High-Frequency Movements of the Term Structure of Interest Rates of the United States: The Role of Oil Market Uncertainty

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Abstract

Using daily data from 3rd January, 2001 to 17th July, 2020, we analyse the impact of oil market uncertainty, computed based on realized volatility of 5-minute intraday oil returns, on the level, slope and curvature factors derived from the term structure of interest rates of the United States (US) covering maturities of 1 to 30 years. The results of the linear Granger causality tests detect no evidence of predictability of oil uncertainty on the three latent factors. However, evidence of nonlinearity and structural breaks indicates misspecification of the linear model. Accordingly, we use a data-driven approach, the nonparametric causality in-quantiles test, which is robust to misspecification due to nonlinearity and regime change. Notably, this test allows us to model the entire conditional distribution of the level, slope and curvature factors, and hence accommodate, via the lower quantiles, the zero lower bound situation observed in our sample period. Using this robust test, we find overwhelming evidence of causality from oil uncertainty for the entire conditional distribution of the three factors, suggesting the predictability of the entire US term structure based on information contained in oil market volatility. Our results have important implications for academics, investors and policymakers.

Keywords: US Term Structure of Interest Rates; Yield Curve Factors; Oil Market Uncertainty; Causality-in-Quantiles Test

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1. Introduction

Existing theories of investment under uncertainty and real options predict that uncertainty, such as oil price uncertainty, induces optimizing firms to postpone investment decisions (Phan et al., 2019), thereby leading to a decline in aggregate output (see for example, Bernanke (1983), Dixit and Pindyck (1994), and more recently, Bloom (2009)). Empirical evidence in favour of this line of reasoning, i.e., recessionary impact of oil price uncertainty, for the economy of the United States (US) can be found in the works of Elder and Serletis (2010, 2011). Oil market volatility has also been shown to drive overall macroeconomic uncertainty (Hailemariam, 2019) and equity markets (Alsalman, 2016; Demirer et al., 2020).

With the role of US Treasury securities as a traditional "safe haven" well-recognized (Kopyl and Lee, 2016; Habib and Stracca, 2017; Hager, 2017) because of its ability to offer portfolio diversification and hedging benefits during periods of heightened uncertainty that negatively impact the equity market (Chuliá et al., 2017; Gupta et al., 2020a), a pertinent link to analyse would be the predictive content of oil price uncertainty for the term structure of US Treasury securities. Understandably, the accurate predictability of movement in Treasury securities is an important issue for both central bankers and bond investors. For central bankers, understanding the evolution of future interest rates helps in the fine tuning of monetary policies. For bond market investors, correct prediction of interest rates is likely to result in higher bond return performance, especially given that fact that US bond market capitalization stands at \$40.7 trillion (compared to a corresponding value of \$30 trillion associated with the stock market), and basically represents nearly two-thirds of the value of the global bond market (Securities Industry and Financial Markets Association (SIFMA)).

In spite of the importance of this question, the predictive ability of oil market uncertainty has mostly been examined in the context of equity markets (e.g., Demirer et al., 2020). Surprisingly, the existing literature considering the predictive power of oil price uncertainty on movements of US Treasury securities is limited to the published works of Balcilar et al. (2020) and Nazlioglu et al. (2020), who use post World War II data.[1] Specifically, Balcilar et al. (2020) analyses causality between oil market uncertainty and bond premia of US Treasury securities, based on a *k*-th order nonparametric causality-in-quantiles framework to account for misspecification due to uncaptured nonlinearity and structural breaks. The authors find that oil

[1] Some recent studies do exist that look into the impact of oil prices or returns and structural oil shocks on the first moment of the US government bond market (see for example, Kang et al. (2014), Wan and Kao (2015), Ioannidis and Ka (2018), Demirer et al. (2020), Gupta et al. (2020b), and Nguyen et al. (2020)).

uncertainty predicts first and second moments of monthly US bond premia associated with maturities of 2 to 5 years relative to 1 year. Nazlioglu et al. (2020), using daily data for 10-year government bond returns and accounting for structural shifts as a smooth process, could however find no evidence of volatility spillover from the oil to the bond market (but the other way around). Unlike Nazlioglu et al. (2020), a recent working paper by Coronado et al. (2020), which must be mentioned at this stage, uses historical monthly data (over the period October, 1859 to March, 2019) to detect time-varying evidence of bi-directional spillovers between oil and 10-year government bond (and high yield corporate bond)[2] returns and volatility.

