# Geopolitical Risks and the High-Frequency Movements of the US Term Structure of Interest Rates#

Rangan Gupta*, Anandamayee Majumdar**, Jacobus Nel*** and Sowmya Subramaniam****

**Abstract**

We use daily data for the period 25th November, 1985 to 10th March, 2020 to analyse the impact of newspapers-based measures of geopolitical risks (GPRs) on United States (US) Treasury securities by considering the level, slope and curvature factors derived from the term structure of interest rates of maturities covering 1 to 30 years. No evidence of predictability of overall GPRs (or for threats and acts) are detected using linear causality tests. However, evidence of structural breaks and nonlinearity are provided by statistical tests performed on the linear model, which indicate that the Granger causality cannot be relied upon, as they are based on a misspecified framework. As a result, we use a data-driven approach, specifically a nonparametric causality-in-quantiles test, which is robust to misspecification due to regime changes and nonlinearity, to reconsider the predictive ability of the overall and decomposed GPRs on the three latent factors. Moreover, the zero lower bound situation, visible in our sample period, is captured by the lower quantiles, as this framework allows us to capture the entire conditional distribution of the three factors. Using this robust model, we find overwhelming evidence of causality from the GPRs, with relatively stronger effects from threats than acts, for the entire conditional distribution of the three factors, with higher impacts on medium- and long-run maturities, i.e., curvature and level factors, suggesting the predictability of the entire US term structure based on information contained in GPRs. Our results have important implications for academics, investors and policymakers.

**Keywords:** Yield Curve Factors, Geopolitical Risks, Causality-in-Quantiles Test

**JEL Codes:** C22, D80, E43

## 1. Introduction

The traditional "safe haven" role of Treasury securities of the United States (US) is well-established due to their strong ability to provide investors with valuable portfolio diversifications and hedging benefits during periods of global turmoil and heightened uncertainties that negatively impact conventional financial markets and the macroeconomy in general (Habib and Stracca, 2015; Kopyl and Lee, 2016). The lack of significant default risk fuelled by the vast revenue stream generated by the US government, which accounts for over 20 percent of global output, has primarily led to the safe-haven nature of US Treasury securities (Bouri et al., 2021). In fact, US bond market capitalization represents nearly two-thirds of the value of the global bond market at $40.7 trillion (a third higher than the corresponding value

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associated with the stock market of $30 trillion) (Securities Industry and Financial Markets Association (SIFMA)). Given this, a pertinent question to analyse would be the predictive content of uncertainty for the US government bond market, which is an important issue for bond investors. Policymakers can also benefit from these studies, as it helps fine tune monetary policies, when they understand the evolution of future interest rates.

In this regard, in terms of global-level uncertainties, geopolitical risks (GPRs) are often cited by central bankers, the financial press, and business investors as a determinant of investment decisions, and hence, have been shown to adversely affect output and equity markets (Clance et al., 2019; Bouri et al., forthcoming). Notably, military and diplomatic conflicts taking place around the world, and their economic impact, were of concern by 75% of the 1000 investors surveyed by Gallup in 2017. Geopolitical risk was ranked ahead of political and economic uncertainty,[1] while Carney (2016) includes these three in the "uncertainty trinity", which could have significant adverse economic effects. More recently, geopolitical uncertainties were highlighted as a salient risk to the economic outlook, by both the European Central Bank (in their April 2017 Economic Bulletin), and the International Monetary Fund (in their October 2017 World Economic Outlook).

Against this backdrop, we aim to analyse the ability of leading global uncertainties, being driven by GPRs, to predict the daily path of zero coupon US Treasury bond yields, given its characteristic as a traditional safe haven, over the period of 25th November, 1985 to 10th March, 2020. As per Litterman and Scheinkman (1991), the three latent factors (level, slope, and curvature) are the only relevant factors that characterize the yield curve, therefore, we use the well-established econometric framework of Nelson and Siegel (1987) from the finance literature to summarize the entire term structure into these factors. We then relate the movement of the level, slope and curvature factors to the news-based GPR indexes (which measure geopolitical risks that have been developed recently by Caldara and Iacoviello (2019). These indexes include not only terror attacks, but also other forms of geopolitical tensions such as war risks, military threats, and Middle East tensions. Hence, these indices allow us to capture GPRs of various forms in a continuous fashion, going beyond the effect of particular events at specific points in time, and in turn, provide a holistic view of risks related to geopolitical events in the world, which has over the years has become more interconnected, thus implying that the effects of GPRs in a particular country spillsover globally.

