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The Role of Oil and Risk Shocks in the High-Frequency Movements of the Term Structure of Interest Rates of the United States

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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 United States covering maturities of 1 to 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 nonlinearity and structural breaks, 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 nonlinearity and regime change, 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 US term structure based on information contained in oil and financial market innovations. Our results have important implications for academics, investors and policymakers.

Keywords: Yield Curve Factors, Oil Supply and Demand Shocks, Risk Shock, Causality-in-Quantiles Test

JEL Codes: E43, C22, C32, G12, Q41

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 (US), is huge, to say the least (see, for example, Balcilar et al. (2015, 2017), or Gupta and Wohar (2017) for detailed reviews in this regard). Interestingly, despite the US bond market capitalization of $40.7 trillion being higher than the corresponding value of $30 trillion associated with the stock market and basically representing nearly two-thirds of value of the global bond market (Securities Industry and Financial Markets Association (SIFMA)), the literature examining the linkages between the US government bond and oil markets is negligible, and limited to the published works of Kang et al. (2014), Ioannidis and Ka (2018), Balcilar et al. (2020), Demirer et al. (2020), Nazlioglu et al. (2020), and Nguyen et al. (2020). This is not only surprising because of the importance of the bond market in comparison to the stock market, but also since the US government bond market is often viewed

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as a safe-haven (Hager, 2017), and the fact that the entire yield curve is considered a predictor of economic activity (Hillebrand et al., 2018). Naturally, the impact of oil shocks on bond market movements (of various maturities) is an important question from the perspectives of both investors and policymakers.

Getting back to studies relating to the government bond and oil markets of the US, one of the early works by Kang et al. (2014) utilized a structural vector autoregressive (SVAR) model to investigate how the demand and supply shocks driving the global crude oil market affect real bond returns of the US at monthly frequency. The authors found that a positive oil market-specific demand shock is associated with significant decreases 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 US, 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 impact of oil price shocks in the global crude oil market on the dynamics of the entire yield curve of the US (and Canada, Norway, and South Korea), as captured by the three factors of level, slope and curvature, derived from maturities of 1 to 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 bond premia of the US Treasury, based on a nonparametric causality-in-quantiles framework to account for misspecification due to uncaptured nonlinearity and structural breaks. They found that oil uncertainty predicts an increase in US bond premia of various maturities (2 to 5 years relative to 1 year), with a stronger impact observed at longer-term maturities. Nazlioglu et al. (2020), using daily data and accounting for structural shifts as a smooth process found, inter alia, that the causality between bond and oil prices in the US runs only in one direction, from the bond market to the oil price, and not the other way.[1, 2]

Against this backdrop, we aim to add to this sparse literature by examining the effects of oil price shocks on the term structure of interest rates for the US. In this regard, given the suggestion of Kilian (2009) that "not all oil price shocks are alike", we first disentangle the oil price movement due to demand, supply and financial risk shocks. Then, as in Ioannidis and Ka (2018), we relate these shocks to the term structure of interest rates, using the well-established framework of Nelson and Siegel (1987, NS) from the finance literature. This model summarizes the entire term structure into three latent yield factors of level, slope, and curvature,

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

[2] A working paper that must be mentioned is the work of Coronado et al. (2020). These authors used historical monthly data from the US 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.

which in turn 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 1 to 30 years in combination with the decomposition of oil price movements due to various causes, enables us to characterize the responses of the yield curve to various shocks and calculate the entire yield curve movement in the wake of these shocks.

Specifically, we rely on high-frequency, i.e. 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 level, slope and curvature of the yield curve using the causality-in-quantiles framework of Jeong et al. (2012). Ready (2018) proposed a novel methodology of disentangling oil price shocks based on information on traded asset prices using return data on a global stock price index of oil producing firms. Taking advantage of the forward looking nature of traded financial asset prices, this model overcomes two main weaknesses of the widely-used standard decomposition technique of Kilian (2009), which are too much weight given to oil-specific demand shocks to the detriment of supply shocks, and the application of the model 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 paper). Given that the period of study involves the zero lower bound (ZLB) situation of the 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, 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 et al., forthcoming).

