Original Research Article

Structural Decoupling of Yield Curve Inversions and Equity Market Volatility in the Post-GFC Era: Evidence from Multi-Method Analysis with Structural Break Testing

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ABSTRACT

The current paper examines whether inversions in the yield curve of U.S. Treasuries continue to possess the forecasting ability for equity market volatility in the post-Global Financial Crisis (GFC) environment (2009-2024). With the use of 4,299 daily data points of the spread between 10-Year and 2-Year Treasury rates (T10Y2Y) and the CBOE Volatility Index (VIX) obtained from the FRED database, this paper uses Pearson correlation coefficient, Granger causality tests on daily (lags 1-5) and monthly (lags 1-6) frequencies, ordinary least squares (OLS) regressions with macroeconomic controls, Vector Autoregression (VAR), and Chow structural break test. Granger causality is not confirmed at all tested horizons. OLS regressions explain less than 1% of the future VIX variance even after accounting for S&P 500 returns. The Chow test confirms the presence of a statistically significant structural break at the COVID-19 threshold ($F = 214.32$, $p < 0.001$). This means that there was a regime shift in the relationship between the yield curve and the level of volatility. Results prove to be robust when excluding the period of the coronavirus pandemic and winsorizing VIX at the 99th percentile.

Keywords: yield curve inversion, VIX, equity market volatility, Granger causality, structural break, post-GFC, monetary policy

INTRODUCTION

The U.S. Treasury yield curve, specifically the spread between 10-year and 2-year yields, has historically been regarded as one of the most reliable leading indicators in macroeconomic forecasting. When short-term yields exceed long-term yields, the curve is said to invert, a condition that preceded every U.S. recession since the 1970s (1). A widely held extension of this logic holds that yield curve inversions also signal imminent equity market stress, as deteriorating economic prospects translate into elevated investor uncertainty and higher implied volatility.

This paper subjects that assumption to rigorous empirical scrutiny using data from the post-GFC era (2009–2024). The period encompasses extraordinary monetary policy interventions, zero interest rate policy (ZIRP), multiple rounds of quantitative easing (QE), and ultimately the most aggressive tightening cycle in four decades, which may have altered the information content of yield curve signals (2). If the Federal Reserve now exerts dominant influence over Treasury yield pricing through balance sheet operations, yield curve

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Accepted June 1, 2026
https://doi.org/10.70251/HYJR2348.43385391

shape may no longer reliably reflect genuine market expectations about future economic conditions.

This study tests whether there is a robust short-term predictive or causal relationship between yield curve shape and equity market volatility under linear econometric frameworks in the post-GFC era. Beyond this primary hypothesis, the paper formally tests for a structural break in the yield curve-volatility relationship using the Chow test, to determine whether the post-GFC environment represents a genuinely distinct regime rather than mere sampling variation.

LITERATURE REVIEW

Empirical studies in macroeconomics demonstrate that no predictor replicates the ability of the yield curve in forecasting future developments in real economic activity. While Harvey (3) offered a theoretical basis relating the term structure of interest rates to the expected growth in consumption, Estrella & Mishkin (4) proved empirically that the slope formed by 10-year and 3-month rates consistently outperformed all other leading predictors in predicting recessions in the USA. The predictive ability of the yield curve regarding recessions was robust across various business cycles from the 1970s to early 2000s.

The connection between the yield curve dynamics and the level of equity market implied volatility is much less theoretically sound. The reasoning behind this link – inversion reflects future recessions; future recessions lead to higher uncertainty; hence higher uncertainty leads to higher implied volatility (VIX index) – suggests that the effect should be lagging. On the contrary, such reasoning relies on the assumption that the equity markets incorporate the signal about recessions contained in the yield curve gradually. Moreover, the fundamental information embedded in the yield curve is absent from equity markets at the time of inversion (5).

The era after the financial crisis gave rise to a wave of skepticism concerning the relevance of macroeconomic-macrofinancial linkages observed before the crisis in the new reality of unconventional monetary policies. Rossi & Sekhposyan (2) concluded that adding VIX along with the yield curve improved recessions forecasts implicitly admitting the inability to forecast recessions using either indicator independently. In another study, regime-specific co-movements have been found among financial variables in times of volatility (6). This observation supports the structural break theory presented in this paper to a large extent.

