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

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reliance of the above-mentioned papers on calibration. In this regard, Berkman et al. (2011, 2017), provides a solution to the small sample problem that would make empirical estimation of these models possible, 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. (2017). As indicated by Balcilar et al. (2017), 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 presents a brief literature review and in the process describes the channels through which rare disaster risks can possibly impact the bonds market. Section 3 describes the econometric frameworks involving the higher-moment nonparametric causality-in-quantiles test. Section 4 presents the data and discusses the empirical results, with Section 5 concluding the paper.

2. Brief Literature Review and Channels Relating Disaster Risks with the Bond Market

A strand of literature dealing with asset pricing, motivated by the failure of existing theoretical pricing models to replicate the movements in assets in the data, has focused on time-varying disaster risks as a factor that can explain the returns and volatility observed in the financial markets (see for example, Rietz (1988), 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))). While

Gourio (2012) argues that an increase in the probability of a disaster creates a collapse of investment and consequently drives the risk of a recession, Wachter (2013) relates the time-varying risk of rare disasters to consumption shocks, which in turn drives returns and volatility in the asset markets. Similarly, Gabaix (2012) proposes a model that uses time-variation in the probability of a rare disaster to explain volatility in financial asset returns. Similarly, using global political instability as a proxy for rare disaster risk, Berkman et al. (2017) document a positive intertemporal relation between disaster probability and financial market risks. Following the arguments by Barro, (2006, 2009), Gourio (2012), Wachter (2013), if uncertainty regarding the probability and size of disasters leads to a great deal of uncertainty in terms of investment growth or consumption patterns, then with asset prices being a function of the state of the economy, one obvious channel that could links disaster risks to asset markets movements, including government bonds, is the potential effect of rare disasters on growth expectations for both output and consumption.

A second channel through which disaster risks can affect bond return dynamics is via its contribution to jump risk in bond prices. The presence of jump risk driving stock and bond returns is well documented in the literature (Maheu and McCurdy, 2004; Huang and Tauchen, 2005; Dunham and Friesen, 2007; Maheu et al. 2013; Guo et al., 2016; Caporin et al., 2016; Gkillas et al., 2018). In the context of asset returns, Wachter (2013) relates time-varying disaster probabilities to large instantaneous changes, i.e. jumps, in aggregate consumption. Suggesting that the financial market is partially driven by the comovement of agents' marginal utility and the price process for the assets in times of disaster (i.e. jump risk), Wachter (2013) shows mathematically that time-varying disaster risk contributes to the asset returns in the form of compensation for jump risk. Given this perspective, one can argue that time-varying rare disaster risks also contribute to the presence of jumps in bond returns in the form of a compensation for consumption shocks such that an increase in the risk of rare disasters increases return and volatility in the bond market.

Finally, given that disaster risks affect the financial markets via changes in the probabilities of consumption and investment shocks, one might expect a direct effect of disaster risks on safe havens, for example the US dollar (Farhi and Gabaix, 2016; Gupta et al., (forthcoming)), just like the effect on stocks and bonds. So when we consider bond returns of foreign economies in local currency, one could argue that higher probability of disasters may drive demand for safe havens and thus greater outflows from foreign denominated assets. In other words, rare disaster risks could affect asset markets, including the bond market, of foreign economies, via an exchange rate spillover channel.

In sum, whether it is by affecting the state of the economy, jump risks or via the exchange rate, bond markets are likely to be impacted by rare disaster risks in many possible ways, and hence, is an important empirical question to analyze.

3. Econometric Framework

In this section, we present the methodology for the detection of nonlinear causality via a hybrid approach as developed by Balcilar et al. (2017), 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.

x_t does not cause y_t in the θ-quantile with respect to $\{y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\}$ if

$$Q_\theta\{y_t \mid y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\} = Q_\theta\{y_t \mid y_{t-1},...,y_{t-p}\} \tag{1}$$

x_t is a prima facie cause of y_t in the θth quantile with respect to $\{y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\}$ if

$$Q_\theta\{y_t \mid y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\} \neq Q_\theta\{y_t \mid y_{t-1},...,y_{t-p}\} \tag{2}$$

where $Q_\theta\{y_t \mid \cdot\}$ is the θth conditional quantile of y_t given ·, which depends on t and $0<\theta<1$.Define $Y_t \equiv (y_{t-1},..., y_{t-p})$, $Z_{t-1} \equiv (y_{t-1},..., y_{t-p}, x_{t-1},..., x_{t-p})$, $V_t = (X_t, Z_t)$, and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ are the conditional distribution function of y_t given Y_{t-1} and Z_{t-1}, respectively.

