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The role of oil and risk shocks in the high-frequency movements of the term structure of interest rates: Evidence from the U.S. Treasury market

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Abstract
We use daily data for the period 5 January 2000 to 31 October 2018 to analyse the impact of structural oil supply, oil demand and financial market risk shocks on the level, slope and curvature factors derived from the term structure of interest rates of the U.S. Treasury securities covering maturities of 1–30 years. Linear causality tests detect no evidence of predictability of these shocks on the three latent factors. However, statistical tests performed on the linear model provide evidence of structural breaks and nonlinearity, and hence indicate that the Granger causality test results are based on a misspecified framework, and cannot be relied upon. Given this, we use a nonparametric causality in-quantiles test to reconsider the predictive ability of the three shocks on the three latent factors, with this model being robust to misspecification due to regime changes and nonlinearity, as it is a data-driven approach. Moreover, this framework allows us to model the entire conditional distribution of the level, slope and curvature factors, and hence can accommodate, via the lower quantiles, the zero lower bound situation seen in our sample period. Using this robust model, we find overwhelming evidence of causality from the two oil shocks and the risk shock for the entire conditional distribution of the three factors, suggesting the predictability of the entire U.S. term structure based on information contained in oil and financial market innovations. Our results have important implications for academics, investors and policymakers.

KEYWORDS
causality-in-quantiles test, oil supply and demand shocks, risk shock, yield curve factors

1 | INTRODUCTION

The existing literature on the impact and oil market price, returns, volatility, and shocks on the moments of equity market of the United States, is huge, to say the least (see, for example, Balcilar, Gupta, and Miller (2015); Balcilar, Gupta, and Wohar (2017) or Gupta and Wohar (2017) for detailed reviews in this regard). Interestingly, despite the U.S. bond market capitalization of \$41.30 trillion being higher than the corresponding value of \$30.43 trillion associated with the stock market and basically representing nearly two-thirds of the value of the global bond market,[1] the literature examining the linkages between the U.S. government bond and oil markets is negligible and limited to the published works of Balcilar, Gupta, Wang, and Wohar (2020), Demirer, Ferrer, and Shahzad (2020), Ioannidis and Ka (2018), Kang, Ratti, and Yoon (2014), Nazlioglu, Gupta, and Bouri (2020), and Nguyen, Nguyen, and Pham (2020). The lack of studies in this field is surprising given the great importance of the bond market compared to the stock market, and the fact that the U.S. government bond market is normally considered by investors as a safe-haven (Hager, 2017) and the yield curve of U.S. government bonds is shown to be useful to forecast macroeconomic variables (Hillebrand, Huang, Lee, & Li, 2018). As a result, the research about the impact of oil shocks on the term structure of U.S. government bond yields is of great research value from the perspectives of both investors and policymakers.

Against this backdrop, this article contributes to this sparse literature by investigating the impacts of oil and risk shocks on the term structure of interest rates in the U.S. Treasury market. Following the suggestion by Kilian (2009) that 'not all oil price shocks are alike', we first distinguish oil price changes into demand, supply and financial risk shocks. Second, as in Ioannidis and Ka (2018), we relate these shocks to the term structure of U.S. interest rates, utilizing the dynamic Nelson–Siegel three-factor model of Diebold and Li (2006). This method decomposes the yield curve into three latent factors of the slope, curvature and level, which in turn represent the movements of yields in the short-, medium- and long-terms (Litterman & Scheinkman, 1991). The three-factor model of the term structure involving interest rates associated with U.S. Treasury securities of maturities 1–30 years, along with the decomposition of oil price movements due to various causes, enables us to study the responses of the yield curve to different types of oil shocks and investigate the role of these oil shocks in the high-frequency movements of the term structure of interest rates in the U.S. Treasury market.

Specifically, we rely on high-frequency, that is, daily, data for the period 5 January 2000 to 31 October 2018 to obtain estimates of oil shocks from a SVAR model proposed by Ready (2018), and relate them to the corresponding daily movements of the slope, curvature, and level of the U.S. yield curve using the causality-in-quantiles framework of Jeong, Härdle, and Song (2012). Ready (2018) proposed a novel methodology of disentangling oil price shocks according to the information in traded asset prices, that is, returns of a stock index consisting of oil-producing firms internationally. Taking advantage of the forward-looking nature of traded asset prices, this methodology overcomes two main shortcomings of the widely used standard oil shocks decomposition technique of Kilian (2009), in which too much weight is given to the oil market-specific demand shocks over the supply shocks, and the applications of the method being limited to a monthly frequency and not able to be estimated at higher frequencies. At the same time, the nonparametric causality-in-quantiles framework of Jeong et al. (2012) allows us to test for predictability emanating from oil shocks over the entire conditional distribution of the level, slope and curvature of the yield curve by controlling for misspecification due to uncaptured nonlinearity and regime changes (both of which we show to exist in a formal statistical fashion in the results section of the article). Given that the period of study involves the zero lower bound (ZLB) situation of the interest rates in the United States 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 three 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 U.S. government bonds by investors, and also allow policymakers to gauge where the low-frequency real and nominal variables in the economy are headed by feeding the information into mixed-frequency models (Caldeira, Gupta, Suleman, & Torrent, 2019).

