Long-Run Movement and Predictability of Bond Spread for BRICS and PIIGS: The Role of Economic, Financial and Political Risks[#]

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Abstract: We examine co-movement and predictability of Bond Spread of BRICS and PIIGS with respect to political risk (PR), financial risk (FR), and economic risk (ER). Our linear Granger causality findings imply that PR is the most important risk in predicting bond spread, followed by ER in both BRICS and in PIIGS, while FR is useful in predicting bond spread in BRICS only. Our nonlinear individual causality results infer that ER is the most important risk in predicting bond spread, followed by FR, and PR. We make a conjecture that linear and nonlinear causality are independent and our findings support this.

Keywords: Country Risk, Bond Spread, Linear and Nonlinear Granger Causality.

1. INTRODUCTION

Country risk is generally considered to be any government action that will negatively affect domestic as well as international investments. Financial market responses to political, economic and financial risk are well documented in the financial literature. Stock prices react to news about politics around the world. For example, investors, expecting Britain to vote to stay in the EU, responded to the Brexit outcome by cutting prices across European equity markets. The FTSE 100 index drop by 8.7%, the German DAX index fell by 7%, and France's CAC index fell by 8.6%. Outside Europe, the S&P 500 fell 3.6%, and Japan's Nikkei index also fell by 8%. More recent example is the surprise election won by Donald Trump as US president resulted in a decline of US 10-year interest rates to 1.72%, coupled with a 12.5% decline in the value of the Mexican Peso.

Traditionally, economists have focused on the economic impact of political risk (see Rodrik (1996); Hassett and Metcalf (1999)), by examining the relationship between tax policy uncertainty and investments. Hermes and Lensink (2001) studied the influence of political risk on capital flows. Previous studies that link the financial markets and political risk found that firms investment, cash flows, and return volatility can be affected by a change of political power (e.g., Kobrin (1979); Diamonte *et al.* (1996)). More recently Suleman and Randal (2016) proposed a framework for predicting market returns and volatility using changes in the country's political risk. They find political risk increase the volatility of returns for the majority of emerging markets.

Political scientists have investigated the links between domestic politics and international financial markets, including the bond market. For example, the yield spread between French 10-year bonds and similar-maturity German bonds debt touched the tightest as anti-euro candidate Marine Le Pen's momentum has slowed in opinion surveys. Political risk referred to an increase of uncertainty due to the possible actions of governments and other political participants within and across countries. This kind of risk suggests ambiguity about future changes in government policies and the effect of such policies on the future economic conditions. Such uncertainty may affect a country's borrowing costs. There is sufficient evidence on political risk and its impact on the country's debt pricing. Further there are some studies on political risk which directly linked it to government bond yields. Bekaert *et al*. (2012) concluded that political risk accounts for one-third of the sovereign

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credit spread in emerging market government bonds issued in US dollars.

However, because political and financial reforms in a country are frequently accompanied by economic downturns, a common challenge for these studies is that it is extremely difficult to empirically to disentangle changes in macroeconomic fundamentals from those of political risk (Kramer, (1971); Hibbs, (1977)). In this study, we overcome this issue of political risk by using the data from an international country risk guide, which provide separate data for political, economic and financial risk. Our research is focused on more recent literature that links political, financial and economic risk to asset prices (Berkman *et al*., (2011); Pastor and Veronesi, (2012); Bekaert *et al*., (2012); Gao and Qi, (2013); Pastor and Veronesi, (2013); Suleman and Daglish, (2015). We extend this line of research and use government bond pricing as our empirical setting to evaluate the asset-pricing implications of political risk along with financial and economic risk. Although research on the link between regular political changes in host countries and government bond yields is abundant (Pantzalis *et al*., (2000); Stein and Streb, (2004); Moser, (2007). The evidence on the role of dramatic political risk in government debt pricing is much rarer. A notable exception is Baldacci *et al*. (2011), who emphasize the importance of domestic political violence and expropriation in emerging market credit prices.

Erb *et al*. (1996a, 1996b) examined the predictive power of different risk measures such as political, economic and financial risk from 1984 to 1995. They concluded that changes in the risk measures predicted the stock market returns but not for bond returns. Erb *et al*. (1999) found a strong relationship between emerging market bond spreads and the composite risk rating (political, economic and financial) from political risk services. Similar findings are reported by Butler *et al*. (2009), who link state corruption to higher municipal bond yields, and Qi *et al*. (2010), who show that greater political rights are associated with lower corporate bond yield spreads.

The existing literature (Bekeart *et al*., (2014); Manzo, (2013) indicated that sovereign spreads are affected by political factors, along with financial and economic. The empirical studies (e.g., Citron and Nickelsburg (1987), Balkan (1992), Rivoli and Brewer (1997) concluded on the importance of political risk and their significant relationship among the probability of sovereign default. Only few researchers examined the political risk by considering the impact of elections and political business cycle (e.g., Vaaler *et al*. (2005, 2006)), government ideology (e.g., Boubakri *et al*., (2009)), and political expropriation (Baldacci *et al*., 2011) on sovereign spreads. More recently, Huang *et al*. (2015) examined the impact of the international political crisis on government bond yields for the period from 1988 to 2007. They found a positive and significant relationship between international political risk and government bond yields (investors demand higher returns during higher political uncertainty periods).

The literature primarily tends to study the effect of political risks on bond spread, and that too based on only linear frameworks. So far, no paper has studied the long-run impact and predictive abilities of political, economic and financial risks for the bond spread. To bridge the gap in the literature, this is the first study to examine the role of political risk (PR), financial risk (FR), and economic risk (ER) in predicting short and long-run movements of bond spreads in Brazil, Russia, India, China, and South Africa (BRICS), and Portugal, Italy, Ireland, Greece and Spain (PIIGS) using both linear and nonlinear models, with the latter approach being of tremendous importance, given the strong evidence of nonlinearity in the relationship between bond market movements and various types of risks.

The choice of the PIIGS was obvious given the important role played by these economies in recent European sovereign debt crisis, which resulted in several European countries facing the collapse of financial institutions, high government debt, and rapidly rising bond yield spreads in government securities. The debt crisis led to a decline in confidence for European businesses and economies. Naturally, factors, in this case PR, FR and ER, that determine the predictability of bond spreads are of utmost importance. The BRICS are chosen as a group for the sake of comparison with the results from the PIIGS, and given their importance in the global economy. The BRICS have grown rapidly and have become more integrated with the developed world in terms of trade and investment. They account for more than a quarter of the world's land area, slightly less than a half of the world's population and about one-sixth of the world's GDP (Mensi *et al*., 2014). Understandably, given the financial dependence in the modern globalized world, the current and potential growth of the BRICS countries has important implications for the capitalization of the international financial markets. Hence, determining the role played by PR, FR and ER in explaining bond spreads of the BRICS are also of tremendous importance for the well-being of the health of the world financial system.

Previewing our results, we find that all the variables in our study are I(1). Our cointegration test shows that strong cointegration relationships between bond spread and risks for all the countries in both BRICS and PIIGS groups because there exist strong cointegration relationships between bond spread and any of the risks for all the countries in either BRICS and PIIGS groups and our individual cointegration test shows that at least one risk is cointegrated with the bond spread for each country, and except a few countries, all risks are cointegrated with the bond spread. This concludes that there is strong long-run comovement between risks and bond spread for both BRICS and PIIGS.

