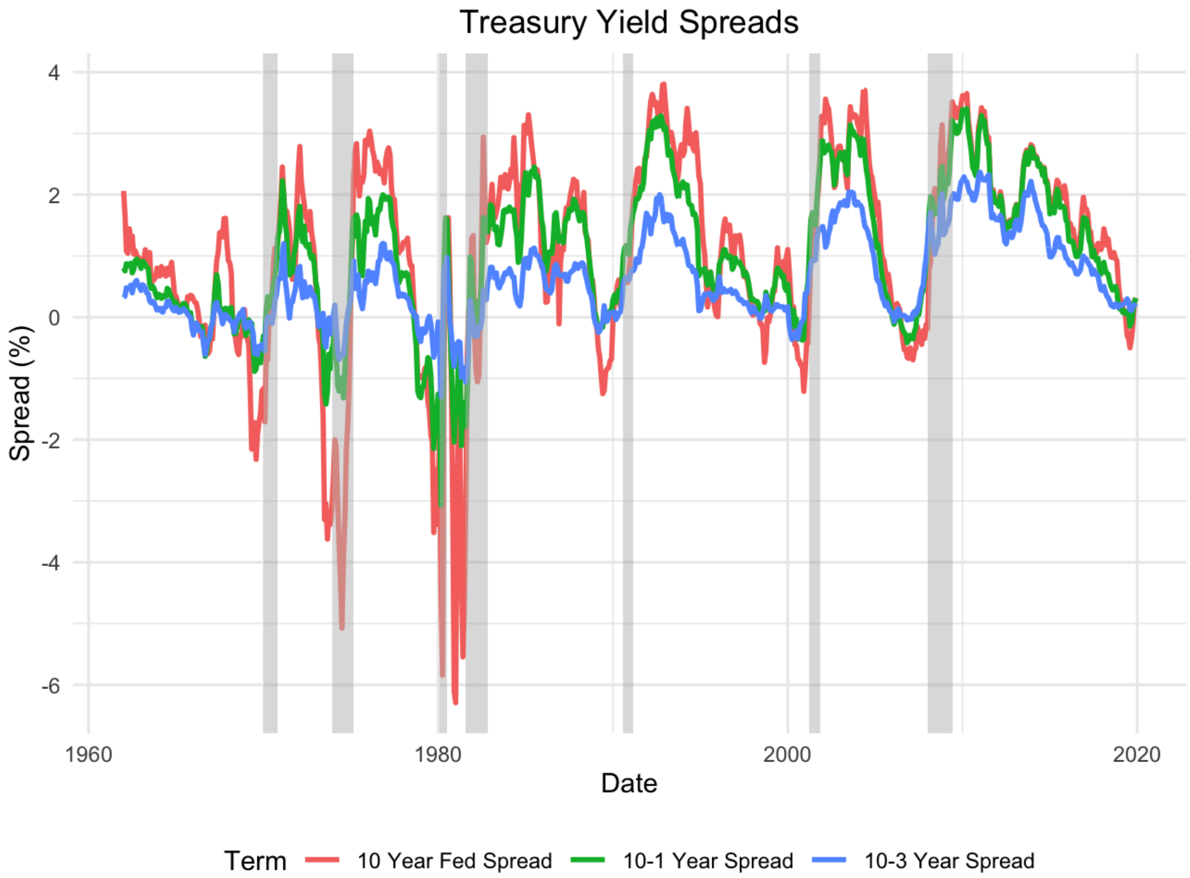
1-Year (Red): Monthly Average 1-Year Treasury Yield

3-Year (Blue): Monthly Average 3-Year Treasury Yield

10-Year (Green): Monthly Average 10-Year Treasury Yield

The market yield on U.S. Treasury securities at a 10-year constant maturity minus the Federal Funds Rate (T10YFF) is provided by the Federal Reserve Bank of St. Louis. This data series is represented in percentage values and is not seasonally adjusted. The data is updated monthly and shows the average for each month. The reason we use the Federal Funds Rate is that it serves as a real-time indicator of interest rates and has a direct influence on other interest rates. We have included it for these reasons, and its use is supported by previous studies, which we have discussed in the literature review section. Furthermore, in the Graph 2 below the 10-1 Year Spread (Green) and the 10-3 Year Spread (Blue) were handcrafted by us, derived from the difference between the 10-Year Treasury yield and the respective 1-Year and 3-Year Treasury yields.

