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Time-Varying Rare Disaster Risks, Oil Returns and Volatility

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Abstract

This paper provides a novel perspective to the predictive ability of rare disaster risks for West Texas Intermediate (WTI) oil market returns and volatility using a nonparametric quantile-based methodology over the monthly period of 1918:01-2013:12. We show that a nonlinear relationship and structural breaks exists between oil returns and various rare disaster risks; hence, linear Granger causality tests are misspecified and the linear model results of non-predictability are unreliable. However, the quantile-causality test shows that rare disaster-risks strongly affect both WTI returns and volatility, with stronger evidence of predictability observed at lower quantiles of the respective conditional distributions. Our results are robust to alternative specification of volatility (based on a GARCH model), and measure of rare disaster risks (based on the number of crises).

Keywords: Oil Returns and Volatility; Rare Disasters; Nonparametric Quantile Causality.
JEL Codes: C22, C58, G14, G15.

1. Introduction

Following the early work of Rietz (1988), a growing body of theoretical and empirical papers has recently provided evidence of the predictive power of rare disaster risks for movements (returns and volatility) in asset prices (see for example, Barro (2006, 2009), Gourio (2008a, b, 2012), Barro and Ursúa (2008, 2009, 2012), Barro and Jin (2011), Berkman et al., (2011, 2017), Gabaix (2012), Nakamura et al., (2013), Wachter (2013), Farhi and Gabaix (2016), Manela and Moreira (2017)). Focusing on asset pricing implications, Berkman et al. (2011) further show that time-varying rare disaster risks are also priced in the cross-section of stock returns, implied by higher returns observed for industries that are more crisis risk sensitive.

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A major obstacle, however, to empirical verification of the rare disaster models is that individual countries rarely face actual major disasters. To avert this small sample problem inherent in the use of actual rare disasters, Berkman et al. (2011) recommend focusing on a much larger sample of potential disasters, i.e., international political crises that are likely to cause changes in perceived rare disaster probabilities. Following the approach in Berkman et al. (2011, 2015), our source of events (i.e., changes in disaster probability), is a detailed database of all international political crises that occurred during the period 1918 to 2013. The International Crisis Behavior project (ICB) database developed by the Center for International Development and Conflict Management contains detailed information on more than 450 (464 to be exact) international political crises. The most important events for each crisis, for instance start and end dates, have been carefully documented, with crises classifications based on numerous characteristics, such as superpower involvement, duration, and gravity. In addition, this ICB database is also attractive due to its definition of crisis, besides the large number of observations and the consistent approach in which crises are measured. According to the ICB database, a crisis does not necessarily start with an attack or military action; instead, it is defined as a perceived change in the probability of a threat that results in the start or end of an international political crisis. This perceived change in the probability of a threat is likely to be closely aligned with the news events to which market particupants are likely to react (Berkman et al., 2011, 2015).

Given this database, the goal of this paper is to examine the predictive power of rare disaster-risks for the return and volatility dynamics of West Texas Intermediate (WTI) oil prices using a long span of historical data over the period 1918:01-2013:12. In the process, we contribute to the literature on rare disaster risks and financial markets from a commodity market perspective by focusing on crude oil that can be regarded perhaps the most important commodity given its influential role in the world economy relative to other commodities,

particularly in terms of its causal effects on recessions (Hamilton, 1983, 2008, 2009, 2013; Elder and Serletis, 2010) and inflation (Stock and Watson, 2003). Additionally, oil is indispensable for the industrial, transportation, and agricultural sectors, whether used as feedstock in production or as a surface fuel in consumption (Mensi, et al., 2014). To that end, given the evidence in Berkman et al. (2011) that industries that are more sensitive to crisis risks yield higher returns, our direct focus on crude oil can provide valuable insights as to whether the crisis risk premium on particular industries are channelled via their sensitivity to oil price fluctuations. Furthermore, knowledge of the factors (in this case, rare disaster risks) that drive oil market returns and volatility is likely to constitute valuable information for economic agents.

To achieve our objective, we conduct the predictability analysis based on the *k*-th order nonparametric causality-in-quantiles test recently developed by Balcilar et al. (2016a). This test studies higher order causality over the entire conditional distribution and is inherently based on a nonlinear dependence structure between the variables, as captured by data-driven nonparametric functions.[1] To the best of our knowledge, this is the first paper that evaluates the predictive power of rare disaster risks for crude oil returns and volatility based on a nonparametric causality-in-quantiles framework.

At this stage, it is important to point out the possible channels through which one could expect disaster risks to affect oil market dynamics. Clearly, uncertainty regarding the probability and size of disasters can lead to a great deal of uncertainty in terms of investment growth, which in turn translates into uncertainties over output growth (GDP). On the demand side, it can also drive economic worries on the part of consumers, thus affecting the level of consumption growth in the economy. Therefore, considering the suggestion by Bernanke

[1] As indicated by Balcilar *et al.* (2016a), the causality-in-quantile approach has the following novelties: Firstly, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series. Secondly, via this methodology, we are able to test for not only causality-in-mean (1st moment), but also causality that may exist in the tails of the distribution of the variables. Finally, we are also able to investigate causality-in-variance and, thus, study higher-order dependency.

(2016) that both oil and stock markets tend to move together as they both react to a common factor reflecting global aggregate demand, one obvious channel that links disaster risks to oil market movements is the potential effect of rare disasters on growth expectations for both output and consumption.

A second channel through which disaster risk can affect oil return dynamics is via its contribution to jump risk in oil prices. While the presence of jump risk driving stock and bond returns is well evidenced in the literature (e.g. Maheu and McCurdy, 2004; Dunham and Friesen, 2007; Huang and Tauchen, 2005; Maheu et al. 2013 and Guo et al., 2015), there is growing evidence suggesting that jumps account for a large part of the variation in crude oil prices and a substantial part of the risk premium in oil derivatives prices is due to jumps (e.g. Larsson and Nossman, 2011; Christoffersen et al., 2016; Baum and Zerilli, 2016). Therefore, it can be argued that rare disaster risks contribute to the presence of jumps in oil prices, which in turn drive return and volatility dynamics in the oil market. To the end, the nonparametric causality tests that we employ in our empirical tests provide an appropriate approach as it allows us to account for possible nonlinearities in the relationship between oil returns and changes in disaster probabilities. By doing so, our analysis also contributes to the strand of literature on jump risks in commodity markets.