It is notable that, in theory, high oil prices raise inflation expectations and hence, increase nominal bond interest rates. Moreover, higher oil prices, especially originating from supply disruptions, are historically known to have a recessionary impact on the U.S. economy (Hamilton, 2013), which is likely to increase demand for government bonds due to their safe-haven characteristics, and hence push up bond prices, and reduce yields. But, if the increase in oil price is due to aggregate demand resulting from global expansion, the yields will increase. Moreover, following the 'US Shale Revolution', and the United States becoming the leading exporter of refined oil products, higher oil prices produce greater domestic income and induce larger demand for investment in financial markets, including the bond market, and hence can push up bond prices, and to cause a reduction in interest rates on the bonds. In addition, Degiannakis, Filis, and Panagiotakopoulou (2018) highlighted how oil supply shocks increase macroeconomic uncertainty, while demand shocks reduce the same. Given this, oil price increases, depending on the source of supply or demand shocks, can increase or decrease, respectively, demand for U.S. government bonds as safe assets, producing a corresponding reduction or hike in yield. Finally, an increase in oil price due to risk in the equity market, resulting from the underlying financialization of the overall commodity market (Bonato, 2019), is likely to be associated with higher bond prices and declining yields.

To the best of our knowledge, this is the first article to study the predictability of disentangled oil demand, oil supply and financial market risk shocks at a daily frequency on the entire conditional distribution of the level, slope and curvature factors characterizing the complete term structure of interest rates of the United States. The remainder of this article is organized as follows: Section 2 discusses the existing literature, with Section 3 presenting the data and explaining the three methodologies associated with the NS model, the SVAR to get the oil shocks, and the causality-in-quantiles approach. Section 4 provides results and discussions, while Section 5 concludes.

2 | LITERATURE REVIEW

We now turn to the studies relating to the government bond and oil markets of the United States in greater details. One of the early works by Kang et al. (2014) utilized a structural vector autoregressive (SVAR) model to examine how the demand- and supply-side oil shocks influence real bond returns of the United States at monthly frequency. The authors reported that a positive oil market-specific demand shock is related to significant declines in real returns of an aggregate bond index. More recently, Demirer et al. (2020) using daily data, among other results, found that not only demand, but also supply shocks in the oil market, tend to negatively impact the 10-year bond returns of the United States, but the financial market risk shock increases the long-term bond returns. Nguyen et al. (2020) used a heteroscedasticity-based event study approach and instrument for changes in oil prices with exogenous shocks that mainly affect oil supply, to show, as in Demirer et al. (2020), that oil price increases reduce returns on a 20 plus-year (long-term) Treasury bond index (as well as that of investment-grade bonds, but increases returns on high-yield bonds). Ioannidis and Ka (2018) used the SVAR model of Kang et al. (2014), but studied the effect of oil price shocks in the global crude oil market on the dynamics of yield curves of the United States (Canada, Norway, and South Korea), as captured by the three factors of level, slope and curvature, derived from maturities of 1–10 years. They find that oil market-specific demand shocks result in increases of the level factor, oil supply disruptions have short-lived negative responses on the slope factor, while demand-side shocks lead to a slope increase, and decline in curvature. Unlike the aforementioned three papers, Balcilar et al. (2020) and Nazlioglu et al. (2020) concentrated on causal linkages between the bond and oil market-related variables rather than analysing the impact of (structural) oil shocks on bond returns. Specifically, Balcilar et al. (2020) analysed causality between oil market uncertainty and the premia of U.S. Treasury bonds, using a nonparametric causality-in-quantiles framework that accounts for misspecifications caused by uncaptured structural breaks and nonlinearity. They found that oil uncertainty can predict an increase in premia of bonds with various maturities (2–5 years relative to 1 year), with a stronger impact observed at longer-term maturities. Nazlioglu et al. (2020), using daily data and considering structural shifts as a smooth process found, inter alia, that the causality between bond and oil prices in the United States runs only in one direction, from the bond market to the oil price, and not the other way.[2,3]

As indicated earlier, this is the first attempt to study the predictability of oil demand, oil supply and financial market risk shocks at a daily frequency on the entire conditional distribution of the level, slope and curvature factors. Given this, our article is a reconsideration of the work of Ioannidis and Ka (2018) at a high frequency based on daily oil shocks which better depicts oil price movements as in Demirer et al. (2020) and Nguyen et al. (2020), but, unlike the latter two papers, we study the entire term structure of U.S. interest rates. Moreover, our article can be considered an extension of these three papers, as we go beyond conditional mean-based analyses, and study the entire conditional distribution of the three factors summarizing the U.S. yield curve.

3 | DATA AND ECONOMETRIC METHODOLOGIES

In this section, we describe the data and the basics of the three methodologies utilized in our empirical analyses.

3.1 | Data

We collect daily zero-coupon yields of Treasury securities with maturities from 1 to 30 years to estimate the yield curve factors for the United States. The zero-coupon bond yields are based on the work of Gürkaynak, Sack, and Wright (2007), and are retrieved from the Federal Reserve Board (FRB) at https://www.federalreserve.gov/data/nominal-yield-curve.htm. This article makes available to researchers and practitioners a long history of high-frequency yield curve estimates of the FRB at a daily frequency. The authors use a simple and well-known smoothing technique that fits the data well, with the resulting estimates employed to calculate bond yields for any horizons.

In order to compute oil demand- and supply-side shocks as well as risk shocks, following Ready (2018) this study uses daily price of the World Integrated Oil and Gas Producer Index (WIOGPI),[4] the volatility index (VIX) from the Chicago Board Options Exchange (CBOE), and the New York Mercantile Exchange (NYMEX) light sweet crude oil futures contract prices at the nearest maturity. These data are obtained from the Datastream database. We use the NYMEX light sweet crude oil futures prices as a proxy for crude oil prices and calculate the residuals from an ARMA (1,1) model using the VIX index to capture innovations linked to the changes in the market discount rate, which tend to covary with the risk attitudes of investors in financial markets. The daily data sample is from 5 January 2000 to 31 October 2018, with the choice of sample period purely driven by data availability of the shocks, given that we obtain the data on the oil and financial market innovations from the work of Demirer et al. (2020).

