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International portfolio diversification possibilities: can BRICS become a destination for US investors?

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ABSTRACT
This paper investigates the portfolio diversification possibilities between BRICS and the US stock market. Using bootstrap full-sample Granger causality and bootstrap rolling-window sub-sample Granger causality tests, we did not find evidence supporting the causal linkage between BRICS and the US stock markets; time-varying causality was observed for particular sub-samples. Our findings imply that BRICS stock markets can provide diversification possibilities for US investors most of the time; however, such opportunities become extremely limited during crisis periods. We also find that stock markets are more likely to be causally linked if they have similar business conditions, excess returns and size premiums.

KEYWORDS
Portfolio diversification; structural breaks; Granger causality; bootstrap rolling-window technique; probit

JEL CLASSIFICATION
F30; G11; G15

I. Introduction

International portfolio diversification can enhance portfolio returns while reducing portfolio risks for investors willing to bear the transaction costs associated with diversifying into foreign equities. Given that the indirect costs associated with international portfolio diversification are on a downward spiral, it is no surprise that a lot of finance literature has focused its attention on international risk diversification and investment management on a global scale. The basic premise behind all international diversification strategies stems from the one fundamental observation that there is a less-than-perfect correlation among returns on national stock markets. The topic of international portfolio diversification has attracted significant attention from academics and institutional investors such as mutual fund, pension fund and hedge fund investors. The resulting public attention, in turn, has pave way for the introduction of a myriad of institutional products that are designed for global investors seeking diversification possibilities on an international scale.

Sharpe (1964) explained that diversification could remove unsystematic risk via portfolio diversification in his seminal paper. Harvey (1995) showed that including emerging stock markets in an optimally-diversified portfolio increased the expected returns substantially. Emerging countries have been experiencing higher economic growth levels than developed countries, which provides opportunities to generate higher returns in international portfolios (Naranjo and Porter 2007; Dewandaru et al. 2017; Mensi et al. 2017). Such findings may explain why the allocation in emerging market assets in developed country investors' portfolios increased from 5% in 2002 to 13% in 2012.[1] However, despite the diversification benefits offered by developing countries, there are several issues that international investors need to consider. First, there is a growing body of literature indicating an increase in the degree of co-movement between advanced economies and emerging financial markets (Bekaert et al. 2014; Wang and Guo 2020; Wan et al. 2020), as well as among several major developing countries (Middleton, Fifield, and Power 2008; Piljak 2011). Second, the spate of economic and currency crises has led to an increase in the return volatilities and a decrease in the risk-adjusted returns for international investors (Lagoarde-Segot and Lucey 2007). Third, causality findings from previous studies (see e.g. Gilmore and McManus 2002; Meric, Ratner, and Meric 2008) indicates that profits from international

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

portfolio diversification appear to be limited. These facts could alter portfolio investment capital flow, which implies that some developing countries' diversification gains have decreased. Thus, international investors might have to consider new emerging markets as potential avenues for obtaining diversification benefits.

This paper investigates the international portfolio diversification possibilities between the US and BRICS economies.[2] We look at the BRICS stock markets for several reasons. First, the BRICS economies are continually improving their market microstructure (e.g. updating investment laws, opening up to international trade). Second, within BRICS governments have been active in promoting the awareness of investment opportunities there.[3] The financial and economic reforms in these countries over recent years seem to have been remarkable. In particular, the BRICS nations have been demonstrating high economic growth rates (at 3%-8%)[4] that are well above those of the western economies, thus maintaining BRICS' white-hot investment place among fund managers and individual investors alike. Figure 1 illustrates the behaviours of different stock markets by plotting the natural logarithms of the monthly Morgan Stanley Capital International (MSCI) stock market indices of BRICS and the US over the period December 2000 to June 2017 (grey columns represent periods of negative shock). Two observations can be made here. First, both the BRICS and the US stock markets were in full-blown bear market during the 2008 Global Financial Crisis (GFC). Second, the US stock market appears to be more volatile than emerging markets, indicating that the US investors are likely to have diversification possibilities among BRICS countries in times of recession.

This study's principal objective is to investigate whether US investors can obtain diversification benefits by investing in the BRICS stock markets. To do so, we adopt a causality framework to examine statistically whether a causal relationship exists between the stock markets. If changes in one stock market cause similar variations in other stock markets, it becomes easier for investors to forecast the price of the latter index by studying the price changes of the former. Thus, the diversification benefits from constructing a portfolio that consists of such stocks are of limited diversification interest.