The rest of this paper is organized as follows: Section 2 describes the econometric frameworks involving the higher-moment nonparametric causality-in-quantiles test, and the (GARCH-based) measure of volatility. Section 3 presents the data and discusses the empirical results. Finally, Section 4 concludes.

2. Econometric Framework

In this section, we briefly present the methodology for the detection of nonlinear causality via a hybrid approach as developed by Balcilar et al. (2016a), which in turn is based on the

frameworks of Nishiyama *et al.* (2011) and Jeong *et al.* (2012). We start by denoting oil returns by y_t and the predictor variable (in our case, the dummies capturing various types of rare disaster risk-related events- discussed in detail in the next section) as x_t. We further let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},..., x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. If we let denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) \mid Z_{t-1}\} = \theta$ with probability one. As a result, the (non)causality in the θ-th quantile hypotheses to be tested are:

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

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

Jeong *et al.* (2012) use the distance measure $J = \{\varepsilon_t E(\varepsilon_t \mid Z_{t-1}) f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null hypothesis in (1), which can only be true if and only if $E[1\{y_t \le Q_\theta(Y_{t-1}) \mid Z_{t-1}\}] = \theta$ or, expressed in a different way, $1\{y_t \le Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Jeong *et al.* (2012) show that the feasible kernel-based sample analogue of J has the following format:

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

where $K(\cdot)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is given by

$$\hat{\varepsilon}_t = 1\{y_t \le Q_\theta(Y_{t-1})\} - \theta. \tag{4}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θth conditional quantile of y_t given Y_{t-1}, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta \mid Y_{t-1}), \tag{5}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left((Y_{t-1}-Y_{s-1})/h\right)1(y_s \le y_t)}{\sum_{s=p+1,s\neq t}^{T} L\left((Y_{t-1}-Y_{s-1})/h\right)}, \tag{6}$$

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

As an extension of Jeong *et al.* (2012)'s framework, Balcilar et al. (2016a) develop a test for the *second* moment which allows to test the causality between the various disaster risk-related dummies and oil return volatility. Adapting the approach in Nishiyama *et al.* (2011), higher order quantile causality can be specified in terms of the following hypotheses as:

$$H_0: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} = 1 \qquad \text{for } k = 1,2,\ldots,K \tag{7}$$

$$H_1: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} < 1 \qquad \text{for } k = 1,2,\ldots,K \tag{8}$$

We can integrate the entire framework and test whether x_t *Granger causes* y_t *in quantile* θ *up to the* k^{th} *moment* using Eq. (7) to construct the test statistic in Eq. (6) for each k. The causality-in-variance test can then be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2 - measuring the volatility of oil returns. However, one can show that it is difficult to combine the different statistics for each $k = 1,2,\ldots,K$ into one statistic for the joint null in Eq. (7) because the statistics are mutually correlated (Nishiyama *et al.*, 2011). Balcilar et al. (2016a), thus, propose a sequential-testing method as described in Nishiyama *et al.* (2011). First, as in Balcilar et al. (2016a), we test for the nonparametric Granger causality in the *first*

moment $(i.e.\, k = 1)$. Nevertheless, failure to reject the null for $k = 1$ does not automatically lead to no-causality in the *second* moment. Thus, we can still construct the test for $k = 2$, as discussed in detail in Balcilar et al. (2016a).

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$. We use a lag order based on the Schwarz information criterion (SIC), which is known to select a parsimonious model as compared with other lag-length selection criteria. The SIC criterion helps to overcome the issue of the over-parameterization that typically arises in studies using nonparametric frameworks. For each quantile, we determine the bandwidth parameter (h) by using the leave-one-out least-squares cross validation method. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

Given the evidence in Sadorsky (2006) that a GARCH(1,1) model fits very well with crude oil price volatility, we also decided to check for the robustness of our results in terms of volatility. Hence, we first recover a measure of conditional volatility from a GARCH(1,1) model and then apply the causality-in-quantiles test to this measure of volatility. The basics of GARCH(1,1) model is as follows:

$$y_t = \mu + \varepsilon_t, \tag{9}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{10}$$

where y_t represents the oil returns series and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (ω), the lagged error (ε_{t-1}^2), and the lagged conditional variance (h_{t-1}).

3. Data

The empirical analysis utilizes monthly data for WTI oil prices and the dummy variables capturing various types of disaster risks over the period of 1918:01 to 2013:12. The start and

end dates are governed purely by the availability of data on disaster risks. Oil price data is sourced from the Global Financial Database, with returns computed as the monthly logarithmic change of oil prices multiplied by 100 to convert the returns into percentages. Since WTI oil price data is available from 1859:09, we do not lose the first observation while computing oil returns. Figures 1(a) and 1(b) present the plot of monthly oil returns and the histogram of the series along with the summary statistics, respectively. We observe that the oil return data is skewed to the left with excess kurtosis, resulting in the null of normality under the Jarque-Bera test being overwhelmingly rejected at the highest level of significance. The non-normal distribution, in turn, provides preliminary motivation for relying on a quantiles-based approach for our analysis.

[Insert Figure 1]

Next we turn our attention to our measure of disaster risks of rare events as obtained from the International Crisis Behavior (ICB) database. ICB database started in 1975 and covers comprehensive information regarding 464 international political crises that occurred during the period of 1918 to 2013 at monthly frequency, involving 1,036 crisis actors. Brecher and Wilkenfeld (1997) provide detail discussion on the ICB database, definition and construction of variables. The ICB data has been used in series of books and empirical research papers in many disciplines, including economics, war and political sciences (see for example, Blomberg, et al., (2004); Berkman, et al., (2011, 2017); Huang et al., (2015))[2]. The underlying motive of the ICB database is to develop a comprehensive list of international political crisis since Word War I. As per the ICB database, the breakpoint of a crisis is an event, act or changes characterized by following three conditions: (a) a threat to basic value, (b) excessive chances of involvement in military hostilities, and (c) time pressure for

[2] The ICB web site (https://sites.duke.edu/icbdata/) provides an overview of studies that used its data.

response. ICB database covers a wide range of alternatives to measure the severity of any crisis and, consequently gives us more information to identify the seriousness of the crisis. Furthermore, other important advantage of these crises events are their likelihood of being exogenous.

