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Global Geopolitical Risk and the Long- and Short-Run Impacts on the Returns and Volatilities of US Treasuries

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ABSTRACT

We examine the impact of global geopolitical risk (GPR) measures on US Treasuries' returns and volatilities, differentiating between long- and short-run investment behaviours among an array of time-to-maturities ranging from 1 month to 30 years, taking into account various economic and financial factors. Using monthly data and a panel autoregressive distributed lag (ARDL) model, the results indicate a negative long-run relationship between US Treasuries' returns and the global GPR index. These results generally hold when we consider geopolitical threats and geopolitical acts, although they exhibit some discrepancies between these two components and across the yield curve. Further results show a positive and strong long-run relationship between the US Treasuries' realized volatilities and the various geopolitical risk measures. The evidence holds true when we disentangle 'bad' from 'good' realized volatilities, although the impact of bad volatility is stronger than that of good volatility, which points to an asymmetric effect of realized volatility in US Treasuries. A sub-sample analysis suggests the robustness of the main results. Our analyses provide the first empirical evidence of the information content of GPR for US Treasury securities' returns and volatilities, which matters to fixed-income investors and decision-makers at the Federal Reserve.

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Global geopolitical risk; threats and acts; long- and short-run effects; returns and volatilities; US treasuries yield curve

Introduction

Scholars have shown growing interest in the impacts of geopolitical risk on financial markets. In fact, political uncertainty tends to induce instability in financial markets through its adverse effect on investment decisions, the demand for equity investment, and aggregate equity fund flows (Markoulis and Katsikides 2020; Wang and Young 2020), whereas more intensified effects often result from terrorist attacks and wars (e.g. Ahmad et al. 2022). The adverse effect of geopolitical risk on the systemic risk in commodity markets (Wang et al. 2022) and risky assets such as equity investments is well recognized (Balcilar et al. 2018; Bouras et al. 2019; Bouri et al. 2019; Alqahtani et al., 2020; Zhang et al. 2022). Further empirical evidence suggests a close correlation between crude oil prices and geopolitical risk (Kollias et al., 2013). As for the effects of geopolitical risk on safe haven assets such as gold and other precious metals, previous studies generally show a positive association between geopolitical risk and the returns and volatility of gold given its safe haven property. For example, Baur and Smales (2020) argue that during times of increased geopolitical risk, investors find a shelter in gold.

Considering fixed income markets, the academic literature often relates political risk to corporate bonds, indicating evidence of a negative impact of political uncertainty on corporate investment (Çolak, Durnev, and Qian 2017; Datta, Doan, and Iskandar-Datta 2019) and risk premiums (Pástor and Veronesi 2013). Few studies consider government bonds. For example, Baldacci, Gupta, and Mati (2011) show that higher political risk can induce an increase in sovereign yield spreads of emerging economies, as a compensation for political instability, which makes dealers and traders of government bonds require higher risk premia. Bekaert et al. (2014) also focus on emerging economics and extract political risk from sovereign yield spreads based on the yield spread between a country's US dollar debt and an equivalent US Treasury bond. After accounting for the effect of global and country-specific economic conditions and the liquidity of the country's bond, they show that lower levels of political risk spreads are associated with an expansion in foreign direct investment.¹ However, the academic literature remains largely silent on the association between the return and volatility of US Treasuries and geopolitical risk, especially about the short- and long-term dynamics of the association and the coverage of a large range of US Treasuries time-to-maturities spanning 1 month to 30 years.

US Treasuries have a distinguishing feature that makes our examination interesting for participants in the US Treasury market and policymakers. In addition to their large size, high liquidity, and low risk, US Treasuries are a very appealing destination for investors during periods of high uncertainty which lead to the so-called 'flight to quality' or 'flight to safety'. Therefore, during intensified geopolitical risk, Treasury prices increase and their yields fall to low levels, which is suggestive of increased risk aversion and a flight to quality or safety. However, given the wide variety of US Treasury yields and the high sensitivity of the short end of the Treasury yield curve, market participants tend to become more vigilant in committing to long-term US Treasuries. This provokes a heterogeneous relationship in the impacts of geopolitical risk, which differs between the shorter-term and longer-term yields.

In this paper, we contribute to the academic literature by examining the impact of the global geopolitical risk (GPR) index on the returns and volatilities of US Treasuries. The methodology involves a panel autoregressive distributed lag (ARDL) model, which allows us to capture potential differences between long- and short-run investment behaviours among the various Treasury yields. Notably, the analysis takes into account the role of various economic and financial factors (Ludvigson and Ng 2009, 2010) on the association between geopolitical risk and US Treasuries, and differentiate between the effects of the two components of GPR, threats and acts.

Our current paper pertains to the academic literature on the impact of GPR on oil prices (Cunado et al. 2020), energy volatility (Liu, Han, and Xu 2021), crude oil volatility (Liu et al. 2019), returns of aggregate stock indices (Alqahtani et al., 2020), returns and volatility of major defence stocks (Apergis et al. 2018; Zhang et al. 2022), and the business cycle of emerging economies (Cheng and Chiu 2018; Mansour-Ichrakieh and Zeaiter 2019).

Our main results show a negative long-run relationship between US Treasuries' returns and the GPR index. The results generally hold when threats and acts are used, although some discrepancies across the yield curve can be detected. Regarding the nexus between the GPR index and the volatilities of US Treasuries, we find evidence of a positive and strong long-run relationship. The evidence is generally the same regardless of whether we use 'bad' or 'good' realized volatilities. However, we find that the impact of bad volatility is stronger than that of good volatility, which suggests an asymmetric effect. Furthermore, we assess the robustness of our results using a subsample analysis. Overall, the results remain qualitatively the same, suggesting their robustness.

Our analyses provide the first empirical evidence of the information content of GPR for US Treasury securities' returns and volatilities, which concerns the nexus of geopolitical uncertainty and asset pricing and has policy implications. The results matter for fixed-income investors and decision-makers at the Federal Reserve.

The rest of the paper is organized in four sections. Section 2 describes the panel ARDL model. Section 3 provides the dataset of GPR indices, US Treasuries, and the various economic and financial

factors used as control variables. [Section 4](#) presents and discusses the main results and includes the robustness analysis. [Section 5](#) concludes.

Methodology

Our methodology involves the use of a panel ARDL model to capture the short-and long-run impacts of various geopolitical risk measures on the returns and volatilities of US Treasuries, while accounting for important factor variables (Ludvigson and Ng 2009, 2010).

We assume that US sovereign bonds' monthly returns derived from US Treasuries' yields and covering a wide span of monthly remaining time-to-maturities follow an ARDL (p, q_1, \dots, q_k) dynamic panel specification of the form:

$$Y_{it} = \sum_{j=1}^p \lambda_{ij} Y_{i,t-j} + \sum_{j=0}^q \delta'_{ij} X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (1)$$

where, Y_{it} is the monthly continuously compounded return of US Treasury securities; $X_{i,t}$ is a $k \times 1$ vector of explanatory variables including geopolitical risk measures as well as nine financial factors; p is the lag of the dependent variable, Y_{it} ; q is the lag of the explanatory variables, X_{it} ; i denotes Treasury securities, specifically US sovereign bonds denominated in local currency, with remaining time-to-maturities in months $i = 1, 2, \dots, 360$; t is a time subscript denoting the time period, with $t = 1, 2, \dots, T$; δ_{it} is a $k \times 1$ coefficient vector; λ_{ij} is a scalar; and μ_i is the Treasury security's time-to-maturity specific effect.

According to Blackburne and Frank (2007), a dynamic heterogeneous panel model can be re-specified in the form of an error correction model using the ARDL technique (see Equation 2), if the variables are cointegrated. In such a case, ε_{it} is a stationary process for all i . The most prominent feature to emphasize within such a context is the responsiveness to deviations from the long-run equilibrium of the nine factors in addition to the geopolitical risk measures, implying an error correction model in which the system's short-run dynamics of these factors are affected by any departure from the long-run relationship.

$$\Delta Y_{it} = \phi_i (Y_{i,t-1} - \theta'_i X_{i,t}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta Y_{i,t-j} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it}^2 \quad (2)$$

where,

$$\begin{aligned} \phi_i &= - \left(1 - \sum_{j=1}^p \lambda_{ij} \right) \\ \theta_i &= \sum_{j=0}^q \delta_{ij} / \left(1 - \sum_k \lambda_{ik} \right) \\ \lambda^*_{ij} &= - \sum_{m=j+1}^p \lambda_{im}, \quad j = 1, 2, \dots, p-1, \\ \text{and } \delta'^*_{ij} &= - \sum_{m=j+1}^q \delta_{im}, \quad j = 1, 2, \dots, q-1. \end{aligned}$$

The parameter ϕ_i is the error-correction speed of adjustment. As clearly mentioned by Pesaran, Shin, and Smith (1999), the stability of the ARDL model ensures this parameter is significant and negative ($\phi_i < 0$) and hence there exists of a long-run relationship between the US bond returns Y_{it} and the various financial factors and/or geopolitical risk measures $X_{i,t}$. In other words, if the speed of adjustment is null ($\phi_i = 0$), then there is no evidence to support the existence of a long-run

equilibrium to which regressors frequently converge. Hence, the importance of the vector θ'_i is that it captures the various long-run slope coefficients.

As revealed by Pesaran, Shin, and Smith (1999), the maximum likelihood method required to estimate Equation 2, with non-linear in parameters, is given by:

$$l_T(\theta', \varphi', \sigma') = -\frac{T}{2} \sum_{i=1}^N \ln(2\pi\sigma_i^2) - \frac{1}{2} \sum_{i=1}^N \frac{1}{\sigma_i^2} \{\Delta y_i - \phi_i \xi_i(\theta)\}' H_i \{\Delta y_i - \phi_i \xi_i(\theta)\} \quad (3)$$

For $i = 1, \dots, N$; $\xi_i(\theta) = y_{i,t-1} - X_i \theta_i$, $H_i = I_T - W_i(W_i' W_i)^{-1} W_i'$, I_T is an order T -identity matrix, and where:

$$W_i = (\Delta y_{i,t-1}, \dots, \Delta y_{i,t-p+1}, \Delta X_i, \Delta X_{i,t-1}, \dots, \Delta X_{i,t-q+1})$$

$$\hat{\phi}_i = \left(\tilde{\xi}_i' H_i \hat{\xi}_i(\theta) \right)^{-1} \tilde{\xi}_i' H_i \Delta y_i$$

$$\hat{\sigma}_i^2 = T^{-1} \left\{ \Delta y_i - \hat{\phi}_i \hat{\xi}_i(\theta) \right\}' H_i \left\{ \Delta y_i - \hat{\phi}_i \hat{\xi}_i(\theta) \right\}$$

We find it appropriate to implement an intermediate approach to the mean group (MG) and fixed-effects (FE) estimators, known as the pooled mean group (PMG), which combines pooling along with averaging. The main characteristic of the PMG is that it allows the short-run coefficients, intercepts, including the speed of adjustment to the equilibrium of US Treasuries' returns, as well as error variances, to vary freely across fixed-income securities groups or sub-portfolios which are clustered in terms of their remaining maturities (as tolerated by the MG estimator), but compels the long-run coefficients to be identical across all clustered maturities of sovereign bonds (as constrained by the FE estimator). Furthermore, the PMG estimator seems particularly appropriate, since it allows, on one hand, the inclusion of the bond return, financial factors and geopolitical risk measures in the long-run equilibrium, and, on the other hand, testing for the existence of separate long- and short-run impacts.