Our study contributes to the existing literature in the following ways. First, although quite a few studies have discussed co-movements among different stock markets and their impacts on international diversification benefits (see Bekaert et al. 2008; Bai and Green 2010), very little attention has been paid to the issue of structural changes. The present paper fills this gap by considering the possibility of structural breaks in the time series that we employ. The examination of structural change is reinforced in our study by the (trending) nature of the time series that we use. In particular, the stylized facts presented in Figure 1 suggest that stock markets can be considered to exhibit at least one break in 2008 due to the Global Financial Crisis (GFC). In this paper, instead of considering structural breaks as exogenous, we apply methods in which the breakpoints are estimated endogenously rather than taken exogenously fixed. To be more specific, before conducting the unit root test, we adopt the techniques of Perron and Yabu (2009) and Kejriwal and Perron (2010) to select the parsimonious model with the optimal number of breaks. Once we have ascertained whether or not there are breaks in the data series, the null hypothesis of a unit root is then examined using the Lee and Strazicich (2003) minimum Lagrange Multiplier (LM) unit root test.

Our second contribution is related to the causality testing method. The results in the literature on the causality between different stock markets vary considerably, especially with respect to the sample period selected (see, e.g. Yinusa 2008; Meric, Ratner, and Meric 2008). A critical issue with the data used in these studies is that of structural changes or regime shifts. Additional variability in the results is due to the way in which the trending properties of the data is handled. The results using

[2]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, leading to the creation of the BRICS association.

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

[4]Data is from the Borysfen Intel website, available online at: http://bintel.com.ua/en/article/briks-perspektivy-jekonomicheskogo-razvitija/