In terms of the US Treasury securities, we study the entire term-structure of interest rates spanning maturities of 1 year to 30 years, rather than concentrating on certain specific maturities. In the process, we are able to obtain a better understanding of whether the predictability of the GPRs is contingent on the time-frame of maturity, which, understandably, has important investment and policy implications in terms of which horizon of yields to focus on relatively more following the occurrence of geopolitical events. Moreover, Hillebrand et al., (2018) points out that entire yield curve is considered a predictor of economic activity, which in turn, makes the issue of studying the impact of GPRs on all the maturities pertinent.

As far as the predictive model is concerned, we relate the US yield curve to the GPRs using the nonparametric causality-in-quantiles framework of Jeong et al., (2012). This model, apart from allowing us to test for predictability emanating from the GPRs over the entire conditional distribution of the three aforementioned yield curve factors, it allows us to control for misspecification due to uncaptured nonlinearity and regime changes (existence of which we show in the results section). Given that our period of study includes the "Great Recession", it also includes the resulting zero lower bound (ZLB) situation of the interest rates in the US. This reinforces the use of a quantiles-based framework, since different quantiles can capture

[1]See http://www.businesswire.com/news/home/20170613005348/en/.

the various phases of the three latent factors accurately, with the lower, median, and upper quantiles corresponding to low, normal, and high interest rates, respectively (unlike a Markov-switching model, which requires an explicit number of regimes to be specified). Understandably, investors can use high-frequency prediction of the term structure of interest rates to design optimal portfolios involving US government bonds in a timely manner, and policymakers can use these high-frequency predictions (by feeding the information into mixed-frequency models) to gauge where the low-frequency real and nominal variables in the economy are headed (Caldeira et al., forthcoming).

To the best of our knowledge, this is the first paper to study the predictability of the entire US term structure due to uncertainty resulting from GPRs covering over 35 years of daily data. The only somewhat related study is the paper by Bouri et al., (2019). This work applied a *k*-th order non-parametric causality-in-quantiles test to examine the causal effect of GPRs on return and volatility dynamics of Islamic equity and bond markets. GPRs are generally found to impact Islamic equity market volatility measures, rather than returns. However, GPRs tend to predict both returns and volatility measures of Islamic bonds. The remainder of the paper is structured as follows: Section 2 discusses the data, along with the basics of the two methodologies associated with the Nelson and Siegel (1987) model, and the nonparametric causality-in-quantiles test of Jeong et al., (2012). Section 3 presents the results, with Section 4 concluding the paper.

## 2. Data and Econometric Methodologies

In this section we present the data and the basics of the two methodologies used for our empirical analyses, which involves the extraction of the three latent yield curve factors and analysing its quantiles-based predictability due to the metric of global uncertainty emanating from GPRs.

### *2.1. Data*

We collect daily zero-coupon yields (are based on the work of Gürkaynak et al., (2007)) of Treasury securities with maturities from 1 year to 30 years, from the Federal Reserve Board (FRB),[2] which we use to estimate the yield curve factors for the US. Gürkaynak et al., (2007) use a simple, well-known smoothing technique, that fits the data well. They make available a long history of yield curve estimates of the FRB at a daily frequency to researchers and practitioners, with the resulting estimates employed to calculate bond yields for any horizons.

The daily measure of GPRs, is based on the work of Caldara and Iacoviello (2019).[3] Caldara and Iacoviello (2019) construct the GPRs index by counting the number of articles that mention words related to geopolitical tensions in 11 leading national and international newspapers (The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post). There are six groups of words that are searched for: Group 1 are for words that are associated with explicit mentions of geopolitical risks, and mentions of military-related tensions involving large regions of the world (and a U.S. involvement); Group 2 is reserved for words relating to nuclear tensions; Groups 3 and 4 are for words relating to threats, so threats of war and terrorism, respectively; Groups 5 and 6 are to capture coverage of actual adverse geopolitical events (in stead of risks), which can be expected to increase geopolitical uncertainty (acts of terror, or beginning of a war). Given this, Caldara and Iacoviello (2019) also decompose the overall GPRs index into GPRs due to threats

[2] The data is downloadable from: https://www.federalreserve.gov/data/nominal-yield-curve.htm.
[3] The data can be downloaded from: https://www2.bc.edu/matteo-iacoviello/gpr.htm.

(GPRs_Threats) and GPRs due to acts (GPRs_Acts) based on search terms 1 to 4 and 5 to 6 respectively.

Based on the data availability of the, our analysis covers the sample period 25th November, 1985 to 10th March, 2020 involving the overall GPR, while with GPRs_Threats and GPRs_Acts, the data ends in 6th January, 2020.

