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International Portfolio Diversification Possibilities: Could BRICS become a Destination for G7 Invesments?

Lei Pan[1] and Vinod Mishra[2]*

Abstract:
We investigate the diversification possibilities between BRICS and G7 stock markets. Our theoretical model suggests that risk-averse investors are diversifying internationally. The findings of cointegration test with multiple structural breaks reveal that apart from China and India, the remaining BRICS equity markets can be a potential diversification destination over the long term. The full sample bootstrap Granger causality tests results imply that G7 stock markets have predictive power for most BRICS stock markets. Both the long-run and shortrun parametric stability tests suggest that the full sample parameters are unstable hence unreliable The bootstrap rolling window estimations outline the causalities between stock markets are increasing during the crisis periods and vary over different sub-samples. Overall, our causality findings suggest that the short-term diversification possibilities are extremely limited. Finally, we analyze the impact of different financial and macroeconomic determinants on the cross-country stock market causality through a probit model. We find the difference in business conditions, excess return and size premium are the main drivers of the causality flows.

Keywords: international diversification, structural breaks, bootstrap rolling windows
JEL Codes: F30, G11, G15

[1] Department of Economics, Monash University, 900 Dandenong Road, Caulfield East, Vic, 3145, Australia. Email: lei.pan@monash.edu
[2] Corresponding author. Department of Economics, Monash University. Wellington Rd, Clayton, Vic, 3800, Australia. Email: vinod.mishra@monash.edu

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"*Be fearful when others are greedy, and be greedy when others are fearful.*"

— *Warren Buffett*

1 Introduction

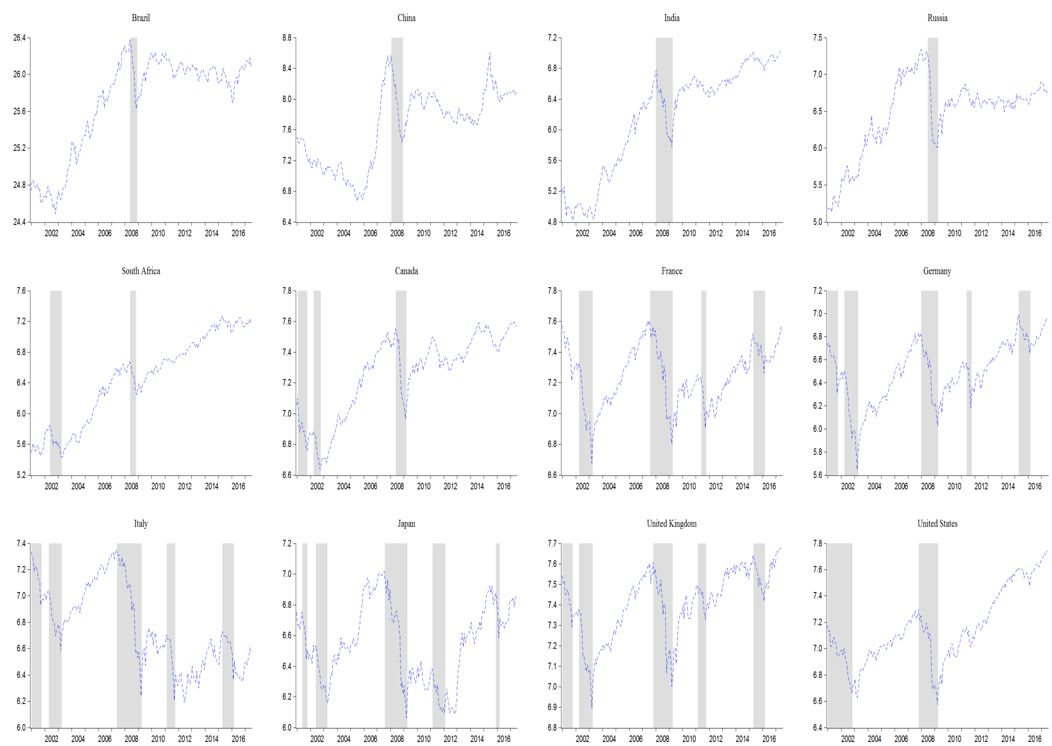
International portfolio diversification has long been advocated as a way of enhancing average returns while reducing portfolio risks for the investors who are diversifying into foreign equities. Since the introduction of portfolio theory by Markowitz in the early 1950s, the financial literature has flourished with international risk diversification and investment management. These benefits stemmed from the observation of less than perfect correlations among returns on national stock markets. This topic has attracted significant interest not only among academics but also among institutional investors such as mutual funds, pension funds and hedge funds investors. The resulting public attention, in turn, paved the way for the birth of a myriad of institutional products designed for an internationally-minded investor looking for diversification possibility in a market place.

Sharpe (1964) in his seminal paper had explained that diversification can remove unsystematic risk via portfolio investments. However in a relatively recent work Hui (2005) argued that international portfolios are capable of reducing systematic risk as well. Therefore investigating diversification possibilities is the most relevant information for investment portfolios and hedging decisions. Harvey (1995) showed that including the so-called emerging stock markets in an optimally diversified portfolio substantially increase expected returns. Developing countries have experienced higher economic growth than developed countries, which provides opportunities to generate higher returns in international portfolios (Butler and Joaquin, 2002; Naranjo and Porter, 2007). This may explain the intensively increase in the allocation of emerging market assets in the portfolios of developed country investors has increased from 5% in 2002 to 13% in 2012.[1] Despite the diversification benefits offered by the developing countries, there are two issues international investors need to concern about. First, there is a growing literature indicated the degree in co-movement becomes higher across advanced and emerging financial markets (Ratanapakorn and Sharma, 2002; Chambet and Gibson, 2008), also among several major developing countries (Tai, 2007; Middleton et al., 2008). Second, due to reservation spate of economic and currency crises, there is an increase in the return volatilities and a decrease in the returns for international investors (Lagoarde-Segot and Lucey, 2007). These facts could alter the flow of portfolio

[1] Refer the IMFBlog website at: https://blogs.imf.org/2014/11/07/portfolio-investment-in-emerging-markets-more-than-just-ebb-and-flow/

investment capital, which implies that the diversification gains from some developing countries has been limited. International investors, therefore, might have to consider new emerging markets as a potential avenue for diversification benefits.

Fig.1: Stock market performance of BRICS and G7 countries (Dec, 2000 - Jun, 2017)



This paper investigates the international portfolio diversification possibilities between the Group of Seven (G7) and BRICS economies. The acronym “BRIC” was coined by the former Goldman Sachs chief economist Jim O’Neill in 2001 to highlight the immense economic potential of the emerging markets of Brazil, Russia, India and China. South Africa joined the group in 2010 which led to the creation of BRICS association. We look at the BRICS stock markets for several reasons. First, the BRICS economies are constantly improving their market microstructure (e.g. updating investment laws, opening up to international trade). Second, BRICS governments have been active in promoting awareness of investment opportunities there.[2] The financial and economic reforms in these countries seem to be remarkable over recent years. In particular, the

[2] For example, issues related to trade and investment promotion were discussed at the recent (year 2017) 7th meeting of the BRICS Ministers of Trade in Shanghai, China. South Africa’s Trade and Industry Minister Rob Davies said cooperation will be strengthened between the investment promotion agencies (IPAs) so as to promote exchange of information on investment facilitation.

BRICS nations have been demonstrated high economic growth rates (at 3%-8%) that are well above those of the west[3] – maintaining BRICS white hot investment place among fund managers and individual investors alike. To illustrate the behaviors of different stock markets, Fig.1 plots the natural logarithm of monthly Morgan Stanley Capital International (MSCI) stock market indices of BRICS and G7 countries in the period from December 2000 to June 2017. Two observations can be made here. First, both BRICS and G7 stock markets were in a full blown bear market during the 2007-2008 Global Financial Crisis (GFC). Second, advanced markets appear to be more volatile than emerging markets (grey column represents period of shock), indicating that investors from developed countries are likely to have diversification possibilities among BRICS countries in times of recession.

Our study contributes to the existing literature in the following manners. First, the portfolio management literature is largely anecdotal, lacking theoretical explanations on the how and why of international diversification. Herein, we established a theoretical model for showing risk-averse investors are diversifying internationally.

Second, although numerous studies have discussed co-movements between different equity markets and their impacts on international diversification benefits (see Errunza et al., 1999; Driessen and Laeven, 2007; Bekaert et al., 2008; Bai and Green, 2010), very little attention has been given to the issue of structural changes. This paper fills the gap by taking into consideration the possibility of structural breaks in the time series we employ. The presence of structural breaks and their potential impact in testing for unit roots, vector autoregession (VAR) estimation, forecasting or causality inference has gained importance in recent years (Kilian and Ohanian, 2002; Ng and Vogelsang, 2002). The examination of structural changes is reinforced in our study given the (trending) nature of the time series we use. In particular, stock markets can be considered to exhibit at least two breaks in the 2001 due to the terrorist attack and in the 2008 because of the GFC. In this paper, instead of considering the structural breaks as exogenous, we apply methods in which the breakpoints are estimated rather than fixed. Specifically, to select the parsimonious model with the optimal number of breaks we employ the recent techniques of Perron and Yabu (2009) and Kejriwal and Perron (2010) which comprise sequential tests for a break in the trend function of a time series occurring at an unknown date, when the noise component can be either stationary or integrated. Once we ascertain whether breaks are, the null hypothesis of unit root is examined under this broken trend specification using the Lee and Strazicich (2003) minimum Lagrange Multiplier (LM) tests. This contributes to the existing studies that just apply a unit

[3] For example, the growth rates for France and Germany are within 0.2%-0.8%. The statistic of economic growth rate is from the Borysfen Intel website, available online at: `http://bintel.com.ua/en/article/briks-perspektivy-jekonomicheskogo-razvitija/`

root testing methodology that allows for endogenous breaks. Such approach suffers from the problem of low power because of the inclusion of extra break dummies in the absence of breaks, thus may lead to misspecification bias and/or create a situation of over-fitting the model to data.

Our third contribution is related to the causality test method. The results in the literature on the causality between different stock markets are at large variability, especially with respect to the sample period selected (e.g. Gilmore and McManus, 2002; Yinusa, 2008; Meric et al., 2008). One important issue relating to the data used in these studies is the structural changes or regime shifts. A further variability in the results is due to the handling of the trending properties of the data. The results using cointegrated models are mostly different than results of those ignoring the integration-cointegration properties of the data. The present study takes these two issues into account by using bootstrap tests and rolling window estimation. To the best of our knowledge, only a few research consider structural changes when testing for causality. We apply bootstrap causality tests for two reasons. First is to be robust against small sample and integration-cointegration properties of the data. Second, the existing studies on portfolio diversification all examined Granger causality in the full sample using several variants of the Granger causality test. All type of Granger causality tests assume (non)existence of of a causal relationship over the full sample. Nevertheless, the causality might not be stable over the time, therefore the causality testing results for the entire sample might be misleading (i.e. When the causal relationship between two variables is time-varying and the non-causality is not rejected, then it is ambiguous what has been rejected). A variable may Granger cause another variable in some periods but not in other times or there might be a switch between unidirectional causality to bidirectional causal relationship or vice-versa under certain conditions. Due to policy changes, the causality between stock markets may shift in time. Moreover, volatile periods during recessions may also be radically different than other periods. As a consequence, in this paper, we investigate the causality in a time-varying fashion using bootstrap Granger causality test. To show the subsample variability of the Granger causality tests and provide an explanation to variability, we use subsample rolling bootstrap tests.

Fourth, we examine the possible determinants of cross-country stock market causality using the probit model. We quantify rather than qualify (most of the existing studies on portfolio management applied) a set of instruments that may explain the causality flows between different stock markets.

Foreshadowing the main results, our theoretical model show that risk-averse investors only invest in risky assets whose expected returns are positive (Proposition 1), and they will invest more on risky assets if they are more wealthier (Proposition 2). Our empirical findings indicate that except China and India, the remaining BRICS stock markets can be good places to diversify portfolio risk in the long term. Moreover, we find the causal linkage between stock markets becomes stronger in the times of recession, the short-run diversification possibilities therefore are extremely limited. All in all, difference in business conditions, excess return and size premium appear to be the significant determinants of causality dynamics between stock markets.

The rest of this paper is organized as follows. In Section 2, we develop our theoretical model. Section 3 and 4 describe data and empirical methodology respectively. Section 5 discusses the empirical results. Section 6 analyses and provides the plausible reasons for stronger co-movements between equity markets in the periods of shocks. Section 7 concludes the paper. In the Online Appendix, we lay out the Kejriwal and Perron (2010) sequential procedure for the estimation of number of structural breaks and parametric bootstrapping procedure used for causality analysis. We also describe the data and procedure used to construct the efficient frontier. Furthermore, we report a detailed break dates description and the results of serial correlation LM tests.

2 The Model

2.1 Model set up

Assume the global financial market consisting of two types of assets, the risk-free asset whose rate of return is denoted as r_f and the risky asset whose rate of return is denoted as r. Consider a rational investor who is risk-averse and his initial endowment of asset is A. Denoting m and a as the amount of money invested in risk-free and risky asset respectively, then the value of investor's asset at the end of current period (W) is:

$$W = m(1 + r_f) + a(1 + r) \tag{1}$$

Due to uncertainty, we further assume there are two investment outcomes, what we call two natural states, S_1 and S_2. When the state of S_1 happens, $r = r_1 > 0$; otherwise, $r = r_2 < 0$. Denote p as the probability of S_1 occurs $(0 \leq p \leq 1)$, accordingly $(1 - p)$ is the probability that S_2 happens, W_i is the asset value with the appearance of S_i, which can be written as:

$$W_1 = m(1 + r_f) + a(1 + r_1), \qquad W_2 = m(1 + r_f) + a(1 + r_2) \tag{2}$$

Since $A = m + a$, Eq.(2) can be rewritten as below.

$$W_1 = A + mr_f + ar_1, \qquad W_2 = A + mr_f + ar_2 \tag{3}$$

The expected value of the investor's asset is:

$$E(W) = pW_1 + (1-p)W_2 = p(A + mr_f + ar_1) + (1-p)(A + mr_f + ar_2) \tag{4}$$

Simplifying Eq.(4), can obtain:

$$E(W) = A + mr_f + a\left[pr_1 + (1-p)r_2\right] = A + mr_f + aE(r) \tag{5}$$

Assume the investor's utility function has the following properties: (i): Consumers are never satisfied (i.e. more consumption, higher utility). Mathematically, $U(\cdot)$ is an increasing function (i.e. $U'(\cdot) \geq 0$). (ii): Because of the risk-averse assumption, we have: $U''(\cdot) < 0$. (iii): Coefficient of absolute risk aversion is decreasing. The coefficient of absolute risk aversion is defined as $R_a(\cdot) = \frac{-U''(\cdot)}{U'(\cdot)}$. Therefore, this property requires $R_a'(\cdot) < 0$. (iv): Coefficient of relative risk aversion is increasing. Pratt (1964) defined the coefficient of relative risk aversion as $R_r'(c) = \frac{-cU''(c)}{U'(c)}$, where c represents consumption. The property requires $R_r'(\cdot) > 0$.

The expected utility of the investor can be specified as:

$$U(E(W)) = pU(W_1) + (1-p)U(W_2) = pU(A + mr_f + ar_1) + (1-p)U(A + mr_f + ar_2) \tag{6}$$

The optimization problem is that investor chooses the amount of money invested in the risky assets (a) to maximize his utility.

$$f(a) = pU(A + mr_f + ar_1) + (1-p)U(A + mr_f + ar_2) \tag{7}$$

The initial value of asset (A) is a constant when $a \geq 0$. The first order condition (F.O.C) with respect to a is:

$$f'(a) = pU'(A + mr_f + ar_1)r_1 + (1-p)U'(A + mr_f + ar_2)r_2 = 0 \tag{8}$$

Simplifying Eq.(8) can get:

$$\frac{p}{1-p}\frac{U'(A + mr_f + a^*r_1)}{U'(A + mr_f + a^*r_2)} = -\frac{r_2}{r_1} \tag{9}$$

The optimal amount of money invested in risky assets (a^*) can be determined by the above equation.

The second order condition with respect to a is:

$$f''(a) = pr_1^2U''(A + mr_f + ar_1) + (1-p)r_2^2U''(A + mr_f + ar_2) \tag{10}$$

Due to the assumption of ration investor, that is, $U''(\cdot) < 0$, then we have $f''(a) < 0$. This suggests that the solution of a given by Eq.(9) is an unique extreme value. From Eq.(2), we can get:

$$\frac{A + mr_f - W_2}{W_1 - A - mr_f} = -\frac{r_2}{r_1} \tag{11}$$

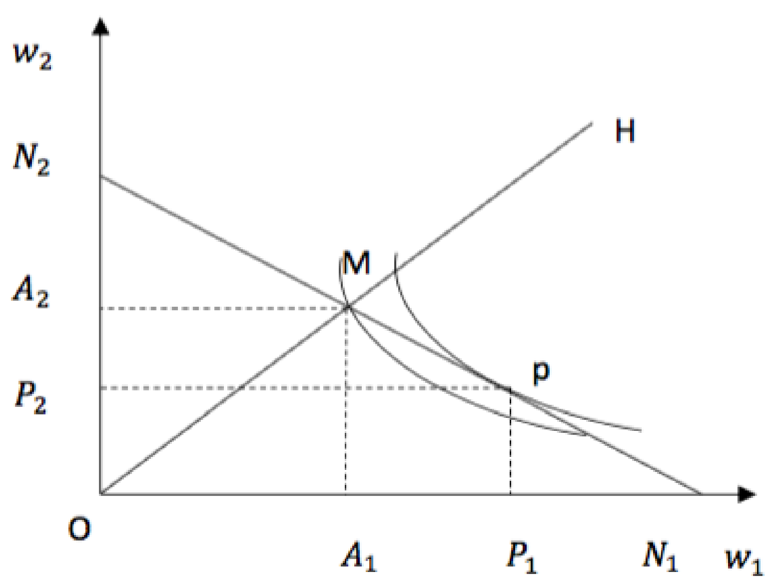
Let $k = -\frac{r_2}{r_1}$, Eq.(11) can be written as:

$$(1 + k)(A + mr_f) = kW_1 + W_2 \tag{12}$$

2.2 Graphic analysis: Optimal portfolio selection and indifference curves

Suppose investor chooses W_1 and W_2 to maximize $f(a)$, where $W_1 \geq 0$ and $W_2 \geq 0$. If there exists an inner solution ($W_1^* \geq 0$, $W_2^* \geq 0$), where W_1 and W_2 can be calculated through Eq.(9) and also satisfy Eq.(12) (shown in Fig.2).