Given this sparse background on the predictive ability of oil market volatility for the US bond market, we aim to extend the literature by examining the effects of oil market uncertainty on the term structure of interest rates for the US. Given the suggestion of McAleer and Medeiros (2008) that that the rich information contained in intraday data can produce more accurate estimates of daily (realized) volatility (RV), we use a measure of oil market uncertainty based on 5-minute sub-samples of oil returns (though we also check for the robustness of our results using the Chicago Board Options Exchange's (CBOE) Crude Oil ETF Volatility Index (OVX)). We relate these metrics of uncertainty to the term structure of interest rates, using the well-established framework of Nelson and Siegel (NS) (1987) from the finance literature. This model summarizes the entire term structure into three latent yield factors, level, slope and curvature, which are considered the only relevant factors that characterise the yield curve (Litterman and Scheinkman, 1991). The factor model of the term structure involving interest rates associated with US Treasury securities of maturities of 1 to 30 years in combination with the uncertainties associated with oil price movements, enable us to characterize the responses of the yield curve to oil market uncertainty, and calculate the entire yield curve movement in the wake of these second moment oil market effects.

Specifically, we rely on daily estimates of oil RV for the period 3rd January, 2001 to 17th July, 2020 (and 10th May, 2007 to 17th July, 2020 for the OVX), and relate oil uncertainty to the corresponding daily movements of the level, slope and curvature of the yield curve using the causality-in-quantiles framework of Jeong et al. (2012). The nonparametric causality-in-quantiles framework of Jeong et al. (2012) allows us to test for predictability emanating from oil uncertainty over the entire conditional distribution of the level, slope and curvature of the

[2] In this regard, it must be mentioned that Gormus et al. (2018) also detect significant Granger causality from the oil market to the high-yield bond market in terms of volatility (and price).

yield curve by controlling for misspecification due to uncaptured nonlinearity and regime change (both of which we show to exist in a formal statistical fashion in the results section of the paper). Given that the period of study involves the zero lower bound (ZLB) situation of interest rates in the US in the wake of the "Great Recession", the simultaneous use of a quantiles-based framework makes perfect sense, since different quantiles (without having to specify an explicit number of regimes like in a Markov-switching model) can capture the various phases of the 3 latent factors accurately, with the lower, median, and upper quantiles corresponding to low, normal, and high interest rates, respectively. Understandably, high-frequency prediction of the term structure of interest rates would allow for the timely design of optimal portfolios involving US government bonds by investors. Furthermore, using the daily information of predictability, policymakers can gauge where the low-frequency real and nominal variables in the economy are headed by feeding the information into mixed-frequency models (Caldeira et al., forthcoming), given that the entire yield curve is considered a predictor of economic activity (Hillebrand et al., 2018), allowing them to make appropriate monetary policy decisions.

To the best of our knowledge, this is the first paper to study the predictability of oil market uncertainty at daily frequency on the entire conditional distribution of the level, slope and curvature factors characterizing the complete term structure of interest rates of the US. Given this, our paper can be seen as a reconsideration of the work of Balcilar et al. (2020) at high, i.e., daily, frequency based on more reliable and accurate estimates of oil price uncertainty derived from intraday data. Furthermore, unlike the maturities of 1- to 5-year US Treasury securities analysed by Balcilar et al. (2020), we study the entire term structure associated with maturities of 1 to 30 years, as summarized by the three latent factors of level, slope and curvature. The remainder of the paper is organized as follows: Section 2 discusses the data, along with the basics of the methodologies associated with the NS model, and the causality-in-quantiles approach. Section 3 presents the main results and robustness analysis, 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.

2.1. Data

We collect daily zero coupon yields of Treasury securities with maturities from 1 year to 30 years to estimate the yield curve factors for the US. The zero coupon bond yields are based on the work of Gürkaynak et al. (2007), and are retrieved from DataStream maintained by Thomson Reuters. Gürkaynak et al. (2007) provide researchers and practitioners with a long history of high-frequency yield curve estimates of the Federal Reserve Board at a daily frequency. They use a well-known and simple smoothing method that is shown to fit the data very well, with the resulting estimates used to compute yields for any horizon.