Note that, theoretically, high oil prices increase inflation expectations and hence, increase nominal bond yields. Moreover, higher oil prices, especially originating from supply disruptions, are historically known to have a recessionary impact on the US 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 US becoming the leading exporter of refined oil products, higher oil prices generate increased domestic income and can result in higher demand for investment in the financial asset market, including bonds, and hence produce higher asset prices or returns on bonds, to cause a reduction ininterest rates on the bonds. In addition, Degiannakis et al. (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 US 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 paper to study the predictability of disentangled oil demand, oil supply and financial market risk shocks 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 is a reconsideration of the work of Ioannidis and Ka (2018) at 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 US interest rates. Moreover, our paper 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 US yield curve. The remainder of the paper is organized as follows: Section 2 discusses the data, along with the outlines of the three methodologies associated with the NS model, the SVAR to get the oil shocks, and the causality-in-quantiles approach. Section 3 presents the results, with Section 4 concluding the paper.

2. Data and Econometric Methodologies

In this section we present the data and the basics of the three 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 the Federal Reserve Board at: https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html. This paper makes available to researchers and practitioners a long history of high-frequency yield curve estimates of the Federal Reserve Board at a daily frequency. The authors 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.

In order to compute oil price demand/supply as well as risk shocks, following Ready (2018) we collect daily price data for the world integrated oil and gas producer index,[3] the nearest maturity NYMEX crude-light sweet oil futures contract, and the Chicago Board Options Exchange (CBOE) volatility index (VIX). These data are all derived from the Datastream database as maintained by Thomson Reuters. We use the first nearest maturity NYMEX crude-light sweet oil futures contract as a proxy for the price of crude oil. Finally, we use the innovations in VIX, obtained as the residuals from an ARMA (1,1) model estimated for the VIX index, to capture shocks related to changes in the market discount rate that tend to co-vary with attitudes towards risk. Our analysis covers the daily period from 5 January 2000 to 31 October 2018, with the start and end dates governed by data availability.

2.2. Methodologies

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] The world integrated oil and gas producer index represents the stock prices of global oil producer companies and includes large publicly traded oil producing firms (i.e., BP, Chevron, Exxon, Petrobras or Repsol), but not nationalized oil producers (such as ADNOC or Saudi Aramco).

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:

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

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 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:

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

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.[4]

2.2.2. SVAR Model for Disentangling Oil Price Shocks

Ready (2018) defines demand shocks as the proportion of returns of a global stock index of oil producing firms that is orthogonal to the innovations of the VIX. The innovations to the VIX control for aggregate changes in market discount rates that affect stock returns of oil producing companies and are used as a proxy for risk shocks. Supply shocks, in turn, are represented by the residual component of oil-price changes that is orthogonal to both demand shocks and risk shocks. To be more specific, the decomposition model by Ready (2018) takes the following matrix form:

[4] 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.

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

where $W_t = [\Delta oil_t, R_t^{Prod}, \xi_{VIX,t}]'$ is a 3×1 vector, Δoil_t denotes the change in oil price in period t, R_t^{Prod} is the return on the global stock index of oil producing firms, and $\xi_{VIX,t}$ stands for innovation of the VIX, based on an ARMA(1,1) specification. Our focus is $Z_t = [ss_t, ds_t, rs_t]'$, which is a 3×1 vector of oil supply, demand and risk shocks represented by ss_t, ds_t and rs_t, respectively. Finally, A is a 3×3 matrix of coefficients defined as:

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

Ready (2018) imposes the following condition to achieve orthogonality among the three types of shocks as follows:

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

where Σ_W denotes the covariance matrix of the variables in W_t, while σ_{ss}^2, σ_{ds}^2 and σ_{rs}^2 are the variance of the supply, demand and risk shocks, respectively. The specification in Eq. (6) represents a renormalization of the standard orthogonalization applied to construct structural shocks in a SVAR model. Note that the volatility of oil-price shocks is not normalized to one, but, instead, the sum of the three shocks has to be, by their very construction, equal to the total variation in the oil price. This method of decomposing oil-price shocks defines an oil supply shock as the component of oil-price fluctuations that cannot be explained by changes in global aggregate demand and changes in financial-market uncertainty.[5]

2.2.3. 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 $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, 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:

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

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

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

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

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:

[5] In a sense, one can argue that supply shocks in this framework relate to region-specific or event-specific information that cannot be accounted for by stock-market related pricing effects.

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

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

The empirical implementation of 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 1 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 three shocks, i.e., oil supply, oil demand and financial market risks are summarized in Table A1, and plotted in Figure A1 in the Appendix to the paper. 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 US, 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. 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 rejection of the null hypothesis of normality under the Jarque-Bera 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 we discuss the findings from the causality-in-quantiles tests, for the sake of completeness and comparability, we conducted the standard linear Granger causality test, with a lag-length of 1, as determined by the SIC. The resulting $\chi^2(1)$ statistics involving the causality running from ss_t, ds_t or rs_t to L_t, S_t, and C_t are reported in Table A2 in the Appendix to the paper. 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 US yield curve.

