

# Oil Price Uncertainty and Movements in the US Government Bond Risk Premia

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## Abstract

In this paper, we analyze the predictability of the movements of bond premia of US Treasury due to oil price uncertainty over the monthly period 1953:06 to 2016:12. For our purpose, we use a higher order nonparametric causality-in-quantiles framework, which in turn, allows us to test for predictability over the entire conditional distribution of not only bond returns, but also its volatility, by controlling for misspecification due to uncaptured nonlinearity and structural breaks, which we show to exist in our data. We find that oil uncertainty not only predicts (increases) US bond returns, but also its volatility, with the effect on the latter being stronger. In addition, oil uncertainty tends to have a stronger impact on the shortest and longest maturities (2- and 5-year), and relatively weaker impact on bonds with medium-term (3- and 4-year) maturities. Our results are robust to alternative measures of oil market uncertainty and bond market volatility.

**Keywords:** Oil Price Uncertainty, Bond Returns and Volatility; Higher-Order Nonparametric Causality-in-Quantiles Test

**JEL Codes:** C22, G12, Q02

## 1. Introduction

The theories of investment under uncertainty and real options predict that uncertainty about, for example, oil prices will induce optimizing firms to postpone investment decisions, thereby leading to a decline in aggregate output (Bernanke, 1983). Empirical evidence in favour of this line of reasoning for the economy of the United States (US) can be found in the works of Elder and Serletis (2010, 2011) (and also verified globally more recently by van Eyden et al., (2019)). Given that oil price uncertainty negatively affects macroeconomic variables (Bams et al., 2017), shows that oil market uncertainty also predicts valuation of stocks in the US.<sup>1</sup>

Against this backdrop, the objective of our study is to analyse the role of oil price uncertainty in predicting movements of risk premia (excess returns) of U.S. government bonds. This is an important question since accurate prediction of interest rate movements are important to bond investors and policymakers. While for central bankers, understanding the evolution of future interest rates help in the fine tuning of monetary policies, for bond market investors, correct prediction of interest rates is likely to result in higher bond returns performance. For our purpose, we use the recently developed higher ( $k$ -th) order nonparametric causality-in-

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<sup>1</sup> Earlier, Elyasiani et al., (2011) shows, using US sectoral data, that oil futures return volatility influences excess returns of oil user industries. In addition, the studies of Choi and Hammoudeh (2010), Kang et al., (2015a, b), and Salisu and Oloko (2015) indicate significant spillover from oil market volatility on US stock returns and volatility.

quantiles model of Balcilar et al., (2018), which in turn, allows us to test for predictability over the entire conditional distributions of both bond returns and volatility simultaneously by controlling for misspecification due to uncaptured nonlinearity. Since we are dealing with uncertainty (in the oil market), we believe that it is likely to have not only an impact on the first-moment, but also the second moment of bond premia – a reasoning in line with recent studies (see for example, Buraschi et al., 2014; Balcilar et al., 2016; Chuliá et al., 2017), which depicts the impact of overall macroeconomic uncertainty on not only returns of financial (bonds, currencies and equities) markets, but also volatility.<sup>2</sup>

There is of course a large number of studies on predicting risk premia of U.S. government bonds (e.g., Cochrane and Piazzesi (2005), Ludvigson and Ng (2009, 2011), Laborda and Olmo (2014), Gargano et al., (2017), Ghysels et al., (2018)).<sup>3</sup> But, these studies highlight the role of macro and financial (often extracted from large data sets), and behavioral factors in predicting (excess) bond returns, over and above the so-called “CP” factor of Cochrane and Piazzesi (2005), which in turn is a linear combination of five forward spreads. To the best of our knowledge, this is the first paper that evaluates the predictive power of oil price uncertainty for US bond returns and volatility based on a nonparametric causality-in-quantiles framework over the monthly period of 1953:06 to 2016:12. The lack of studies analysing the impact of oil price movements on the US bond market is quite puzzling, given the well-established importance US Treasury securities as a global safe haven (Kopyl and Lee, 2016; Habib and Stracca, 2017), and also the fact that the bond market in 2018 was valued at more than \$40 trillion US dollars, which in turn was \$10 trillion US dollars more than the corresponding capitalization of the stock market (Bloomberg). The only study, which is somewhat related to our work is that of Kang et al., (2014), whereby the authors utilize a structural vector autoregressive model to investigate how the demand and supply shocks driving the global crude oil market affect real bond returns. This study found that a positive oil market-specific demand shock is associated with significant decreases in real returns of an aggregate bond index for 8 months following the shock. The remainder of the paper is organized as follows: Section 2 outlines the methodology, while Section 3 discusses the data and econometric results. Section 4 conducts several robustness checks, with Section 5 concluding the paper.

## 2. Econometric Methodology

In this section, we briefly describe the methodology for testing nonlinear causality via a hybrid approach as developed by Balcilar et al., (2018), which is based on the frameworks of Nishiyama et al., (2011) and Jeong et al., (2012). Let  $y_t$  denote excess bond returns and  $x_t$  the oil market uncertainty. 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  $F_{y_t|\cdot}(y_t|\cdot)$  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  $\theta$ -th quantile hypotheses to be tested are:

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

$$H_1: P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad (2)$$

<sup>2</sup> In this regard, see also Bouri et al., (2017, 2018), whereby these studies provide evidence of commodity and oil market volatility on sovereign risks of emerging and frontier countries.

<sup>3</sup> Important earlier studies are Keim and Stambaugh (1986), Fama and Bliss (1987), Fama and French (1989), and Campbell and Shiller (1991).

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

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \quad (3)$$

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  $\theta$ -th conditional quantile and  $\mathbf{1}\{\bullet\}$  is the indicator function. The *Nadarya-Watson* kernel estimator of  $\hat{Q}_\theta(Y_{t-1})$  is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \quad (4)$$

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

Balcilar *et al.*, (2018) extend Jeong *et al.*, (2012)'s framework, based on Nishiyama *et al.*, (2011), to the *second* (or higher) moment, which allows us to test the causality between oil price uncertainty and excess bond returns volatility. In this case, the null and alternative hypotheses are given by:

$$H_0: P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1, \quad k = 1, 2, \dots, K \quad (5)$$

$$H_1: P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1, \quad k = 1, 2, \dots, K \quad (6)$$

The causality-in-variance test can then be calculated by replacing  $y_t$  in Eqs. (3) and (4) with  $y_t^2$ . As pointed out by Balcilar *et al.*, (2018) a rescaled version of the  $\hat{J}_T$  has the standard normal distribution. Testing approach is sequential and failing to reject the test for  $k = 1$  does not automatically lead to no-causality in the *second* moment; one can still construct the test for  $k = 2$ .

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  $K(\bullet)$  and  $L(\bullet)$ . Our lag order is based on the Schwarz Information Criterion (SIC), with  $h$  determined by the leave-one-out least-squares cross validation, and, for  $K(\bullet)$  and  $L(\bullet)$ , we use Gaussian kernels.