Fig.2: The condition of risk-averse investors investing in risky assets ($E(r) > 0$)



The line N_1N_2 stands for the budget line that (W_1, W_2) satisfies Eq.(12) (or what we called "opportunity line"). The horizontal intercept of N_1N_2 can be obtained by setting $W_2 = 0$ in Eq.(12), thus $ON_1 = \frac{1+k}{k}(A + mr_f)$. Similarly, letting $W_1 = 0$ in Eq.(12), we can get the vertical intercept, that is, $ON_2 = (1 + k)(A + mr_f)$. The intersection point of the angular bisector of forty-five degree angle (OH) and N_1N_2 is M. Therefore, $A_1 = A_2$ which is investor's initial value of asset (A). Moreover, from Eq.(2), we know that at point M, $a = 0$, that is, investor puts all his money on risk-free asset (we call OH the "line of certainty").

The indifference curve is the set of (W_1, W_2) in the following equation.

$$pU(W_1) + (1-p)U(W_2) = constant \tag{13}$$

Taking the total derivative, can obtain:

$$\frac{dW_2}{dW_1} = -\frac{p}{1-p}\frac{U'(W_1)}{U'(W_2)} \tag{14}$$

From Eq.(9), we know that the optimal point P is the point at which the opportunity line OH tangent to the indifference curve.

Proposition 1. *For the risk-averse investors, they only invest in risky assets whose expected rate of returns are positive.*

Proof. In Fig.2, notice that: $OP_1 = A + mr_f + a^*r_1$, $OP_2 = A + mr_f + a^*r_2$. Furthermore, $A_1P_1 = OP_1 - OA_1 = a^*r_1$ and $A_2P_2 = OA_2 - OP_2 = -a^*r_2$.

If $a^* > 0$, then $W_1^* = A + mr_f + a^*r_1 > W_2^* = A + mr_f + a^*r_2$. Thus, $U'(W_1^*) < U'(W_2^*)$. Given the above inequality and from Eq.(9), can get: $\frac{1-p}{p}k < 1$. Therefore, we have:

$$E(r) = pr_1 + (1-p)r_2 > 0 \tag{15}$$

■

2.3 Comparative static analysis

The optimal amount of money invested in risky assets (a^*) depends on different parameters. In this section, we only analysis the effect of change in A on a^*.

Proposition 2. *If investors are risk-averse and the coefficient of absolute risk aversion is decreasing, then increase in the value of initial assets will increase the investment on risky assets.*

Proof. Taking the derivative with respective to A for both sides of Eq.(9) and (12) respectively.

$$U''(W_1^*)dW_1^* = \frac{1-p}{p}kU''(W_2^*)dW_2^* \tag{16}$$

$$(1+k)dA = kdW_1^* + dW_2^* \tag{17}$$

From Eq.(16), we can obtain:

$$dW_2^* = \frac{p}{1-p}\frac{1}{k}\frac{U''(W_1^*)}{U''(W_2^*)}dW_1^* \tag{18}$$

Plugging Eq.(18) into (17), can get:

$$(1+k)dA = (k + \frac{p}{1-p}\frac{1}{k}\frac{U''(W_1^*)}{U''(W_2^*)})dW_1^*$$

Rearrange above equation, get:

$$\frac{dW_1^*}{dA} = \frac{1+k}{k + \frac{p}{1-p}\frac{1}{k}\frac{U''(W_1^*)}{U''(W_2^*)})}$$

Simplifying above equation, can obtain:

$$\frac{dW_1^*}{dA} = \frac{1-p}{p}\frac{k(1+k)U''(W_2^*)}{U''(W_1^*) + \frac{1-p}{p}k^2U''(W_2^*)} \tag{19}$$

Multiplying $\frac{1}{dA}$ on both sides of Eq.(17), get:

$$1 + k = kd\frac{dW_1^*}{dA} - \frac{dW_2^*}{dA}$$

Solving for $\frac{dW_2^*}{dA}$ in the above equation, can get:

$$\frac{dW_2^*}{dA} = (1+k) - k\frac{dW_1^*}{dA} \tag{20}$$

Plugging Eq.(19) into Eq.(20), we have:

$$\frac{dW_2^*}{dA} = (1+k) - \frac{k^2(1-p)(1+k)U''(W_2^*)}{pU''(W_1^*) + (1-p)k^2U''(W_2^*)}$$

The above equation can be written as:

$$\frac{dW_2^*}{dA} = \frac{(1+k)[pU''(W_1^*) + (1-p)k^2U''(W_2^*)] - k^2(1-p)(1+k)U''(W_2^*)}{pU''(W_1^*) + (1-p)k^2U''(W_2^*)}$$

Simplifying the above equation, can get:

$$\frac{dW_2^*}{dA} = \frac{(1+k)pU''(W_1^*)}{pU''(W_1^*) + (1-p)k^2U''(W_2^*)} \tag{21}$$

Dividing p for both nominator and denominator on the right hand side of Eq.(21), we have:

$$\frac{dW_2^*}{dA} = \frac{(1+k)U''(W_1^*)}{U''(W_1^*) + \frac{1-p}{p}k^2U''(W_2^*)} \tag{22}$$

Because $U''(\cdot) < 0$, thus $\frac{dW_1^*}{dA} > 0$ and $\frac{dW_2^*}{dA} > 0$. Calculating the difference between W_1^* and W_2^*, we can get:

$$W_1^* - W_2^* = a^*(r_1 - r_2) \tag{23}$$

Taking the derivative with respect to A on both sides of Eq.(23), obtain:

$$\frac{dW_1^*}{A} - \frac{dW_2^*}{A} = (r_1 - r_2)\frac{da^*}{dA} \tag{24}$$

From Eq.(24), we have:

$$\frac{da^*}{dA} = \frac{1}{(r_1 - r_2)}(\frac{dW_1^*}{A} - \frac{dW_2^*}{A})$$

Plugging Eq.(19) and (22) into above equation, get:

$$\frac{da^*}{dA} = \frac{1}{(r_1 - r_2)}[\frac{\frac{1-p}{p}k(1+k)U''(W_2^*) - (1+k)U''(W_1^*)}{U''(W_1^*) + \frac{1-p}{p}k^2U''(W_2^*)}] \tag{25}$$

From Eq.(19), we have:

$$\frac{1-p}{p} = \frac{1}{k}\frac{U'(W_1^*)}{U'(W_2^*)} \tag{26}$$

Plugging Eq.(26) into Eq.(25), can obtain:

$$\frac{da^*}{dA} = \frac{1}{(r_1 - r_2)}\frac{[\frac{(1+k)U'(W_1^*)U''(W_2^*)}{U'(W_2^*)} - (1+k)U''(W_1^*)]}{U''(W_1^*) + \frac{1-p}{p}k^2U''(W_2^*)}$$

Extracting the common factor $(1+k)U'(W_1^*)$ out from the nominator of the second term on the right hand side of the above equation, we can get:

$$\frac{da^*}{dA} = \frac{1}{(r_1 - r_2)}\frac{(1+k)U'(W_1^*)(\frac{U''(W_2^*)}{U'(W_2^*)} - \frac{U''(W_1^*)}{U'(W_1^*)})}{U''(W_1^*) + \frac{1-p}{p}k^2U''(W_2^*)} \tag{27}$$

Since $R_a(\cdot) = -\frac{U''(\cdot)}{U'(\cdot)}$, Eq.(27) can be further written as:

$$\frac{da^*}{dA} = \frac{1}{(r_1 - r_2)} \frac{-(1+k)U'(W_1^*)(R_a(W_2^*) - R_a(W_1^*))}{U''(W_1^*) + \frac{1-p}{p}k^2 U''(W_2^*)} \tag{28}$$

Because $U''(\cdot) < 0$ and $R_a'(\cdot) < 0$, we can get $\frac{da^*}{dA} > 0$.

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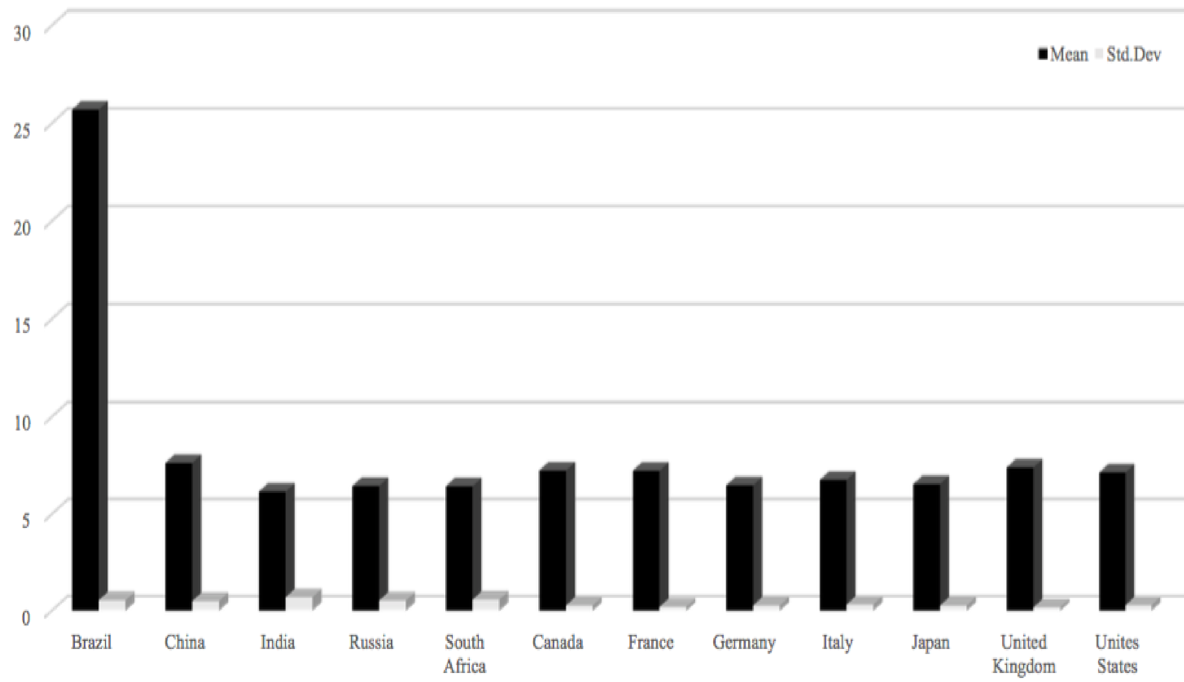
3 Data

The variable of interest is the stock market indices in BRICS and G7 nations. As suggested by Christou (2008), monthly data is most commonly used in portfolio management research, in this study, therefore, we use monthly MSCI stock market price indices for the period from December 2000 to June 2017 as proxies for stock market performance. Data is retrieved from the Thomson Reuters DataStream Database, they are all broad country level indices, created using the same methodology across countries. All series are converted into natural logarithmic form to reduce large volatility spikes and to increase the reliability of results.

Fig.3 plots the mean and standard deviations (SD) of the stock market price index by country. It shows that except for Brazil the index level varies slightly from country to country. The volatility of stock market as measured by the SD highlights a clear country-wise pattern. Specifically, in developed countries the volatility is low, while in BRICS countries it is high.

The descriptive statistics of the stock market price indices are presented in Table 1. The term CV denotes the coefficient of variation which is a measure to compare the degree of variation from one series to another due to the mean values of the stock market price indices are different among countries. This statistic is helpful to determine how much risk a person has to bear compared to the returns from investments. In particular, lower the ratio, better the risk-return trade-offs. Table 1 reveals that investors in almost all BRICS countries face a worse risk-return trade-off compare to their counterparts in developed countries. The only exception in BRICS is Brazil, which has the lowest CV with a relatively high systematic risk. Brazil has the largest market capitalization in Latin American region. Shortcomings in its legal and regulatory framework contribute a lion's share to the investment risk, high cost of capital and low valuation. The low CV of Brazilian stock market may due to its high stock market return. Given the fact that Brazil's stock market is concentrated in a small number of large energy companies, and because of the acceleration of industrialization, energy sector is always the most profitable industry. The high return of Brazilian stock market, therefore, is possibly a reflection of its energy sector's performance. In addition, all series are non-normal since the null hypothesis of normality for Jarque-Bera (JB) test is rejected at the 10% level or better.

Fig.3: Mean values and standard deviations of MSCI stock market price indices (in level form)



4 Empirical Methodology

4.1 Unit root properties of data

Existing studies indicate that macroeconomic and financial time series contain unit roots dominated by stochastic trends. Therefore, it is important to perform unit root tests to investigate the stationarity property of the variables before conducting any further analysis. Furthermore, a necessary but not sufficient condition for cointegration is that each of the stock market price indices should be integrated of the same order. The reason is to ensure no incorrect inference are made due to spurious regression. In this paper, we apply the augmented Dickey and Fuller (1979, ADF) test, the Phillips and Perron (1988, PP) test and the KPSS (Kwiatkowski et al., 1992) test to detect the mean-reverting tendency of the series. The stationary null hypothesis of KPSS test makes it a perfect candidate to validate the results of the ADF and PP tests, both with unit root null.

4.2 Structural breaks

One of the common features or stylized facts in a time series data is the presence of structural breaks. Structural breaks can be described as unexpected shifts in the data generating process

Table 1: Descriptive statistics for stock market indices

ln(MSCI stock market index)	Obs.	Mean	Std.Dev.	Min	Max	CV (%)	Skewness	Kurtosis	J-B stats
Panel A: *BRICS countries*									
Brazil	199	25.70	0.53	24.50	26.40	2.06	-0.966	2.465	33.512***
China	199	7.64	0.49	6.67	8.61	6.41	-0.285	1.968	11.518***
India	199	6.16	0.69	4.82	7.03	11.20	-0.668	2.045	22.354***
Russia	199	6.46	0.52	5.13	7.34	8.05	-0.884	3.140	26.093***
South Africa	199	6.44	0.57	5.43	8.85	8.85	-0.315	1.815	14.927***
Panel B: *G7 countries*									
Canada	199	7.25	0.26	6.64	7.59	3.59	-0.726	2.301	21.555***
France	199	7.24	0.19	6.68	7.61	2.62	-0.242	2.354	5.392*
Germany	199	6.49	0.26	5.64	6.99	4.01	-0.475	2.767	7.945**
Italy	199	6.77	0.31	6.19	7.35	4.58	0.233	1.882	12.167***
Japan	199	6.55	0.26	6.06	7.02	3.97	-0.044	1.953	9.156**
United Kingdom	199	7.41	0.17	6.89	7.69	2.29	-0.701	2.782	16.711***
United States	199	7.15	0.28	6.57	7.75	3.92	0.344	2.344	7.503**

Note: Countries under each panel are listed in alphabetical orders. CV stands for coefficient of variation.

*, **, *** Denotes statistically significant at the 10%, 5% and 1% level respectively.

(DGP), often caused by macroeconomic shocks such as changes in interest rates, economic policies and business cycles etc. Ignoring the presence of structural breaks can lead to serious misspecification biases in the model. On the one hand, it results in non-rejection of unit root null (Perron, 1989; Zivot and Andrews, 1992); significant overestimation of the volatility in the conditional heteroskedasticity models (Lamoureux and Lastrapes, 1990); showing long-term dependence while there is none (Diebold and Inoue, 2001). On the other hand, overlooking structural breaks can return spurious results for cointegration tests (Gregory and Hansen, 1996) and also lead to incorrect descriptive statistics (Valentinyi-Endrész, 2004).

To avoid these pitfalls and to select the appropriate model with the optimal number of structural breaks, we use the tests developed by Perron and Yabu (2009) and Kejriwal and Perron (2010), prior to implementing the unit root tests with structural breaks. We, therefore, first examine whether breaks are present, before applying stationarity tests that allow for identification of such breaks. The Perron and Yabu (2009) method[4] is performed first to test the null hypothesis of no breaks against the alternative hypothesis of one break. For those stock markets where Perron and Yabu (2009) identified there is one break, the Kejriwal and Perron (2010) procedure[5] is used to test the null of one break against the alternative of two breaks.

4.2.1 Lee and Strazicich (2003) unit root test with structural breaks

In his pioneering work, Perron (1989) showed that the presence of an unaccounted structural break in a time series data can lead to a bias that lowers the power of a unit root test to reject a false unit root null hypothesis. Perron (1989) suggested allowing for one known structural break into an ADF test to correct this bias. Subsequent literature (Zivot and Andrews, 1992; Perron, 1997; Lumsdaine and Papell, 1997) extended the ADF-type unit root tests to determine the break point "endogenously" from the data and included the possibility of more than one structural break in the series. Nevertheless, a common problem to ADF-type endogenous break unit root tests is that their critical values are obtained by assuming no break(s) under the null. Nunes et al. (1997) showed that this assumption can lead to size distortions in the presence of a unit root with structural break. Therefore, when conducting ADF-type endogenous break unit root tests, one might conclude a time series is trend stationary, yet in fact the series is non-stationary with break(s), implying that a spurious rejection as a real possibility.

[4] Perron and Yabu test statistic (called $Exp - W_{FS}$) is based on a quasi-Feasible Generalized Least Squares (FGLS) approach using an autoregression for the noise component, with a truncation to one when the sum of the autoregressive coefficients is in some neighborhood of one, along with a bias correction. For given break dates, Perron and Yabu (2009) proposed an F-test for the null of no structural break in the deterministic components using the Exp function developed in Andrews and Ploberger (1994).

[5] The procedure is described in Online Appendix.

Lee and Strazicich (2004) developed two versions of the Schmidt and Phillips (1992) LM unit root test that allowed for one structural break in the series. Applying the nomenclature of Perron (1989), Model A is known as the "crash" model which allows for a one-time change in the intercept under the alternative hypothesis. Model A can be specified as $Z_t = [1, t, D_t]'$, where $D_t = 1$ for $t \geq T_B + 1$ and zero otherwise, T_B stands for the structural break date, and $\delta' = (\delta_1, \delta_2, \delta_3)$. Model C is so called the "crash-cum-growth" model which allows for a shift in the intercept and a change in the trend slope under the alternative hypothesis that can be described as $Z_t = [1, t, D_t, DT_t]'$, where $DT_t = t - T_B$ for $t \geq T_B + 1$ and zero otherwise.