The ICB database distinguishes each crisis on the basis of 81 dimensions including the control variables and crisis mediation, with the possibility of tracing the background of each crisis in detail from the website of ICB database. Further, the ICB database considers those crises only in which the crisis actor is a sovereign entity and has significant participation in any of political conflict. As indicated above, the ICB database covers comprehensive dimensions of each crisis and we take into account many of these dimensions, following Berkman, et al., (2011, 2017), to analyze the impact of international political risk on oil returns and volatility. The foremost variable of our study is total number of crisis (*Crisis*) in any month *t*. Some crisis can be more severe than others, therefore it is expected that more devastating crisis may have stronger effect. Following the Berkman, et al., (2011, 2017), we created the following crisis variables: (1) violent break (*Violent Break*) includes all the crisis that starts with violent act, (2) violent (*Violent*) crisis includes all the crisis that comprises either serious clashes or full scale war, (3) war (*War*) includes all the crisis that involves full-scale wars, (4) all crisis that involves grave value threats (*Grave Threat*), (5) protracted conflicts (*Protracted*) includes all the crisis with protracted conflict, protracted and crisis outside this conflict, and (6) major power (*Major Power*) includes the crisis only if at least one superpower or great power is there in both side of conflict. Finally, we also construct a crisis severity index (*Crisis Severity Index*) that summarizes different aspects of crisis severity into one measure by aggregating the six variables above. For all the above crisis variables, we created the dummy variables, which is equal to 1 if the crisis in that group occurs in a specific month, and zero otherwise. The dummy variables are normalized to have

a mean of zero and variance of unity, so that we can compare the strength of predictability across the various disaster risks.

4. Empirical Findings

Before we begin our discussion of the findings from the causality-in-quantiles tests, for the sake of completeness and comparability, we first provide the findings from the standard linear Granger causality tests with null hypothesis that a specific rare disaster risk does not affect oil returns. As shown in Table 1, the standard linear Granger causality tests yield no evidence of causality that goes from any of the disaster risk variables to oil returns. Therefore, standard linear tests imply no significant causal relationships between rare disaster risks and oil returns.

[Insert Table 1]

Given the insignificant results obtained from linear causality tests, next we statistically examine the presence of nonlinearity in the relationship between oil returns and the predictor variables representing rare disaster risks. For this purpose, we apply the Brock et al., (1996, BDS) test on the residuals from the return equation used in the linear causality tests involving the rare disaster risk dummies. The results of the BDS test of nonlinearity presented in Table 2 provide strong evidence of rejection of the null hypothesis of *i.i.d.* residuals at various embedded dimensions (m). Thus, we conclude that there exists nonlinearity in the relationship between oil returns and the rare disaster risk dummies. This evidence also indicates that the findings based on the linear Granger causality test as presented in Table 1 cannot be deemed robust and reliable.

In addition to the BDS test, we also apply the Bai and Perron (2003) tests of multiple structural breaks on the oil return equation used to test linear Granger causality based on the various types of disaster risks. Using the powerful *UDmax* and *WDmax* tests, and allowing for a maximum of five breaks with fifteen percent endpoint trimming as well as

heterogeneous error distributions across breaks, we detect three breaks (1941:07, 1971:12, and 1986: 04) in all cases.[3] The presence of these breaks further confirms our earlier findings, based on nonlinearity tests, that the linear model is misspecified.

Given the strong evidence of nonlinearity and regime changes in the relationship between oil returns and the crises dummies, we now turn our attention to the causality-in-quantiles test, which is robust to possible misspecification due to nonlinearity and structural breaks given its nonparametric (i.e. data-driven) structure.

[Insert Table 2]

Table 3 presents the findings from the causality-in-quantiles tests estimated over the quantile range from 0.10 to 0.90. Panels A and B present the findings for WTO oil returns and volatility (squared returns) respectively and the null hypothesis is that rare disaster risk dummies (in columns) do not Granger cause oil returns and volatility. Unlike the insignificant findings from linear tests reported in Table 1, we observe in Table 3 that the null is consistently rejected, implying strong evidence of predictability running from all the various disaster risks dummies to both returns and volatility in the oil market. Interestingly however, we see that causality is particularly strong at the lower end of the respective conditional distributions, while the strongest effect on volatility is observed at quantile of 0.10 with the same observed at the quantile of 0.30 in the case of oil return. We also see that this pattern is consistent across the various disaster risk proxies. These findings suggest that, while the predictive power of rare disaster risks over oil market dynamics is statistically significant for the entire conditional distributions of returns and volatility, the causal effect is strongest when the returns and volatility are in the lowest quantile, corresponding to negative oil returns coupled with low return volatility. It can thus be argued that rare disaster risks relate to negative jumps in oil prices (implied by lower quantiles), while these jumps are not

[3] Complete details of the Bai and Perron (2003) tests of structural breaks are available upon request from the authors.

necessarily associated with high volatility, possibly due to lower trading activity or other factors driving investor behaviour.

[Insert Table 3]

In order to further confirm the causal effects of rare disaster risks on oil return volatility, we present in Table 4, the findings for the tests of causality from the disaster risk dummies to the conditional volatility estimates obtained from the GARCH(1,1) model discussed earlier. Again, barring three individual exceptions (i.e. the quantile of 0.60 and 0.50-0.60 for 'War' and 'Grave Threat', respectively), we observe strong evidence of predictability for the GARCH-based volatility measures emanating from the rare disaster risk dummies. As observed for squared returns in Table 3, we see again that the dummy capturing all possible crises tends to be the strongest predictor, consistently at all quantiles. However, unlike the findings reported in Table 3, we see that the causal effects are not necessarily the strongest at lower quantiles of the respective conditional distributions. It must, however, be noted that Balcilar et al. (2016b) suggests that one should rely on the results obtained under squared returns as a measure of volatility, rather than a model-based measure of the same, since the analysis for the squared returns follows directly from the *k*-th order test of nonparametric causality-in-quantiles.

