

Time-varying causality between bond and oil markets of the United States: Evidence from over one and half centuries of data

Semei Coronado¹ | Rangan Gupta² | Saban Nazlioglu^{3,5} | Omar Rojas⁴ 

¹Independent Consultant, San Diego, California

²Department of Economics, University of Pretoria, Pretoria, South Africa

³Department of International Trade and Finance, Faculty of Economics and Administrative Sciences, Pamukkale Universitesi, Denizli, Turkey

⁴Facultad de Ciencias Económicas y Empresariales, Universidad Panamericana, Zapopan, Mexico

⁵Department of Economics and Finance, Nisantasi University, Istanbul, Turkey

Correspondence

Omar Rojas, Facultad de Ciencias Económicas y Empresariales, Universidad Panamericana, Zapopan, Jalisco, 45010, Mexico.

Email: orojas@up.edu.mx

Funding information

Pamukkale University, Grant/Award Number: 2020KRM005-009

Abstract

This paper analyzes the time-varying causality between government bond and oil returns of the United States over the monthly period of 1859:10 to 2019:03, that is, the longest possible span of historical data, starting from the beginning of the modern era of the petroleum industry. While the standard constant parameter causality test fails to pick up any evidence of causality, the time-varying framework shows evidence of bi-directional spillovers over the entire sample period. The results are robust to the inclusion of stock returns as a control variable in the model. We also detect evidence of 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.

KEYWORDS

bond and oil markets, returns and volatility spillovers, time-varying causality

JEL CLASSIFICATION

C32; G12; Q02

1 | INTRODUCTION

The existing literature on the relationship between price (or returns) of oil and equity markets of the United States is huge, to say the least (see, e.g., [Balcilar, Gupta, & Wohar, 2017, Balcilar, Gupta, & Miller, 2015; Coronado, Jiménez-Rodríguez, & Rojas, 2018; Degiannakis, Filis, & Arora, 2018; Smyth & Narayan, 2018] for detailed reviews in this regard). In comparison, the literature examining the causal linkage between the sovereign bond and oil markets related to the United States is negligible (see, e.g., [Balcilar, Gupta, Wang, & Wohar, 2019; Demirer & Gupta, 2018; Kang, Ratti, & Yoon, 2014; Nazlioglu, Gupta, & Bouri, 2020]), especially when one also accounts for the fact that a growing number of recent studies have

concentrated on the role of oil (and commodity) market movements in driving the sovereign credit default swap (CDS) of both developed and developing countries (see, e.g., [Apergis, 2019; Bouri, 2019; Bouri, Jalkh, & Roubaud, 2019; Bouri, Kachacha, & Roubaud, 2019, Bouri, Shahzad, Raza, & Roubaud, 2018, Bouri, de Boyrie, & Pavlova, 2017; Filippidis, Filis, & Kizys, 2020; Shahzad, Naifar, Hammoudeh, & Roubaud, 2017]).

As far as the studies related to the United States are concerned, (Kang et al., 2014) utilized a structural vector autoregressive (VAR) model to investigate how the demand and supply shocks driving the global crude oil market affect real bond returns of the United States at monthly frequency. They 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 & Gupta, 2018), using daily data, among other results, found that not only demand but also supply shocks in the oil market, tend to negatively impact the bond returns of the United States. Unlike the aforementioned two papers, (Balcilar et al., 2019; Nazlioglu et al., 2020), concentrated more on causal linkages between the bond and oil markets-related variables rather than trying to analyze the impact of (structural) oil shocks on bond returns. Specifically, (Balcilar et al., 2019) analyzed causality between oil market uncertainty and bond premia of US Treasury, based on a non-parametric 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. Moreover, (Nazlioglu et al., 2020), using daily data and by accounting for structural shifts as a smooth process found, *inter alia*, that the causality between bond and oil prices in the United States ran only in one direction, and that was from the bond market to the oil price, and not the other way around.¹ In sum, the evidence of causality involving the US bond and oil markets is mixed.

The general lack of attention to analyzing the relationship between oil and bond prices (barring the few studies mentioned above), and mere concentration on the oil-stock nexus, is quite baffling, given that the bond market is comparatively bigger in size than the stock market in the functioning of the US financial system, and is often viewed as a safe-haven (Habib & Stracca, 2015; Hager, 2017; Kopyl & Lee, 2016). The US stock market capitalization in 2017 stood at about \$30 trillion, but the corresponding value of the US bond market was \$40.7 trillion (Securities Industry and Financial Markets Association [SIFMA, 2018]). Against this backdrop of limited evidence despite the importance of the bond market, we aim to provide a comprehensive analysis on the causal relationship between the returns in bond and oil markets of the United States, by looking at the longest possible span of monthly historical data covering 1859:10 to 2019:03. Note that, with the start date corresponding to the beginning of the modern era of the petroleum industry with the drilling of the first oil well in the United States at Titusville, Pennsylvania in 1859, our analysis does not suffer from the possibility of any sample selection bias like the above-mentioned studies based on post World War II data. Since we are analyzing over one and a half centuries of data capturing the joint evolution of the bond and oil markets in the United States, which have undergone regime changes (as we show below via statistical tests), from an econometric perspective, we use a full-fledged time-varying parameter-based test of causality as recently developed by Rossi and Wang (2019). To the best of our

knowledge, this is the first attempt to analyze the time-varying causality between returns on US government bond and West Texas Intermediate (WTI) oil covering 161 years (1859 to 2019) of monthly historical data.