Lee and Strazicich (2003) proposed a version of LM unit root test to incorporate two structural breaks. The two-break minimum LM unit root can be considered as follows. Model AA which is an extension of Model A accommodates two shifts in the intercept. Model CC which is an extension for Model C allows for two changes in the intercept and slope. Sen (2003) pointed out that Model C minimizes the loss of power, therefore, is relatively superior to Model A. Moreover, given the fact that stock price has a time trend, we use the Model C and Model CC of the test. The model can be specified as $Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]'$, where $DT_{jt} = t - T_{Bj}$ for $t \geq T_{Bj} + 1, j = 1, 2$ and zero otherwise. The hypothesis for Model CC are as follows:

$$H_0 : y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + d_3 D_{1t} + d_4 D_{2t} + y_{t-1} + v_{1t}$$

$$H_A : y_t = \mu_1 + \gamma t + d_1 D_{1t} + d_2 D_{2t} + d_3 DT_{1t} + d_4 DT_{2t} + v_{2t}$$

where v_{1t} and v_{2t} are stationary error terms; $B_{jt} = 1$ for $t = T_{Bj} + 1, j = 1, 2$ and zero otherwise. Based on the LM (score) principle, the test statistic can be obtained from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \bar{S}_{t-1} + \mu_t \tag{29}$$

where $\bar{S}_t = y_t - \hat{\psi}_x - Z_t \hat{\delta}_t, t = 2, ..., T$; $\hat{\delta}$ refers to the coefficients of ΔZ in Eq.(29); $\hat{\psi}_x$ equals $y_t - Z_t \delta$; and y_1 and Z_1 denote the first observations of y_t and Z_t respectively. The LM test statistic is defined as: $\bar{\tau} = t$ for the null hypothesis that $\phi = 0$. The location of structural break (T_B) is endogenously determined by selecting all possible break points for the minimum t-statistic as below:

$$lnf \tilde{\tau}(\bar{\lambda}_i) = lnf_{\lambda} \tilde{\tau}(\lambda)$$

where $\lambda = T_B / T$.

The grid search is conducted over the trimming region ($0.15T$,$0.85T$), where T denotes number of observations. Critical values for the one break and two break tests are tabulated in Lee and Strazicich (2004) and Lee and Strazicich (2003) respectively.

4.2.2 Narayan et al. (2016) GARCH-based unit root test with structural breaks

There is substantial evidence suggest that the global stock markets are high volatile (i.e. they exhibit conditional heteroscedasticity) and have witnessed several structural shifts in response to shocks as well (Diebold and Yilmaz, 2009). Furthermore, our preliminary observation (see Fig.1) is a clear indication of the conditional heteroscedasticity and structural changes in the global equity markets. Therefore, as a robustness check for the stationarity test results, we adopt Narayan et al. (2016) GARCH-based unit root test to more carefully capture the inherent statistical behaviour of the series.

Similar to the ADF type tests, a series of new unit root tests are gradually emerged which are more suitable for testing the stationarity of a high-frequency data series. The development in this field was pioneered by Kim and Schmidt (1993) and further improved by Ling and Li (1998), Seo (1999) and Cook (2008). The tests proposed in this strand of literature are known as GARCH-based unit root tests as these tests assume GARCH error rather than the white noise error in the conventional ADF-type unit root tests. One of the prominent advantages of using GARCH-based unit root tests is that they can deal with conditional heteroskedasticity and non-normality which are the common features for most high frequent time series data. Kim and Schmidt (1993) and Haldrup (1994) demonstrated that ignorance of the error in the ADF-type test regression that follows a GARCH process can result in moderate size distortion. However, one of the main limitations for the GARCH-based unit root tests is that they do not consider the issue of structural changes, thus, may lead to invalid estimations in the presence of break(s). Narayan et al. (2016) extended the GARCH-based unit root test by incorporating two structural breaks and the test is proved to have better size and power than the tests without breaks.

Narayan et al. (2016) GARCH-based unit root test with two endogenous breaks considers a GARCH(1,1) unit root model as follows:

$$y_t = \alpha_0 + \pi y_{t-1} + D_1 B_{1t} + D_2 B_{2t} + \varepsilon_t \tag{30}$$

where y_t denotes the series under consideration; the parameter α_0 represents intercept. $B_{it} = 1$ for $t > T_{Bi}$ otherwise $B_{it} = 0$; T_{Bi} stands for the date of the structural break where $i = 1, 2$. D_1 and D_2 refer to break dummy coefficients and π is the autocorrelation coefficient. The error term ε_t follows the first order GARCH(1,1) model of the form:

$$\varepsilon_t = \eta_t \sqrt{h_t}, \qquad h_t = \mu + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{31}$$

where $\mu > 0$, $\alpha \geq 0$ and $\beta \geq 0$, and η_t is a sequence of i.i.d random variables with zero mean and unit variance. Narayan et al. (2016) used joint maximum likelihood (ML) estimation to estimate these equations. The break dates (T_{Bi}) are estimated by a sequential procedure and the underlying null hypothesis for the test is that there is a unit root in the series ($H_0 : \pi = 1$).

4.3 Maki's (2012) cointegration test with multiple structural breaks

As argued in Narayan and Smyth (2005), if two stock markets are cointegrated, then the forecasting ability of each stock market can be enhanced by utilizing information in the other stock market, implying that it is not a wise decision to select securities from the cointegrated market to construct the optimal portfolio. Westerlund and Edgerton (2006) pointed out that the standard cointegration tests that do not consider structural breaks are likely to provide biased results for long term relationships. There are newer approaches in the relevant literature that take into account of the issue of structural changes in the series. Among them the most widely used approaches are Gregory and Hansen (1996), Carrion-i-Silvestre and Sansó (2006), Westerlund and Edgerton (2006) and Hatemi-J (2008) methods that allow only one or two breaks in their frameworks. Maki (2012) developed a new cointegration test that internally incorporates structural breaks up to five different points in time. Maki (2012) emphasized that we generally do not have a priori information about the true number of breaks. Therefore, if the true number of structural breaks are two, then the Gregory and Hansen (1996) test is misspecified and will lead to poor performance. Similarly, if the true number of break is one, the Hatemi-J (2008) test will have the same issue. In addition, both tests will have poor performance if the cointegration relationship has more than two breaks or persistent Markov switching shifts. To be consistent with the stationarity analysis, we implement Maki's (2012) cointegration test by allowing for up to two breaks in the cointegration regression.

The algorithm of Maki's (2012) cointegration test can be explained as follows. First, each period is assumed to be a possible breaking point and t-statistic is calculated for every period. Then periods with the lowest t-ratios are identified as break points. The test requires all series needs to contain an autoregressive unit root ($I(1)$ case). Maki (2012) developed four different models to test for cointegration. We use Model 4 of the test since it is the only model that considers breaks in intercept, coefficients, and trend.[6] The model is specified as below:

Model 4: with break in intercept, coefficients, and trend

$$y_t = \mu + \sum_{i=1}^{k} \mu_i K_{i,t} + \gamma t + \sum_{i=1}^{k} \gamma_i t K_{i,t} + \beta x_t + \sum_{i=1}^{k} \beta_i x_i K_{i,t} + v_t \tag{32}$$

where y_t and x_t stand for observable $I(1)$ variables, v_t is the equilibrium error. K_i represents

[6] The other three models are Model 1: with break in intercept, but without trend; Model 2: with break in intercept and coefficients, but without trend; Model 3: with break in intercept and coefficients, and with trend.

dummy variables which defined by Maki (2012) as:

$$K_i = \begin{cases} 1, & \text{for } t > T_B \\ 0, & \text{otherwise} \end{cases} \tag{33}$$

where T_B denotes the date of the structural break.

Critical values to test the null hypothesis of no cointegration in the presence of structural breaks are computed via Monte-Carlo simulations and are provided in Maki (2012).

4.4 Bootstrap Granger non-causality and a fixed-size rolling window estimation

In the present study, instead of assuming structural stability over the full sample, we argue that the nature and direction of causality between stock markets can differ significantly depending on the sample period selected. We, therefore, allow temporal causal relationship between stock markets vary over time. Furthermore, we also consider the presence of structural changes in causality analysis.

We follow the approach proposed by Balcilar et al. (2010) to investigate the temporal causality between stock markets using VAR framework. In particular, we employ Granger non-causality method to examine whether one series can significantly forecast another. If the variables are integrated or cointegrated, the commonly used test statistic in the VAR framework such as the Wald, likelihood ratio (LR) and LM for testing the Granger causality are likely to have non-standard asymptotic properties, further leading to difficulties in the level estimation of VAR models (Park and Philips, 1989; Toda and Philips, 1993).

Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) developed a solution to obtain standard asymptotic distribution for the Wald tests by estimating an augmented VAR with $I(1)$ variables, or the coefficients of long-run causality test of VAR(p) processes. The solution requires at least one unrestricted coefficient matrix under the null hypothesis. Shukur and Mantalos (1997a) used Monte Carlo simulations to study the size and power properties of eight versions of Granger causality tests in standard and modified form. Their findings showed that the Wald test did not possess the correct size in small and medium sized samples. Moreover, Shukur and Mantalos (1997b) demonstrated that the critical values can be improved by using the residual-based bootstrap (RBB) method, so that the true size of the RESET test, in systems ranging from one to ten equations, approaches its nominal value. Furthermore, Mantalos and Shukur (1998) examined properties of the RRB method in VAR systems with cointegrated time series generates robust critical values compared to asymptotic ones.

Shukur and Mantalos (2000) investigated the properties of various versions of Granger causality tests that are not based on RBB and proved that small sample corrected LR tests exhibit best size and power, even in small samples. Their results, however, showed that in the absence of cointegration, all standard tests that are not based on RBB perform poorly, especially in small samples. Using Monte Carlo simulations, Mantalos (2000) compared the bootstrap, Wald and corrected LR tests in both cointegrated and non-cointegrated process and concluded that bootstrap test performs best regardless of cointegration properties. Based on these findings, we, therefore, adopt the RBB modified-LR statistic to examine the causal linkage between stock markets.

Consider the following bivariate VAR(p) process:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + \epsilon_t, \qquad t = 1, 2, ..., T \tag{34}$$

where $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t})'$ is a independent white noise process with zero mean and non-singular covariance matrix Σ. The order of process p is known, the lag length is determined by the Akaike Information Criterion (AIC). To simplify the equation, we partition y_t in two subvectors, which relating to the stock market in country i and j respectively and Eq.(34) can be written more compactly in the following form:

$$\begin{bmatrix} y_{i,t} \\ y_{j,t} \end{bmatrix} = \begin{bmatrix} \phi_i \\ \phi_j \end{bmatrix} + \begin{bmatrix} \phi_{i,i(L)} & \phi_{i,j(L)} \\ \phi_{j,j(L)} & \phi_{j,i(L)} \end{bmatrix} \begin{bmatrix} y_{i,t} \\ y_{j,t} \end{bmatrix} + \begin{bmatrix} \epsilon_{i,t} \\ \epsilon_{j,t} \end{bmatrix} \tag{35}$$

where $\phi_{i,j(L)} = \sum_{k=1}^{p} \phi_{ij,k} L^k$, L is the lag operator defined as $L^k \chi_t = \chi_{t-k}$.

In this setting, the null hypothesis that country i's stock market does not Granger cause country j's stock market can be tests by imposing zero restrictions on the coefficients, namely, $\phi_{i,j,m} = 0$ for $m = 1, 2, ...p$. Analogously, we are also able to test the null that country i's stock market does not Granger cause country j's stock market by imposing the restriction $\phi_{j,i,m} = 0$ for $m = 1, 2, ...p$. The direction of causality between two country's stock markets has important implications for equity investors. If a unidirectional causality running from country i's stock market to country j's stock market, then movements in the former market help to forecast the latter market. Similarly, a bi-directional causality implies a feedback system where both stock markets react to each other. Therefore, the existence of causality indicates no short term diversification opportunities between the two stock markets. In the case of no causality in either direction, the performance of one stock market cannot affect the other, which implies there are diversification possibilities in the short-run between the two stock markets.

One of the most important assumptions for Granger non-causality test is that parameters of the VAR models used are constant over time. Structural changes, however, make this assumption fragile. Granger (1969) emphasized that the structural instability may be one of the most challenging issues for recent empirical research. The widely used ways of incorporating and identifying the presence of structural breaks into estimation are sample splitting and dummy variables. These techniques, however, often lead to pre-test bias. Thus, to overcome parameter non-consistency and avoid pre-test bias, the present study applies the Balcilar et al. (2010) rolling-window bootstrap estimation.

We investigate the impact of structural break using rolling-window Granger causality tests, which are based on the modified bootstrap test. In the presence of structural breaks, it may lead to shifts in the parameters and the dynamic pattern of the causal relationship will show instability across different sub-samples. Considering these two issues, in addition to full sample, we employ the bootstrap causality test[7] to rolling-window sub-samples for $t = \tau - l + 1, \tau - l, .., \tau, \tau = l, l + 1, .., T$, where l represents the size of the rolling window. The rolling-window approach employs a fixed-length moving window sequentially from the beginning to the end of the sample by adding one observation from ahead and dropping one from behind, where each rolling-window sub-sample entails l observations. In each step, we apply the causality test to each sub-sample, proving a $(T - l)$ sequence of causality tests rather than just one.

5 Results and discussion of findings

To visualize the international diversification possibilities, under short sales constraint,[8] we plot the efficient frontier[9] for BRICS and G7 stock markets based on the mean-variance model developed by Markowitz (1952). Fig.4 shows that except India not a single country's portfolio is on the efficient frontier of investment, suggesting that substantial advantage can be attained through portfolio diversification in foreign securities. Notably, French, German, Italian and Japanese stock markets are far from the efficient frontier. In comparison, these equity markets have lower returns but higher risk. Moreover, the global minimum variance portfolio has an annual average return of 4.88% and a standard deviation of 3.45%, which requires investors to put 9.67%, 23.54%, 53.41% and 13.38% of their money in Chinese, South African, Canadian and U.S. stock market respectively. The finding implies the existence of diversification benefits among BRICS economies. This is, however, a preliminary observation of the simple properties to raw cross-country data. As a step to the more rigorous analysis, this paper employs the latest advances in time series techniques to explore the diversification possibilities among BRICS stock markets for G7 investors.

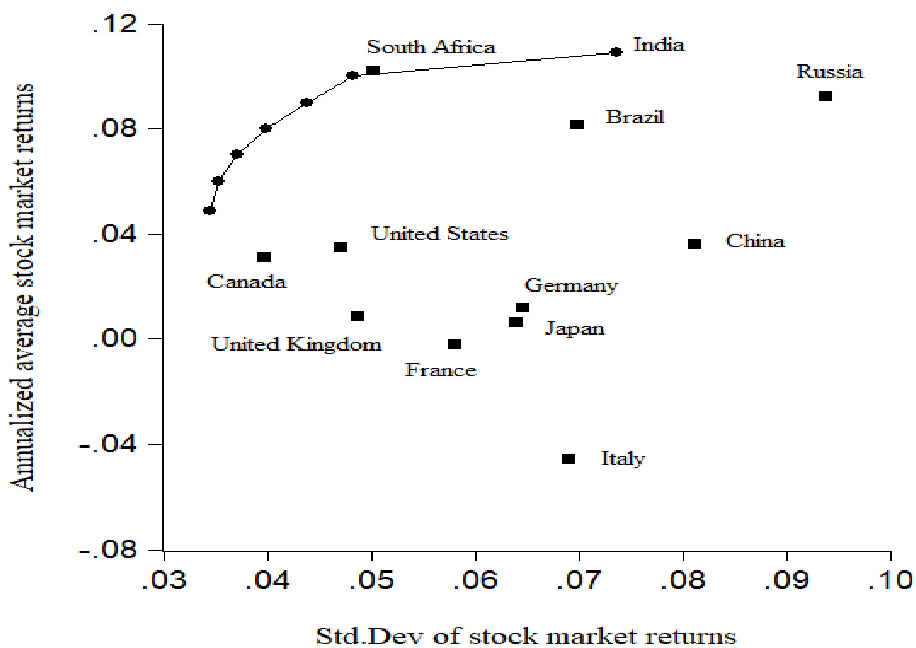
[7] We use a model based on parametric bootstrapping method, where the bootstrap samples come from mean adjusted residuals. The Online Appendix describes the detailed procedure used to deal with the issue of structural changes and minimize the pre-test bias.

[8] It refers to weights can neither be greater than one nor be negative.

[9] The data and procedure is described in Online Appendix.

Table 2 presents the results for conventional unit root tests. For all stock market price indices at level, both ADF and PP tests fail to reject the unit root null at 5% level of significance or better. Looking at the first difference, both ADF and PP test statistics suggest that all variables are stationary at 1% level of significance. The KPSS test results indicate the rejection of the null of stationarity in levels for almost all the series and a failure to reject null of stationarity in the first difference for each series. These results of traditional unit root tests mutually reinforce each other and suggest that all series are integrated of order one.

Fig.4: Stock market risk, returns and efficient frontier



The results of the Perron and Yabu (2009) and Kejriwal and Perron (2010) tests for identifying number of breaks in each country's stock market price index series are reported in Table 3. Apart from Brazilian and Japanese stock market which have only one break, all the remaining market exhibit the presence of two breaks in the series. The break dates in Table 3 are associated with the events that had significantly affected the global stock market. Specifically, the September 11 terrorist attacks in 2001 in the U.S.; the 2002 global stock market downturn; the 2003 second Gulf War and the GFC (2007-2008).

The results of the LM unit root tests with the number of structural breaks suggested by the Perron and Yabu (2009) and Kejriwal and Perron (2010) tests are provided in Table 4. For those countries that their stock market price indices for which the Perron and Yabu (2009) and

Table 2: ADF, PP and KPSS unit root tests results

	Test Statistic					
ln(MSCI stock market index)	ADF	Lag Length	PP	Bandwidth	KPSS	Bandwidth
Level						
Panel A: *BRICS countries*						
Brazil	-1.408	0	-1.453	2	0.387***	11
China	-3.272*	4	-2.569	8	0.119*	11
India	-1.965	0	-2.272	6	0.288***	11
Russia	-2.030	0	-2.165	4	0.301***	11
South Africa	-2.235	0	-2.294	1	0.161**	10
Panel B: *G7 countries*						
Canada	-2.686	1	-2.613	6	0.203**	10
France	-2.537	0	-2.631	5	0.106	11
Germany	-2.864	0	-3.020	5	0.097	10
Italy	-2.188	0	-2.283	6	0.137*	11
Japan	-1.751	0	-1.898	4	0.158**	11
United Kingdom	-3.165*	0	-3.181*	5	0.071	10
United States	-2.373	0	-2.515	6	0.228***	11
1st difference						
Panel A: *BRICS countries*						
d(Brazil)	-13.341***	0	-13.341***	0	0.053	1
d(China)	-7.248***	1	-12.652***	8	0.058	8

Continued on next page

Table 2 – *Continued from previous page*

d(India)	-13.511***	0	-13.562***	5	0.058	5
d(Russia)	-12.637***	0	-12.637***	3	0.051	4
d(South Africa)	-13.620***	0	-13.615***	3	0.043	3
Panel B: *G7 countries*						
d(Canada)	-11.407***	0	-11.585***	5	0.062	6
d(France)	-14.045***	0	-14.052***	4	0.073	4
d(Germany)	-13.128***	0	-13.111***	3	0.069	4
d(Italy)	-14.407***	0	-14.405***	5	0.066	5
d(Japan)	-14.271***	0	-14.289***	4	0.072	4
d(United Kingdom)	-15.022***	0	-15.090***	4	0.068	3
d(United States)	-13.533***	0	-13.548***	5	0.051	5

Note: d stands for the 1st difference operator. For the ADF test, the lag length is decided by using Swartz Information Criterion (SIC). For PP and KPSS test, the optimal bandwidth is selected by Newey-West method using Bartlett kernel. All unit root tests are performed with the assumption of constant term and linear trend in the natural logarithm form of stock market index series with the null hypothesis of unit root for all tests except for the KPSS test that there is an affirmative null of stationarity. The maximum lag length selected in all cases is 8 based on the formula $lag\ length_{max} = int(12(T/100)^{0.25})$ proposed by Hayashi (2000).