[Insert Table 4]

As explained earlier in the data description, the findings reported in Tables 3 and 4 utilize dummy variables that represent various definitions of rare disaster risks. In addition to these dummy variables, the ICB dataset also provides the monthly count for the risk variables under the various categories as well as information on their start and end dates, i.e. the span of the crisis. Therefore, as a robustness check, we repeat our analysis using the monthly counts for various risk categories instead. The findings in Table 5 further confirm our previous results in Table 3 that are based on the crisis dummy variables, indicating strong

evidence of predictability for both oil returns and volatility over the entirety of the respective conditional distributions. The causal effects from rare disaster risks are found to be significant irrespective of what phase the month is classified as, i.e. start, end and duration of the crisis. Furthermore, we observe that the pattern of the strength of the causal relationship with the count data is similar to that observed when the dummies are used as predictors, along with the importance of the predictive ability of the predictor variable capturing all the crises. In short, our findings yield significant evidence of a causal relationship between rare disaster risks and oil return and volatility with the effect being particularly strong at low quantiles of the conditional distribution representing periods of negative oil returns.

[Insert Table 5]

As additional robustness checks, we also used the news-based measures of implied volatility (NVIX) as developed by Manela and Moreira (2017)[4] and geopolitical risks (GPRs) of Caldara and Iacoviello (2017)[5], as possible alternative measures of rare disaster risks. As can be seen from the results reported in Tables A1 (covering the period of 1889:07 to 2016:03) and A2 (over the period of 1899:01 to 2017:06) in the Appendix of the paper, there is strong evidence of predictability for oil returns and volatility (squared returns) due to

[4] The news dataset to construct the NVIX includes the title and abstract of all front-page articles of the Wall Street Journal. Manela and Moreira (2017) focus on front-page titles and abstracts in order to ensure feasibility of data collection, and also because these are manually edited and corrected following optical character recognition, which in turn, improves their earlier sample reliability. The NVIX data is found to peak during stock market crashes, times of policy-related uncertainty, world wars, and financial crises. The reader is referred to Manela and Moreira (2017) for further details, who also discuss how they decompose the aggregate NVIX into its components. The NVIX components capture uncertainty stemming from (with the words searched for in brackets) government policy (tax, money, rates, government, plan), intermediation (banks, financial, business, bank, credit), natural disaster (fire, storm, aids, happening, shock), securities markets/stock markets (stock, market, stocks, industry, markets), and wars (war, military, action,world war, violence). There is also available data for an "unclassified" component (U.S., special, Washington, treasury, gold). The data is available for download from: http://apps.olin.wustl.edu/faculty/manela/data.html.

[5] Caladara and Iacoviello (2017) construct a long-span monthly GPR index dating back to 1899, based on terms related to geopolitical risks covered in three newspapers namely, the New York Times, Chicago Tribune, and the Washington Post. The phrases considered for constructing the index are: "geopolitical risk(s)", "geopolitical concern(s)", "geopolitical tension(s)", "geopolitical uncertainty(ies)", "N/3" ("crisis" OR "uncertain")), "war risk(s)" (OR "risk(s) of war"), state of war" OR "declaration of war", "war" OR "military" and "military threat(s)", "terrorist threat(s)", "terrorist act(s)", "Middle East AND tensions". The data can be downloaded from: https://www2.bc.edu/matteo-iacoviello/gpr.htm.

aggregate measures of NVIX and GPR and their respective components, (i.e., uncertainty associated with government policy, intermediation, natural disaster, securities markets, war and unclassified events under the NVIX, and GPR acts and GPR threats under GPRs) respectively. Note that, the pattern associated with strength of causality is similar to those reported for the rare-disaster risks.

5. Conclusion

This paper extends the literature on the effect of rare disaster risks on financial market returns to the commodity market, in particular crude oil. Unlike other applications to stock and bond returns, we provide a novel perspective to the predictive ability of rare disaster risks for returns and volatility in the WTI oil market using a *k*-th order nonparametric quantile-based methodology that allows to capture nonlinear causal effects. Using monthly data on oil returns and various disaster risk proxies for the period of 1918:01 to 2013:12, we first show that standard linear causality tests yield insignificant results in terms of the predictive power of rare disasters over WTI returns. However, additional tests reveal strong evidence of nonlinearity and regime changes in the relationship between oil returns and the rare disaster risk proxies, indicating that the linear Granger causality test is misspecified, thus the results cannot be relied on.

Applying the nonparametric quantile-causality test, which is robust to misspecification due to nonlinearity and structural breaks, we show that rare disaster risk proxies strongly predict both returns and volatility for oil, with stronger causal effects observed at the lower ends of their respective conditional distributions. We argue that rare disaster risks potentially contribute to jump risk in oil returns (more significantly to negative jumps in this case) that has been documented in several previous studies (Larsson and Nossman, 2011; Christoffersen et al., 2016; and Baum and Zerilli, 2016).

From the perspective of an academic, our results tend to suggest that the WTI market cannot be categorized as weakly efficient. Furthermore, the finding of strong asymmetric causal effects on oil returns, particularly at low quantiles, suggests that models of jump risk as well as jump diffusion models with stochastic volatility for crude oil dynamics can be improved by integrating proxies of rare disaster risks. From a pricing perspective, following the evidence by Christoffersen et al. (2016) that jumps command a premium in crude oil derivatives prices, our findings suggest that rare disaster risk proxies can be integrated in pricing models in order to improve forecasting models for crude oil prices.

From a policy making perspective, the strong evidence of a rare disaster effect on crude oil return and volatility suggests that policy makers who are worried about the potential negative impact of oil price fluctuations on the real economy should build rare disaster risk proxies into their forecasting models. This is particularly important given the evidence in the paper that causal effects are especially strong at the lower quantiles of the conditional distribution of oil returns. However, it must be noted that nonlinearity and possible structural breaks must be taken into account in order to correctly capture the effect of rare disaster risks on oil returns as our results show that using a linear model is likely to lead to incorrect inferences. Hence, in general, our results highlight the importance of testing for nonlinearity and structural changes, and if it exists, use a data-driven nonlinear approach to analyze causal relationships. The results also highlight the importance of having a nonlinear pricing framework that integrates disaster risks in the pricing model, perhaps via models that utilize higher order moments. As part of future research, it would be interesting to extend our analysis to a forecasting exercise, as in Bonaccolto et al., (forthcoming), since in-sample predictability does not guarantee the same over- and out-of-sample.