3.2 | Methodologies

3.2.1 | 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 U.S. Treasury securities. The yield 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 follows:

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

where r_t 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 changes all yields equally, hence L_t is the level factor, which 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, which mimics the movements of short-term yields. The loading for C_t starts at 0 and decays to zero, with a hump in the middle. An increase in C_t increases the yield curve curvature, hence it is the curvature factor, which mimics medium-term yield movements. The DNS model follows a VAR process and is modelled in state-space form using the Kalman filter. The measurement equation relating the yields and latent factors is:

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

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

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

where $r_t(\tau)$ and u_t are $m \times 1$ dimensional vectors for interest yields with associated maturities (in our case 1–30 years) and the error terms, respectively. $f_t = [L_t, S_t, C_t]$ is a 3×1 dimensional vector. Continuing with the transition equation: $\tilde{f}_t = f_t - \bar{f}$ is the demeaned time-varying shape parameter matrix, G is a $m \times m$ diagonal matrix. η_t is a 3×1 error vector and η_t is assumed to be independent of u_t. Γ presents the dynamic relationship across shape parameters. R is a 3×3 variance and covariance matrix.[5]

3.2.2 | SVAR model for disentangling oil Price shocks

According to Ready (2018), the demand-side shocks are defined as the proportion of returns of the WIOGPI that is orthogonal to the VIX innovations. The innovations to the VIX are used as a proxy for risk shocks, while supply shocks are captured by the residuals of oil-price changes that are orthogonal to demand and risk shocks. To be more specific, the decomposition model by Ready (2018) takes the following matrix form:

$$W_t = AZ_t, \tag{4}$$

where $W_t = \left[\Delta \mathrm{oil}_t, R_t^{\mathrm{Prod}}, \xi_{\mathrm{VIX},t}\right]'$ is a 3×1 vector, $\Delta \mathrm{oil}_t$ represents oil price changes at time t, R_t^{Prod} denotes price changes of the WIOGPI at time t, and $\xi_{\mathrm{VIX},t}$ is for the VIX innovation. $Z_t = [\mathrm{ss}_t, \mathrm{ds}_t, \mathrm{rs}_t]'$ is a 3×1 vector of oil supply-, demand-side shocks and risk shocks denoted by ss_t, ds_t and rs_t, respectively. A is a 3×3 coefficients matrix.

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix}. \tag{5}$$

In order to achieve orthogonality among the three types of shocks, the following condition is imposed:

$$A^{-1}\Sigma_W \left(A^{-1}\right)^T = \begin{bmatrix} \sigma_{\mathrm{ss}}^2 & 0 & 0 \\ 0 & \sigma_{\mathrm{ds}}^2 & 0 \\ 0 & 0 & \sigma_{\mathrm{rs}}^2 \end{bmatrix}, \tag{6}$$

where Σ_W is the covariance matrix of the variables in W_t, while σ_{ss}^2, σ_{ds}^2 and σ_{rs}^2 represent the variance of the supply-, demand-side shocks and risk shocks, respectively. The specification in Equation (6) denotes a renormalization of a standard orthogonalization applied to construct structural shocks in a SVAR model. Note that the oil shocks volatility is not normalized to one, but the sum of the three shocks, by constructions, equals to the total variations of oil prices. This approach of decomposing oil price changes defines an oil supply shock as the component of oil price movement that cannot be explained by changes in global aggregate demand and changes in financial-market uncertainty.[6]

3.2.3 | Causality-in-quantiles model

Finally, 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 ss_t, ds_t or rs_t, considered in turn in a bivariate set-up. Further, let $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t|\cdot)$ denote the conditional distribution of y_t given $\cdot$. 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:

$$H_0 : P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1, \tag{7}$$

$$H_1 : P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1. \tag{8}$$

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

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s, \tag{9}$$

where $K(\cdot)$ 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 $\mathbf{1}\{\cdot\}$ is the indicator function. The Nadarya–Watson kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by:

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)}, \tag{10}$$

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

The implementation of causality testing via quantiles involves setting up three key parameters: the lag order (p), the bandwidth (h), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use Gaussian kernels for $K(\cdot)$ and $L(\cdot)$. p is optimally selected to be 1 according to the Schwarz Information Criterion (SIC). The SIC is known to select a parsimonious number of lags and, thereby, prevents over-parameterization problems associated with nonparametric approaches. Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an overparameterized model, while the SIC is asymptotically consistent. h is determined by the leave-one-out least-squares cross-validation.

4 | EMPIRICAL RESULTS

4.1 | Preliminary analyses

The data for the three yield curve factors of level, slope and curvature and three shocks, that is, oil supply, oil demand and financial market risks are summarized in Table A1 and plotted in Figure A1 in the Appendix of the article. 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 is in line with Kim and Park (2013) who also used daily bond yields of the United States and is indicative of liquidity issues for bonds with very long maturities. The curvature factor is also the most volatile among the three factors, followed by the slope and level factors.[7] The supply shock has the highest positive mean value, with negative average values for the risk and demand shocks. Unsurprisingly, the risk shock is most volatile, with the variance of the supply shock being greater than that of the demand shock. Due to the overwhelming rejections of the null hypothesis of normality under the Jarque-Bera (J-B) test, all variables are non-normal, and this result, particularly for L_t, S_t and C_t, provides preliminary motivation to look into a quantiles-based approach, to analyse the influence of shocks on these variables.