Note that, theoretically (and intuitively), one would expect causality between the bond and oil returns to be bi-directional. High oil prices increase inflation expectations and hence, increase nominal bond yields, which in turn move bond prices or returns in the opposite direction. Moreover, higher oil prices are historically known to have a recessionary impact on the US economy (Gupta & Wohar, 2017; Hamilton, 2013), which is likely to increase demand for the government bonds due to their safe-haven characteristics and hence push up bond prices. In other words, oil price hikes can either decrease or increase nominal bond prices. At the same time, bond prices can impact oil prices via the asset-value channel, when one realizes that oil reserves are a key asset in an oil-producing country like the United States, which is arbitrated against financial assets like government bonds (Arora, 2011; Arora & Tyers, 2012). Thus, when the yield on government bonds falls, that is, bond prices rise, retaining oil reserves becomes more attractive to the oil-producing countries, which then have less incentive to accommodate demand rises, and so the oil price rises. Moreover, given the recent financialization of the commodity sector, the oil market is now also considered as a profitable alternative investment in portfolio decisions (Bahloul, Balcilar, Cunado, & Gupta, 2018; Bonato, 2019), and hence portfolio reallocations are likely to have feedback from the bonds market to the oil market. More specifically, an increase in bond returns might be associated with the moving of funds into the bond market at the expense of investment in oil as an asset, thus reducing its price. Hence, an increase in bond returns can positively or negatively affect oil returns.

The remainder of this paper is organized as follows: Section 2 discusses the data and the methodology for testing time-varying causality and Section 3 presents the empirical results, along with robustness and additional analyses. Finally, Section 4 concludes the paper by drawing implications of our results.

2 | DATA AND ECONOMETRIC METHODOLOGY

The analysis mainly involves two variables: 10-year government bond total return indices and nominal WTI oil prices, with both these variables derived from the Global Financial Database.² The monthly data sample runs from 1859:09 to 2019:03, with the start and end dates being purely driven by the availability of data at the time of

writing this paper. Since the time-varying causality, which we describe below, requires stationary data, we work with the log-returns (in percentages) of these variables,³ which have been plotted in Figure S1, and summarized in Table S1 in the supplementary information of the paper. Since we lose one observation due to the transformation, our effective sample is from 1859:10 to 2019:03. Both these variables depict higher volatility towards the start and end of the sample period, with the oil market being more volatile than the bond market. Note that the WTI oil price was administered between the end of the “Great Depression” till the first oil shock

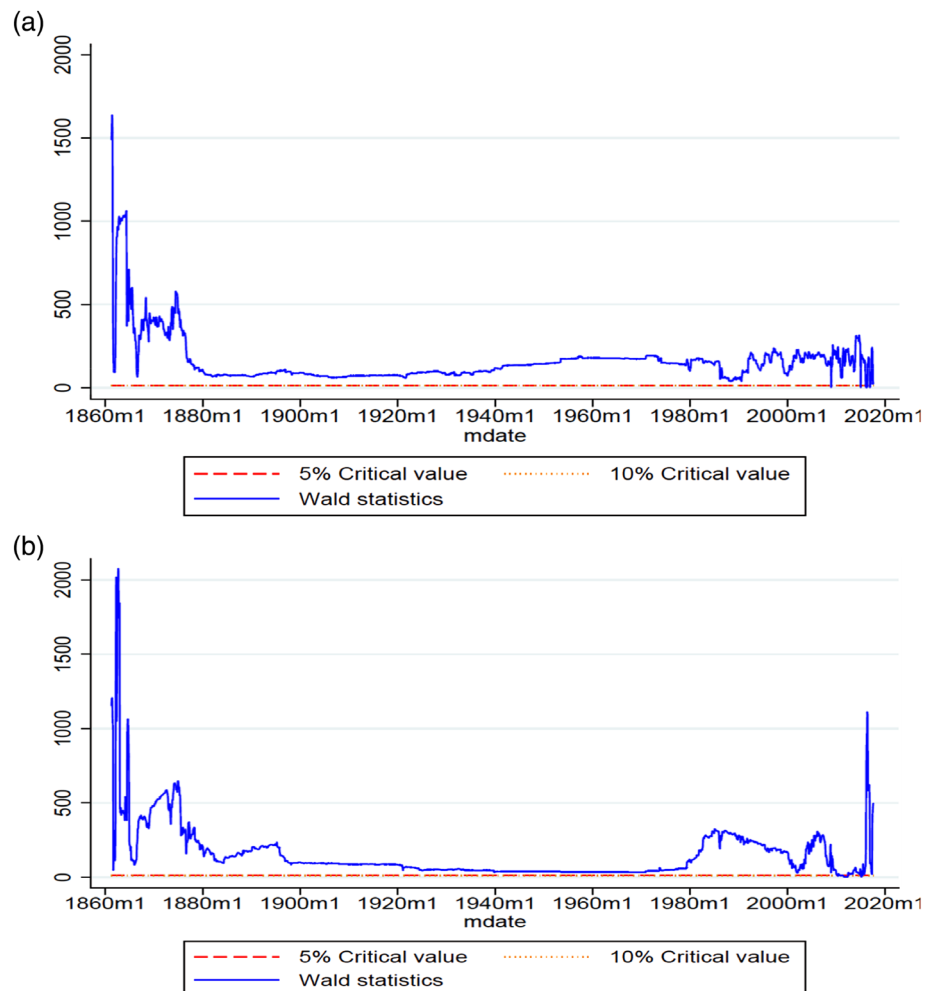
of 1973, and hence shows discontinuous movements. Not surprisingly, the returns depict non-normality, due to excess kurtosis in both cases, and negative and positive skewness for oil and bond returns, respectively.