GRAPH 2



10 Year Fed Spread (Red): 10-Year Treasury Yield Minus Federal Funds Rate

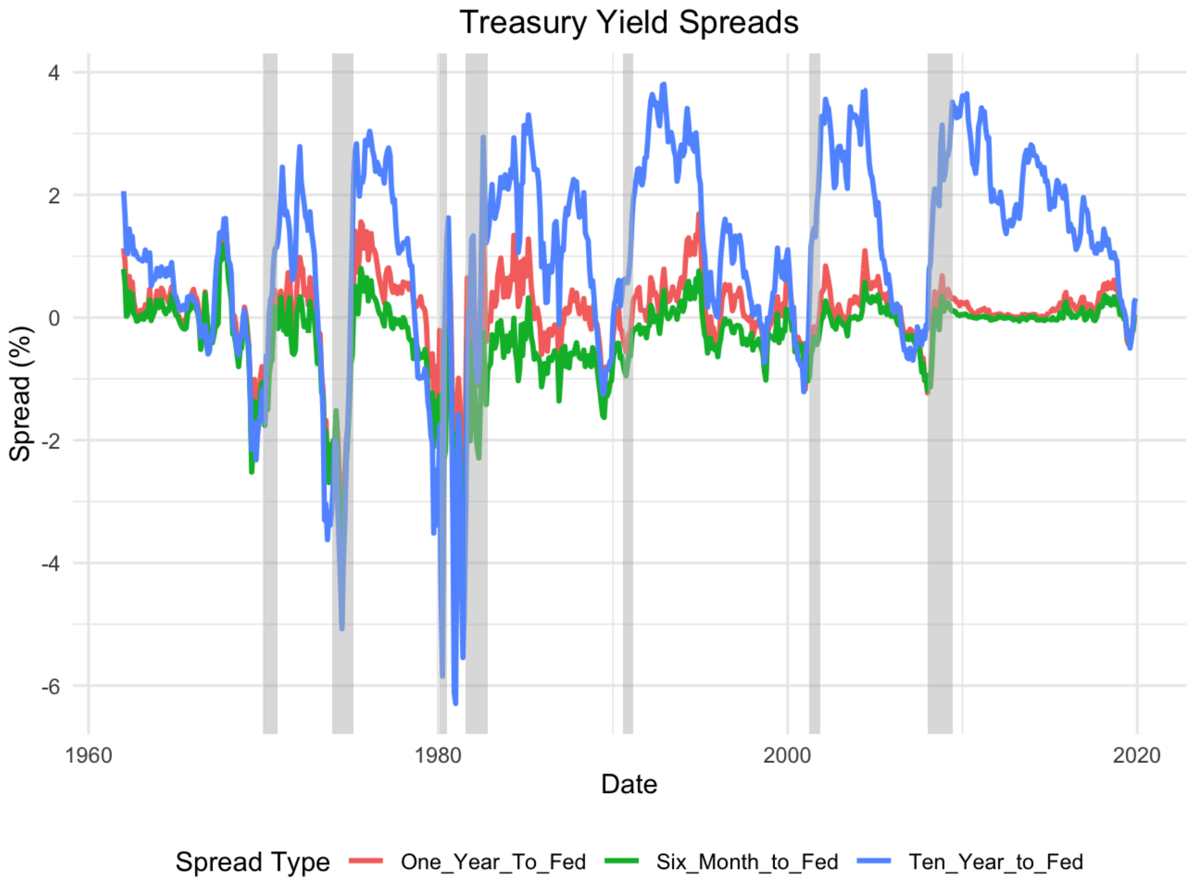
10-1 Year Spread (Green): 10-Year Treasury Yield Minus 1-Year Treasury Yield

10-3 Year Spread (Blue): 10-Year Treasury Yield Minus 3-Year Treasury Yield

The market yield on U.S. Treasury securities at a 1-year constant maturity minus the Federal Funds Rate (T1YFF) is provided by the Federal Reserve Bank of St. Louis. This data series is represented in percentage values and is not seasonally adjusted in the Graph 3 below. The data is updated monthly and shows the average for each month.

The market yield on U.S. Treasury securities at 6-Month Treasury Bill minus the Federal Funds Rate (TB6SMFFM) is provided by the Federal Reserve Bank of St. Louis. This data series is represented in percentage values and is not seasonally adjusted in the Graph 3 below. The data is updated monthly and shows the average for each month.

GRAPH 3



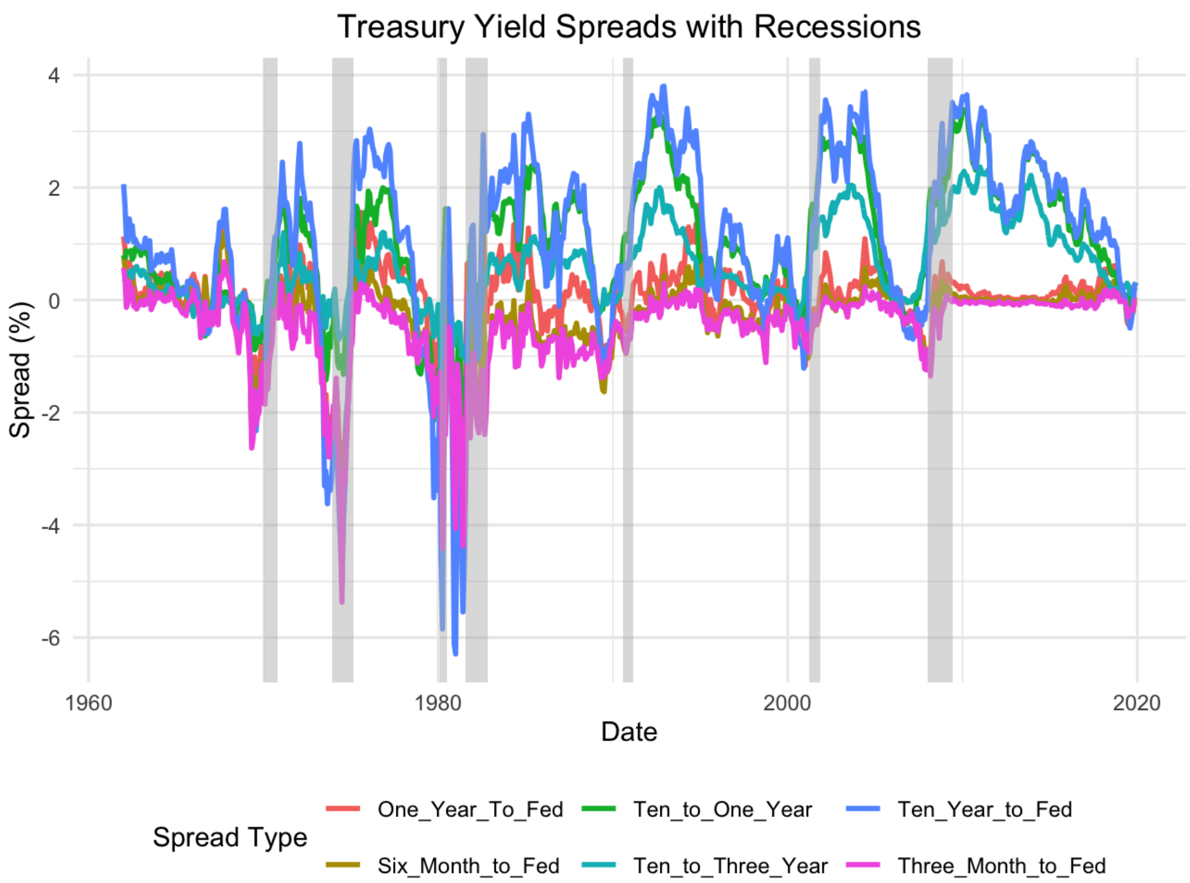
One_Year_To_Fed (Red): 1-Year Treasury Yield Minus Federal Funds Rate