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Figure 1(a). Monthly Oil Returns

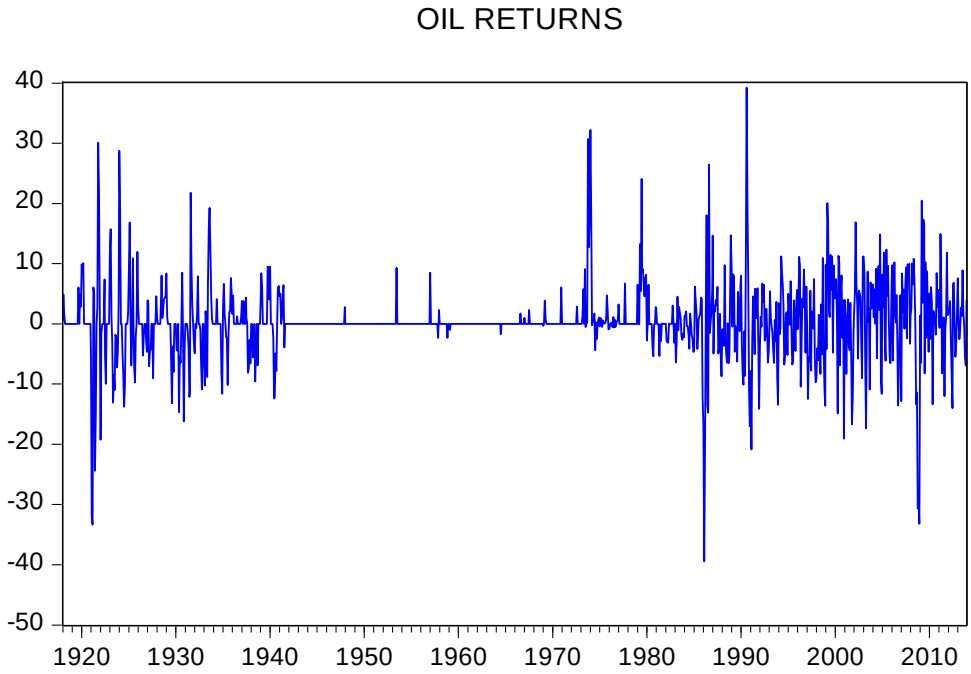

Figure 1(b). Histogram and Summary Statistics for Monthly Oil Returns

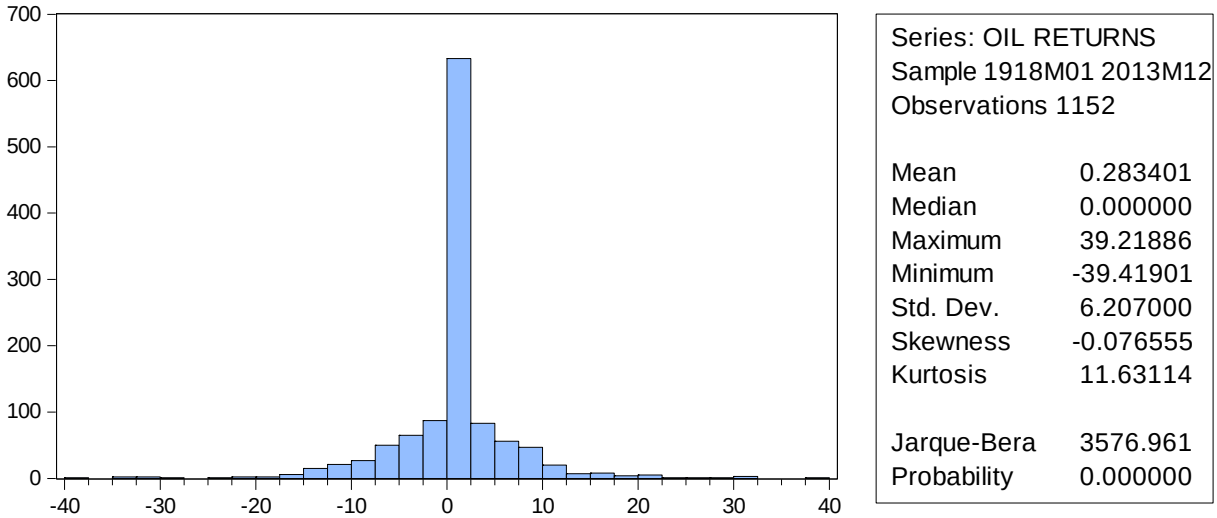

Table 1. Linear Granger Causality Test for WTI Returns.

Predictor Variable	***F*-stat**	***p*-value**
All	0.248	0.619
Violent	0.257	0.612
War	0.393	0.531
Violent Break	0.657	0.418
Protracted	0.187	0.665
Major Power	0.130	0.719
Grave Threat	3.681	0.055
Crisis Severity Index	1.375	0.241

Note: The null hypothesis is that a specific rare disaster-risk does not affect WTI returns.

Table 2. Brock et al. (1996) (BDS) Test of Nonlinearity.

Predictor Variable	**Dimension**				
	2	**3**	**4**	**5**	**6**
All	11.930***	14.668***	16.648***	18.965***	22.139***
Violent	11.800***	14.612***	16.711***	19.048***	22.215***
War	11.955***	14.705***	16.867***	19.189***	22.293***
Violent Break	11.968***	14.667***	16.744***	19.056***	22.144***
Protracted	11.861***	14.694***	16.813***	19.114***	22.287***
Major Power	11.599***	14.351***	16.516***	18.849***	21.986***
Grave Threat	12.159***	14.753***	16.772***	19.101***	22.181***
Crisis Severity Index	11.918***	14.654***	16.639***	18.967***	22.053***

Notes: The table reports the *z*-statistic of the BDS test corresponding to the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the oil returns equation used to test linear Granger causality. *** indicates rejection of the null hypothesis at the 1 per cent level of significance.

Table 3. Causality-in-Quantiles Test for WTI Returns and Volatility (Squared Returns).