Before discussing our findings of the causality-in-quantiles testing results, for the purpose of completeness and comparability, we performed the standard linear test of Granger causality, with a lag of 1. The $\chi^2(1)$ statistics involving the causality running from cross-validation, ds_t or rs_t to L_t, S_t, and C_t are reported in Table A2 in the Appendix of the article. The null hypothesis, that the three oil shocks do 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, with only the demand shocks shown to weakly (at the 10% level) predict the slope component. Therefore, based on the standard linear test, we conclude no significant oil and risk shock-related effects on the level, slope or curvature of the U.S. yield curve.

Due to the insignificant results from the linear causality testing, we examined statistically the existence of structural breaks and nonlinearity in the relationship between the three latent factors of the term structure with the three shocks. The presence of regime changes and nonlinearity would motivate the use of the nonparametric quantiles-in-causality testing, as this quantiles-based test would address structural breaks and nonlinearity in the relationships between the investigated variables in a bivariate set-up. For this reason, we use the Brock, Dechert, Scheinkman, and LeBaron (1996) (BDS) test on the residuals from the L_t, S_t, and C_t equations involving one lag of the three factors and ss_t, ds_t or rs_t. Table A3 in the Appendix shows the BDS testing results of nonlinearity. As indicated in the table, the results show strong evidence for the rejections of the null hypothesis of *i.i.d.* residuals at various dimensions (m), which suggests nonlinearity in the relationships between the factors and the shocks. In order to further justify the use of the causality-in-quantiles method, in Table A4, we also used the UDmax and WDmax tests of Bai and Perron (2003), to detect $1 - M$ structural breaks in the relationships between L_t, S_t and C_t with ss_t, ds_t or rs_t, allowing for the heterogeneous error distributions across breaks. While applying these tests to the L_t, S_t and C_t equations involving one lag of the three factors and the three shocks in a bivariate structure, we were able to detect as many as five breaks under all nine cases, as reported in Table A3. The regime changes were found to correspond to sharp increases in global demand and speculative bubbles in the early 2000s, the global financial and European sovereign debt crises, and the oil price shock of mid-2014 which lasted until the first quarter of 2015.

4.2 | Causality-in-quantiles results

Because of the strong evidence of structural breaks and nonlinearity in the relationships between the latent factors and shocks, we next turn our investigations into the causality-in-quantiles testing. It must be realized that by analysing the entire conditional distribution of the three latent factors, with low and high quantiles capturing low and high values of the same, we are capturing asymmetric causality.[8] As shown in Figure 1, which presents the results of this test for the quantile range 0.05–0.95, the null hypothesis that ss_t, ds_t or rs_t do not Granger cause L_t, S_t and C_t is overwhelmingly rejected at the 5% significance level over the entire conditional distribution. In fact, the null hypothesis is rejected at the 1% significance level over the quantile range 0.10–0.90 in all cases, and also at the lowest quantile of 0.05 for all the shocks affecting the level, and risk and supply shocks for slope and curvature. The results suggest that, when accounting for structural breaks and nonlinearity in a nonparametric approach, there is strong evidence of predictability from all the shocks to the three factors characterizing the U.S. term structure of interest rates, with the highest impact at the median for L_t and C_t, and at the quantile of 0.55 for S_t, unlike the complete lack of causality reported in the results using the linear method. To put it another way, the oil and risk shocks 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 all these shocks is in line with the findings of Demirer et al. (2020) and Nguyen et al. (2020) in terms of the supply shock, but now we show