*, **, *** Denote statistically significant at the 10%, 5% and 1% level respectively.

Table 3: Results for Perron and Yabu (2009) and Kejriwal and Perron (2010) tests

ln(MSCI stock market index)	Model	ExpW(1|0)		ExpW(2|1)	
		Test	Break Date	Test	Break Date
Panel A: *BRICS countries*					
Brazil	III	12.468***	Jul-08	2.101	-
China	III	6.683***	Nov-06	3.798**	Dec-05
India	III	5.504***	Nov-05	5.847***	Jun-03
Russia	III	57.121***	Aug-08	10.393***	Sep-01
South Africa	III	3.478**	Jul-05	5.128***	Nov-03
Panel B: *G7 countries*					
Canada	III	5.562***	Aug-08	3.827**	Apr-03
France	III	12.561***	Sep-08	4.516**	Oct-03
Germany	III	9.890***	Jul-03	5.190***	Jul-02
Italy	III	8.570***	Sep-08	5.211***	May-03
Japan	III	12.257***	Sep-08	2.043	-
United Kingdom	III	23.362***	Jul-03	5.192***	Jun-02
United States	III	37.000***	Sep-08	4.301**	Apr-03

Note: (1) Model III refers to the presence of structural breaks in both intercept and slope. (2) We follow a sequential procedure which first test the null hypothesis of none versus one break. For the series that the null is rejected, we further test the null of one break versus two breaks in the slope. (3) The Gauss code for conducting these tests can be downloaded from Pierre Perron's homepage at: `http://people.bu.edu/perron/code/breakcode.zip`
, * Denote statistically significant at the 5% and 1% level respectively.

Kejriwal and Perron (2010) methods identified that the optimal number of break is one, we report that break date and for countries' stock market price indices for which two breaks are optimal we report both break dates. Table 4 presents the results of the LM unit root test with a break (Model C) and two breaks (Model CC) in the intercept. In Model C, the unit root null hypothesis cannot be rejected for any of the series. In Model CC, the LM test statistic indicates that all series are non-stationary except for Chinese, Indian and Russian stock market price indices. Since majority of models suggest the results of non-stationarity, our overall conclusion is that all series contain a unit root in the presence of structural changes.

We now turn to investigate the locations of break points. The break dates in Tables 4 varies from those in Tables 3, which is to be expected given the break points are determined endogenously, it is possible that break dates will differ across different methods. Most of the breaks in Tables 4 are also linked to the global events that have affected the global stock market. Notice

Table 4: LM unit root test with one and two structural break results (Model C and Model CC)

	ln(MSCI stock market index)	Lag Order	TB1	TB2	$B1(t)$	$B2(t)$	$D1(t)$	$D2(t)$	LM test statistic
Model C	Brazil	0	Oct-07	-	0.021(0.298)	-	0.002(0.154)	-	-3.378
	Japan	6	May-13	-	-0.129**(-1.980)	-	0.018(1.556)	-	-2.211
Model CC	**Panel A:** *BRICS countries*								
	China	7	Oct-06	Apr-09	-0.121(-1.539)	0.085(1.139)	0.161***(5.602)	-0.109***(-5.035)	-5.862**
	India	5	Apr-03	Aug-08	-0.113(-1.637)	-0.052(-0.746)	0.123***(5.187)	-0.099***(-5.514)	-5.586*
	Russia	7	May-08	Dec-09	0.212**(2.280)	0.026(0.277)	-0.224***(-6.709)	0.190***(5.894)	-6.382***
	South Africa	5	Dec-03	May-06	0.083*(1.723)	-0.174***(-3.597)	-0.008(-0.578)	0.017(1.338)	-4.027
	Panel B: *G7 countries*								
	Canada	4	Mar-03	Aug-08	0.003(0.073)	-0.138***(-3.960)	0.050***(4.681)	-0.038***(-4.804)	-4.913
	France	5	Aug-04	Aug-08	0.006(0.107)	-0.023(-0.395)	0.078***(4.117)	-0.063***(-3.736)	-4.469
	Germany	5	Apr-03	Aug-08	-0.004(-0.068)	-0.022(-0.348)	0.073***(4.386)	-0.081***(-4.466)	-4.835
	Italy	5	Aug-04	Jul-08	0.004(0.064)	0.101(1.479)	0.077***(3.443)	-0.078***(-3.621)	-4.253
	United Kingdom	5	Jul-04	Jul-08	-0.057(-1.205)	0.066(1.392)	0.073***(4.323)	-0.052***(-3.835)	-4.744
	United States	8	Jul-04	Sep-08	-0.091**(-2.309)	-0.346***(-8.873)	0.069***(4.208)	-0.012(-1.489)	-4.500

Critical values for Model C

Location of break, λ	0.1	0.2	0.3	0.4	0.5
1% significance level	-5.11	-5.07	-5.15	-5.05	-5.11
5% significance level	-4.50	-4.47	-4.45	-4.50	-4.51
10% significance level	-4.21	-4.20	-4.18	-4.18	-4.17

Critical values for Model CC

λ_2		0.4			0.6			0.8	
λ_1	1%	5%	10%	1%	5%	10%	1%	5%	10%
0.2	-6.16	-5.59	-5.27	-6.41	-5.74	-5.32	-6.33	-5.71	-5.33
0.4	-	-	-	-6.45	-5.67	-5.31	-6.42	-5.65	-5.32
0.6	-	-	-	-	-	-	-6.32	-5.73	-5.32

Note: TB1 and TB2 stand for the dates of the structural breaks, $B1(t)$ and $B2(t)$ refer to the dummy variables for the structural breaks in the intercept, $D1(t)$ and $D2(t)$ represent the dummy variables for the structural breaks in the trend. Statistic in parentheses are t-statistics. For Model CC, critical values depend on the locations of the breaks. λ_j denotes the break locations. *,**,*** Denote statistically significant at the 10%, 5% and 1% level respectively.

that these events can only be treated as possible events[10] associated with breaks but not as evidence of a statistical linkage with the proposed events or with the time periods of structural breaks.

For the vast majority of G7 countries, the early break appeared between 2003 to 2004, whereas only two BRICS countries (India and South Africa) experienced a structural break at the similar time. This period was associated with the 2003 global economic boom. Prior to this time, the 1997-1999 Asian financial crisis caused a collapse of demand in most of the developing economies in Asia. Soon after came the IT dot bubble, the 2000s energy crisis and the global recession of 2001. Yet, these negative shocks gave way to a positive shock. In particular, the world has experienced an unprecedented economic growth since 2003. Growth in even Sub-Saharan Africa accelerated from 2.4% in the 1990s to 5.5% in 2003.[11] A global boom has lifted all boats around including both BRICS and G7 nations.

Between the year 2007 to 2008, a time that is clearly linked to the GFC, seven countries had their latter breaks. As evident, the GFC led to a considerable slowdown in most developed countries. Specifically, most advanced stock markets were down more than 40% from their recent highs and leading indicators of global economic activities, such as shipping rates, were decreasing at alarming rates.[12] In contrast, nearly half of the BRICS economies (China and South Africa) were isolated from this global financial turmoil. In practice, BRICS economies and their stock markets were still growing strongly, the global financial meltdown had let their economies unscathed. Unlike developed countries, strong foreign exchange reserves and increasing domestic demand allowed BRICS nations to withstand the crisis and kept growing, strengthening their positions as major consumer markets. With unforeseeable shocks rumbling on, it seems that BRICS countries rather than G7 countries, hold the high cards.

Overall, the results of detecting structural breaks show that BRICS and G7 countries are sensitive to both internal and external shocks. As developing countries continue their integration in to the world economy, this sensitivity is likely to increase in the future.

Table 5 outlines the results of Narayan et al. (2016) GARCH-based unit root test. The test statistics for the vast majority of sample countries are not statistically significant at the 5% level or better, which confirms the LM test findings.

To visualize our empirical findings, we superimpose the level and trend break(s) for all series

[10] Detailed events around the identified break dates for each country are reported in Online Appendix.

[11] Refer the article "Mystery of India's economic growth unravelled" by Swaminathan S Anklesaria Aiyar on the Economic Times website, available online at: https://economictimes.indiatimes.com/swaminathan-s-a-aiyar/mystery-of-indias-economic-growth-unravelled/articleshow/2444003.cms

[12] Refer the article "The global financial crisis and developing countries" by Dirk Willem te Velde, available online at: https://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/3339.pdf

identified by the LM unit root tests and plot the log of stock market price index in each country. Linear trends are estimated via Ordinary Least Squares regression (OLS) to connect the structural break points. Fig.5 shows the results and illustrates that the break date(s) for each stock market are coincide with the visualization of the series.

Table 5: Narayan et al. (2016) GARCH-based unit root test with two endogenous structural breaks results

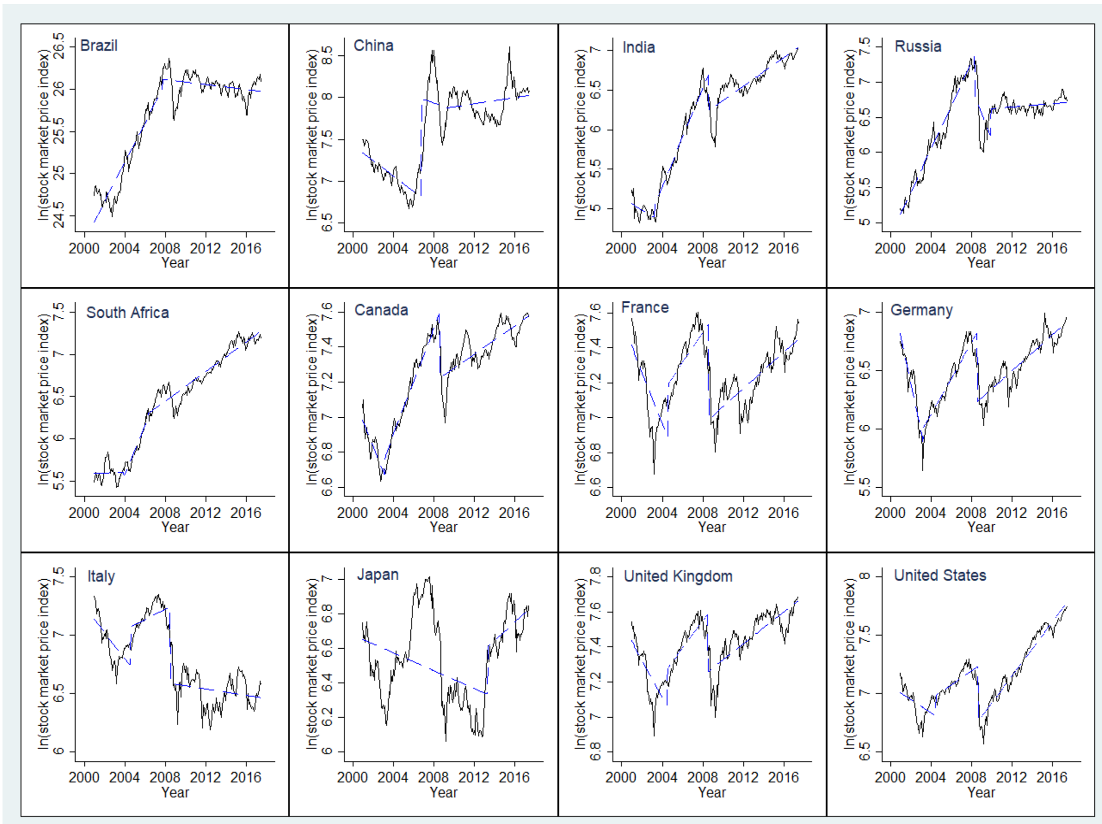
ln(MSCI stock market index)	Test Statistic	TB1	TB2
Panel A: *BRICS countries*			
Brazil	-4.324*	Aug-03	Jul-06
China	-3.434	Apr-06	Apr-08
India	-4.753*	Jun-03	Jul-06
Russia	-3.999*	Jan-05	Oct-08
South Africa	-2.845	Aug-04	Apr-09
Panel B: *G7 countries*			
Canada	-2.902	Oct-02	Jul-13
France	-2.518	Apr-03	Feb-15
Germany	-2.537	Apr-03	Jul-12
Italy	-6.134*	Sep-04	Oct-08
Japan	-0.746	May-03	Mar-07
United Kingdom	-2.972	Apr-03	Jul-12
United States	-2.244	Apr-03	Dec-12

Note: TB1 and TB2 stand for the dates of the structural breaks. The 5% critical value for the test statistic is -3.76, obtained from Narayan et al. (2016) [Table 3 for $N = 250$ and GARCH parameters $[\alpha, \beta]$ chosen as [0.05, 0.90]]. Narayan et al. (2016) provide critical values for the 5% significance level only.

* Denotes statistically significant at the 5% level.

Because all series are integrated of the same order, applying Maki's (2012) approach is suitable. Results of cointegration test with multiple breaks are outlined in Table 6. The null hypothesis of no cointegration can be rejected between Indian and all the G7 stock markets. Furthermore, we find Chinese equity market has a long-run association with both French and German equity market. Thus, our results of Panel A and B indicate that most of the BRICS stock markets are suitable for G7 investor to hedge portfolio risk in the long term. To make the analysis comparable, we also conduct the cointegration analysis within G7 countries. Our finding (Panel C) suggest that except the Japanese stock market G7 investors can benefit from diversifying their portfolios in most of the other group members' stock markets.

Fig.5: Log of MSCI stock market price index



Note: Sample consists of monthly data for the period of Dec, 2000 to Jun, 2017.

This paper adopts the residual based modified-LR tests, as suggested by Mantalos (1997a, b, 2000), Mantalos and Shukur (1998), Mantalos (2000) and Hacker and Hatemi-J (2006), to examine the causal relationship between different stock markets. We use the Akaike Information Criterion (AIC) to determine the lag order of the VAR model. The type of VAR depends on the results from Table 6. When two variables are not cointegrated, we conduct unrestricted VAR. Otherwise, vector error correction model (VECM) is used. Starting with $p = 1$, we sequentially increase the lag up to ten. To test the null hypothesis that the stock market in country i does not Granger cause the stock market in country j, we estimate the full sample bootstrap LR statistic.

The results[13] of full sample Granger causality tests are provided in Table 7. As evident, the null hypothesis of G7 stock markets do not Granger cause BRICS is rejected at the 10% level or better for 8 of the 35 pairs in Panel B. Specifically, more than half of the G7 stock markets

[13] The Breusch-Godfrey serial correlation LM tests results are presented in Online Appendix.

Table 6: Maki's (2012) cointegration test with multiple structural breaks results

Cointegration model: ln(MSCI stock market index in $country_i$) = f(ln(MSCI stock market index in $country_j$))

Dependent Variable	Brazil	China	India	Russia	South Africa		
	(1)	(2)	(3)	(4)	(5)		
Panel A: *Between BRICS and G7 countries (BRICS countries as dependent variable)*							
Canada	-7.396*	-5.519	-7.832*	-5.726	-5.825		
	Nov-08, Jun-14	Apr-02, Apr-10	May-03, May-09	Jan-08, Sep-09	Oct-07, Nov-08		
France	-5.337	-5.340	-6.525*	-5.604	-4.677		
	Nov-08, Feb-15	Dec-03, Jun-15	Dec-07, May-09	Nov-06, Oct-10	Mar-06, Aug-07		
Italy	-5.483	-5.514	-6.899*	-6.282*	-5.127		
	Nov-08, Nov-14	Nov-02, Dec-15	Jun-03, Jan-11	Jun-06, Apr-10	Nov-05, Nov-08		
Japan	-5.493	-5.742	-6.615*	-5.723	-5.748		
	Sep-09, Jul-15	Dec-03, Apr-15	May-03, Apr-09	Apr-04, Oct-10	Jun-06, Mar-13		
United Kingdom	-5.936	-4.781	-6.321*	-5.442	-5.359		
	Aug-03, Feb-09	Feb-03, Dec-15	Mar-07, May-14	Jan-08, Feb-09	Apr-04, Oct-07		
United States	-5.970	-5.808	-6.163*	-5.819	-6.198*		
	Oct-09, Oct-14	Nov-03, Nov-14	May-09, Dec-11	Jan-08, May-12	Dec-03, Aug-07		
	Canada	France	Germany	Italy	Japan	United Kingdom	United States
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B: *Between BRICS and G7 countries (G7 countries as dependent variable)*							
Brazil	-5.901	-4.633	-4.727	-5.002	-4.756	-5.397	-6.090
	Nov-01, Apr-16	Mar-03, Feb-16	Feb-03, Sep-11	Jun-02, Apr-16	Mar-02, Apr-16	Feb-04, Feb-10	Sep-08, Feb-10
China	-4.886	-6.258*	-6.119*	-4.335	-3.855	-4.436	-4.948
	Oct-07, Sep-08	Oct-02, Feb-16	Aug-02, May-11	Oct-01, Feb-16	Apr-02, Feb-16	May-03, Sep-08	Jul-07, Sep-08
India	-5.653	-5.022	-6.681*	-5.751	-5.501	-5.550	-5.768
	Apr-03, Aug-08	Mar-04, May-09	Jan-03, Feb-04	Mar-03, Jul-04	Feb-04, May-16	Jun-02, Jul-07	Sep-08, Mar-13
Russia	-5.514	-4.723	-5.678	-4.410	-4.740	-4.584	-4.647
	Aug-11, Jul-15	Oct-03, May-11	Mar-03, Jan-08	Nov-07, Feb-15	Jan-03, Feb-16	Mar-03, Oct-08	Oct-02, Sep-08
South Africa	-5.456	-5.580	-6.017	-4.794	-5.979	-5.498	-6.552*
	Jan-05,Aug-08	Feb-08, Aug-11	Mar-03, Dec-11	Nov-08, Aug-11	Jan-03, Jan-04	Mar-03, Feb-08	Aug-06, Sep-08
Panel C: *Within G7 countries*							
Canada	-	-6.533*	-6.984*	-5.242	-5.506	-6.966*	-6.090
	-	Jan-03, Feb-09	Jan-03, Jan-09	Feb-09, Feb-15	Feb-09, Feb-12	Nov-08, Jun-14	Sep-08, Mar-13
France	-5.510	-	-6.361*	-5.584	-6.466*	-5.522	-4.779
	Jan-03, Apr-09	-	May-07, Jul-15	Sep-07, Feb-09	Jul-08, Mar-13	Feb-10, May-13	Sep-08, Sep-10

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Table 6 – *Continued from previous page*

Germany	-5.454	-4.347	-	-5.272	-6.539*	-4.871	-5.576
	Nov-05, Apr-09	May-07, Jul-15	-	Oct-07, Jul-13	Aug-07, Mar-13	Oct-07, Feb-10	Dec-03, Sep-08
Italy	-5.306	-5.108	-6.317*	-	-6.511*	-4.642	-4.810
	Sep-08, Jan-10	Nov-04, Feb-08	Jul-05, Mar-12	-	Feb-09, Jan-13	Nov-08, Feb-10	Sep-08, Jul-09
Japan	-5.781	-6.109*	-5.511	-6.757*	-	-5.822	-5.766
	Oct-08, Sep-13	Mar-03, Jul-07	Jul-02, Sep-11	Nov-11, Jul-13	-	Mar-03, Feb-10	Sep-08, Jul-09
United Kingdom	-6.377*	-5.765	-5.641	-3.970	-4.428	-	-5.463
	Nov-08, Mar-10	Apr-07, Sep-13	Mar-08, Oct-15	Feb-15, Jun-16	Aug-07, Jul-12	-	Sep-07, Oct-08
United States	-6.025	-5.220	-5.705	-5.237	-6.206*	-4.153	-
	Aug-07, Jul-16	Nov-01, Jun-14	Feb-03, Aug-11	Nov-13, Feb-15	Jan-03, Jan-13	Feb-03, Feb-10	-

Note: Critical values for the 5% significance level is -6.10, obtained from the Table 1 of Maki (2012).