### 3. Data and Results

Our analysis involves two variables namely, the excess bond returns and oil price uncertainty over the monthly period of 1953:06 to 2016:12, with the start- and end-dates being purely driven by data availability of the bond prices.  $rx^{(n)}$  denote the continuously compounded excess returns on an  $n$ -year zero coupon bond, with  $n = 2, 3, 4$  and  $5$ .<sup>4</sup> We obtain monthly US Treasury bond prices from the Fama and Bliss (1987) dataset, which is available at the Center for Research in Security Prices (CRSP). As far as oil price uncertainty (*OILUNCI*) is concerned, we use the fitted conditional variance derived from a Generalized Autoregressive Conditional

<sup>4</sup> In line with Cochrane and Piazzesi (2005), we use the following notation for the (log) yield of an  $n$ -year bond:  $y_t^{(n)} \equiv -\frac{1}{n} p_t^{(n)}$ , where  $p_t^{(n)} = \ln P_t^{(n)}$  is the log-price of the  $n$ -year zero coupon bond at time  $t$ . A forward rate at time  $t$  for loans between time  $t + n - 1$  and  $t + n$  is defined as:  $f_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$ . The log holding period return from buying an  $n$ -year bond at time  $t$  and selling it as an  $n - 1$  year bond at time  $t + 1$  is:  $r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}$ . The risk premium on an  $n$ -year discount bond over a short-term bond is the difference between the holding period returns of the  $n$ -year bond and the 1-period interest rate,  $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$ . Alternatively,  $rx_t^{(n)} \equiv r_t^{(n)} - y_{t-1}^{(1)}$ .

Heteroskedasticity (GARCH(1,1)) model along the lines of Elder and Serletis (2010, 2011), and following Sadorsky (2006), Bos et al., (2018) and Gupta and Yoon (2018).<sup>5</sup> In this regard, we use the West Texas Intermediate (WTI) oil price data derived from the Global Financial Database.

The variables of interest, i.e., the bond risk premia with maturities of 2-, 3-, 4-, and 5-year, as well as the derived measure of oil price uncertainty have been plotted in Figure A1, with their basic statistics summarized in Table A1, both of which can be found in the Appendix of the paper. As can be seen from Table A1, the null hypothesis of normality is rejected for both variables ( $rx^{(n)}$  and *OILUNCI*) of concern, and hence, provides preliminary motivation to rely on a quantiles-based analysis instead of a standard linear test of causality.

Before we discuss the findings from the causality-in-quantiles test, for the sake of completeness and comparability, we first provide the findings from the standard linear Granger causality test reported in Table A2 in the Appendix of the paper. As shown in Table A2, the null of no-causality from *OILUNCI* to  $rx^{(n)}$ , with  $n = 2, 3, 4$  and  $5$ , cannot be rejected even at the 10% level of significance. In other words, a standard linear test of predictability fail to provide any evidence of significant oil uncertainty-related effects on excess bond returns.

Given the insignificant results obtained from the linear causality tests, next we statistically examine the presence of nonlinearity and structural breaks in the relationship between excess bond returns and oil price uncertainty, motivated from the evidence provided by Gargano et al., (2017) on the instability in the relationship between bond premia and its predictors. For these purposes, we apply the Brock et al., (1996) (BDS) test of nonlinearity on the residuals recovered from excess bond returns equation of the Granger causality test, and the Bai and Perron (2003) tests of multiple structural breaks on the same excess returns equation. As can be seen from Table A3 in the Appendix of the paper, the null hypothesis of *i.i.d.* residuals at various embedded dimensions ( $m$ ) is rejected at the highest significance level by the BDS test. In other words, the relationship between excess bond returns at the four maturities considered and the oil price uncertainty is in fact nonlinear. Further, based on the structural break test, we were able to detect one break each at 1981:12, 1981:11, 1981:07, and 1981:07 in the relationship between *OILUNCI* with  $rx^{(2)}$ ,  $rx^{(3)}$ ,  $rx^{(4)}$ , and  $rx^{(5)}$  respectively. These break dates seem to be in line with the findings of Smith and Taylor (2009) regarding a shift in the term-structure, and is believed to be a result of Paul Volcker's strong disinflationary policies to curb double digit inflation rates in the US (to some extent due to the second major oil-price shock in 1979). In sum, in the presence of nonlinearity and regime changes, the findings based on the linear Granger causality test cannot be deemed robust and reliable. Hence, we now turn our attention to the causality-in-quantiles test, which is robust to linear misspecification given its nonparametric (i.e., data-driven) estimation, besides its ability to study the entire conditional distribution of not only returns, but also volatility (squared returns) of the US bond market.

In Figure 1, we present the results for the  $k$ -th order causality-in-quantiles test for excess bond returns and squared returns, i.e., volatility, emanating from *OILUNCI* over the quantile range of 0.05 to 0.95. Note the test statistic, proposed by Balcilar et al., (2018), follows a standard normal distribution, and we evaluate the existence or non-existence of causality at a specific quantile ( $\tau$ ), if the test statistic is greater than or less than the conventional 5% critical value of

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<sup>5</sup> Complete details of the estimation of the GARCH(1,1) model is available upon request from the authors.

1.96. We find that for  $rx^{(1)}$  and its squared-value, the predictability holds over the entire conditional distribution, with stronger effects around the tails. A similar picture emerges for  $rx^{(5)}$  though, there is no evidence of predictability around the quantile range of 0.4250 to 0.500 for the bond returns. Interestingly, the impact of *OILUNC1* on  $rx^{(3)}$  and  $rx^{(4)}$  are also quite similar. For excess bond returns of maturities of 3 and 4-year, causality hold over the moderately high quantile range of 0.700 to 0.850, and at  $\tau = 0.250$  for the latter. In terms of squared returns, i.e., volatility of these two maturities, the coverage of causality over the conditional distributions is much broader and ranges between 0.100 to 0.800, and 0.100 to 0.700 for the 3- and 4-year squared bond premia respectively.

**[INSERT FIGURE 1]**

Although we can derive robust predictive inference based on the causality-in-quantiles test, it would also be interesting to estimate the direction of the effects of oil uncertainty on bond market movements at various quantiles. However, in a nonparametric framework, this is not straightforward, with us requiring to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can experience complications because nonparametric methods exhibit slow convergence rates, which can depend on the dimensionality and smoothness of the underlying conditional expectation function. But one could 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). We use the locally polynomial quantile kernel regression approach of Chaudhuri et al., (1997), to estimate the partial ADs. The confidence intervals for AD estimates are obtained using the bootstrap method of Cai et al., (2000). The sign of the impact of oil price uncertainty on excess bond returns and volatility is reported in Figure 2. As can be observed, the effect of *OILUNC1* on the returns and variance of bond premia of the four maturities considered is generally positive and significant at the 5% level, corresponding to the quantiles for which predictability was detected based on the causality-in-quantiles test.