It is of paramount importance to investors, market participants and academics to mention that investigating the presence of long-run equilibria in sovereign bond returns is not restricted to the presence of statistical properties found in panel data. Rather, macroeconomic and financial theories (e.g. term structure of interest rates theories, portfolio management theories) also provide the necessary background as to whether such a long-run relationship underpins the investment behaviour of a wide range of participants in fixed-income markets, from institutional and retail investors to traders.

Having asserted the above, our purpose is to thoroughly investigate the macroeconomic effect and role played by the endorsed GPR measures, above and beyond the financial and economic factors of US Treasuries' returns and volatilities, affecting both long- and short-run investment behaviour among an array of time-to-maturities.

The GPR index (described in the data section) is often pointed to by economic and monetary authorities – especially the International Monetary Fund, central banks and regulators – as well as rating agencies, financial media and/or business investors, as being a major salient determinant reshaping investment decisions, which makes GPR capable of influencing business cycles and financial market behaviours (see, Caldara and Iacoviello 2022; Jung, Lee, and Lee 2021).² Notably, by considering the role of two additional geopolitical measures, the geopolitical threats index (GPT) and the geopolitical acts index (GPA), we conjointly control for the effect of adverse geopolitical events attributable to geopolitical risks. Consequently, $X_{i,t}$, the 10×1 vector of explanatory variables that includes GPR index and nine financial and economic factors (described in the data section), i.e. $X_{i,t} = \{GPR, F_1, F_2, \dots, F_9\}$, translates to an 11×1 vector of explanatory variables:

$$X_{i,t} = \{GPA, GPT, F_1, F_2, \dots, F_9\}$$

Furthermore, it is worth mentioning that sufficiently long lags are necessary for the reliability of the ARDL approach, whereas specifying longer lags than necessary can lead to estimates with poor small sample properties.³ For the sum of coefficients and their standard errors, we use the method proposed by Chudik et al. (2016).⁴

Data Description

We use balanced panel data covering the monthly period February 1986 to December 2018, with the start date being determined by the availability of real GPR metrics (GPR, GPT, and GPA). In the robustness analysis, we use a sample that starts from 1961, given that a historical version of the three GPR metrics of Caldara and Iacoviello (2022) is available from that time. The monthly data on the real global GPR, GPA and GPT indices are available for download from <https://www.matteoiacoviello.com/gpr.htm>. The news-based geopolitical risk indices, developed by Caldara and Iacoviello (2022), are based on the occurrence of words related to geopolitical tensions in 11 leading national and international newspapers.⁵ An automated search algorithm identifies press articles containing terms with an affiliation to six groups. The first group (Group 1) includes terms related to explicit mentions of geopolitical risk, as well as terms, statements, or declarations of military-related tensions implicating a considerable part of the globe and US involvement. The second group (Group 2) comprises words that are directly related to nuclear tensions. The third and fourth groups (Groups 3 and 4) include terms directly or incidentally referencing war threats and terrorist threats, respectively. Lastly, the fifth and sixth groups (Groups 5 and 6) include words related to real adverse geopolitical events (as opposed to just risks) which can reasonably be expected to exacerbate geopolitical uncertainty. Hence, as constructed, this measure allows us to transcend the limited effect of a specific event-specific date approach, thereby offering a more holistic approach to GPRs.

By developing two additional indexes, GPT and GPA, Caldara and Iacoviello (2022) extricate the direct effect of adverse geopolitical events from the effect of neat geopolitical risks. The GPT index encompasses only words referenced in Groups 1 to 4. The GPA index includes only words in Groups 5 and 6. Besides Caldara and Iacoviello (2022), many other studies (e.g. Apergis et al. 2018; Bouri et al. 2019; Lee, Lee, and Li 2020; Cunado et al. 2020) emphasize the importance of the GPR index for assets and financial markets. Figure 1 plots the GPR index and the GPT and GAP indices.

Our dataset includes the yields of various US Treasury securities, extracted from DataStream, covering maturities of 1 month to 30 years and their monthly realized volatilities, calculated as the sum of the squared continuously compounded (log) daily returns.

We also use the nine factors from Ludvigson and Ng (2009, 2010), extracted from a large macroeconomic data set.⁶ According to Ludvigson and Ng (2010), the first factor, which is a real activity factor, loads heavily on employment and output data. The second factor loads heavily on interest rate spreads, while the third and fourth factors load on prices. The fifth factor loads on interest rates (much more strongly than interest rate spreads). The sixth factor loads heavily on housing variables, while the seventh factor loads on measures of money supply. The eighth factor loads on variables relating to the stock market. Hence, loosely speaking, factors 5 to 8 are strongly related to money, credit, and finance.

It is important to indicate that the factors explaining most of the variation in the large macroeconomic panel data are not necessarily the same factors predicting bond returns or even (associated) excess returns. However, the nine factors, besides geopolitical factors, are included in our analysis for three main reasons. Firstly, macro factors have strong predictive power for bond (excess) returns (see Ludvigson and Ng 2010; Favero, Niu, and Sala 2012; Coroneo, Giannone, and Modugno

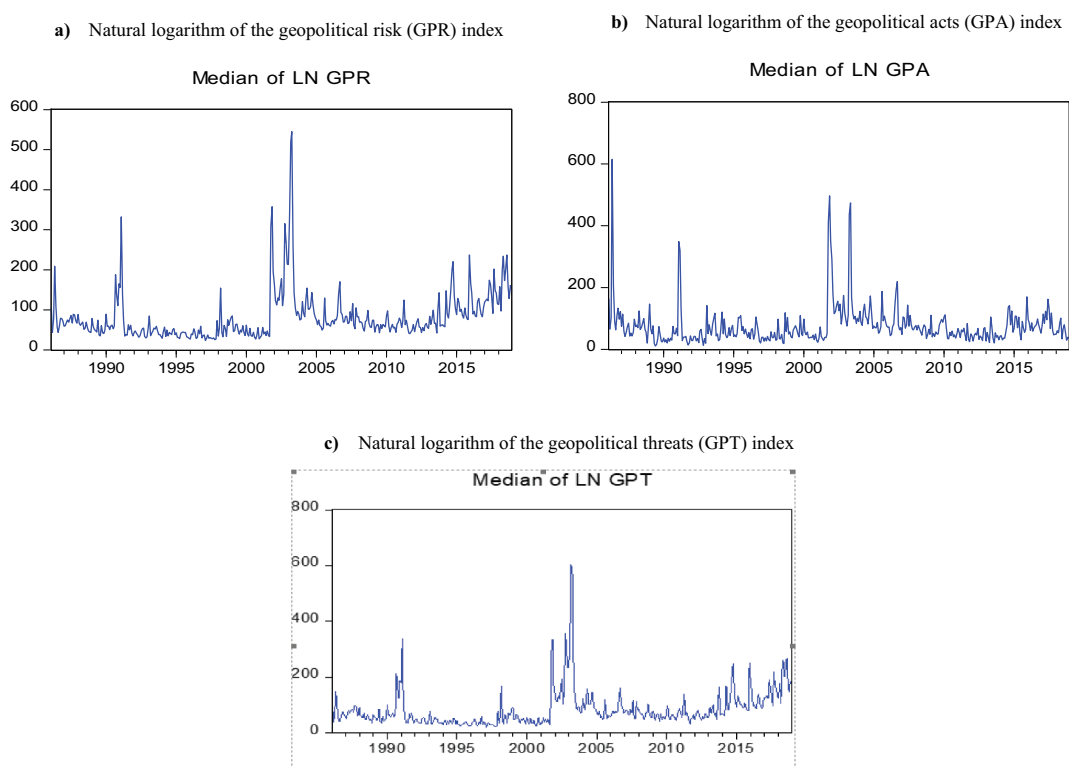


Figure 1. Plots of geopolitical indices.

2016; Li et al. 2021), and this finding holds up regardless of which estimation method is used to extract the factors (Ludvigson and Ng 2010). Secondly, when the estimated factors are used to forecast excess returns, bond and yield risk premia are found to be counter-cyclical, which implies that investors require to be compensated for risks when recessions occur. Thirdly, technically, estimated factors need to be integrated into the estimation framework as control variables to avoid causing endogeneity and/or estimation biases.

On a related front, it is worth mentioning that, to avoid quickly running into degrees-of-freedom problems as the dimensions of the dataset increase, and where, consequently, the estimation is no longer feasible (when $N + K > T$), Ludvigson and Ng (2010) adopt an approach in which they posit that the dataset of macroeconomic and financial variables has a factor structure. If revealed, estimated factors would be used in a 'factor augmented regression', a convenient framework to assess the importance of the variables⁷ via the estimated factors.

As clearly shown in Table 1, the global GPR index and GPT index show an average positive annualized monthly change, unlike the GPA index. Furthermore, the distributions of all three geopolitical risk measures are right-skewed, as corroborated by high positive skewness figures and by means being skewed to the right of the typical centre of the data, despite the fact that right-tailed distributions usually appear left-leaning. Table 1 shows that GPR and GPT have relatively higher kurtosis than GPA, consequently asymptotically approaching zero in a slower fashion than a Gaussian would normally do, resulting in a greater extremity of deviations (or outliers). Moreover, the Jarque-Bera test statistics reveal the non-normality of all GPR metrics. Likewise, all nine factors suffer from non-normality in their distributions.

Table 1. Summary statistics of geopolitical risk indices and nine factors.