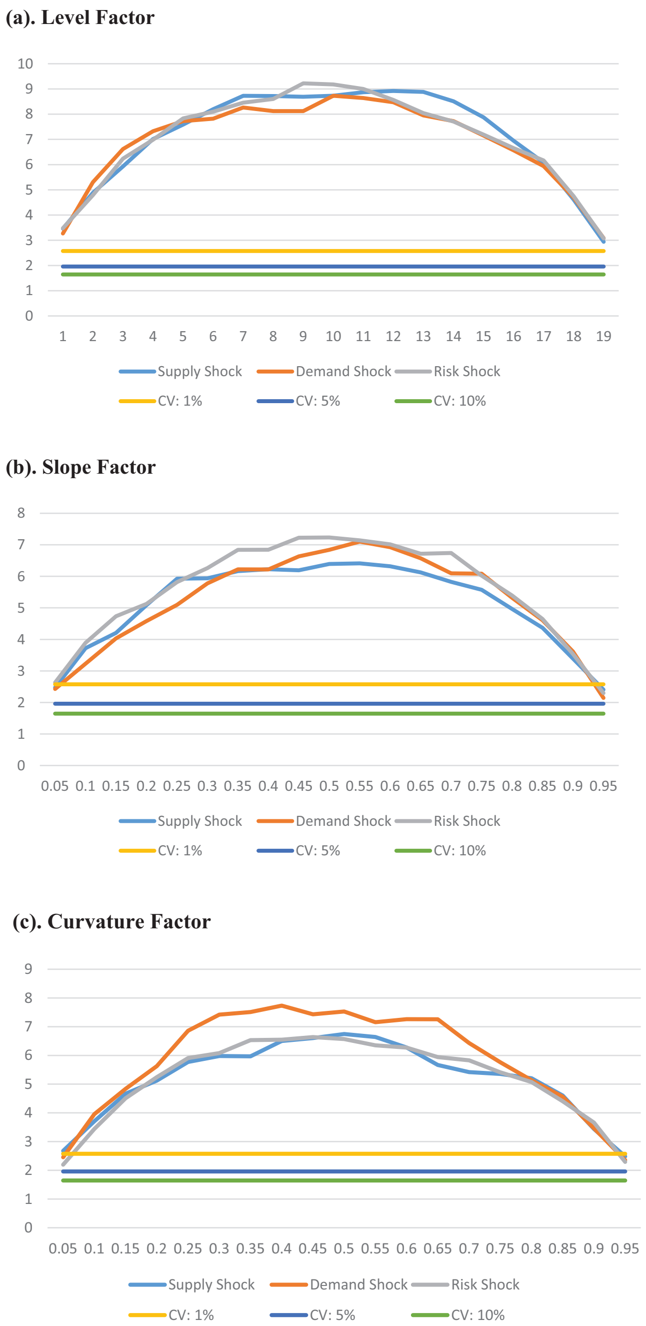

FIGURE 1 Causality-in-quantiles test results for the U.S. term structure factors due to oil supply, oil demand and financial market risk shocks. (a) Level factor; (b) slope factor; (c) curvature factor. The horizontal axis represents the quantiles, while the vertical axis presents the causality-in-quantiles test statistic indicating the rejection or non-rejection of the null hypothesis that a particular shock does not Granger cause a specific term structure factor at a specific quantile, if the statistic is above or below the critical values [Colour figure can be viewed at wileyonlinelibrary.com]

that these shocks actually affect the entire yield curve over all their phases rather than just the bonds with maturities of 10 years and 20-plus years, respectively, at their conditional means. Moreover, while Ioannidis and Ka (2018) pointed out that oil supply and demand shocks only impact the slope, we are able to show that oil shocks can actually predict all three yield curve factors based on a data-driven model. The strongest evidence of predictability at and around the median, which corresponds to the normal state of the yield factors, is in line with the findings of Ioannidis and Ka (2018), who, based on a pre-global financial crisis sub-sample found that oil market disturbances cause relatively stronger impacts on interest rates, compared to when the rates are extremely low under the ZLB situation, which in our case is characterized by the lower quantiles of the conditional distributions of L_t, S_t and C_t.

We now dig deeper into our results, in terms of the strength of each of these shocks in predicting the three factors, which we are able to do, given that we standardized the shocks to have unit variance, by dividing the oil supply and demand, and risk shocks by their respective standard deviations. While, in general, the predictive ability of these shocks is quite similar for the factors, we find that the risk shocks are associated with a relatively stronger impact on the slope (see Figure 1b), and the oil supply shock on the curvature (see Figure 1c). As far as the level factor is concerned, the results are quantile-specific with demand shocks having a stronger influence at the lower quantiles, risk shocks around the median, and supply shocks at the moderately high upper quantiles (see Figure 1a). In general, monetary policy, that is, the slope factor, is shown to respond strongly to financial market risks, that is, uncertainty (a result in line with Çekin, Hkiri, Tiwari, & Gupta, 2020), while higher inflation expectations arising from the negative supply shocks tend to drive the medium-term interest rates, especially around the conditional median of the curvature – something also observed to some degree by Ioannidis and Ka (2018) for the pre-crisis sub-sample.

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

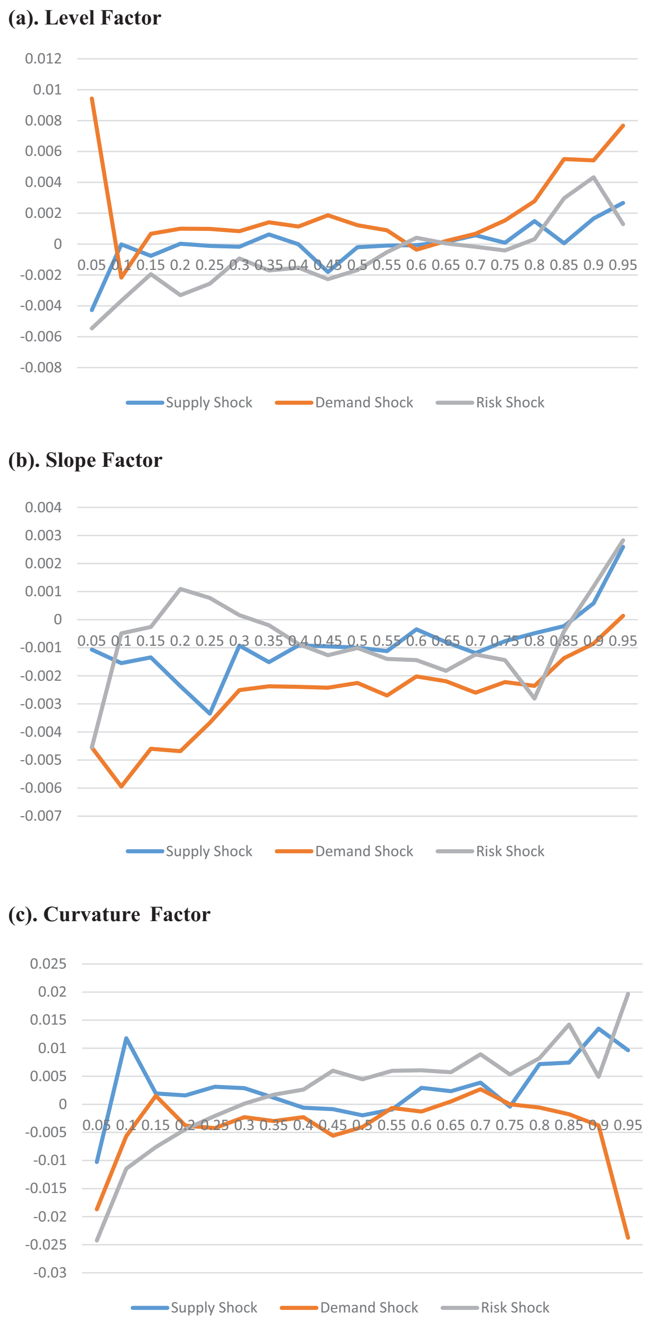

FIGURE 2 The sign of the impact on the U.S. term structure factors due to oil supply, oil demand and financial market risk shocks. (a) Level factor; (b) slope factor; (c) curvature factor. The figures plot the average derivative at each quantile of the three factors of the term structure due to the oil supply, oil demand and financial market risk shocks [Colour figure can be viewed at wileyonlinelibrary.com]