**[INSERT FIGURE 2]**

In sum, we can draw the following observations: (a) Impact of oil price uncertainty is stronger on bond volatility than returns across the four maturities considered, which is somewhat expected in the sense that uncertainty being itself capturing volatility (risk) in the oil market, is likely to have stronger higher-order impact on the bond market (see, Bonaccolto et al., (2018) for a detailed discussion in this regard); (b) Further, the effect of oil uncertainty on both returns and volatilities of the bonds with shortest and longest maturities is stronger relative to the corresponding metrics of the bonds with medium-term maturities. Intuitively, this result seems to be in line with the widespread observation that the two-ends of the term-structure tends to be affected by shocks relatively more compared to its other parts. For instance, the strong-movement in the 2-year bond premium due to oil uncertainty is probably due to the (expansionary) response of monetary policy to oil market uncertainty (to curb the recessionary impact), given the findings of Bauer (2015) and Tillmann (forthcoming), that bonds with shorter maturities are tied more strongly with monetary policy decisions. At the same time, the stronger impact of oil uncertainty on the 5-year bond premium is due to the possibility of the longer maturities being tied more closely to economic activity and inflationary expectations (Ang et al., 2011) - both of which (output and inflation) are affected by oil volatility (Castillo

et al., 2007; Lu et al., 2010), and; (c) Finally, oil market uncertainty is priced in the excess bond returns, and also increases variability of the associated risk, with the result being in line with observations made for equity markets in the wake of increased overall macroeconomic uncertainty (Pástor and Veronesi, 2013). Note that, risks due to recession and inflationary expectations results in higher bond premium for the longest maturity, as investors need to be compensated for holding these bonds. As far as the shortest maturity is concerned, expansionary monetary policy shocks would enhance consumption growth and lead to lower returns on risk-free assets. Thus, when consumption growth is expected to be high, a decrease in the bond's payoff should make investors less willing to invest in shorter-term bonds and lead to a higher risk premium (Rudebusch and Swanson, 2012).

#### 4. Robustness and Additional Analyses

In this section, we conduct robustness and additional analyses based on the causality-in-quantiles framework.<sup>6</sup> We start-off by analysing the causal impact of two alternative measures of oil price uncertainty. Then, we also test for predictability of the movements of equity premium and corporate bond premium based on our benchmark measure of uncertainty. Finally, we also test for predictability of our GARCH(1,1)-based measure of oil price uncertainty on bond market variance derived from indices of implied volatility of the US Treasury market. Below, we discuss the results of each of these robustness checks in detail derived:

- (i) We first derive two alternative measures of oil uncertainty, with *OILUNC2* based on a time-varying parameter stochastic volatility (TVP-SV) model of Chan (2017),<sup>7</sup> and *OILUNC3* being a monthly measure of realized volatility, derived from sum of daily squared returns over a month as suggested in Andersen and Bollerslev (1998). In addition to these two measures of uncertainty, we also use the crude oil volatility index of the Chicago Board Options Exchange (CBOE), as the third alternative measure of oil market uncertainty (*OILUNC4*).<sup>8</sup> Note that the analysis based on *OILUNC2* ranges from 1953:06 to 2016:12, while given the availability of daily data (again sourced from the Global Financial Database), the causality-in-quantiles test with *OILUNC3* covers 1977:08 to 2016:12. As far as *OILUNC4* corresponding to the Oil VIX is concerned, the sample period is 2007:05 to 2016:12.<sup>9</sup> As can be seen from Figure 3, our benchmark results reported in Figure 1 with *OILUNC1*, in

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<sup>6</sup> As with the bond premia, linear causality tests failed to detect any evidence of causality in the first moment of all the dependent variables considered below corresponding to various measures of oil price uncertainty, and the BDS test showed significant evidence of nonlinearity. Hence, we decided to rely on the causality-in-quantiles test. In addition, oil uncertainty was consistently observed to have positive impact on the first- and second-moments of the alternative variables of interest, as in the case of the bond premia. Complete details of these test results are available upon request from the authors.

<sup>7</sup> Complete details of the parameters derived from a Bayesian estimation of this model is available upon request from the authors.

<sup>8</sup> The CBOE Crude Oil ETF Volatility Index ("Oil VIX") measures the market's expectation of 30-day volatility of crude oil prices by applying the VIX methodology (see, <http://www.cboe.com/vix> for details) to United States Oil Fund, LP options spanning a wide range of strike prices. The daily data is available for download from: <http://www.cboe.com/products/vix-index-volatility/volatility-on-etfs/cboe-crude-oil-etf-volatility-index-ovx>.

<sup>9</sup> We take averages of the daily data over a month to convert the Oil VIX to the corresponding monthly frequency of *OILUNC4*. Using the last day of the month to measure the corresponding monthly value of *OILUNC4*, yielded qualitatively and quantitatively similar results to those reported in the paper, which in turn are available upon request from the authors.

general, continues to hold under the two alternative measures of oil price uncertainty, i.e., *OILUNC2* and *OILUNC3*. Specifically, we continue to see stronger impact (in terms of the coverage of the conditional distributions over which causality holds) on bond premium volatility relative to the excess returns, and also that the predictability of bond market movements (mean and variance) for shortest (2-year) and longest (5-year) maturities is relatively more powerful than the medium-term maturities (3- and 4-year). When it comes to *OILUNC4*, the impact on bond premia and volatility across the various maturities are quite similar, with no evidence of predictability at the extreme ends. In addition, the causality tends to get more powerful in strength as the maturity lengthens. In other words, compared to *OILUNC1*, *OILUNC2*, *OILUNC3*, there are some differences in the nature of predictability under the CBOE implied volatility index, i.e., *OILUNC4*, but more importantly, this measure too contains predictive power for the first- and second-moments of the bond market;

**[INSERT FIGURE 3]**

- (ii) To validate the results of Bams et al., (2017) of predictability of the stock market movements due to oil uncertainty (*OILUNC1*), we applied the causality-in-quantiles test on the equity premium (*EP*) and its squared value, i.e., volatility. The equity premium is obtained from the CRSP stock returns minus the risk free-rate,<sup>10</sup> and cover the period of 1953:06 to 2016:12 to correspond to the same sample period of the bond market data. As can be seen from Figure 4, *OILUNC1* fail to cause the extreme ends of the conditional distribution of excess returns, i.e.,  $\tau=0.050$  to  $0.100$ , and  $\tau=0.825$  to  $0.950$ , and similar results are also obtained for stock market volatility, with no prediction over  $\tau=0.050$  to  $0.100$ , and at  $\tau=0.950$ . Hence, as with the bond premia, oil uncertainty does affect both stock returns and volatility, with the effect being relatively stronger (in terms of coverage of the conditional distribution where the null of no-causality is rejected) for the latter;

**[INSERT FIGURE 4]**

- (iii) As an additional analysis, we also conducted the causality-in-quantiles test from *OILUNC1* on excess corporate bond premium (*ECBPI*), which is measured as long-term high yield corporate bond returns minus the risk free-rate,<sup>11</sup> over the sample period of 1953:06 to 2016:12. As can be seen from Figure 5, predictability holds over the entire respective conditional distributions of the corporate bond premium and its volatility, with the impact being stronger on volatility than the first moment of corporate premium (especially from the quantile ( $\tau$ ) equal to 0.25 and above), just as in the case of the US Treasury bond premia;<sup>12</sup>

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<sup>10</sup> Data on both these variables are available for download from the website of Professor Amit Goyal at: <http://www.hec.unil.ch/agoyal/>.