The data for the realized volatility (RV) of oil returns, as a measure oil market uncertainty, is obtained directly from Risk Lab, maintained by Professor Dacheng Xiu at the Booth School of Business, University of Chicago.[3] Risk Lab collects trades at their highest frequencies available and cleans them using the prevalent national best bid and offer (NBBO) that is available up to every second. The estimation procedure for realized volatility follows Xiu (2010), and is based on the quasi-maximum likelihood estimates (QMLE) of volatility built on moving-average models MA(q), using non-zero returns of transaction prices sampled up to the highest frequency available, for days with at least 12 observations. In this paper, we use the RV estimates based on 5-minute subsampled returns of the NYMEX light crude oil futures, the only publicly available source of robust estimates of RV associated with the oil market. Our main analysis covers the period 3rd January, 2001 to 17th July, 2020, with the start and end dates determined by the availability of data on RV and the zero coupon yields respectively. As a robustness check, we also use CBOE's OVX (derived from the FRED database of the Federal Reserve Bank of St. Louis)[4] as an alternative measure of oil-related uncertainty instead of the RV, and, based on data availability, the corresponding period of coverage is 10th May, 2007 to 17th July, 2020.

2.2. Methodology

2.2.1. Extraction of the Yield Curve Factors

The dynamic Nelson-Siegel three-factor model of Diebold and Li (2006) (DNS, hereafter) is applied in this study to fit the yield curve of zero coupon US Treasury securities. The yield

[3] Data are downloadable from: https://dachxiu.chicagobooth.edu/#risklab.
[4] Data are downloadable from: https://fred.stlouisfed.org/series/OVXCLS.

curve is decomposed into three latent factors using the Nelson and Siegel (1987) representation in a dynamic form. The DNS with time-varying parameters is represented as:

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

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

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

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

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

where $r_t(\tau)$ and u_t are $m \times 1$ dimensional vectors for yield rates with given maturities (in our case 1 year to 30 years) and the error terms, respectively. The coefficient matrix in the measurement equation follows the structure introduced by Nelson and Siegel (1987), $f_t = [L_t, S_t, C_t]$ is a 3×1 dimensional vector, and comprises the yield rate shape parameters which vary over time. Continuing with the transition equation: $\tilde{f}_t = f_t - \overline{f}$ is the demeaned time-varying shape parameter matrix, Γ illustrates the dynamic relationship across shape parameters, η_t is a 3×1 dimensional error vector which is assumed to be independent of u_t, G is a $m \times m$

dimensional diagonal matrix and R is a 3×3 dimensional variance-covariance matrix, allowing the latent factors to be correlated.[5]

2.2.2. Causality-in-Quantiles Model

We describe the nonparametric causality-in-quantiles approach of Jeong et al. (2012).
Let y_t denote L_t, S_t or C_t and x_t correspond to RV_t. Further, 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 $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are:

$$H_0: \; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{4}$$

$$H_1: \; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{5}$$

Jeong et al. (2012) show that the feasible kernel-based test statistic has 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 $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The Nadarya-Watson kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by:

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

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

[5] Details of the estimation procedure are beyond the scope of this study, and interested readers are referred to Diebold and Li (2006). Complete details of the parameter estimates of the model are available upon request from the authors.

The empirical implementation of Granger causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag order of 4 based on the Schwarz Information Criterion (SIC). We determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

3. Empirical Results

3.1. Preliminary Analyses

The data for the three yield curve factors of level, slope and curvature, and the realized volatility of the oil market are summarized in Table A1, and plotted in Figure A1 in the Appendix. Among the dependent variables, the average value of the slope factor is negative, indicating that, on average, yields increase along with maturities. The curvature associated with medium-term maturities has a higher average value than the level factor, which corresponds to long-term yields. This result, which is in line with Kim and Park (2013), who also use daily bond yields of the US, is indicative of liquidity issues for bonds with very long maturities. The curvature factor is also the most volatile of the three factors, followed by the level and slope. Due to the rejection of the null hypothesis of normality under the Jarque-Bera test, level, slope and oil uncertainty are strongly non-normal, with curvature being weakly so. This result, particularly for L_t, S_t, and C_t, provides preliminary motivation to look into a quantile-based approach, to analyse the influence of RV on these variables.

