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FROM BONDS TO PROSPERITY: ECHOES OF YIELD SPREADS ON GDP GROWTH

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Abstract

This finance master's thesis examines the predictive efficacy of the 10-year and 3-month (10Y3M) and the 10-year and 2-year (10Y2Y) U.S. Treasury bond yield spread in forecasting Real GDP fluctuations from Q1 1982 to Q2 2022, analyzing quarterly historical data from St. Louis Federal Reserve Economic Data and Bloomberg for 10Y3M, 10Y2Y, real GDP growth, and VIX series (1990 Q1 to 2022 Q2). Results suggest that relying solely on spreads for GDP predictions can be misleading and underscore their limited and inconclusive predictive ability, emphasizing the need for additional variables, such as the VIX index, to enhance predictive power.

Keywords

Yield spread, yield curve, term structure, economic downturn, VIX.

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Introduction

In the last quarter of 2019 major financial media outlets such as Bloomberg, CNBC, and Yahoo Finance reported that investors were pricing in a looming recession as the 10Y2Y spread inverted, reaching negative values. In the subsequent months after the signal, around early March 2020, countries worldwide closed borders and enforced the cessation of non-essential economic activities to control the spread of COVID-19, causing a significant downturn in the global economy.

The decision to incorporate the 10Y2Y spread as a key variable in this master's thesis stems from its potential as a signal among market participants regarding the future trajectory of the U.S. economy. Incorporating the 10Y2Y spread into this research aligns with its recognized influence on market sentiment. However, it's important to highlight that the Federal Reserve of the United States (Fed) rejects the 10Y2Y spread as a technical signal. The Fed emphasizes that it should not be used as an indicator for investment strategies or monetary policies.

The goal of this thesis is to examine the validity of the 10Y2Y spread as a reliable signal for anticipating downward economic movements. Despite conflicting perspectives between market sentiment and official statements from the Fed, there exists a gap in conclusive evidence supporting either stance. This research aims to provide an answer to the question of whether the 10Y2Y spread holds genuine predictive power or if its observed patterns are coincidental.

By investigating the relationship between the 10Y2Y spread and subsequent economic conditions, this thesis seeks to contribute insights to the ongoing debate surrounding the utility of the 10Y2Y spread as a leading indicator. The absence of convincing findings supporting or refuting its effectiveness emphasizes the need for a comprehensive examination, making this thesis a pertinent endeavor in the field of financial analysis and economic forecasting.

For decades, there has been a growing emphasis on studying yield spreads as key indicators of economic conditions. These spreads, reflecting the difference between long-term and short-term bond yields, are analyzed due to their predictive capacity for economic trends. They encapsulate the market's assessment of future economic prospects, making them valuable tools for economic forecasting. Yields could reflect investors' distrust about what could happen in the long run even if macroeconomic indicators such as GDP growth and low unemployment are solid, they could show signs that the economy is running out of strength.

Economic conditions and financial markets interact, with financial markets anticipating future valuations, unlike economists who analyze the past. This distinction enables using financial variables as predictors for changes in the economy.

The yield curve, which mirrors the relationship between short and long-term interest rates, acts as a signal for anticipating forthcoming economic conditions, offering a predictive opportunity for economic trend shifts. Using yield spread as a predictor enables proactive implementation of macroeconomic tools, fostering a smooth transition in the economic cycle and enabling a quick recovery, known as soft landing. On the other hand, it can be used as a tool for crafting investment strategies to position oneself effectively to face economic downturns, such as investing in defensive/counter-cyclical assets.

The U.S. Treasury yield curve, closely monitored globally, holds significance for financial markets. Fed views the 3M yield surpassing the 10Y as a technical recession signal, while some investors anticipate a recession with a 10Y2Y inversion. The Fed considers the 10Y2Y inversion coincidental, attributing it to emotional factors that do not impact the 10Y3M inversion.

The 10Y3M incorporates yield curve information, reflecting market expectations for future economic behavior. The yield curve typically slopes upward, indicating higher long-term yields. Variations in the reliability of the yield curve as a forecasting tool are evident in monetary policy regimes and structural break tests like those by Bai and Perron.

Historical analysis indicates yield curve flattening or inversion before recessions, with the yield spread consistently turning negative before nearly all past recessions. During early and middle expansion, the yield curve has a positive slope. When a slowdown or recession is anticipated, short-term rates are expected to rise, prompting investors to buy safe longer-term assets. This demand raises long-term bond prices and lowers their rates due to bonds' convexity. Conversely, short-term yields increase, leading to lower prices given the lack of confidence in the near-term economic outlook (Wheelock and Wohar 2009).

Research indicates a direct correlation between the yield spread and future GDP expansion. A steeper yield curve is linked to higher subsequent rates of GDP growth, while a less steep curve is associated with lower growth rates. Despite its reliability, the yield curve's predictive ability lacks a comprehensive theoretical explanation (Wheelock and Wohar 2009).

Historically, the 10Y2Y spread has been negative between 4 to 6 quarters before a recession, and the 10Y3M spread has been negative 2 quarters before. 10Y2Y early signaling provides utility for implementing contingency measures ahead of economic slowdowns. The potential of this series as an economic predictor is analyzed employing econometric tools, covering quarterly data from Q1 1982 to Q2 2022.

If econometric validity is established, the 10Y2Y can serve as an additional tool for investment strategies and monetary policy decisions. Conversely, if no validity is found, the spread inversion would be disregarded, avoiding noise and herd bias depicted in mainstream media.

Following "The Yield Curve as a Predictor of U.S. Recessions" (Estrella and Mishkin 1998, 46) study on the 10Y3M spread's recession prediction using a probit model, this study replicates the methodology with two key changes: employing the 10Y2Y spread as explanatory variable and assessing the dichotomous variable for the economic trend as an upward or downward movement, rather as recessions to enhance data significance, broadening the study scope, given that there are only 13 periods that meet the technical definition of a recession: “significant decline in economic activity that is spread across the economy and lasts more than a few months” (NBER n.d.), throughout the analyzed period, whereas there are 83 instances of negative shifts in real GDP growth.

In the base research, conducted to assess the yield curve's ability to forecast U.S. recessions, 10Y3M historical data was analyzed spanning multiple decades. Using statistical methods, its authors aimed to unveil correlations and patterns between the yield curve and economic recessions.