Due to the simplicity of the classical linear Granger causality approach (originated by [Granger, 1969]), it is one of the most commonly used methods for testing in-sample predictability. However, VAR model-based analyses, upon which the linear causality test relies upon, face major technical difficulties in handling relationships involving time-series data associated with financial markets characterized by structural breaks or regime changes, which in turn

TABLE 1 Constant parameter and time-varying parameter Granger causality tests

	Test statistic				
	$\chi^2(1)$	<i>ExpW</i>	<i>MeanW</i>	<i>Nyblom</i>	<i>SupLR</i>
$OR \not=> BR$	0.6531 [.4190]	98.7530 [.0000]	159.7125 [.0000]	2.1088 [.1002]	1,637.0088 [.0000]
$BR \not=> OR$	0.2377 [.6259]	155.5935 [.0000]	150.2756 [.0000]	18.1085 [.0000]	2074.7678 [.0000]

Note: $\not=>$ implies the non-causality null hypothesis. Entries correspond to the test statistics, with *p* values in square brackets. Abbreviations: *BR*, bond returns; *OR*, oil log-returns.



results in the estimates of VARs being also sensitive to instabilities (Boivin & Giannoni, 2006; Clark & McCracken, 2006; Rossi, 2013). Moreover, the traditional Granger-causality test requires stationarity, which may also lead to an erroneous inference in the presence of instabilities. To overcome these limitations, Rossi and Wang (2019) propose a robust causality test, which is more powerful than the traditional Granger-causality test, following the time-varying methodologies suggested earlier by Rossi (2005)). Furthermore, in our particular case which covers the longest possible data span involving the bond and oil returns jointly, the approach helps us to analyze the time-varying causal relationships between these two markets and hence provides a more appropriate picture of the relationship than a constant parameter Granger causality method.

The VAR model with time-varying parameters is described as

$$y_t = \Psi_{1,t}y_{t-1} + \Psi_{2,t}y_{t-2} + \dots + \Psi_{p,t}y_{t-p} + \varepsilon_t \quad (1)$$

where $\Psi = [\Psi_{1,t}, \Psi_{2,t}, \dots, \Psi_{p,t}]'$ is the time-varying coefficient matrix, $y_t = [y_{1,t}, y_{2,t}, \dots, y_{n,t}]'$ is an $(n \times 1)$ -vector, and ε_t is the idiosyncratic shocks.

The variables included in our VAR model constitute of the log-returns of the bond (*BR*) and oil (*OR*) markets. We test the null hypothesis that *OR* (*BR*) does not Granger cause *BR* (*OR*), for all t where the null hypothesis is $H_0 : \phi_t = 0$ for all $t = 1, 2, \dots, T$, given that ϕ_t is a proper subset of $vec(\Psi_{1,t}, \Psi_{2,t}, \dots, \Psi_{p,t})$. To this end, Rossi (2005)) suggested four alternative test statistics, namely: the exponential Wald (*ExpW*), mean Wald (*MeanW*), Nyblom (*Nyblom*), and Quandt Likelihood Ratio (*SupLR*) tests. Based on the Schwarz Information Criterion (SIC), the VAR model is estimated with one lag. In an effort to cover as much of the data as possible, we use an end-point trimming of 1% rather than the conventional 15% used in the structural break literature, which in turn amounts to losing over just one and half-years of observations from both ends.⁴