<sup>11</sup> Data on the long-term corporate bond returns, derived from Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook, is available for download from the website of Professor Amit Goyal at: <http://www.hec.unil.ch/agoyal/>, with.

<sup>12</sup> In addition, we also analyzed the predictability due to *OILUNC1* of an alternative measure of excess corporate bond premium (*ECBP2*) as developed by Gilchrist and Zakrajšek (2012). The data on *ECBP2* is available for download from: <https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/recession-risk-and-the-excess-bond-premium-20160408.html>. Based on the sample period of 1973:01 to 2016:12, we observe from Figure A2 in the Appendix, that *ECBP2* is predictable from just below the median till moderately high quantiles

## [INSERT FIGURE 5]

- (iv) Finally in Figure 6, we also report the causality-in-quantiles test (for mean only) on the implied volatilities of US Treasuries with maturities of 5(TIV5y)-, 10(TIV/TYVIX)- and 30(TIV30y)-years, which were developed by Choi et al., (2017).<sup>13</sup> The sample periods, based on data availability are: 1990:01-2012:09, 1985:05-2015:12, and 1982:10-2012:09 for TIV5y, TIV/TYVIX, and TIV30y respectively. *OILUNCI* causes the entire conditional distribution of TIV30y and TIV/TYVIX (at the 10% level of significance for quantile ( $\tau=0.95$ ), and also predicts TIV5y, barring the ends of its conditional distribution, i.e., ( $\tau=0.050$  to  $0.225$ , and  $\tau=0.850$  to  $0.950$ ). These results tend to corroborate the earlier findings related to bond market volatility based on squared excess bond returns, i.e., of the strong impact of oil uncertainty on bond volatility especially at longer maturities.

## [INSERT FIGURE 6]

### 5. Concluding Remarks

In this paper, we test the predictability of the movements of excess returns on US Treasury bonds due to oil price uncertainty over the monthly period of 1953:06 to 2016:12. We first indicate that, the relationship between bond premia of maturities of 2-, 3-, 4- and 5-year with oil uncertainty is nonlinear and has undergone regime-changes, and hence, the evidence of no-causality derived from the misspecified linear model cannot be relied upon. Given this, we use the recently developed  $k$ -th order nonparametric causality-in-quantiles framework of Balcilar et al., (2018), which in turn, allows us to test for predictability over the entire conditional distribution of not only bond returns, but also volatility, by controlling for misspecification due to uncaptured nonlinearity and structural breaks. Our results point out that oil uncertainty not only predicts US bond returns, but also volatility, with the effect on the latter being stronger. In addition, the impact is positive, i.e., oil uncertainty increases the bond premia and its volatility across maturities. In line with the theory of term-structure, our results also show that oil uncertainty tends to have a stronger impact on the shortest and longest maturities considered, and relatively weaker impact on bonds with medium-term maturities. These main results are found to be robust under alternative measures of oil market uncertainty and implied measures of bond volatility. Finally, oil uncertainty is also shown to impact the equity premium and excess returns on corporate bonds, as well as their respective volatilities.

Our results have important implications for not only bond investors and policymakers, but also for academics in finance, who are all looking to predict interest rates movements accurately. The finding that oil uncertainty impact the evolution of future interest rates and its volatility can help policymakers in better design monetary policy, by accounting for oil price volatility.

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(i.e.,  $\tau=0.475$  to  $0.850$ ). The volatility of *ECBP2*, i.e., squared *ECBP2* is caused by *OILUNCI* over the moderately low quantiles of  $\tau=0.225$  to  $0.350$ . Unlike the case of US Treasury bonds and the long-term corporate bonds, the predictability due to oil uncertainty seems to be more stronger on the alternative measure of the excess corporate bond premium (*ECBP2*) than its volatility. Notwithstanding the differences in the sample period, the muted impact on *ECBP2* compared to *ECBP1* from *OILUNCI*, could be due to the fact that the former is a component of corporate bond credit spreads that is not directly attributable to expected default risk (Gilchrist and Zakrajšek, 2012). But in general again, the role of oil market uncertainty in predicting movements of the corporate bond premium cannot be ignored.

<sup>13</sup> The data on the implied volatility of US Treasuries can be downloaded from the website of Professor Andrea Vedolin at: <https://sites.google.com/site/andreavedolin/>.



Bond investors can improve investment strategies by exploiting the role of the oil price uncertainty for interest-rate predictability. Finally, researchers may find our results useful for developing better asset-pricing models that appropriately use the information embedded in estimates of oil market uncertainty.

As part of future research, it would be interesting to extend our analysis to a full-fledged forecasting exercise involving the bond market as in Ludvigson and Ng (2009, 2011), since in-sample predictability does not guarantee the same over an out-of-sample period.