A notable negative yield spread indicates an impending recession, while a positive yield spread suggests economic expansion. These findings align with existing literature, reaffirming the yield spread's reliability as a forecaster of economic transitions.

Accurate economic forecasting is vital for policymakers, investors, and financial institutions to shape effective strategies. Reliable indicators aid in optimizing portfolios, managing transactions, and assessing risks, offering valuable insights for informed decision-making in the financial sector.

Existing research establishes yield spreads as reliable indicators for predicting economic cycles, setting the stage for examining the unique relationship between the 10Y2Y spread and future economic conditions.

This study aims to examine the yield spread's effectiveness as an indicator for predicting future economic conditions. By investigating the relationship between the yield spread and subsequent economic outcomes, it seeks to contribute insights to the finance field, enabling market participants to make informed decisions in dynamic financial and economic environments.

Part I: Theoretical Background and Literature Review

Research indicates interest rate series, especially the term structure, predict future economic behavior. Investment growth aligns closer with output growth than consumption growth. The ability to predict output growth is linked to firm-level decisions, with increased investment plans driving economic growth. Sub-sample analyses highlight differences in prognostic strength based on economic regimes or Bai and Perron tests.

Scholars recognize the term structure of interest rates for predicting economic conditions. Unlike short-term interest rates, it reliably predicts consumption growth. Financial market series predict both output and investment growth, making the term structure the most effective tool for macroeconomic growth forecasting. The term structure consistently exhibits anticipatory influence, while stock returns are more predictive during stable periods, and short-term interest rates are more predictive during uncertainty (McMillan 2021, 338)**.**

The term spread effectively projected future economic conditions, including real GDP growth, inflation rates, industrial production, consumption pace, and recession likelihood. Its forecasting effectiveness varied across countries and time periods. The positive and statistically significant correlation between the term spread and GDP growth occurred when lagged by two to six quarters, but not when lagged by one quarter. Research revealed an inverse relationship, indicating that increased GDP expansion in a quarter was associated with a less sharply angled yield curve in subsequent quarters.

The predictive power of the yield curve slope is influenced by factors like economic conditions, volatility, and regime shifts in monetary policy. A key factor is inflation persistence, the slope's predictive ability is further dependent on economic conditions, providing better forecasts of output growth when inflation is highly persistent or less volatile. As for monetary policy, central banks tightening policy may decrease/invert the yield curve slope due to a swift surge in short-term rates relative to long-term rates, signaling heightened investor risk aversion. During recessions, low short-term interest rates stimulate consumption, while higher long-term rates anticipate future rate hikes. The underlying theoretical framework for these observations remains limited. These findings underscore the importance of economic conditions in shaping the yield curve slope's predictive capacity (Hännikäinen 2017, 1058).

Technically evaluating the slope's predictive ability involves regression models, parameter estimations, and considering the exponential decay rate for yield curve fitting. Using rolling windows within a specific timeframe, the analysis accounts for inflation volatility affecting investor behavior and regime shifts in monetary policy influencing the slope's predictive content (Ng 2012).

(Argyropoulos 2016, 295) highlights term structure components' forecasting abilities, providing insights into future economic activity up to five years. The curvature factor is influential for shorter/medium-term horizons, while the spread predicts long-term business condition changes. Kalman filter analysis extracts signals, with Diebold-Mariano (DM) and Giacomini's/Rossi's (GR) tests assessing forecasting performance. A negative DM statistic indicates superior forecasting, and the GR statistic identifies structural break issues. Focused on 3, 6, and 12 months, the study underscored the spread's importance in predicting business cycle changes, with the curvature factor linked to short and medium-term monetary policy fluctuations.

A Fed study (Estrella 2005) reveals that 10Y3M yield curve inversions occurred 10 times in the past 60 years, consistently preceding U.S. recessions or economic slowdowns by about a year, except for 1966. This thesis strives to investigate if the U.S. economy experiences an economic slowdown following a 10Y2Y spread inversion, mirroring the pattern observed with the 10Y3M.

The 10Y2Y spread showed a positive relationship with output and consumption growth from 1979 to 1982. Results were statistically meaningful for four quarters of real GDP growth at a 10% significance level. The study also highlighted the impact of short-term interest rates on investment and consumption growth over one and four quarters. During economic ambiguity, like the late 1970s and the 2007-2009 financial crisis, the shift in short-term interest rates exhibited a negative relationship with output and investment growth. Further analysis, using Bai and Perron structural break tests, identified sub-samples and monetary policy regimes, supporting yield spreads' forecasting capability in periods of greater economic risk. The study suggests yield spreads and interest rates are more reliable predictors during times of high economic uncertainty and risk (McMillan 2021, 334).

The 10Y2Y was a reliable recession predictor before the mid-1980s, offering crucial insights for consumers, investors, and policymakers. The yield curve's narrowing or inversion consistently forecasts economic trends, including output growth and recessions. Notably, most recessions were preceded by yield curve changes, with inversions reliably signaling recessions, except in 1970. Over the past 50 years, the United Kingdom experienced recessions in 1974, 1979, 1990, and 2008, each coinciding with a yield curve inversion.

While the association between output expansion and the term spread is generally robust, it is not always significant, it is essential to consider potential influences from other variables. For instance, if investors are willing to pay premium prices for longer-term securities, yields on these securities may decline relative to shorter tranches, potentially diminishing the effectiveness of the term spread as a predictor.

Recent research diverges on the term spread's predictive power for economic fluctuations. While some experts argue the yield curve's slope predicts real GDP changes, others emphasize its effectiveness in forecasting both consumption and output growth. However, since the mid-1980s, the yield curve's direction's (upward, downward, or flat) ability to predict economic growth has weakened, potentially due to reduced volatility in output and key macroeconomic statistics. Despite being a significant predictor, recent studies suggest a decline in its capacity to estimate output expansion (Wheelock and Wohar 2009)**.**

Regarding models employed to analyze these variables, static probit models lack a dynamic structure for time series data, facing limitations. Pinpointing the current economic state, particularly during recessions, is challenging due to publication delays. Conversely, using a 25% threshold has proven to yield more reliable forecasts during recessions with new datasets. Proposed models, incorporating four recession risk factors (financial market expectations, credit or liquidity risks, negative wealth effects, and deteriorating macroeconomic fundamentals), outperform conventional static models, offering higher accuracy in predicting recession months. While advanced dynamic probit models excel in predicting recession duration, the static probit model with proposed risk factors performs equally well in forecasting business cycle peaks (Ng 2012, 114).