### *2.2. Methodology*

#### *2.2.1. Extraction of the Yield Curve Factors*

As mentioned above, we use the dynamic Nelson-Siegel three-factor model of Diebold and Li (2006) (DNS, hereafter) to fit the yield curve of zero coupon US Treasury securities. To achieve this, we decompose the yield curve into three latent factors using the Nelson and Siegel (1987) representation in a dynamic form. The DNS with time-varying parameters is represented as:

$$r_t(\tau) = L_t + S_t \left(\frac{1-exp^{-\lambda\tau}}{\lambda\tau}\right) + C_t\left(\frac{1-exp^{-\lambda\tau}}{\lambda\tau} - exp^{-\lambda\tau}\right) \tag{1}$$

where $r_t$ is the yield rate at time $t$ and $\tau$ is the time to maturity (effectively maturity minus $t$). The factor loading of $L_t$ is 1 and loads equally for all maturities. $L_t$ represents the movements of long-term yields and gives the level factor, as a change in $L_t$ can change all yields equally. The loading of $S_t$ starts at 1 and monotonically decays to zero. $S_t$ mimics the movements of short-term yield movements, since it changes the slope of the yield curve, and hence is the slope factor. The loading for $C_t$ starts at 1 and decays to zero, with a hump in the middle. $C_t$ mimics the medium-term yield movements, as an increase in $C_t$ leads to an increase in the yield curve curvature, and hence it is the curvature factor. The DNS model follows a VAR process and is modelled in state-space form using the Kalman filter. The measurement equation relating the yields and latent factors is:

$$\begin{pmatrix} r_t(\tau_1) \\ r_t(\tau_2) \\ \vdots \\ r_t(\tau_n) \end{pmatrix} = \begin{pmatrix} 1 & \left(\frac{1-exp^{-\tau_1\lambda}}{\tau_1\lambda}\right) & \left(\frac{1-exp^{-\tau_1\lambda}}{\tau_1\lambda} - exp^{-\tau_1\lambda}\right) \\ 1 & \left(\frac{1-exp^{-\tau_2\lambda}}{\tau_2\lambda}\right) & \left(\frac{1-exp^{-\tau_2\lambda}}{\tau_2\lambda} - exp^{-\tau_2\lambda}\right) \\ \vdots & \vdots & \vdots \\ 1 & \left(\frac{1-exp^{-\tau_n\lambda}}{\tau_n\lambda}\right) & \left(\frac{1-exp^{-\tau_n\lambda}}{\tau_n\lambda} - exp^{-\tau_n\lambda}\right) \end{pmatrix}' f_t + \begin{pmatrix} u_t(\tau_1) \\ u_t(\tau_2) \\ \vdots \\ u_t(\tau_1) \end{pmatrix}, \quad u_t \sim N(0, R) \tag{2}$$

The transition equation relating the dynamics of the latent factors is:

$$\tilde{f}_t = \Gamma \tilde{f}_{t-1} + \eta_t \qquad \eta_t \sim N(0, G) \tag{3}$$

where $r_t(\tau)$ and $u_t$ represent the yield rates with given maturities (in our case 1 year to 30 year) and the error terms, respectively, both are $m \times 1$ dimensional vectors. The coefficient matrix in the measurement equation follows the structure introduced by Nelson and Siegel (1987), while $f_t$ gives the time-varying yield rate shape parameters, $f_t = [L_t, S_t, C_t]$, and is a $3 \times 1$ dimensional vector. In the transition equation, $\tilde{f}_t$ is the demeaned time-varying shape parameter (i.e., $\tilde{f}_t = f_t - \overline{f}$), $\Gamma$ gives the dynamic relationship across shape parameters, $\eta_t$ is the error term (assumed to be independent of $u_t$ and is a $3 \times 1$ dimensional vector), $G$ is a

$m \times m$ dimensional diagonal matrix and $R$ is a $3 \times 3$ dimensional variance-covariance matrix, allowing the latent factors to be correlated.[4]