Nonetheless, our panel and individual linear Granger causality concludes that PR is the most important risk to bond spread because it strongly panel linear Granger causes bond spread for both BRICS and PIIGS and our individual linearly causality test shows that PR linear Granger causes bond spread in 3 and 2 countries in BRICS and PIIGS, respectively, followed by ER, and FR. It is interesting to find that FR does not panel linear Granger causes a bond spread in either BRICS or PIIGS, but it does weakly linear Granger causes a bond spread in 2 countries in BRICS but still no country in PIIGS. This implies that PR is the most important risk in predicting bond spread, followed by ER in both BRICS and PIIGS while FR is only weakly useful in predicting bond spread in BRICS but not in PIIGS.

In this paper, we make a conjecture that linear and nonlinear causality are independent in the sense that sometimes there exists linear causality, but there is no nonlinear causality, sometimes there is no linear causality but there exists nonlinear causality, and so on. For example, our panel nonlinear causality finds that only PR panel nonlinear causes bond spread in BRICS but all the risks (ER, FR, and PR) panel nonlinear causes bond spread in PIIGS. Nevertheless, different from our linear causality results claim that PR is the most important risk in predicting bond spread linearly, followed by ER, while FR can weakly predict bond spread linearly in India and South Africa, our nonlinear individual causality results infer that ER is the most important risk in predicting bond spread nonlinearly, followed by FR, and PR. The outcomes of this paper are useful for portfolio managers, investors in the fixed income market and government agencies. The reminder of the paper is organized as follows: Section 2 discusses the data and econometric methodologies, while Section 3 presents the results from the various statistical tests conducted in both linear and non-linear frameworks. Finally, Section 4 concludes.

2. DATA AND METHODOLOGY

2.1. Data

For the empirical analysis, we use two groups of countries: BRICS and PIIGS. BRICS countries consist of Brazil, Russia, India, China, and South Africa, whereas Piigs include Portugal, Ireland, Italy, Greece, and Spain.

Bond Market

Monthly data on 10-year government bonds used for analysis is obtained from Datastream for the period of April 1996 to October 2016. We use the monthly data for all the data because the political, economic and financial data are on a monthly basis. For the BRICS countries the bond spread is calculated as the difference between the 10-year government bond's yield to maturity and that of a US 10-year government bond of the same maturity, whereas for the PIIGS, we calculated the difference relative to Germany's 10-year government bond.

Political Risk

Political risk (PR) is a qualitative measure. In order to analyse its contribution to financial data, we need to quantify it. A number of institutions such as the Bank of America, Business Environment Risk Intelligence, Economist Intelligence Unit, Euromoney, Institutional Investor, Standard and Poor's Rating Group, Political Risk Service Group, Coplin-O'Leary Ratings system, and Moody's Investment Service offer country-by-country analysis of political risk. However, few of these agencies or institutes provide quantitative analysis, and most of them are on a semi-annual or annual basis. Since January 1984, the ICRG has been compiling economic, financial, and political risk ratings for over 90 countries on a monthly basis. From December 2014 onwards, these four risk ratings have been quantified and are available for a total of 140 countries. This study employs political risk indices developed by the ICRG and compiled by the PRGS Group.

According to the International Country Risk Guide (ICRG), their risk ratings have been cited by experts at the IMF, World Bank, United Nations, and other international institutions as a standard measure against other ratings can be measured. The ICRG has been acclaimed by publications such as Barron's and The Wall Street Journal for the strength of its analysis and rating system. For example, Howell and Chaddick (1994) find that ICRG indices are more reliable and can predict risk better than other major political risk information providers. On the other hand, Hoti and McAleer (2005) examine the qualitative comparison of the country risk rating system used by seven leading agencies and find that ICRG is the best one to forecast the political, financial, and economic risk. More recently, Bekaert, *et al*. (2014) find that risk ratings from ICRG predict the political events well and political risk ratings provided by ICRG can be used as an alternative to present political events.

We use the data from ICRG for the period from April 1996 to October 2016, with the start and end periods being driven by data availability on the country-risks and sovereign bond yields.[1] ICRG provides four types of indices, including political risk index, economic risk index, and financial risk index. Political risk compounds the degree of political uncertainty in a given country and consists of twelve components, whereas financial and economic risk consists of five components each. The maximum number of 100 reflects the lowest risk and, on the other hand, a score of zero represents the highest risk.

Economic Risk

We also use an economic risk (ER) which is a measure of assessing a country's current economic strengths and weaknesses. The economic risk expressed as a percentage of GDP consists of five components, including per capita GDP, the real GDP growth rate, inflation, and fiscal and current account balances. The rating of economic risk is between 0 and 50 and a high rating indicates sound economic conditions whereas a low rating demonstrates weak economic conditions in the country.

Financial Risk

In addition, we use a financial risk (FR) which provides a measure of a country's ability to finance its official, commercial, and trade debt obligations. This risk consists of five components like economic risk which is external debt as a percentage of GDP, foreign debt as a percentage of export of goods and services, current accounts as a percentage of goods and services, net liquidity in a month, and exchange rate stability against the US dollar. The financial risk fluctuates between 0 and 50, a high rating display a low level of external exposure and vice versa. Similar to bond yield spread, we calculate the political, financial, and economic risk spread relative to the USA for each of the BRICS group of countries, and the same relative to Germany for the PIIGS. The decision to use the spread relative to the US with respect to the BRICS and Germany with respect to the PIIGS comes from standard practice in this line of research (see for example, Koop and Korobilis, (2015); Ben Nasr *et al*., (2018), Ji *et al*., (2018a)), due to the strong economic, financial, political and trade linkages the BRICS and the PIIGS have with the USA and Germany respectively.

Note that, there is an overall composite index of risks maintained by the ICRG, with political risks accounting for 50% of the composite risk ratings, while each of the other two ratings, i.e., economic and financial risks, have a weight of 25% each of the composite. We however, did not use the overall index, as results based on alternative types of risks are more informative from the policy perspective than the overall risk. Also depending upon which of the risk-types have a stronger influence and given their weights, they could be driving the results, both significant and insignificant, derived from the overall index, and lead to incorrect inferences.[2]

To get an idea about which of the risks are stronger predictors, we conducted the causality tests by standardizing the risks to have unit variance, so that the size of the test statistic is a direct indication of the relative strength of the predictors. Ideally however, it would be interesting to conduct variance decomposition analyses in a multivariate vector autoregressive (VAR) framework.

2.2. Methodology

We will conduct both simple and panel cointegration and linear and nonlinear causality in our study. We will apply some commonly used tools like unit root test and nonlinearity test in our paper. Since these tools are well known, we skip discussion their methodology and only discuss simple and panel cointegration and linear and nonlinear causality in our study. We first discuss the simple and panel cointegration.

[1]Note we could not go beyond 2016, as our ICRG data was obtained from a co-author of ours, who in turn could not renew his subscription due to the exceptionally high cots issues associated with the data set. But, we believe that having the data set till 2016, covers all the recent important financial market turmoil like, the East Asian, Global Financial, and the Sovereign Debt Crises.

[2]This was indeed the case, where we obtained contradictory results based on the composite index. Complete details of these results are available upon request from the authors.

2.2.1. Cointegration

We will conduct both simple and panel cointegration between the bond spread, y_{it}, and risk, x_{it}, to be each risk of PR, FR, and ER, respectively, for each country in BRICS and PIIGS, in this paper.

2.2.1.1. Simple Cointegration

To estimate the long-run relationship between y_{it} and x_{it}, we employ the following simple cointegration

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it}, \tag{1}$$

Where ε_{it} is the residuals for $t = 1,\ldots T; i = 1,\ldots,N$. The test examines the residuals in regression (1) of *I(1)* variables. If the variables are cointegrated, then the residuals will be *I(0)*. If the variables are not cointegrated, then the residuals will be *I(1)*.