Panel A: Returns								
Quantile	All	Violent	War	Violent Break	Protracted	Major Power	Grave Threat	Crisis Severity Index
0.1	***7.2167***	***5.9849***	***5.4766***	***5.7708***	***7.7755***	***6.1204***	***5.4457***	***6.9386***
0.2	***19.5019***	***17.1903***	***14.4331***	***15.7936***	***19.2176***	***14.8955***	***14.3119***	***18.6151***
0.3	***279.2003***	***238.5665***	***208.7500***	***213.8353***	***243.1471***	***210.4238***	***217.6757***	***275.6247***
0.4	***173.4119***	***149.0373***	***129.4330***	***132.5578***	***152.2913***	***130.6833***	***135.0629***	***171.4894***
0.5	***102.5227***	***88.6373***	***76.3466***	***78.2232***	***91.2805***	***77.2979***	***79.6206***	***101.6765***
0.6	***53.6906***	***47.1067***	***40.0197***	***40.8640***	***48.9061***	***40.7026***	***41.6172***	***53.5231***
0.7	***29.0606***	***25.8022***	***21.5436***	***22.6722***	***27.0010***	***22.1472***	***22.6865***	***29.3225***
0.8	***16.1053***	***14.5167***	***11.7761***	***12.5703***	***14.7595***	***12.0140***	***12.2454***	***16.1916***
0.9	***5.7863***	***5.2800***	***4.1152***	***4.6741***	***5.3899***	***4.4439***	***4.3940***	***6.1935***
Panel B: Volatility (Square Returns)								
Quantile	All	Violent	War	Violent Break	Protracted	Major Power	Grave Threat	Crisis Severity Index
0.1	***631.1909***	***539.6444***	***466.3895***	***481.3387***	***556.0854***	***473.1998***	***478.6326***	***621.0273***
0.2	***349.2724***	***299.6418***	***257.6132***	***265.9864***	***309.8051***	***261.8596***	***263.9420***	***344.0051***
0.3	***213.4727***	***184.0816***	***157.0160***	***162.3453***	***191.2074***	***160.1548***	***160.6011***	***210.5786***
0.4	***128.8988***	***111.9472***	***94.5197***	***97.7984***	***117.1264***	***96.8104***	***96.3064***	***127.4379***
0.5	***72.3227***	***63.5989***	***52.7842***	***54.7027***	***67.3249***	***54.5118***	***53.4791***	***71.7795***
0.6	***34.3296***	***30.9207***	***24.9338***	***25.8610***	***33.5145***	***26.2367***	***24.9599***	***34.3277***
0.7	***24.7935***	***23.1330***	***18.1842***	***19.5660***	***25.7776***	***18.3414***	***18.3407***	***24.8117***
0.8	***14.1292***	***13.3836***	***10.1449***	***11.2249***	***14.9017***	***10.3858***	***10.2733***	***14.1644***
0.9	***6.0922***	***5.5954***	***4.2872***	***4.9774***	***6.3375***	***4.5782***	***4.3707***	***6.4134***

Note: Entries correspond to the quantile causality test statistic for the null hypothesis that various disaster risk dummies (in separate columns) does not Granger cause oil returns and volatility; entries in bold-italic indicates rejection at the 5% significance level.

Table 4. Causality-in-Quantiles Test for GARCH(1,1)-based WTI Volatility Estimates.

	Volatility (GARCH (1,1) Model-Based)							
Quantile	All	Violent	War	Violent Break	Protracted	Major Power	Grave Threat	Crisis Severity Index
0.1	***5.2345***	***4.3334***	***4.0593***	***4.2123***	***4.7818***	***4.3514***	***4.1827***	***5.1350***
0.2	***8.4311***	***6.5370***	***6.2099***	***6.4308***	***6.4431***	***6.4207***	***7.2190***	***8.2695***
0.3	***5.0632***	***4.4685***	***4.2592***	***4.2502***	***3.9384***	***4.0504***	***4.8567***	***5.0498***
0.4	***3.6314***	***3.7429***	***4.5695***	***4.1455***	***4.3216***	***4.6548***	***2.7718***	***3.8262***
0.5	***2.5816***	***2.6178***	***4.0084***	***5.3662***	***4.1678***	***6.0842***	1.7399	***2.8590***
0.6	***2.2468***	***2.0950***	1.5835	***4.7149***	***2.4144***	***2.1570***	1.9013	***1.9956***
0.7	***5.7037***	***6.1404***	***3.9138***	***9.6417***	***8.8365***	***7.0366***	***4.3595***	***5.2521***
0.8	***6.3596***	***6.6967***	***5.2354***	***5.1396***	***6.6526***	***6.1611***	***5.0586***	***6.0322***
0.9	***4.6533***	***4.0788***	***3.4723***	***3.4463***	***4.2418***	***3.6229***	***3.5172***	***4.4707***

Note: Entries correspond to the quantile causality test statistic for the null hypothesis that various disaster risk dummies (in separate columns) does not Granger cause GARCH-based oil volatility; entries in bold-italic indicates rejection at the 5% significance level.

Table 5. Causality-in-Quantiles Test for WTI Returns and Volatility Based on the Monthly Counts of Rare Disaster Risks over Different Phases.