Chernozhukov, Chetverikov, and Fernandez-Val (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 2, and the signs of the impacts of the shocks are quantile-specific.

As shown in Figure 2a, demand shocks tend to positively impact the level factors associated with long-term yields, which could be due to higher inflation expectations but could also signal lower demand for safe assets in the wake of a growing economy, and hence lower macroeconomic uncertainty. The impact of supply shocks is generally positive at the upper quantiles associated with higher inflation expectations, as observed by Nguyen et al. (2020) for long-term Treasury bonds. But, the effect is negative at lower quantiles, to around the median, which could suggest that, in the wake of supply disruption causing economic slowdown and heightened uncertainty, agents would want to invest in a safe haven, that is, government bonds, due to its high returns corresponding to the lower quantiles of long-term yields. Higher financial market risk shocks also show a similar impact on the level factor. While the negative sign at the lower quantiles can be explained by the flight-to-safety channel, at upper quantiles of the long-term yields the positive sign could suggest that higher risks cause 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). As far as the impact of these shocks on the slope is concerned, Figure 2a shows that, generally, oil and risk shocks are associated with a negative impact on the slope, suggesting a loose monetary policy to revive the economy due to the negative impact of the supply (as in Ioannidis and Ka (2018)) and risk shocks, and keeping the economy growing following a positive oil demand shock, especially given the current role of the United States as a major exporter of refined oil products. Indeed, a positive impact on the upper end of the conditional distribution of the slope due to higher inflation expectations is observed. The slope also increases to risk shocks, at some moderately low quantiles to possibly prevent the bond market from getting overheated, and at extreme upper quantiles of short-term yields, which, in turn, might be due to investment in alternative safe assets with higher returns. In terms of the impact on curvature, as shown in Figure 2c, supply shocks have a positive impact on medium-term yields due to higher inflation expectations, which is in line with the observations of Demirer et al. (2020) for U.S. Treasury securities with a maturity of 10 years. Demand shock reduces medium-term yields as in Ioannidis and Ka (2018), and could be associated with a growing economy, which increases the demand for medium-term bonds. The risk shock also negatively impacts medium-term yields at lower quantiles, possibly due to higher demand for bonds of these maturities as they have higher returns – a finding similar to Demirer et al. (2020). However, at quantiles beyond 0.25 of the curvature, risk shocks have a positive impact, suggesting declining returns, with possible diversification by investors into other less risky assets, which might pay higher returns at that moment. Although we cannot provide a one-to-one correspondence of our results with the literature as we used a quantiles-based approach rather than conditional mean-based models, overall our results highlight the importance of using the former framework which is more informative than the latter, as it allows us to identify the various channels of the oil and risk shocks that are at work affecting the three latent factors conditional on their initial states. Moreover, we use daily data on all available maturities of U.S. Treasury securities, that is, 1–30 years, rather than the 1–10 years used in existing studies.

5 | CONCLUSION

Against the backdrop of sparse literature on the impact of oil shocks on the government bond market of the United States, we analyse the impact of oil supply, oil demand and financial market risk shocks, derived from a SVAR, on the entire term structure of interest rates, by obtaining three latent factors, level, slope and curvature. Using daily data from 5 January 2000 to 31 October 2018, we show that standard linear tests of causality fail to detect any evidence of predictability running from the shocks to the three yield curve factors. However, we show that the linear model is misspecified due to structural breaks and nonlinearity. As a result, we use a nonparametric causality-in-quantiles framework to reconsider the impact of the three shocks 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 being a data-driven approach robust to misspecification due to regime changes and nonlinearity 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 all three shocks over the entire conditional distributions of the three factors of the U.S. term structure, with the strongest impact observed around the conditional median. In other words, our results highlight the importance of controlling for model misspecification to obtain correct inferences when analysing the impact of oil and risk shocks on the U.S. term structure, with our findings providing evidence that such shocks are important drivers of the entire yield curve, irrespective of its alternative phases.

Understandably, our findings using high-frequency, that is, daily data have multi-dimensional implications. The observation that oil and risk shocks contain 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 these shocks affect the slope factor of the yield curve, which captures movements of short-term interest rates. Moreover, investors and risk managers can improve their interest-rate prediction models and investment and risk management strategies by exploiting the important role of oil and risk shocks in the high-frequency movements of the term structure of interest rates. Last, academic researchers may also use the findings of this article to explain deviations from asset-pricing models by accounting for oil supply- and demand-side shocks, and financial market risk shocks in their pricing kernels, which, however, need to be nonlinear.

While we concentrate on U.S. 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. Further, it would be interesting to extend the current data set from 2018 to recent dates, to account for the massive fluctuations in the oil market (with oil price even becoming negative for a day), due to the Russia-Saudi Arabia price war, and also the impact of the COVID-19 outbreak. In terms of the latter issue, instead of the VIX, we can use the recently developed financial market volatility index due to various infectious diseases by Baker, Bloom, Davis, and Terry (2020).