Differing views indicate changes in inflation persistence do not align closely with the spread's predictive effectiveness. Unconventional monetary policies during the zero lower bound impact the spread's immediate relevance for industrial production growth. Diminished yield curve informativeness is linked to increased stability in U.S. economic expansion. In less volatile forecasts, simple benchmarks may suffice, challenging additional leading indicator identification. The spread offers precise forecasts for real economic movements, while the curve's level and curvature are less adept. The weakening predictive ability of the yield curve slope since the mid-1980s is widely acknowledged. (Ng 2012, 124).

Part II: Methodology

In 1998 Arturo Estrella and Frederic Mishkin carried out a study on the prediction of recessions with the 10Y3M spread, using as a dependent variable whether there was a recession or not. For this they made a probit model defined by the following equation:

$$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 X_1 t + \alpha_2 X2_t + \cdots) \quad (1)$$

$Where\ the\ dependent\ variable\ in\ the\ model\ is$

$R_{t+k} = 1\ in\ case\ the\ economy\ is\ in\ recession\ in\ x\ quarter$

$R_{t+k} = 0\ in\ case\ the\ economy\ is\ not\ in\ recession\ in\ x\ quarter$

$F = normal\ cumulative\ distribution\ function$

$\alpha_0 = constant$

$\alpha_1, \alpha_2, \ldots =$ explanatory variables coefficients

$X_1 t, X_2 t, \ldots =$ spreads at time t (explanatory variables)

The effect of applying the function F to the weighted sum is to transform the result into the likelihood of an economic downturn will result in quarter t+k. A probability close to 1 indicates a strong prediction of a recession, whereas the opposite is true of a probability close to 0 (Estrella & Mishkin, 1998, 46).

Making use of a linear regression model is inappropriate when working with a dichotomous dependent variable. Instead, one should opt for a logit or probit model. The logit model is typically employed to estimate the odds of a variable assuming a particular value, while the probit model is preferred when aiming to calculate the probabilities of the variable falling into specific categories.

Spreads were analyzed using a dynamic autoregressive probit model. Evaluation criteria include pseudo-R^2, *p*-values and confusion arrays. In relation to bearish periods, the National Bureau of Economic Research business cycle dates were used as a guide (NBER n.d.).

A comprehensive analysis of each variable will now be conducted to understand its econometric behavior before constructing the respective probit models.

Part III: Empirical Results

TABLE 1 – SUMMARY STATISTICS OF US TREASURY BONDS CHARACTERISTICS

Variable	Mean	σ	Minimum	Maximum
10Y3M	1.73%	1.08%	-0.63%	3.61%
10Y2Y	1.04%	0.82%	-0.39%	2.80%
Real GDP Growth	0.67%	1.09%	-7.89%	7.76%

Notes: Sample period: 1982: Q1 – 2022: Q2; Observations = 163.

The econometric analysis begins with an examination of basic characteristics for each variable with 163 observations. Returns stylized facts are found: Real GDP growth has a mean close to 0 and its outliers are found in clusters, shown in Figure 1. 10Y3M has a higher mean than 10Y2Y on account of lower risk in the shorter tranche, causing a larger difference in normal circumstance where there is not much volatility. Spreads do not follow typical return patterns as they are yield variations.

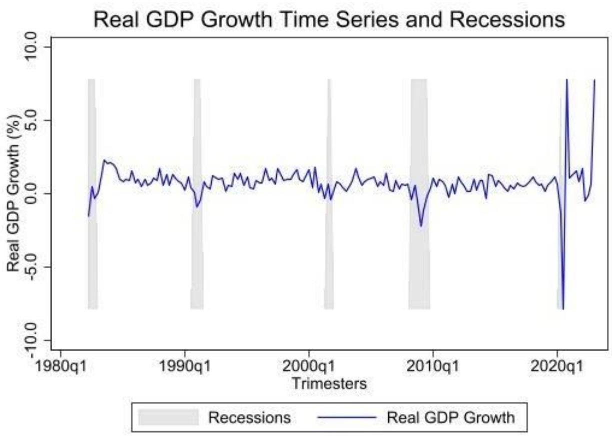
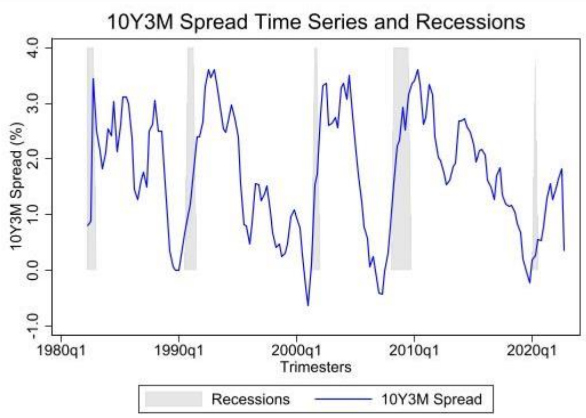


FIGURE 1. REAL GDP GROWTH TIME SERIES.
Notes: data is plotted at the quarterly frequency. Grey areas are recessions, dates are provided by NBER.

As expected, real GDP growth series comply with stylized facts about univariate financial return series depicted on Figure 1: graph tends to move around its mean, which is 0 and it is its expected return. Extreme returns appear in clusters, and volatility appears to vary over time.



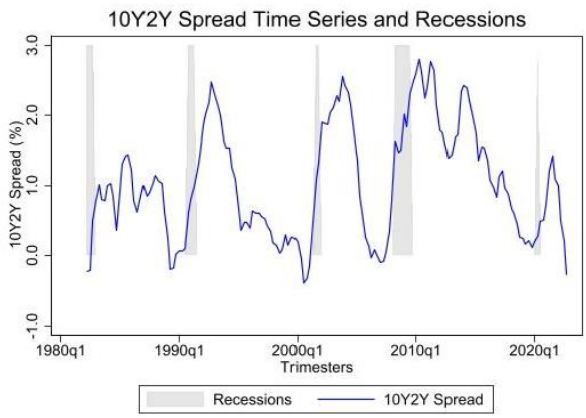
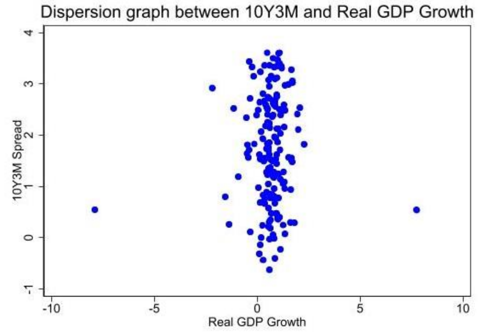


FIGURE 2. 10Y3M SPREAD SERIES

FIGURE 3. 10Y2Y SPREAD SERIES

Notes: data is plotted at the quarterly frequency. Grey areas are recessions, dates are provided by NBER.