(% Change)	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera P-value
GPR	0.44%	-7.72%	769.79%	-441.98%	123.67%	2.6179	25.0961	0.00
GPA	-1.12%	-1.86%	718.29%	-531.68%	181.99%	1.9956	16.1304	0.00
GPT	0.62%	-9.58%	796.52%	-457.96%	130.16%	2.3293	24.0330	0.00
F1	20.59%	4.76%	657.83%	-195.93%	110.59%	6.4807	33.5551	0.00
F2	23.34%	23.71%	440.65%	-274.41%	85.45%	1.5027	20.1466	0.00
F3	18.77%	19.40%	451.96%	-395.11%	94.25%	-0.0490	22.6971	0.00
F4	-7.77%	-3.78%	255.95%	-264.03%	67.29%	-0.3349	13.2831	0.00
F5	-1.20%	1.42%	164.36%	-201.48%	65.88%	-0.8971	11.1886	0.00
F6	-11.15%	-12.77%	170.50%	-197.45%	57.95%	0.7970	12.3526	0.00
F7	-0.23%	-5.04%	434.27%	-163.59%	62.02%	5.3510	38.4744	0.00
F8	-10.77%	-10.18%	128.21%	-161.33%	49.26%	-0.0399	11.0825	0.00
F9	27.45%	0.00%	2372.29%	-62.68%	182.39%	32.6720	356.9290	0.00

Notes: Annualized monthly values. Number of observations ($N \times T$): 142,200. GPR (geopolitical risk index); GPA (geopolitical axis index); GPT (geopolitical threats index); F1-F9 are the nine factors of Ludvigson and Ng (2009, 2010), extracted from a large macroeconomic data set.

Empirical Results

GPR and Returns of US Treasury Securities

Laying out the theoretical aspects of the model is imperative for understanding the types of restrictions models impose. It is necessary to ensure that the equilibrium return on sovereign bonds varies over time in a manner consistent with both the macro-economy and the US Treasury market. In such a context, it is important to mention that, besides policymakers, investors closely watch the two-year US Treasury yield, which typically moves in step with interest rate expectations. No less importantly, the part of the US Treasury yield curve measuring the gap between yields on 2-year and 10-year Treasury-Notes is similarly carefully monitored as it is a prominent indicator of economic expectations. Accordingly, the empirical results should be interpreted from this perspective.

The results of the ARDL model covering the full sample period spanning March 1986 to December 2018 are presented in Table 2. The most vital thing to mention is the extreme statistical significance of all negative error-correction or speed of adjustment coefficients underpinning the stability of the ARDL model, ensuring the existence of a long-run relationship between the US Treasuries' returns and the various geopolitical risk measures and financial factors.

Results across Treasury securities groups (or sub-portfolios), clustered by their remaining time-to-maturities, suggest an inverse long-run relationship between sovereign bond returns and the global GPR index. Models (1), (3), (5), (7), and (9) show negative GPR coefficients with extreme statistical significance, even at the 1 percent level, with values ranging from negative 0.003 to negative 0.024, and taking a deeper dive into negative territory as the remaining time-to-maturity increases. When the disentanglement of the direct effect of adverse geopolitical events from the effect of geopolitical risks is considered, through the replacement of GPR by GPA and GPT, the outputs reveal an inverse long-run relationship between Treasury securities' returns and the GPA index, except at the long-term end of the yield curve. Models (2), (4), (6), and (8) show that the coefficients of GPA are similarly negative with extreme statistical significance at the 1 percent level, ranging from negative 0.002 to negative 0.028, however quadratically decaying to negative territory before returning to above zero at the largest remaining time-to-maturities. For the GPT index, Table 2 shows an inverse long-run relationship with Treasury-Bond returns with maturities at the long-term end of the yield curve, with the exception of those with less than 10 years remaining. Models (6), (8), and (10) show extremely significant negative GPT coefficients, with values quadratically decaying from negative 0.025 to negative 0.063. Put another way, geopolitical threats do not have a negative impact on short- and medium-term yields, including those of US Treasuries with a remaining time-to-maturity of less than 10 years.

Table 2. GPR and the return of US Treasury securities – sample analysis covering March 1986 to December 2018.

Dependent Variable: $\Delta(Y)$	Maturity 01 M – 60 M		Maturity 61 M – 120 M		Maturity 121 M – 180 M		Maturity 181 M – 240 M		Maturity 241 M – 360 M	
	Coefficient. (P-value) Model (1)	Coefficient. (P-value) Model (2)	Coefficient. (P-value) Model (3)	Coefficient. (P-value) Model (4)	Coefficient. (P-value) Model (5)	Coefficient. (P-value) Model (6)	Coefficient. (P-value) Model (7)	Coefficient. (P-value) Model (8)	Coefficient. (P-value) Model (9)	Coefficient. (P-value) Model (10)
Long Run Equation										
RGPR RGPA	-0.003 (0.000)	-0.002 (0.000)	-0.006 (0.000)	-0.011 (0.000)	-0.012 (0.000)	-0.014 (0.000)	-0.021 (0.000)	-0.028 (0.000)	-0.024 (0.000)	0.008 (0.000)
RGPT		0.003 (0.000)		0.004 (0.000)		-0.043 (0.000)		-0.063 (0.000)		-0.025 (0.000)
F1	0.025 (0.000)	0.021 (0.000)	0.050 (0.000)	0.050 (0.000)	0.046 (0.000)	0.050 (0.000)	0.062 (0.000)	0.053 (0.000)	0.074 (0.000)	0.073 (0.000)
F2	0.001 (0.080)	0.003 (0.000)	0.043 (0.000)	0.056 (0.000)	0.105 (0.000)	0.171 (0.000)	0.149 (0.000)	0.264 (0.000)	0.202 (0.000)	0.205 (0.000)
F3	0.004 (0.000)	-0.004 (0.000)	-0.011 (0.000)	-0.014 (0.000)	-0.004 (0.200)	-0.098 (0.000)	-0.013 (0.000)	-0.176 (0.000)	-0.025 (0.000)	-0.026 (0.000)
F4	0.040 (0.000)	0.030 (0.000)	0.156 (0.000)	0.150 (0.000)	0.200 (0.000)	0.159 (0.000)	0.273 (0.000)	0.172 (0.000)	0.360 (0.000)	0.363 (0.000)
F5	-0.032 (0.000)	-0.024 (0.000)	-0.121 (0.000)	-0.108 (0.000)	-0.131 (0.000)	-0.121 (0.000)	-0.168 (0.000)	-0.124 (0.000)	-0.201 (0.000)	-0.201 (0.000)
F6	0.007 (0.000)	-0.003 (0.000)	-0.028 (0.000)	-0.020 (0.000)	-0.019 (0.000)	-0.008 (0.200)	-0.066 (0.000)	-0.022 (0.010)	-0.092 (0.000)	-0.091 (0.000)
F7	0.029 (0.000)	0.016 (0.000)	0.067 (0.000)	0.070 (0.000)	0.071 (0.000)	0.100 (0.000)	0.073 (0.000)	0.103 (0.000)	0.096 (0.000)	0.091 (0.000)
F8	0.010 (0.000)	0.005 (0.000)	0.024 (0.000)	0.032 (0.000)	0.052 (0.000)	-0.023 (0.000)	0.054 (0.000)	-0.054 (0.000)	0.116 (0.000)	0.116 (0.000)
F9	-0.005 (0.000)	-0.004 (0.000)	-0.001 (0.040)	-0.003 (0.000)	0.005 (0.000)	-0.010 (0.000)	-0.007 (0.000)	-0.019 (0.000)	-0.012 (0.000)	-0.011 (0.000)
Short Run Equation										
COINTEQ01	-1.173 (0.000)	-0.999 (0.000)	-1.510 (0.000)	-5.146 (0.000)	-1.321 (0.000)	-1.328 (0.000)	-1.244 (0.000)	-1.387 (0.000)	-1.203 (0.000)	-1.201 (0.000)
$\Delta(Y(-1))$	-0.068 (0.040)		0.500 (0.000)	0.183 (0.000)				0.251 (0.000)		
$\Delta(Y(-2))$				-0.218 (0.000)						
$\Delta(\text{RGPR} \mid \text{RGPA})$	0.001 (0.000)	0.000 (0.000)	0.010 (0.000)	0.003 (0.000)	0.017 (0.000)	0.005 (0.000)	0.025 (0.000)	0.021 (0.000)	0.027 (0.000)	-0.028 (0.000)
$\Delta(\text{RGPR}(-1) \mid \text{RGPA}(-1))$	0.000 (0.030)			0.004 (0.000)	0.004 (0.000)	0.017 (0.000)		0.031 (0.000)		
$\Delta(\text{RGPR}(-2) \mid \text{RGPA}(-2))$	0.000 (0.000)					0.014 (0.000)		0.018 (0.000)		

(Continued)

Table 2. (Continued).