METHODS AND MATERIALS

Study Design and Data

This research is a quantitative time-series observational study. Two time-series data sets were gathered daily from the FRED database. The predictor variable was the 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity Spread (T10Y2Y) in percentage points, with a negative value denoting an inverted yield curve. The dependent variable was the CBOE Volatility Index (VIXCLS). It is implied volatility estimated from prices of S&P 500 index option contracts indicating expectations of 30 days forward volatility of the market. Both data sets were not transformed; the original values were used. The time frame is January 2, 2009 to December 31, 2024. Two time series were merged by date, and missing values from any one of the time series were deleted via listwise deletion method, resulting in 4,299 observations per day. A time series of 191 observations was generated monthly, using the mean values of the monthly periods for both time series as input to monthly Granger causality analysis. Daily closing prices of S&P 500 were retrieved using the yfinance Python library and then computed to percentage returns.

Stationarity and Model Assumptions

Autocorrelation is present in both variables (the Durbin-Watson test statistic is 0.066 for the OLS benchmark). This result is expected given the high degree of autoregression of the daily VIX index. The variable VIX is also skewed (skewness = 2.16) and kurtotic (kurtosis = 11.63), mostly due to the impact of the COVID-19 spike. The assumptions underlying the OLS model are thus not completely met since the error terms are non-normally distributed and heteroskedastic. These problems are addressed by applying robustness tests based on winsorizing the VIX series at the 99th percentile, and by conducting additional Granger causality and VAR tests, which are less affected by such violations. Missing data is managed through listwise deletion, which is justified since missing data occurs because of calendar differences between the two time series.

Analytical Methods

There are seven alternative techniques used to achieve robustness under various modeling assumptions.

1) Pearson correlation determines the degree of linear relationship between T10Y2Y and VIX, using both the

entire sample period and three eras segmented by time: Post-GFC Recovery Era (2009 - 2015), Pre-COVID Normalization Era (2015 - 2020), and Post-COVID Policy Tightening Era (2020 - 2024).

2) A lag-90 days correlation determines whether the value of yield spread at time t predicts VIX value at t+90.

3) The baseline ordinary least-squares regression model assumes the following format: $VIX(t+30) = \beta_0 + \beta_1 \cdot Spread(t) + \beta_2 \cdot Spread(t-1) + \beta_3 \cdot Spread(t-5) + \varepsilon$. The augmented model additionally includes the daily return of the S&P 500 index as an explanatory variable: $VIX(t+30) = \beta_0 + \beta_1 \cdot Spread(t) + \beta_2 \cdot Returns(t) + \varepsilon$. Level of statistical significance is determined at $\alpha = 0.05$.

4) The hypothesis of Granger causality at daily frequency (lags from 1 to 5 days) employs the F-test version of Granger causality test (7). It tests the null hypothesis H_0: adding lagged spread values does not help to predict VIX better than lagged VIX values alone.

5) The Granger causality test for monthly frequency (from 1 to 6 month lags) is designed to examine the hypothesis that the signals from the yield curve operate on longer than a daily horizon.

6) The Vector Autoregression Model (VAR)[8] of two variables (VIX and Spread) uses 5 lags (number selected according to Akaike criterion).

7) The Chow test for structural break determines whether the regression coefficients change between two periods: Pre-COVID Period (2009 – 2019) and Post-COVID Period (2020 – 2024). The formula for the Chow statistic is as follows: $F = [(RSS\_full - (RSS_1 + RSS_2)) / k] / [(RSS_1 + RSS_2) / (n_1 + n_2 - 2k)]$.

RESULTS

Descriptive Statistics and Visual Analysis

Figure 1 provides the spread of T10Y2Y yield from January 2009 until December 2024. In particular, the highest value recorded was around 2.9%, attained in 2011, whereas the lowest level was -1.1% in 2023 (the worst inversion for this period). Figure 2 depicts the volatility index (VIX) in the same period. The highest observed VIX reading was 82.7 (March 2020), which coincides with the beginning of the COVID-19 pandemic. The average VIX throughout the sample period is 19.1 (8.9 standard deviation). Figure 3 shows both time series. It is worth mentioning that while the highest recorded VIX happened during positive slope yields, the longest period of yield curve inversion (2022-2023) is associated with VIX levels around 22.