As shown by Figure 2 and 3 spreads series do not tend towards their mean, but towards a positive value, since under normal circumstances a long-term bond has a higher yield than a short-term one, which implies that its difference is positive. At abnormal times, negative values could be observed, where short-term tranches yield more than longer ones.



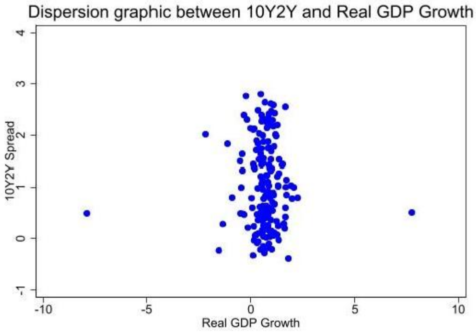
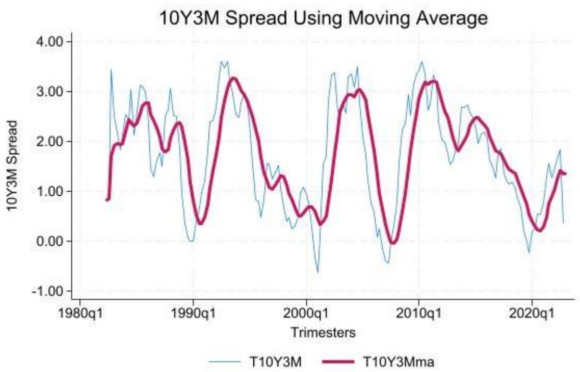


FIGURE 4. DISPERSION GRAPH BETWEEN 10Y3M AND REAL GDP GROWTH
FIGURE 5. DISPERSION GRAPH BETWEEN 10Y2Y AND REAL GDP GROWTH

Notes: Extreme atypical values where found during the COVID-19 crisis.

Vertical lines in Figures 4 and 5 suggest stability in long-term interest rate expectations. Atypical points during the pandemic reflect economic and financial reactions to the crisis, common in uncertain times. Widening spreads and decreasing real GDP might indicate investor anticipation of a recession.



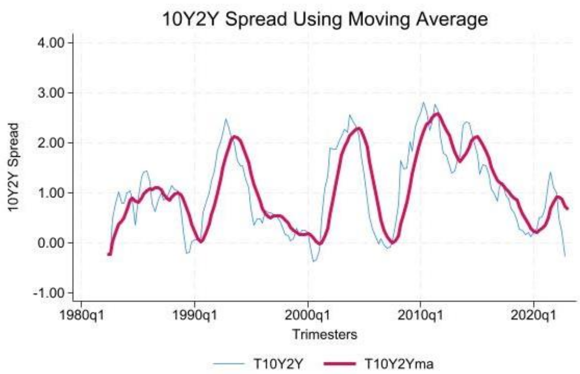
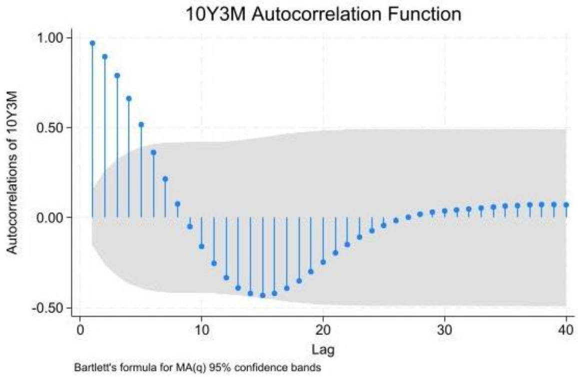


FIGURE 6. 10Y3M SPREAD USING MOVING AVERAGE FIGURE 7. 10Y2Y SPREAD USING MOVING AVERAGE

Notes: smoothing process using a 6-period moving average which considers the current observation along with six periods behind. Equal-weighting scheme is employed, resulting in a simple moving average that equally incorporates all values within the window.

To reduce noise on series, these were filtered with a moving average of 6 lagged terms considering the current observation, without any forward term, results are depicted on Figures 6 and 7.



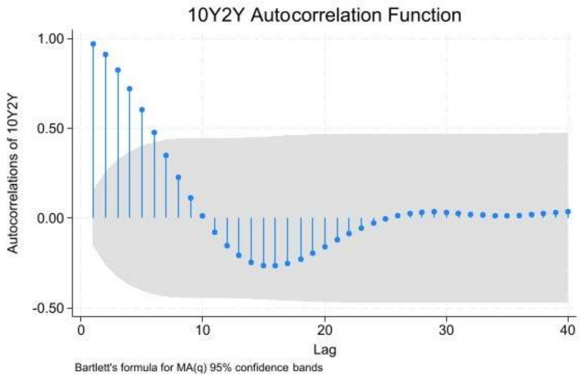
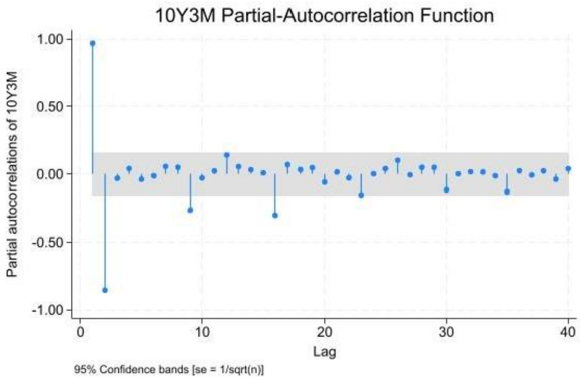


FIGURE 8. 10Y3M SPREAD AUTOCORRELATION FUNCTION
FIGURE 9. 10Y2Y SPREAD AUTOCORRELATION FUNCTION

Figure 8 indicates a linear relationship close to 1 for up to five lags in the autocorrelation function, with a 95% confidence level. Figure 9 for 10Y2Y shows a linear relationship close to 1 for up to six lags at the same confidence level. This suggests an additional useful period for analyzing the current term compared to the 10Y3M.