Given the insignificant results obtained from the linear causality tests, we statistically examined the presence of nonlinearity and structural breaks in the relationship between the three latent factors of the term structure with the three shocks. 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 one lag of the three factors and ss_t, ds_t or rs_t. Table A3 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 the shocks. To further motivate the causality-in-quantiles approach, we next used 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 ss_t, ds_t or rs_t, allowing for heterogenous error distributions across the breaks. When we applied these tests again 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.

3.2. Causality-in-Quantiles Results

Given the strong evidence of nonlinearity and structural breaks in the relationship between the latent factors and shocks, we 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 ss_t, ds_t or rs_t do not Granger cause L_t, S_t, and C_t is overwhelmingly rejected at the 5% level of significance (given the critical value of 1.96) over the entire conditional distribution. 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, 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. In other words, when we account for nonlinearity and structural breaks using a nonparametric approach, we are able to find strong evidence of predictability emanating from all the shocks onto the three factors characterizing the US 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 observed under the linear framework. 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 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 1(b)), and the oil supply shock on the curvature (see Figure 1(c)). 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 1(a)). In general, monetary policy, i.e., the slope factor, is shown to respond strongly to financial market risks, i.e., uncertainty (a result in line with Çekin et al. (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 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 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 2, and the signs of the impacts of the shocks are quantile-specific.

As shown in Figure 2(a), 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, i.e., 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 2(a) 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 US 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 2(c), 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 US 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 US Treasury securities, i.e., 1 to 30 years, rather than the 1 to 10 years used in existing studies.

4. Conclusion

Against the backdrop of sparse literature on the impact of oil shocks on the government bond market of the US, 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. Based on daily data covering the period 5 January 2000 to 31 October 2018, we find 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 nonlinearity and structural breaks. Given this, 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 nonlinearity and regime changes 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 US 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 US 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 at high-frequency, i.e., 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, bond investors can improve their investment strategies by exploiting the role of oil and risk shocks in their interest-rate prediction models, while risk managers can develop asset allocation decisions conditional on the level of these shocks. Finally, researchers may utilize our findings to explain deviations from asset-pricing models by embedding oil supply and demand, and financial market risk shocks in their pricing kernels, which, however, need to be nonlinear.

While we concentrate 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.

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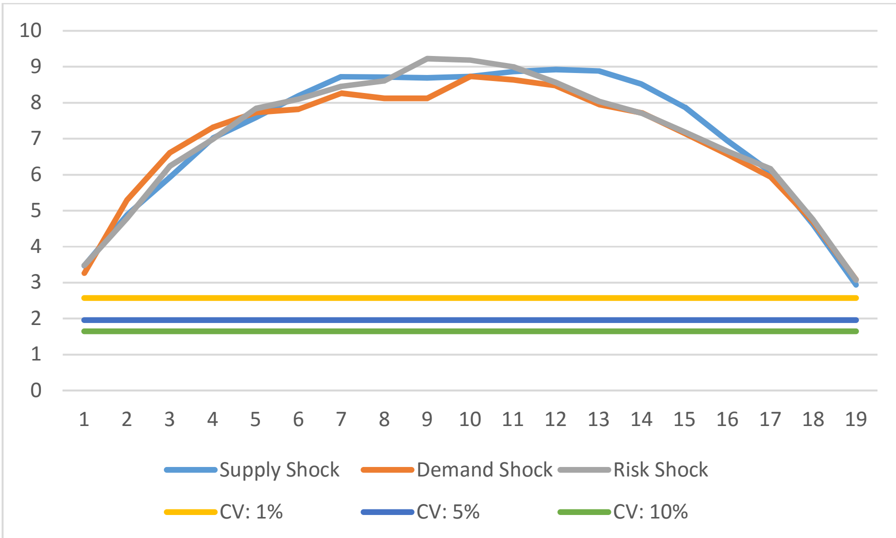
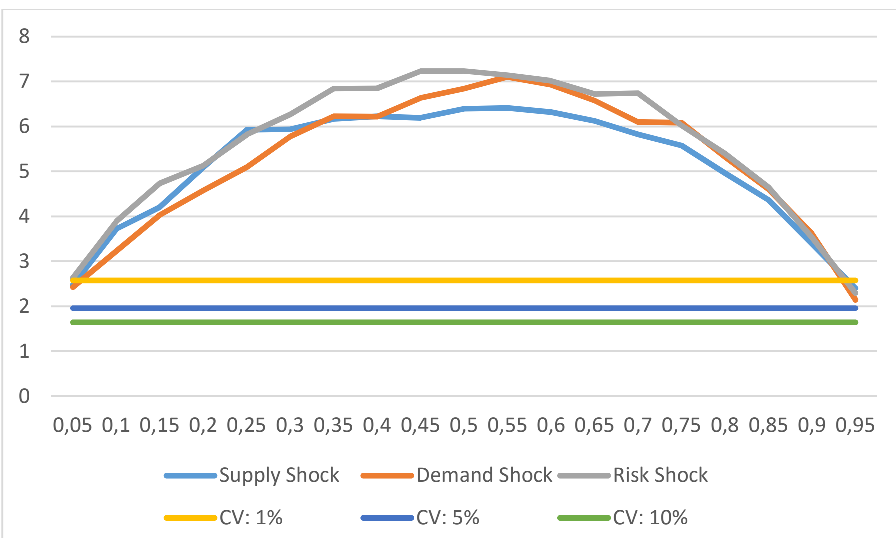
Figure 1. Causality-in-Quantiles Test Results for the US Term Structure Factors due to Oil Supply, Oil Demand and Financial Market Risk Shocks