Six_Month_to_Fed (Green): 6-Month Treasury Bill Minus Federal Funds Rate

Ten_Year_to_Fed (Blue): 10-Year Treasury Yield Minus Federal Funds Rate

The market yield for the U.S. Treasury securities at 3-Month Treasury Bill minus the Federal Funds Rate (TB3SMFFM) is provided by the Federal Reserve Bank of St. Louis. This data series is represented in percentage values and is not seasonally adjusted in the Graph 4 below. The data is updated monthly and shows the average for each month.

GRAPH 4



One_Year_To_Fed (Red): 1-Year Treasury Yield Minus Federal Funds Rate

Ten_to_One_Year (Green): 10-Year Treasury Yield Minus 1-Year Treasury Yield

Ten_Year_to_Fed (Blue): 10-Year Treasury Yield Minus Federal Funds Rate

Six_Month_to_Fed (Brown): 6-Month Treasury Bill Minus Federal Funds Rate

Ten_to_Three_Year (Light Blue): 10-Year Treasury Yield Minus 3-Year Treasury Yield

Three_Month_to_Fed (Pink): 3-Month Treasury Bill Minus Federal Funds Rate

In Graph 4, we would like to show the inversion of the yield spreads (when the spread turns negative) before many recessions, for example, before the recessions in the early 1980s, early 1990s, early 2000s, and the Great Recession (2007-2009), where several spreads became inverted at the wake of the crises.

The One_Year_to_Fed spread frequently goes negative before recessions, signaling that short-term rates, influenced by the Federal Funds Rate, are higher than long-term rates. Similarly, the Ten_Year_to_Fed spread often turns negative before recessions, indicating a flat or inverted yield curve, a classic recession predictor.

The short-term spreads (One_Year_to_Fed, Six_Month_to_Fed, Three_Month_to_Fed) tend to be more volatile and show more frequent inversions, reflecting the immediate impacts of Federal Reserve policy changes. In contrast, the long-term spreads (Ten_to_One_Year, Ten_to_Three_Year) provide a smoother view of the yield curve's shape over longer periods and tend to be less volatile but still show inversion before major recessions.

The consistent pattern of yield curve inversion before recessions supports the use of yield spreads as predictive indicators of economic downturns. This is particularly evident in the Ten_Year_to_Fed and One_Year_to_Fed spreads. After recessions, the spreads generally return to positive territory, reflecting a normalizing yield curve as economic conditions stabilize and the Federal Reserve eases monetary policy.

EMPIRICAL RESULTS

4.1 A Brief Outline of the Methods Implemented

We have utilized a rolling window technique at which to estimate our binary recession data spanning from dates T to X different logistic regressions with predictors situated at dates T-12 months to X-12 months, T-15 months to X-15 months, T-18 months to X-18 months, T-21 months to X-21 months and T-24 months to X-24 months have been trained, respectively. At the test stage of each logistic regression, the predictions greater than or equal to 0.2 were classified as recessions (depicted as positive values in a binary setting, i.e. as "1"), later to be compared with actual values in our test data to determine accuracy rates of our models. The choice 0.2 stems from the abundance of 0 values in our training data sets, which deems a cut-off point of 0.5 unrealistic. To ensure 0.2 is an ideal classification threshold, we have redesigned our tests with thresholds 0.15 and 0.25; first, although significantly increasing the area under our ROC curves, creating an excess amount of false-positive results, hence severely restricting the predictive capability of our models, while the latter resulting in a massive increase in false-negative values and decreasing specificity, accompanied by a decrease in the ratio of true positive values to the positive values in our test data (i.e. a decrease in sensitivity), turning our logistic regression estimations to mere coin-tosses in terms of forecasting ability: further strengthening our opinion regarding the ideality of 0.2 as a threshold for classification purposes.