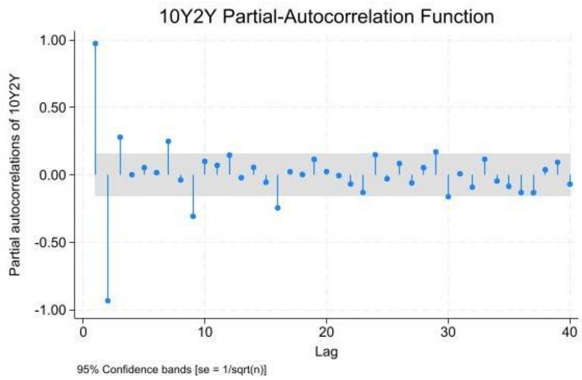


FIGURE 10. 10Y3M SPREAD PARTIAL AUTOCORRELATION FUNCTION
FIGURE 11. 10Y2Y SPREAD PARTIAL AUTOCORRELATION FUNCTION

Despite the idea mentioned above, Figures 10 and 11 show that two lags can be used in the AR term of an ARIMA model according to the partial autocorrelation function for both spreads.

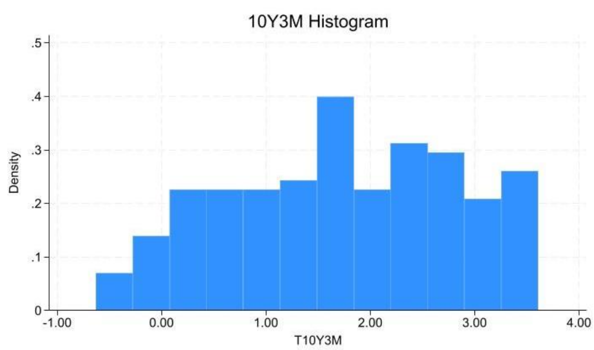


FIGURE 12. 10Y3M SPREAD HISTOGRAM

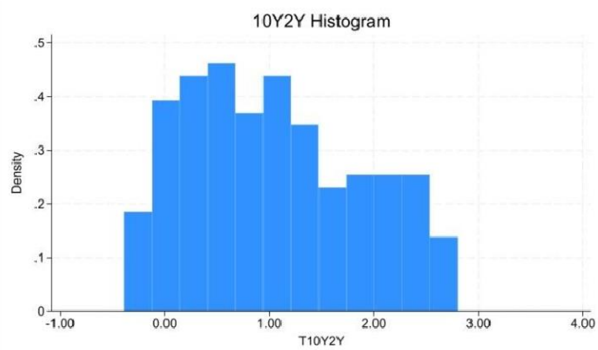


FIGURE 13. 10Y2Y SPREAD HISTOGRAM

According to Figure 12, 10Y3M data distribution tends to be further away from its mean by more than one standard deviation. As for 10Y2Y, on Figure 13 there is not a clear bell shape, and it has fat tails. Hence, neither spread follows a normal distribution.

Following the statistical description of variables, probit models were constructed, on which the dichotomous variable signifies an upward or downward economic movement relative to the prior quarter (not seasonally adjusted). 1 represents a bearish movement and 0 a bullish one.

TABLE 2 - SUMMARY STATISTICS OF PROBIT MODELS DICHOTOMOUS VARIABLE CHARACTERISTICS

Variable	Mean	σ	Minimum	Maximum
Trend	0.51	0.50	0	1

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Probit model is estimated with an intercept and one regressor as indicated. Dependent variable is the economic trend.

Different probit models were created to get the highest Pseudo-R^2, the ones shown were the best models obtained based on this metric.

TABLE 3 - 10Y3M SPREAD WITH 4 LAGS PROBIT MODEL STATISTICAL INFERENCE

Variable	Coefficient	SE	Z	$p > \| Z \|$	95% Confidence Interval	
Spread	0.06	0.09	0.66	0.50	-0.11	0.24
Constant	-0.05	0.19	-0.27	0.79	-0.42	0.32

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Probit model is estimated with an intercept and one regressor as indicated. The independent variable is the 10Y3M Spread with 4 lags and the dependent variable is the economic trend, which indicates whether it is an upward when its coefficient is equal to 0 in case it is 1 indicates that there is a bearish outcome. Entries in the table denotes the estimates of the probit model coefficients.

Results in Table 3 show that the 10Y3M spread with 4 lags has a coefficient of 0.06, representing the estimated change in log-odds for a one-unit increase in the explanatory variable. The low standard error indicates higher precision. The Z-value (0.66) is small, suggesting a lack of statistical significance, supported by the high *p*-value (0.5). The confidence interval includes zero, reinforcing the idea that the spread with 4 lags is not a statistically significant predictor of economic trends.

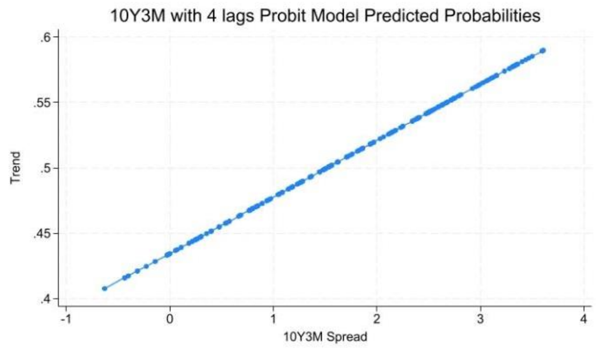
The positive coefficient implies a positive link between the 10Y3M spread with 4 lags and a lower probability of a downward economic movement. However, statistical tests (Z-value and *p*-value) reveal insignificance. The wide confidence interval indicates imprecision, and its inclusion of zero suggests the 10Y3M spread with 4 lags may not be a reliable predictor for future economic outcomes.