2.2.1.2. Panel Cointegration

To run a panel cointegration, we use the Kao Cointegraion test (Kao, 1999) which is based on Engle-Granger's (1987) two-step approach. Different to the Pedroni (1999, 2004) tests, the Kao Cointegraion test specifies cross-section specific intercepts and homogeneous coefficients on the first-stage regressors. We first run equation (1) and obtain the residual ε_{it} for $t = 1,\ldots,T \text{ and } i = 1,\ldots,N.$. We then run the following augmented version of the pooled auxiliary regression:

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + \sum_{j=1}^{k} \varphi j \Delta\varepsilon_{it-j} + v_{it} \tag{2}$$

Under the null, H_0, of no cointegration, Kao (1999) shows that the ADF statistics can be constructed as:

$$ADF = \frac{t_\rho + \sqrt{6N}\hat{\sigma}_v / (2\hat{\sigma}_{0v})}{\sqrt{\dfrac{\hat{\sigma}_{0v}^2}{(2\hat{\sigma}_v^2)} + \dfrac{3\hat{\sigma}_v^2}{(10\hat{\sigma}_{0v}^2)}}} \tag{3}$$

Which converges to $N(0,1)$ asymptotically if H_0 is true, where t_ρ is the t-statistic augmented version of the pooled auxiliary regression, the estimated variance is $\hat{\sigma}_v^2 = \hat{\sigma}_u^2 - \hat{\sigma}_{u\in}^2 \hat{\sigma}_\in^{-2}$ and long run variance $\hat{\sigma}_{0v}^2 = \hat{\sigma}_{0u}^2 - \hat{\sigma}_{0u\in}^2 \hat{\sigma}_{0\in}^{-2}$ is defined in Kao (1999). We note that the Kao Cointegraion test in equation (3) is to test for the panel data for all countries in BRIC and PIIGS.

2.2.2. Causality

Granger causality is used to examine whether past information of one series could contribute to the prediction of another series (Granger, 1969). In this paper, we conduct both simple and panel linear and nonlinear causality. Since simple linear and nonlinear causality are well known, we skip discuss it and only discuss the methodology of the panel linear and nonlinear causality in this paper. We first discuss the methodology of the panel linear causality in the next subsection and thereafter discuss the methodology of the panel nonlinear causality.

2.2.2.1. Panel Linear Granger Causality

Consider *I* panels *i*=1,..,*I* and at time *t* in the *i*th panel, there are J_i dependent stationary variables $X_{i,j,t}(j = 1,\ldots,J_i)$ and K_i independent stationary variables $Y_{i,k,t}(k = 1,\ldots,K_i)$. To test the linear causality relationship between two vectors of stationary time series, $X_t = (X_{1,1,t},\ldots,X_{1,J_1,t},\ldots,X_{I,1.,t},\ldots,X_{I,J_I,t})'$ and $Y_t = (Y_{1,1,t},\ldots,Y_{1,k_1,t},\ldots,Y_{I,1.,t},\ldots,Y_{I,k_I,t})'$, one could construct the following vector autoregressive regression (VAR) model:

$$\begin{pmatrix} X_t \\ Y_t \end{pmatrix} = \begin{pmatrix} A_{x[n_1\times 1]} \\ A_{y[n_2\times 1]} \end{pmatrix} + \begin{pmatrix} A_{xx}(L)_{[n_1\times n_1]} & A_{xy}(L)_{[n_1\times n_2]} \\ A_{yx}(L)_{[n_2\times n_1]} & A_{yy}(L)_{[n_2\times n_2]} \end{pmatrix} \begin{pmatrix} X_{t-1} \\ Y_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_x \\ \varepsilon_y \end{pmatrix} \tag{4}$$

where $A_{x[n_1\times 1]}$ and $A_{y[n_2\times 1]}$ are two vectors of intercept terms, $A_{xx}(L)_{[n_1\times n_1]}$, $A_{xy}(L)_{[n_1\times n_2]}$, $A_{yx}(L)_{[n_2\times n_1]}$ and $A_{yy}(L)_{[n_2\times n_2]}$ are matrices of lag polynomials, $e_{x,t}$ and $e_{y,t}$ are the corresponding error terms, $n_1 = \sum\sum J_i$, $n_2 = \sum\sum K_i$, and we can rewrite $(X_{1,1,t},\ldots,X_{1,J_1,t},\ldots,X_{I,1.,t},\ldots,X_{I,J_I,t})' = (X_{1,t},\ldots,X_{n_1,t})'$. $(Y_{1,1,t},\ldots,Y_{1,k_1,t},\ldots,Y_{I,1.,t},\ldots,Y_{I,k_I,t})' = (Y_{1,t},\ldots,Y_{n_2,t})'$. Readers may refer to Chow, *et al*. (2018) for more information on the testing whether there is any bidirectional or unidirectional linear causality relationship between X_t and Y_t.

If the time series are cointegrated, one should impose the error-correction mechanism (ECM) on the VAR to construct a vector error correction model (VECM) to test Granger causality between the variables of interest. In particular, when testing the causality relationship between two vectors of non-stationary time series, we let $\Delta x_t = (\Delta X_{1,t},\ldots,\Delta X_{n_1,t})'$ and $\Delta y_t = (\Delta Y_{1,t},\ldots,\Delta Y_{n_2,t})'$, be the corresponding stationary differencing series such that there are 10 series in total. If x_t and y_t are cointegrated, then, instead of using the VAR in (4), one should adopt the following VECM model:

$$\begin{pmatrix} \Delta x_t \\ \Delta y_t \end{pmatrix} = \begin{pmatrix} A_{x[n_1\times 1]} \\ A_{y[n_2\times 1]} \end{pmatrix} + \begin{pmatrix} A_{xx}(L)_{[n_1\times n_1]} & A_{xy}(L)_{[n_1\times n_2]} \\ A_{yx}(L)_{[n_2\times n_1]} & A_{yy}(L)_{[n_2\times n_2]} \end{pmatrix} \begin{pmatrix} \Delta x_{t-1} \\ \Delta y_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_{x[n_1\times 1]} \\ \alpha_{y[n_2\times 1]} \end{pmatrix} ecm_{t-1} + \begin{pmatrix} e_{x,t} \\ e_{y,t} \end{pmatrix}, \tag{5}$$

Where ecm_{t-1} is lag one of the error correction term, $\alpha_{x[n_1\times 1]}$ and $\alpha_{y[n_2\times 1]}$ are the coefficient vectors for the error correction term ecm_{t-1}. There are now two sources of causation of $y_t(x_t)$ by $x_t(y_t)$, either through the lagged dynamic terms $\Delta x_{t-1}(\Delta y_{t-1})$, or through the error correction term ecm_{t-1}. Thereafter, one could test the null hypothesis $H_{01}: A_{xy}(L)=0(H_{02}: A_{yx}(L)=0)$ and/or $H_{03}:\alpha_x=0(H_{04}:\alpha_y=0)$ to identify Granger causality relation using the LR test.