Before we discuss the findings from the causality-in-quantiles tests, for the sake of completeness and comparability, we conduct the standard linear Granger causality test, with a lag-length of 4, as determined by the SIC. The resulting $\chi^2(4)$ statistics (with p-values in parenthesis) associated with the causality running from RV_t to L_t, S_t, and C_t are found to be equal to 0.4688 (0.7587), 1.1715 (0.3213), and 0.2009 (0.9380). Given these results, the null hypothesis, that oil uncertainty does not Granger cause the three latent factors of the yield curve considered in turn in a bivariate set-up, cannot be rejected at the conventional 5% level of significance, or even at the weak 10% level. Therefore, based on the standard linear test, we conclude no significant oil uncertainty-related effects on the level, slope or curvature of the US yield curve.

Given the insignificant results obtained from the linear causality tests, we statistically examine the presence of nonlinearity and structural breaks in the relationship between the three latent factors of the term structure with the *RV* of oil. Nonlinearity and regime changes, if present, would motivate the use of the nonparametric quantiles-in-causality approach, as the quantiles-based test would formally address nonlinearity and structural breaks in the relationship between the variables under investigation in a bivariate set-up. For this purpose, we apply the Brock et al. (1996) (BDS) test on the residuals from the L_t, S_t, and C_t equations involving four lags of the three factors and RV_t. Table A2 in the Appendix presents the results of the BDS test of nonlinearity. As shown in this table, we find strong evidence, at the highest level of significance, for the rejection of the null hypothesis of *i.i.d.* residuals at various embedded dimensions (m), which, in turn, is indicative of nonlinearity in the relationship between the factors and oil uncertainty. To further motivate the causality-in-quantiles approach, we next use the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to M structural breaks in the relationship between L_t, S_t, and C_t with RV_t, allowing for heterogenous error distributions across the breaks. When we apply these tests again to the L_t, S_t, and C_t equations involving four lags of the three factors and RV_t in a bivariate structure, we detect two breaks under each of the three cases at: 11/02/2004, 29/08/2006; 02/03/2005, 19/04/2007; and 07/04/2004, 29/08/2006, respectively. The break dates are in line with sharp oil price increases and associated volatility between 2004 and 2007.

3.2. Causality-in-Quantiles Test: Main Results and Robustness Check

Given the strong evidence of nonlinearity and structural breaks in the relationship between the latent factors and oil uncertainty, we now turn our attention to the causality-in-quantiles test, which is robust to misspecification due to its nonparametric (i.e., data-driven) approach. As seen in Figure 1, which reports the results of this test for the quantile range 0.05 to 0.95, the null hypothesis that RV_t does not Granger cause L_t, S_t, and C_t is overwhelmingly rejected (unlike the complete lack of causality observed under the linear framework) at the 5% level of significance (given the critical value of 1.96) virtually over the entire conditional distribution, with the exception of the lowest quantile of L_t, and the highest quantile of C_t (where causality holds at the 10% level, i.e., for a critical value of 1.645). In fact, the null hypothesis is rejected at the 1% level of significance (given the critical value of 2.575) over the quantile range 0.10 to 0.90 in all cases. In other words, when we account for nonlinearity and structural breaks using a nonparametric approach, we find strong evidence of predictability emanating from oil market uncertainty, as captured by RV_t, onto the three factors characterizing the US term structure of interest rates, with the highest impact at the quantiles 0.65, 0.45, and 0.70 for L_t, S_t, and C_t, respectively. To put it alternatively, oil market uncertainty can predict the yield curve factors, irrespective of the magnitude of these factors as captured by the various quantiles of the conditional distribution of L_t, S_t, and C_t. The importance of oil uncertainty is in line with the findings of Balcilar et al. (2020), but now we show that these shocks actually affect the entire yield curve over all their phases rather than just the bonds with maturities of 1 to 5 years, with the effect being strongest for long-term maturities as captured by the level factor (in 11 of the 19 quantiles considered), followed by the medium-term US Treasury securities (in the remaining 8 quantiles).