Truth Tables For A 18-Months Lagged (T-18) Model With Three 10-Year Yield Spreads

```
          Reference
Prediction    0    1
         0  203    8
         1   23   18
```

Threshold = 0.15

```
          Reference
Prediction    0    1
         0  223   12
         1    6   14
```

Threshold = 0.2

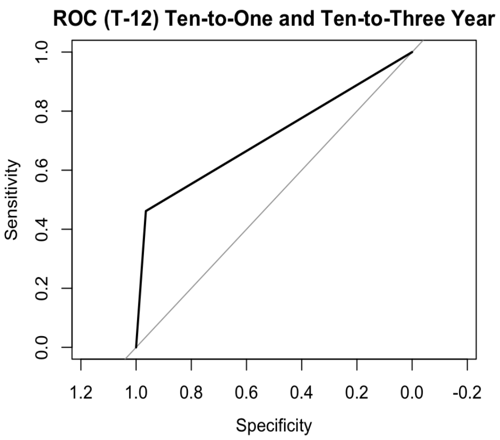
```
          Reference
Prediction    0    1
         0  224   19
         1    2    7
```

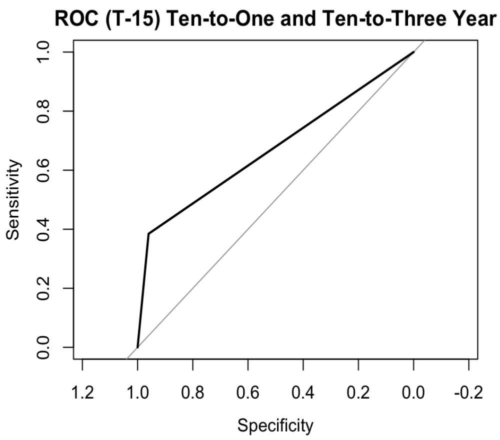
Threshold = 0.25

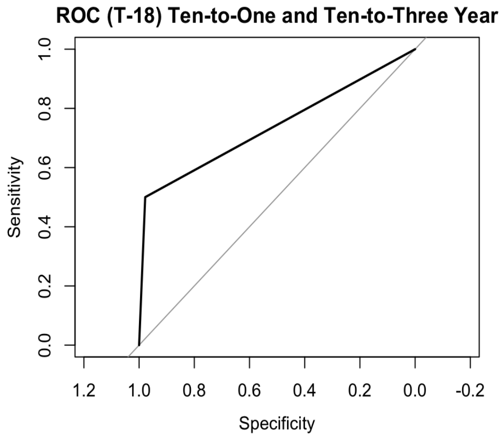
Where the data is abundant, we have combined logistic regressions with Principal Component Analysis, to obtain healthy and significant results from noisy data via dimension reduction using eigen-vectors of the principal components created. Thanks to this setting, we were able to effectively assess the nature of the relationship between yield curve spreads, also used as a measure of yield curve slope, and the recessions emerging in the future 12-24 months after the observation dates of negative spreads, with 3-month intervals in between.

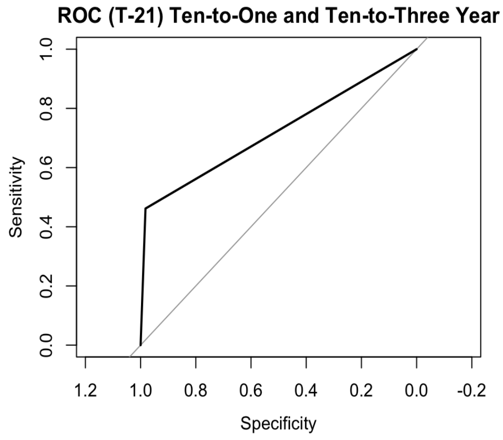
4.2 10 Year Treasury Spreads as Primary Estimators

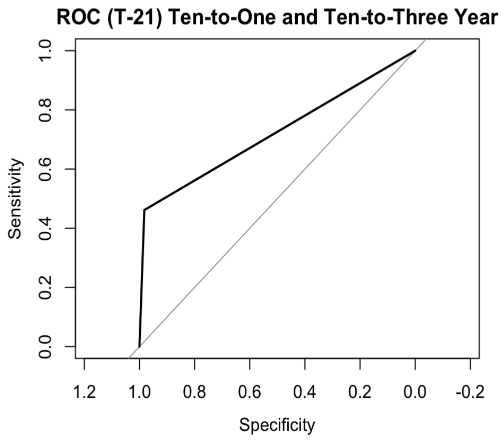
We have started our analysis by assessing the relationship between growth rates and yield spreads between 10-year and 3-year US treasury bonds and spreads between 10-year and 1-year US treasury bonds (hereafter referred to as ten-to-three-year spread and ten-to-one-year spread, respectively), with the latter turning out to be statistically significant at each model at a 99% confidence level. For 12, 15, 18, 21 and 24-month lags; area under our ROC curves (AUCs) after we have made predictions with the test data have been 0.7131, 0.6724, 0.7389, 0.7219 and 0.6812, respectively. Although showing satisfying accuracy rates, the sensitivity of our models has been mediocre; with the highest sensitivity obtained being 0.5 at the model with an 18-month lag, and lowest being 0.38 with a 15-month lag. Yet, it should be noted that, as long as sensitivities close to 0.5 are concerned, the ability to predict downturns with a near 50% probability of being true *for a specific period* still has economic value, inviting analysts to be cautious when the model gives signals of an upcoming recession after encountering an inversion of the yield curve, i.e. a negative spread.