2.2.3. Panel Nonlinear Granger Causality

Baek and Brock (1992) and Hiemstra and Jones (1994) develop The nonlinear causality tests is bivariate setting (Baek and Brock, (1992); Hiemstra and Jones, (1994), multivariate setting (Bai, *et al*., (2010, 2011, 2018)) and panel setting (Chow *et al*., 92018)) have been well established. To test whether there is any nonlinear causality relationship between two vectors of stationary panel time series, $X_t=(X_{1,1,t},\ldots,X_{1,J_1,t},\ldots,X_{I,1.,t},\ldots,X_{I,J_I,t})'$ and $Y_t=(Y_{1,1,t},\ldots,Y_{1,k_1,t},\ldots,Y_{I,1.,t},\ldots,Y_{I,k_I,t})'$, one has to apply the VAR model as stated in equation (4) or the VECM model as stated in equation (5) to the series X_t and Y_t to identify their linear causal relationships and obtain their corresponding residuals $\varepsilon_{y,t}$ and $\varepsilon_{x,t}$. Thereafter, one has to apply a nonlinear Granger causality test to the residual series $\varepsilon_{y,t}$ and $\varepsilon_{x,t}$. We rewrite $(X_{1,1,t},\ldots,X_{1,J_1,t},\ldots,Y_{I,1.,t},\ldots,Y_{I,J_I,t})'=(X_{1,t},\ldots,X_{n_1,t})'$. $(Y_{1,1,t},\ldots,Y_{1,k_1,t},\ldots,Y_{I,1..t},\ldots,Y_{I,k_I,t})'=(Y_{1,t},\ldots,Y_{n_2,t})'$, and without loss of generality, we assume that X_t and Y_t are the corresponding residuals $\varepsilon_{x,t}$ and $\varepsilon_{y,t}$. Under this modeling setting and under some regularity conditions, the following test statistic

$$X=\sqrt{n}\left(\frac{C_1(M_x+L_x,L_y,e,n)}{C_2(L_x,L_y,e,n)}-\frac{C_3(M_x+L_x,e,n}{C_4(L_x,e,n)}\right), \qquad (8)$$

is distributed as $N(0,\sigma^2(M_x,L_x,L_y,e))$ if the null hypothesis, H_0, that $Y_t=(Y_{1,1,t},\ldots,Y_{1,k_1,t},\ldots,Y_{I,1.,t},\ldots,Y_{I,k_I,t})'$ does not strictly Granger cause $(X_{1,1,t},\ldots,X_{1,J_1,t},\ldots,X_{I,1.,t},\ldots,X_{I,J_I,t})'$ nonlinearly is true.[3]

[3]Readers may refer to Baek and Brock (1992), Hiemstra and Jones (1994), Bai, *et al*. (2010, 2011, 2018), and Chow *et al*. (2018) for all the terms used in Equation (8) and the detailed information including the regularity conditions about the test statistic in (8).

3. EMPIRICAL RESULTS

3.1. Summary Statistics

Table **1** shows the summary statistics of our data for bond spreads and risks, including ER, FR, and PR. From the table, we find that for BRICS group, the bond Spread falls within a range from -0.44 to 105.20, with a mean value of 5.70, ER falls within the range from -21.50 to 11.00 with a mean value -2.00, FR is between -13.50 to 18.00 with a mean value 7.73, and PR falls within the range from -47.00 to -6.00 with a mean value -18.83, with all mean values being significant at 1% level. On the other hand, for PIIGS group, the bond spread falls within a range from 39.84 to -0.22, with a mean value of 1.94; ER lies within the range from 7.00 to -22.50 with a mean value -4.52, FR lies within the range from 7.50 to -13.50 with a mean value 4.96, and PR falls within the range from 11.00 to -21.00 with a mean value -6.07, with all mean values being significant at 1% level. The skewness estimates reveal that for BRICS group only bond Spread is skewed to the right while ER, FR, and PR are skewed to the left and for PIIGS group, only ER is skewed to the left and bond spread, FR, and PR are skewed to the right, with all skewness estimates being significant at 1% level. On the other hand, Kurtosis estimates show that except ER, and FR in PIIGS group that are not significant, all other values in both BRICS and PIIGS groups are significant at 1% level.

3.2. Panel Unit Root Test

Tables **2a** and **2b** show the results of the panel unit root test for both BRICS and PIIGS groups. In order to have more reliable results, we apply both Levin–Lin–Chu test (2002, LLC test) and Im–Pesaran–Shin test (2003, IPS test) to test for the existence of unit roots in the panel data models. Both tests suggest that all series contain a unit root while their first differences do not contain unit roots. Thus, we conclude that all series are I(1). The results suggest that all variables contain a unit root, while their first differences are found to be stationary.

3.3. Panel Cointegration

Before testing for causality, we test for cointegration among the variables. Tables **3a** and **3b** show the results of Kao residual cointegration test for all the countries in BRICS and PIIGS groups, respectively. From the tables, the null hypothesis of no cointegration between bond spread and any of ER, FR, and PR for all the countries in either BRICS and PIIGS groups is

Table 1: Summary Statistics

Variable	Max	Min	Mean	SD	Skewness	Kurtosis
BRICS group						
Bond Spread	105.20	-0.44	5.70***	9.21	7.57***	66.26***
ER	11.00	-21.50	-2.00***	4.75	-0.50***	4.38***
FR	18.00	-13.50	7.73***	5.89	-1.09***	4.39***
PR	-6.00	-47.00	-18.83***	6.49	-0.99***	4.42***
PIIGS group						
Bond Spread	39.84	-0.22	1.94***	3.86	4.60***	32.34***
ER	7.00	-22.50	-4.52***	4.50	-0.39***	3.25
FR	7.50	-13.50	-4.96***	3.75	0.22***	2.95
PR	11.00	-21.00	-6.07***	6.50	0.22***	2.58***

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 2a: Panel Unit Root Test (BRICS)

Test statistics	*Bond Spread*		*ER*		*FR*		*PR*	
	Level	First difference	Level	First difference	Level	First difference	Level	First difference
LLC test	-8.52	-21.72***	0.07	-11.01	-3.03	-34.77***	1.58826	-36.92***
IPS test	-7.93	-20.13***	-0.32	-13.99	-2.86	-31.00***	2.33442	-32.02***

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 2b: Panel Unit Root Test (PIIGS)

Test statistics	*Bond Spread*		*ER*		*FR*		*PR*	
	Level	First difference	Level	First difference	Level	First difference	Level	First difference
LLC test	-0.31	-34.81***	-0.55	-27.36***	0.77	-34.44***	-0.11	-32.11***
IPS test	0.27	-28.48***	-0.30	-23.82***	-1.27	-28.08***	-0.02	-24.52***

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 3a: Kao Residual Cointegration Test (BRICS)

Dependent Variable	Independent Variable	t-Statistic
Bond Spread	*ER*	-6.19***
ER	*Bond Spread*	-3.07***
Bond Spread	*FR*	-5.05***
FR	*Bond Spread*	-1.29*
Bond Spread	*PR*	-8.10***
PR	*Bond Spread*	-1.93**

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 3b: Kao Residual Cointegration Test (PIIGS)

Dependent Variable	Independent Variable	t-Statistic
Bond Spread	*ER*	-2.82***
ER	*Bond Spread*	-3.64***
Bond Spread	*FR*	-1.66**
FR	*Bond Spread*	-1.69**
Bond Spread	*PR*	-2.31**
PR	*Bond Spread*	-1.81**

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 4a: Cointegration for each Country in BRICS for each Risk

