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The Role of Time-Varying Rare Disaster Risks in Predicting Bond Returns and Volatility

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Abstract

This paper aims to provide empirical evidence to the theoretical claim that rare disaster risks affect government bond market movements. Using a nonparametric quantiles-based methodology, we show that rare disaster-risks affect only volatility, but not returns, of ten-year government bond of the US over the monthly period of 1918:01 to 2013:12. In addition, the predictability of volatility holds for the majority of the conditional distribution of the volatility, with the exception of the extreme ends. Moreover, in general, similar results are also obtained for long-term government bonds of an alternative developed country (UK) and an emerging market (South Africa).

Keywords: Bond Returns and Volatility; Rare Disasters; Nonparametric Quantile Causality.
JEL Codes: C22, C58, G12.

1. Introduction

Following the early work of Rietz (1988), a growing number of calibrated theoretical models have recently provided evidence of the ability of rare disaster risks in affecting movements (returns and volatility) of asset prices (see for example, Barro (2006, 2009), Gourio (2008a, b, 2012), Barro and Ursúa (2008, 2009, 2012), Barro and Jin (2011), Gabaix (2012), Nakamura et al., (2013), Wachter (2013), Farhi and Gabaix (2016), and Lewis and Liu (2017)).

A major obstacle, however, to full-fledged empirical verification of the rare disaster models is that individual countries rarely face actual major disasters, resulting in a small sample problem inherent in the use of actual rare disasters, which in turn, explains the reliance of the above-mentioned papers on calibration. In this regard, Berkman et al. (2011,

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2017), provides a solution to the small sample problem that would make empirical estimation of these models, by recommending to focus on a much larger sample of potential disasters (international political crises) that are likely to cause changes in perceived rare disaster probabilities. Using a detailed database of all international political crises, namely the International Crisis Behavior project (ICB) database developed by the Center for International Development and Conflict Management, Berkman et al. (2011, 2017) provides empirical evidence that various international crises, over the period of 1918 to 2006, does indeed affect equity returns and volatility of large number of developed and emerging economies.

Using an extended version of the ICB database, the goal of this paper is to examine, the predictive power of rare-disaster risks for the return and volatility dynamics of ten-year government bonds of the U.S. over the monthly period of 1918:01-2013:12. As a matter of comparison, we also analyze the same for the long-term government bonds for another developed country (UK) over the period of 1933:01-2013:12 and an emerging market (South Africa) covering 1918:01-2013:12.

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. (2016). As indicated by Balcilar et al. (2016), 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. Understandably, this test is comparatively superior to the conditional mean-based standard linear Granger causality test, as it not only studies the entire conditional distribution of both returns and volatility, but, being a data-driven nonparametric approach, also controls for misspecification due to possible nonlinearity – as discussed in detail by Gargano et al., (2017) and Byrne et al., (forthcoming). In this regard, while nonlinear causality tests of Hiemstra and Jones. (1994), and Diks and Panchenko (2005, 2006) can control for misspecification due to nonlinearity, they are restricted to the conditional mean of the first-moment of exchange rates only. Finally, the causality-in-quantiles test is also superior to the standard GARCH models, since the latter specifies a linear relationship between returns and volatility with the predictors being studied, besides being restricted to the analysis of the conditional mean.

To the best of our knowledge, this is the first paper that evaluates the predictive power of rare disaster risks for long-term government bond returns and volatility based on a nonparametric causality-in-quantiles framework. The rest of this paper is organized as follows: Section 2 describes the econometric frameworks involving the higher-moment nonparametric causality-in-quantiles test. Section 3 presents the data and discusses the empirical results, with Section 4 concluding the paper.

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. (2016), which in turn is based on the frameworks of Nishiyama et al. (2011) and Jeong et al. (2012). We start by denoting government bond returns by y_t and the predictor variable (in our case, various types of rare disaster risk-related events, as discussed in detail in the data segment) 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

$F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\}=\theta$ with probability one. As a result, the (non)causality in the θ-th quantile hypotheses to be tested are:

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

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

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 $E[1\{y_t \le Q_\theta(Y_{t-1})|Z_{t-1}\}]=\theta$ 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 θ^{th} conditional quantile of y_t given Y_{t-1}, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

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

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

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

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

As an extension of Jeong et al. (2012)'s framework, Balcilar et al. (2016) develop a test for the *second* moment which allows us to test the causality between the various disaster risks on government bond market volatility. Adapting the approach in Nishiyama et al. (2011), higher order quantile causality can be specified in terms of the following hypotheses as:

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

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

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 government bond returns. However, one can show that it is difficult to combine the different statistics for each $k=1,2,...,K$ into one statistic for the joint null in Eq. (7) because the statistics are mutually correlated (Nishiyama et al., 2011). Balcilar et al. (2016), thus, propose a sequential-testing method as described in Nishiyama et al. (2011). First, as in Balcilar et al. (2016), 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. (2016).