[INSERT FIGURE 1]

As a robustness check, we replace *RV* with OVX, and re-conducted the causality-in-quantiles test to analyse the impact on the three latent factors, as shown in Figure 2.[6] While there are subtle differences[7] across the two metrics of oil market uncertainty in terms of the pattern of causality, our main message remains the same. That is, we again find strong evidence of predictability from the OVX over the entire conditional distributions of L_t, S_t, and C_t at least at the 5% level of significance, with stronger predictability, i.e., at the 1% level holding over the quantile range 0.10 to 0.90. In other words, our result for oil uncertainty impacting the entire conditional distribution of the complete term structure of interest rates of the US is robust across measures of oil market uncertainty.

[INSERT FIGURE 2]

Although robust predictive inference is derived based on the causality-in-quantiles test, it is also interesting to estimate the sign of the effect of oil uncertainty on the level, slope and curvature at various quantiles. However, in a nonparametric framework, this is not straightforward, as we need to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can have complications, because nonparametric methods exhibit slow convergence rates, due to the dimensionality and smoothness of the

[6] The linear Granger causality test again fails to pick up any evidence of predictability from OVX to the three factors even at the 10% level of significance, which is not surprising given the strong evidence of nonlinearity detected using the BDS test, and regime-changes picked-up in June of 2009 for the level and curvature factors, and October of 2009 for the slope factor. Complete details of these results are available upon request from the authors.

[7] The highest impact is now observed at the quantiles 0.70 and 0.35 for S_t, and C_t, respectively, while the effect is strongest for medium-term maturities (in 12 of the 19 quantiles considered), followed by the long- and short-term US Treasury securities (in 4 and 3 quantiles, respectively).

underlying conditional expectation function. However, one can look at a statistic that summarizes the overall effect or the global curvature (i.e., the global sign and magnitude), but not the entire derivative curve. In this regard, a natural measure of the global curvature is the average derivative (AD) using the conditional pivotal quantile, based on approximation or the coupling approach of Belloni et al. (2019), which allows us to estimate the partial ADs. The pivotal coupling approach can also approximate the distribution of AD using Monte Carlo simulation. These results are reported in Figure 3, and show the signs of the impacts of oil uncertainty on the three latent factors.

As shown in Figure 3, oil uncertainty reduces short-term yields, as it negatively impacts the slope factor at all quantiles (barring the quantile of 0.30), while the long-term yields primarily go down at lower conditional quantiles of the level factor (and at quantiles of 0.50 and 0.65). Figure 3 also plots the sign of oil uncertainty on the curvature factor corresponding to medium-term maturities of US Treasury securities, and in general has an intermittent (barring the quantiles 0.25-0.40 and 0.50-0.55) negative impact till quantile 0.80, and thereafter is positively affected. These results suggest that, in the wake of heightened oil uncertainty, agents would prefer to invest mainly in short- and medium-term government bonds, and also in bonds with long-term maturities, but primarily when they produce high returns corresponding to the lower conditional quantiles of their yields.[8] In other words, the flight-to-safety channel associated with the safe-haven nature of government bonds is specific to maturities and quantiles, i.e., initial values of the yields, when there is an increase in oil return uncertainty. The consistent negative impact on the slope factor is also not surprising from the point of view that it captures bonds with short-term maturities and reflects monetary policy decisions (Ioannidis and Ka, 2018), in this case an expansionary policy given increases in oil market uncertainty and the associated recessionary impact on the real economy. Interestingly, at upper conditional quantiles of medium- and long-term government bonds, oil price uncertainty positively impacts the corresponding yields, suggesting that higher uncertainty causes agents to look beyond bonds with low returns, and possibly invest in other types of safe haven such as commodities (e.g., gold) and currencies (e.g., Swiss francs).

[INSERT FIGURE 3]

[8] A qualitatively similar pattern emerges when we look at the quantile-specific signs of the OVX on the three factors, complete details of which are available upon request from the authors.