Variable	Maturity 01 M – 60 M		Maturity 61 M – 120 M		Maturity 121 M – 180 M		Maturity 181 M – 240 M		Maturity 241 M – 360 M	
	Coefficient. (P-value) Model (1)	Coefficient. (P-value) Model (2)	Coefficient. (P-value) Model (3)	Coefficient. (P-value) Model (4)	Coefficient. (P-value) Model (5)	Coefficient. (P-value) Model (6)	Coefficient. (P-value) Model (7)	Coefficient. (P-value) Model (8)	Coefficient. (P-value) Model (9)	Coefficient. (P-value) Model (10)
$\Delta(\text{RGPA}(-3))$						0.006 (0.000)		0.007 (0.000)		
$\Delta(\text{RGPT})$		0.001 (0.000)		0.006 (0.000)		0.068 (0.000)		0.094 (0.000)		0.049 (0.000)
$\Delta(\text{RGPT}(-1))$				-0.002 (0.000)		0.043 (0.000)		0.061 (0.000)		
$\Delta(\text{RGPT}(-2))$						0.034 (0.000)		0.053 (0.000)		
$\Delta(\text{RGPT}(-3))$						0.021 (0.000)		0.029 (0.000)		
$\Delta(\text{F1})$	0.009 (0.000)	0.037 (0.000)	0.076 (0.000)	0.095 (0.000)	0.196 (0.000)	0.190 (0.000)	0.245 (0.000)	0.257 (0.000)	0.332 (0.000)	0.359 (0.000)
$\Delta(\text{F1}(-1))$	0.006 (0.000)			0.037 (0.000)	0.038 (0.000)	0.029 (0.000)		0.055 (0.000)		
$\Delta(\text{F1}(-2))$	0.005 (0.000)					-0.018 (0.000)		0.006 (0.000)		
$\Delta(\text{F1}(-3))$						-0.033 (0.000)		-0.041 (0.000)		
$\Delta(\text{F2})$	-0.009 (0.000)	-0.021 (0.000)	-0.143 (0.000)	-0.191 (0.000)	-0.264 (0.000)	-0.381 (0.000)	-0.225 (0.000)	-0.508 (0.000)	-0.222 (0.000)	-0.217 (0.000)
$\Delta(\text{F2}(-1))$	-0.005 (0.000)			-0.092 (0.000)	-0.141 (0.000)	-0.209 (0.000)		-0.270 (0.000)		
$\Delta(\text{F2}(-2))$	0.003 (0.000)					-0.067 (0.000)		-0.113 (0.000)		
$\Delta(\text{F2}(-3))$						-0.166 (0.000)		-0.223 (0.000)		
$\Delta(\text{F3})$	-0.011 (0.000)	-0.017 (0.000)	-0.090 (0.000)	-0.116 (0.000)	-0.163 (0.000)	-0.077 (0.000)	-0.129 (0.000)	-0.005 (0.000)	-0.102 (0.000)	-0.096 (0.000)
$\Delta(\text{F3}(-1))$	-0.009 (0.000)			-0.077 (0.000)	-0.110 (0.000)	-0.009 (0.000)		0.067 (0.000)		
$\Delta(\text{F3}(-2))$	0.000 (0.010)					0.070 (0.000)		0.118 (0.000)		
$\Delta(\text{F3}(-3))$						-0.055 (0.000)		-0.067 (0.000)		
$\Delta(\text{F4})$	0.005 (0.000)	0.020 (0.000)		-0.075 (0.000)	-0.068 (0.000)	-0.016 (0.000)	-0.066 (0.000)	0.004 (0.100)	-0.060 (0.000)	-0.080 (0.000)
$\Delta(\text{F4}(-1))$	0.006			0.007	0.020	0.099		0.165		

(Continued)

Table 2. (Continued).

Dependent Variable: $\Delta(Y)$	Maturity 01 M – 60 M		Maturity 61 M – 120 M		Maturity 121 M – 180 M		Maturity 181 M – 240 M		Maturity 241 M – 360 M	
	Coefficient. (P-value) Model (1)	Coefficient. (P-value) Model (2)	Coefficient. (P-value) Model (3)	Coefficient. (P-value) Model (4)	Coefficient. (P-value) Model (5)	Coefficient. (P-value) Model (6)	Coefficient. (P-value) Model (7)	Coefficient. (P-value) Model (8)	Coefficient. (P-value) Model (9)	Coefficient. (P-value) Model (10)
$\Delta(F4(-2))$	(0.000) 0.006 (0.000)			(0.050)	(0.000)	(0.000) 0.137 (0.000)		(0.000) 0.214 (0.000)		
$\Delta(F4(-3))$						-0.047 (0.000)		-0.054 (0.000)		
$\Delta(F5)$	-0.018 (0.000)	-0.055 (0.000)	-0.129 (0.000)	-0.190 (0.000)	-0.326 (0.000)	-0.368 (0.000)	-0.365 (0.000)	-0.442 (0.000)	-0.400 (0.000)	-0.420 (0.000)
$\Delta(F5(-1))$	-0.012 (0.000)			-0.121 (0.000)	-0.130 (0.000)	-0.098 (0.000)		-0.063 (0.000)		
$\Delta(F5(-2))$	-0.001 (0.010)					0.154 (0.000)		0.238 (0.000)		
$\Delta(F5(-3))$						-0.034 (0.000)		-0.029 (0.000)		
$\Delta(F6)$	0.011 (0.000)	0.041 (0.000)	0.161 (0.000)	0.182 (0.000)	0.281 (0.000)	0.304 (0.000)	0.323 (0.000)	0.405 (0.000)	0.403 (0.000)	0.395 (0.000)
$\Delta(F6(-1))$	0.003 (0.000)			0.064 (0.000)	0.081 (0.000)	0.140 (0.000)		0.202 (0.000)		
$\Delta(F6(-2))$	0.000 (0.740)					0.083 (0.000)		0.148 (0.000)		
$\Delta(F6(-3))$						0.094 (0.000)		0.126 (0.000)		
$\Delta(F7)$	-0.004 (0.000)	-0.002 (0.000)	-0.075 (0.000)	-0.088 (0.000)	-0.121 (0.000)	-0.166 (0.000)	-0.112 (0.000)	-0.181 (0.000)	-0.101 (0.000)	-0.083 (0.000)
$\Delta(F7(-1))$	-0.001 (0.010)			-0.033 (0.000)	-0.042 (0.000)	-0.089 (0.000)		-0.083 (0.000)		
$\Delta(F7(-2))$	-0.001 (0.000)					-0.030 (0.000)		-0.014 (0.000)		
$\Delta(F7(-3))$						-0.032 (0.000)		-0.026 (0.000)		
$\Delta(F8)$	0.005 (0.000)	0.013 (0.000)	0.025 (0.000)	0.022 (0.000)	0.055 (0.000)	0.136 (0.000)	0.096 (0.000)	0.220 (0.000)	0.093 (0.000)	0.098 (0.000)
$\Delta(F8(-1))$	0.005 (0.000)			0.007 (0.000)	0.006 (0.000)	0.065 (0.000)		0.124 (0.000)		
$\Delta(F8(-2))$	0.006 (0.000)					0.050 (0.000)		0.089 (0.000)		
$\Delta(F8(-3))$						-0.039 (0.000)		-0.051 (0.000)		

(Continued)



Table 2. (Continued).

Variable	Maturity 01 M – 60 M		Maturity 61 M – 120 M		Maturity 121 M – 180 M		Maturity 181 M – 240 M		Maturity 241 M – 360 M	
	Coefficient. (P-value) Model (1)	Coefficient. (P-value) Model (2)	Coefficient. (P-value) Model (3)	Coefficient. (P-value) Model (4)	Coefficient. (P-value) Model (5)	Coefficient. (P-value) Model (6)	Coefficient. (P-value) Model (7)	Coefficient. (P-value) Model (8)	Coefficient. (P-value) Model (9)	Coefficient. (P-value) Model (10)
$\Delta(F9)$	0.001 (0.000)	0.002 (0.000)	0.011 (0.000)	0.008 (0.000)	0.032 (0.000)	0.029 (0.000)	0.063 (0.000)	0.042 (0.000)	0.076 (0.000)	0.072 (0.000)
$\Delta(F9(-1))$	0.000 (0.650)			-0.005 (0.000)	-0.039 (0.000)	-0.021 (0.000)		-0.023 (0.000)		
$\Delta(F9(-2))$	0.001 (0.000)					-0.013 (0.000)		-0.017 (0.000)		
$\Delta(F9(-3))$						0.041 (0.000)		0.050 (0.000)		
Constant	0.000 (0.000)	0.001 (0.000)	0.003 (0.000)	0.002 (0.000)	0.002 (0.000)	0.006 (0.000)	0.007 (0.000)	0.012 (0.000)	0.007 (0.000)	0.007 (0.000)
@TREND	0.000 (0.000)		0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Mean dependent variable	0	0	0	0	0	0	0	0	0	0
S.E. of regression	0.155	0.15	0.158	0.179	0.192	0.207	0.197	0.242	0.138	0.162
SSR	522.2	514	569.8	709.4	821.3	896.9	887.3	1217	869.4	1198.4
Log likelihood	98,648.3	97,326.4	67,803.4	68,620	55,475.1	57,035.1	46,827.5	48,819.4	78,871.4	79,241.9
Std. dependent variable	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059
AIC	-8.162	-8.146	-5.65	-5.653	-4.564	-4.574	-3.885	-3.876	-3.262	-3.272
BIC	-7.504	-7.877	-5.361	-5.097	-4.091	-3.61	-3.616	-2.891	-2.971	-2.959
HQC	-7.949	-8.059	-5.556	-5.473	-4.41	-4.261	-3.798	-3.556	-3.17	-3.174

$\Delta(Y)$ is the first difference of the dependent variable. F1-F9 are the nine factors of Ludvigson and Ng (2009, 2010), extracted from a large macroeconomic data set. $\Delta(Y(-t))$ is the first difference of the t-periods lag of Y, $\Delta(F1(-t))$ to $\Delta(F9(-t))$ represent the first difference of the lagged t-periods variables F1-F9. $\Delta(RGPR)$ | RGPA is the first difference of either RGPR or RGPA. Likewise, $\Delta(RGPT)$ is the first difference of RGPT. $\Delta(RGPT(-t))$, $\Delta(RGPA(-t))$ and $\Delta(RGPR(-t))$ represent the first difference of the t-periods lagged variables RGPT, RGPA, and RGPR. Std. dependent variable is the standard deviation of the dependent variable.

However, it is obvious that the GPT index does have an effect on Treasury-Bills and Treasury-Notes, which tend to be influenced by the markets' expectations for US Federal Reserve policy, and consequently, how investors would react to events leading to an uncertain outlook. Hence, GPT plays a vital role in inducing changes at the long-end of the yield curve, without ignoring the potential other. Of other factors such as the outlook for inflation, economic growth, supply and demand, and depressed/elevated risk appetites.

The rationale is that, when the GPT index surges, short-to-medium term sovereign bond yields decrease due to market participants going long on Treasury-Bills and Treasury-Notes, putting upward pressure on prices and decreasing yields. A clearer picture is drawn by close examination of the short-run relationship. The statistically significant and positive coefficients associated with changes in GPT imply a probable proactive long position in both Treasury-Bills and Treasury-Notes. This is a clear manifestation of depressed risk appetites often improving the price of long-term bonds and causing yields to fall. Whereas, the negative coefficient of roughly a third of the magnitude associated with previous changes in GPT implies a relatively quicker attenuation of GPT shocks on Treasury-Notes than Treasury-Bills in the short-term. Hence, the associated statistically significant and negative long-run coefficients are to be interpreted as a gradual or partial unwinding of previously held positions. When contrasted with results of the remaining Treasury securities groups, the empirical findings show lower GPT coefficients pertaining to sub-portfolios with longer average remaining time-to-maturities. This has an impact on both the 'slope' and 'curvature', shoring up the flattening of the yield curve. In fact, a closer look at the short-run relationship, notably the change in the second factor that loads heavily on interest rate spreads, reveals statistically significant negative coefficients across the entire board, a totally expected phenomena. There is an inverse relationship between an increase in the yield spread and a drop in bond prices and consequently returns. In conjunction with well-grounded inflationary concerns,⁸ this could prompt monetary policy makers to take additional measures, starting with the tapering of large-scale asset purchases. A close investigation of the short-term relationship related to the change in the eighth factor that loads on variables relating to the stock market, shows statistically significant positive coefficients across the entire board of sub-portfolios. It is well acknowledged that, amid concerns that the Federal Reserve may take a more aggressive stance to combat soaring prices, stock markets probably retreat, a move that raises the risk of pushing the economy toward recession. It is worth mentioning that 5-year yields, which are more sensitive to imminent monetary policy decisions, usually rise with dollar. Any failure to act promptly, i.e. if effective monetary policy adjustments are not undertaken within the available window to keep inflation expectations well-anchored, would probably lead to an inversion in the yield curve, and turn a transitory inflation characterization into a policy mistake with widespread and unnecessary damage, sending real yield into negative territory.