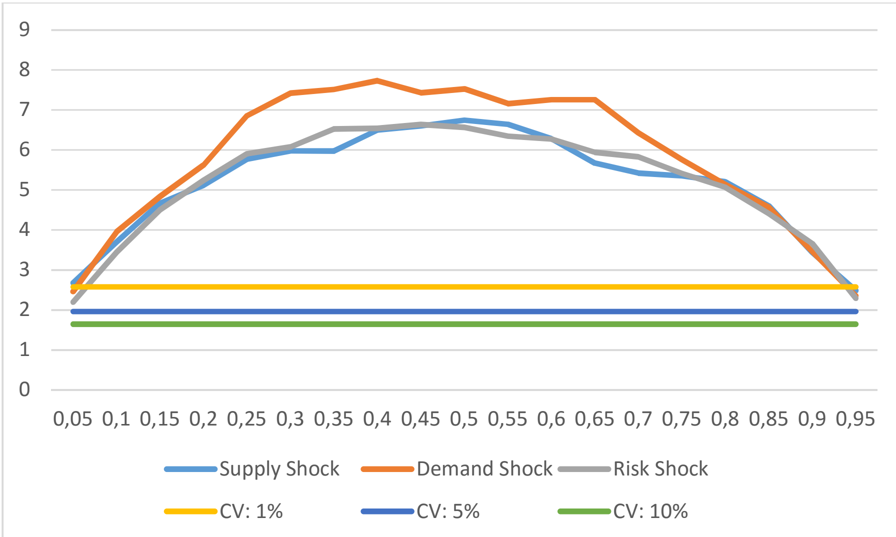
1(a). Level Factor



1(b). Slope Factor



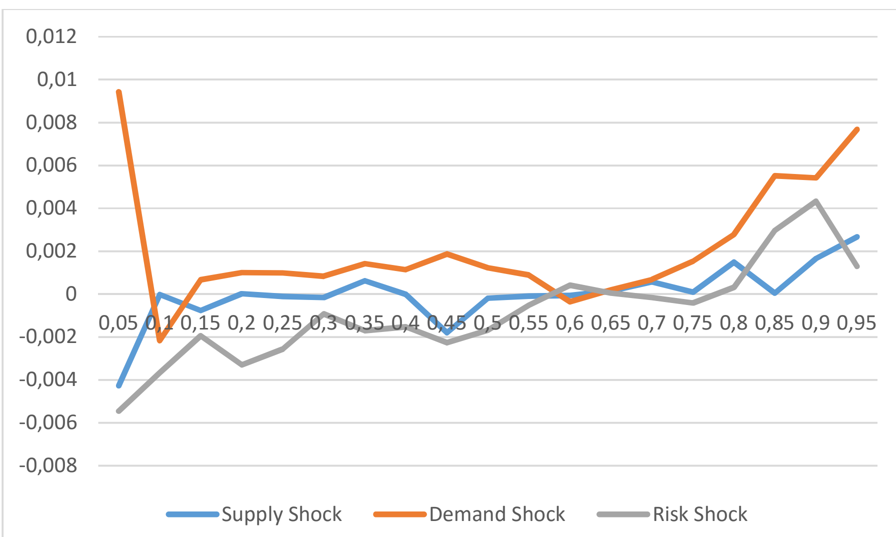
1(c). Curvature Factor



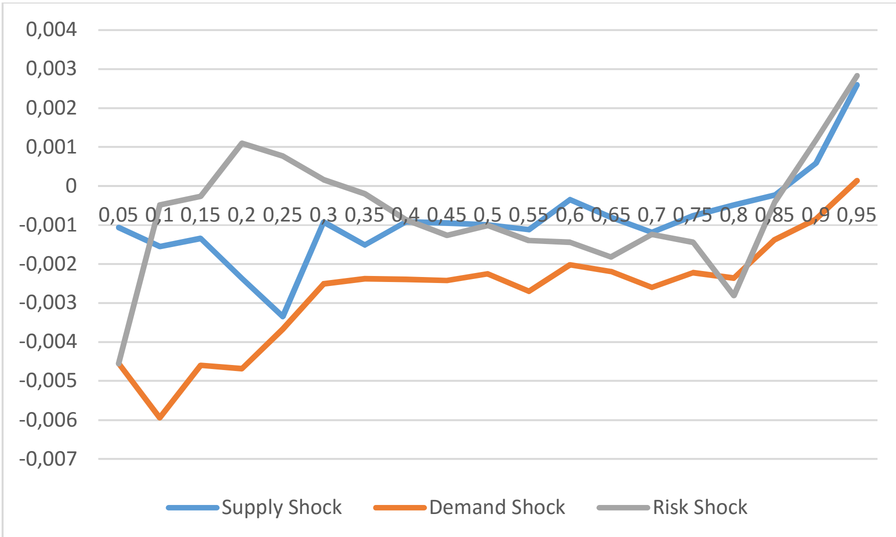
Note: The horizontal axis represents the quantiles, while the vertical axis presents the causality-in-quantiles test statistic indicating the rejection or non-rejection of the null hypothesis that a particular shock does not Granger cause a specific term structure factor at a specific quantile, if the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

Figure 2. The Sign of the Impact on the US Term Structure Factors due to Oil Supply, Oil Demand and Financial Market Risk Shocks