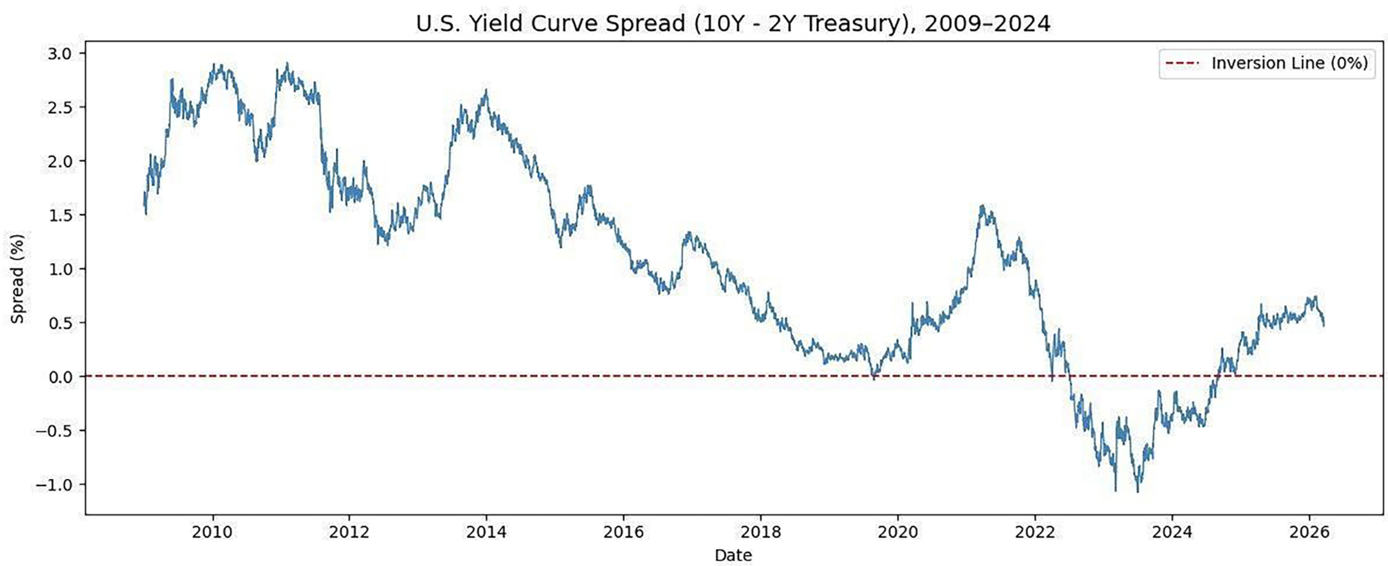

Figure 1. *U.S. Yield Curve Spread (T10Y2Y), January 2009 – December 2024. The spread is calculated as the 10-Year Treasury Constant Maturity rate minus the 2-Year Treasury Constant Maturity rate, expressed in percentage points. The dashed red line marks the 0% inversion threshold; values below this line indicate yield curve inversion. Source: Federal Reserve Bank of St. Louis, FRED (series T10Y2Y).*