### 2.2.2. *Nonparametric Causality-in-Quantiles Model*

We now describe the nonparametric causality-in-quantiles approach proposed by Jeong et al. (2012). Consider a bivariate set-up and let $y_t$ denote *L<sub>t</sub>*, *S<sub>t</sub>* or *C<sub>t</sub>* and $x_t$ correspond to GPRs, GPRs_Threats or GPRs_Acts. Also, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of $y_t$ given $\bullet$. Defining $Q_\kappa(Z_{t-1}) \equiv Q_\kappa(y_t|Z_{t-1})$ and $Q_\kappa(Y_{t-1}) \equiv Q_\kappa(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\kappa(Z_{t-1})|Z_{t-1}\} = \kappa$ with probability one. The (non)causality in the $\kappa$-th quantile hypotheses to be tested are:

$$H_0\colon\ P\{F_{y_t|Z_{t-1}}\{Q_\kappa(Y_{t-1})|Z_{t-1}\} = \kappa\} = 1 \tag{4}$$

$$H_1\colon\ P\{F_{y_t|Z_{t-1}}\{Q_\kappa(Y_{t-1})|Z_{t-1}\} = \kappa\} < 1 \tag{5}$$

Jeong et al. (2012) show that feasible kernel-based test statistics have the following format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{6}$$

where $K(\bullet)$ is the kernel function with bandwidth $h$, $T$ is the sample size, $p$ is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\kappa(Y_{t-1})\} - \kappa$ is the regression error, where $\mathbf{1}\{\bullet\}$ is the indicator function and $\hat{Q}_\kappa(Y_{t-1})$ is an estimate of the $\kappa$-th conditional quantile. The Nadarya-Watson kernel estimator of $\hat{Q}_\kappa(Y_{t-1})$ is given by:

$$\hat{Q}_\kappa(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{7}$$

with $L(\bullet)$ denoting the kernel function.

Implementing quantile causality requires three key parameters to be set up: the lag order ($p$), the bandwidth ($h$), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use Gaussian kernels for $K(\cdot)$ and $L(\cdot)$, $p$ is selected according to the Schwarz Information Criterion (SIC), and $h$ is determined by the leave-one-out least-squares cross-validation.

## 3. Empirical Results

We start our results by briefly discussing key summary statistics of the data for the three yield curve factors of level, slope and curvature, and the three GPRs, i.e., overall GPRs, GPRs_Threats and GPRs_Acts which is given in Table A1 in the Appendix, along with time-plots in Figure A1. For the dependent variables, the slope factor has a negative average value, which indicates that, on average, yields increase along with maturity. The curvature (medium-term maturities) has a higher average value than the level factor (long-term yields), which is in line with Kim and Park (2013) who also used daily bond yields of the US, and is indicative of liquidity issues for bonds with very long maturities. The level factor is also the least volatile among the three factors, followed by the slope and curvature factors. For the independent variables, GPRs_Acts is more volatile than GPRs_Threats, though the latter has a higher mean value. The Jarque-Bera (J-B) test indicate that the null hypothesis of normality is rejected at a 1% significance level for all variables (that is, all variables are non-normal). These results, particularly for $L_t$, $S_t$, and $C_t$, provides preliminary motivation to look for non-linear causality, a quantiles-based approach, to analyse the influence of geopolitical events and threats on these three factors of US yield curve.

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[4] Complete details of the parameter estimates of the model are available upon request from the authors.

We performed a standard Granger causality test, for the purpose of completeness and comparability, where the $\chi^2(p)$ statistics involving the causality running from overall GPRs, GPRs_Acts and GPRs_Threats to $L_t$, $S_t$, and $C_t$ are reported in Table A2 in the Appendix to the paper, with $p$ =5 under GPRs and GPRs_Threats, and $p$=6 for GPRs_Acts (the lag lengths, were chosen to minimize the Schwarz Information Criterion). We cannot reject the null hypotheses (even at a 10% significance level), that any of the three GPR indexes do not Granger cause any of the three latent factors of the yield curve considered in a bivariate set-up. Therefore, based on the standard linear test, we conclude no significant geopolitical risks-related effects on the level, slope or curvature of the US yield curve.

Given the insignificant results above (the linear Granger causality tests and Jarque-Bera normality tests), we examined the statistical existence of structural breaks and nonlinearity in the relationship between the three latent factors of the US yield curve with the GPRs indexes. If there are regime changes and/or nonlinearity present, it would motivate the use of the nonparametric quantiles-in-causality test, as this quantiles-based test would address structural breaks and nonlinearity in the relationships between the investigated variables in a bivariate set-up, as it is robust against misspecification. We first investigate this, by using the Brock et al. (1996) (BDS) test on the residuals from the $L_t$, $S_t$, and $C_t$ equations involving SIC-determined lags of the three factors and overall GPRs, GPRs_Acts and GPRs_Threats (reported in Table A3 in the Appendix). The results suggests nonlinearity in the relationships between the facts and the GPR indexes, as there is strong evidence for the rejections of the null hypothesis of *i.i.d.* residuals at various dimensions ($m$). In order to further justify the use of the causality-in-quantiles method and to test for regime changes, we also employ the *UDmax* and *WDmax* tests of Bai and Perron (2003), which detects 1 to $M$ structural breaks in the relationships between $L_t$, $S_t$, and $C_t$ with overall GPRs, GPRs_Acts and GPRs_Threats. Table A4 gives the results (where we allow for the heterogeneous error distributions across breaks on the SIC-bsed lags of the three factors and three GPR indexes) where we are able to detect at least one break under all nine cases, especially during the global financial crisis.