The conditional distribution $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$is assumed to be absolutely continuous in y_t for almost all V_{t-1}. If we 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,

$$F_{y_t|Z_{t-1}}\{Q_q(Z_{t-1}) \mid Z_{t-1}\} = q \qquad \text{w.p.1}$$

Consequently, the hypothesis to be tested based on definitions (1) and (2) are

$$H_0 = P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} = 1 \text{ a.s.} \tag{3}$$

$$H_1 = P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} < 1 \text{ a.s.} \tag{4}$$

Jeong et al. (2012) employs a distance the 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 arises from the fact that the null hypothesis in (3) can only be true if and only if $E[1\{y_t \le Q_\theta(Y_{t-1}) \mid Z_{t-1}\}] = \theta$ or equivalently$1\{y_t \le Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $1\{\cdot\}$ is the indicator function. Jeong et al. (2012) specify the distance function as

$$J = E[\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} - q\}^2 f_Z(Z_{t-1})] \tag{5}$$

In equation (3), it is important to note that $J \ge 0$ and the equality holds if and only if the null hypothesis H_0 in equation (5) is true, while $J > 0$ holds under the alternative H_1 in equation (4). Jeong et al. (2012) shows that the feasible kernel-based test statistic based on J has the following form:

$$\hat{J}_T = \frac{1}{T(1-1)h^{2p}} \sum_{t=1}^{T} \sum_{s \neq t}^{T} K\left(\frac{Z_{t-1} - Z_s}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{6}$$

where $K(\cdot)$ is the kernel function with bandwidth h and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated from

$$\hat{\varepsilon}_t = 1\{y_t \leq Q_\theta(Y_{t-1}) - \theta\} \tag{7}$$

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

$$\hat{Q}_q(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(q \mid Y_{t-1}) \tag{8}$$

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

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s \neq t} L(Y_{t-1} - Y_s) 1(Y_s \leq Y_{t-1})}{\sum_{s \neq t} L \frac{(Y_{t-1} - Y_s)}{h}} \tag{9}$$

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

As an extension of Jeong et al. (2012)'s framework, Balcilar et al. (2017) develop a test for the *second* moment which allows us to test the causality between the various disaster risks on government bond market volatility. Causality in the mth moment implies causality in the k th moment for $k < m$. To test for nonparametric Granger quantile causality in variance we employ the general nonparametric Granger quantile causality test by Nishiyama et al. (2011). Equation (10) is an illustration of the causality in higher order moments given as

$$y_t = g(Y_{t-1}) + \sigma(X_{t-1})\varepsilon_t \tag{10}$$

where $X_{t-1} = (x_{t-1}, x_{t-2}, ..., x_{t-p})$, ε_t is a white noise process, $g(\cdot)$ and $\sigma(\cdot)$ are unknown functions that satisfy certain conditions for stationarity. The specification in equation (12), does not allow Granger causality from x_t to y_t, but certainly allows predictive power (in the Granger causality test) from x_t to y_t^2. $\sigma(\cdot)$ is a general nonlinear function. The Granger causality in variance definition does not require an explicit specification of squares of X_{t-1}. A model like equation (10) has a null and alternative hypothesis for causality in variance given by

$$H_0 = P\{F_{y_t^2|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} = 1 \text{ a.s.} \tag{11}$$

$$H_1 = P\{F_{y_t^2|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} < 1 \text{ a.s.} \tag{12}$$

To obtain the feasible test statistic for testing the null hypothesis H_0 in equation (10) we replace y_t in equations (6)-(9) with y_t^2. To overcome the problem that causality in the conditional first moment (mean) implies causality in the second moment (variance), we interpret quantile causality in higher order moments using the following model:

$$y_t = g(X_{t-1}, Y_{t-1}) + \varepsilon_t \tag{13}$$

Higher order quantile causality for this model can be specified as

$$H_0 = P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} = 1 \text{ a.s.} \quad \text{for } k = 1,2,...,K \tag{14}$$

$$H_1 = P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} < 1 \text{ a.s.} \quad \text{for } k = 1,2,...,K \tag{15}$$

Following this definition, x_t Granger causes y_t in quantile θ up to Kth moment. The null specified in equation (11) is used to construct the test statistic in equation (6) for each k. It is impossible to combine the different statistics for each $k = 1,2,...,K$ into one statistic for the joint null in equation (11) because the statistics are mutually correlated (Nishiyama et al. (2011)). To address this problem, we follow the sequential testing approach in Nishiyama et al. (2011). This approach first tests for nonparametric Granger causality in the first moment $(k=1)$. Rejecting the null hypothesis of non-causality means that we can stop and interpret this result as a strong indication of possible Granger quantile causality in variance. However, failure to reject the null for $k=1$, does not automatically translate to no causality in the second moment and, thus, we can still construct the tests for $k=2$. This approach allows us to test the existence of causality only in variance as well as the causality in the mean and variance successively.