4. Conclusion

In light of the sparse literature on the impact of oil uncertainty on the government bond market of the US, we analyse the impact of daily realized volatility (RV) of crude oil prices on the level, slope and curvature factors derived from the term structure of interest rates of the US covering maturities of 1 to 30 years. Using daily data covering the period 3rd January, 2001 to 17th July, 2020, we find that standard linear tests of Granger causality fail to detect any evidence of predictability running from RV to the three yield curve factors. However, we show that the linear model is misspecified due to nonlinearity and structural breaks. Given this, we use a nonparametric causality-in-quantiles framework to reconsider the impact of RV on the three factors, with this econometric model allowing us to test for predictability over the entire conditional distribution of level, slope and curvature, while simultaneously, as a data-driven approach, being robust to misspecification due to nonlinearity and regime change associated with the linear model. Note that, with our sample period including the zero lower bound, the lower quantiles of the level, slope and curvature allow us to capture this situation without carrying out a sub-sample analysis involving pre- and post-global financial crisis data. Using the causality-in-quantiles test, we find overwhelming evidence of predictability emanating from RV over the entire conditional distributions of the three factors of the US term structure. In other words, our results highlight the importance of controlling for model misspecification to obtain correct inferences when analysing the impact of oil RV on the US term structure, with our findings providing evidence that oil market uncertainty is an important driver of the entire yield curve, irrespective of its alternative phases. Moreover, our results continue to hold when we use an alternative metric of oil market uncertainty, based on its implied volatility, i.e., the OVX index of oil. From the perspective of gauging the safe-haven property of US Treasury securities, we find that, in the wake of heightened oil uncertainty, investors prefer to invest mainly in short- and medium-term government bonds, and also in bonds with long-term maturities, but primarily when yields are low.

Understandably, our findings with high-frequency, i.e., daily, data have multi-dimensional implications. Firstly, the observation that oil uncertainty contains predictive information over the evolution of future interest rates in a nonparametric set-up can help policymakers fine-tune their monetary policy models, given that oil volatility affects the slope factor of the yield curve, which captures movements of short-term interest rates. Secondly, bond investors can improve their investment strategies by exploiting the role of oil uncertainty in their interest-rate prediction models, while risk managers can develop asset allocation decisions conditional on the level of the volatility of the oil market. Thirdly, researchers may use our findings to explain deviations from asset-pricing models by embedding oil uncertainty in their pricing kernels, which, however, need to be nonlinear.

While our current study concentrates on US Treasury securities given their global dominance in the sovereign bond market, as part of future research, it would be interesting to extend our analysis to the term structure factors associated with the government bond markets of other developed and emerging countries, and also possibly distinguishing between oil exporters and importers.

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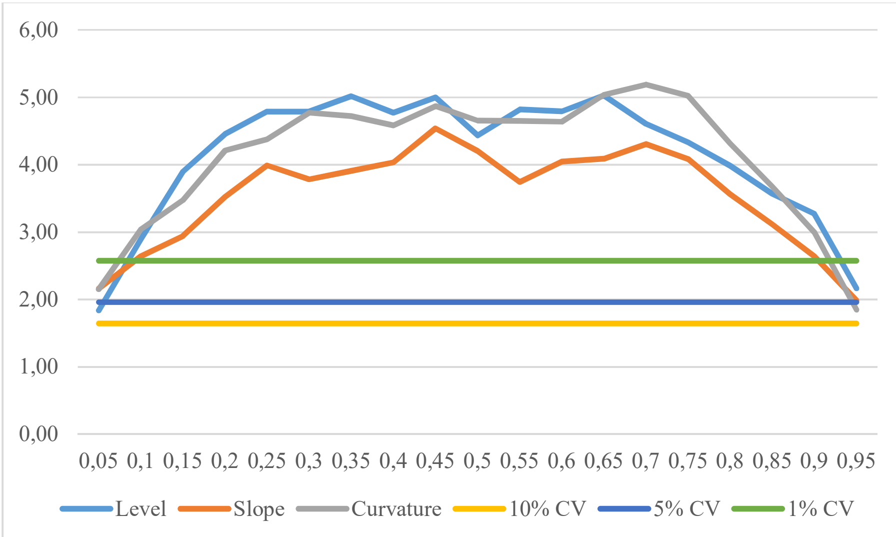
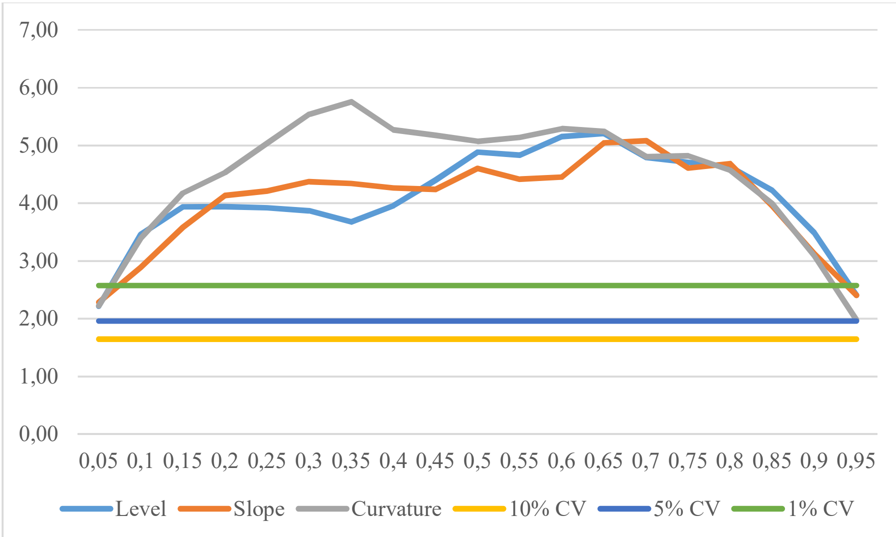
Figure 1. Causality-in-Quantiles Test Results for the US Term Structure Factors due to Oil Price Uncertainty Measured by Realized Volatility (RV)