Due to the strong evidence of the presence of structural breaks and nonlinearity in the relationships between the latent factors and shocks (shown above), we now turn our investigations to the causality-in-quantiles testing. Figure 1 shows the results of this test (over the quantile range 0.05 to 0.95). From these results, we reject the null hypothesis that GPRs do not Granger cause $L_t$, $S_t$, and $C_t$ at the 5% significance level over the entire conditional distributions of the dependent variables, barring the case of $S_t$ at the 0.95 quantile, where the result holds at the 10% level. In fact, the null hypothesis is rejected at the 1% significance level over the quantile range 0.10 to 0.90 in all cases, and also at the lowest quantile of 0.05 for the level and curvature factors. The results suggest that there is strong evidence of predictability from GPRs to the three factors characterizing the US term structure of interest rates over their respective conditional distribution (when accounting for structural breaks and nonlinearity in a nonparametric approach), as opposed to linear method that showed a complete lack of causality reported. In general, at lower conditional quantiles (0.05-0.40), strongest predictive effects are observed for the level factor, and beyond the median the same holds for the curvature. In other words, GPRs have higher impact on medium to long-term bonds than on the shorter-terms, as the former groups are generally associated with higher risks.

Furthermore, when we compare the predictability across GPRs_Acts and GPRs_Threats in Figure 2, the latter depicts stronger evidence of impact in terms of the higher statistics, as well as the coverage of the conditional distribution. The latter conclusion can be drawn because of the lack of prediction observed at the extreme quantiles of the three factors due to acts, unlike the predictability of the entirety of the conditional distributions of level, slope and curvature due to threats. In sum, we can say that it is GPRs_Threats rather than GPRs_Acts that tend to drive the result for the overall GPRs. The finding that the threats of adverse events has larger predictability compared to their realization supports the findings of theoretical models where agents form expectations using a worst case probability (Ilut and Schneider, 2014), which leads to stronger negative impacts on the stock market and overall economy of the US (Caldara and Iacoviello, 2019).

## 4. Conclusion

Given the sparse literature on the impact of geopolitical risks (GPRs) on the US government bond market, we analyse the impact of overall geopolitical risks (as well as acts and threats), on the entire term structure of interest rates, by obtaining three latent factors, level, slope and curvature. We use daily data from 25th November, 1985 to 10th March, 2020 and show that, due to the presence of nonlinearity and structural breaks in the relationships (i.e. the models are misspecified), standard linear tests of causality fail to detect any evidence of predictability running from the GPRs to the three yield curve factors. We reconsider the impact of the GPR indexes on the three latent factors, by using a nonparametric causality-in-quantiles framework. This econometric model is robust against misspecification (as the linear model does not account for regime changes and nonlinearity), due to being a data-driven approach, and allows us to test for predictability over the entire conditional distribution of level, slope and curvature. Note that, as our sample period includes the global financial crisis (and the resulting zero lower bound situation) the lower quantiles of the level, slope and curvature allow us to capture this without the need to carry out a sub-sample analysis involving pre- and post- crisis data. Using the nonparametric causality-in-quantiles test, we find overwhelming evidence of predictability emanating from overall GPRs, and such risks due to acts and threats over the entire conditional distributions of the three factors of the US term structure, with the stronger impacts observed for the level and curvature factors associated with medium- and long-term maturities. Moreover, GPRs due to threats have higher predictive content than GPRs due to actual acts. Our results also highlight the importance of checking and controlling for model misspecification to obtain correct inferences, especially when analysing the impact of GPRs on the US term structure, as our findings provide evidence that such risks are important drivers of the entire yield curve, irrespective of its alternative phases, and despite the results we obtained from the linear causality tests.

Understandably, our findings using high-frequency, i.e., daily data, have multi-dimensional implications. Policymakers can use the observation that GPRs contain predictive information over the evolution of future interest rates (in a nonparametric set-up) to fine-tune their monetary policy models, as these risks affect the slope factor of the yield curve (besides its curvature and level), which captures movements of short-term interest rates. On the other hand, investors and risk managers can use our finding that GPRs affect in the high-frequency movements of the term structure of interest rates, in particular, for medium- and long-term maturities, to improve their interest-rate prediction models, and investment and risk management strategies. Lastly, academic researchers may also use the findings of this paper to explain (and reduce) deviations from asset-pricing models by accounting for GPRs in their pricing kernels, which, however, need to be nonlinear.