However, when the GPR index surges, sovereign bond yields increase, due to the fact that market participants, both institutional and retail investors, are going short on Treasury-Bills, Treasury-Notes and Treasury-Bonds, putting downward pressure on prices and consequently sending yields to the upside in the long-run. According to our empirical findings, the statistically significant negative coefficients, ranging from negative 0.003 to negative 0.024 are clearly showing a decreasing trend in negative territory with longer-dated US Treasuries. In fact, this is attributable to the fact that when GPR surges, longer-dated securities suffer the most from that bearish shift, pushing their yields higher by more than those at the short end, and consequently widening the spread between the two. It is worth mentioning that this bearish shift can occur while the curve is either steepening or flattening. This 'bull steepening' of the yield curve occurs, when the Federal Reserve holds rates steady at low levels but other forces – mainly geopolitical political frictions (GPR and GPA) – weigh on growth prospects, or tepid inflation encourages the buying of longer-term Treasury Inflation Protected Securities (TIPS) instead. A thorough examination of [Table 2](#), from short- to long-term relationships, provides a complete picture. Notably, positive coefficients associated with previous changes in GPT and GPR, reveal a crucial property pertaining to the short-term nature of the associated shocks, the relatively long-lasting GPR and GPT short-term shocks. This might be

explained by the nature of market uncertainty caused by geopolitical tensions and threats. This probably implies a short-term proactive long position to the unwinding of pre-held long-term positions in US Treasury markets. Such a change in the front end of the yield curve leads to a deleveraging of much traditional fixed income relative value and carry-focused strategies globally. This suggests that market participants, including hedge funds, proactively reduced risk exposure. However, when losses instigated by the rise in front-end of the curve are not endured, the unwinding of short positions in the long-end is much slower than for US Treasuries with a remaining time-to-maturity of 10 years. This phenomenon fosters the flattening effect. Hence, negative long-run coefficients are the concretization of a gradual ‘flight to quality’ or ‘flight to safety’ during persisting periods of high uncertainty, buttressed by the buy-back bias toward shorter-term sovereign bonds.

Generally, off-the-run short-term yields tend to rise when the Federal Reserve is expected to raise interest rates, and tend to fall when the Federal Open Market Committee (FOMC) is expected to cut rates. US Federal Reserve policymakers may, infrequently, give markets a better steer on how long they will continue to buy bonds to provide support to an economy struggling to recover from a historic recession or deeply affected by an exogenous event. This case often occurs when a quantitative easing (QE) programme is put in place, or after a yield curve control (YCC) strategy is considered after bringing short-term rates into negative territory or near zero has not been successfully stimulating. It is worth mentioning that under YCC, the Federal Reserve targets some longer-term rates and pledges to buy enough long-term bonds to keep the rate from rising above its target. Hence, the central bank commits to purchase whatever amount of bonds market participants want to supply at its target price. Once bond markets internalize the central bank’s commitment, the target price becomes the market price. In fact, when US Federal Reserve policymakers and staff considered potential unconventional policy options to reduce long-term rates in late 2008, they looked back at the 1942–1947 YCC experience as evidence that asset purchases or other similar policies could be a suitable instrument of monetary policy.

Global GPR makes policymakers worried about downside economic risks, notably with diminished odds for further significant fiscal support. It is agreed among US central bankers that asset purchases provide accommodation for the economy and serve as ‘insurance’ against the economic hardship that could emerge due to uncertainty.

Furthermore, some market participants think the Federal Reserve could provide more accommodation by lengthening the maturity of the securities purchased or increasing the pace of purchases, according to FOMC deliberations.⁹ Such an accommodation can strengthen the output results and provide a rationale. However, if huge quantities of cheap funds flood the market as a form of government support, and if repurchase transactions step in to relieve investor anxiety, mixed signals appear. Notably, such a form of government support would be more related to credit risk events and liquidity shortages which sour market sentiment and induce spillover effects in interbank yields.

The results reported in the Appendix [Table A1](#) show that our main results on the short- and long-run effects of GPR on the returns of US Treasury securities remain qualitatively unchanged when we use various sub-sample analyses covering the period November 1961 to December 2018.

GPR and the Realized Volatility of US Treasury Securities

In this section, we empirically investigate the impact of geopolitical risk (GPR) as measured by Caldara and Iacoviello (2022) on the realized volatilities of various Treasury securities groups (or sub-portfolios), clustered by their remaining time-to-maturities. The results of the ARDL models covering the full sample period (March 1986 to December 2018) are presented in [Table 3](#). They mainly show the extreme statistical significance of all negative error-correction or speed of adjustment coefficients, which indicates the existence of a positive and strong long-run relationship between the US Treasuries’ realized volatilities and the various geopolitical risk measures.

Table 3. GPR and the realized volatility of US Treasury securities

a) Realized Volatility and US Treasury Securities																								
RV MODEL	Group 1: maturity 1Y-5Y				Group 2: maturity 6Y-10Y				Group 3: maturity 11Y-15Y				Group 4: maturity 16Y-20Y				Group 5: maturity 21Y-25Y				Group 6: maturity 26Y-30Y			
Dependent Variable: Δrv																								
Variable	Coefficient (P-value)	Model (1)	Coefficient (P-value)	Model (2)	Coefficient (P-value)	Model (3)	Coefficient (P-value)	Model (4)	Coefficient (P-value)	Model (5)	Coefficient (P-value)	Model (6)	Coefficient (P-value)	Model (7)	Coefficient (P-value)	Model (8)	Coefficient (P-value)	Model (9)	Coefficient (P-value)	Model (10)	Coefficient (P-value)	Model (11)	Coefficient (P-value)	Model (12)
Long Run Relationship (ECT)																								
ΔLnGPR / ΔLnGPT	0.002 (0.000)		0.004 (0.000)	0.049 (0.000)	0.195 (0.000)	0.157 (0.000)	0.188 (0.000)	0.347 (0.000)	-1.893 (0.000)	0.091 (0.000)	0.177 (0.000)	0.580 (0.000)	0.620 (0.000)											
ΔLnGPA			0.004 (0.000)		0.145 (0.000)		0.120 (0.000)		0.373 (0.000)		0.161 (0.000)		0.467 (0.000)											
mm3rv	0.569 (0.000)		0.570 (0.000)	0.595 (0.000)	0.598 (0.000)	0.633 (0.000)	0.636 (0.000)	0.674 (0.000)	0.675 (0.000)	0.709 (0.000)	0.709 (0.000)	0.703 (0.000)	0.702 (0.000)											
mm12rv	0.374 (0.000)		0.373 (0.000)	0.341 (0.000)	0.338 (0.000)	0.308 (0.000)	0.306 (0.000)	0.279 (0.000)	0.278 (0.000)	0.254 (0.000)	0.253 (0.000)	0.261 (0.000)	0.262 (0.000)											
Short Run Relationship																								
ECT	(1.280) (0.000)	-1.280 (0.000)	-1.264 (0.000)	-1.263 (0.000)	-1.249 (0.000)	-1.248 (0.000)	-1.247 (0.000)	-1.246 (0.000)	-1.243 (0.000)	-1.244 (0.000)	-1.253 (0.000)	-1.253 (0.000)	-1.253 (0.000)											
ΔLnGPR / ΔLnGPT	(0.003) (0.000)	-0.005 (0.000)	-0.062 (0.000)	-0.246 (0.000)	-0.196 (0.000)	-0.234 (0.000)	-0.433 (0.000)	2.359 (0.000)	-0.113 (0.000)	-0.220 (0.000)	-0.726 (0.000)	-0.726 (0.000)	-0.776 (0.000)											
LΔLnGPR) /Δ(LnGPT)	0.000 (0.020)	0.000 (0.060)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.080)	0.000 (0.370)	0.000 (0.370)	0.000 (0.370)											
ΔLnGPA		-0.005 (0.000)		-0.184 (0.000)		-0.150 (0.000)	0.907 (0.000)	-0.465 (0.000)		-0.200 (0.000)	-0.585 (0.000)		-0.585 (0.000)											
Δ(LnGPA)		0.000 (0.040)			0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)											
Δmm3rv	0.835 (0.000)	0.837 (0.000)	0.898 (0.000)	0.899 (0.000)	0.894 (0.000)	0.893 (0.000)	0.893 (0.000)	0.905 (0.000)	0.927 (0.000)	0.926 (0.000)	0.921 (0.000)	0.921 (0.000)	0.922 (0.000)											
Δmm12rv	2.678 (0.000)	2.659 (0.000)	2.398 (0.000)	2.361 (0.000)	2.164 (0.000)	2.134 (0.000)	1.881 (0.000)	1.860 (0.000)	1.582 (0.000)	1.576 (0.000)	1.633 (0.000)	1.633 (0.000)	1.641 (0.000)											
Constant	0.000 (0.020)	0.000 (0.020)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)											
(Continued)																								

(Continued)

Table 3. (Continued).