			Panel A: Returns								
			Quantile								
			0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Predictor Variable	All	Start	***5.1716***	***12.9689***	***206.5232***	***127.3447***	***74.6036***	***38.5437***	***20.3688***	***12.2930***	***4.1364***
		During	***3.7048***	***9.6465***	***142.8184***	***88.9412***	***52.8967***	***28.2987***	***15.6252***	***9.3775***	***3.4676***
		End	***5.1549***	***13.8405***	***210.5747***	***130.6526***	***77.0738***	***40.4343***	***21.1958***	***11.4054***	***4.0676***
	Violent	Start	***5.6236***	***14.1621***	***241.8836***	***149.4038***	***87.7656***	***45.5902***	***24.3756***	***14.6022***	***4.8317***
		During	***4.6675***	***10.6503***	***168.3541***	***105.2965***	***63.1316***	***34.1884***	***18.9571***	***10.5154***	***3.8185***
		End	***6.0709***	***16.0094***	***246.1472***	***152.8604***	***90.5965***	***47.7724***	***25.8346***	***13.9315***	***5.2249***
	War	Start	***6.3649***	***16.4106***	***261.4659***	***161.3431***	***94.6121***	***49.0383***	***26.4206***	***15.1556***	***5.1082***
		During	***5.5375***	***12.4886***	***187.7850***	***115.5533***	***67.5294***	***34.8535***	***18.8620***	***10.3348***	***3.5494***
		End	***6.7475***	***17.1432***	***270.5904***	***168.0624***	***99.5071***	***52.3566***	***28.5023***	***15.5796***	***5.4612***
	Violent Break	Start	***5.9239***	***15.3591***	***255.0803***	***158.0143***	***93.1315***	***48.5376***	***26.2836***	***15.5090***	***5.2287***
		During	***5.2601***	***12.4718***	***189.4150***	***117.4787***	***69.5026***	***36.5251***	***19.3914***	***11.0037***	***4.1793***
		End	***6.2177***	***16.1215***	***250.3852***	***154.8100***	***90.6280***	***46.9340***	***24.0758***	***13.2603***	***4.6565***
	Protracted	Start	***5.8064***	***14.8070***	***226.8717***	***139.4141***	***81.1998***	***41.5549***	***21.8364***	***12.5854***	***4.3244***
		During	***4.1411***	***10.2976***	***150.5307***	***91.9034***	***53.2208***	***27.2696***	***14.7159***	***8.5673***	***3.0378***
		End	***5.6843***	***14.7801***	***232.0793***	***143.7675***	***84.5036***	***44.1693***	***23.1960***	***12.2923***	***4.4940***
	Major Power	Start	***6.2857***	***16.8404***	***248.5036***	***152.6959***	***88.9468***	***45.5694***	***24.3411***	***13.9456***	***4.5157***
		During	***4.8588***	***12.1484***	***187.8661***	***115.1947***	***66.9947***	***34.2445***	***18.6869***	***11.3279***	***3.4997***
		End	***6.3855***	***16.4141***	***252.5816***	***156.4097***	***92.2356***	***48.2892***	***25.8975***	***14.4934***	***4.9939***
	Grave Threat	Start	***6.5843***	***16.1351***	***238.9133***	***146.5758***	***85.1058***	***43.2358***	***22.7628***	***12.8493***	***4.5356***
		During	***5.6463***	***13.3429***	***186.1368***	***115.8432***	***68.8334***	***36.3960***	***18.8309***	***10.5851***	***3.4656***
		End	***6.3824***	***16.5350***	***247.6358***	***153.6194***	***90.8302***	***47.6535***	***25.2277***	***13.4846***	***4.8168***
	Crisis Severity	Start	***4.8258***	***11.6802***	***195.7207***	***120.5679***	***70.5955***	***36.4085***	***19.1289***	***12.0723***	***3.7954***
		During	***4.2226***	***9.4656***	***125.3339***	***77.1260***	***45.6234***	***24.4122***	***13.5715***	***7.9047***	***3.2473***
		End	***4.6249***	***12.2467***	***197.6395***	***122.3397***	***71.8925***	***37.6039***	***19.3346***	***10.4685***	***3.7854***

			Panel B: Volatility (Squared Returns)								
			Quantile								
			0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Predictor Variable	All	Start	***460.6440***	***253.4433***	***153.5153***	***91.7051***	***50.6115***	***23.4591***	***16.8897***	***9.7357***	***4.1373***
		During	***318.9497***	***177.1216***	***109.0432***	***66.5300***	***38.0622***	***18.9874***	***13.3426***	***7.5048***	***3.1895***
		End	***464.3643***	***256.6528***	***156.3600***	***94.2065***	***52.7238***	***25.1016***	***17.6939***	***9.1628***	***3.8367***
	Violent	Start	***533.4983***	***293.4282***	***177.4928***	***105.8948***	***58.2940***	***26.8978***	***19.1097***	***10.3746***	***4.1855***
		During	***368.6370***	***204.3183***	***125.4213***	***76.3047***	***43.4855***	***21.6663***	***15.4297***	***8.5565***	***3.5161***
		End	***542.7639***	***300.0835***	***182.7438***	***110.1483***	***61.6375***	***29.2113***	***21.1353***	***11.3256***	***4.5127***
	War	Start	***580.9649***	***319.7572***	***194.0219***	***115.8919***	***63.9103***	***29.4757***	***21.5090***	***11.4492***	***4.6249***
		During	***414.0083***	***227.3790***	***137.6786***	***81.9483***	***44.9262***	***20.6102***	***14.8798***	***8.0359***	***3.5673***
		End	***589.2315***	***325.0654***	***197.8577***	***118.7341***	***65.9463***	***30.7932***	***23.3724***	***12.5753***	***5.3188***
	Violent Break	Start	***571.1849***	***315.2845***	***191.5169***	***115.0125***	***63.9838***	***29.9889***	***21.3754***	***12.2114***	***4.7408***
		During	***417.9153***	***230.6764***	***140.4567***	***84.4227***	***47.0500***	***22.2185***	***16.1277***	***9.3264***	***3.8620***
		End	***557.8717***	***307.6923***	***186.7069***	***111.9372***	***62.0953***	***28.9448***	***19.7289***	***11.0509***	***4.3793***
	Protracted	Start	***512.0709***	***281.7724***	***170.5019***	***101.7777***	***56.0822***	***25.8833***	***18.2355***	***10.2872***	***4.2530***
		During	***333.0975***	***182.5595***	***110.2886***	***65.5902***	***36.1091***	***17.0402***	***12.4983***	***7.1074***	***3.2317***
		End	***509.7019***	***281.3213***	***170.9593***	***102.6843***	***57.1228***	***26.8430***	***18.9778***	***9.8857***	***4.2587***
	Major Power	Start	***556.4041***	***305.6352***	***184.4195***	***109.6527***	***60.0262***	***27.3179***	***21.0164***	***11.6939***	***4.7736***
		During	***410.0123***	***224.8077***	***135.7949***	***80.5087***	***43.9531***	***20.0988***	***15.4284***	***8.9582***	***3.5743***
		End	***563.4318***	***311.3441***	***189.4044***	***113.9677***	***63.6147***	***30.0516***	***22.6502***	***12.0315***	***4.8157***
	Grave Threat	Start	***539.8804***	***296.5435***	***178.9597***	***106.4004***	***58.2337***	***26.4965***	***18.9978***	***10.8051***	***4.6855***
		During	***424.3693***	***235.6935***	***144.7436***	***88.1735***	***50.1599***	***24.5610***	***17.1283***	***9.0300***	***3.6014***
		End	***555.3447***	***307.4066***	***187.4633***	***113.2047***	***63.5755***	***30.3238***	***21.6248***	***11.0939***	***4.5889***
	Crisis Severity	Start	***430.8691***	***236.7581***	***143.0065***	***85.2339***	***46.8880***	***21.6498***	***15.7156***	***9.1964***	***4.0031***
		During	***180.3850***	***99.5430***	***60.7115***	***36.8083***	***20.9936***	***10.7989***	***7.9973***	***5.0821***	***2.5212***
		End	***429.0339***	***236.7450***	***143.6837***	***86.2671***	***48.0267***	***22.6734***	***15.8463***	***8.0267***	***3.1621***