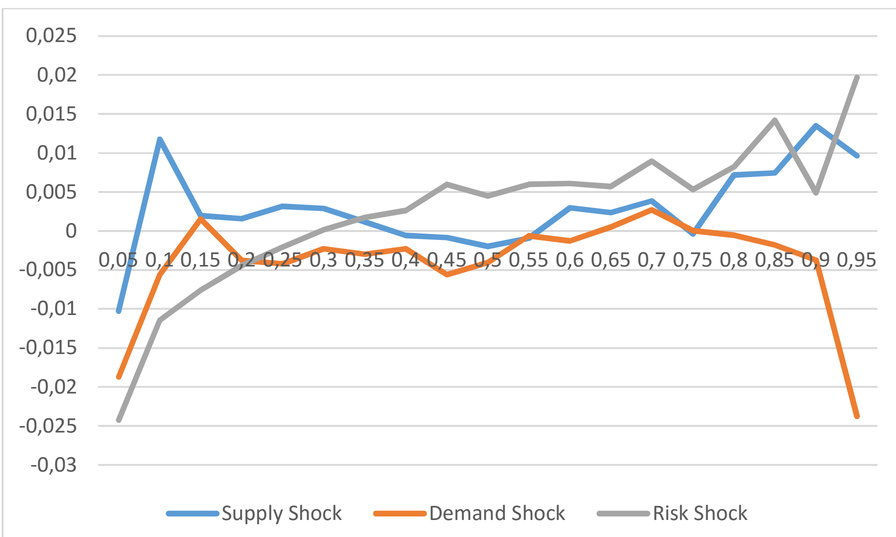
2(a). Level Factor



2(b). Slope Factor



2(c). Curvature Factor



Note: 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.

APPENDIX:

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	5964.3060[#]	272.3718[#]	38.1354[#]	5934.3570[#]	7688.7710[#]	12575.7600[#]
Observations	4712					

Note: [#] 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

Note: [*] indicates rejection of the null hypothesis of causality at 10% level of significance.

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

Dependent Variable	Independent Variable	*Dimension (m)* 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