Dependent Variable	Independent Variable	tau-Statistic
Brazil		
Bond Spread	*ER*	-3.12
ER	*Bond Spread*	-4.25**
Bond Spread	*FR*	-3.62**
FR	*Bond Spread*	-3.50**
Bond Spread	*PR*	-2.70
PR	*Bond Spread*	-1.85
China		
Bond Spread	*ER*	-2.09
ER	*Bond Spread*	-2.45
Bond Spread	*FR*	-2.717170
FR	*Bond Spread*	-4.068091***
Bond Spread	*PR*	-1.48
PR	*Bond Spread*	-1.14
India		
Bond Spread	*ER*	-1.38
ER	*Bond Spread*	-3.16*
India		
Bond Spread	*FR*	-2.13
FR	*Bond Spread*	-3.15*
Bond Spread	*PR*	-5.02***
PR	*Bond Spread*	-4.25**
Russia		
Bond Spread	*ER*	-4.03**
ER	*Bond Spread*	-3.75*
Bond Spread	*FR*	-2.13
FR	*Bond Spread*	-3.15*
Bond Spread	*PR*	-5.02***
PR	*Bond Spread*	-4.25***
South Africa		
Bond Spread	*ER*	-3.59**
ER	*Bond Spread*	-2.85
Bond Spread	*FR*	-3.94**
FR	*Bond Spread*	-3.80**
Bond Spread	*PR*	-5.91***
PR	*Bond Spread*	-4.91***

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 4b: Cointegration for each Country in PIIGS for each Risk

Dependent Variable	Independent Variable	tau-Statistic
Portugal		
Bond Spread	ER	-3.04
ER	Bond Spread	-4.11***
Bond Spread	FR	-1.56
FR	Bond Spread	-3.74**
Bond Spread	PR	-2.18
PR	Bond Spread	-2.27
Ireland		
Bond Spread	ER	-2.88
ER	Bond Spread	-3.43**
Bond Spread	FR	-1.56
FR	Bond Spread	-1.80
Bond Spread	PR	-1.82
PR	Bond Spread	-1.88
Italy		
Bond Spread	ER	-2.96
ER	Bond Spread	-4.25***
Bond Spread	FR	-2.91
FR	Bond Spread	-3.20*
Bond Spread	PR	-2.26
PR	Bond Spread	-3.28*
Greece		
Bond Spread	ER	-3.55**
ER	Bond Spread	-3.64**
Bond Spread	FR	-3.34*
FR	Bond Spread	-3.43**
Bond Spread	PR	-3.51**
PR	Bond Spread	-2.06
Spain		
Bond Spread	ER	-3.53**
ER	Bond Spread	-4.32***
Bond Spread	FR	-3.01
FR	Bond Spread	-3.72**
Bond Spread	PR	-2.49*
PR	Bond Spread	-2.04

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

rejected in all cases. Thus, we conclude that there are panel cointegration relationships between bond spread and any of the risks including ER, FR, and PR for all the countries in either BRICS and PIIGS groups.

3.4. Cointegration for each Country

However, when we examine whether there is any simple cointegration between the bond spread and each risk of PR, FR, and ER for each country in BRICS and PIIGS, we exhibit the results in Tables **4a** and **b** and find that except a few, most of the pairs are cointegrated. Also, *for each country, there is at least one risk that is cointegrated with the bond spread while except a few countries (Brazil and China in BRICS and Portugal and Ireland in PIIGS), all risks are cointegrated with the bond spread.*

3.5. Panel Linear Granger Causality

We turn to examine causality relationship among all variables studied in this paper. Since causality analysis

Table 5: Panel Linear Granger Causality

	Lag 1	Lag 2	Lag 3	Lag 4
Null Hypothesis				
BRICS group				
ER does not Granger cause Bond Spread	7.26***	8.26**	8.73**	14.70***
FR does not Granger cause Bond Spread	1.62	1.94	3.73	4.94
PR does not Granger cause Bond Spread	2.28	5.10*	10.87**	11.60**
PIIGS group				
ER does not Granger cause Bond Spread	0.06	0.06	1.28	1.83
FR does not Granger cause Bond Spread	0.25	1.94	3.34	5.19
PR does not Granger cause Bond Spread	8.44***	8.64**	7.27*	11.10**

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

requires the data to be stationary, different from cointegration test, we will examine whether there is any linear and nonlinear causality between first differences of these variables because all the variables are I(1) while the first differences of all the variables are stationary.

We first examine whether there is any panel linear Granger causality from any of the risks including ER, FR, and PR to bond spread for all the countries in either the BRICS and PIIGS groups. Given the cointegration test results, we employ the VECM models in equation (5) to test whether there is any panel linear Granger causality for all countries in either BRICS or PIIGS groups. In the panel linear Granger causality test, the number of lags to be used is a key decision. In addition, various information criteria could recommend different lag lengths for each of the explanatory variables and different criteria could lead to conflicting results. To circumvent the limitation, we use lag one to lag four in applying the panel linear Granger causality test for each pair of variables for all countries in either BRICS or PIIGS groups and exhibit the results in Table **5**.

The result of panel linear Granger causality is interesting. Different from the result in cointegration that there are cointegration relationships between bond spread and ER, FR, and PR for all the countries in both BRICS and PIIGS groups, Table **5** reveals that the results of the panel linear Granger causality are different in both BRICS and PIIGS groups: some significant and some not significant. To be precise, there is significant panel linear Granger causality from ER and PR to bond spread in BRICS group, while, there is the only PR that significant panel linear Granger causes a bond spread in PIIGS group. These results infer that *1) PR significant panel linear Granger causes bond spread in both BRICS and PIIGS groups, 2) ER significant panel linear Granger causes bond spread only in BRICS, and 3) there is NO significant panel linear Granger causality from FR to bond spread in both BRICS and PIIGS group.* We note that in this paper we are only interested in examining the unidirectional causality from any of the risks like ER, PR, and FR to Bond spread but we are not interested in studying the causality from Bond spread to any of the risks. Thus, we skip reporting the causality results from Bond spread to any of the risks in this paper.

3.6. Simple Linear Granger Causality

The panel linear Granger causality test can only lead us draw conclusion whether there is any panel linear Granger causality from any of the risk, say, ER, to Bond spread for all countries in either BRICS or PIIGS, but cannot tell whether ER linear Granger causes bond spread in each of the countries in either BRICS or PIIGS. Thus, to complement the analysis of the panel linear Granger causality test, we conduct the simple linear Granger causality tests for each of the countries in BRICS and PIIGS and report the results in Table **6a** for BRICS and Table **6b** for PIIGS.

From Tables **6a** and **6b**, we find that the individual linearly causality results are consistent with the panel linear Granger causality that there are more individual linearly causality in the BRICS group than in the PIIGS groups. The main findings from the simple linear Granger causality tests include: 1) for BRICS, there is at least one risk from ER, and PR significantly linear-causes bond spread for each of the countries, Russia gets two risks: ER and PR linear-cause bond spread; while India gets all the risks: ER, FR, and PR linear-cause bond spread. However, 2) for PIIGS, most (3 out of 5) countries do not have any risk that linear-causes

Table 6a: Individual Linear Granger Causality Test (BRICS Group)

Null Hypothesis	Lag 1	Lag 2	Lag 3	Lag 4
Brazil				
ER does not Granger cause Bond Spread	0.02	0.96	2.16	3.54
FR does not Granger cause Bond Spread	2.40	3.56	3.65	5.34
PR does not Granger cause Bond Spread	1.23	4.40	8.02*	7.96*
China				
ER does not Granger cause Bond Spread	0.00	0.09	2.19	8.20*
FR does not Granger cause Bond Spread	2.47	2.76	4.25	4.51
PR does not Granger cause Bond Spread	1.43	2.84	2.37	2.52
India				
ER does not Granger cause Bond Spread	2.73*	5.79*	21.66***	25.31***
FR does not Granger cause Bond Spread	0.66	0.75	6.03	8.06*
PR does not Granger cause Bond Spread	6.38**	6.02**	6.07	11.05**
Russia				
ER does not Granger cause Bond Spread	1.99	5.85*	19.28***	24.23***
FR does not Granger cause Bond Spread	0.77	2.61	4.83	4.62
PR does not Granger cause Bond Spread	0.59	2.68	9.61**	9.07*
South Africa				
ER does not Granger cause Bond Spread	0.63	0.97	1.35	7.35
FR does not Granger cause Bond Spread	3.05*	5.69*	6.17	8.59*
PR does not Granger cause Bond Spread	1.43	2.84	3.32	2.87