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 $L(\cdot)$ in equations (6) and (9), respectively. 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.[1] For each quantile, we determine the bandwidth parameter (h) by using the leave-one-out least-squares cross validation method.[2] Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels for the cases of both returns and volatility.

4. 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

[1] Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an over-parameterized model, while the SIC is asymptotically consistent.
[2] For each quantile, we determine the bandwidth using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

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.

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 bond returns. As shown in Table A1 in the Appendix of the paper, the standard linear Granger causality tests yield no evidence of causality that goes from any of the disaster risk variables to bond returns for the US, barring the case of *Major Powers*. While for the UK predictability is detected under *All Crisis*, *Grave Threat*, *Violent Break* and *Violent Crisis*, no causality is obtained for South Africa.

Next we statistically examine the presence of nonlinearity in the relationship between bond 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 risks. The results of the BDS test of nonlinearity, presented in Table A2, 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 bond 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 A1 cannot be deemed robust and reliable.

In addition to the BDS test, we also report in Table A2, the Bai and Perron (2003) tests of multiple structural breaks on the bond 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 two breaks in cases of the US and the UK and one for South Africa. 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 bond returns and the rare disaster risks, 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.

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 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, as is *Violent Break*, especially in terms of the size of its impact. Recall that, since all the predictors have been standardized, the higher is the test statistic corresponding to a predictor, the stronger it is in terms of its causal ability.

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

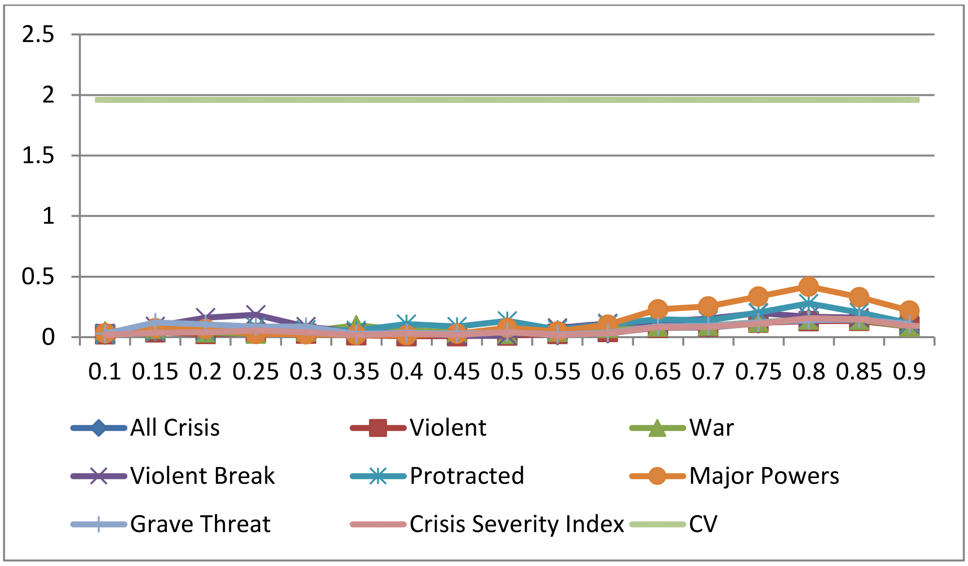
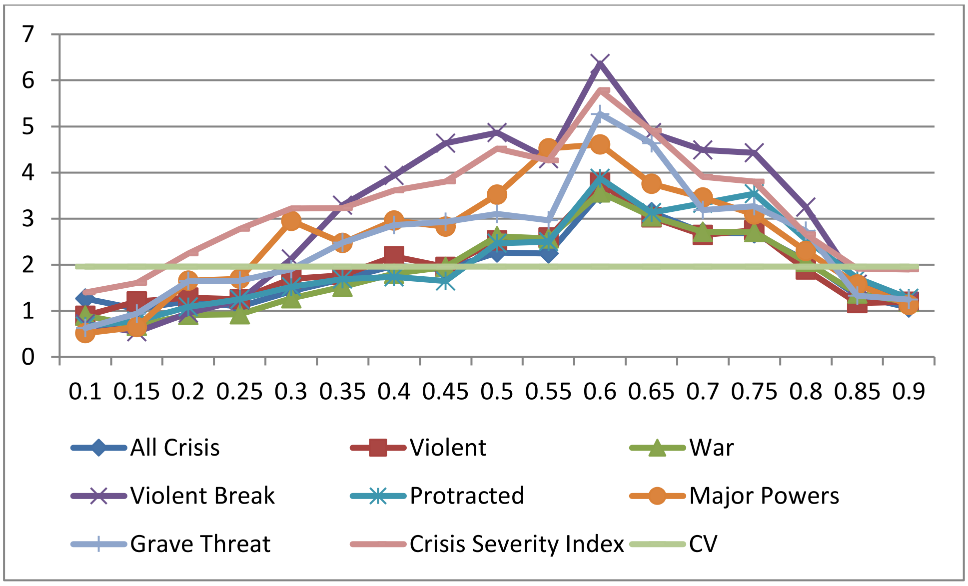