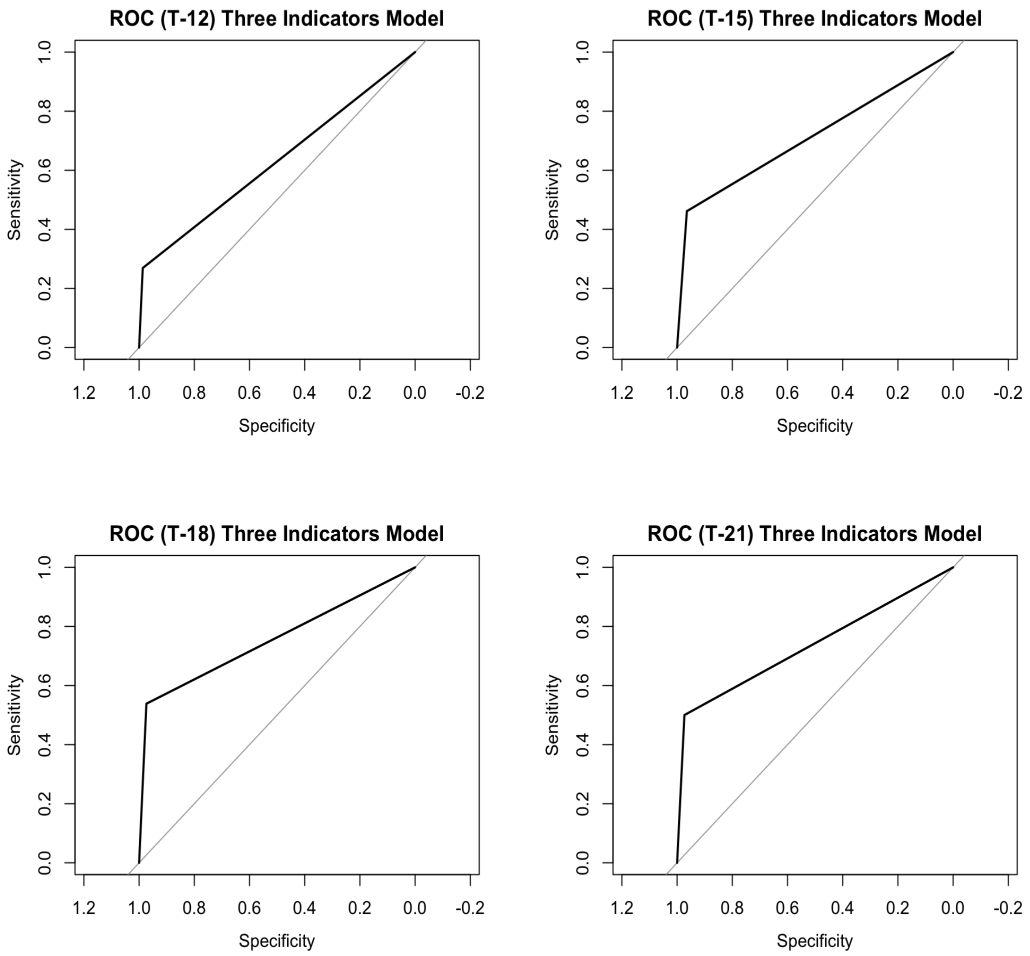
So, at their initial stage, although lacking satisfaction, our models generated hopeful results, provoking us to find additional metrics to improve their performance. At that point, the spread between 10-year US treasury bonds and Federal Funds rate (hereafter referred to as ten-year-to-fed spread) stood out as the ideal candidate, not only due to the latter's' strong correlation with yields of short-term bonds and treasury bills, but also due to its central importance as a key economic indicator of growth and recessions. Coupling this new spread with the previous two, we have analyzed the predictive capability of ten-to-three-year, ten-to-one-year and ten-year-to-fed spreads, and results turned out to be promising.

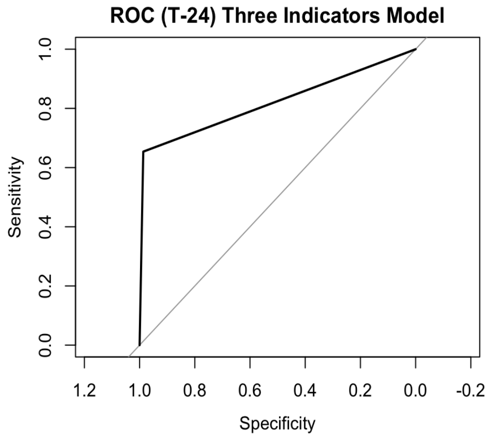
For our new models with 3 indicators and 12, 15, 18, 21 and 24-month lags; areas under our ROC curves we have obtained were 0.628, 0.7131, 0.756, 0.7367 and 0.8203, respectively. In models with 12 and 15-month lags, the statistically most significant variable was ten-year-to-fed spread, later giving way for ten-to-one spread rate as the predictor with primary importance at 18, 21 and 24-month lagged models; ten-year-to-three-year rate also being statistically significant at a 90% confidence level for the 24-month lagged period.

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.79826    0.19739  -9.110  < 2e-16 ***
TENTOTHREE  -1.18618    1.01390  -1.170  0.24203
TENTOONE    -0.06639    0.59190  -0.112  0.91069
TENTOFED    -0.60317    0.20698  -2.914  0.00357 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.4793     0.1677  -8.821  < 2e-16 ***
TENTOTHREE    1.1574     0.9252   1.251  0.21095
TENTOONE     -1.5067     0.5520  -2.730  0.00634 **
TENTOFED      0.1141     0.1719   0.664  0.50686
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Three Indicators Model Summaries, 12-Month Lagged (Top) and 21-Month Lagged (Bottom)





Despite the drop of AUC and sensitivity in the 12-month lagged model (sensitivity of the model without ten-year-to-fed spread being 0.462, as opposed to a value of 0.27 in the latest model, although accuracy rates being 0.9127 for both); as the gap between the date of predictors and the date for recession estimations increased, so did the predictive ability of our models, as implied by higher AUC and sensitivity rates for all periods except the lag of 12-months, with sensitivity of the 18-month lagged model being 0.538, predicting 14 out of 26 recessionary months and surpassing the peak 0.5 of the previous model which occurred at the same lagging-period. Furthermore, the model with 24-month lag, achieved a sensitivity rate of 0.65 and an accuracy rate of 0.9524, correctly estimating 17 out of 26 recessionary months in our 252-month test data set!