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Datastream database and https://www.federalreserve.gov/data/nominal-yield-curve.htm

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ENDNOTES

[1] The data are according to the Securities Industry and Financial Markets Association (SIFMA)'s Capital Markets Fact Book in 2019.

[2] Wan and Kao (2015) found that positive shocks in oil prices decrease the spreads between the AAA and BAA rated bonds, and hence, provided early evidence of the relationship between the oil market and investment bonds. In this regard, Gormus, Nazlioglu,

and Soytas (2018) too detected significant causality from the oil market to the high-yield bond market in terms of both price and volatility.

[3] A working paper that must be mentioned is the work of Coronado, Gupta, Nazlioglu, and Rojas (2020). These authors used historical monthly data from the United States over the period 1859:10 to 2019:03 to detect time-varying evidence of bi-directional spillovers between oil and 10-year government bond returns, which is robust to the inclusion of stock returns as a control variable in the model. They detected time-varying causality-in-volatility between sovereign bond and oil markets, as well as spillovers in returns and volatility from the oil market to corporate bonds.

[4] The index of world integrated oil and gas producer consists of the world's largest oil-producing firms listed in international stock markets. It captures the stock price movements of global oil producer firms, such as Exxon, BP, Repsol, Chevron, etc., but excludes those nationalized oil producers, such as Saudi Aramco and ADNOC.

[5] Please refer to Diebold and Li (2006) for detailed estimation procedures.

[6] In a sense, it can be argued that in this framework supply-side shocks relate to event- or region-specific information that is not accounted for by the impacts related to financial markets.

[7] Based on the suggestion of an anonymous referee, following Ludvigson and Ng (2009, 2010), we regressed the 1–30 year yields considered in turn on the three latent factors of level, slope and curvature in a bivariate set-up, and recorded the R^2 of each of these regressions. The highest R^2 were consistently recorded for the level factor, followed by slope and curvature factors for all the 30 yields considered. This result suggested that the movements in the yield curve are primarily captured by bonds of longer maturities.

[8] An anonymous referee suggested that we should apply the asymmetric causality test of Hatemi-J (2012) to capture the impact of positive and negative shocks on the positive and negative components of the latent factors. While we are able to capture low and high values of the dependent variable, that is, the factors, to analyse the impact of low and high values of the shocks, we applied the portmanteau test of Han, Linton, Oka, and Whang (2016) derived from a cross-quantilogram. We rely on this methodology since the asymmetric causality test of Hatemi-J (2012) is not applicable in our context as it requires non-stationary data, while our underlying variables must be stationary, besides the fact that the test is also conditional mean-based and less informative. Using the cross-quantilogram method, as with our causality-in-quantiles test, we found that, in general, the shocks have the strongest effects around the conditional median, but now with the added, non-surprising, information that higher values of the shocks have a stronger predictability on the level, slope and curvature factors. The complete details of these results are available upon request from the authors.

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APPENDIX A.

TABLE A1 Summary statistics

	Variable					
Statistic	**Level**	**Slope**	**Curvature**	**Supply shock**	**Demand shock**	**Risk shock**
Mean	2.5351	−1.1521	8.2426	0.0024	−0.0004	−0.0056
Median	2.6493	−1.5435	9.3066	0.0358	0.0232	−0.5744
Maximum	6.1090	6.1745	27.2988	17.4887	9.4707	78.6970
Minimum	−6.1235	−4.8061	−4.2672	−17.7642	−8.9221	−31.9382
Std. Dev.	1.6891	1.7062	5.3420	2.0846	1.1575	6.7924
Skewness	−1.5885	0.5813	−0.1545	−0.0644	−0.0609	1.1110
Kurtosis	7.5039	2.8111	3.3143	8.4963	9.2568	10.6887
Jarque-Bera	5,964.3060*	272.3718*	38.1354*	5,934.3570*	7,688.7710*	12,575.7600*
Observations	4,712					

*Indicates rejection of the null hypothesis of normality at 1% level of significance.

TABLE A2 Linear Granger causality test results

	$\chi^2(1)$ Statistic		
	Independent variable		
Dependent variable	**Demand shock**	**Supply shock**	**Risk shock**
Level	2.3744	0.0114	0.0056
Slope	3.7633*	8.00E−05	0.8565
Curvature	1.0165	0.2773	0.0815

*Indicates rejection of the null hypothesis of causality at 10% level of significance.

TABLE A3 Brock et al. (1996) (BDS) test of nonlinearity

		Dimension (m)				
Dependent variable	**Independent variable**	**2**	**3**	**4**	**5**	**6**
Level	Demand shock	21.4110*	26.1543*	29.2440*	32.0890*	34.9449*
	Supply shock	21.3531*	26.0730*	29.1570*	32.0114*	34.8799*
	Risk shock	21.3315*	26.0138*	29.0911*	31.9104*	34.7450*
Slope	Demand shock	20.8799*	24.9129*	27.7581*	31.2403*	34.6187*
	Supply shock	20.8838*	24.9576*	27.8415*	31.2155*	34.4759*
	Risk shock	20.8799*	24.8768*	27.7012*	31.1188*	34.3935*
Curvature	Demand shock	20.2598*	24.5034*	27.5736*	30.3580*	33.1265*
	Supply shock	20.0849*	24.3450*	27.4582*	30.2410*	33.0220*
	Risk shock	20.0808*	24.3775*	27.4722*	30.2628*	33.0172*

Note: Entries correspond to the z-statistic of the BDS test with the null hypothesis of *i.i.d.* residuals, with the test applied to the residuals recovered from the three yield curve factor equations with one lag each of level, slope and curvature, and demand, supply, and risk shocks.
*Indicates rejection of the null hypothesis at 1% level of significance.