TABLE 4 – 10Y3M WITH 4 LAGS PROBIT MODEL ASSESS GOODNESS OF FIT

Measures	Coefficients
Likelihood Ratio	1.02
Probability > Chi^2	0.51
Pseudo R^2	0.00

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Probit model is estimated with an intercept and one regressor as indicated. Dependent variable is the economic trend. Entries in the table denotes the estimates of the probit model coefficients.

The likelihood ratio test, with a *p*-value of 0.51, suggests that the model's improvement over a null model lacks statistical significance. Based on Table 4 coefficients one fails to reject the H_0. This implies the overall model is not statistically significant. The Pseudo-R^2 value of 0.00 further indicates the model explains a minimal amount of variation in the dependent variable, reinforcing the statement that 10Y3M with 4 lags alone is not a robust predictor of future economic outcomes anymore in the current context.



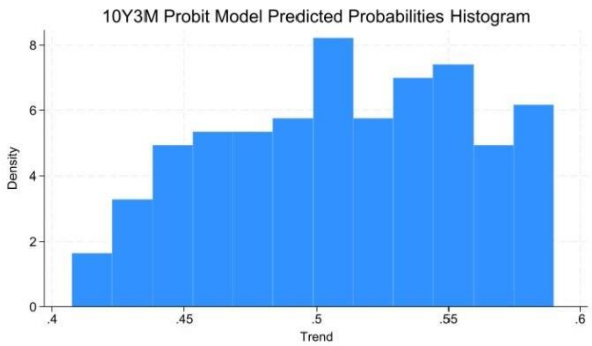


FIGURE 14. 10Y3M WITH 4 LAGS PROBIT MODEL PREDICTED PROBABILITIES
FIGURE 15. 10Y3M WITH 4 LAGS PROBIT MODEL PREDICTED PROBABILITIES HISTOGRAM

Based on Figure 14, it is inferred that there is linear relationship between the independent variable and the dichotomous event, therefore, the spread does influence the economic direction, and following the line of the positive coefficient, if 10Y3M increases, there will be a lower probability that a bearish movement will take place. Furthermore, its predicted probabilities follow a distribution concentrated on the right tail as shown in Figure 15.

TABLE 5 - 10Y3M WITH 4 LAGS PROBIT MODEL PREDICTED PROBABILITIES DESCRIPTIVE STATISTICS

Measures	Mean	σ	Minimum	Maximum
Values	0.52	0.03	0.47	0.57

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Probit model is estimated with an intercept and one regressor as indicated. Dependent variable is the economic trend. Entries in the table denotes the estimates of descriptive statistics.

TABLE 6 - 10Y3M WITH 4 LAGS PROBIT MODEL CONFUSION MATRIX

$^{Actual}/_{Predicted}$	0	1	Total
0	19	59	78
1	20	65	85
Total	39	124	163

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163; Observations = 163. Entries in the table denotes the estimates of the confusion matrix coefficients.

Table 6 was constructed establishing a probability threshold set at 0.5. This means that when the predicted probability is 0.5 or higher, it is considered as "1" (indicating the event occurred); otherwise, it is labeled as "0" (indicating the event did not occur). Although the model shows a moderate overall accuracy of 67%, its precision is 52%, and specificity is 24%, indicating low performance in correctly identifying positive cases and true negatives. This suggests that although the model correctly identifies some downward economic movements, it also has a notable number of false positives.

TABLE 7 - 10Y2Y WITH 4 LAGS PROBIT MODEL

Variable	Coefficient	SE	Z	P > | Z |	95% Confidence Interval	
Spread	0.08	0.12	0.65	0.52	-0.16	0.32
Constant	-0.03	0.16	-0.18	0.86	-0.35	0.29

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Probit model is estimated with an intercept and one regressor as indicated. The independent variable refers to the 10Y2Y spread with 4 lags and the dependent variable is the economic trend, which indicates whether it is an upward when its coefficient is equal to 0 in case it is 1 indicates that there is a bearish outcome. Entries in the table denotes the estimates of the probit model coefficients.

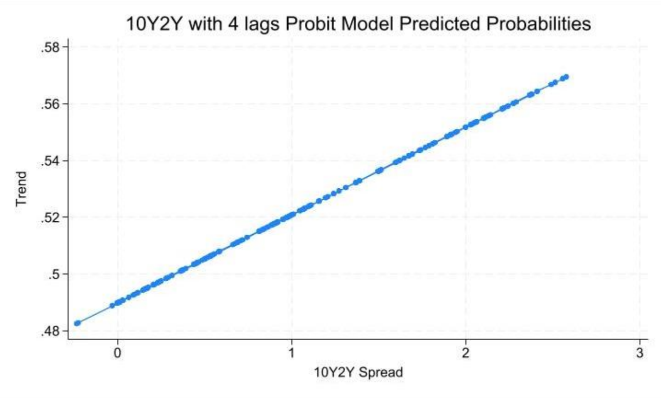
Based on Table 7, the positive coefficient suggests a positive relationship between the spread with 4 lags and the likelihood of a downward economic movement. However, the statistical tests (Z-value and *p*-value) indicate that this relationship is not statistically significant (P > | Z | is greater than α). The wide confidence interval further indicates uncertainty about the precision of the estimate, and the fact that it includes zero implies that the spread with 4 lags may not reliably predict future economic outcomes.

TABLE 8 - 10Y2Y WITH 4 LAGS PROBIT MODEL ASSESS GOODNESS OF FIT

Measures	Coefficients
Likelihood Ratio	1.17
Probability > Chi^2	0.52
Pseudo R^2	0.00

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Probit model is estimated with an intercept and one regressor as indicated. Dependent variable is the economic trend. Entries in the table denotes the estimates of assess goodness of fit.

Based on measures depicted on Table 8, the likelihood ratio test and associated *p*-value suggest that the model's improvement in fit compared to a null model is not statistically significant. This weakens the evidence that the spread with 4 lags significantly contributes to predicting the economic trend. The Pseudo-R^2 value of 0.00 indicates that the model explains very little, if any, variability in the dependent variable. This reinforces the idea that the 10Y2Y spread with 4 lags is not a strong predictor either of future economic outcomes.