	Reference	
Prediction	0	1
0	223	9
1	3	17

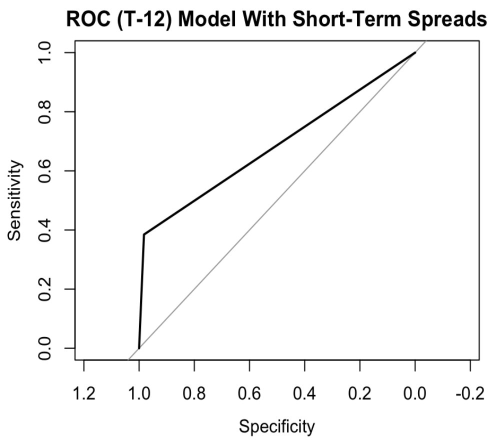
Truth Table For T-24 Three Indicators Model

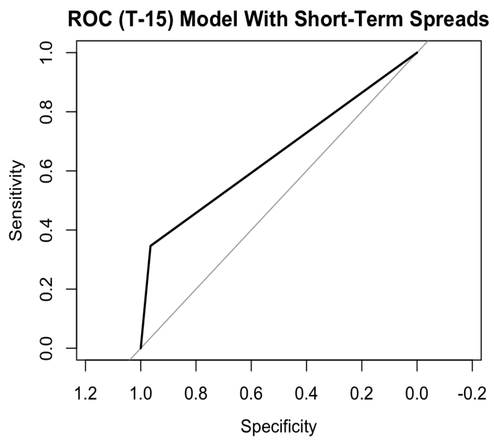
4.3 Including Short-Term Spreads

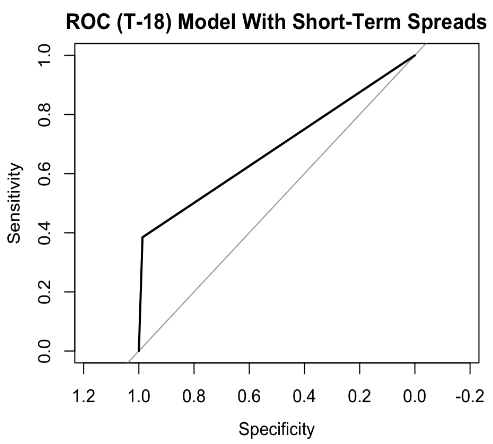
Later, we have included three short term spread rates in our model, to see in spite of the fact that they are inaccurate predictors for future recessions by themselves due to their limited timespan whether they would prove to be useful additions into our models when combined with spreads of relatively longer durations. The spreads included were 1 Year US Treasury rate minus Federal Funds Rate, 6-month US Treasury rate minus Federal Funds

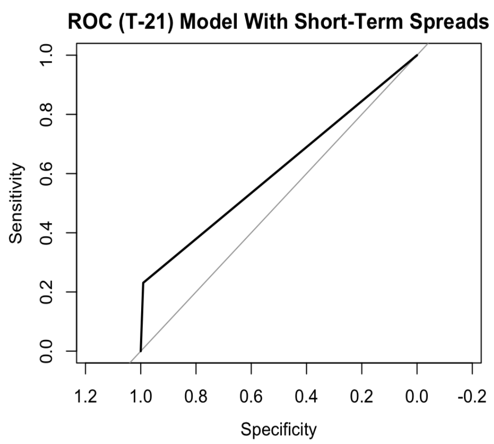
Rate, and 3-month US Treasury rate minus Federal Funds Rate (hereafter named as one-year-to-fed spread, six-month-to-fed spread, and three-month-to-fed spread, respectively); allowing us to account for changes in yields of short term maturities.

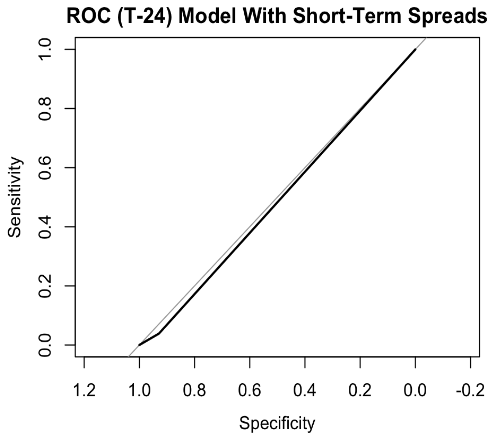
Disappointingly, the newly added spreads affected our models' estimation capabilities negatively, creating AUC values of 0.6835, 0.6554, 0.6857, 0.611 and 0.4838; for 12, 15, 18, 21 and 24-month lagged periods, respectively, the last period performing even worse than a coin toss! The sensitivity rates for any period couldn't surpass 0.4, with the highest sensitivity obtained being 0.38 for the 18-month lagged period. Coupling these findings with the fact that with one-year-to-fed spread being an exception, almost *none* of the variables have been consistently statistically significant, it becomes obvious that newly short-term spreads create noise in our forecasts, distorting the predictive capabilities we have obtained with the models we have developed above due them being shortsighted by construction.