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 6b: Individual Linear Granger Causality Test (PIIGS Group)

Null Hypothesis	Lag 1	Lag 2	Lag 3	Lag 4
Portugal				
ER does not Granger cause Bond Spread	0.05	0.28	0.97	1.90
FR does not Granger cause Bond Spread	0.05	0.76	1.01	0.91
PR does not Granger cause Bond Spread	0.42	0.78	1.18	0.83
Ireland				
ER does not Granger cause Bond Spread	0.75	2.39	4.24	6.26
FR does not Granger cause Bond Spread	2.22	2.32	2.61	2.42
PR does not Granger cause Bond Spread	0.35	0.36	1.50	3.65
Italy				
ER does not Granger cause Bond Spread	0.87	1.09	1.47	1.41
FR does not Granger cause Bond Spread	0.03	0.06	0.17	0.39
PR does not Granger cause Bond Spread	1.05	2.15	2.49	6.79
Greece				
ER does not Granger cause Bond Spread	0.11	0.37	1.60	2.01
FR does not Granger cause Bond Spread	0.17	1.72	3.08	7.59
PR does not Granger cause Bond Spread	12.00***	11.72***	10.44**	20.15***
Spain				
ER does not Granger cause Bond Spread	0.45	5.05*	4.39	5.40
FR does not Granger cause Bond Spread	0.32	0.72	1.82	3.27
PR does not Granger cause Bond Spread	3.31*	3.77	4.45	5.36

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 7a: BDS Test on Residual for BRICS

Country/Dimension	2	3	4	5	6
Brazil					
Residual of Bond Spread-ER equation	-0.34	0.87	2.66***	3.23***	3.82***
Residual of Bond Spread-FR equation	0.13	-0.26	1.72*	2.43**	2.65***
Residual of Bond Spread-PR equation	0.20	-0.00	1.92*	2.65***	2.94***
China					
Residual of Bond Spread-ER equation	0.19	0.11	0.12	5.74***	8.69***
Residual of Bond Spread-FR equation	0.28	0.18	0.22	6.46***	9.76***
Residual of Bond Spread-PR equation	0.22	0.14	0.16	5.95***	9.00***
India					
Residual of Bond Spread-ER equation	0.47	1.62	1.62	2.13**	2.26**
Residual of Bond Spread-FR equation	1.63	2.67***	2.78***	3.19***	3.32***
Residual of Bond Spread-PR equation	1.42	2.25**	2.30**	2.62***	2.64***
Russia					
Residual of Bond Spread-ER equation	1.37	2.09**	2.15**	2.54**	2.52**
Residual of Bond Spread-FR equation	1.12	2.13**	2.31**	2.75***	2.86***
Residual of Bond Spread-PR equation	1.37	2.21**	2.39**	2.73***	2.86***
South Africa					
Residual of Bond Spread-ER equation	0.69	2.48**	2.95***	3.03***	3.29***
Residual of Bond Spread-FR equation	0.61	2.17**	2.47**	2.39**	3.32***
Residual of Bond Spread-PR equation	0.08	2.01**	2.28**	2.58***	2.78***

Table 7b: BDS Test on Residual for PIIGS

Country/Dimension	2	3	4	5	6
Portugal					
Residual of Bond Spread-ER equation	10.08***	11.97***	13.85***	15.60***	17.60***
Residual of Bond Spread-FR equation	9.75***	12.06***	13.81***	15.58***	17.48***
Residual of Bond Spread-PR equation	8.86***	11.13***	13.02***	14.89***	16.86***
Ireland					
Residual of Bond Spread-ER equation	7.82***	9.30***	11.03***	12.36***	13.79***
Residual of Bond Spread-FR equation	8.02***	9.64***	11.04***	12.45***	14.06***
Residual of Bond Spread-PR equation	7.27***	9.01***	10.16***	11.37***	12.73***
Italy					
Residual of Bond Spread-ER equation	5.87***	8.85***	10.52***	11.85***	13.26***
Residual of Bond Spread-FR equation	5.22***	8.13***	9.71***	11.00***	12.39***
Residual of Bond Spread-PR equation	5.16***	8.24***	9.92***	11.25***	12.47*****
Greece					
Residual of Bond Spread-ER equation	7.03***	8.70***	10.68***	12.39***	13.83***
Residual of Bond Spread-FR equation	6.60***	8.09***	9.24***	10.60***	11.61***
Residual of Bond Spread-PR equation	6.78***	8.47***	9.86***	11.42***	12.78***
Spain					
Residual of Bond Spread-ER equation	1.53	1.45	1.32	1.78*	2.12**
Residual of Bond Spread-FR equation	2.83***	2.40**	2.02**	4.71***	6.82***
Residual of Bond Spread-PR equation	7.62***	10.10***	11.75***	13.56***	15.30***

bond spread, and only one risk (PR) linear-causes bond spread for both Greece and Spain. 3) The strong 1% or 5% significant risk that linear-causes bond spread is in India (ER and PR) and Russia (ER and PR) from BRICS and Greece (PR) from PIIGS. (4) From (3), we can conclude that ER and PR linear-causes bond spread more significantly and FR only linear-causes bond spread weakly if the linear-causality exists.

3.7. Nonlinearity

As far we know, literature only consider linear causality between Bond spread and risks, see, for example, Benbouzid *et al*. (2017) and Ribeiro *et al*. (2017). We believe that there could be nonlinear causality between Bond Spread and risks. We set this believe in the following conjectures:

Conjecture 1: In most real data analysis, there exists nonlinearity in the residual of the dependent variable after removing all the linear causality from explanatory variables.

Conjecture 2a: If there exists nonlinearity in the residual of dependent variable after removing all the linear causality from explanatory variables, then usually there should exist nonlinear causality from explanatory variables to the dependent variable.

Conjecture 2b: If the nonlinearity in the residual of dependent variable after removing all the linear causality from explanatory variables is strong (weak), then usually the nonlinear causality from explanatory variables to dependent variable is strong (weak).

We first examine whether Conjecture 1 holds true. To do so, we apply Brock *et al*.'s (BDS, 1996) nonlinearity test to test whether there is any nonlinearity in the residuals obtained from the linear causality model stated in Equation (4) and report the result in Tables **7a** and **7b** for BRICS and PIIGS groups, respectively. From the tables, the BDS test result indicates that nonlinearity in all residual series is strong. This implies that the linear causality in Equation (4) have not captured all the variability of bond spread by the explanatory variables and if Conjecture 2a is true, there could exist nonlinear Granger causality from risks to Bond spread.

The results of the nonlinearity test exhibited in Tables **7a** and **7b** are interesting. Table **7a** shows that the nonlinearity exists mainly when the dimension is 3 ,4, 5 or 6 but not in dimension 1 while Table **7b** shows that the nonlinearity exists mostly in all dimension, including dimensions 1 to 4.

As far as we know, there is no theory for Conjectures 2a and 2b, and thus, we set these conjectures. We cannot prove whether Conjectures 2a and 2b hold, but we would like to demonstrate whether these conjectures hold true in our illustration as shown in the next subsection.