* Denotes statistically significant at the 5% level.

Table 7: Full sample Granger causality tests results

Direction of causality	Brazil		China		India		Russia		South Africa					
$Y \rightarrow X$	LR-statistic	p	LR-statistic	p	LR-statistic	p	LR-statistic	p	LR-statistic	p				
Panel A: *Between BRICS and G7 countries (BRICS countries as independent variable (Y))*														
Canada	60.905***	3	7.413**	4	51.640***	4	51.872***	3	37.003***	3				
France	1.375	1	-0.753	5	6.470	6	4.843	2	-0.555	1				
Germany	3.088	1	2.835	2	7.231	5	-0.456	1	-0.534	1				
Italy	-0.637	1	1.619	8	5.323	5	-0.861	1	-0.426	1				
Japan	-0.007	1	2.957	5	-0.510	5	7.547*	3	-0.308	1				
United Kingdom	15.066**	2	2.314	6	6.154	5	6.270*	2	-1.167	1				
United States	0.491	1	0.815	5	6.595	4	-0.863	1	-0.688	1				
	Canada		France		Germany		Italy		Japan		United Kingdom		United States	
	LR-statistic	p	LR-statistic	p	LR-statistic	p	LR-statistic	p	LR-statistic	p	LR-statistic	p	LR-statistic	p
Panel B: *Between BRICS and G7 countries (G7 countries as independent variable (Y))*														
Brazil	0.410	3	1.205	1	5.773	1	0.543	1	-0.568	1	4.008	2	0.676	1
China	3.623	4	5.724**	5	0.376	2	23.876***	8	5.739*	5	4.537	6	5.823*	5
India	12.199**	4	1.488	6	7.806	5	4.026	5	0.922	5	11.190*	5	-0.618	4
Russia	2.314	3	-0.412	2	3.981	1	-0.813	1	-0.873	3	-0.701	2	-0.475	1
South Africa	0.306	3	2.963	1	9.594**	1	1.048	1	0.331	1	9.006**	1	3.785	1
Panel C: *Within G7 countries*														
Canada	-	-	41.197***	4	40.094***	4	40.901***	4	28.662***	4	39.690***	4	66.494***	4
France	6.493	4	-	-	58.753*	10	6.377	1	5.211	5	16.143	2	29.009***	1
Germany	8.615*	4	39.749	10	-	-	8.683	1	-0.747	1	1.122	1	28.181***	1
Italy	3.480	4	9.467	1	11.708	1	-	-	8.621	5	11.172*	1	16.729**	1
Japan	0.067	4	2.787	5	-0.824	1	-2.253	5	-	-	-0.047	2	1.413	2
United Kingdom	5.166	4	7.428	2	27.594**	1	2.381	1	-0.609	2	-	-	37.367**	7
United States	5.763	4	13.650*	1	29.125***	1	-0.484	1	5.020	2	34.656*	7	-	-

Note: The optimal lag order (p) is determined by the Akaike information criterion (AIC). The p-values are the bootstrap probability values calculated through 1000 bootstrap repetitions.

*, **, *** Denote statistically significant at the 10%, 5% and 1% level respectively.

(France, Italy, Japan and U.S.) can affect movement of the Chinese stock market. Moreover, both the German and UK stock markets can Granger cause the South African stock market, and also the Indian stock market can be influenced by the Canadian and UK stock markets. On the other hand, the null hypothesis that BRICS stock markets do not Granger cause G7 stock markets cannot be rejected at the 10% significance level or better for 27 out of 35 pairs in Panel A. In particular, Canadian stock market can be affected by all G7 markets. Furthermore, both Brazilian and Russian stock markets can influence the performance of the UK stock market. There is also a one way causality running from the Russian stock market to the Japanese stock market. It can be derived from the results of Panel A that although some positive steps have been taken up by the BRICS countries, which are responsible for the substantial improvement of their stock markets, these may not sufficient enough to become matured ones and therefore not integrated with the G7 markets so far. Within G7 countries, bi-directional causal relationships are found between the three European stock markets (France, Germany and UK) and the U.S. stock market. The causality results between the U.S. and European stock markets are obvious since the U.S. market is the world?s foremost securities market and has a heavy influence on other stock markets. Thus, one may not be surprised that the U.S. stock market can Granger cause the European markets in the short run. More rationally, several macroeconomic factors (such as: economic connection, regulatory structures similarity, exchange rate policy and trade flows) may provide a good explanation of the bi-directional causality. With the start of the liberalization of the global economy, there has been a steady improvement in Europe-U.S. trade relations in recent years. France, Germany and UK are all identified as the top 15 destinations of U.S. exports, which account for 2.1%, 3.4% and 3.6% of the U.S. total exports respectively.[14] Also U.S. is in the list of the three main import partners for France, Germany and UK with the percentage share of 7%, 10% and 15% of the trade value in 2015 respectively.[15] These statistics suggest that U.S. and European economy are important to each other, which seems to be in line with our results of bidirectional causality. Overall, the findings from full sample bootstrap Granger causality test indicate that the G7 stock markets appear to have predictive power for almost half of the BRICS stock markets, suggesting that there is no short term gains among BRICS security markets for G7 investors.

Previous studies examined the causal relationship between different stock markets using different sample periods and model specifications. Most of the research based their analysis on VAR models like Eq.(34), but never tested the stability of the estimates. As argued in Salman

[14] See the U.S. Census Bureau website at: `https://www.census.gov/foreign-trade/statistics/highlights/toppartners.html`

[15] Refer the article "EU?s top trading partners in 2015: the United States for exports, China for imports", available online at: `http://ec.europa.eu/eurostat/documents/2995521/7224419/6-31032016-BP-EN.pdf`

and Shukur (2004), the inference based on Granger causality analysis can be misleading when the assumption of parameter constancy (due to structural changes or regime shifts) is violated. Various tests are proposed in the literature to examine the temporal stability of VAR models (e.g. Hansen, 1992; Andrews, 1993; Andrews and Ploberger, 1994). Although it is easy to test the stability of parameters when variables are stationary, we need to take into account the non-stationary nature of variables in our model and consider the integration-cointegration property of data. The causality tests are conducted on a standard (sometimes first differenced) VAR if variables are cointegrated. All parameters correspond to short-run dynamics in a non-cointegrated VAR and hence only short-run stability is investigated. Otherwise, variables form a VECM in a cointegrated VAR, and therefore stability of both the long-run and short-run parameters should be examined. If the long-run (cointegration) parameters are stable, the model exhibits long-run stability. Moreover, the model has full structural stability if the short-run parameters are also stable. We, therefore, test the stability of our model using a two-step procedure. We examine the stability of the cointegration parameters in the first step. Then we test the stability of the short-run parameters if the long-run parameters are stable. To investigate the stability of the long-run parameters, we employ the L_c test developed by Nyblom (1989) for $I(0)$ series and then extened to $I(1)$ series by Hansen (1992). This LM test examines the null of stability of the parameters against the alternative hypothesis that the coefficients follow a random walk (i.e. the coefficients are time-varying and stochastic in nature). In what follows, the Supermum Wald (Sup-Wald) and Supermum Likelihood Ratio (Sup-LR) tests proposed by Andrews (1993) and Andrews and Ploberger (1994) are used to examine the short-run stability of parameters (swift regime shifts). These tests are based on the sequence of LM test statistic that test the null of parameter stability against the alternative of a one-time structural change at each possible time in the sample. Furthermore, unlike the L_c test, these tests need data trimming from the ends of sample. Following Andrews (1993), we calculate the test statistics using a fraction of the sample in [0.15, 0.85] with 15% trimming.

The results of both long-run and short-run parameter stability tests are presented in Table 8. The estimates of the L_c test indicate that long-run parameters of all bivariate VAR(p) processes are unstable at the 1% significance level. The system L_c test statistics show that the VAR models as a whole are inconsistent at the 1% significance level for all stock market pairs. The Sup-LR and Sup-Wald tests results for Panel A imply that except for the equations of Brazilian and South African stock markets, there is a significant evidence of short-run parameter instability in the equations of the remaining BRICS countries' stock markets. Moreover, the Panel C results suggest that apart from Canadian stock market, the VAR models consider only the remaining G7 nations' stock markets exhibit stable short-run parameters. Thus, we conclude that the VAR

Table 8: The results of parameter stability tests

Biviaraite VAR(p) systems		Long-run stability tests		Short-run stability tests	
Dependent variable	Independent variable	L_c	L_c for system	Sup-LR	Sup-Wald
Panel A: *Between BRICS and G7 countries (BRICS countries as dependent variable)*					
Brazil	Canada	3.225***	7.832***	5.714**	39.997**
	France	3.938***	9.270***	1.948	5.845
	Germany	4.091***	8.916***	2.612	7.836
	Italy	3.888***	8.724***	2.492	7.477
	Japan	4.449***	9.615***	2.111	6.333
	United Kingdom	3.747***	17.741***	2.104	10.070
	United States	4.981***	10.307***	4.312	12.937
China	Canada	3.464***	7.182***	5.828***	52.451***
	France	2.255***	4.643***	2.422	26.640
	Germany	3.424***	5.691***	4.980**	24.901**
	Italy	1.475***	3.964***	2.940**	44.103**
	Japan	1.830***	5.094***	4.222***	46.441***
	United Kingdom	2.046***	3.467***	3.342*	36.764*
	United States	5.454***	8.688***	2.776*	30.537*
India	Canada	1.476***	3.527***	3.352*	30.169*
	France	4.324***	9.584***	3.166*	34.828*
	Germany	3.951***	9.708***	4.574**	50.318**
	Italy	3.597***	8.365***	4.520**	49.723**
	Japan	4.077***	10.007***	6.363***	69.998***
	United Kingdom	2.890***	15.648***	5.565***	61.211***
	United States	4.008***	11.280***	4.360*	39.243*
Russia	Canada	1.027***	2.755***	6.995***	48.964***
	France	3.419***	14.930***	7.763***	38.816***

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Table 8 – *Continued from previous page*

	Germany	3.090***	15.016***	5.185	15.555
	Italy	3.117***	6.106***	7.206*	21.617*
	Japan	5.193***	9.705***	10.866***	76.065***
	United Kingdom	1.930***	15.101***	7.744***	38.722***
	United States	6.316***	11.514***	10.542**	31.627**
South Africa	Canada	1.154***	3.110***	4.035**	28.245**
	France	4.512***	7.479***	2.111	6.334
	Germany	4.663***	7.942***	2.311	6.933
	Italy	2.261***	4.591***	2.194	6.582
	Japan	3.759***	8.282***	4.246	12.739
	United Kingdom	3.069***	5.785***	2.777	8.332
	United States	5.060***	10.992***	3.109	9.326
Panel B: *Between BRICS and G7 countries (G7 countries as dependent variable)*					
Canada	Brazil	6.570***	-	4.266**	29.864**
	China	0.833***	-	3.448*	31.036*
	India	4.053***	-	5.049***	45.440***
	Russia	4.477***	-	9.694***	67.860***
	South Africa	0.521**	-	3.565	24.956
France	Brazil	7.724***	-	6.544*	19.633*
	China	2.241***	-	5.440***	59.840***
	India	6.817***	-	2.174	23.917
	Russia	7.723***	-	5.711*	28.556*
	South Africa	3.252***	-	2.765	8.296
Germany	Brazil	6.715***	-	8.244*	24.731*
	China	1.980***	-	4.904	24.520
	India	6.124***	-	1.529	16.815

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Table 8 – *Continued from previous page*

	Russia	7.983***	-	3.371	10.114
	South Africa	3.510***	-	2.443	7.329
Italy	Brazil	7.854***	-	2.706	8.118
	China	2.086***	-	1.412	21.179
	India	6.237***	-	3.040	33.440
	Russia	4.773***	-	7.220**	21.660**
	South Africa	1.827***	-	3.512	10.535
Japan	Brazil	5.762***	-	7.150	21.451
	China	1.800***	-	2.344	25.788
	India	4.616***	-	3.085	33.939
	Russia	4.851***	-	6.230***	43.607***
	South Africa	1.999***	-	3.735	11.205
United Kingdom	Brazil	8.961***	-	5.295	26.476
	China	1.820***	-	1.892	20.814
	India	8.030***	-	4.126	45.387
	Russia	9.218***	-	7.849**	39.247**
	South Africa	3.962***	-	3.331	9.992
United States	Brazil	6.933***	-	8.676	26.028
	China	1.442***	-	5.901***	64.908***
	India	6.087***	-	3.691	33.220
	Russia	7.887***	-	20.521***	61.563***
	South Africa	4.025***	-	1.887	5.661
Panel C: *Within G7 countries*					
Canada	France	6.337***	9.646***	3.333*	29.997*
	Germany	6.463***	9.721***	3.506*	31.556*

Continued on next page

Table 8 – *Continued from previous page*

	Italy	4.715***	8.796***	1.824	16.416
	Japan	7.498***	12.759***	4.493**	40.441**
	United Kingdom	6.038***	8.993***	3.580*	32.217*
	United States	8.965***	13.488***	4.991**	44.921**
France	Canada	6.107***	-	6.273***	56.457***
	Germany	2.970***	6.506***	1.940	36.861
	Italy	5.993***	9.455***	4.838	14.514
	Japan	2.036***	8.035***	5.075**	55.825**
	United Kingdom	1.316***	6.565***	1.187	5.933
	United States	7.542***	15.963***	2.444	7.332
Germany	Canada	5.960***	-	5.564***	50.073***
	France	3.103***	-	2.062	39.184
	Italy	5.586***	8.435***	3.115	9.345
	Japan	3.132***	10.408***	4.453	13.360
	United Kingdom	1.101***	3.116***	2.642	7.925
	United States	4.262***	12.508***	2.155	6.466
Italy	Canada	3.818***	-	6.202***	55.818***
	France	5.643***	-	3.385	10.156
	Germany	5.859***	-	2.983	8.948
	Japan	5.044***	12.091***	3.490**	38.395**
	United Kingdom	2.831***	5.092***	4.806	14.417
	United States	7.429***	15.617***	2.993	8.979
Japan	Canada	3.143***	-	6.654***	59.887***
	France	1.733***	-	3.894*	42.838*
	Germany	2.589***	-	6.188	18.565
	Italy	2.782***	-	4.127**	45.398**

Continued on next page

Table 8 – *Continued from previous page*

	United Kingdom	1.743***	6.229***	6.203	18.608
	United States	4.344***	12.663***	5.547	16.642
United Kingdom	Canada	7.717***	-	5.032***	45.288***
	France	4.079***	-	2.485	12.424
	Germany	2.493***	-	6.012	18.036
	Italy	3.030***	-	6.258	18.773
	Japan	2.475***	-	5.278	15.835
	United States	8.818***	14.033***	1.720	22.357
United States	Canada	6.114***	-	5.818***	52.366***
	France	2.673***	-	4.188	12.564
	Germany	1.993***	-	4.888	14.664
	Italy	5.557***	-	5.366	16.097
	Japan	3.576***	-	3.602	10.805
	United Kingdom	1.795***	-	1.676	21.784

Note: The Hansen-Nyblom L_c long-run parameter stability test is conducted to each equation separately and to the VAR systems as a whole. The Sup-LR and Sup-Wald test statistics are appropriate to examine a swift regime shift. The p-values are obtained from a bootstrap approximation to the null distribution of the test statistic, constructed by Monte Carlo simulation using 1000 samples generated from a VAR model with constant parameters.

*, **, *** Denote statistically significant at the 10%, 5% and 1% level respectively.

systems under consideration have undergone structural and regime changes. As a consequence, the overall evidence based on the parameter stability tests indicate that the VAR model parameters are not constant over time, and thus examining the causality between different countries' stock markets, using the short-run parameters of the differenced or cointegrated VAR, can lead to misleading results with biased inference and inaccurate forecasts. Moreover, the temporal Granger causality test of the full sample VAR model will show sensitivity to changes in the sample period selected, hence the inference drawn using the test are not reliable.

To accommodate the structural shifts and changes in the causal relationship over time, each of the VAR models discussed above is estimated using a rolling window technique. The rolling estimators, also known as fixed-window estimators, are obtained by sequentially changing the subsample of fixed length that moves from the beginning of the sample to the end. In each step, the VAR model and then the bootstrap causality tests are applied. This gives us a sequence of tests rather than just one causality test. Following this approach has some advantages in comparison to the full sample casualty test. First, the procedure of fixed windows rolling estimation allows the system to evolve over time. Second, the approach addresses the subsample instability issue in a convenient way, using a sequence of different subsamples.