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, and hence, help us 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.

3. Data and Empirical Results

The empirical analysis utilizes monthly data for ten-year government bond total return indices for US, UK and South Africa, and the count on various types of disaster risks. Barring the case of UK, the period covered is 1918:01 to 2013:12. In the case of UK, we start from 1933:01. The start and end dates for US and South Africa are governed purely by the availability of data on disaster risks. While, in the case of UK, the start date corresponds to the availability of data on the bond index, but the end date again matches the end point of the variables measuring rare disaster risks. The ten-year government bond total return indices are sourced from the Global Financial Database, with returns computed as the monthly logarithmic change of the total return index multiplied by 100 to convert the returns into percentages, and volatility being measured by the squares of these generated returns. Note that, besides the US, the decision to consider UK as an alternative developed country, and South Africa as a representative emerging market, is purely driven by availability of data.

Next we turn our attention to our measure of disaster risks of rare events as obtained from the International Crisis Behavior (ICB) database: https://sites.duke.edu/icbdata. The ICB database 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. 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 response. 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 exchange rate 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 basically use the monthly count for the risk variables under the various categories. The disaster risk variables are normalized to have a variance of unity, so that we can compare the strength of predictability across them.

Figure 1 presents the findings for US government bond from the causality-in-quantiles tests estimated over the quantile range of 0.10 to 0.90. Panels A and B for the figure present the findings for ten-year US government bond returns and volatility (squared returns) respectively, with the null hypothesis that rare disaster risks does not Granger cause bond returns and volatility. Starting with returns, as observed from Figure 1(a), there is no evidence of predictability from any of the disaster risk variables considered. However, when we turn our attention to squared returns, all the disaster risks predict predict volatility, barring the extreme end of its conditional distribution, i.e., when volatility is either quite low or high. The most important predictor is the *Crisis Severity Index*, both in terms of its coverage of the conditional distribution of volatility (0.20-0.80) and also in its strength.

Turning to the results for UK and South Africa in Figures 2 and 3 respectively, as a matter of robustness check, we observe, as with the US, disaster risks fail to predict bond returns in both these countries well, as shown in Figures 2(a) and 3(a). In terms of volatility, for UK, as shown in Figure 2(b), predictability is observed in all cases barring *Violent Break* and *Grave Threats*. Unlike the US, strongest predictability is observed under *Major Powers* over the quantile range of 0.40 to 0.75, followed by the *Crisis Severity Index*, which however, tend to have the widest coverage of the conditional distribution of volatility over the quantile range of 0.40 to 0.85. As far as volatility of South African government bonds are concerned, as shown in Figure 3(b), just like the US, all the disaster risks show evidence of predictability, and in some cases, namely under *War* and *Grave Threat*, even at the extreme upper quantiles. These two disaster risks also tends to be most important of the predictors concerned in terms of strength of predictability as well. In sum, disaster risks are shown to affect ten-year government bond volatility, but not returns, with the result, in general, holding across an alternative developed country and an emerging market as well.

[INSERT FIGURES 1 TO 3 HERE]

Note that, based on the theoretical models discussed in the introduction, rare disasters increase the probability of government default, and hence, affects bond returns. The fact that we do not observe the international political crises to predict the government bond returns, is possibly due to the perception on behalf of the investors that these disaster risks that we are measuring are not high enough to cause a default on part of the government (Brookes and Daoud, 2012). However, when it comes to volatility, which can also be interpreted as risk in the government bond markets are affected, given that we are after all analysing the impact of disaster risks, which in turn, are more likely to affect the second moment (Bonaccolto et al., forthcoming), especially when volatility is not exceptionally low or high (i.e., at the extreme ends of the distribution). Understandably, when volatility is low (i.e., markets are calm), agents do not require information from predictors (in our case rare disaster risks) to predict the path of future volatility, and when volatility is already at its upper end, information from disaster risks should be of no value in any case, given that agents are likely to be herding (Balcilar and Demirer, 2015).