3.8. Panel Non-Linear Granger Causality

In this subsection, we examine whether there is any panel nonlinear causality between Bond Spread and whether Conjectures 2a and 2b hold true, In addition, we make the following conjecture:

Conjecture 3: Linear and nonlinear causality are independent in the sense that sometimes there exists linear causality, but there is no nonlinear causality, sometimes there is no linear causality but there exists nonlinear causality, sometimes there exist both linear

Table 8: Panel Non-Linear Granger Causality

	Lag 1	Lag 2	Lag 3	Lag 4
Null Hypothesis				
BRICS group				
ER does not Granger cause Bond Spread	1.01	-0.33	-0.56	-0.31
FR does not Granger cause Bond Spread	1.27	1.18	0.91	0.89
PR does not Granger cause Bond Spread	1.94**	1.56*	-0.35	0.75
PIIGS group				
ER does not Granger cause Bond Spread	0.80	1.13	1.93**	1.64*
FR does not Granger cause Bond Spread	-1.92**	-1.35*	-1.41*	0.88
PR does not Granger cause Bond Spread	0.73	1.39*	0.99	-0.55

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

and nonlinear causality, and sometimes there does not exist any linear or nonlinear causality.

To provide answers for the above conjectures, in this section we first conduct the recently developed nonlinear Granger causality test (Bai, *et al*., (2010, 2011, 2018); Chow, *et al*., (2018)) to test whether there is any nonlinear Granger causality between bond spread and risks and exhibit the results in Table **8**. The results of panel nonlinear causality from risks to bond spread exhibited in Table **8** are very interesting. From the table, we observe that (1) only PR panel nonlinear causes bond spread in BRICS but all the risks (ER, FR, and PR) panel nonlinear causes bond spread in PIIGS. (2) Among them, all panel nonlinear causality are strong (5% significant level) except PR that only weakly (10% significant level) panel nonlinear causes bond spread in PIIGS. From Tables **7a**, **7b**, and **8**, we observe the following: (3) The panel nonlinear causality could be strong up to 5% significant level but not as strong as the nonlinearity as shown in Tables **7a** and **7b** that nonlinearity is extremely strong in all countries, regardless whether it is from BRICS or PIIGS. This observation does sometimes but not always support Conjecture 2a that sometimes when there exists nonlinearity in the residual of bond spread after removing all the linear causality from explanatory variables of risks, there exists nonlinear causality between bond spread and risks. (4) In some cases, for example, ER and FR in BRICS, there does not exist any significant panel nonlinear causality, but there is strong nonlinearity in all countries. This observation does sometimes but not always support Conjecture 2b that the nonlinearity in the residual is stronger for PIIGS than that for BRICS and the nonlinear causality is stronger for PIIGS than that for BRICS in general. However, Conjectures 2a and 2b hold in general though not always hold true.

Our observations in (3) and (4) could suggest that the nonlinearity could be from the nonlinearity "causality" from the past data of the dependent variable. However, there is no formal nonlinearity "causality" test from the past data of the dependent variable, and thus, we do not further explore this issue, but academics could consider developing such test for this purpose.

Now, we examine whether Conjecture 3 holds true by comparing the results of the panel linear Granger causality results displayed in Table **5** with the results of the panel non-linear Granger causality exhibited in Table **8**, When we compare the results of the panel linear Granger causality results displayed in Table **5** with the results of the panel non-linear Granger causality exhibited in Table **8**, we get very interesting findings: Table **5** shows that there is more panel linear Granger causality in BRICS than PIIGS while Table **8** shows that there is more panel nonlinear Granger causality in PIIGS than BRICS. In addition, the findings in Tables **4** and **7** support the arguments in Conjecture 2 that linear and nonlinear causality are independent. The tables show that sometimes there exists linear causality, but there is no nonlinear causality, sometimes there is no linear causality but there exists nonlinear causality, and sometimes there exist both linear and nonlinear causality, but the tables do not show the case for there does not exist any linear or nonlinear causality.

3.9. Simple Nonlinear Granger Causality

Again, the panel non-linear Granger causality test in Section 3.8 can only lead us draw conclusion for non-linear Granger causality from any risk to the bond spread for all the countries in either BRICS or PIIGS, but not for any particular country. Thus, to complement the analysis of the panel non-linear Granger causality test, we conduct the simple nonlinear Granger causality test for each of the countries in BRICS or PIIGS and report the results in Table **9a** for each of the countries in BRICS and Table **9b** for each of the countries in PIIGS.

From Table **9a**, we find that in the BRICS group, ER strongly non-linearly Granger causes Bond spread for Brazil, India and South Africa, while there is only a weak non-linearly causality effect from ER to bond spread for China and Russia. In addition, FR strongly non-linearly Granger causes bond spread for Brazil, China, and South Africa, there is only a weak non-linearly causality effect from FR to bond spread for Russia, and there is no non-linearly causality from FR to bond spread for India. Moreover, PR strongly non-linearly Granger causes bond spread for both Brazil and South Africa, while there is no non-linearly causality from PR to bond spread for China, India and Russia.

Table **9b** shows in the PIIGS group that ER strongly non-linearly Granger causes bond spread for Ireland, Greece, and Spain, there is only a weak non-linearly causality effect from ER to bond spread for Italy, and there is no non-linearly causality from ER to bond spread for Portugal. In addition, we observe that FR strongly non-linearly Granger causes bond spread for

Table 9a: Individual Non-Linear Granger Causality Test (BRICS Group)

Null Hypothesis	Lag 1	Lag 2	Lag 3	Lag 4
Brazil				
ER does not Granger cause Bond Spread	2.13**	1.89**	2.02**	1.46*
FR does not Granger cause Bond Spread	0.73	1.82**	1.38*	1.27
PR does not Granger cause Bond Spread	2.01**	1.85**	1.75**	2.66***
China				
ER does not Granger cause Bond Spread	1.30*	-0.62	0.25	-0.32
FR does not Granger cause Bond Spread	-1.46*	0.02	1.70**	2.49***
PR does not Granger cause Bond Spread	0.35	1.07	0.99	1.17
India				
ER does not Granger cause Bond Spread	1.67**	1.09	1.08	1.39*
FR does not Granger cause Bond Spread	-0.38	0.27	1.08	1.18
PR does not Granger cause Bond Spread	1.15	0.69	0.88	1.19
Russia				
ER does not Granger cause Bond Spread	-1.55*	-0.92	-0.76	0.78
FR does not Granger cause Bond Spread	1.39*	1.02	1.02	0.21
PR does not Granger cause Bond Spread	-0.62	1.07	1.01	0.70
South Africa				
ER does not Granger cause Bond Spread	1.32*	0.88	1.54	1.59*
FR does not Granger cause Bond Spread	-0.07	-1.49*	1.58*	1.92**
PR does not Granger cause Bond Spread	1.42*	2.07**	1.88**	1.16

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Table 9b: Individual Non-Linear Granger Causality Test (PIIGS Group)

Null Hypothesis	Lag 1	Lag 2	Lag 3	Lag 4
Portugal				
ER does not Granger cause Bond Spread	0.40	0.65	-0.66	0.50
FR does not Granger cause Bond Spread	-0.79	-1.83**	-1.30*	-1.18
PR does not Granger cause Bond Spread	0.70	-0.47	-0.72	-0.27
Ireland				
ER does not Granger cause Bond Spread	1.48*	1.74**	1.20	1.85**
FR does not Granger cause Bond Spread	0.22	-1.10	-0.46	0.83
PR does not Granger cause Bond Spread	-1.81**	0.29	1.16	0.57
Italy				
ER does not Granger cause Bond Spread	0.44	1.51*	1.06	1.02
FR does not Granger cause Bond Spread	-2.45***	-1.13	0.02	-0.06
PR does not Granger cause Bond Spread	2.24**	1.85**	0.79	1.43*
Greece				
ER does not Granger cause Bond Spread	-1.91**	-1.72**	-1.60*	0.72
FR does not Granger cause Bond Spread	0.10	0.26	0.57	0.35
PR does not Granger cause Bond Spread	-1.02	-0.97	-0.87	0.76
Spain				
ER does not Granger cause Bond Spread	1.23	1.60*	1.74**	2.06**
FR does not Granger cause Bond Spread	0.79	0.39	0.63	0.79
PR does not Granger cause Bond Spread	1.22	-0.84	-1.09	-0.69

Notes: The *, **, and *** denote the significance at 10%, 5% and 1% levels, respectively.