Figure 1(b). Causality-in-Quantiles Test Results for Volatility (Squared Returns) of the Ten-Year Government Bond Yield of US



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.

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,[3] with the result, in general, holding across an alternative developed country and an emerging market as well.[4]

[3] We also used the aggregate, natural disasters and war components of the recently developed news-based volatility index (NVIX) of Manela and Moreira (2017) to recomputed our causality tests. These authors base the index on the title and abstract of all front-page articles of the Wall Street Journal. 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. Again, we observed impact of the aggregate NVIX, natural disasters and wars on bond market volatility, but not returns for the three economies under consideration. Complete details of these results are available upon request from the authors.

[4] Based on the suggestion of the editor, we re-estimated our models over the period of 1950:01 to 2013:12. Our results continued to be robust for this shortened sample period in the sense that, rare disaster risks were again found to cause only bond market volatility, but not returns. Complete details of these results are available upon request from the authors. These results also highlighted the fact that, fixed exchange rate regime does not necessarily imply bigger effects of rare disaster risks on bond market volatility, which is a possibility if the currency is pegged to the US dollar, since the assets will have greater sensitivity to disaster risks as they will be directly influenced by whatever is driving the volatility in the value of the dollar. On the other hand, if the currency is floating, the market is likely to consider local factors which may ease the volatility effects.

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

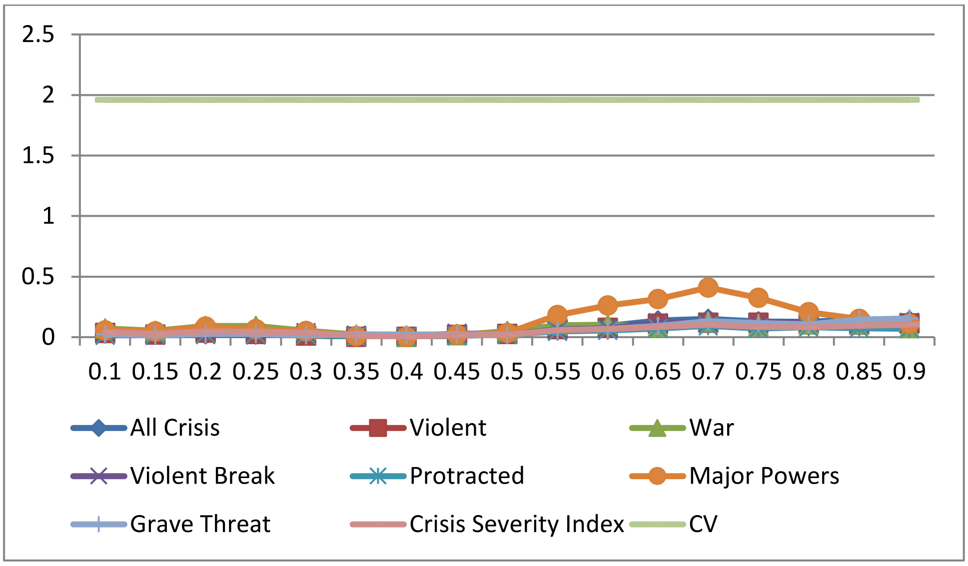
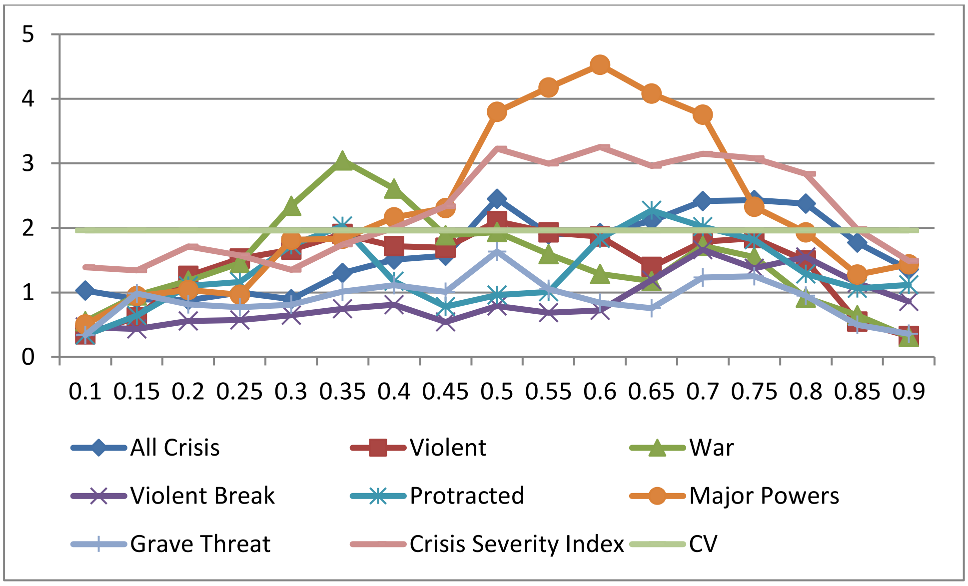