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)	Model (12)
<i>Long Run Relationship (ECT)</i>												
$\Delta \text{LnGPR} / \Delta \text{LnGPT}$	0.001 (0.000)	-0.003 (0.000)	0.023 (0.000)	0.013 (0.000)	0.174 (0.000)	0.324 (0.000)	-0.114 (0.000)	-0.066 (0.000)	0.048 (0.000)	0.107 (0.000)	0.075 (0.000)	0.119 (0.000)
ΔLnGPA		0.001 (0.000)		0.019 (0.000)		0.282 (0.000)		-0.156 (0.000)		0.045 (0.000)		0.100 (0.000)
mm3brv	0.593 (0.000)	0.595 (0.000)	0.619 (0.000)	0.621 (0.000)	0.623 (0.000)	0.624 (0.000)	0.646 (0.000)	0.647 (0.000)	0.685 (0.000)	0.685 (0.000)	0.693 (0.000)	0.692 (0.000)
mm12brv	0.347 (0.000)	0.344 (0.000)	0.320 (0.000)	0.317 (0.000)	0.316 (0.000)	0.314 (0.000)	0.301 (0.000)	0.299 (0.000)	0.273 (0.000)	0.273 (0.000)	0.270 (0.000)	0.270 (0.000)
<i>Short Run Relationship</i>												
ECT	-1.302 (0.000)	-1.303 (0.000)	-1.302 (0.000)	-1.301 (0.000)	-1.291 (0.000)	-1.291 (0.000)	-1.277 (0.000)	-1.278 (0.000)	-1.263 (0.000)	-1.264 (0.000)	-1.249 (0.000)	-1.245 (0.000)
$\Delta \text{LnGPR} / \Delta \text{LnGPT}$	-0.001 (0.000)	0.003 (0.000)	-0.030 (0.000)	-0.017 (0.000)	-0.224 (0.000)	-0.419 (0.000)	0.146 (0.000)	0.084 (0.000)	-0.061 (0.000)	-0.135 (0.000)	-0.093 (0.000)	-0.149 (0.000)
$\text{L}(\Delta \text{LnGPR}) \Delta (\text{LnGPT})$	0.000 (0.440)	0.000 (0.810)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.010)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.800)
ΔLnGPA		-0.001 (0.000)		-0.025 (0.000)		-0.364 (0.000)		0.200 (0.000)		-0.057 (0.000)		-0.124 (0.000)
$\Delta (\text{LnGPA})$		0.000 (0.480)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)
Δmm3brv	0.887 (0.000)	0.882 (0.000)	0.924 (0.000)	0.920 (0.000)	0.910 (0.000)	0.905 (0.000)	0.893 (0.000)	0.889 (0.000)	0.882 (0.000)	0.880 (0.000)	0.858 (0.000)	0.855 (0.000)
$\Delta \text{mm12brv}$	2.395 (0.000)	2.393 (0.000)	2.190 (0.000)	2.179 (0.000)	2.230 (0.000)	2.230 (0.000)	2.073 (0.000)	2.074 (0.000)	1.765 (0.000)	1.765 (0.000)	1.740 (0.000)	1.748 (0.000)
Constant	0.000 (0.020)	0.000 (0.020)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

Δ is the first difference. rv is the first difference of the realized volatility. $\text{nGPR}|\text{LnGPT}$, and LnGPA represent the rate of change of GPR, GPT and GPA, respectively. LnGPR , L , and LnGPA represent the lagged values of the rate of change of GPR, GPT, GPA, mm3brv and mm12brv are the 3- and 12-month moving average of the realized volatility, respectively. mm3brv and mm12brv are the first difference of the rate of change of GPR, GPT and GPA, respectively. LnGPR , LnGPA represent the rate of change of GPR, GPT and GPA, respectively. LnGPR , LnGPT , and $\text{L}(\text{LnGPA})$ represent the lagged values of the rate of change of GPR, GPT, GPA, mm3brv and mm12brv are the 3- and 12-month moving average of the good realized volatility, respectively. mm3brv and mm12brv are the first difference of mm3brv and mm12brv , respectively. Δ is the first difference. rv is the first difference of the realized volatility. $\text{nGPR}|\text{LnGPT}$, and LnGPA represent the rate of change of GPR, GPT and GPA, respectively. LnGPR , L , and LnGPA represent the lagged values of the rate of change of GPR, GPT, GPA, mm3brv and mm12brv are the 3- and 12-month moving average of the bad realized volatility, respectively. mm3brv and mm12brv are the first difference of mm3brv and mm12brv , respectively. Δ is the first difference. rv is the first difference of the realized volatility. $\text{nGPR}|\text{LnGPT}$, and LnGPA represent the rate of change of GPR, GPT and GPA, respectively. LnGPR , L , and LnGPA represent the lagged values of the rate of change of GPR, GPT, GPA, mm3brv and mm12brv are the 3- and 12-month moving average of the bad realized volatility, respectively. mm3brv and mm12brv are the first difference of mm3brv and mm12brv , respectively.

Furthermore, after controlling for both the 3-month and 12-month moving average of realized volatility, the reported results confirm the existence of a very strong long-run relationship between sovereign bonds' realized volatilities and the global GPR index across all Treasury security clusters. Models (1), (3), (5), (7), and (9) show positive GPR coefficients with an extreme statistical significance at the 1 percent level, with values ranging from 0.002 to 0.58, and snowballing in positive territory with increasing remaining time-to-maturity.

Next, we estimate the results, differentiating between the two components of the GPR index, GPA and GPT, given in [Table 3](#). Put another way, disentangling the direct effect of adverse geopolitical events from the effect of geopolitical risks by substituting GPA and GPT, reveals a positively and strong long-run relationship between Treasury securities' realized volatilities and the GPA index, along the entire yield curve. Models (2), (4), (6), (8), (10), and (12) show that the coefficients of GPA are similarly positive with extreme statistical significance at the 1 percent level, ranging from positive 0.004 to positive 0.467. For the GPT index, [Table 3](#) shows a positive long-run relationship with Treasury-Bonds' realized volatilities with maturities along the entire yield curve, with the exception of those with remaining time-to-maturity of between 16 and 20 years.

A closer look at the short-run relationship section of [Table 3](#) reveals that the negative coefficients associated with previous changes in the natural logarithm of GPT and those of GPR over the entire yield curve, show a vital property pertaining to the short-term nature of the associated shocks with respect to realized volatility. Negative coefficients that are consistent with market uncertainty, as instigated by geopolitical tensions and threats, imply a proactive exposure reduction to, or the unwinding of, pre-held positions in the US Treasury markets, sending prices down and lowering short-term realized volatility along the entire yield curve.

The results reported in the Appendix [Table A2](#) show that our main results for the short- and long-run effects of the GPR on the realized volatility of US Treasury securities remain qualitatively unchanged when we use various sub-sample analyses, and disentangle 'bad' from 'good' realized volatilities.

In the energy market, the impact of geopolitical uncertainty is likely to be transmitted through threats to adverse geopolitical events relative to their realizations, as mentioned by Liu, Han, and Xu (2021), who find the impact of GPA on long-run volatilities to be slight and insignificant. However, we find that, for US Treasuries, the impact of geopolitical risk is transmitted through threats to adverse geopolitical events as well as through their realizations, and with similar intensities. Given the paramount importance policymakers and investors put on the 2-year US Treasury yield, which typically moves in step with interest rate expectations, as well as the gap between the former and 10-year US Treasury-Notes, which is seen as a prominent indicator of economic expectations, geopolitical risk significantly influences US sovereign bond market volatility cross the entire yield curve and may lead to changes in the expectations of major participants.

Compared to Liu et al. (2019), who find the lags of long-run realized volatilities to have a significant positive impact on the long-run component of WTI oil volatility, our results reveal statistically significant long-run 3-month- and 12-month-moving averages of realized volatilities with a positive impact on the long-run component of US securities' realized volatilities across the entire yield curve. Furthermore, we find that long-run 3-month-moving averages of bad realized volatilities have slightly higher positive impacts on the long-run component of US securities' realized volatilities across the entire yield curve relative to the long-run 3-month-moving averages of good realized volatilities. The reverse is found for long-run 12-month-moving averages of realized volatilities, except for the long end of the yield curve. These findings support the presence of an asymmetric effect of realized volatility in US Treasury markets, which is not covered in the academic literature. This may reshape investors and policymakers' decisions, which makes GPR, GPA, and GPT capable of influencing interest rate and economic expectations, financial market behaviours and subsequent business cycles. Our findings are in line with those of Fernández-Villaverde et al. (2011), who present empirical evidence that the volatility of the real interest rates at which small open emerging economies borrow have an important effect on the business cycle, and those of Cheng and Chiu

(2018), who find that shocks to global geopolitical risk carry considerable business cycle implications for emerging economies, specifically significant economic contractions. However our findings also extend to the US Economy. Consequently, they enrich the broad international economics literature, which investigates the macroeconomic consequences of geopolitical risk, as well as the strand investigating the relationship between political uncertainty and the business cycle, as pioneered by Azzimonti and Talbert (2014) and Azzimonti (2018).

Conclusion

Geopolitical risk has been shown to influence financial markets mainly through its adverse effect on investment decisions. Recent studies relate geopolitical risk to risk premia. However, in the fixed-income literature, the academic debate remains silent on the potential effect of GPR on the returns and volatilities of US Treasuries and whether the impact is on the short-or long-run Treasury yield curve.

Using a rich monthly dataset covering the period February 1986 to December 2018, and accounting for the role of nine macro factors, we provide reasonable evidence to suggest the existence of a negative long-run association between sovereign bond returns and the global GPR index that holds along the entire yield curve. We also find evidence of a positive and strong long-run relationship between US Treasuries' realized volatilities and the various geopolitical risk measures. The evidence holds true when we disentangle 'bad' from 'good' realized volatilities, although it points to an asymmetric effect of realized volatility in US Treasury markets as evidenced by the stronger impact of bad volatility compared to good volatility. These findings are robust to a sub-sample analysis.

Our findings have implications for participants in the US Treasury markets. For investors, they imply the utility of paying attention to geopolitical risks in the context of predicting US Treasury returns and volatility as well as trading and risk management along the yield curve. For policymakers, such as decision-makers at the Federal Reserve, our findings provide a key message indicating that geopolitical risk and its components contain valuable information that should be considered when making monetary decisions that involve US Treasuries.

This current paper has certain limitations, reflected in its inability to consider the potential heterogeneous impacts of geopolitical risk across the distributions of US Treasury returns and volatilities. Therefore, a possible extension of our analysis would involve the use of a quantile-based approach to panel data revealing whether the impact is heterogeneous across upper, middle, and lower quantiles. Another extension would involve the examination of the impact of geopolitical risk in the context of government bond yields of European and Asian countries.