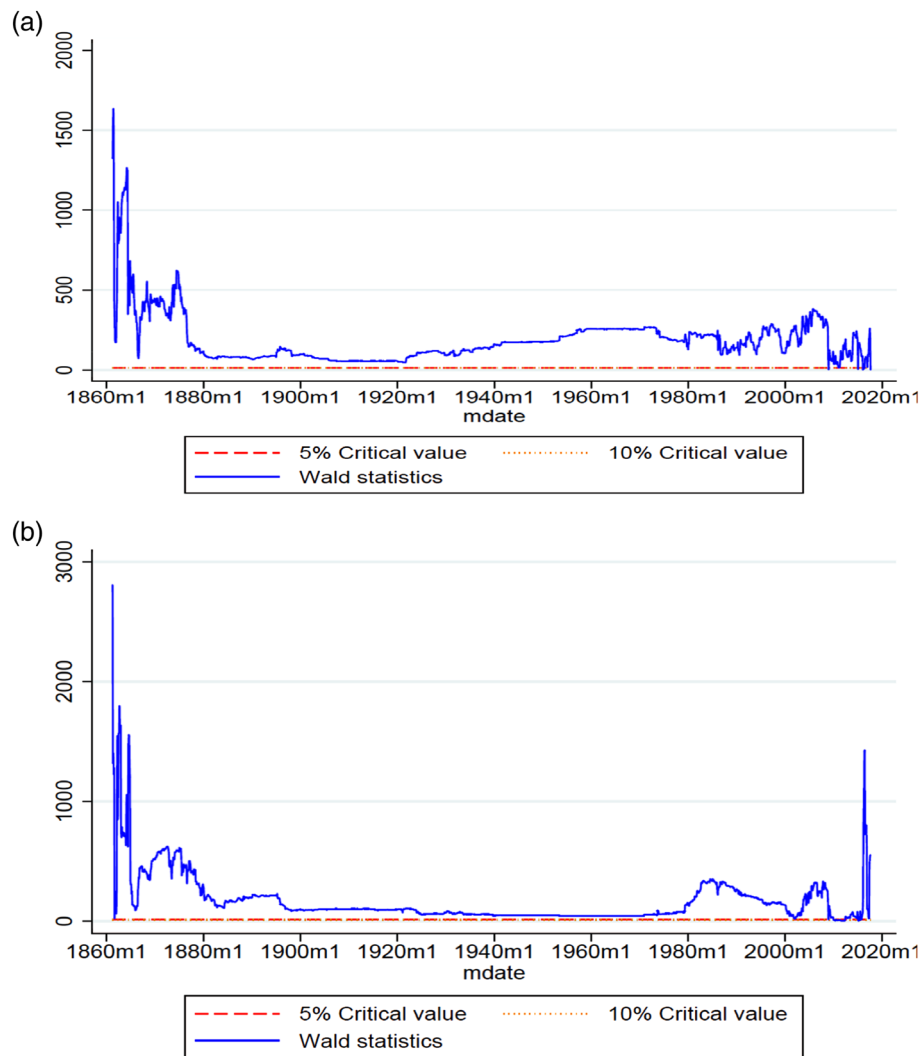


FIGURE 2 (a) Time-varying Wald statistics in a Tri-Variate VAR(1) Model: *OR* does not Granger Cause *BR*. (b) Time-varying Wald statistics in a Tri-Variate VAR(1) Model: *BR* does not Granger Cause *OR*. Note: See Notes to Figure 1 [Colour figure can be viewed at wileyonlinelibrary.com]

3 | EMPIRICAL RESULTS

In Table 1, we first started with the standard constant parameter Granger causality test and found no evidence of causality in any direction. In contrast, when we look at the *ExpW*, *MeanW*, *Nyblom*, and *SupLR* tests of Rossi and Wang (2019) based on the time-varying VAR also reported in Table 1, the null of no-Granger causality from *BR* to *OR* is overwhelmingly rejected under all the tests, while *OR* is found to Granger cause *BR* strongly for 3 of the 4 test statistics, with weak (at the 10% level of significance) causality observed under *Nyblom*.^{5,6}

Next, in Figure 1, we present the whole sequence of the Wald statistics across time, which gives more information on when the Granger-causality occurs. As can be seen from Figure 1a, *OR* Granger causes *BR* basically over the entire sample, barring few periods towards the end of the sample period. When we look at Figure 1b, a similar picture emerges in terms of causality running from *BR* to *OR*. The periods where lack of causality is observed basically corresponds to the recent turmoil in the financial markets in the wake of the Global Financial and the European sovereign debt crises, and a sharp decline in oil

prices that were observed in 2008 and 2014 following the slowdown of the global economy in the wake of these crises.⁷

Next, we conduct some robustness and additional analyses. As part of the robustness check, we introduce into our model log-returns of the S&P 500, raw data for which is also derived from the Global Financial database. Note that it is the multivariate nature of the Rossi and Wang test (Rossi & Wang, 2019) that led us to use this approach, even though there are other available alternative methods that can also conduct time-varying Granger causality analysis, but are restricted to a bivariate set-up only (see, e.g., [Lu, Hong, Wang, Lai, & Liu, 2014]).⁸ The decision to include stock returns in the model to control for possible omitted variable bias is obvious given the large existing literature on the nexus between stock and oil returns (as indicated in the introduction), and historical stockbond returns interrelationship for the United States (see, e.g., [Demirer & Gupta, 2018; Gupta, Kollias, Papadamou, & Wohar, 2018; Selmi, Gupta, Kollias, & Papadamou, 2019]). The time-varying Wald statistics corresponding to the null hypotheses that *OR* does not Granger cause *BR*, and *BR* does not Granger cause *OR* from a trivariate VAR(1) model (with the lag-length

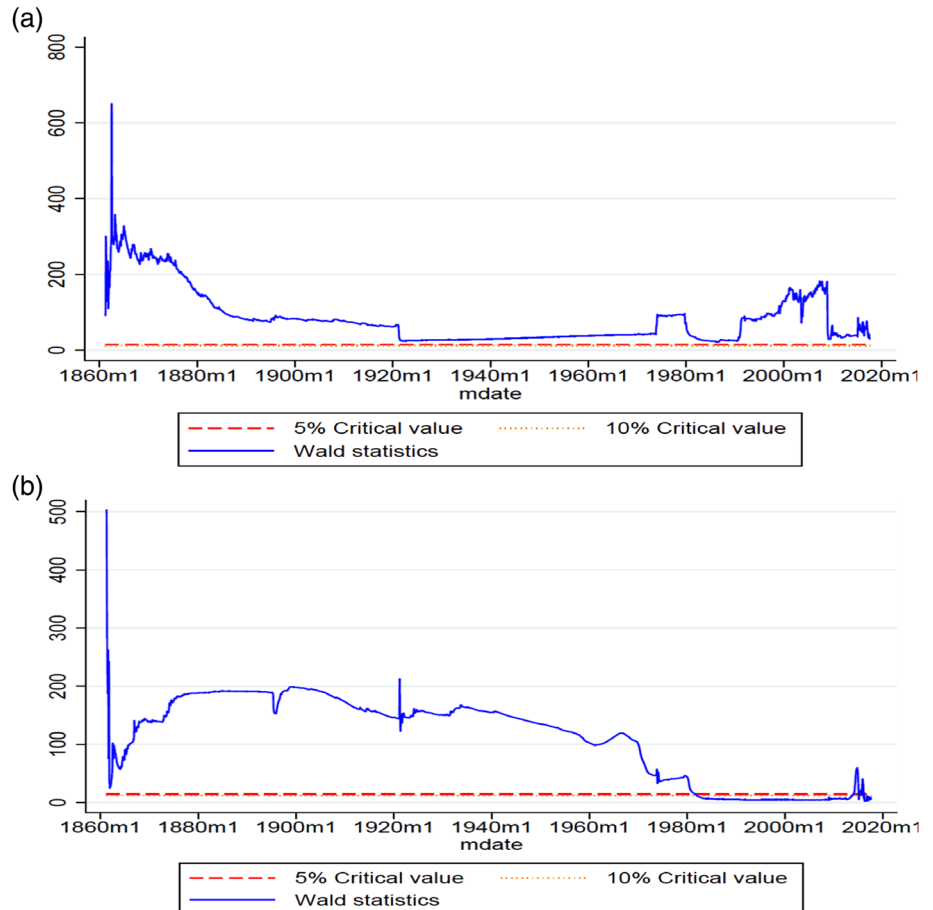


FIGURE 3 (a) Time-varying Wald statistics in a Bi-Variate VAR(1) Model: *ORV* does not Granger Cause *BRV*.