As part of future research, it would be interesting to extend the paper to out-of-sample forecasting, and analysis of the impact of such risks on the volatility of the US Treasury securities. One of the limitations of the current work is that the underlying nonparametric causality-in-quantiles framework does not allow beyond a bivariate model of testing causality.

While it is true that GPRs are known to lead several macroeconomic and financial variables which are known to affect the bond market (see Ludvigson and Ng (2009, 2011)), it remains to be seen if our results continue to hold when these factors are used as control variables in a quantiles-based nonparametric model that is able to handle simultaneously multiple predictors.

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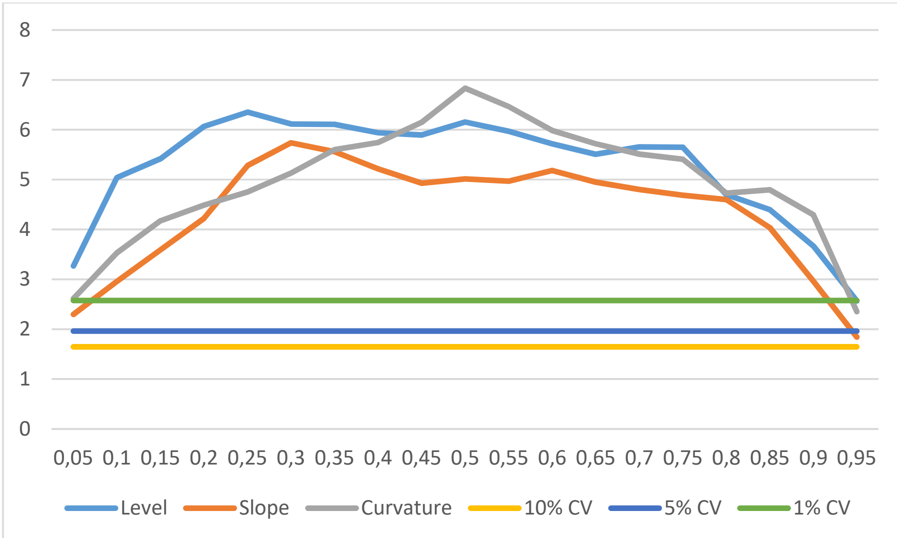
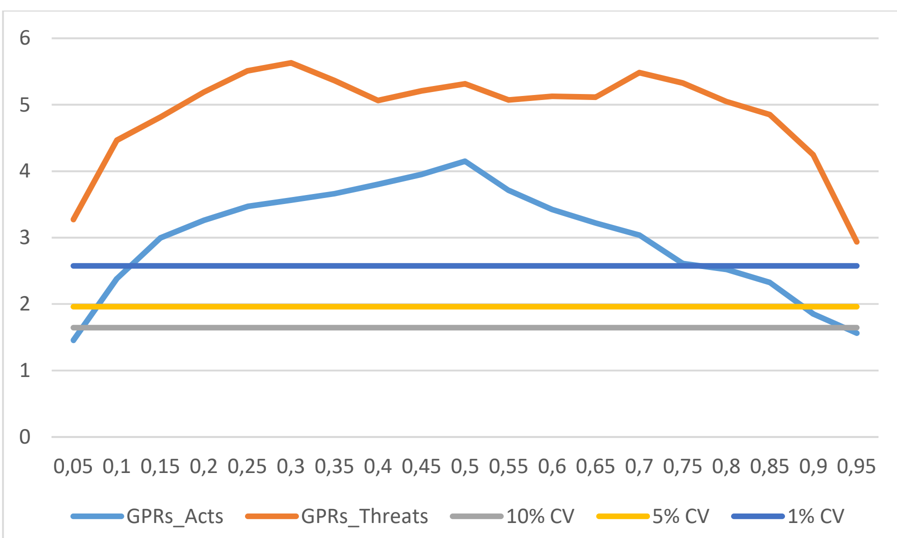
**Figure 1. Causality-in-Quantiles Test Results for the US Term Structure Factors due to GPRs**