4. Conclusion

Recently developed theoretical models claim that rare disaster risks tend to move asset markets, including bond markets. Given this, using a causality-in-quantiles test, which captures higher order causality over the entire conditional distributions of returns and volatility, and an unique database of international political crises, we show that that rare disaster-risks affect only volatility, but not returns, of ten-year government bond of the US over the monthly period of 1918:01 to 2013:12. In addition, the predictability of volatility holds for majority of the conditional distribution of the volatility, with the exception of the extreme ends, i.e., relatively low and high quantiles. Moreover, our results carry over in general, for the ten-year government bonds of an alternative developed country and an emerging market, namely UK and South Africa respectively.

Note that, when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices in general. Further, to price an option, one needs reliable estimates of the volatility. Given this, the fact that rare disaster risks can predict volatility is of paramount importance to bond fund managers. In addition, as indicated by Pan and Chan (2017), government bond volatility can also play an important role in predicting the equity premium, which in turn, helps practitioners in finance for asset allocation, and academics in finance to produce more realistic asset pricing models, since they have important implications for tests of market efficiency (Rapach and Zhou, 2013). 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). Causality-in-Quantiles Test Results for Returns of the Ten-Year Government Bond Yield of US

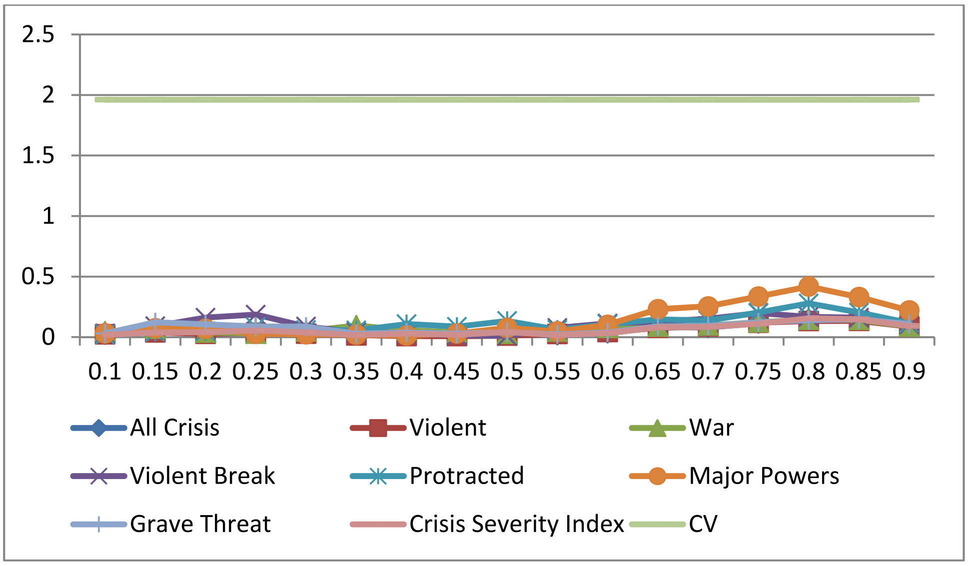
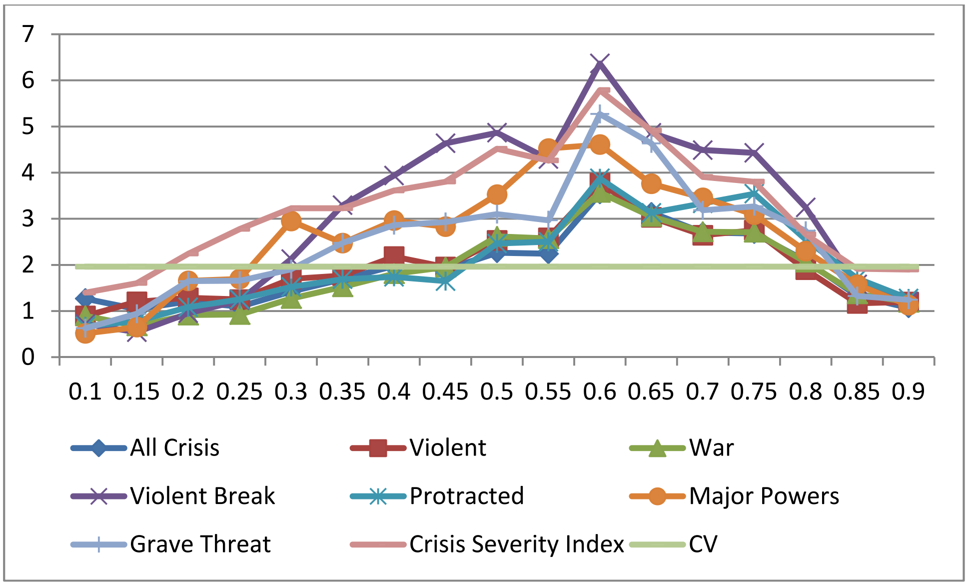