Figure 2(b). Causality-in-Quantiles Test Results for Volatility (Squared Returns) of the Ten-Year Government Bond Yield of UK



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

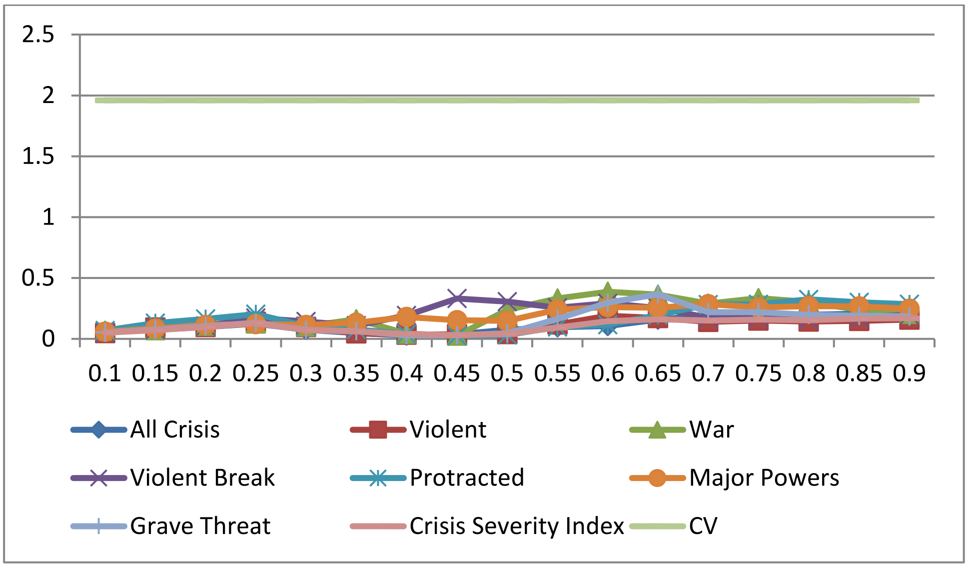
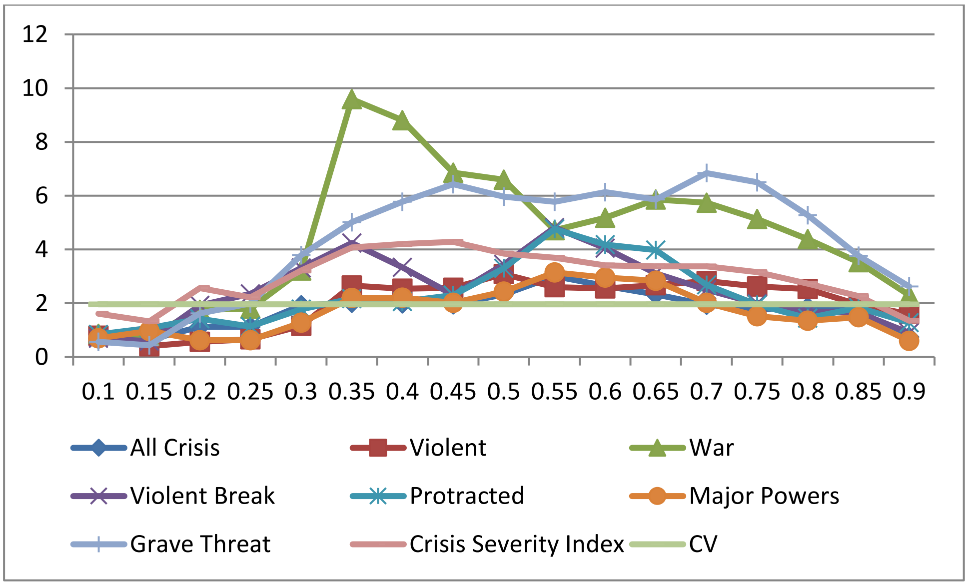