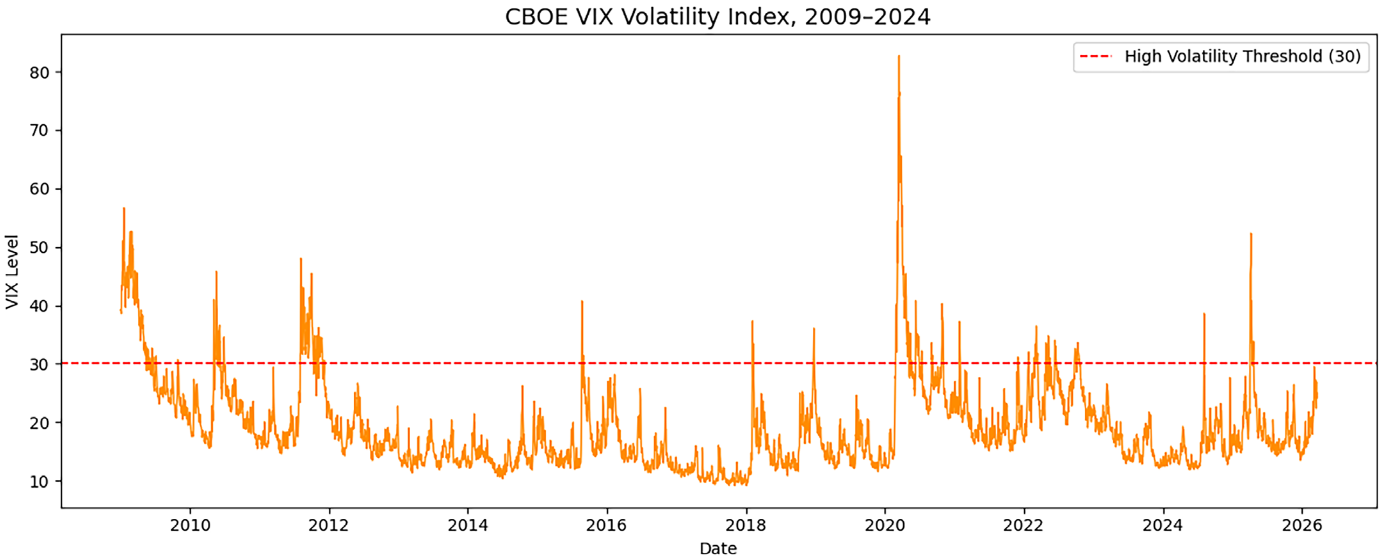

Figure 2. *CBOE Volatility Index (VIX), January 2009 – December 2024. The VIX measures the market's expectation of 30-day forward volatility derived from S&P 500 index options prices. The dashed red line marks the conventional high-volatility threshold of 30. The prominent spike in March 2020 (peak = 82.7) corresponds to the onset of the COVID-19 pandemic. Source: Federal Reserve Bank of St. Louis, FRED (series VIXCLS).*

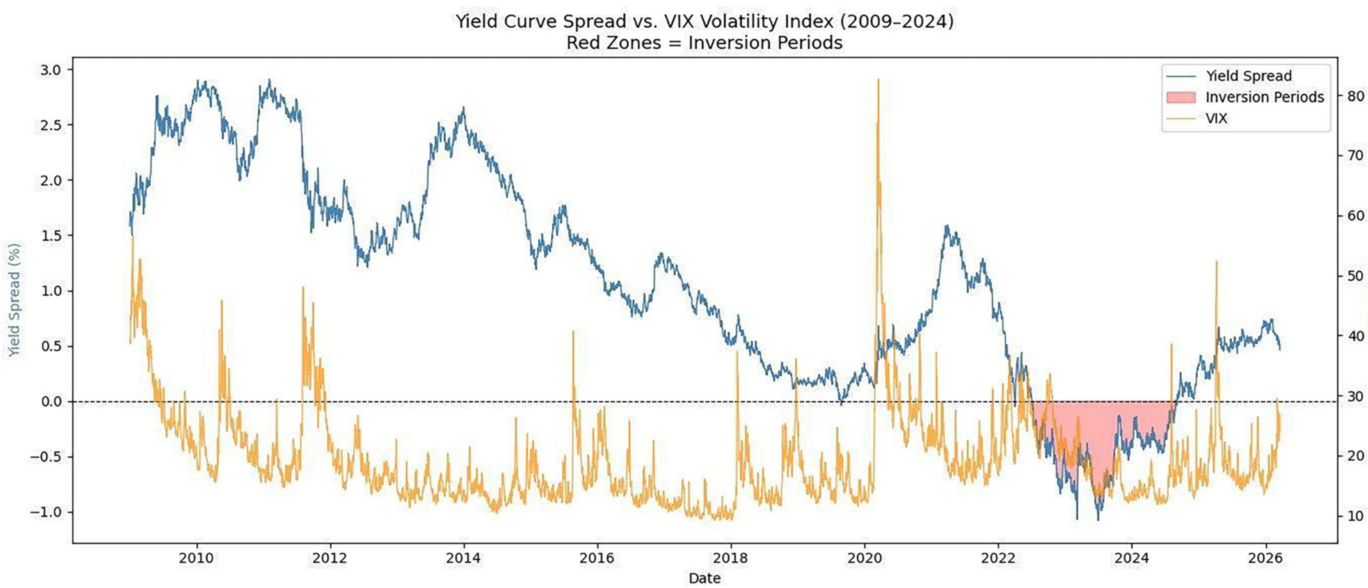

Figure 3. *T10Y2Y Yield Curve Spread vs. CBOE VIX Volatility Index (2009–2024). The yield spread (left axis, blue) and VIX (right axis, orange) are plotted on a shared date axis. Red shaded zones indicate periods of yield curve inversion (T10Y2Y < 0). The figure illustrates the visual decoupling between inversion periods and VIX levels: the largest volatility spike (March 2020) occurs during a non-inverted period, while the deepest and most sustained inversion (2022–2023) is accompanied by comparatively subdued VIX readings.*