As argued in Balcilar et al. (2010) and Tang and Tan (2015), there is a trade-off between the window size l and the number of estimation windows when using a rolling window Granger causality estimator. The heterogeneity in the data may render more precise estimates based on a large window size, but such estimates will not be representative of the true parameters due to fewer windows of estimates. On the other hand, smaller windows will provide a large number of estimates but can increase the variance of estimates. Following Koutris et al. (2008), to estimate the tests with higher accuracy we adopt a small size rolling window and bootstrap technique to each window. Nevertheless, there is no strict rule for selecting the window size in rolling window estimation. Pesaran and Timmermann (2005) investigated the window size under structural change in terms of root mean square error. Their Monte Carlo simulations results suggested that in the presence of frequent breaks, the bias in autoregressive (AR) parameters are minimized with window size around 10 - 20. Pesaran and Timmermann (2005) highlighted two conflicting demands when deciding the optimal window size. The degree of freedom of estimation (potential of multiple structural breaks) requires a larger (smaller) sample size to estimate the parameters accurately. Following the suggestions based on the simulation results in Pesaran and Timmermann (2005), we select a window size of 15 (excluding the observations required for lags).

The null hypothesis that country i's stock market does not Granger cause country j's stock market and the opposite case is examined by the bootstrap p-values of the rolling test statistics. The bootstrap p-values for the BRICS and G7 stock market are plotted in Fig.6. In all the plots,

Fig.6: Rolling window estimates of Granger non-causality between BRICS and G7 nations' stock markets

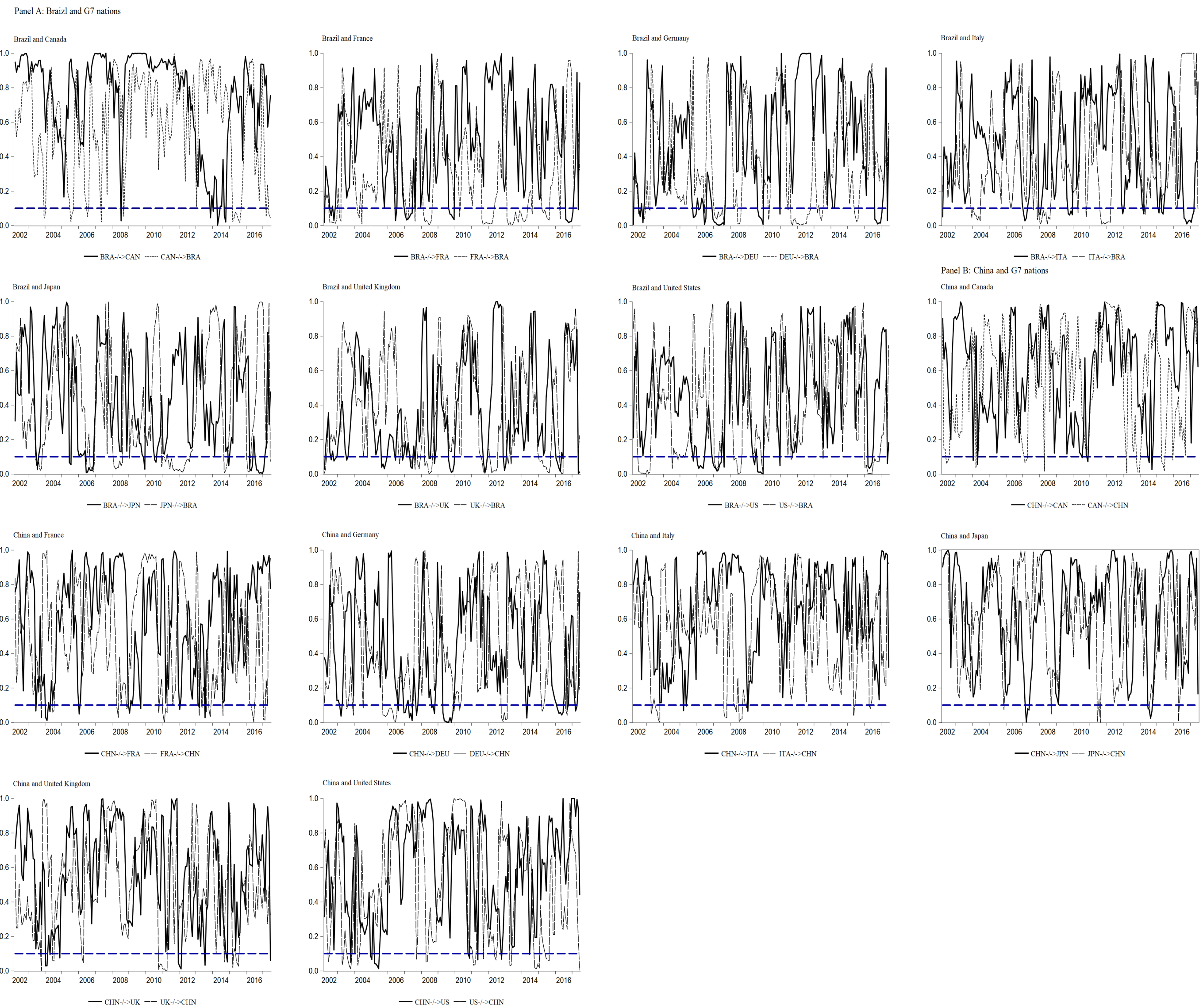


Fig.6: Continued

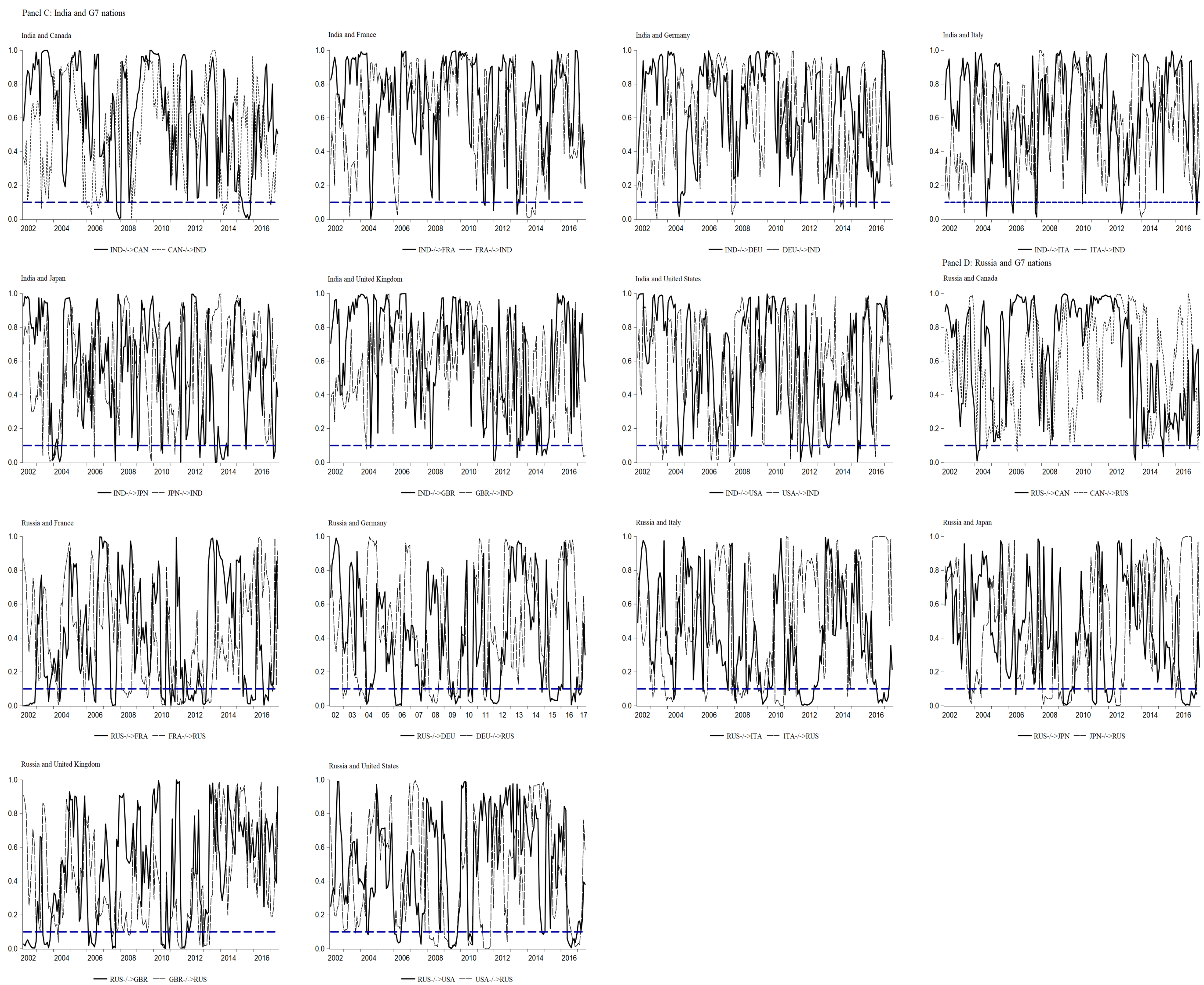
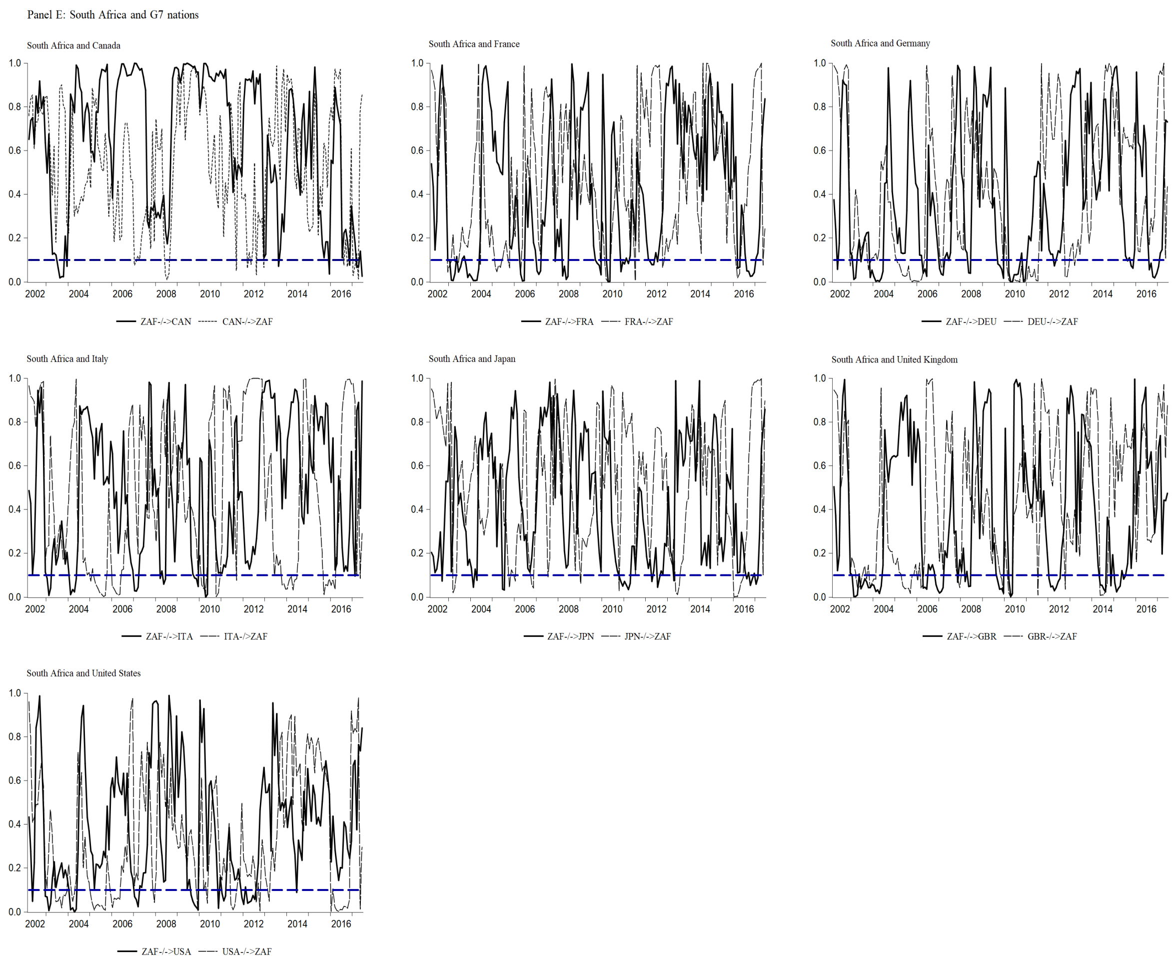


Fig.6: Continued



Note: The blue line indicates significance level at the 10% level. The relationship y -/->x stands for y does not Granger-cause x. The *p*-values are generated using a bootstrap procedure with 1000 repetitions.

the horizontal axes show the time period starting from the first rolling window to the end. The null hypothesis that country i's stock market does not Granger-cause country j's stock market is rejected when the *p*-values are below the horizontal blue line, indicating a higher than the 10% significance level. The results in Figure 4 Panel A illustrate that the null hypothesis of the Brazilian stock market does not cause the G7 nations' stock markets and vice versa is rejected during the years 2006-2008. Hence, there is a bi-directional causality between the Brazil's and G7 countries' security markets during the GFC period. Furthermore, other than the U.S. stock market, the remaining six developed countries' stock market can cause the Brazilian stock market in the period of 2011-2012. The results plotted in Fig.6 point to two common features: First, the causality between BRICS and G7 stock markets does not exist over most of the time periods. Second, we observe an increase of causality during periods of crises. For example, in Panel B, almost all country pairs show increased causality during the GFC period except for China and UK. Similarly, Panel C, D and E also illustrate rising causality during the GFC period between BRICS and most of the G7 nations. Yet, the frequency of causality varies between different country pairs. In particular, in Panel D and E causality appears in most of the periods of large shocks (e.g. 2007-2008 GFC; 2010-2012 chronic sovereign debt crises in the Eurozone; 2016 Britain exiting from the European Union which known as "Brexit").

The results illustrated in Fig.7 suggest a greater crisis effect on causality between G7 countries' stock markets. Specifically, either a unidirectional or bidirectional causality between G7 country pairs is found in the early 2000s (dot-com bubble), 2003-2004 (2000s energy crisis oil price bubble), 2006-2008 (GFC), 2010-2012 (European sovereign debt crisis) and 2016 (Brexit). During these periods, the markets were uncertain of the future. Therefore, we mostly find causal links in volatile periods.

Overall, the above findings indicate that the causal relationship between stock markets vary with time and are inconsistent over time. The investment decisions (e.g., hedging, speculative, arbitrage or long term investing) should be made by considering the dynamics of stock markets relationships and with due caution that these relationships are subject to changes. Moreover, the findings of rising causality between BRICS and G7 nations' stock markets in the periods of shocks suggest no diversification possibilities for investors in such times.

6 Determinants of cross-country stock market causality

After identifying the episodes of significant Granger-causality for the different stock markets, we use the probit regression models to analyze the determinants of the causality of those stock markets. For this, the dependent variable (y) takes the value of one if the Granger casualty is significant at the 10% level and zero otherwise. Our objective is to examine a set of instruments (X) that are likely to explain the dynamics of Granger causality between BRICS and G7 stock markets (i.e. the probability of occurrence of this event (y)). To do so, the probability of observing a value of one is modeled as:

$$\Pr(y = 1)X, \beta) = 1 - \Phi(-X'\beta) = \Phi(X'\beta) \tag{36}$$

where Φ is the cumulative distribution function of the standard normal distribution. We use the standard convention by assuming that the index specification is linear in the parameters and has

Fig.7: Rolling window estimates of Granger non-causality within G7 nations' stock markets