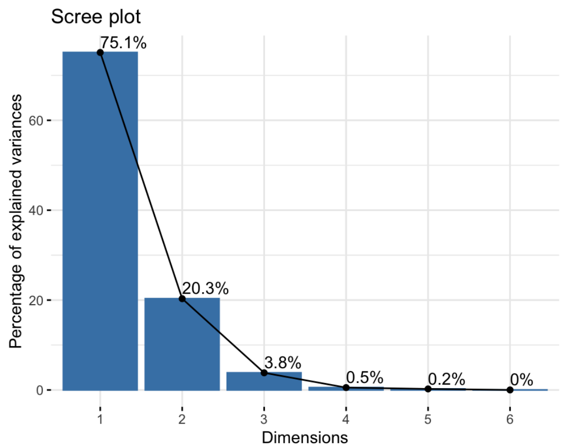


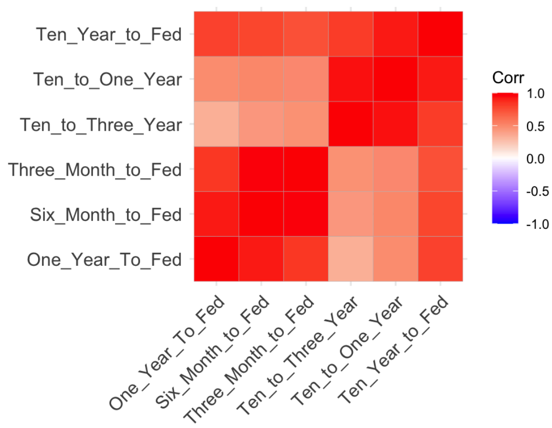




4.4 Removing the Noise: Principal Component Analysis

Since newly added spreads resulted in poor predictive capabilities, the need for a methodology by which we could extract the most valuable information from our enlarged data set arises. For this purpose, we use Principal Component Analysis to obtain a dimensionality reduction, and conclude that three components, namely Principal Component 1 (PC1), Principal Component 2 (PC2) and Principal Component 3 (PC3 explains 99.3% of the variance in our latest data set.





Proportion of the Variance Explained by each Principal Component (Right) and The Correlation Matrix of six different spreads on which PCA has been applied (Left)

Thus, instead of using 6 different variables, we have measured the relationship between PC1, PC2, PC3 and recessions. The technique allowed us to create almost identical models with fewer dimensions, with AUCs 0.5725, 0.5488, 0.4934, 0.5 and 0.5; for 12, 15, 18, 21 and 24-month lagged periods, respectively, again last periods performing like a coin toss. Sensitivity rates, although similar, managed to surpass the 0.4 threshold at some instances, for example reaching 0.42 for the 15-month lagged period. Yet, the most striking observation from PCA, is PC1 and PC2 being statistically significant at a 99% confidence level for all periods, meaning PCA was able to remove the noise from our data set and retrieved a combination of inputs which effectively explains the data at hand. Furthermore, although performing poorly due to the structure of data on which PCA is applied, the analysis managed to construct models that perform identically to the models obtained using the entire data set before the dimensionality reduction, implying PCA serves its function flawlessly.

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept)  -3.1209     0.3144  -9.928  < 2e-16 ***
PC1           0.7470     0.1019   7.331 2.28e-13 ***
PC2          -0.6108     0.2108  -2.897  0.00377 ** 
PC3          -0.4472     0.4027  -1.110  0.26685    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

12-Month Lagged Model

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) -2.70325    0.26366 -10.253  < 2e-16 ***
PC1          0.57742    0.08685   6.648 2.97e-11 ***
PC2         -0.39303    0.18990  -2.070   0.0385 *  
PC3         -0.60802    0.38962  -1.561   0.1186    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

15-Month Lagged Model

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) -2.57681    0.24535 -10.503  < 2e-16 ***
PC1          0.49166    0.07979   6.162 7.19e-10 ***
PC2         -0.52255    0.17614  -2.967  0.00301 ** 
PC3         -0.21027    0.34515  -0.609  0.54239    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