(b) Time-Varying Wald statistics in a Bi-Variate VAR(1) Model: *BRV* does not Granger Cause *ORV*.

Note: *BRV* and *ORV* stands for bond and oil log-returns volatility, respectively, derived from univariate EGARCH models [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

determined by the SIC) have been reported in Figures 2a,b, respectively, with 1% trimming. As can be seen from the figures, our results obtained in a bivariate set-up remain robust upon the inclusion of the stock returns.⁹

We next analyze whether there are second-moment spillovers as observed for the US bond and oil markets following (Balcilar et al., 2019; Nazlioglu et al., 2020).¹⁰ We estimate univariate EGARCH(1,1) models¹¹ (as developed by [Nelson & Nelson, 1991]) for bond and oil returns, and then use the fitted variance series in the VAR model to conduct the Rossi and Wang test (Rossi & Wang, 2019) of time-varying causality with 1% trimming. The time-varying Wald tests corresponding to the null hypotheses that volatility of *OR* (*ORV*) does not cause volatility of *BR* (*BRV*), and *BRV* does not cause *ORV*, is presented in Figures 3a,b, respectively. As can be seen, while *ORV* predicts *BRV* over the entire sample period, there is feedback from *BRV* to *ORV* primarily in the pre-1980 period, and also for a few months toward the end of the sample. This lack of volatility spillover from bonds to oil in the post-1980 phase of the data could be an indication of stable monetary policy, and hence, interest rates following the Paul Volcker era. However, when we look at the results from a historical perspective, we tend to find bi-directional volatility spillovers in general—a result more in line with Tivari, Cunado, Gupta, and Wohar (2018)), who analyzed such causal relationships at a global scale. The finding of causality in both directions is also similar to the combined findings of Balcilar et al. (2019) and Nazlioglu et al. (2020) with the former suggesting that *ORV* causes *BRV*, and the latter the other way around.^{12,13}

4 | CONCLUSION

The literature on the causal relationship between returns of the US government bond and oil markets is limited to only few studies based on post-World War II data. Given the importance of both these markets for investors and policymakers (as well as academics), this is quite baffling, and this paper thereby aims at addressing this limitation in a definitive manner. We analyze returns spillovers between the sovereign bond and crude oil covering the historical monthly period of 1859:10 to 2019:03, with our start date corresponding to the beginning of the modern era of the petroleum industry. In the process of looking at the entire history of the evolution of the oil market, we make sure that our study does not suffer from any sample selection bias and hence can provide comprehensive evidence. Given that we look at 161 years of data, we also rely on a full-fledged time-varying approach recently

developed by Rossi and Wang (2019) to study this causal relationship in an attempt to make sure that our results are not sensitive to joint regime changes in these two markets, which, as we show statistically, does indeed exist. Unlike the mixed findings of the existing studies, we provide comprehensive evidence of time-varying bi-directional causality, which was not picked-up by the constant parameter-based standard Granger causality tests. Our results were found to be robust to the inclusion of stock returns in the model—a variable that is known to be strongly related to both bond and oil markets. Hence, we were able to indicate that there is no issue of possible omitted variable bias associated with our findings. In addition, we also detected evidence of volatility spillovers across these two markets. Finally, when we considered the corporate bond market using monthly data from 1926 onward, causality for first- and second-moments were also detected between these high-yield bonds and the oil market, with the spillovers primarily running from the oil sector.

Our results have important implications for academicians, investors, and policymakers. First of all, as far as researchers are concerned, we show that to derive appropriate statistical inferences when analyzing causal relationships between the bond and oil bond markets, it is of paramount importance that structural changes are incorporated into the modeling frameworks through time-varying parameters; otherwise, statistically insignificant results would be derived. Second, from the perspective of bond investors, they can improve investment strategies by exploiting the predicting role of the oil returns, but they would require to use a time-varying model. At the same time, investors aiming to include oil (bonds) in a portfolio comprising bond (oil), should be careful of risk spillovers from the oil (bond) market. However, in recent years, the causality-in-volatility has primarily been from the oil market to government bonds. This, along with the finding that the correlation between bond and oil returns have mostly been negative from the post-World War I period, indicates that the US Treasuries can indeed be used to diversify away the risks associated with the oil market. Corporate bonds could also be used by investors in a similar fashion. Finally, evidence that oil prices tend to move long-term government bonds, could be an indication, using the idea of the yield curve, that the Federal Reserve takes into account oil prices in their interest rate setting behavior. But the policymakers should simultaneously be mindful of the fact that frequent interest rate changes to respond to oil price movements, could lead to a volatile bond market, which in turn will be transmitted to the volatility of the oil market at times, and affect economic activity in a negative manner (Elder & Serletis, 2010, 2011).

As part of future research, one could look into the time-varying spillovers of returns and volatility associated with the bond and oil markets for major oil exporters and importers. Moreover, realizing the importance of associating oil price movements to different structural shocks, like, oil-specific supply, demand and inventory shocks, and demand shock due to changes in global economic activity (see, among others, [Kilian, 2009; Kilian & Murphy, 2014]), it would be interesting to analyze the time-varying impact of these various oil shocks, rather than aggregate oil price, on the movements of the entire term-structure of the US bond market (see e.g., [Ioannidis & Ka, 2018]), but this might mean relying on only post World War II data.