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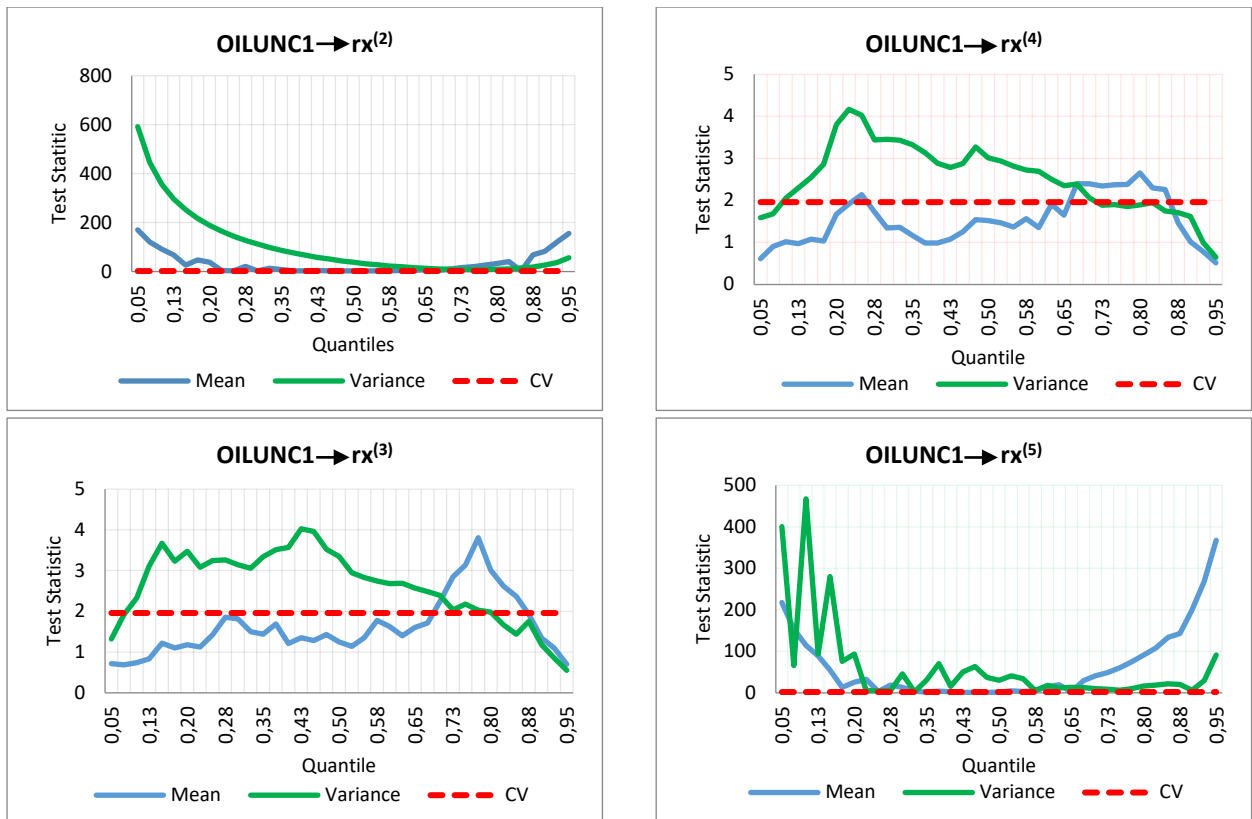
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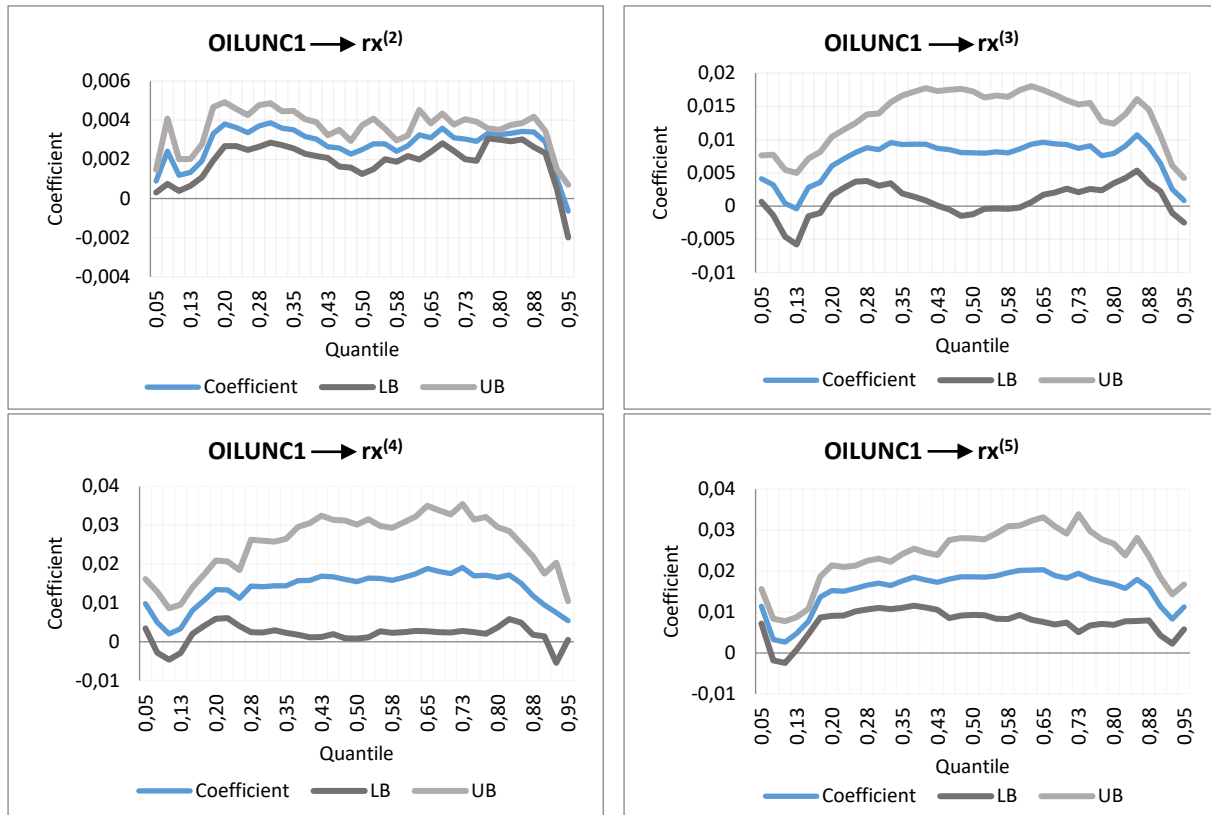
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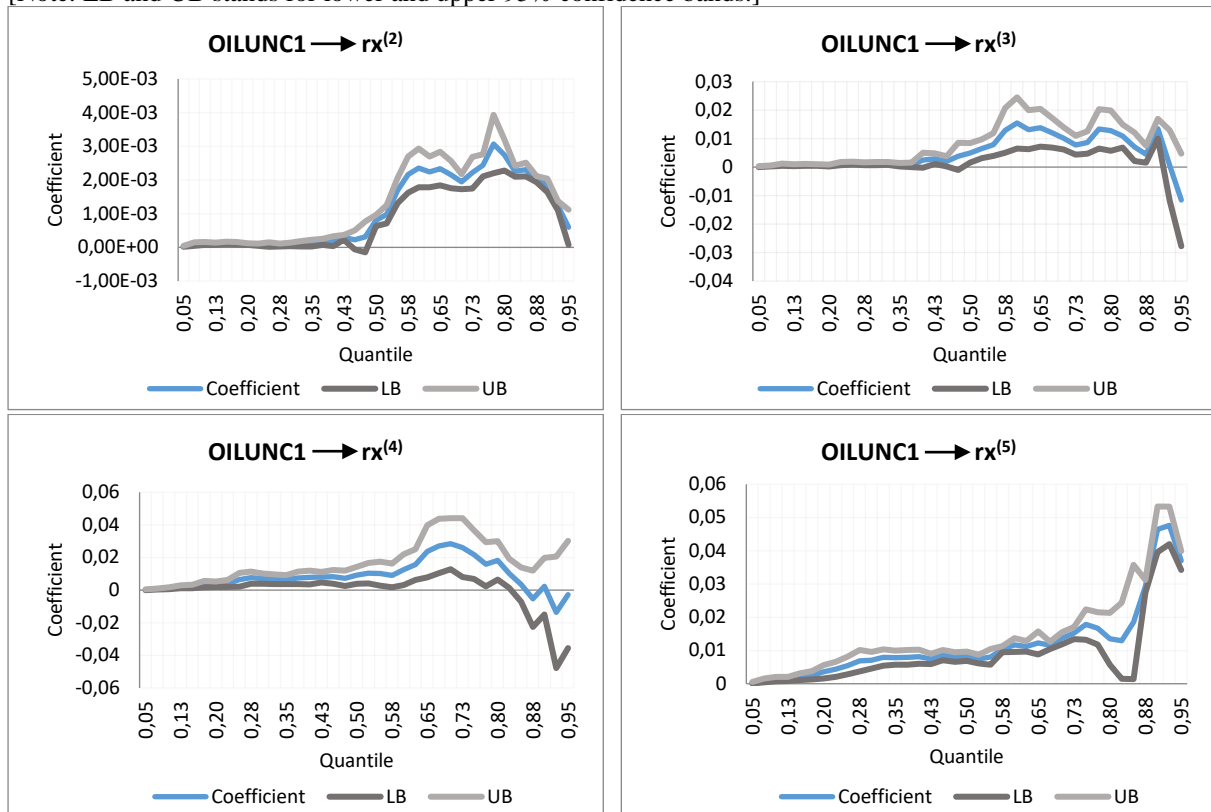


**Figure 1.** Causal Impact of GARCH (1,1) Model-Based Oil Uncertainty on Bond Premium and Volatility  
 [Note: CV is 5% critical value of 1.96].