Figure 1(b). Causality-in-Quantiles Test Results for Volatility (Squared Returns) of the Ten-Year Government Bond Yield of US



Notes: CV is the 5 percent critical value of 1.96. The horizontal axis measures the various quantiles while the vertical axis captures the tests statistic. The lines corresponding to All Crisis, Violent, War, Violent Break, Protracted, Major Powers, Grave Threat, and Crisis Severity Index shows the rejection (non-rejection) of the null of no Granger causality from the various measures of disaster risks on government bond returns or volatility at the 5 percent level, if the lines are above (below) 1.96 for a specific quantile.

Figure 2(a). Causality-in-Quantiles Test Results for Returns of the Ten-Year Government Bond Yield of UK

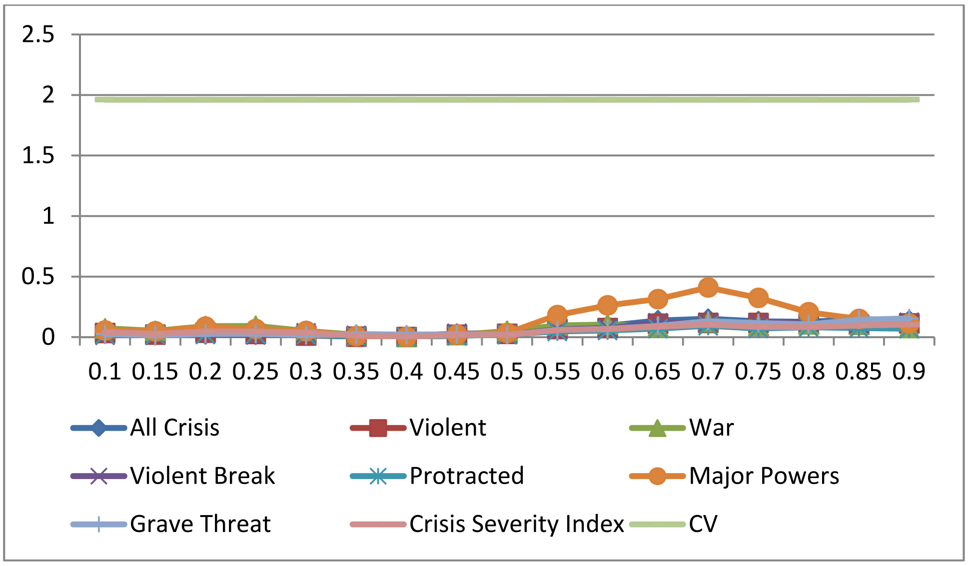
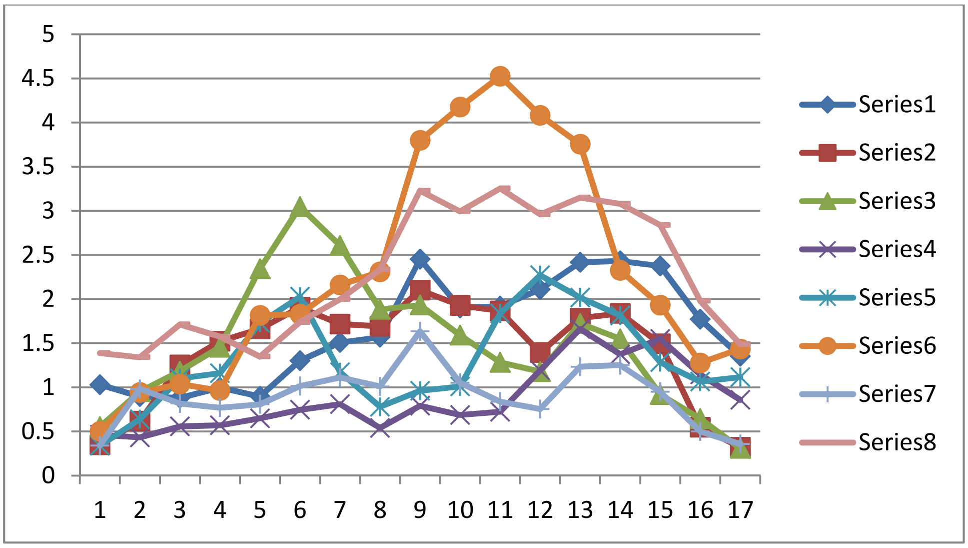


Figure 2(b). Causality-in-Quantiles Test Results for Volatility (Squared Returns) of the Ten-Year Government Bond Yield of UK



Notes: See Notes to Figure 1.