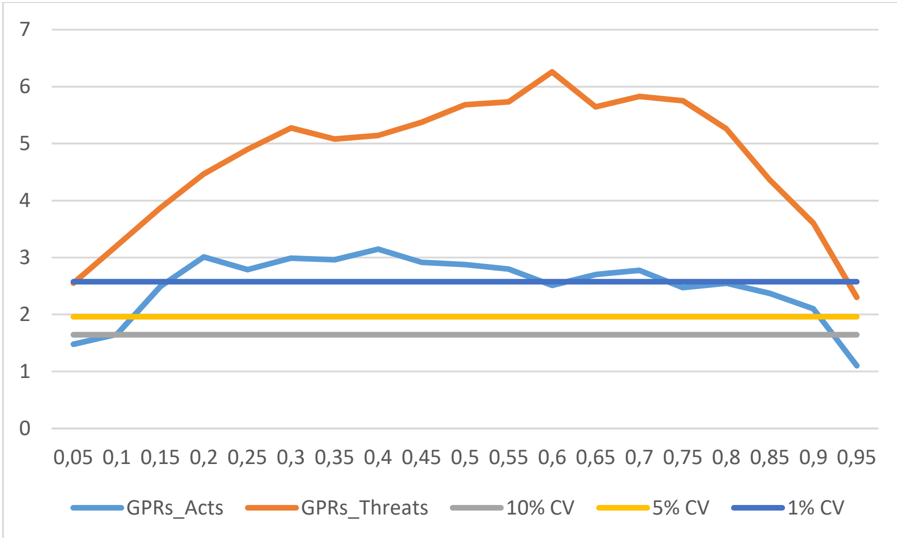

**Note:** The horizontal axis represents the quantiles, while the vertical axis presents the causality-in-quantiles test statistic indicating the rejection or non-rejection of the null hypothesis that GPRs does not Granger cause a specific term structure factor at a specific quantile, if the statistic is above or below the critical values.

**Figure 2. Causality-in-Quantiles Test Results for the US Term Structure Factors due to GPRs_Acts and GPRs_Threats**

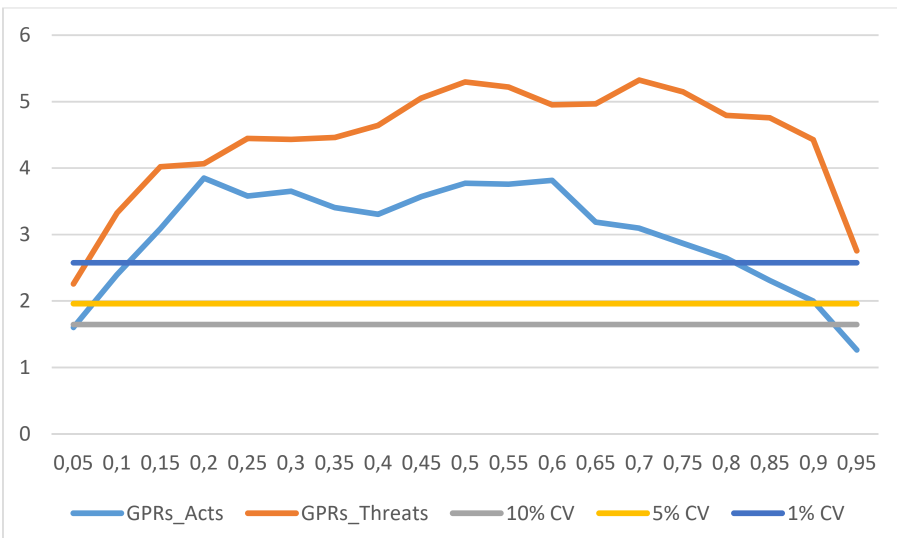
**(a) Level Factor:**



**(b) Slope Factor:**




**(c) Curvature Factor:**




**Note:** The horizontal axis represents the quantiles, while the vertical axis presents the causality-in-quantiles test statistic indicating the rejection or non-rejection of the null hypothesis that GPRs_Acts or GPRs_Threats does not Granger cause a specific term structure factor at a specific quantile, if the statistic is above or below the critical values.