TABLE A4 Bai and Perron (2003) test of multiple structural breaks

Dependent variable	Independent variable	Break dates				
Level	Demand shock	11/07/2002	10/13/2005	12/16/2008	12/08/2011	10/06/2014
	Supply shock	11/07/2002	10/13/2005	12/15/2008	10/27/2011	3/18/2015
	Risk shock	11/07/2002	10/13/2005	12/16/2008	10/20/2011	3/16/2015
Slope	Demand shock	12/17/2002	10/13/2005	10/15/2009	10/16/2012	8/25/2015
	Supply shock	12/17/2002	10/13/2005	2/10/2009	1/05/2012	2/20/2015
	Risk shock	12/17/2002	10/13/2005	10/15/2009	10/16/2012	8/17/2015
Curvature	Demand shock	2/14/2003	3/20/2006	1/14/2009	1/09/2012	11/10/2014
	Supply shock	2/14/2003	3/20/2006	1/14/2009	1/09/2012	3/18/2015
	Risk shock	2/14/2003	3/20/2006	1/14/2009	1/09/2012	11/10/2014

Note: Entries correspond to the break dates obtained from the three-yield curve factor equations with one lag each of level, slope and curvature, and demand, supply and risk shocks.

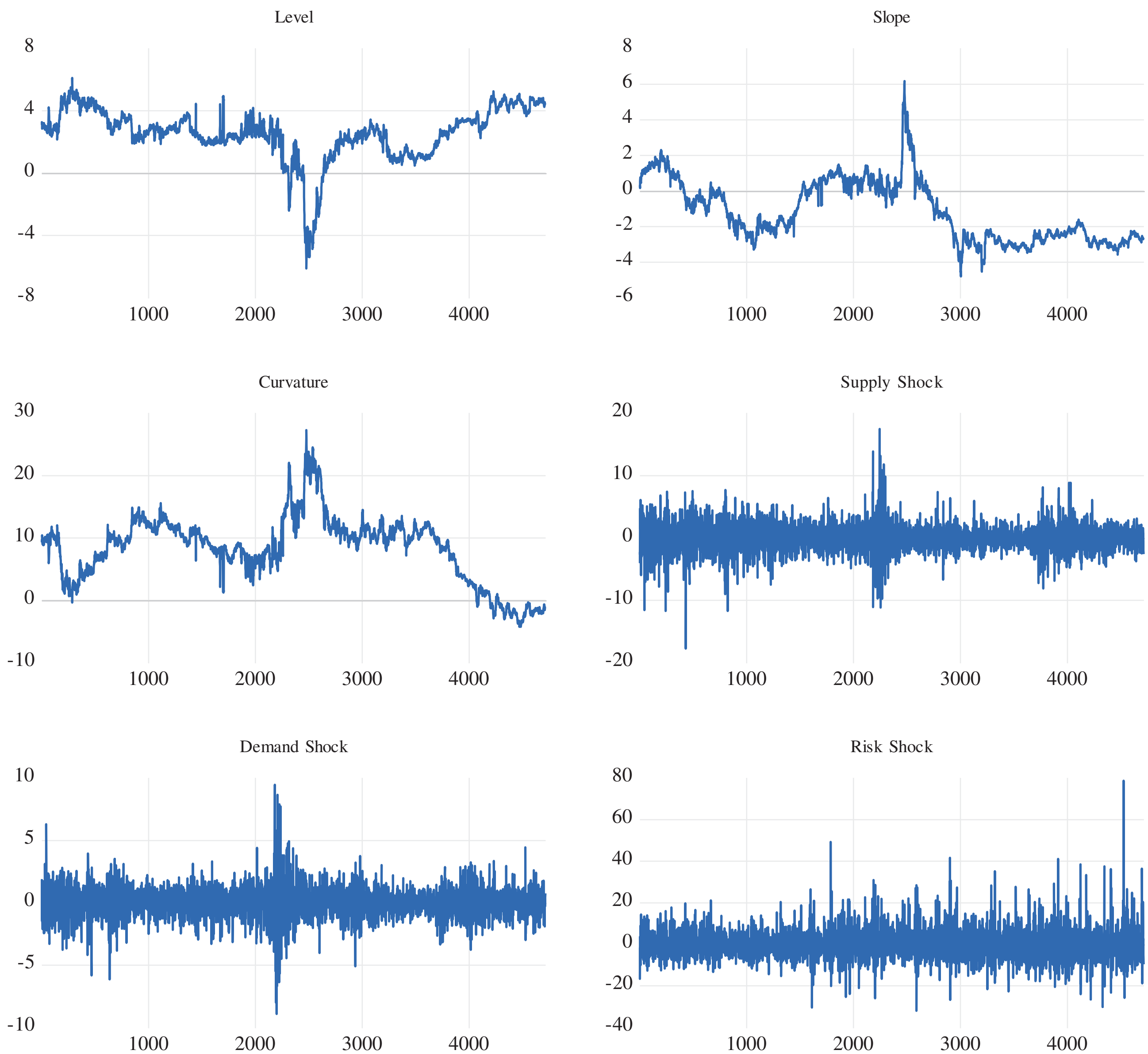

FIGURE A1 Data plots [Colour figure can be viewed at wileyonlinelibrary.com]