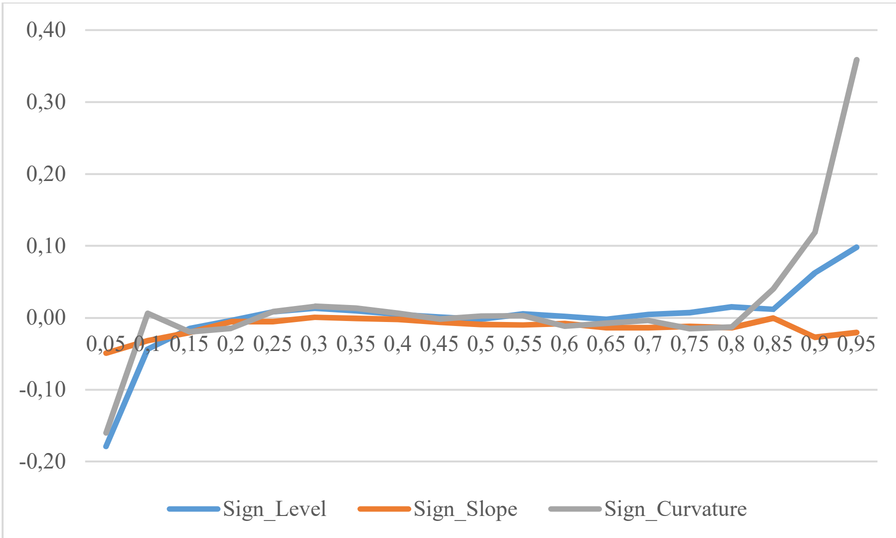
Note: The horizontal axis represents the quantiles, while the vertical axis presents the causality-in-quantiles test statistic indicating the rejection or non-rejection of the null hypothesis that oil uncertainty does not Granger cause a specific term structure factor at a specific quantile, if the statistic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

Figure 2. Causality-in-Quantiles Test Results for the US Term Structure Factors due to Oil Price Uncertainty Measured by CBOE's Oil OVX Index



Note: See Notes to Figure 1.

Figure 3. The Sign of the Impact on the US Term Structure Factors due to Oil RV



Note: The figures plot the average derivative (Sign_Level, Sign_Slope, and Sign_Curvature) at each quantile of the three factors, i.e., level, slope and curvature, of the term structure due to the realized volatility of oil.