Notes

1. Another line of literature considers the predictability of the term structure of US interest rates based on crude oil uncertainty (Bouri et al. 2022) and risk aversion (Bouri et al. 2021).
2. <https://www.ft.com/content/6f198784-c938-4674-af6f-d760b18fcb2d>.
3. We refer the reader to Chudik et al. (2013).
4. Regarding the sum of coefficients and their standard errors, Chudik et al. (2016) propose two methods, the cross-sectionally augmented ARDL (CS-ARDL) and the cross-sectionally augmented distributed lag (CS-DL) estimator. An alternative method is an error correction model (ECM).
5. The Boston Globe, Chicago Tribune, Daily Telegraph, Financial Times, Globe and Mail, Guardian, Los Angeles Times, New York Times, Times, Wall Street Journal, and Washington Post.
6. The set extends that used by Stock and Watson (2005), which has since been used in a number of factor analyses, see, for example, Bai and Ng (2008) and De Mol, Giannone, and Reichlin (2008).
7. Some series need to be transformed to be stationary. In general, real variables are expressed in growth rates, first differences are used for nominal interest rates, and second log differences are used for prices.
8. A close examination of the short-run relationship, especially the third and fourth factors, which are strongly related to prices, reveals statistically significant negative coefficients across Treasury securities groups (or sub-

portfolios). It is well known that higher inflation induces higher required yield and negatively impacts Treasury security returns, hence the importance of inflation expectation being closely monitored by market participants, via either 5-year, 5 year forward contracts or 5-year forward 5-year interest rate swaps. The implications of this number go well beyond economics and finance, with important social and political implications.

9. We refer the reader to FOMC November 5th, 2020 meeting (<https://www.federalreserve.gov/monetarypolicy/fomcminutes20201105.htm>).

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APPENDIX

Table A1. GPR and the return of US Treasury securities - sub-sample analysis covering November 1961 to December 2018.

Sample	1961M11 2018M12			1971M12 2018M12			1972M03 2018M12			1981M10 2018M12			1986M03 2018M12		
Dependent Variable: $\Delta(Y)$	Maturity 01M - 84M			Maturity 85M - 120M			Maturity 121M - 180M			Maturity 181M - 240M			Maturity 241M - 360M		
Variable	Coefficient (P-value)	Model (1)	Model (2)	Coefficient (P-value)	Model (3)	Model (4)	Coefficient (P-value)	Model (5)	Model (6)	Coefficient (P-value)	Model (7)	Coefficient (P-value)	Model (8)	Coefficient (P-value)	Model (9)
<i>Long Run Relationship</i>															
RGPR RGPA	-0.005 (0.000)		-0.002 (0.000)	-0.025 (0.000)	-0.019 (0.000)	-0.019 (0.000)	-0.034 (0.000)	0.059 (0.000)	-0.016 (0.000)	-0.052 (0.000)	-0.034 (0.000)	-0.024 (0.000)	-0.025 (0.000)	-0.025 (0.000)	-0.025 (0.000)
RGPT			-0.001 (0.000)			-0.003 (0.050)			-0.018 (0.000)		-0.015 (0.000)			0.008 (0.000)	0.008 (0.000)
F1	0.025 (0.000)		0.024 (0.000)	0.057 (0.000)	0.057 (0.000)	0.057 (0.000)	0.059 (0.000)	0.059 (0.000)	0.063 (0.000)	0.110 (0.000)	0.110 (0.000)	0.074 (0.000)	0.073 (0.000)	0.073 (0.000)	0.073 (0.000)
F2	0.013 (0.000)		0.012 (0.000)	0.074 (0.000)	0.073 (0.000)	0.073 (0.000)	0.119 (0.000)	0.119 (0.000)	0.096 (0.000)	0.142 (0.000)	0.146 (0.000)	0.202 (0.000)	0.205 (0.000)	0.205 (0.000)	0.205 (0.000)
F3	0.003 (0.000)		0.002 (0.000)	-0.029 (0.000)	-0.028 (0.000)	-0.028 (0.000)	-0.049 (0.000)	-0.049 (0.000)	-0.025 (0.000)	-0.054 (0.000)	-0.059 (0.000)	-0.025 (0.000)	-0.026 (0.000)	-0.026 (0.000)	-0.026 (0.000)
F4	0.057 (0.000)		0.058 (0.000)	0.174 (0.000)	0.174 (0.000)	0.174 (0.000)	0.221 (0.000)	0.221 (0.000)	0.207 (0.000)	0.277 (0.000)	0.278 (0.000)	0.360 (0.000)	0.363 (0.000)	0.363 (0.000)	0.363 (0.000)
F5	-0.038 (0.000)		-0.038 (0.000)	-0.119 (0.000)	-0.119 (0.000)	-0.119 (0.000)	-0.143 (0.000)	-0.143 (0.000)	-0.139 (0.000)	-0.168 (0.000)	-0.169 (0.000)	-0.201 (0.000)	-0.201 (0.000)	-0.201 (0.000)	-0.201 (0.000)
F6	-0.004 (0.000)		-0.003 (0.000)	-0.021 (0.000)	-0.021 (0.000)	-0.021 (0.000)	-0.036 (0.000)	-0.036 (0.000)	-0.040 (0.000)	-0.088 (0.000)	-0.087 (0.000)	-0.092 (0.000)	-0.091 (0.000)	-0.091 (0.000)	-0.091 (0.000)
F7	0.024 (0.000)		0.025 (0.000)	0.063 (0.000)	0.064 (0.000)	0.064 (0.000)	0.044 (0.000)	0.044 (0.000)	0.075 (0.000)	0.027 (0.000)	0.027 (0.000)	0.096 (0.000)	0.091 (0.000)	0.091 (0.000)	0.091 (0.000)
F8	0.006 (0.000)		0.008 (0.000)	0.015 (0.000)	0.015 (0.000)	0.015 (0.000)	-0.007 (0.090)	-0.007 (0.090)	-0.006 (0.160)	0.035 (0.000)	0.032 (0.000)	0.116 (0.000)	0.116 (0.000)	0.116 (0.000)	0.116 (0.000)
F9	-0.001 (0.000)		-0.001 (0.000)	0.002 (0.010)	0.002 (0.010)	0.002 (0.010)	0.015 (0.000)	0.015 (0.000)	0.013 (0.000)	-0.012 (0.000)	-0.011 (0.000)	-0.012 (0.000)	-0.011 (0.000)	-0.011 (0.000)	-0.011 (0.000)
<i>Short Run Relationship</i>															
Δ COINTEQ01	-1.218 (0.000)		-1.214 (0.000)	-1.555 (0.000)	-1.553 (0.000)	-1.553 (0.000)	-1.292 (0.000)	-1.292 (0.000)	-1.381 (0.000)	-1.305 (0.000)	-1.302 (0.000)	-1.203 (0.000)	-1.201 (0.000)	-1.201 (0.000)	-1.201 (0.000)

(Continued)

Table A1. (Continued).

Sample	1961M11 2018M12			1971M12 2018M12			1972M03 2018M12			1981M10 2018M12			1986M03 2018M12																			
Dependent Variable: Δ(Y)	Maturity 01M - 84M			Maturity 85M - 120M			Maturity 121M - 180M			Maturity 181M - 240M			Maturity 241M - 360M																			
	Coefficient (P-value)	Coefficient (P-value)	Model (1)	Coefficient (P-value)	Coefficient (P-value)	Model (2)	Coefficient (P-value)	Coefficient (P-value)	Model (3)	Coefficient (P-value)	Coefficient (P-value)	Model (4)	Coefficient (P-value)	Coefficient (P-value)	Model (5)	Coefficient (P-value)	Coefficient (P-value)	Model (6)	Coefficient (P-value)	Coefficient (P-value)	Model (7)	Coefficient (P-value)	Coefficient (P-value)	Model (8)	Coefficient (P-value)	Coefficient (P-value)	Model (9)	Coefficient (P-value)	Coefficient (P-value)	Model (10)		
Variable																																
Δ (M(-1))									0.396 (0.000)			0.396 (0.000)																				
ΔΔ (M(-2))																																
Δ (RGPR RGPA)	0.004 (0.000)	-0.001 (0.000)		0.023 (0.000)	-0.002 (0.000)																											
Δ (RGPR(-1) RGPA (-1))	-0.001 (0.000)	0.000		0.002 (0.000)	0.000																											
Δ (RGPA(-2))	(0.000)	(0.000)		(0.000)	(0.000)																											
Δ (RGPT)		0.005 (0.000)			0.023 (0.000)																											
Δ (RGPT(-1))		-0.001 (0.000)			0.001 (0.000)																											
Δ (RGPT(-2))		(0.000)			(0.000)																											
Δ (F1)	0.033 (0.000)	0.033 (0.000)		0.058 (0.000)	0.059 (0.000)																											
Δ (F1(-1))	0.013 (0.000)	0.012 (0.000)		0.015 (0.000)	0.013 (0.000)																											
Δ (F1(-2))																																
Δ (F2)	-0.038 (0.000)	-0.039 (0.000)		-0.205 (0.000)	-0.205 (0.000)																											
Δ (F2(-1))	-0.010 (0.000)	-0.009 (0.000)		-0.093 (0.000)	-0.092 (0.000)																											
Δ (F2(-2))																																
Δ (F3)	-0.034 (0.000)	-0.034 (0.000)		-0.090 (0.000)	-0.091 (0.000)																											
Δ (F3(-1))	-0.011 (0.000)	-0.011 (0.000)		-0.050 (0.000)	-0.051 (0.000)																											

(Continued)



Table A1. (Continued).