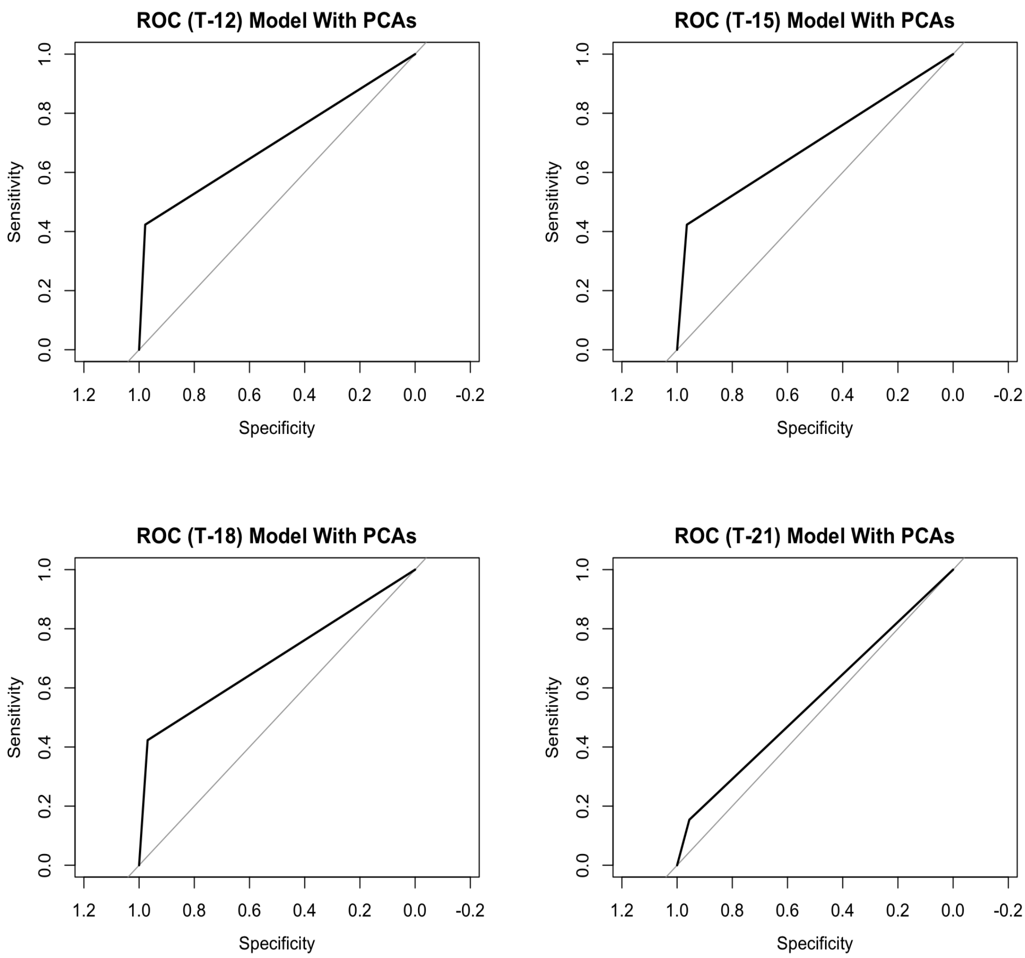
18-Month Lagged Model

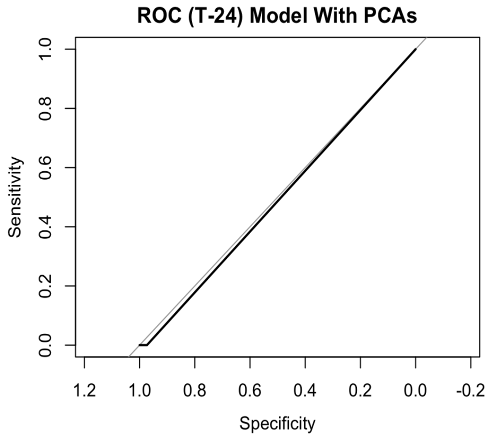
```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) -2.41571    0.22452 -10.760  < 2e-16 ***
PC1          0.38544    0.07367   5.232 1.68e-07 ***
PC2         -0.53549    0.16501  -3.245  0.00117 ** 
PC3          0.11092    0.31775   0.349  0.72702    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

21-Month Lagged Model

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) -2.32672    0.21283 -10.932  < 2e-16 ***
PC1          0.27978    0.07136   3.920 8.84e-05 ***
PC2         -0.56141    0.16065  -3.495 0.000475 ***
PC3          0.47489    0.29946   1.586 0.112788    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

24-Month Lagged Model




ROC (T-24) Model With PCAs
Sensitivity
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
Specificity

COMMENT ON FINDINGS

Our findings can be analyzed under two main aspects. First is regarding the usefulness of 10 Year US Treasury yield spreads, and by extension of the slope of the yield curve as a recession predictor. Second, is about the potential benefits of applying dimensionality reduction techniques for creating logistic regression models using treasury yield spreads as estimators for economic downturns.

We have observed that a 10 Year Treasury yield spread is not only strong indicators for recessions by itself, but also has the capability to magnify the predictive capability of a logistic regression model when merged with other 10 Year Treasury spreads, as it has been the case when we added ten-year-to-fed spread to our model with ten-year-to-three-year and ten-year-to-one-year spreads. With high accuracy, AUC and desirable sensitivity rates, our findings were in line with the convention of 10 year spread rate turning negative, i.e. yield curve inverting, being an effective estimator for future recessions to be experienced in the following 12 to 24 months. When contrasted with the poor performance of models with shorter-term spreads included, the value of 10 Year Treasury spreads, (i.e. the slope of the yield curve) as a recession predictor becomes even more evident.

Regarding PCA, on the other hand, as explained above, we have used the analysis to replicate the results of a 6-dimensional model with only 3 dimensions and have been successful within the limits of the original model. Given the demonstrated ability of PCA to generate similar outcomes with fewer dimensions and the proven reliability of 10 Year Treasury spreads to estimate recessions, we believe there is space in financial literature to create more effective models using multiple 10 Year Treasury spreads with ambiguously large data points coupled with Principal Component Analysis to create extremely precise models with fewer dimensions and ease of use, the details and means of which being beyond the scope of this paper.

CONCLUSION

The predictive power of the yield curve as an indicator of recessions has been reaffirmed through this study. Utilizing data from the Federal Reserve Economic Data (FRED) spanning from 1962 to 2019, we employed logistic regression models and Principal Component Analysis (PCA) to examine the relationship between various Treasury spreads and economic downturns. Our findings reveal that specific long-term spreads, particularly the 10-year to 1-year and 10-year to 3-year spreads, as well as the 10-year Treasury yield relative to the Federal Funds Rate, are strong indicators of future recessions.

Our empirical results demonstrated that models incorporating long-term spreads achieved high accuracy and desirable sensitivity rates, with the predictive capability of the models as the lag between predictor and recession remaining ambiguous. Nevertheless, the models using 10-year spreads, specifically the model with a 24-month lag including three different 10-year spreads, achieved remarkable success in forecasting recessionary periods. The paper shows that while short-term spreads introduced noise and reduced model accuracy, the use of PCA allowed us to eliminate this noise and extract significant components.

In summary, our results show that the yield curve, specifically the long-term spreads, remains a relevant and powerful tool for predicting recessions, reinforcing its value as a key economic indicator and providing insights for further research and application in economic forecasting. Our findings suggest that future studies combining multiple long-term Treasury spreads with dimensionality reduction techniques may yield more precise and reliable forecasting models.

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