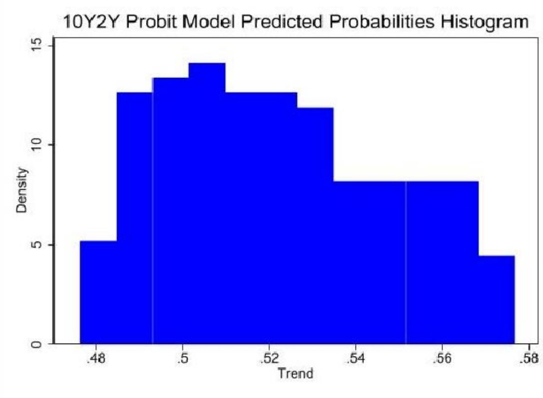


FIGURE 16. 10Y2Y WITH 4 LAGS PROBIT MODEL PREDICTED PROBABILITIES
FIGURE 17. 10Y2Y WITH 4 LAGS PROBIT MODEL PREDICTED PROBABILITIES HISTOGRAM

Predicted probabilities for 10Y2Y also have a positive linear relationship with the economic movement, meaning that it has an influence into its trend.

TABLE 9 - 10Y2Y WITH 4 LAGS PROBIT MODEL PREDICTED PROBABILITIES DESCRIPTIVE STATISTICS

Measures	Mean	σ	Minimum	Maximum
Values	0.52	0.03	0.48	0.58

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Probit model is estimated with an intercept and one regressor as indicated.

TABLE 10 - 10Y2Y WITH 4 LAGS PROBIT MODEL CONFUSION MATRIX

$^{Actual}/_{Predicted}$	0	1	Total
0	22	56	78
1	19	66	85
Total	41	122	163

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Entries in the table denotes the estimates of the confusion matrix coefficients.

Based on Table 10, it can be inferred that the model has a moderate level of accuracy (67%), but the precision (54%) and specificity (28%) are relatively low. This suggests that while the model correctly identifies some downward economic movements, it also has a notable number of false positives.

These model results align with the ones for 10Y3M, indicating that both spreads with 4 lags are not statistically significant when predicting economic trends. The lack of improvement in model fit and the low Pseudo-R^2 suggest that those models need additional variables to enhance its predictive power. Taking the above into consideration, a probit model using both spreads as explanatory variables is constructed pursuing a higher pseudo-R^2. This has not been done in previous studies as spreads have been studied individually or along with other explanatory variables. This approach evaluates an opportunity for explanation by examining both the spread acknowledged by the Fed as a technical indicator and the spread that investors use as an early signal of a change in economic trends, allowing to incorporate emotional factors as well as technicality.

TABLE 11 - SPREADS WITH 4 LAGS PROBIT MODEL

Trend	Coefficient	SE	Z	P > | Z |	95% Confidence Interval	
10Y3M	0.04	0.18	0.21	0.84	-0.32	0.40
10Y2Y	0.04	0.24	0.15	0.88	-0.44	0.51
Constant	-0.05	0.19	-0.25	0.80	-0.42	0.32

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Both 10Y3M and 10Y2Y with 4 lags are being used as explanatory variables and the dependent variable is the economic trend, which indicates whether it is an upward when its coefficient is equal to 0 in case it is 1 indicates that there is a bearish outcome. Entries in the table denotes the estimates of the probit model coefficients.

Based on Table 11, both spreads do not have statistically significant coefficients based on the high *p*-values and confidence intervals that include zero. This model does not seem to improve upon the previous models in terms of statistical significance of the spread coefficients.

TABLE 12 - SPREADS PROBIT MODEL ASSESS GOODNESS OF FIT

Measures	Coefficients
Likelihood Ratio	0.93
Probability > Chi^2	0.79
Pseudo R^2	0.00

Notes: The data sample spans 1982:Q1 to 2022:Q2; Observations = 163. Dependent variable is the economic trend. Entries in the table denotes the estimates of the assess goodness of fit.

In Table 12, the Likelihood Ratio of 0.93 is close to 1, indicating that the model might not exhibit a significant improvement compared to a null model. The associated *p*-value for the likelihood ratio test is 0.79, and its relatively elevated value implies that the enhancement in fit offered by the model, in contrast to a null model, lacks statistical significance. Finally, Pseudo R^2 is 0.00 indicating that the model does not explain a significant amount of variation in the dependent variable.

Part IV: Conclusion

In summary, this master's thesis has delved into the complex realm of predicting economic trends through making use of U.S. government bond spreads. The empirical analysis has yielded compelling evidence that relying solely on 10Y3M and 10Y2Y spreads, falls short in achieving precise economic forecasting.

To enhance effectiveness and robustness of economic forecasting, a more intricate model is imperative, one that encompasses a broader range of explanatory variables, including economic indicators like nonfarm payrolls, PMI, housing starts, CPI, and VIX, which market participants employ to anticipate real GDP growth data. These variables offer a more comprehensive perspective on economic conditions and can capture a wider spectrum of factors that influence economic trends.

This research underscores the significance of adaptability and sophistication in economic forecasting models, particularly in an era characterized by rapidly evolving economic dynamics. By embracing a multifaceted approach and incorporating an extensive set of explanatory variables, one can aspire to achieve more precise predictions of economic trends, ultimately benefiting both investors and policymakers.

Anne Lundgaard has formulated a probit model that integrates the VIX as an explanatory factor alongside the yield spread, based upon that: "recessionary periods are characterized by a combination of high levels of the VIX index and a flat yield curve. This relationship is robust and has repeated itself through all business cycles for which VIX index data are available. In broad terms, VIX–yield curve cycles capture the interplay between financial markets and the stance of monetary policy" (Lundgaard 2024, 409). VIX index and yield spreads exhibit synchronized counterclockwise movements in line with the economic cycle.