Sample	1961M11 2018M12			1971M12 2018M12			1972M03 2018M12			1981M10 2018M12			1986M03 2018M12		
Dependent Variable:	Maturity 01M - 84M			Maturity 85M - 120M			Maturity 121M - 180M			Maturity 181M - 240M			Maturity 241M - 360M		
Variable	Model (1)	Coefficient (P-value)	Model (2)	Model (3)	Coefficient (P-value)	Model (4)	Model (5)	Coefficient (P-value)	Model (6)	Coefficient (P-value)	Model (7)	Coefficient (P-value)	Model (8)	Coefficient (P-value)	Model (9)
Δ (F3(-2))															
Δ (F4)	0.014 (0.000)	0.014 (0.000)		-0.150 (0.000)	-0.150 (0.000)	-0.150 (0.000)	-0.161 (0.000)	-0.158 (0.000)	-0.158 (0.000)	-0.198 (0.000)	-0.198 (0.000)	-0.206 (0.000)	-0.060 (0.000)	-0.080 (0.000)	
Δ (F4(-1))	0.035 (0.000)	0.035 (0.000)		-0.022 (0.000)	-0.022 (0.000)	-0.019 (0.000)	0.009 (0.000)	0.061 (0.000)	0.061 (0.000)						
Δ (F4(-2))								0.126 (0.000)	0.126 (0.000)						
Δ (F5)	-0.056 (0.000)	-0.056 (0.000)		-0.147 (0.000)	-0.147 (0.000)	-0.148 (0.000)	-0.252 (0.000)	-0.263 (0.000)	-0.263 (0.000)	-0.484 (0.000)	-0.484 (0.000)	-0.496 (0.000)	-0.400 (0.000)	-0.420 (0.000)	
Δ (F5(-1))	0.019 (0.000)	0.021 (0.000)		-0.015 (0.000)	-0.015 (0.000)	-0.010 (0.000)	0.012 (0.000)	0.037 (0.000)	0.037 (0.000)						
Δ (F5(-2))								0.086 (0.000)	0.086 (0.000)						
Δ (F6)	0.058 (0.000)	0.056 (0.000)		0.171 (0.000)	0.171 (0.000)	0.170 (0.000)	0.231 (0.000)	0.239 (0.000)	0.239 (0.000)	0.347 (0.000)	0.347 (0.000)	0.345 (0.000)	0.403 (0.000)	0.395 (0.000)	
Δ (F6(-1))	0.017 (0.000)	0.017 (0.000)		0.059 (0.000)	0.059 (0.000)	0.059 (0.000)	0.070 (0.000)	0.107 (0.000)	0.107 (0.000)						
Δ (F6(-2))								0.053 (0.000)	0.053 (0.000)						
Δ (F7)	-0.011 (0.000)	-0.011 (0.000)		-0.100 (0.000)	-0.100 (0.000)	-0.099 (0.000)	-0.099 (0.000)	-0.141 (0.000)	-0.141 (0.000)	-0.141 (0.000)	-0.141 (0.000)	-0.138 (0.000)	-0.101 (0.000)	-0.083 (0.000)	
Δ (F7(-1))	0.015 (0.000)	0.015 (0.000)		-0.021 (0.000)	-0.021 (0.000)	-0.021 (0.000)	0.003 (0.000)	-0.033 (0.000)	-0.033 (0.000)						
Δ (F7(-2))								-0.013 (0.000)	-0.013 (0.000)						
Δ (F8)	0.016 (0.000)	0.014 (0.000)		0.041 (0.000)	0.041 (0.000)	0.038 (0.000)	0.086 (0.000)	0.091 (0.000)	0.091 (0.000)	0.083 (0.000)	0.083 (0.000)	0.076 (0.000)	0.093 (0.000)	0.098 (0.000)	
Δ (F8(-1))	0.005 (0.000)	0.003 (0.000)		-0.001 (0.000)	-0.001 (0.000)	-0.002 (0.000)	-0.006 (0.000)	0.020 (0.000)	0.020 (0.000)						
Δ (F8(-2))								0.029 (0.000)	0.029 (0.000)						
Δ (F9)	0.009	0.008		0.011	0.010	0.010	0.014	0.012	0.012	0.066	0.066	0.062	0.076	0.072	(Continued)



Table A1. (Continued).

Sample	1961M11 2018M12			1971M12 2018M12			1972M03 2018M12			1981M10 2018M12			1986M03 2018M12		
Dependent Variable: $\Delta(Y)$															
	Maturity 01M - 84M			Maturity 85M - 120M			Maturity 121M - 180M			Maturity 181M - 240M			Maturity 241M - 360M		
	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	Coefficient (P-value)	
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)					
$\Delta(F9(-1))$	(0.000) -0.001 (0.000)	(0.000) -0.001 (0.000)	(0.000) -0.007 (0.000)	(0.000) -0.005 (0.000)	(0.000) -0.023 (0.000)	(0.000) -0.019 (0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
$\Delta(F9(-2))$						0.007 (0.000)									
Constant	0.000 (0.360)	0.001 (0.000)	0.002 (0.000)	0.002 (0.000)	0.002 (0.000)	0.005 (0.000)	0.025 (0.000)	0.025 (0.000)	0.007 (0.000)	0.007 (0.000)					
@TREND	0.000 (0.000)				0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)					
Mean dependent variable	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
S.E. of regression	0.010	0.010	0.020	0.020	0.030	0.030	0.040	0.040	0.050	0.050					
SSR	5.630	5.620	7.110	7.080	30.480	28.960	40.180	39.880	100.810	99.200					
Log likelihood	203007.000	203125.000	52283.000	52320.000	71354.000	72055.000	49431.000	49527.000	78871.000	79242.000					
Std. dependent variable	0.020	0.020	0.040	0.040	0.060	0.060	0.080	0.080	0.080	0.080					
AIC	-6.960	-6.960	-5.040	-5.040	-4.130	-4.120	-3.620	-3.620	-3.260	-3.270					
BIC	-6.660	-6.640	-4.720	-4.680	-3.790	-3.550	-3.380	-3.360	-2.970	-2.960					
HQC	-6.860	-6.860	-4.930	-4.920	-4.020	-3.940	-3.540	-3.540	-3.170	-3.170					

Table A2. GPR and realized volatility of US Treasury securities - sub-samples analysis

a) Realized Volatility and US Treasury Securities																			
RV MODEL	SMPL 5: 21y-30y ≥1986m10				SMPL 1 1y-7y ≥1962m5				SMPL 2 8y-10y ≥ 1972m7				SMPL 2 8y-10y ≥ 1972m7				SMPL 4 16y-20y ≥ 1982m6		
Dependent Variable: Δrv																			
Variable	Model (13)	Coefficient (P-value)	Model (14)	Coefficient (P-value)	Model (15)	Coefficient (P-value)	Model (16)	Coefficient (P-value)	Model (17)	Coefficient (P-value)	Model (18)	Coefficient (P-value)	Model (19)	Coefficient (P-value)	Model (20)	Coefficient (P-value)	Model (21)	Coefficient (P-value)	
Long Run Relationship (ECT)																			
ΔLnGPR / ΔLnGPT	0.172 (0.000)		0.321 (0.000)		0.009 (0.000)		0.017 (0.000)		0.289 (0.000)		0.567 (0.000)		0.519 (0.000)		2.752 (0.000)		0.009 (0.000)		0.017 (0.000)
ΔLnGPA			0.272 (0.000)				0.036 (0.000)				0.284 (0.000)				1.645 (0.000)				0.010 (0.000)
mm3rv	0.706 (0.000)		0.705 (0.000)		0.597 (0.000)		0.596 (0.000)		0.658 (0.000)		0.656 (0.000)		0.680 (0.000)		0.679 (0.000)		0.752 (0.000)		0.751 (0.000)
mm12rv	0.257 (0.000)		0.258 (0.000)		0.376 (0.000)		0.376 (0.000)		0.317 (0.000)		0.318 (0.000)		0.293 (0.000)		0.294 (0.000)		0.232 (0.000)		0.233 (0.000)
Short Run Relationship (ECT)																			
ECT	(1.248) (0.000)		(1.248) (0.000)		(1.258) (0.000)		(1.258) (0.000)		(1.259) (0.000)		(1.259) (0.000)		(1.278) (0.000)		(1.278) (0.000)		(1.276) (0.000)		(1.276) (0.000)
ΔLnGPR / ΔLnGPT	(0.215) (0.000)		(0.401) (0.000)		(0.012) (0.000)		0.021 (0.000)		(0.364) (0.000)		(0.714) (0.000)		(0.664) (0.000)		(3.517) (0.000)		0.012 (0.000)		0.021 (0.000)
L(ΔLnGPR) / L(ΔLnGPT)	0.000 (0.000)		0.000 (0.640)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)		0.000 (0.150)		0.000 (0.000)
ΔLnGPA			(0.340)				0.045		(0.357)		(0.357)				(2.102)				0.013

(Continued)

Table A2. (Continued).

<i>Short Run Relationship (ECT)</i>												
ECT	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	(1.256)	(1.255)	(1.263)	(1.088)	(1.319)	(1.319)	(1.319)	(1.348)	(1.347)	(1.254)	(1.254)	(1.254)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta \text{LnGPR} / \Delta \text{LnGPT}$	(0.065)	(0.086)	0.041	(0.003)	(0.167)	(0.239)	(0.973)	(1.028)	0.012	0.018	0.018	0.018
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$L(\Delta \text{LnGPR}) / L(\Delta \text{LnGPT})$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.020)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔLnGPA		(0.060)		0.102		0.963	(0.514)			0.014		0.014
		(0.000)		(0.000)		(0.000)	(0.000)			(0.000)		(0.000)
$L(\Delta \text{LnGPA})$		0.000		0.000		0.000	0.000			0.000		0.000
		(0.600)		(0.020)		(0.000)	(0.000)			(0.000)		(0.000)
Δmm3brv	0.870	0.867	0.913	0.900	0.901	0.904	0.918	0.919	0.894	0.894	0.894	0.894
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta \text{mm12brv}$	1.752	1.756	2.681	2.788	2.495	2.499	2.439	2.449	1.718	1.726	1.726	1.726
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Δ is the first difference. Δgrv is the first difference of the good realized volatility. ΔLnGPR , ΔLnGPT , and ΔLnGPA represent the rate of change of GPR, GPT and GPA, respectively. $L(\Delta \text{LnGPR})$, $L(\Delta \text{LnGPT})$, and $L(\Delta \text{LnGPA})$ represent the lagged values of the rate of change of GPR, GPT, GPA, respectively. mm3grv and $\Delta \text{mm12grv}$ are the first difference of mm3grv and mm12grv , respectively. Δ is the first difference. Δrv is the first difference of the realized volatility. ΔLnGPR , ΔLnGPT , and ΔLnGPA represent the rate of change of GPR, GPT and GPA, respectively. $L(\Delta \text{LnGPR})$, $L(\Delta \text{LnGPT})$, and $L(\Delta \text{LnGPA})$ represent the lagged values of the rate of change of GPR, GPT, GPA, respectively. mm3rv and mm12rv are the first difference of mm3rv and mm12rv , respectively. Δ is the first difference. Δbrv is the first difference of the bad realized volatility. ΔLnGPR , ΔLnGPT , and ΔLnGPA represent the rate of change of GPR, GPT and GPA, respectively. $L(\Delta \text{LnGPR})$, $L(\Delta \text{LnGPT})$, and $L(\Delta \text{LnGPA})$ represent the lagged values of the rate of change of GPR, GPT, GPA, respectively. mm3brv and mm12brv are the 3- and 12-month-moving average of the bad realized volatility, respectively. Δmm3brv and $\Delta \text{mm12brv}$ are the first difference of mm3brv and mm12brv , respectively.