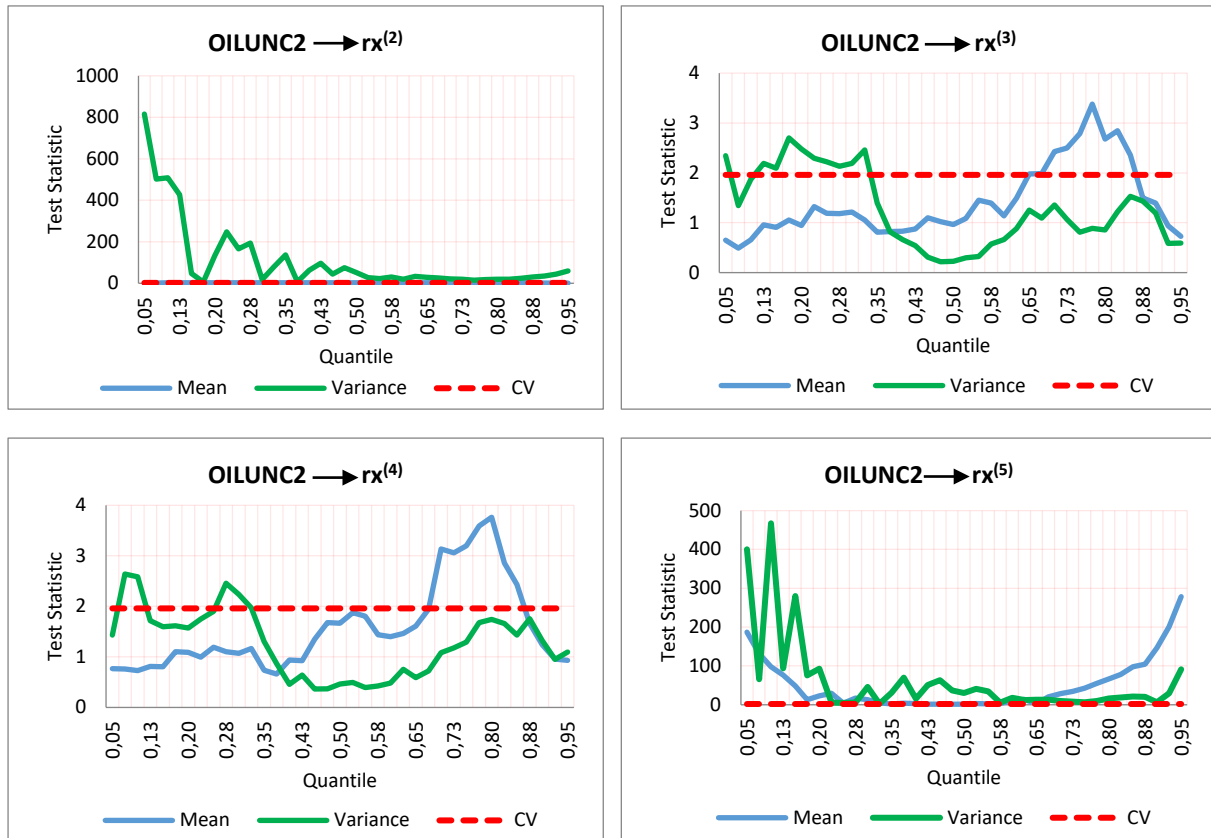


**Figure 2(a).** Sign of the Impact of Oil Uncertainty on Bond Premia

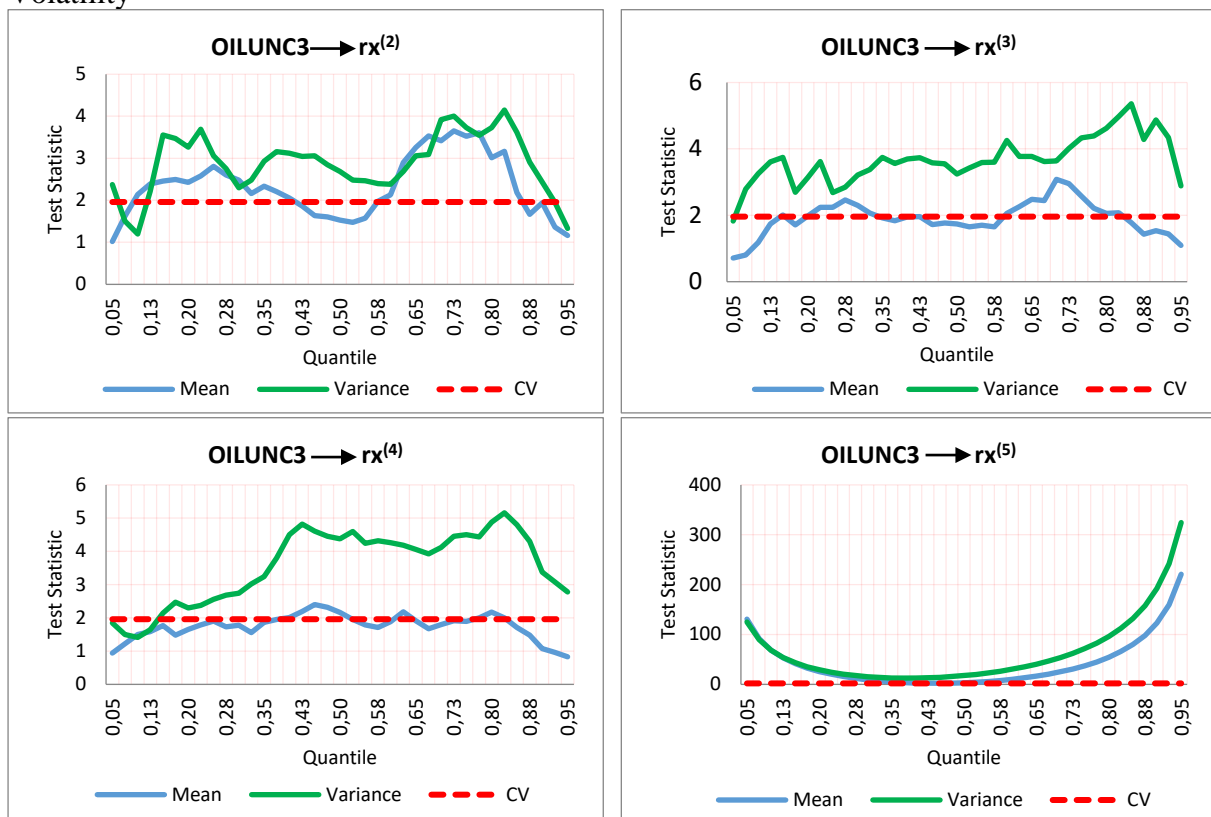
[Note: LB and UB stands for lower and upper 95% confidence bands.]