Portugal, there is only a weak non-linearly causality effect from FR to bond spread for Italy, and there is no non-linear causality from FR to Bond spread for Ireland, Greece, and Spain. Moreover, we document that PR strongly non-linearly Granger causes bond spread for Italy, there is only a weak non-linearly causality effect from FR to bond spread for Ireland, and there is no non-linearly causality from FR to bond spread for Portugal, Greece, and Spain.

When we compare the results of the simple linear Granger causality results displayed in Tables **6a** and **6b** with the results of the panel non-linear Granger causality exhibited in Tables **9a** and **9b**, we get very interesting findings: 1) Table **6a** shows that there are many strongly linear Granger causality relationships in BRICS while Table **9a** also shows that there are many strongly nonlinear Granger causality relationships in BRICS. However, on the other hand, 2) Table **6b** shows that there are only a few (3 out of 20) linear Granger causality relationships in PIIGS but Table **9b** shows that there are many (11 out of 20) nonlinear Granger causality relationships in PIIGS and Tables **9a** and **9b** contain all the cases stated in Conjecture 3. Together with the findings from both the panel linear and nonlinear Granger causality, this observation suggests authors should examine whether there is any nonlinear causality in their study, no matter whether they find any linear causality in their study.

In sum, we can conclude, that while linear model results are informative, given the presence of nonlinearity in the relationships between spreads and risks, the results from the linear model cannot be relied upon, as the model is misspecified. Given this, when we look at nonlinear causality, we find that economics risks are more relevant in explaining bond spreads in the BRICS and the PIIGS relative to financial and political risks. These results tend to make sense, given that these economies are in general politically stable, and also have sound financial system overall, except during the global turmoil that resulted in the financial and sovereign debt crises, especially in the PIIGS, and during the East Asian crisis in India and China especially. However, given the nature of these economies, the importance of economic risks driven by factors involving growth, inflation, hence monetary policy, and management of fiscal and the current account balances, are likely to drive the bond spreads more, given that economic risks tend to affect the underlying state of the economy, i.e., the fundamentals. But it must also be pointed out that to reach to this inference, one needs to pursue a correct modeling strategy that involves nonlinearity and not a linear framework.

4. CONCLUDING REMARKS

This study examines the impacts of political risk (PR), financial risk (FR), and economic risk (ER) to bond spread. We find that all the variables in our study are I(1). There are panel cointegration relationships between Bond spread and any of the risks for all the countries in either BRICS and PIIGS groups and for each country, there is at least one risk that is cointegrated with the bond spread while except a few countries (Brazil and China in BRICS and Portugal and Ireland in PIIGS), all risks are cointegrated with the bond spread. This concludes that there is a strong panel cointegration link between risks and bond spread, and thus, we conclude that there is long run comovement between all the risks and bond spread for both BRICS and PIIGS.

Nonetheless, different from the strong cointegration relationships between bond spread and risks for all the countries in both BRICS and PIIGS groups, our panel linear Granger causality concludes that PR is the most important risk to bond spread because it strongly panel linear Granger causes bond spread for both BRICS and PIIGS; followed by ER that strongly panel linear Granger causes bond spread for only BRICS but not PIIGS; while FR is the least important because it does not panel linear Granger causes bond spread in either BRICS or PIIGS. Our individual linearly causality results show that the main significance is from India and Russia from BRICS that in these two countries, ER, and PR, especially for ER, strongly linear-cause bond spread. The rests are either weakly linear-cause bond spread or no linear causality at all. For the PIIGS groups, there is no linear causality for nearly all the cases except PR strongly linear-causes bond spread for Greece and weakly linear-causes Bond spread for Spain. It is not surprising that our individual linearly causality results support the finding from our panel linear Granger causality that PR is the most important risk to bond, followed by ER because PR linear Granger causes bond spread in 3 (out of 5) countries in BRICS and 2 (out of 5) countries in PIIGS while ER linear Granger causes bond spread in 3 countries in BRICS but only 1 (out of 5) countries in PIIGS. Nonetheless, it is interesting to notice that FR does not panel linear Granger causes bond spread in either BRICS or PIIGS but it does weakly linear Granger causes bond spread in 2 countries in BRICS but still no country in PIIGS. This can lead us to conclude that FR is still weakly useful in predicting bond spread in India and South Africa in BRICS but not in PIIGS.

In this paper, we make a conjecture that linear and nonlinear causality are independent in the sense that sometimes there exists linear causality but there is no nonlinear causality, sometimes there is no linear causality but there exists nonlinear causality, and so on. For example, our panel nonlinear causality test concludes that only PR panel nonlinear causes bond spread in BRICS but all the risks (ER, FR, and PR) panel nonlinear causes bond spread in PIIGS. On the other hand, our pairwise individual non-linear Granger causality test shows all the risks (ER, FR, and PR) can predict bond spread nonlinearly in Brazil and South Africa in BRICS and Italy in PIIGS; both ER and FR can predict bond spread nonlinearly in China and Russia in BRICS; ER and PR can predict bond spread nonlinearly in Ireland in PIIGS; ER can predict bond spread nonlinearly in India in BRICS and Greece and Spain in PIIGS; but FR can predict bond spread nonlinearly in Portugal in PIIGS. Nevertheless, different from our linear causality results claim that PR is the most important risk in predicting bond spread linearly, followed by ER, while FR can weakly predict bond spread linearly in India and South Africa, our nonlinear individual causality results infer that ER is the most important risk in predicting bond spread nonlinearly, followed by FR, and PR because they can be used in predicting bond spread nonlinearly in 9, 6, and 4 countries, respectively.

The outcomes of this paper have important implication for a number of audiences such as portfolio managers, investors in the fixed income market and government agencies. The investment and risk managers should be careful about the political, economic and financial risk as it could destabilise the government bond spread. Further, for diversification purpose, the financial institutions, global investors and central banks frequently hold government bonds, the significant results of political risk and other variables on government bonds suggest that diversification benefit will be lower.

There is another important observation in our paper that our findings infer that there could be other factors, for example, nonlinearity "auto-causality" from the past data of the dependent variable, to cause the nonlinearity, besides from nonlinear causality. However, there is no formal nonlinearity "auto-causality" test from the past data of the dependent variable, and thus, our finding suggests academics could develop such test to explore another type of nonlinearity from the dependent variable, which we consider as a future area of research. Of course, one could use other nonlinear approaches to study dependence as in Ji *et al*., (2018b), and Kumar *et al*., (2019). In addition, given that in-sample predictability does not guarantee out-of-sample gains (Campbell, 2008), it would be interesting to extend our analysis to a full-fledged forecast exercise.

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