Figure 3(b). Causality-in-Quantiles Test Results for Volatility (Squared Returns) of the Ten-Year Government Bond Yield of South Africa



Notes: See Notes to Figure 1.

Although robust predictive inference is derived based on the causality-in-quantiles test, it would also be interesting to estimate the direction of the effects of rare disaster risks on bond market movements at various quantiles. However, in a nonparametric framework, this is not straightforward. We need to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can experience complications because nonparametric methods exhibit slow convergence rates, which can depend on the dimensionality and smoothness of the underlying conditional expectation function. What one could however do is to look at a statistic that summarizes the overall effect or the global curvature (i.e., the global sign and magnitude), but not the entire derivative curve. In this regard, a natural measure of the global curvature is the average derivative (AD). One could use the conditional pivotal quantile, based on approximation or the coupling approach of Belloni et al., (2017), to estimate the partial ADs. The pivotal coupling approach additionally can approximate the distribution of AD using Monte Carlo simulation. Given that in our case, the focus is on predictability of the bond market movements, and not necessarily on the sign (direction) of the effect at this stage, we report the results in Figures A1 to A3 for bond market volatility only (as there is no statistically significant predictability for bond returns) in the Appendix of the paper. As can be seen from these figures, rare disaster risks are found to increase bond market volatility – a result we would intuitively expect, i.e., increases in these risks should also make the bond market riskier.

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 more likely to be affected, primarily through the jump-risks (bad-volatility) channel has discussed in Section 2.[5] This is because, we are analysing the

[5] Based on the suggestion of an anonymous referee, we modelled volatility using a GARCH(1,1) model and re-conducted the causality-in-quantiles test. While, predictability was observed from the rare disaster risks on bond market volatility of the US, no-causality could be detected for the UK and South Africa. As suggested by Balcilar et al., (2018), that since squared returns as a measure of volatility follows directly from the *k*-th order

impact of disaster risks, which in turn, are more important for the second moment (Bonaccolto et al., 2018), especially when volatility is not exceptionally low or high (i.e., not 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).[6]

5. 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

test and is independent of a model-based estimate of volatility (which could vary depending on what GARCH model we choose), the use of squared returns is more appropriate in our context. Complete details of these results are available upon request from the authors.

[6] The first anonymous referee was concerned that by the time the crisis is measured, it is no longer an indicator of crisis risk, it is actually a crisis. Hence, the impact of a political crisis on the bond market is likely to be very different from the impact of crisis risk. Given this, and based on the suggestion of the second anonymous referee, we repeated the analysis using alternative measures of rare disaster risks. In this regard, we used the news-based indexes of total geopolitical risks, and the same due to acts and threats, as recently developed by Caladara and Iacoviello (2018), details of which can be found at: https://www2.bc.edu/matteo-iacoviello/gpr.htm. Caladara and Iacoviello (2018) construct monthly indices of GPRs by counting the occurrence of words related to geopolitical tensions in three leading international newspapers (The New York Times, the Chicago Tribune, and the Washington Post). The authors search for articles containing references to words associated with: explicit mentions of geopolitical risk, as well as mentions of military-related tensions involving large regions of the world and a U.S. involvement; nuclear tensions; war threats and terrorist threats; actual adverse geopolitical events (as opposed to just risks) which can be reasonably expected to lead to increases in geopolitical uncertainty, such as terrorist acts or the beginning of a war. Our results were qualitatively similar to those reported in the paper, and are available upon request from the authors. One exception was the impact observed on South African bond returns, not picked up previously by the rare disaster risks. But more importantly, the use of the threats index, accounts for the concern of the first anonymous referee.