**APPENDIX:**

**Table A1. Summary Statistics**

| | Variable | | | | | |
|---|---|---|---|---|---|---|
| Statistic | Level | Slope | Curvature | GPRs | GPRs_Acts | GPRs_Threats |
| Mean | 4.2295 | -0.9713 | 6.5238 | 88.9155 | 77.4488 | 90.1840 |
| Median | 3.8424 | -1.0093 | 6.0226 | 63.7362 | 47.6594 | 63.6429 |
| Maximum | 11.5968 | 6.6251 | 29.6086 | 1168.8850 | 1908.2320 | 1243.8140 |
| Minimum | -7.0564 | -4.8584 | -3.4930 | 0.0000 | 0.0000 | 0.0000 |
| Std. Dev. | 2.6131 | 1.5544 | 5.2643 | 86.5878 | 117.0595 | 92.9396 |
| Skewness | -0.1817 | 0.5377 | 0.6020 | 3.2557 | 4.2635 | 3.2264 |
| Kurtosis | 3.7479 | 3.2337 | 3.3993 | 21.2441 | 37.6590 | 20.7477 |
| Jarque-Bera | $246.4414^{***}$ | $431.6839^{***}$ | $573.5671^{***}$ | $133759.8000^{***}$ | $451778.0000^{***}$ | $126465.8000^{***}$ |
| Observations | 8555 | 8555 | 8555 | 8555 | 8511 | 8511 |

**Note:** $^{***}$ indicates rejection of the null hypothesis of normality at 1% level of significance.

**Table A2. Linear Granger Causality Test Results**

| | Independent Variable | | |
|---|---|---|---|
| Dependent Variable | GPRs | GPRs_Acts | GPRs_Threats |
| Level | 4.0485 | 0.7960 | 5.2535 |
| Slope | 8.4252 | 4.2551 | 8.0809 |
| Curvature | 2.6313 | 1.8716 | 4.8274 |

**Note:** Entries correspond to the $\chi^2(p)$ statistic that GPRs, GPRs_Acts or GPRs_Threats does not Granger cause a specific term structure factor, with $p$ = 5, 6 and 5, respectively.

**Table A3. Brock et al. (1996) (BDS) Test of Nonlinearity**

| Independent Variable | $m$=2 | $m$=3 | $m$=4 | $m$=5 | $m$=6 |
|---|---|---|---|---|---|
| **Level** | | | | | |
| GPRs | 36.0855*** | 44.0605*** | 50.4943*** | 56.698*** | 63.4723*** |
| GPRs_Acts | 35.9709*** | 43.7875*** | 50.1697*** | 56.3169*** | 63.0686*** |
| GPRs_Threats | 35.8718*** | 43.7903*** | 50.1755*** | 56.3332*** | 63.0533*** |
| **Slope** | | | | | |
| Independent Variable | $m$=2 | $m$=3 | $m$=4 | $m$=5 | $m$=6 |
| GPRs | 33.5831*** | 40.5889*** | 46.2994*** | 52.1366*** | 58.4256*** |
| GPRs_Acts | 33.4015*** | 40.3044*** | 45.9768*** | 51.7755*** | 58.0298*** |
| GPRs_Threats | 33.3734*** | 40.3298*** | 45.9859*** | 51.7613*** | 57.9759*** |
| **Curvature** | | | | | |
| Independent Variable | $m$=2 | $m$=3 | $m$=4 | $m$=5 | $m$=6 |
| GPRs | 34.1735*** | 41.6177*** | 47.3540*** | 52.8172*** | 58.9330*** |
| GPRs_Acts | 34.0006*** | 41.3182*** | 46.9831*** | 52.4020*** | 58.4961*** |
| GPRs_Threats | 33.9240*** | 41.3210*** | 47.0061*** | 52.4181*** | 58.4712*** |

**Note:** Entries correspond to the *z*-statistic of the BDS test with the null hypothesis of *i.i.d.* residuals, with the test applied to the residuals recovered from the three yield curve factor equations with SIC-based lags (see Note to Table A2) each of level, slope and curvature, and GPRs, GPRs_Acts or GPRs_Threats across dimensions *m*; *** indicates rejection of the null hypothesis at 1% level of significance.

**Table A4. Bai and Perron (2003) Test of Multiple Structural Breaks**

| Independent Variable | Level | Slope | Curvature |
|---|---|---|---|
| GPRs | 4/07/1995, 9/13/2006 | 12/10/2008 | 8/13/2008 |
| GPRs_Acts | 4/12/1991, 6/17/1996, 5/08/2003, 8/20/2008, 7/15/2014 | 12/11/1991, 5/06/1998, 4/14/2004, 10/15/2009, 11/19/2014 | 2/05/1993, 4/13/1998, 5/29/2003, 8/14/2008, 6/27/2014 |
| GPRs_Threats | 2/05/1993, 3/27/1998, 5/08/2003, 7/28/2008, 8/29/2013 | 12/10/2008 | 8/20/2008 |

**Note:** Entries correspond to the break dates obtained from the three yield curve factor equations with SIC-based lags (see Note to Table A2) each of level, slope and curvature, and GPRs, GPRs_Acts or GPRs_Threats.

**Figure A1. Data Plots**