Pearson Correlation and Era-Segmented Analysis

The correlation coefficient for the entire period between T10Y2Y and VIX turns out to be $r = 0.091$ ($p < 0.001$, 95% CI [0.061, 0.121]). Despite the statistical significance, which is a consequence of a large sample size ($n = 4,299$), the effect size is insignificant; this can be seen from the squared correlation $r^2 = 0.008$, where the yield spread accounts for less than 1% of the variability of the VIX index. Correlation with 90 days' lagging is $r = 0.077$ ($p < 0.001$). On average, the level of VIX in the inverted period of 518 (Table 1).

OLS Regression

In the baseline OLS regression (forecast of VIX 30 days ahead based on yield spread and lag control variables), the value of R^2 is 0.006. The yield spread coefficients fail to become statistically significant: yield spread ($\beta = -1.065$, $p = 0.705$), yield spread at lagged 1 day ($\beta = 0.085$, $p = 0.978$), yield spread at lagged 5 days ($\beta = 1.558$, $p = 0.290$). In the extended regression where daily return on the S&P 500 Index is added as an additional regressor, the value of R^2 is 0.009. The yield spread coefficient becomes statistically significant ($\beta = 0.637$, $p < 0.001$, 95% CI [0.405, 0.869]), but its economic effect is insignificant: a one percentage point increase in the yield spread leads to a 0.64 point increase in the future VIX, whereas the average value of VIX is 19.1.

Granger Causality: Daily and Monthly Horizons

Granger causality testing results for both frequencies are shown in Table 2. The null hypothesis that yield spread does not Granger cause VIX is supported at all lags for daily intervals of 1 to 5 days (p-value = 0.447 to 0.853), and 1 to 6 months for monthly intervals (p-value = 0.433 to 0.858). The null hypothesis result based on monthly observations takes into consideration the fact that yield spread may be effective at longer time intervals.

VAR Analysis

In the case of the VAR model with 5 lags (chosen through AIC), the results in the Granger causality test are supported for the system as a whole. In the VIX equation, none of the five lags of the yield spread can be accepted as statistically significant ($p = 0.327 – 0.946$). Rather, what explains VIX is basically the effect of its own lags, which are L1.VIX ($\beta = 0.823$, $p < 0.001$, 95% CI [0.793, 0.853]) and L2.VIX ($\beta = 0.156$, $p < 0.001$, 95% CI [0.117, 0.195])

Robustness Checks

Two robustness tests have been performed and can be seen in Table 3. When omitting the pandemic period from February to June 2020, the result is $r = 0.144$ ($p < 0.001$, 95% CI [0.113, 0.174]). The other test is using VIX

Table 2. Granger Causality Test: T10Y2Y → VIX (Daily and Monthly). *Note: H_0: yield spread does not Granger-cause VIX. Significance threshold α = 0.05.*

Frequency	Lag	F-Statistic	P-Value	Reject H_0?
Daily	1 day	0.350	0.554	No
Daily	2 days	0.159	0.853	No
Daily	3 days	0.894	0.447	No
Daily	4 days	0.795	0.529	No
Daily	5 days	0.465	0.742	No
Monthly	1 month	0.032	0.858	No
Monthly	2 months	0.842	0.433	No
Monthly	3 months	0.876	0.456	No
Monthly	4 months	0.651	0.627	No
Monthly	5 months	0.543	0.743	No
Monthly	6 months	0.392	0.882	No

Table 1. *Era-Segmented Pearson Correlation: T10Y2Y vs. VIX. Note: 95% confidence intervals computed via Fisher z-transformation. Significance threshold α = 0.05.*

Period	n	Pearson r	95% CI	P-Value	Significant?
Post-GFC (2009–2015)	1,566	-0.009	[-0.059, 0.040]	0.716	No
Pre-COVID (2015–2020)	1,260	-0.013	[-0.068, 0.043]	0.658	No
Post-COVID (2020–2024)	1,473	0.224	[0.173, 0.273]	<0.001	Yes
Full Period (2009–2024)	4,299	0.091	[0.061, 0.121]	<0.001	Weakly