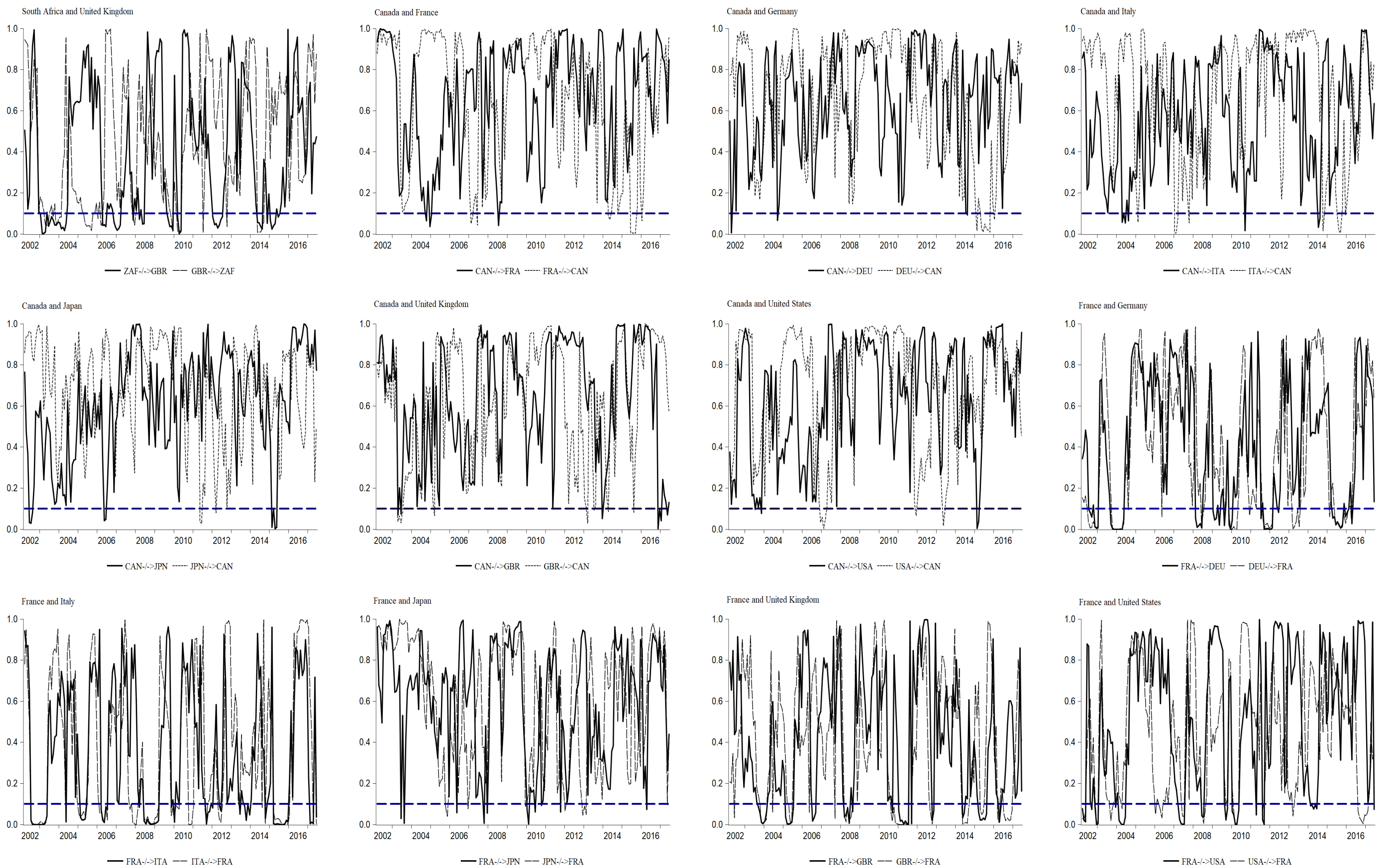
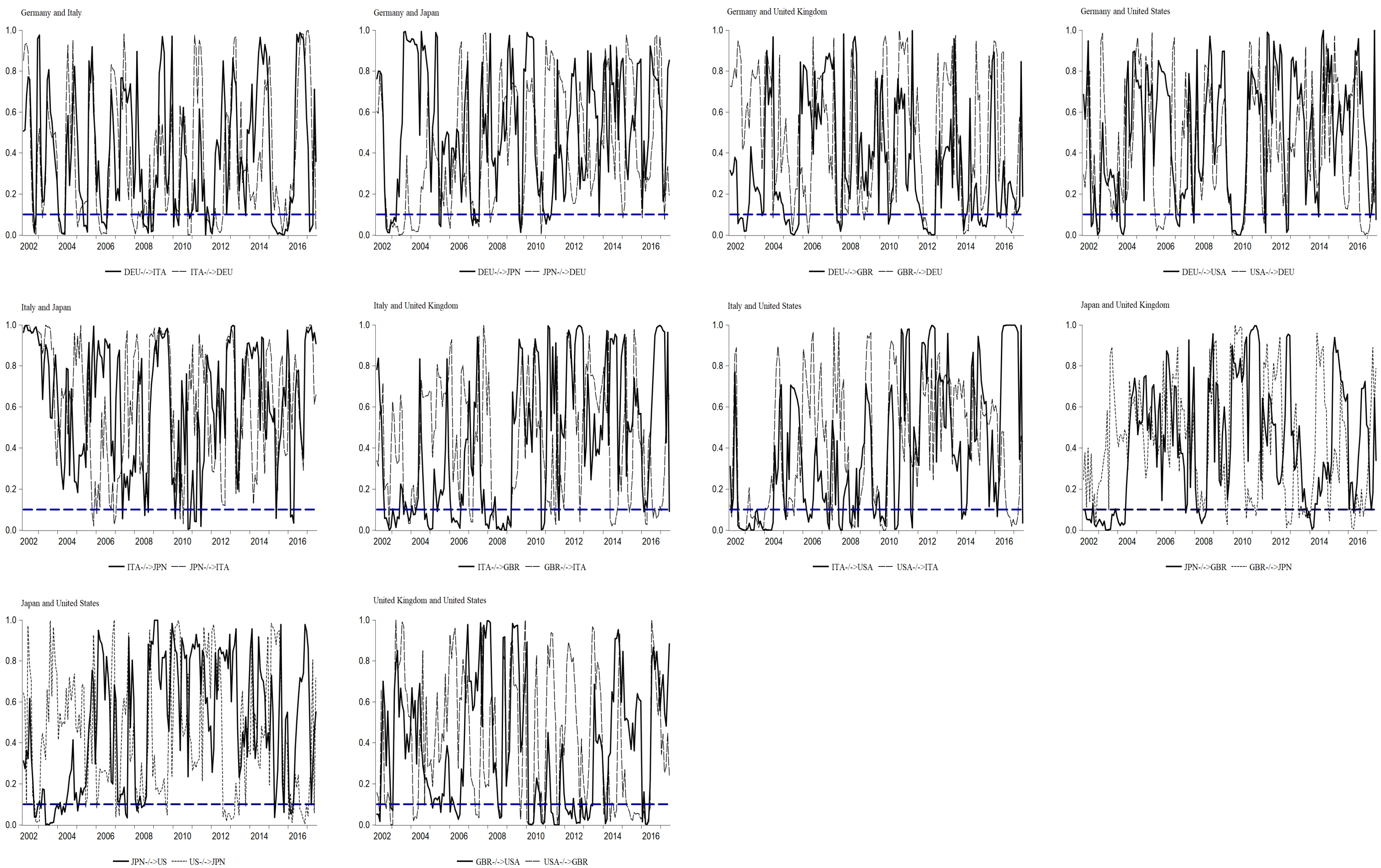


Fig.7: Continued



Note: The blue horizontal line indicates significance level at the 10% level. The relationship y -/->x stands for y does not Granger-cause x. The *p*-values are generated using a bootstrap procedure with 1000 repetitions.

the form $X'\beta$.

The independent variables in our model are known to affect a country pair's stock markets and hence hypothesize that these variables may explain the causal relationships between these markets as well. In our model, we include the absolute value of the difference of the general business conditions as proxied by the business confidence index and the Fama-French factor between country i and country j as the explanatory variables. Taking the absolute value of the difference of the variables is to reflect the closeness between two stock markets. It is evident from the Granger causality that the stock markets are influenced by the GFC (2008) and the Eurozone sovereign debt crisis (2010-2012). To reflect the impact of these changes, we also use dummy variables for these crises times as explanatory variables in the model. The definitions, sources and related references are provided in Table 9.

Table 9: Explanatory variables in the probit model

Name	Variables	Source
diff_BCI	Absolute value of the difference of Business Confidence Index between country i and country j	OECD data website[16]
diff_$(R_m - R_f)$	Absolute value of the difference of excess return on the market between country i and country j	Stefano Marmi website[17]
diff_SMB	Absolute value of the difference of Small Minus Big between country i and country j	Stefano Marmi website
diff_HML	Absolute value of the difference of High Minus Low between country i and country j	Stefano Marmi website
DM1	Dummy variable for the GFC (2008)	Crisis period takes the value 1 and 0 otherwise
DM2	Dummy variable for the Euro Area recession (2010-2012)	Crisis period takes the value 1 and 0 otherwise

Note: Due to the data availability, these variables are for Brazil, China, UK and U.S. The excess return on the market refers the difference between the market return and the risk-free rate of return. The market return for Brazil, China, UK and U.S. refers to the value-weighted return on all stocks on Sao Paulo, Shanghai and Shenzhen, London, and New York, Amex and Nasdaq stock exchanges respectively. The risk-free rate of return for Brazil, China, UK and U.S. is the Brazil Treasury bill rate, the China 91 days Treasury bill rate, the UK 3 months Treasury bill rate, the U.S. 91 days Treasury bill rate respectively. SMB is the average return on three small portfolios minus the average return on three big portfolios. HML is the average return on the two value portfolios minus the average return on the two growth portfolios.

The estimation of the probit model is conducted adopting the general-to-specific approach based on the theory of reduction (Hendry, 1995, Ch.9). We initially analyze a general statistical model with all the explanatory variables and then eliminate the statistically insignificant ones. We first estimated the probit model for the case when the UK and U.S. stock markets Granger cause the Brazilian and Chinese stock markets.[18] The results are presented in Table 10. The

[16]Available online at: https://data.oecd.org/leadind/business-confidence-index-bci.htm

[17]Available online at: http://homepage.sns.it/marmi/Data_Library.html#datalibrary

[18] Results for the case between Brazilian, Chinese stock markets and the remaining G7 countries' stock markets are available upon request.

z-statistics and the robust standard errors are calculated using the Huber-White quasi-maximum likelihood method. The coefficients of the probit regressions are not a direct interpretation of the effect of an independent variable on dependent variable. We are interested in the *centeris paribus* impacts of changes in the explanatory variables affecting the probability of causality. To do so, we calculate the marginal effects and report them in squared brackets below the probit regression coefficient for each predicting variable. These marginal effects can be interpreted as the effect of a unit change in a given regressor on the probability that the country i's stock market Granger-causes country j's stock market or vice versa, keeping all the other regressors constant. The results are calculated using the average values of the variables[19] and the distinction of the coefficient signs is made by shading the relative table cells (i.e. the negative coefficients are shaded with light gray color).

An increase in the difference of business confidence index decreases the probability of the UK stock market Granger causing the Chinese stock market. Furthermore, we find that the difference of SMB portfolio returns (size premium) decreases the probability of causality running from the U.S. market to Chinese market. Notably, the dummy variables used to reflect the GFC (2008) and the European debt crisis (2010-2012) increases the chances of causal flow from UK and U.S. stock markets to Brazilian and Chinese stock markets. The findings that UK, U.S. stock market Granger-cause Brazilian, Chinese stock market during the periods of GFC and European debt crisis imply that under volatile market conditions, the UK and U.S. stock markets reflect the market information more more quickly than the Brazilian and Chinese stock markets in comparison with normal market conditions.

We, now, estimate the probit models to investigate the determinants of cross-country stock market causality from the Brazil, China to UK, U.S. The results are reported in Table 11. A similar influence on the causality flow is observed with the increase of the difference of the business conditions. In particular, increase in the business conditions decrease the probability of casual flows from both the Chinese to UK stock market and the Brazilian to U.S. stock market. The difference in excess return is another important factor driving the causality flows from the Brazilian and Chinese stock markets to U.S. stock market. An increase in the difference of excess return would decrease the probability of Brazilian and Chinese stock markets causing U.S. stock market.

Overall, the difference in business conditions, the excess return and the size premium are the main drivers of causality between BRICS and G7 stock markets. Our finding of business conditions as a determinant of cross-country stock market causality is in line with the results of

[19] However, the direction of the impact of a change in any independent variable depends only on the sign of the estimated coefficient where a positive value indicates that an increase in a given explanatory variable will increase the probability of one stock market causing the other, where a negative value suggests the opposite.

Table 10: Probit models: Causality running from UK, US market to Brazilian, Chinese market

Dependent Variable	UK to Brazil	UK to China	US to Brazil	US to China
	(1)	(2)	(3)	(4)
diff_BCI	-	-0.731**	0.766***	0.837
		(0.340)	(0.251)	(0.522)
		[-0.096]	[0.153]	[0.007]
diff_$(R_m - R_f)$	-	-	-	-
diff_SMB	-	-	-	-0.215*
				(0.121)
				[-0.002]
diff_HML	-	-	-	-
DM1	5.406***	-	-	5.677***
	(0.369)			(0.919)
	[0.770]			[0.048]
DM2	4.840***	-	-	6.333***
	(0.233)			(1.274)
	[0.689]			[0.054]
R^2	0.173	0.116	0.207	0.274
non-missing obs.	59	63	63	63

Note: Standard errors(in parentheses) are robust to arbitrary heteroskedasticity, while the associated marginal effects are provided in the squared brackets. R^2 (McFadden) measures the goodness of fit and mirrors the R-squared in OLS. Values between 0.2-0.4 indicate (according to McFadden) excellent model fit. Sample period for column (2), (3) and (4) is from Jan, 2008 to Mar, 2013, while for column (1) it is from Jan, 2008 to Nov, 2012.
*, **, *** Denote statistically significant at the 10%, 5% and 1% level respectively.

Table 11: Probit models: Causality running from Brazilian, Chinese market to UK, US market

Dependent Variable	Brazil to UK	China to UK	Brazil to US	China to US
	(1)	(2)	(3)	(4)
diff_BCI	0.601**	-0.611**	-1.022***	-1.229
	(0.234)	(0.251)	(0.254)	(0.788)
	[0.141]	[-0.047]	[-0.107]	[-0.016]
diff_$(R_m - R_f)$	-	-	-0.106*	-0.124*
			(0.056)	(0.074)
			[-0.011]	[-0.002]
diff_SMB	-	-	-	-
diff_HML	-	0.158**	-	-0.225
		(0.074)		(0.164)
		[0.012]		[-0.003]
DM1	-	-	-	-
DM2	-	-	-2.010***	-
			(0.599)	
			[-0.211]	
R^2	0.150	0.150	0.352	0.209
non-missing obs.	59	63	63	63

Note: Standard errors(in parentheses) are robust to arbitrary heteroskedasticity, while the associated marginal effects are provided in the squared brackets. R^2 (McFadden) measures the goodness of fit and mirrors the R-squared in OLS. Values between 0.2-0.4 indicate (according to McFadden) excellent model fit. Sample period for column (2), (3) and (4) is from Jan, 2008 to Mar, 2013, while for column (1) it is from Jan, 2008 to Nov, 2012.
*, **, *** Denote statistically significant at the 10%, 5% and 1% level respectively.

Masson (1998), among other studies on equity market contagion. Masson (1998) considered the stock market integration is associated with changes in investors' expectation (e.g. expected risk and returns on stocks, business conditions) that are not related to a country's macroeconomic fundamentals, known as monsoonal effects. The importance of the excess return and size premium as strong determinants is also highlighted by Pritsker (2001) who summarized four separate channels of financial market contagion. The former factor can be explained by the channel of cross-market hedging (Calvo and Mendoza, 2000; Kodres and Pritsker, 2002). Contagion appears through this channel because investors respond to shocks by readjusting their hedges to macroeconomic risks. Readjusting refers to a change in the composition of a portfolio and involves a purchase of one asset and a sale of another asset. It occurs when new information affecting returns in one market makes investors want to change portfolio holdings in that market. This change can also cause a change in portfolio holdings in other markets even there was no new information about these markets. The latter factor is related to the correlated information channel (von Furstenberg and Jeon, 1989; King and Wadhwani, 1990) or the wake-up call hypothesis[20] (Saçhs et al., 1996). Specifically, if an observable negative real shock attacks country i, this shock is transmitted to the real sector of country j through real linkages, then the stock markets of both countries will respond to the real shocks. It usually happens between countries that are trade partners. Country i suffering from crisis reduce its import demand, which leads to country j's enterprises that rely on exports contracts their outputs. Unemployment rate rises once a country's output decreases, which further results in a sizable appreciation of its currency. As a consequence, the crisis spread to country j because its products become uncompetitive in the export market. Size of economy explains a great deal about patterns of global trade. In fact, roughly half of all world trade involves shipping goods between the fairly similar high-income economies[21] (i.e. intra-industry trade). The finding in Fig.7 that the existence of bidirectional causality between the European stock markets and U.S. stock market can be attributed to the fact that the European Union (EU) and U.S. have the largest bilateral trade[22] and enjoy the most integrated economic relationship in the world. The economic growth for vast majority of European countries are heavily rely on exports to the world's largest economy: U.S. Therefore, it is reasonable to expect strong causality within the European stock markets during the period of European sovereign debt crisis as highlighted in Fig.7.

[20] The term was coined by Goldstein (1998) during the Asian financial crisis. The Thai currency crisis in 1997 acted as a wake-up call for investors who realized in the end that the so-called "Asian miracle" of the time was rather an "Asian mirage". Thus, let the international investors reassess the creditworthiness of Hong Kong, Indonesia, Korea, Malaysia and Singapore.

[21] Available online at: https://opentextbc.ca/principlesofeconomics/chapter/33-3-intra-industry-trade-between-similar-economies/

[22] About 60% of U.S. trade and 60% of European trade is intra-industry trade. Available online at: https://opentextbc.ca/principlesofeconomics/chapter/33-3-intra-industry-trade-between-similar-economies/

7 Concluding Remarks

This paper investigates diversification possibilities between BRICS and G7 stock markets both theoretically and empirically. Our theoretical model shows that risk-averse investors are diversifying internationally. In doing so, they only invest in risky assets whose expected rate of returns are positive. Furthermore, they invest more on risky assets when they become wealthier. Using the latest advances in time series techniques, the results of unit root tests with structural breaks suggest that BRICS and G7 countries' stock markets are vulnerable to both internal and external shocks. The vulnerability may increase in the near future due to the ongoing trend of increasing integration between developing countries with the world economy. The findings of cointegration test with structural breaks reveal that except China and India, the remaining BRICS equity markets are desired places for investors to diversify their portfolio risk in the long run. Moreover, the bootstrap Granger causality tests are used to examine the short-term diversification possibilities. The tests are conducted using both the full sample and rolling window subsamples, where the latter is adopted to cater for structural changes and their impacts on the Granger causality estimates. The results of the full sample bootstrap tests indicate that more than half of the G7 stock markets have predictive power for Chinese market; German and UK stock markets can Granger cause South African stock market and also the Indian stock market can be affected by the Canadian and UK stock markets. The results of parameter stability tests indicate that both the full sample long-run and short-run parameters are unstable due to structural changes and regime shifts caused mostly by the external shocks. The rolling window approach provides strong empirical evidence that the lead-lag relationship between stock markets is dynamic with varying degrees of causalities because of structural breaks. The causality is increasing between BRICS and G7 stock markets during the periods of GFC and European debt crisis. In addition, we find a greater crisis effect on causality between G7 equity markets. Overall, our causality analysis suggests that there are no short-term diversification possibilities in BRICS stock markets.

Further, the study investigates some of the possible determinants of the cross-country stock market causality through the probit model. The overall results imply that difference in business conditions, excess return and size premium are the major determinants of the causality. The findings also suggest that the impacts of the macro-economic determinants on this relationship are country-dependent and that different market conditions is likely to increase or decrease the probability of the Granger causality between different stock markets.

Although several implications are made in this research, there are some limitations for our study, such as assuming relationships between stock markets are linear. There are several avenues for future research. First, future research can investigate moderate variable effects, such as innovation and trust, which can be linked with other theories (e.g. institutional theory, knowledge-based view or transaction cost theory). Second, future study can focus on multiple-level analysis of independent variables such as industrial level, market or region level. . Finally, since non-linearity can exist between different stock markets, relevant techniques can be used to investigate the issue of diversification possibilities.

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Online Appendix

"International Portfolio Diversification Possibilities: Could BRICS become a Destination for G7 Investments?"

by Lei Pan and Vinod Mishra

Appendix A: Technical Appendix

A.1. Kejriwal and Perron (2010) procedure

Kejriwal and Perron (2010) developed a sequential procedure which allows consistent estimation of the number of structural breaks, as in Bai and Perron (1998). Kejriwal and Perron (2010) considered three types of test statistics for testing multiple structural breaks. First, they developed a *supWald* test with the null hypothesis of no structural break ($m = 0$) versus the alternative hypothesis that there are a fixed (arbitrary) number of structural breaks ($m = k$):

$$supF_T^*(k) = \sup_{\lambda \in \Lambda_\epsilon} \frac{SSR_0 - SSR_k}{\hat{\sigma}^2} \tag{A.1}$$

where SSR_0 represents the sum of squared residuals under the null hypothesis of no structural breaks, SSR_k refers to the sum of squared residuals under the alternative hypothesis of k structural breaks, $\lambda = \{\lambda_1, ..., \lambda_m\}$ is the vector of break fractions defined by $\lambda_i = \frac{T_i}{T}$ for $i = 1, ..., m$, T_i denotes the dates of structural breaks.