ACKNOWLEDGMENT

Saban Nazlioglu gratefully acknowledges the support from Pamukkale University (grant number 2020KRM005-009).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the Global Financial database (2019) Retrieved from <http://www.globalfinancialdata.com/>.

ORCID

Omar Rojas  <https://orcid.org/0000-0002-0681-3833>

ENDNOTES

- ¹ In a mimeo, Nguyen, Nguyen, & Pham, 2018, showed that oil price declines benefiting safer assets such as US long-term Treasury bonds. Moreover, Nguyen et al., (2018) showed that oil price declines hurt riskier assets such as high-yield bonds, while benefiting US investment-grade corporate bonds. In the latter regard, Wan and Kao (2015) earlier found that positive shocks in oil prices decrease the spreads between the AAA and BAA rated bonds, and hence, provided some earlier evidence on the relationship between the oil market and investment bonds.
- ² <http://www.globalfinancialdata.com/>.
- ³ Complete details of the unit root tests are available upon request from the authors.
- ⁴ Note that, since we use 1% trimming, we also need to take a parsimonious approach in choosing the lag-length to provide enough degrees of freedom for worthwhile initial inference, and hence we use the SIC rather than the Akaike Information Criterion (AIC). However, our results were qualitatively similar over the common period, when we used a trimming of 15% and a lag-length of eight chosen by the AIC. This was also the case, when we worked with real bond and oil returns, with the real values derived by deflating the nominal prices with the Consumer Price Index (CPI). The CPI data was derived from the online data segment of Professor Robert J. Shiller at: <http://www.econ.yale.edu/~shiller/data.htm>. With the CPI data starting from 1871:01, our analysis involving real returns covered the period of 1871:02 to 2019:03. Complete details of these results are available upon request from the authors.

- ⁵ This result is not surprising, since based on the multiple structural break tests of Bai and Perron (2003), used to detect 1 to M structural breaks in the individual equations of the VAR (1) model, allowing for heterogenous error distributions across the breaks and 5% trimming, yielded 3 (1874:09, 1981:10, 2002:10) and 5 (1874:02, 1882:12, 1895:06, 1986:04, 2008:04) break points for the *BR* and *OR* equations, respectively.
- ⁶ When we applied the Brock et al., (1996, BDS) test of nonlinearity on the residuals of the two equations of the VAR(1) model, the null hypothesis of *i.i.d.* residuals were overwhelmingly rejected at the highest level of significance (across all dimensions), suggesting the existence of uncaptured nonlinear dependence between the two returns. Given this, we used the cross-bicorrelation test of Brooks and Hinich (1999) which permit us to identify existence of any nonlinear causal dependence between the two variables. In this case, when *BR* and *OR* were separated into equal length of non-overlapping moving time windows (60 months) and frames (31), the null of no causality from *OR* to *BR*, and from *BR* to *OR* were rejected under 83.9 and 87.1% of the cases respectively, thus highlighting the need to look into a time-varying approach to study the causal dependence between *BR* and *OR*. Complete details of these results are available upon request from the authors.
- ⁷ To get a feel for the time-varying sign of the relationship between the two returns, we estimated a dynamic conditional correlation-(exponential) generalized autoregressive conditional heteroskedasticity (DCC-(E)GARCH) model of Engle (2002), complete details of the parameter estimates of which are available upon request from the authors. Note an EGARCH specification instead of a GARCH one for the volatility processes is used due to better fit under the former. Figure S2 reported in the supplementary information, showed that the correlation is indeed time-varying and is primarily positive in the early part of the sample and then turns mostly negative from around the beginning of World War I. This result highlights the fact that the inflation expectations and asset value channels at the beginning, and recessionary and portfolio allocation channels later on, were at work in driving the sign of the correlations of bond and oil returns to vary over time, and in the process warrants the time-varying causal approach undertaken by us.
- ⁸ Of course, we could have also used the rolling, recursive, and recursive-rolling window multivariate causality tests of Shi et al., (2018, forthcoming), but then this test requires the specification of an initial (rolling) window with the causality results known to be sensitive to the size of this window.
- ⁹ Based on Wald tests for the null hypothesis of joint zero parameter restrictions, Hill (2007) developed a sequential multiple-horizon non-causality test procedure for tri-variate VAR processes (with one auxiliary variable). When we conducted the sequential testing procedure of Hill (2007), the null hypotheses associated with whether these bond and oil returns ever cause each other, and whether they cause each other at one-step-ahead were overwhelmingly rejected at the highest possible level of significance based on a parametric bootstrap procedure in the presence of the stock returns as the auxiliary variable. Hence, we were able to establish that bidirectional causality between bond and oil returns not only exist at a horizon of one-month-ahead, but at any possible horizon beyond the first-step, that is, bi-directional causality holds infinitely. Complete details of these results are available upon request from the authors.