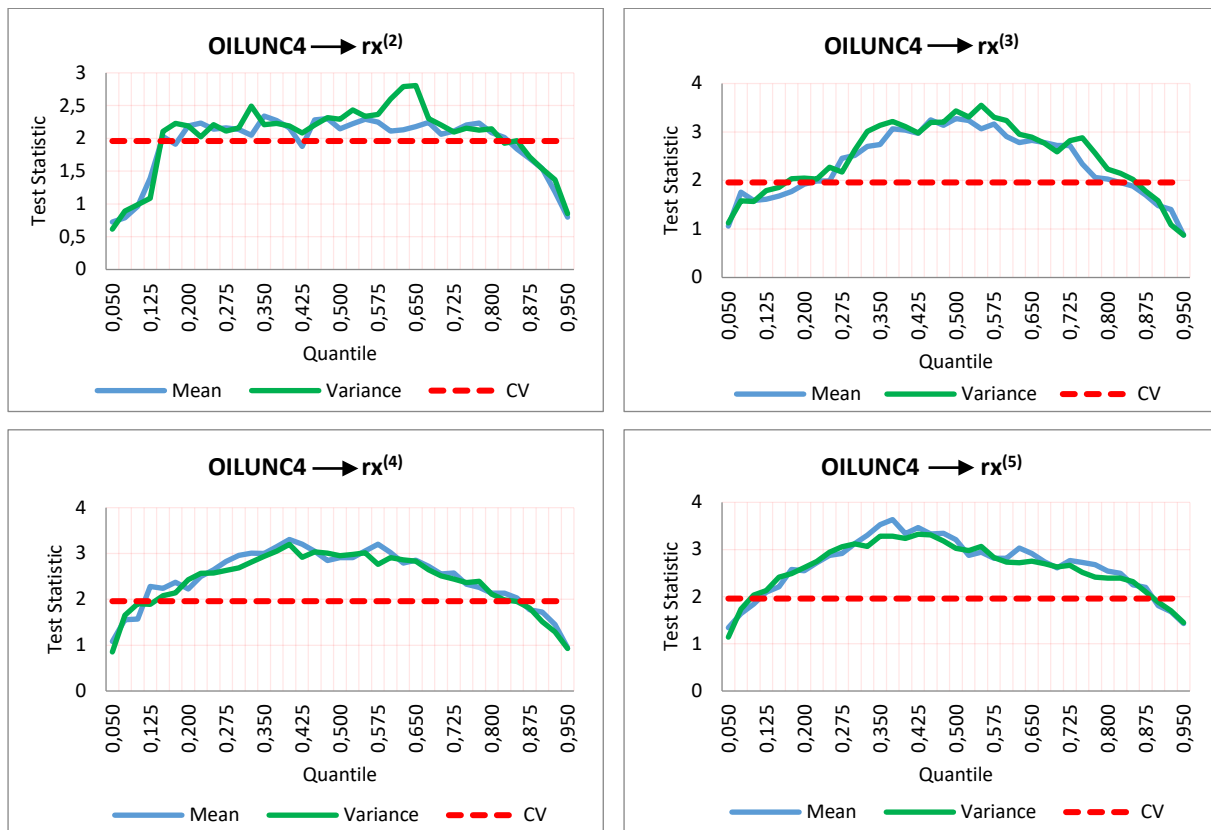
**Figure 2(b).** Sign of the Impact of Oil Uncertainty on Volatility of Bond Premium [Note: See Notes to Figure 2(a)]



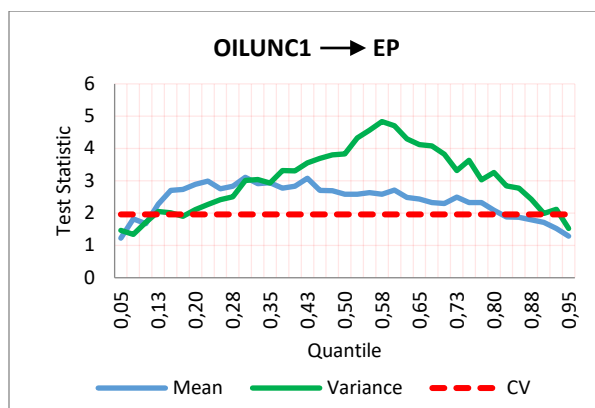
**Figure 3(a).** Causal Impact of TVP-SV Model-Based Oil Uncertainty on Bond Premium and Volatility



**Figure 3(b).** Causal Impact of RV-Based Oil Uncertainty on Bond Premium and Volatility

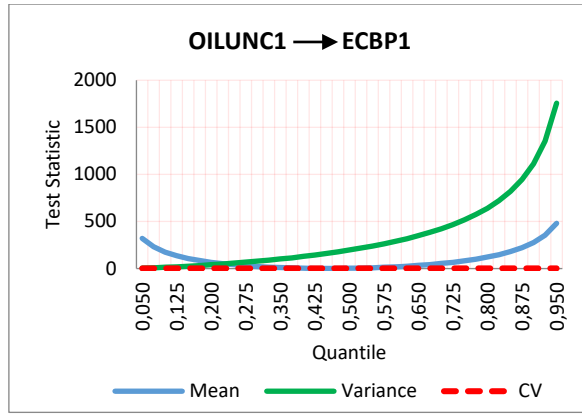


**Figure 3(c).** Causal Impact of Oil VIX on Bond Premium and Volatility

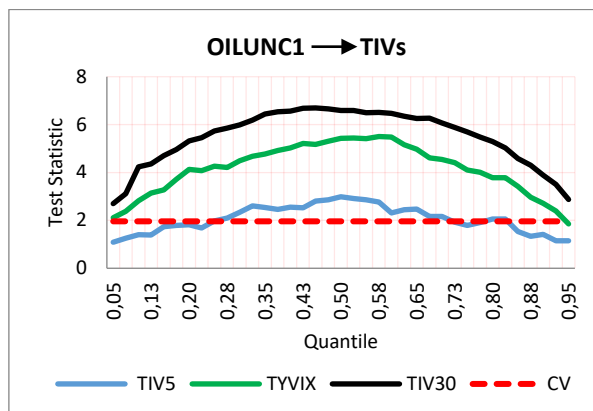


**Figure 4.** Causal Impact of GARCH (1,1) Model-Based Oil Uncertainty on Equity Premium and Volatility





**Figure 5.** Causal Impact of GARCH (1,1) Model-Based Oil Uncertainty on Corporate Bond Premium and Volatility



**Figure 6.** Causal Impact of GARCH (1,1) Model-Based Oil Uncertainty on Implied Volatility of US Treasury Bonds

**APPENDIX:**

**Table A1.** Summary Statistics

Statistic	Variable				
	$rx^{(2)}$	$rx^{(3)}$	$rx^{(4)}$	$rx^{(5)}$	<i>OILUNCI</i>
Mean	0,0043	0,0080	0,0106	0,0115	63,2612
S.D.	0,0162	0,0297	0,0413	0,0511	115,4474
Min	-0,0554	-0,1037	-0,1352	-0,1755	1,1983
Max	0,0594	0,1023	0,1438	0,1694	993,5588
Skewness	0,1311	0,0267	0,0626	0,0456	3,8018
Kurtosis	0,9157	1,0223	0,9240	0,8313	17,8715
JB	29.4570***	34.0070***	28.2550***	22.7680***	12061.6820***
Q(1)	660.7826***	665.2451***	665.1334***	652.6695***	593.7249***
Q(4)	2084.6733***	2076.6458***	2080.8662***	2028.0013***	1547.2661***
ARCH(1)	500.3694***	517.3975***	509.5801***	479.0856***	393.5762***
ARCH(4)	503.0007***	527.9408***	518.7801***	482.6395***	409.0156***
Observations	1953:06-2016:12 (763)				