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., (2018), since in-sample predictability does not guarantee the same over- and out-of-sample.

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APPENDIX

Table A1: Granger Causality Test

Country	Disaster risk	$\chi^2(p)$	*probability*
US	All crisis	0.0852	0.7704
	Crisis severity index	0.3279	0.5670
	Grave Threat	0.0026	0.9594
	Major Powers	4.3581	0.0371**
	Protracted	2.3966	0.1219
	Violent Break	0.1311	0.7174
	Violent crisis	0.0002	0.9900
	War	0.0934	0.7599
UK	All crisis	4.1593	0.0417**
	Crisis severity index	3.1492	0.0763
	Grave Threat	5.5567	0.0186**
	Major Powers	3.4632	0.0631
	Protracted	0.1009	0.7508
	Violent Break	5.1251	0.0238**
	Violent crisis	4.1462	0.0420**
	War	0.8528	0.3560
South Africa	All crisis	0.0717	0.7889
	Crisis severity index	0.0496	0.8237
	Grave Threat	0.5616	0.4538
	Major Powers	3.5937	0.0583
	Protracted	0.1005	0.7513
	Violent Break	2.9724	0.0850
	Violent crisis	0.5403	0.4625
	War	1.0780	0.2994

Note: * represents rejection of the null hypothesis of no Granger causality from the various rare disaster risks to bond returns at the 5% level of significance; *p* is the lag-length chosen based on SIC.

Table A2: Brock et al., (1996, BDS) test of nonlinearity

Disaster risk	Dimension				
	2	3	4	5	6
			US		
All crisis	9.918***	13.864***	17.179***	20.322***	23.649***
Crisis severity index	9.895***	13.832***	17.153***	20.292***	23.612***
Grave Threat	9.969***	13.896***	17.206***	20.345***	23.671***
Major Powers	9.867***	13.792***	17.096***	20.203***	23.474***
Protracted	9.857***	13.738***	17.059***	20.203***	23.488***
Violent Break	9.964***	13.907***	17.215***	20.361***	23.691***
Violent crisis	9.961***	13.892***	17.203***	20.345***	23.674***
War	10.023***	13.964***	17.271***	20.412***	23.743***
			UK		
All crisis	9.490***	12.489***	16.131***	19.239***	22.096***
Crisis severity index	9.602***	12.569***	16.217***	19.331***	22.200***
Grave Threat	9.819***	12.734***	16.363***	19.529***	22.481***
Major Powers	10.066***	12.680***	16.369***	19.511***	22.400***
Protracted	9.865***	12.677***	16.369***	19.524***	22.371***
Violent Break	9.822***	12.761***	16.396***	19.512***	22.408***
Violent crisis	9.610***	12.528***	16.211***	19.326***	22.214***
War	9.866***	12.688***	16.350***	19.485***	22.324***
			South Africa		
All crisis	10.674***	12.758***	14.158***	15.697***	17.699***
Crisis severity index	10.663***	12.780***	14.209***	15.781***	17.815***
Grave Threat	10.784***	12.932***	14.373***	15.947***	18.004***
Major Powers	10.997***	13.086***	14.524***	16.084***	18.157***
Protracted	10.697***	12.765***	14.157***	15.676***	17.662***
Violent Break	10.614***	12.832***	14.345***	15.972***	18.045***
Violent crisis	10.651***	12.804***	14.247***	15.826***	17.883***
War	10.618***	12.781***	14.297***	15.900***	17.944***

Note: 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 bond returns equation used to test linear Granger causality. *** indicates rejection of the null hypothesis at the 1 per cent level of significance.

Table A3: Bai and Perron (2003) multiple structural break test

Country	Disaster risk	Date
US	All crisis	1980:03, 1996:02
	Crisis severity index	1980:03, 1999:08
	Grave Threat	1981:10, 1999:09
	Major Powers	1980:01, 1996:02
	Protracted	1980:03, 1996:02
	Violent Break	1981:10, 1996:02
	Violent crisis	1981:10, 1999:09
	War	1981:10, 1996:02
UK	All crisis	1975:01, 1987:02
	Crisis severity index	1975:01, 1987:02
	Grave Threat	1975:01, 2001:02
	Major Powers	1975:01, 1987:06
	Protracted	1975:01, 1987:06
	Violent Break	1975:01, 1999:02
	Violent crisis	1975:01, 1987:06
	War	1975:01, 1994:02
South Africa	All crisis	1985:03
	Crisis severity index	1985:03
	Grave Threat	1982:08
	Major Powers	1985:03
	Protracted	1985:03
	Violent Break	1985:03
	Violent crisis	1985:03
	War	1985:03

Note: The table reports the break dates obtained from the Bai and Perron (2003) test of multiple structural breaks, with the test applied to the bond returns equation used to test linear Granger causality.