- ¹⁰ We must point out that when we applied the standard Hafner and Herwartz (2006) causality-in-variance test to our two returns, the null of non-causality could not be rejected in either direction even at the 10% level of significance. However based on the Brooks and Hinich approach (Brooks & Hinich, 1999), the null hypotheses of no causality from *ORV* to *BRV*, and from *BRV* to *ORV* were rejected under 81.1 and 48.4% of the cases respectively, thus highlighting the need to undertake a time-varying approach. Complete details of these results are available upon request from the authors.
- ¹¹ Note that, we decided to use the EGARCH model rather than the GARCH model, since the former provided a better fit by accounting for asymmetric effects of positive and negative returns. Complete details on the parameter estimates of the EGARCH models are available upon request from the authors.
- ¹² Using the Brooks and Hinich (1999) approach, the null hypotheses of no causality from *OR* to *BR*, and from *BR* to *OR* were rejected for 72.2 and 83.3% of the cases respectively, while the null hypotheses of non-causality from *ORV* to *BRV*, and from *BRV* to *ORV* were rejected under 70.8 and 58.5% of the cases respectively. Complete details of these results, which in general provide support to the findings of the time-varying causality, especially for volatilities, are available upon request from the authors.
- ¹³ As an additional exercise, we also analyzed the causal relationship between returns, as well as volatility, of corporate bonds and the oil market. The corporate bond returns data is derived from the website of Professor Amit Goyal (<http://www.hec.unil.ch/agoyal/>), and starts in 1926:01. This analysis is motivated based on the work of (Gormus, Nazlioglu, & Soytaş, 2018), who conducted price and volatility transmission tests of the high-yield US bond market, by accounting for gradual structural shifts. Since the focus of our paper is on government bonds, the results for the returns and (best-fitting) EGARCH-based volatility derived from the time-varying causality tests have been presented in Figures S3 and S4 in the supplementary information of the paper. While there are periods (primarily toward the beginning and end of the sample period), where corporate bond returns (*CBR*) and corporate bond returns volatility (*CBRV*) causes *OR* and *ORV* respectively, the causality in terms of both returns and volatility generally runs from the oil market, and basically over the entire sample period. These findings are in line with (Gormus et al., 2018) who too detected significant causality from the oil market to the high-yield bond market in terms of both price and volatility.

REFERENCES

- Apergis, N. (2019). Oil prices and corporate high-yield spreads: Evidence from panels of nonenergy and energy European firms. *The Quarterly Review of Economics and Finance*, 72, 34–40. <https://doi.org/10.1016/j.qref.2019.01.012>
- Arora, V. (2011). Asset value, interest rates and oil price volatility. *The Economic Record*, 87, 45–55.
- Arora, V., & Tyers, R. (2012). Asset arbitrage and the price of oil. *Economic Modelling*, 29, 142–150.
- Bahloul, W., Balcilar, M., Cunado, J., & Gupta, R. (2018). The role of economic and financial uncertainties in predicting commodity futures returns and volatility: Evidence from a nonparametric causality-in-quantiles test. *Journal of Multinational Financial Management*, 45, 52–71.
- Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1–22. <https://dx.doi.org/10.1002/jae.659>.
- Balcilar, M., Gupta, R., & Miller, S. M. (2015). Regime switching model of US crude oil and stock market prices: 1859 to 2013. *Energy Economics*, 49, 317–327.
- Balcilar, M., Gupta, R., Wang, S., & Wohar, M. E. (2019). Oil Price uncertainty and movements in the US government bond risk Premia. *The North American Journal of Economics and Finance*, 52, 101147.
- Balcilar, M., Gupta, R., & Wohar, M. E. (2017). Common cycles and common trends in the stock and oil markets: Evidence from more than 150 years of data. *Energy Economics*, 61, 72–86.
- Boivin, J., & Giannoni, M. P. (2006). Has monetary policy become more effective? *The Review of Economics and Statistics*, 88, 445–462.
- Bonato, M. (2019). Realized correlations, betas and volatility spillover in the agricultural commodity market: What has changed? *Journal of International Financial Markets, Institutions and Money*, 62, 184–202.
- Bouri, E. (2019). The effect of jumps in the crude oil market on the sovereign risks of major oil exporters. *Risks*, 7, 118.
- Bouri, E., de Boyrie, M. E., & Pavlova, I. (2017). Volatility transmission from commodity markets to sovereign CDS spreads in emerging and frontier countries. *International Review of Financial Analysis*, 49, 155–165.
- Bouri, E., Jalkh, N., & Roubaud, D. (2019). Commodity volatility shocks and BRIC sovereign risk: A GARCH-quantile approach. *Resources Policy*, 61, 385–392.
- Bouri, E., Kachacha, I., & Roubaud, D. (2019). Oil market conditions and sovereign risk in MENA oil exporters and importers. *Energy Policy*, 137, 111073.
- Bouri, E., Shahzad, S. J. H., Raza, N., & Roubaud, D. (2018). Oil volatility and sovereign risk of BRICS. *Energy Economics*, 70, 258–269.
- Brooks, C., & Hinich, M. J. (1999). Cross-correlations and cross-bicorrelations in Sterling exchange rates. *Journal of Empirical Finance*, 6, 385–404.
- Brock, W., Dechert, D., Scheinkman, J., & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews*, 15, 197–235. <https://dx.doi.org/10.1080/07474939608800353>.
- Clark, T. E., & McCracken, M. W. (2006). The predictive content of the output gap for inflation: Resolving in-sample and out-of-sample evidence. *Journal of Money, Credit and Banking*, 38, 1127–1148.
- Coronado, S., Jiménez-Rodríguez, R., & Rojas, O. (2018). An empirical analysis of the relationships between crude oil, gold and stock markets. *The Energy Journal*, 39, 193–207. <https://doi.org/10.5547/01956574.39.SI1.scor>
- Degiannakis, S., Filis, G., & Arora, V. (2018). Oil prices and stock markets: A review of the theory and empirical evidence. *The Energy Journal*, 39(5), 85–130.
- Demirer, R., & Gupta, R. (2018). Presidential cycles and time-varying bond-stock market correlations: Evidence from more than two centuries of data. *Economics Letters*, 167, 36–39.
- Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, 42, 1137–1159.
- Elder, J., & Serletis, A. (2011). Volatility in oil prices and manufacturing activity: An investigation of real options. *Macroeconomic Dynamics*, 15, 379–395.
- Filippidis, M., Filis, G., & Kizys, R. (2020). Oil price shocks and EMU sovereign yield spreads. *Energy Economics*, 86, 104656.

- Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics*, 20(3), 339–350. <https://dx.doi.org/10.1198/073500102288618487>.
- Gormus, A., Nazlioglu, S., & Soytaş, U. (2018). High-yield bond and energy markets. *Energy Economics*, 69, 101–110.
- Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37, 424–438.
- Gupta, R., Kollias, C., Papadamou, S., & Wohar, M. E. (2018). News implied volatility and the stock-bond nexus: Evidence from historical data for the USA and the UK markets. *Journal of International Financial Management*, 47, 76–90.
- Gupta, R., & Wohar, M. (2017). Forecasting oil and stock returns with a Qual VAR using over 150 years off data. *Energy Economics*, 62, 181–186.
- Habib, M. M., & Stracca, L. (2015). Is there a global safe haven? *International Finance*, 18, 281–298.
- Hafner, C. M., & Herwartz, H. (2006). A Lagrange multiplier test for causality in variance. *Economics Letters*, 93, 137–141.
- Hager, S. B. (2017). A global bond: Explaining the safe-haven status of US Treasury securities. *European Journal of International Relations*, 23, 557–580.
- Hamilton, J. D. (2013). Historical oil shocks. In R. E. Parker & R. M. Whaples (Eds.), *Routledge handbook of major events in economic history* (pp. 239–265). New York, NY: Routledge Taylor and Francis Group.
- Hill, J. B. (2007). Efficient tests of long-run causation in trivariate VAR processes with a rolling window study of the money-income relationship. *Journal of Applied Econometrics*, 22, 747–765. <https://dx.doi.org/10.1002/jae.925>.
- Ioannidis, C., & Ka, K. (2018). The impact of oil price shocks on the term structure of interest rates. *Energy Economics*, 72, 601–620.
- Kang, W., Ratti, R. A., & Yoon, K. H. (2014). The impact of oil price shocks on US bond market returns. *Energy Economics*, 44, 248–258.
- Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *The American Economic Review*, 99, 1053–1069.
- Kilian, L., & Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29, 454–478.
- Kopyl, K. A., & Lee, J. B.-T. (2016). How safe are the safe haven assets? *Financial Markets and Portfolio Management*, 30, 453–482.
- Lu, F., Hong, Y., Wang, S., Lai, K., & Liu, J. (2014). Time-varying Granger causality tests for applications in global crude oil markets. *Energy Economics*, 42, 289–298.
- Nazlioglu, S., Gupta, R., & Bouri, E. (2020). Movements in international bond markets: The role of oil prices. *International Review of Economics & Finance*, 68, 47–58. <https://dx.doi.org/10.1016/j.iref.2020.03.004>.
- Nelson, D. B., & Nelson, D. B. (1991). Conditional Heteroskedasticity in asset returns: A new approach. *Econometrica*, 59, 347–370. <https://doi.org/10.2307/2938260>
- Nguyen, H., Nguyen, & H., Pham, A. (2020). Oil price declines could hurt U.S. financial markets: the role of oil price level. *The Energy Journal*, 41(01), 1–22. <http://dx.doi.org/10.5547/01956574.41.5.hngu>.
- Rossi, B. (2005). Optimal tests for nested model selection with underlying parameter instability. *Economic Theory*, 21, 962–990.
- Rossi, B. (2013). Chapter 21: Advances in forecasting under instability. In G. Elliott, A. Timmermann, & G. Elliott (Eds.), *Handbook of Economic Forecasting*, 2, 1203–1324. Amsterdam: Elsevier. <https://dx.doi.org/10.1016/B978-0-444-62731-5.00021-X>
- Rossi, B., & Wang, Y. (2019). Vector autoregressive-based Granger causality test in the presence of instabilities. *The Stata Journal: Promoting communications on statistics and Stata*, 19(4), 883–899. <https://dx.doi.org/10.1177/1536867x19893631>.
- Selmi, R., Gupta, R., Kollias, C., & Papadamou, S. (2019). The stock-bond nexus and investors' behavior in mature and emerging markets. *Studies in Economics and Finance*. <http://dx.doi.org/10.1108/sef-08-2017-0224>.
- Shahzad, S. J. H., Naifar, N., Hammoudeh, S., & Roubaud, D. (2017). Directional predictability from oil market uncertainty to sovereign credit spreads of oil-exporting countries: Evidence from rolling windows and crossquantilogram analysis. *Energy Economics*, 68, 327–339. <https://doi.org/10.1016/j.eneco.2017.10.001>
- SIFMA. 2018. Securities industry and financial markets association (SIFMA) fact book [WWW Document].
- Smyth, R., & Narayan, P. K. (2018). What do we know about oil prices and stock returns? *International Review of Financial Analysis*, 57, 148–156. <https://doi.org/10.1016/j.irfa.2018.03.010>
- Shi, S., Phillips, P. C. B., & Hurn, S. (2018). Change detection and the causal impact of the yield curve. *Journal of Time Series Analysis*, 39(6), 966–987. <https://dx.doi.org/10.1111/jtsa.12427>.
- Tivari, A. K., Cunado, J., Gupta, R., & Wohar, M. E. (2018). Volatility spillovers across global asset classes: Evidence from time and frequency domains. *The Quarterly Review of Economics and Finance*, 70, 194–202.
- Wan, J. Y., & Kao, C. W. (2015). Interactions between oil and financial markets-do conditions of financial stress matter? *Energy Economics*, 52, 160–175. <https://doi.org/10.1016/j.eneco.2015.10.003>

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Coronado S, Gupta R, Nazlioglu S, Rojas O. Time-varying causality between bond and oil markets of the United States: Evidence from over one and half centuries of data. *Int J Fin Econ*. 2023;28:2239–2247. <https://doi.org/10.1002/ijfe.2534>