Figure 3(a). Causality-in-Quantiles Test Results for Returns of the Ten-Year Government Bond Yield of South Africa

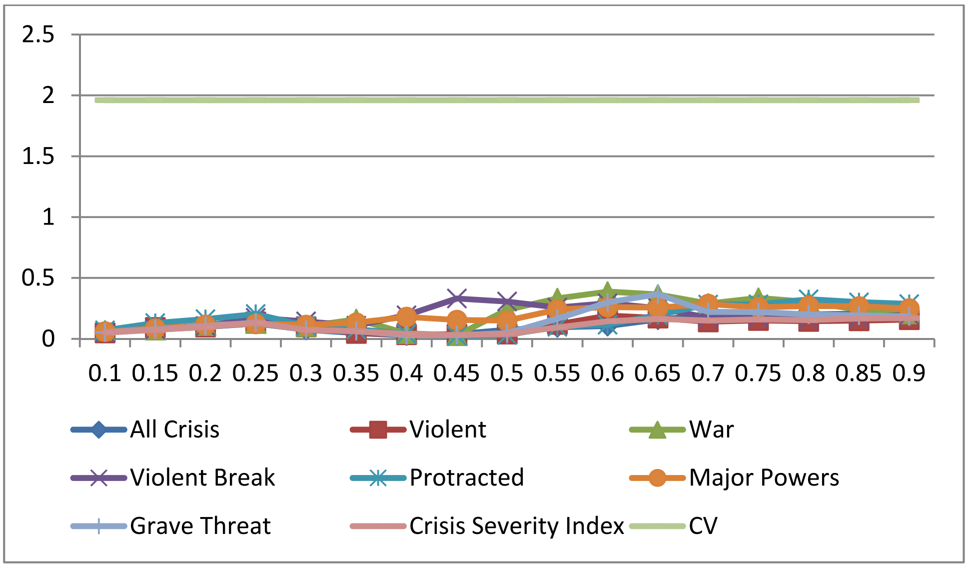
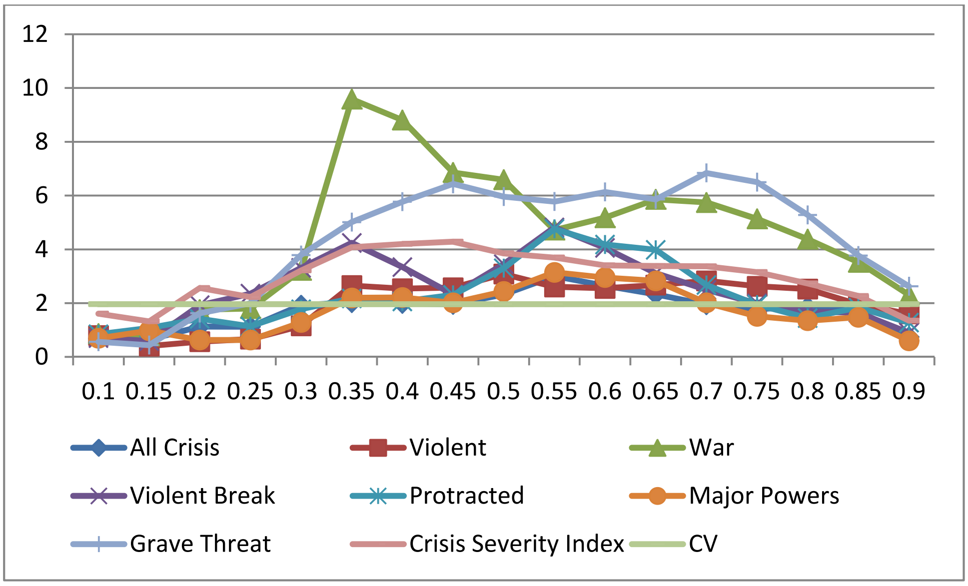


Figure 3(b). Causality-in-Quantiles Test Results for Volatility (Squared Returns) of the Ten-Year Government Bond Yield of South Africa



Notes: See Notes to Figure 1.