Figure A1. Sign of the Impact of Rare Disaster Risks on Bond Returns Volatility (Squared Returns) in the US

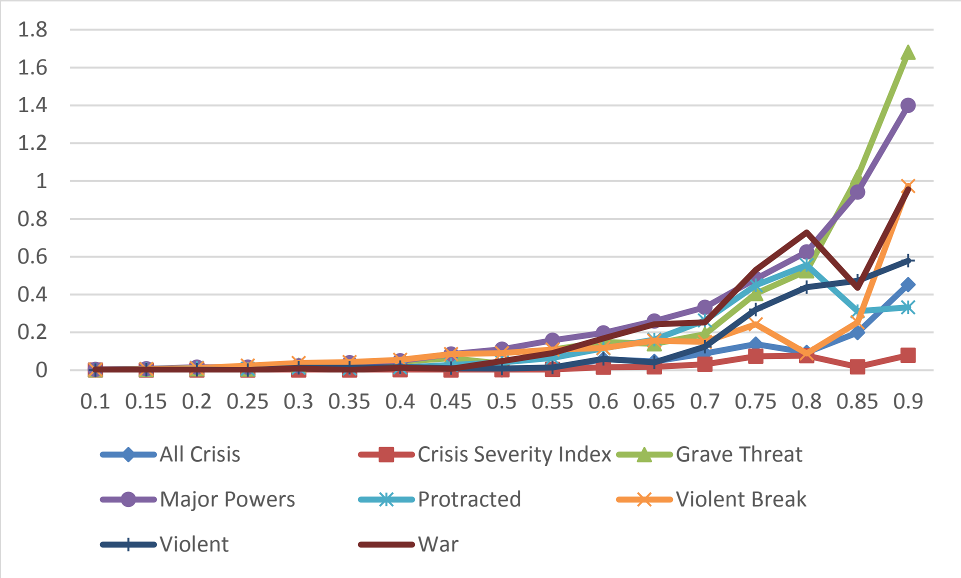

Figure A2. Sign of the Impact of Rare Disaster Risks on Bond Returns Volatility (Squared Returns) in the UK

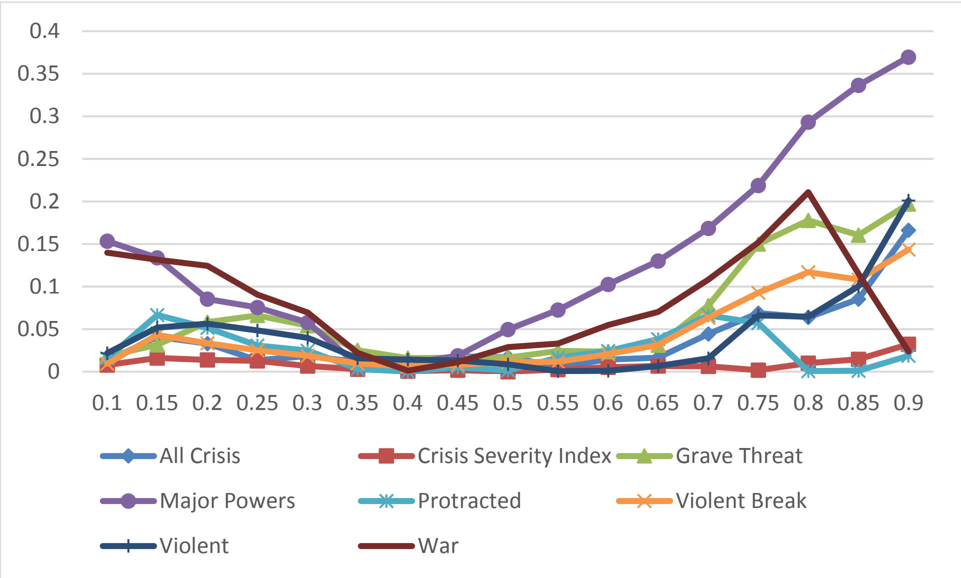

Figure A3. Sign of the Impact of Rare Disaster Risks on Bond Returns Volatility (Squared Returns) in South Africa