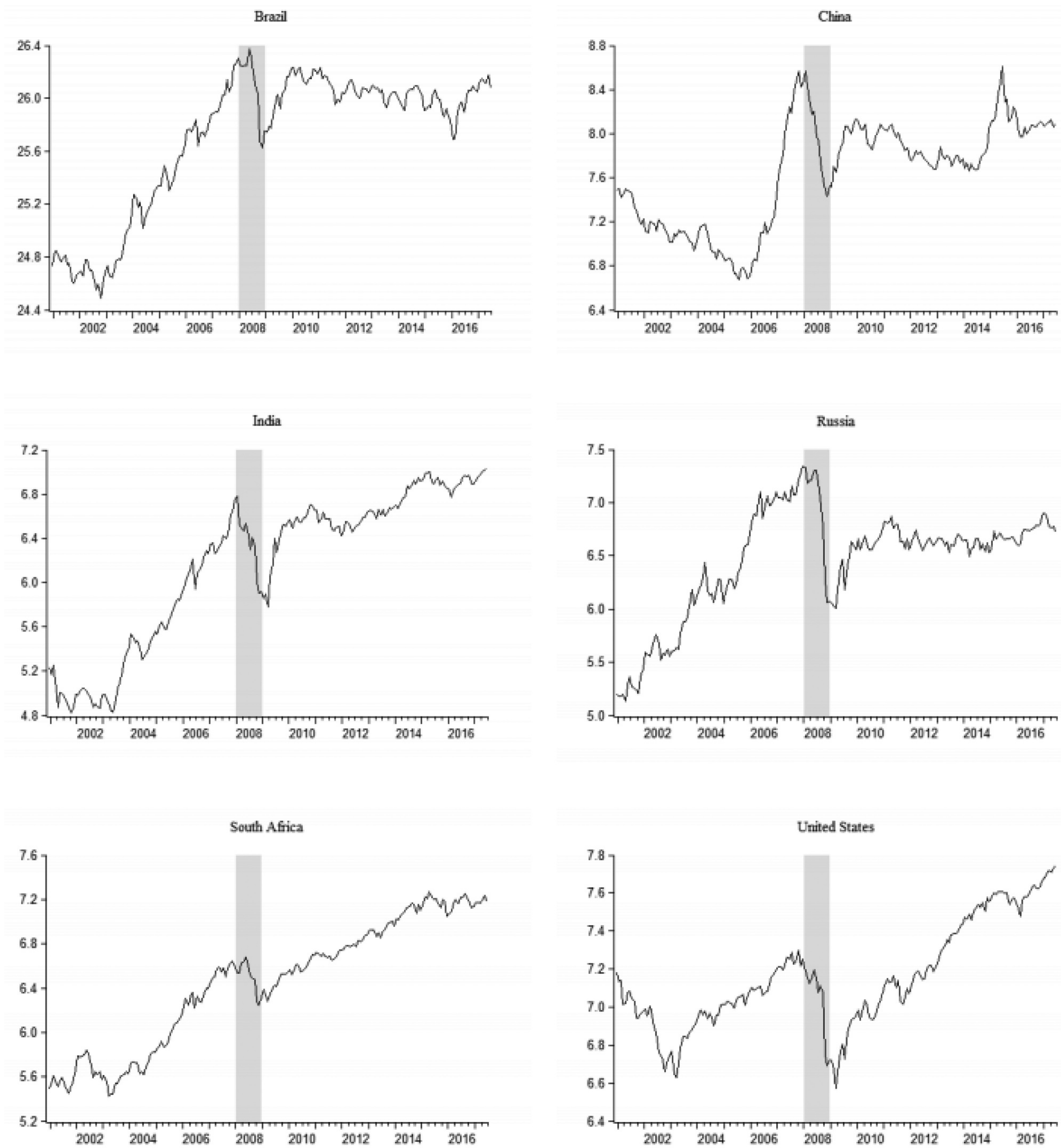

Figure 1. Stock market performance of BRICS and the US economies (Dec 2000-Jun 2017)
Note: The grey bars in the figure represent periods of negative shocks. The data for monthly MSCI stock market indices is obtained from the Thomson Reuters Datastream which are converted into natural logarithm form.

cointegrated models mostly differ from those where the data's integration and cointegration properties are ignored. The present study takes these two issues into account by using bootstrap tests and rolling window estimation. Few studies have considered structural changes when testing for causality, to the best of our knowledge. As one step further, using the probit model, we explore the possible determinants of the causal links for the stock markets and evaluate the forecasting of causality using fitted vs. empirical causality estimates. Foreshadowing the main results, we find that causality between the BRICS and the US stock markets does not exist most of the time. The causal linkage,

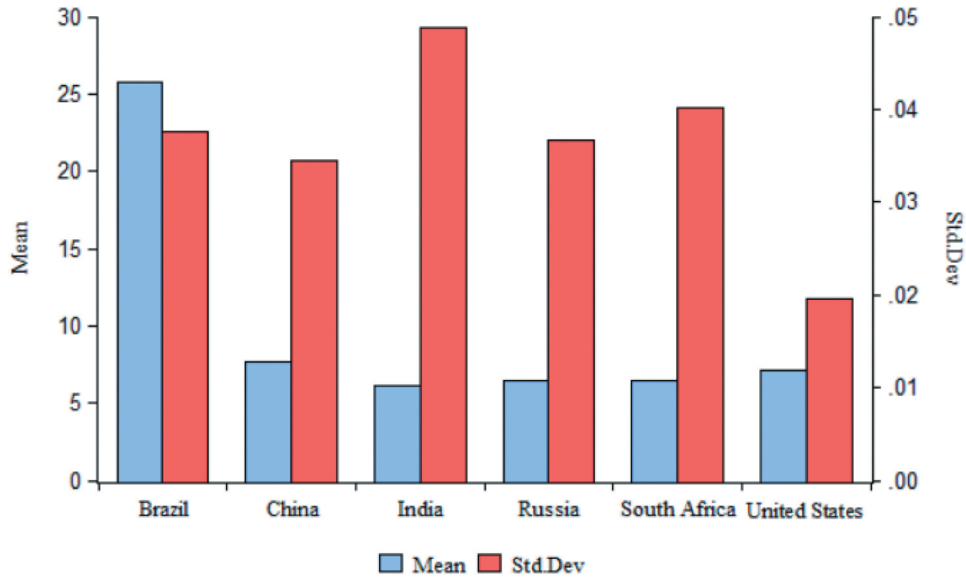

Figure 2. Means and standard deviations of the natural log of the MSCI stock market price indices
Note: The data for monthly MSCI stock market indices are obtained from the Thomson Reuters Datastream. The mean and standard deviation are based on authors' calculations.

however, becomes more vital in the recession periods. Thus, BRICS stock markets can provide portfolio diversification benefits for the US investors; such possibilities, however, are extremely limited during volatile periods. Our analysis also shows that stock markets are more likely to be causally linked if they have similar business conditions, excess returns and size premiums.