Second, they proposed a test of the null hypothesis of no structural break ($m = 0$) versus the alternative hypothesis that there is an unknown number of structural breaks given some upper bound M ($1 \leq m \leq M$):

$$UDmaxF_T^*(M) = \max_{1 \leq k \leq m} F_T^*(k) \tag{A.2}$$

In addition, Kejriwal and Perron (2010) developed a sequential test of the null hypothesis of k structural breaks versus the alternative hypothesis of $k+1$ structural breaks:

$$SEQ_T(k+1|k) = \max_{1 \leq j \leq k+1} \sup_{T \in \Lambda_{j,\epsilon}} T \left\{ SSR_T(\hat{T}_1, ..., \hat{T}_k) \right\} - \frac{\left\{ SSR_T(\hat{T}_1, ...\hat{T}_{j-1}, \tau, \hat{T}_j, ..., \hat{T}_k) \right\}}{SSR_{k+1}} \tag{A.3}$$

where $\Lambda_{j,\epsilon} = \left\{ \tau : \hat{T}_{j-1} + (\hat{T}_j - \hat{T}_{j-1})\epsilon \leq \tau \leq \hat{T}_j - (\hat{T}_j - \hat{T}_{j-1})\epsilon \right\}$. The model with k structural breaks is obtained by a global minimization of the sum of squared residuals, as in Bai and Perron (1998).

A.2. Bootstrap rolling window causality test procedure

To describe the modified LR test for the Granger causality, following Shukur and Mantalos (2000) we define:

$$
\begin{aligned}
Y &= (y_1, y_2, ..., y_T) \qquad (2 \times T) \text{ matrix} \\
B &= (\Phi_0, \Phi_1, ..., \Phi_T) \qquad (2 \times (2p+1)) \text{ matrix} \\
Z_t &= (1, y_t, y_{t-1}, ..., y_{t-p+1})' \qquad ((2p+1) \times 1) \text{ matrix} \\
Z &= (Z_0, Z_1, ..., Z_{t-1}) \qquad ((2p+1) \times T) \text{ matrix} \\
\eta &= (\epsilon_1, \epsilon_2, ..., \epsilon_T) \qquad (2 \times T) \text{ matrix}
\end{aligned}
$$

Using these notations, we can write the VAR(p) model for $t = 1, 2, ..., T$ including the constant term Φ_0 compactly as below:

$$Y = BZ + \eta \tag{A.4}$$

The Least squares (LS) estimator of B in Eq.(A.4) can be written as:

$$\hat{B} = YZ'(Z'Z)^{-1} \tag{A.5}$$

The $(2 \times T)$ matrix estimated residuals from the unrestricted regression Eq.(A.5) is denoted as η_u and the equivalent matrix of residuals from the restricted regression under the null hypothesis of no causality imposed by η_r. The matrix of cross-products of these residuals are denoted by $S_u = \eta_u' \eta_u$ and $S_r = \eta_r' \eta_r$ respectively. he modified-LR statistic for testing the null hypothesis that the country i's stock market does not Granger cause country j's stock market or vice versa can be written as:

$$LR = (T - k) ln(\frac{detS_r}{detS_u}) \tag{A.6}$$

where T stands for the number of observations and $k = 2 \times (2p + 1) + p$ is the small sample correction term, p refers to the lag order of the VAR model, ln represents the natural logarithm and det is the determinant of the respective matrix. The LR statistic in Eq.(A.6) follows a χ^2 distribution with the degrees of freedom equal to the number of tested restrictions, which equals p under the null hypothesis of no causality from the country i's stock market to the country j's stock market, or vice versa.

The distribution of LR statistic used is known only asymptotically for special cases (see e.g. Park and Phillips, 1989; Toda and Phillips, 1993, 1994; Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996). Therefore, the tests are likely not to have the correct size and the statistical inference based on them may be misleading. Several economists (see e.g. Shukur and Mantalos, 1997a,1997b,2000; Mantalos and Shukur, 1998; Mantalos, 2000; Hacker and Hatemi-J, 2006) demonstrated that Granger causality tests have serious size distortions when the variables in the VAR systems are integrated-cointegrated. Yet, the bootstrap technique can be applied to improve the critical values so that the true size of the test approaches its nominal value.

One of the most common ways to conduct bootstrap method is re-sampling the errors η with replacement. The model given by Eq.(A.4) is estimated by Ordinary Least Squares (OLS) and the residuals obtained using the OLS estimates from Eq.(A.5) are resampled instead due to the errors are not observable. A direct re-sampling of OLS residuals gives:

$$Y^* = \hat{B}Z^* + \eta^* \tag{A.7}$$

where η^* are i.i.d. observations $\eta_1^*, \eta_2^*, ..., \eta_T^*$, drawn from the empirical distribution F_η putting mass to the mean adjusted OLS residuals $(\eta_r - \bar{\eta}_r)$. Efron (1979) developed this RB approach and its consistency properties are later studied in Basawa et al. (1991) and Datta (1996) for the first order autoregressive process, AR(1), model with a unit root and further studied in Inoue and Kilian (2002) for the pth order autoregressive process, AR(p), model ($p > 1$) with a unit root. The principle of hypothesis testing using bootstrap method involves drawing a number of "bootstrap samples" from the restricted model under the null hypothesis, then calculate the bootstrap test statistic and compare it with the observed test statistic. In our case, a bootstrap sample comes from Eq.(A.7) and the test statistic LR^* on this RB sample would be compared with the observed test statistic LR. Normally, the bootstrap test statistic LR^* is generated by repeating this process N_b times. Then the $(1-\alpha)$th quintile of the bootstrap distribution of LR^* provides the bootstrap α-level critical value that we compare to the observed LR statistic. Following Davidson and MacKinnon (1996), we recommend using bootstrap p-values rather than bootstrap critical values in this paper. A bootstrap estimate of the p-value for testing null hypothesis of no causality is given by Prob*($LR^* \geq LR$).

More specifically, the RB bootstrap procedure employed in this study is as follows: We first estimate the LR test statistic in Eq.(A.6) as discussed earlier. Then we draw i.i.d. $\eta_1^*, \eta_2^*, ..., \eta_T^*$ data using adjusted OLS residuals $(\eta_r - \bar{\eta}_r)$ for $i = 1, ..., T$, and obtain $Y^* = BZ^* + \eta^*$. Next, we compute the test statistic LR^* as discussed above, using both restrictions under the null hypothesis of no causality (i.e. by adopting the Granger causality test procedure). Repeating this step N_b times generates LR^* statistic for each bootstrap $i = 1, 2, ..., N_b$. Then these N_b bootstrap LR^* statistic are used to obtain p-values of the tests, which are defined as Prob*($LR^* \geq LR$). Moreover, we not only applying to full sample, but also repeat the steps above for rolling subsample $t = \tau - l + 1, \tau - l, ..., l, \tau = l, l + 1, ..., T$, where l stands for the size of the rolling window. Last, we decide the bootstrap repetition size N_b. Horowitz (1994) estimated bootstrap critical values using $N_b = 100$, while Davidson and MacKinnon (1997) used $N_B = 1000$ to obtain the p-value.

Following Davidson and MacKinnon (1997), we choose $N_B = 1000$.

Appendix B: Data for constructing efficient frontier

We construct the efficient frontier for BRICS and G7 stock markets based on the mean-variance model proposed by Markowitz (1952). The procedure is as follows. First, we calculate the log stock market returns by taking the first differences of log MSCI stock market price indices. Time span of the monthly average stock market returns is from January, 2001 to June, 2017. Then, we annualize the monthly average return by multiplying the annualization factor. Specifically, we use twelve months as the number of trading months in a particular year on average. Table A1 presents the summary statistics for the stock market returns used to construct the efficient frontier. Third, we compute the covariance matrix for monthly average stock market returns. Next, the covariance matrix for annualized average stock market returns is obtained through the covariance matrix in the last step multiply annualization factor (12 trading months). The whole matrix is outlined in Table A2. Last, we use the algorithm from Vitali Alexeev's website[1] to find the global minimum variance portfolio and the efficient frontier for BRICS and G7 stock markets.

Table A1: Summary statistics for stock market returns

Stock Market	Obs.	Monthly Average Return	Std.Dev	Annualized Average Return
Panel A: *BRICS countries*				
Brazil	198	0.0068	0.0699	0.0816
China	198	0.0030	0.0813	0.0360
India	198	0.0091	0.0738	0.1092
Russia	198	0.0077	0.0938	0.0924
South Africa	198	0.0085	0.0502	0.1020
Panel B: *G7 countries*				
Canada	198	0.0026	0.0397	0.0312
France	198	-0.0002	0.0581	-0.0024
Germany	198	0.0010	0.0646	0.0120
Italy	198	-0.0038	0.0691	-0.0456
Japan	198	0.0005	0.0640	0.0060
United Kingdom	198	0.0007	0.0487	0.0084
United States	198	0.0029	0.0471	0.0348

Note: Annualized average return is obtained by using the formula: *monthly average return* $\times$ 12, where 12 is the annualization factor. All statistics are based on authors' calculations.

[1] The template for constructing efficient frontier can be download at: http://valexeev.yolasite.com/teaching.php

Table A2: Covariance matrix for annualized average stock market returns

Stock Market	Brazil	China	India	Russia	South Africa	Canada	France	Germany	Italy	Japan	United Kingdom	United States
Brazil	0.0586											
China	0.0183	0.0794										
India	0.0373	0.0162	0.0653									
Russia	0.0525	0.0162	0.0497	0.1056								
South Africa	0.0254	0.0071	0.0251	0.0330	0.0303							
Canada	0.0022	0.0012	0.0020	0.0026	0.0014	0.0032						
France	0.0292	0.0084	0.0301	0.0352	0.0212	0.0141	0.0405					
Germany	0.0315	0.0116	0.0330	0.0371	0.0223	0.0150	0.0422	0.0500				
Italy	0.0305	0.0108	0.0326	0.0368	0.0198	0.0153	0.0435	0.0455	0.0573			
Japan	0.0250	0.0131	0.0280	0.0377	0.0162	0.0116	0.0306	0.0327	0.0342	0.0492		
United Kingdom	0.0250	0.0069	0.0241	0.0294	0.0189	0.0116	0.0303	0.0310	0.0315	0.0234	0.0284	
United States	0.0250	0.0078	0.0254	0.0303	0.0158	0.0117	0.0278	0.0299	0.0293	0.0250	0.0234	0.0266

Note: The matrix is computed through the covariance matrix for monthly average returns times the annualization factor (12 trading months).

Appendix C: Additional results

Table A3: Major events in BRICS and G7 countries around the break dates

Countries	Break dates	Major events around the break dates
Panel A: *BRICS countries*		
Brazil	Oct-07	Oct-2007: In South Africa, the leaders of Brazil, India and South Africa vowed to push the interests of poor countries in stalled international trade talks and said any agreements would have to benefit the developing world.
China	Oct-06, Apr-09	Oct-2006: The Industrial & Commercial Bank of China, China's biggest bank, went public and created a record of $19.1 billion with an option to increase to $21.9 billion[1]. Apr-2009: China announced a $10 billion infrastructure fund and $15 billion in credits and loans to help Southeast Asian countries combat the GFC.
India	Apr-03, Aug-08	Apr-2003: Prime minister of India acknowledged the government had manipulated elections in Indian-controlled Kashmir and promised residents it would not be repeated. Aug-2008: The summit of the 15th South Asian Association for Regional Cooperation (SAARC), opened amid extraordinary security in Sri Lanka[2]. A draft summit declaration called for collective action to combat "all forms of terrorist violence" that was threatening "peace, stability and security." The leaders also agreed to implement a regional trade pact, which was signed in 1995 but never fully implemented.

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Table A3 – *Continued from previous page*

Russia	May-08, Dec-09	May-2008: Dmitry Medvedev was elected as Russia's president, pledging to bolster the country's economy and civil rights, which signals a departure from his predecessor's heavy-handed tactics. Dec-09: The prime minister of Russia Vladimir Putin declared that Russia will build new weapons to offset the planned US missile defense and resulted in Washington to share detailed data about its missile shield under a new arms control deal.
South Africa	Dec-03, May-06	Jan-04: The South African president Thabo Mbeki signed the Broad-Based Black Economic Empowerment Act. The Act. imposed a host of obligations on companies that wished to do business with the government. June-06: In South Africa, a one-day national strike organized by the main trade union to protest poverty and unemployment hit production in the mining and car-manufacturing industries and had a patchy response in other sectors.
Panel B: *G7 countries*		
Canada	Mar-03, Aug-08	Mar-03: The Bank of Canada increased the key overnight interest rate from 2.75% to 3%, as it fretted about a higher inflation rate. Oct-08: The Toronto stock exchange fell 401 points making a drop of 3942 points. As the Canadian Prime Minister Harper spoke to reassure business people, autoworkers held a funeral march to mark the loss of 67,000 jobs over the past year.

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Table A3 – *Continued from previous page*

France	Aug-04, Aug-08	Sep-04: The French government signaled it will cut its public overspending next year to in line with EU rules in a 2005 budget published today and forecast economic growth of 2.5%. Jul-08: The president of France Nicolas Sarkozy bid to rewrite France's political rules with sweeping constitutional changes worked, but just barely[3].
Germany	Apr-03, Aug-08	May-03: The economies of Germany, Netherlands and Italy contracted during the first three months of 2013 as the European Union (EU) as a whole had no growth for the first time in almost two years. Oct-08: Leaders of France, Germany, Italy and UK met in Paris at a summit on the GFC threatening banks, growth and jobs across the continent[4]. On the second day of summit, Germany also joined Ireland and Greece in guaranteeing all private bank accounts, putting Europe's largest economy at odds with calls for a unified European response to the GFC.
Italy	Aug-04, Jul-08	Jul-04: The Italian parliament approved structural economic reforms which included raising the retirement age from 57 to 60 effective in 2008. Jun-08: Italy's biggest bank by capitalization, Unicredit, said it would cut 9,000 jobs in western Europe and invest in central and eastern Europe to raise profits following massive acquisitions.
Japan	May-13	Jun-13: The prime minister of Japan Shinzo Abe announced the "thrid arrow" (fiscal stimulus) of Abenomics, his plan to pull the country out of its long recession.

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Table A3 – *Continued from previous page*

United Kingdom	Jul-04, Jul-08	Jul-04: The Warwick agreement[5] came about as a compromise between British Labour Government and trade unions at the Labour Party's National Policy forum. Jul-08: The US president Barack Obama met the UK prime minister Gordon Brown in London, focusing on key foreign policy issues facing both countries, particularly Afghanistan and Iraq.
United States	Jul-04, Sep-08	June-04: The US returns sovereignty to an interim government in Iraq, but keeps roughly 135,000 troops in the country to fight an increasing number of insurgencies. Sep-08: Major Wall Street investment bank Lehman Brothers collapses and other big US financial players face growing troubles due to the "credit crunch". Billions of dollars wiped out in bad loans and a prolonged property slump. The US faces its most severe financial crisis since the Great Depression.

Note: The break dates reported in this table are based on the significant breaks identified by the Model C and Model CC of the LM unit root tests.

1. The previous IPO record was raised by NIT DoCoMo for $18.4 billion in 1998.

2. Leaders of Afghanistan, Bangladesh, Bhutan, India, The Maldives, Nepal, Pakistan and Sri Lanka attended the summit.

3. The reform gives parliament greater power, but also adds a new privileges to France's already strong presidency, notably allowing the chief of state to address together the two houses of congress. Nevertheless, it limits the president to two five-year terms.

4. They vowed to do all they could to prevent the turmoil of Wall Street from destabilizing their banking systems. The second largest commercial property lender, Hypo Real Estate Holding AG, said its $48 billion rescue plan had unraveled when private banks pulled out.

5. The agreement is a deal signed in July 2004 at Warwick University between the Labour government and UK trade unions. The purpose was to secure continued union affiliation and funding for Labour after a period of deteriorating relations. In return, it helped form Labour's election manifesto in 2005.

Table A4: Results for VAR residual Breusch-Godfrey serial correlation LM test

Bivariate VAR(p) systems	LM-statistic	p-value
Panel A: *Between BRICS and G7 countries*		
(Brazil, Canada)	0.033	1.000
(Brazil, France)	5.082	0.279
(Brazil, Germany)	3.271	0.514
(Brazil, Italy)	5.091	0.278
(Brazil, Japan)	1.577	0.813
(Brazil, United Kingdom)	4.394	0.355
(Brazil, United States)	1.262	0.868
(China, Canada)	1.614	0.806
(China, France)	3.674	0.452
(China, Germany)	8.321*	0.081
(China, Italy)	1.167	0.884
(China, Japan)	5.342	0.254
(China, United Kingdom)	2.262	0.688
(China, United States)	4.279	0.370
(India, Canada)	0.898	0.925
(India, France)	4.255	0.373
(India, Germany)	7.230	0.124
(India, Italy)	0.343	0.987
(India, Japan)	4.546	0.337
(India, United Kingdom)	1.051	0.902
(India, United States)	1.334	0.856
(Russia, Canada)	2.204	0.698
(Russia, France)	3.105	0.540
(Russia, Germany)	7.120	0.130
(Russia, Italy)	4.244	0.374
(Russia, Japan)	3.664	0.453
(Russia, United Kingdom)	5.288	0.259
(Russia, United States)	5.217	0.266
(South Africa, Canada)	1.952	0.745
(South Africa, France)	1.188	0.880
(South Africa, Germany)	2.593	0.628
(South Africa, Italy)	3.565	0.468
(South Africa, Japan)	1.960	0.743
(South Africa, United Kingdom)	5.161	0.271
(South Africa, United States)	2.811	0.590

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Table A4 – *Continued from previous page*

Panel B: *Within G7 countries*		
(Canada, France)	2.181	0.703
(Canada, Germany)	3.817	0.431
(Canada, Italy)	2.076	0.722
(Canada, Japan)	0.312	0.989
(Canada, United Kingdom)	0.422	0.981
(Canada, United States)	5.027	0.285
(France, Germany)	5.325	0.256
(France, Italy)	7.688	0.104
(France, Japan)	0.898	0.925
(France, United Kingdom)	5.099	0.277
(France, United States)	8.697*	0.069
(Germany, Italy)	1.565	0.815
(Germany, Japan)	4.699	0.320
(Germany, United Kingdom)	7.507	0.111
(Germany, United States)	6.419	0.170
(Italy, Japan)	4.781	0.311
(Italy, United Kingdom)	6.454	0.168
(Italy, United States)	7.481	0.113
(Japan, United Kingdom)	0.453	0.978
(Japan, United States)	4.270	0.371
(United Kingdom, United States)	2.914	0.572

Note: Each pair of country in the parentheses represents a bi-variate VAR(p) process.

* Denotes statistically significant at the 10% level.

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