Note: Entries correspond to the quantile causality test statistic for the null hypothesis that various disaster risk counts at its start, during and end phases does not Granger cause oil returns and volatility; entries in bold-italic indicates rejection at the 5% significance level.

APPENDIX:

Table A1. Causality-in-Quantiles Test for WTI Returns and Volatility (Squared Returns) Based on News-Based Measure of Disaster Risks (NVIX and Components)

	Returns						
	Predictor Variable						
Quantile	NVIX	Government	Intermediation	Natural Disaster	Securities Markets	War	Unclassified
0.1	***6.4206***	***4.9679***	***5.7493***	***4.0758***	***7.1407***	***4.3490***	***5.3588***
0.2	***12.9224***	***10.6596***	***13.4384***	***10.5224***	***18.0269***	***11.5988***	***11.4614***
0.3	***23.7779***	***18.0387***	***23.1145***	***19.6249***	***31.0261***	***20.6908***	***21.5147***
0.4	***102.5567***	***79.8043***	***104.6187***	***106.6468***	***117.4449***	***113.2903***	***100.5753***
0.5	***61.0115***	***46.5777***	***62.6492***	***60.1245***	***69.6136***	***62.2860***	***58.8065***
0.6	***32.9857***	***25.2983***	***34.8826***	***29.6699***	***37.4304***	***30.3684***	***30.9819***
0.7	***20.2650***	***16.9381***	***22.4840***	***19.1358***	***23.3822***	***19.5013***	***19.4769***
0.8	***11.7443***	***10.1552***	***13.2996***	***10.8269***	***12.8133***	***11.9613***	***11.1295***
0.9	***4.4747***	***4.4432***	***5.0132***	***4.1819***	***4.9108***	***4.1955***	***4.3027***
	Volatility (Squared Returns)						
	Predictor Variable						
Quantile	NVIX	Government	Intermediation	Natural Disaster	Securities Markets	War	Unclassified
0.1	***45.7090***	***40.9852***	***46.3816***	***125.8735***	***50.9710***	***50.8902***	***45.6798***
0.2	***28.1338***	***25.4910***	***28.2832***	***68.6608***	***30.8221***	***29.8482***	***27.9251***
0.3	***20.6017***	***18.9120***	***20.5306***	***41.6931***	***22.1305***	***20.7916***	***20.2640***
0.4	***16.5782***	***15.4747***	***16.3745***	***25.5186***	***17.3983***	***15.9446***	***16.1374***
0.5	***14.2497***	***13.5339***	***13.9418***	***15.0452***	***14.5919***	***13.1595***	***13.7264***
0.6	***13.1642***	***12.9271***	***13.0136***	***9.5228***	***13.5086***	***12.1310***	***12.6522***

0.7	***12.0080***	***11.8190***	***11.9256***	***7.5614***	***12.0319***	***11.1460***	***11.3894***
0.8	***10.2668***	***10.0481***	***9.9955***	***5.0497***	***10.0523***	***9.1129***	***9.8164***
0.9	***7.3948***	***7.4433***	***7.1194***	***2.8865***	***7.2265***	***6.3844***	***7.1151***

Note: Entries correspond to the quantile causality test statistic for the null hypothesis that aggregate and components of news-based volatility index (NVIX) does not Granger cause oil returns and volatility; entries in bold-italic indicates rejection at the 5% significance level.

Table A2. Causality-in-Quantiles Test for WTI Returns and Volatility (Squared Returns) Based on News-Based Measure of Geopolitical Risks

	Returns		
	Predictor Variable		
Quantile	GPR	GPR Acts	GPR Threats
0.1	***4.3612***	***4.7848***	***4.6160***
0.2	***8.8046***	***10.3587***	***9.3838***
0.3	***15.3373***	***20.1353***	***15.5939***
0.4	***61.6984***	***86.2895***	***57.5383***
0.5	***39.8033***	***54.1275***	***37.3023***
0.6	***24.6144***	***31.7634***	***23.2817***
0.7	***15.7158***	***20.0685***	***14.9661***
0.8	***9.5360***	***11.3614***	***8.9023***
0.9	***4.5662***	***4.6731***	***4.4975***
	Volatility (Squared Returns)		
	Predictor Variable		
Quantile	GPR	GPR Acts	GPR Threats
0.1	***54.9345***	***78.5399***	***54.8733***
0.2	***32.3526***	***44.1667***	***32.7087***
0.3	***22.3492***	***28.6157***	***22.8947***

0.4	***16.6481***	***19.5465***	***17.3002***
0.5	***13.2402***	***13.8711***	***13.9309***
0.6	***11.4198***	***10.5223***	***12.1437***
0.7	***10.7158***	***10.0206***	***11.0620***
0.8	***9.0443***	***7.7320***	***9.2269***
0.9	***6.3694***	***5.5274***	***6.6189***

Note: Entries correspond to the quantile causality test statistic for the null hypothesis that aggregate and components of news-based geopolitical risks (GPRs) does not Granger cause oil returns and volatility; entries in bold-italic indicates rejection at the 5% significance level.