The rest of this paper is organized as follows. Sections 2 and 3 describe the data and empirical methodology, respectively. Section 4 discusses the empirical results, analyses and provides plausible reasons for the stronger co-movements between stock markets in the volatile periods. Section 5 concludes.

II. Data

The variables of interest are the stock market indices in the US and BRICS nations. As indicated by Christou (2008), monthly data are used most commonly in portfolio management research; therefore, we use monthly MSCI stock market price indices as proxies for stock market performances. Our sample period span is from December 2000 to June 2017. The data are 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 minimize large volatility while increasing the reliability of the results.

Figure 2 plots the mean and standard deviation (SD) of the country's stock market price index. It shows that the index level varies slightly between countries, except for Brazil. The mean value of the Brazilian stock market is much higher than others. The Brazilian stock market index outperformed the other BRICS and the US markets substantially based on the sample period. As the world's ninth largest economy, Brazil has long been a focus of emerging markets investments, ever since it was anointed as a member of BRICS. The technology ecosystem in Brazil has presented an exponential growth trajectory supported by the country's fast growing, internet-savvy middle class and hyper-urban population. These factors, in the context of a country with incipient digitalization across industries, create attractive opportunities for technology investment. Hence Brazil experienced a significant increase in stock market capitalization during the sample period. Brazil's stock market capitalization in 2000 was about a third of GDP, while the average in high-income countries was over 114%. In 2007, Brazil's same figure was above 100%, effectively converging to levels similar to those of high-income countries (Bonizzi 2015). The volatility of the stock market as measured by the SD, highlights a clear country-wise pattern. Specifically, market volatility in the US is relatively low, compared to the high level of volatility within BRICS markets.

III. Empirical methodology

Bootstrap full-sample Granger causality test

To investigate the causal relationship between the US and BRICS stock markets, we first employ the bootstrap full-sample Granger causality test based on a residual bootstrap procedure with a modified likelihood ratio (LR) test.

Consider the following bivariate VAR(p) process:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \ldots + \Phi_p y_{t-p} + \in_t, t = 1, 2, \ldots, T \quad (1)$$

where $\in_t = (\in_{1t}, \in_{2t})'$ is an independent white noise process with zero mean and non-singular covariance matrix Σ. The order of process p is known, and the lag length is determined by the Akaike Information Criterion (AIC). We simplify the equation by partitioning y_t into two subvectors, which relate to the stock markets in countries i and j, respectively; then, Equation (1) can be written more compactly as:

$$\left[y_{i,t} y_{j,t}\right] = \left[\phi_i \phi_j\right] + \phi_{i,i(L)} \phi_{i,j(L)} \phi_{j,j(L)} \phi_{j,i(L)} \left[y_{i,t} y_{j,t}\right] + \left[\in_{i,t} \in_{j,t}\right] \quad (2)$$

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

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

Parameter non-constancy test

One restrictive assumption of the Granger causality test is that the VAR models' parameters are constant over time. However, structural changes make the validity of this assumption questionable. Hence, the results from bootstrap full-sample Granger causality test always tend to be biased. The literature has proposed various tests for examining the temporal stability of VAR models (e.g. Hansen 1992; Andrews 1993; Andrews and Ploberger 1994). Although it is easy to test the parameter stability when the variables are stationary, we also need to consider the non-stationary nature of the variables in our model and consider the integration-cointegration property of the data. If the variables are cointegrated, the causality tests are conducted on a standard (sometimes first differenced) VAR. All parameters correspond to short-run dynamics in a non-cointegrated VAR, and hence, only short-run stability is investigated. Otherwise, variables from a VECM in a cointegrated VAR, and therefore the 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. Therefore, we test the stability of our model using a two-step procedure: first we examine the stability of the cointegration parameters, then we test the stability of the short-run parameters if the long-run parameters are stable. We investigate the stability of the long-run parameters by employing the L_c test that was developed by Nyblom (1989) for $I(0)$ series and then extended to $I(1)$ series by Hansen (1992). This LM test examines the null of the parameters' stability against the alternative hypothesis that the coefficients follow a random walk (i.e. the coefficients are time-varying and stochastic). In what follows, the Supremum Wald (Sup-Wald) and Supremum 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 statistics 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 the sample. Following Andrews (1993), we calculate the test statistics using a fraction of the sample in [0.15, 0.85] with 15% trimming.