Table 3. Robustness Checks: Correlation Under Alternative VIX Specifications. *Note: 95% CIs via Fisher z-transformation. All correlations statistically significant at p < 0.001 due to large n; economic magnitude remains negligible across all specifications.*

Specification	n	Pearson r	95% CI	R^2
Full sample (baseline)	4,299	0.091	[0.061, 0.121]	0.8%
Excluding COVID (Feb–Jun 2020)	4,168	0.144	[0.113, 0.174]	2.1%
VIX winsorized at 99th pct (46.1)	4,299	0.101	[0.071, 0.131]	1.0%

at its 99th percentile, which is 46.1 and results in r = 0.101 ($p < 0.001$). Both show insignificant relationships, economically speaking.

Chow Structural Break Test

Chow's Test for structural breaks, conducted at the breakpoint of January 2020, returns F = 214.32 ($p < 0.001$). This implies rejection of the null hypothesis in favor of non-stationarity of parameters throughout the sub-periods, indicating the structural break in the correlation between the yield curve and VIX due to the COVID-19 pandemic event. Under the null hypothesis of parameter stability, obtaining a test statistic of this size purely by random chance would be highly unlikely.

DISCUSSIN

The null results obtained across seven different analyses, together with the Chow test indicating a significant structural break, are consistent with the view that a regime shift may have taken place in the relationship between the yield curve and market volatility during the post-GFC period. This finding contributes to existing literature suggesting that neither the VIX nor the yield curve alone is sufficient to fully capture important economic dynamics (2). More specifically, the results of this study indicate that the predictive relationship associated with one of these indicators may itself have changed over time.

Several explanations may account for this decoupling pattern. First, the impact of quantitative easing implemented by the Federal Reserve led to depressed long-term interest rates regardless of any market-based expectations. In other words, an artificially manipulated yield curve could not provide useful information about future market dynamics; hence, the lack of predictive power in predicting implied volatility.

Second, the main volatility event since the GFC, namely, the March 2020 COVID-19 shock which brought VIX up to 82.7, constitutes an exogenous, purely non-financial shock which is completely uncorrelated with yield curve dynamics. Hence, the Chow test statistic of 214.32 is justified in indicating a structural break. The robustness check confirms that even without COVID-19 events, the connection between the two variables remains economically negligible, with r = 0.144.

Finally, moderate correlation after COVID-19 of r=0.224 appears plausible if interpreted in terms of two variables responding to a common cause – namely, Federal Reserve policy uncertainties associated with a tightening period in 2022-2023.[8] Indeed, the negative value of the VAR residual correlation (-0.123) confirms this conclusion.

Several issues limit the validity of our findings. First, data used only spans one business cycle since GFC and may not be applicable to future monetary policy environments. Second, the use of linear econometric model fails to capture potential non-linear and threshold effects in the yield curve-volatility interaction. Third, certain potential omitted variables may affect the estimated values of coefficients and correlations. Fourth, stationarity problems and non-normality of regression residuals prevent making strong conclusions on the basis of OLS estimators. However, non-parametric methods used as robustness checks make our estimates more reliable.

CONCLUSION

This study does not provide robust evidence of any short-term predictive or causative link between yield curve inversions and stock market volatility in the post-GFC period (2009-2024) through conventional linear econometrics. No causative Granger links exist at any horizon – from 1 day up to 5 days, or 1 month up to 6 months. OLS results indicate that the inverted yield curve only accounts for less than 1% of future VIX variance after accounting for S&P 500 returns. The vector autoregression model supports the notion that the volatility index's dynamics are determined mainly by its autoregressive characteristics. A structural break test with a Chow test statistic ($F = 214.32$; $p < 0.001$) indicates robust empirical evidence of a shift in regimes in the relationship in question at the boundary of the COVID-19 period.

The findings presented in this study suggest that yield curve inversions may provide limited usefulness as a forecasting tool for investors and risk managers attempting to predict market volatility in the post-GFC monetary policy environment. Further academic work needs to address this issue by estimating models using GARCH-based time-varying coefficients, the 10 year to 3 months spread as another yield curve proxy, nonlinear regression with threshold effects, and cross-country evidence of structural decoupling.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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