APPENDIX:

Table A1. Summary Statistics

	Variable			
Statistic	Level	Slope	Curvature	RV
Mean	2.4915	-1.2335	7.8227	0.3242
Median	2.6922	-1.5452	8.9035	0.2779
Maximum	5.4867	6.2586	27.7910	3.0000
Minimum	-6.2829	-4.7938	-3.6539	0.0477
Std. Dev.	1.7155	1.5843	5.6426	0.2046
Skewness	-1.8250	0.7545	0.0945	4.5212
Kurtosis	8.3217	3.6872	3.0197	42.5143
Jarque-Bera	$6159.6590^{\#}$	$406.6256^{\#}$	$5.3432^{\$}$	$243049.2000^{\#}$
Observations	3550			

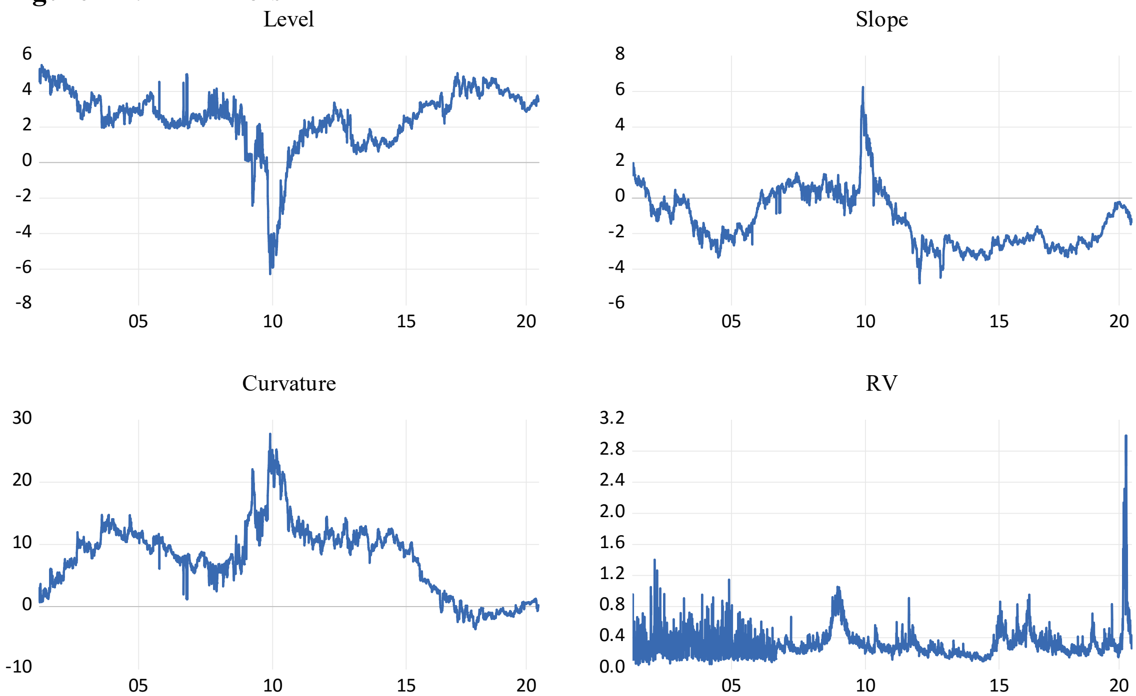
Note: RV: Realized volatility of oil based on 5-minute intraday returns; $^{\#}$ and $^{\$}$ indicate rejection of the null hypothesis of normality at 1% and 10% levels of significance respectively.

Table A2. Brock et al. (1996) (BDS) Test of Nonlinearity

	Dimension (m)				
Dependent Variable	2	3	4	5	6
Level	$18.7412^{\#}$	$22.9119^{\#}$	$25.8979^{\#}$	$28.7743^{\#}$	$31.5540^{\#}$
Slope	$16.2800^{\#}$	$19.9320^{\#}$	$23.0757^{\#}$	$26.0187^{\#}$	$28.7339^{\#}$
Curvature	$16.4682^{\#}$	$19.7297^{\#}$	$22.4651^{\#}$	$25.1304^{\#}$	$27.6114^{\#}$

Note: See Notes to Table A1; 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 four lags each of level, slope and curvature, and oil RV; $^{\#}$ indicates rejection of the null hypothesis at 1% level of significance.

Figure A1. Data Plots



Note: See Notes to Table A1.