**Note:**  $rx^{(i)}$ ,  $i=2, 3, 4$  and  $5$  represents the bond premium (relative to the 1-year bond) with maturities 2-, 3-, 4-, and 5-year; *OILUNCI*: is the GARCH(1,1) based estimate of oil price volatility, i.e., uncertainty; S.D.: Standard Deviation; JB: Jarque-Bera test of normality; \*\*\* indicates rejection of the null hypotheses of normality (JB), autocorrelation (Q-stat), and heteroskedasticity (ARCH) at 1% level of significance.

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

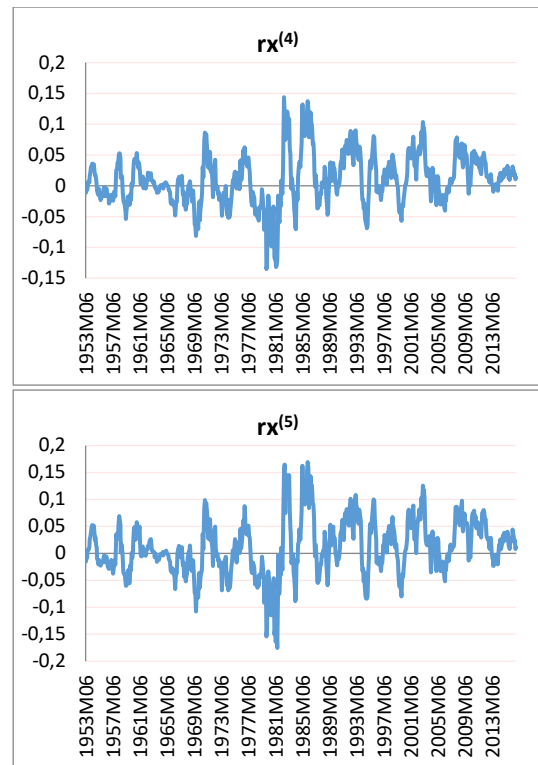
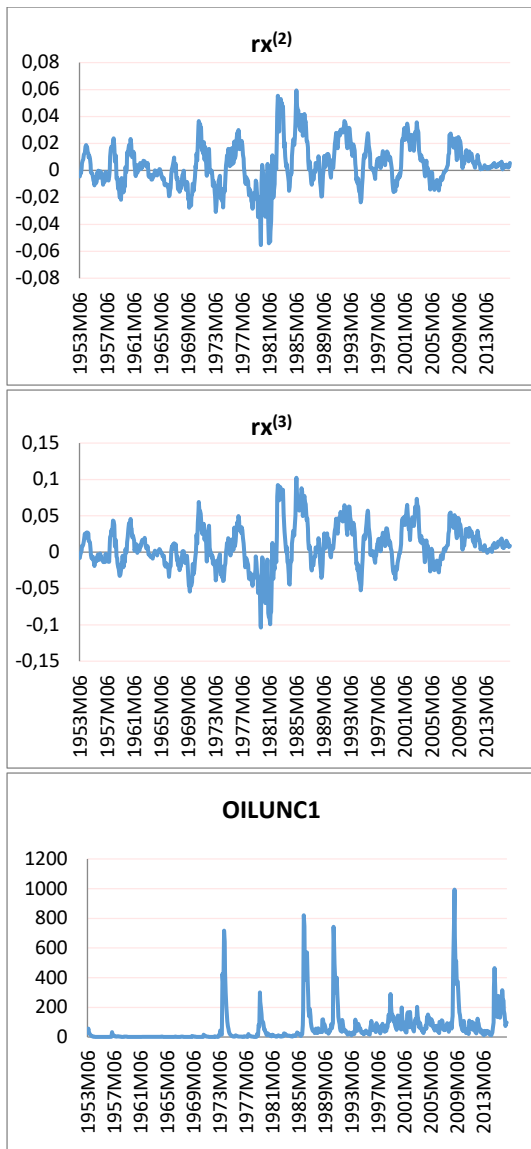
Dependent Variable	<i>F</i> -statistic	<i>p</i> -value	Lag(s)
$rx^{(2)}$	0.5045	0.6039	2
$rx^{(3)}$	0.5150	0.5976	2
$rx^{(4)}$	0.7048	0.4944	2
$rx^{(5)}$	0.9414	0.3321	1

**Note:** See Notes to Table A1. The *F*-statistic has a null that OILUNC1 does not Granger causes  $rx^{(i)}$ , with  $i=2, 3, 4, 5$ , with optimal lag lengths chosen by the Schwarz Information Criterion (SIC).

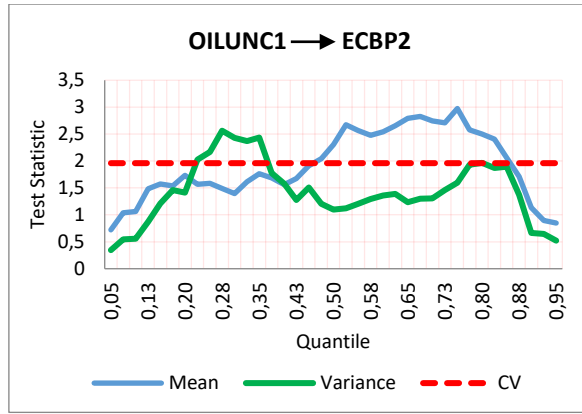
**Table A3.** Brock *et al.* (1996, BDS) Test of Nonlinearity

Dependent Variable	Dimension ( <i>m</i> )				
	2	3	4	5	6
$rx^{(2)}$	8.4213***	12.1166***	17.8607***	26.0588***	40.3976***
$rx^{(3)}$	5.2045***	6.7576***	9.2053***	12.4543***	18.1014***
$rx^{(4)}$	5.5024***	6.9490***	8.8202***	12.2750***	18.4230***
$rx^{(5)}$	6.4392***	7.6316***	9.8353***	14.3125***	23.3143***

**Note:** See Notes to Table A1. Entries correspond to the *z*-statistic of the BDS test which has the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the excess bond returns ( $rx^{(i)}$ ) equation for  $i=2, 3, 4$ , and 5, used in the Granger causality test due to OILUNC1 reported in Table A2; \*\*\* indicates rejection of the null hypothesis at 1% level of significance.



**Figure A1.** Data Plots



**Figure A2.** Causal Impact of GARCH (1,1) Model-Based Oil Uncertainty on an Alternative Measure of Corporate Bond Premium and Volatility