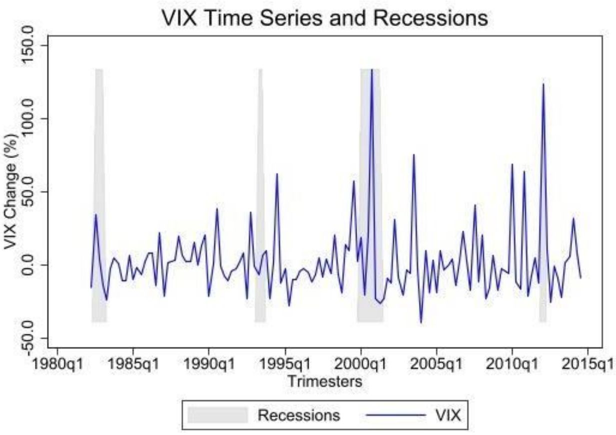
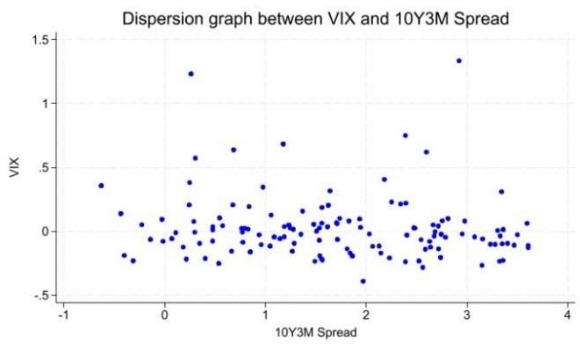


FIGURE 18. VIX SERIES



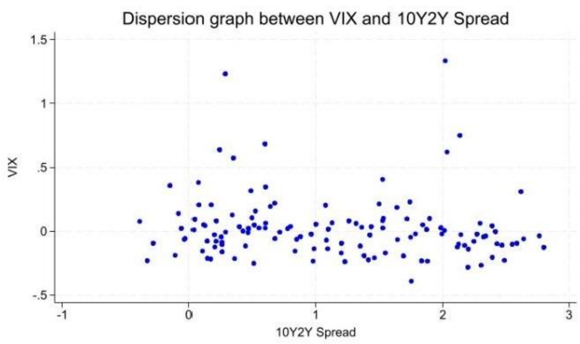


FIGURE 19. DISPERSION GRAPH BETWEEN VIX AND 10Y3M
FIGURE 20. DISPERSION GRAPH BETWEEN VIX AND 10Y2Y
Notes: data is plotted at the quarterly frequency.

The model is defined by the following equation:

$$Pr(Y_{t+h} = 1|X_t) = \Phi(\beta_0 + \beta'_1 X_t)\ (\cdot) \quad (2)$$

Where the dependent variable in the model is
$Y_t = 1$ *in case the economy is in recession* at time t

$Y_t = 0$ *in case the economy is not in recession* at time t

$\Phi\ (\cdot)$ = *standard normal cumulative distribution function*

TABLE 13 - SPREADS WITH 4 LAGS AND VIX PROBIT MODEL

Variable	Coefficient	SE	Z	P > | Z |	95% Confidence Interval	
10Y3M	0.01	0.28	0.04	0.97	-0.53	0.56
10Y2Y	0.14	0.36	0.38	0.71	-0.57	0.84
VIX	1.65	0.62	2.68	0.01	0.44	2.85
Constant	-0.18	0.22	-0.82	0.41	-0.60	0.25

Notes: The data sample spans 1990:Q1 to 2022:Q2; Observations = 130. The dependent variable is the economic trend, which indicates whether it is an upward when its coefficient is equal to 0 in case it is 1 indicates that there is a bearish outcome. Entries in the table denotes the estimates of the probit model coefficients.

In this model, both 10Y3M and 10Y2Y spreads do not seem to be statistically meaningful indicators of economic shifts in this model, given their elevated *p*-values and confidence intervals encompassing zero. Conversely, the VIX index emerges as statistically significant, implying that alterations in the VIX index are linked to changes in the probability of economic downturns. Compared to the spreads, the VIX index seems to be more useful in predicting economic outcomes in this specific model.

TABLE 14 - SPREADS WITH 4 LAGS AND VIX PROBIT MODEL ASSESS GOODNESS OF FIT

Measures	Coefficients
Likelihood Ratio	1.44
Probability > Chi^2	0.02
Pseudo R^2	0.06

Notes: The data sample spans 1990:Q1 to 2022:Q2; Observations = 130. Dependent variable is the economic trend. Entries in the table denotes the estimates of the assess goodness of fit.

The likelihood ratio test and associated *p*-value suggest that the model's improvement in fit compared to a null model is statistically significant. This is a positive sign for the model's efficacy. The Pseudo-R^2 value of 0.06 indicates a small but nonzero amount of explanatory power. While it's not a high Pseudo-R^2, it suggests that the model captures some variability in the economic trend, considering the dichotomous nature of the dependent variable.

These goodness-of-fit results align with the findings from the individual coefficient analyses. While the spreads did not show statistical significance in predicting economic movements, the addition of the VIX index appears to have contributed to a statistically significant improvement in model fit. The model with both spreads and the VIX index seems to provide a better representation of the relationship with the economic trend compared to models that solely rely on the spreads.

Given the statistically significant likelihood ratio test and the nonzero Pseudo-R^2, it's reasonable to consider the model as an improvement over simpler models that only include spreads.

TABLE 15 – SPREADS WITH 4 LAGS AND VIX PROBIT MODEL CONFUSION MATRIX

$^{Actual}/_{Predicted}$	0	1	Total
0	39	24	63
1	30	37	67
Total	69	61	130

Notes: The data sample spans 1990:Q1 to 2022:Q2; Observations = 130. Entries in the table denotes the estimates of the confusion matrix coefficients.

The model has a moderate level of accuracy (61%), meaning it correctly predicted the economic trend for 61% of the instances. The precision and sensitivity are balanced, with both around 60%, indicating a reasonable trade-off between minimizing false positives and false negatives. Specificity is slightly higher than sensitivity, suggesting the model is relatively better at correctly predicting instances of upward economic movement.

In conclusion, the predictive power lies in the interplay between monetary policy and financial markets corrections. The analysis of this paper centers on predictive power and does not consider causal effects. Indeed, the combination of a flat yield curve and a high VIX index reflects that investors are incorporating the potential risk of a recession into market valuations.

Results obtained support the recent perspectives on the diminished predictive capacity of yield spreads for Real GDP. It is noteworthy that despite the heightened volatility experienced during the pandemic crisis, marked by a rapid decline and recovery, the predictive nature of spreads did not revert to its historical predictive power before the mid-1980s, characterized by volatility on growth rate. Spreads had predictive reliability in uncertain times, however, in a period of much higher volatility than the historical average as in the COVID-19 crisis, spreads also lacked predictive capacity. This emphasizes the changing dynamics and challenges the reliability of United States Treasury bond yield spreads as a consistent predictor in contemporary economic conditions.

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