Residual based bootstrap sub-sample rolling-window technique

Balcilar, Ozdemir, and Arslanturk (2010) first developed a residual-based bootstrap rolling-window Granger causality test which is widely used to examine the time-varying causal nexus between two variables. This sample splitting technique is appealing as the causality can be examined at particular periods and tackle pre-test bias from structural breaks. The rolling-window approach applies a fixed-length moving window sequentially from the beginning to the end of the sample by adding one observation at the start of the sample and dropping one from the end. In particular, given a fixed-size rolling-window including l observations, the full-sample can be converted to a sequence of $T - l$ sub-samples, that is, $\tau - l + 1, \tau - l, \ldots, \tau$ for $\tau = l, l + 1, \ldots, T$. We then apply the residual-based modified-LR causality test to each sub-sample, providing a sequence of $(T - l)$ causality tests rather than just one. Possible changes in the causality between two stock markets are identified by calculating the bootstrap p-values of observed LR-statistic rolling through $(T - l)$ sub-samples.

IV. Results and discussion of findings

To ensure the estimation is reliable, we first conduct unit root tests developed by Lee and Strazicich (2003) to investigate the data series's unit root properties. The bootstrap full-sample Granger causality test is then implemented to examine the diversification possibilities between the US and BRICS stock markets. To verify the results from full-sample estimations are reliable, we conduct parameter non-constancy tests. Further to provide time-varying causal inference, the bootstrap sub-sample rolling window Granger causality test is performed. Finally, using the probit model, we examine the possible determinants of cross-country stock market causality.

Unit root test

One of the standard features of time series data is the presence of structural breaks. Structural breaks can be described as unexpected shifts in the data generating process (DGP), often due to macroeconomic shocks such as changes in interest rates, economic policies, business cycles, etc. Ignoring the presence of structural breaks can lead to serious misspecification bias in the modelling. Besides, overlooking structural breaks can cause incorrect descriptive statistics. We avoid these pitfalls and select the appropriate model with the optimal number of structural breaks by using the tests developed by Perron and Yabu (2009) and Kejriwal and Perron (2010), before implementing the unit root tests with structural breaks. Thus, we begin by determining whether breaks are present, then apply stationarity tests that allow such breaks to be identified. Perron and Yabu (2009) method 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) method identified one break, we used Kejriwal and Perron (2010) procedure to test the null of one break against the alternative of two

Table 1. Results for the 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
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
Unites States	III	37.000***	Sep-08	4.301**	Apr-03

(1) Model III refers to the presence of structural breaks in both the intercept and the slope. (2) We follow a sequential procedure which first tests the null hypothesis of no breaks versus one break. For the series for which the null is rejected, we further test the null of one break in the slope versus two breaks. (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 (4) Asterisks (**) and (***) denote statistical significance at the 5% and 1% levels, respectively.

breaks. The results of the tests of Perron and Yabu (2009) and Kejriwal and Perron (2010) for identifying the number of breaks in each country's stock market price index series are reported in Table 1. Apart from the Brazilian stock market, which has only one break, all remaining markets exhibit two breaks. The break dates given in Table 1 are associated with events that had significant effects on the global stock market; most notably the September 11th terrorist attacks in the US in 2001; the 2003 second Gulf War and the 2008 GFC.

We then apply the LM unit root test of Lee and Strazicich (2003) with structural breaks to investigate our data series' stationarity properties. A common problem with ADF-type endogenous break unit root tests is that their critical values are obtained by assuming no breaks under the null. Nunes, Newbold, and Kaun (1997) showed that this assumption could lead to size distortions in the presence of a unit root with a structural break(s). Therefore, when conducting ADF-type endogenous break unit root tests, one might conclude that a time series is trend stationary, whereas it is non-stationary with a break(s), implying that a spurious rejection is a real possibility. The LM unit root test, on the other hand, remains unaffected by breaks under the null hypothesis of a unit root. This study employs Lee and Strazicich (2003) Model C and Model CC specifications of the LM unit root test, which can accommodate two structural breaks in the intercept and the slope. This test relies on determining the breaks at which the endogenous two-break LM t-test statistic is at a minimum. Table 2 provides the results of the LM unit root tests[5] with the optimal number of structural breaks suggested by the Perron and Yabu (2009) and Kejriwal and Perron (2010) tests, as well as the date(s) of the break(s). The table also presents the LM unit root test results with both one break (Model C) and two breaks (Model CC) in the

Table 2. Results of the LM unit root tests with one and two structural breaks (Models C and CC).

ln(MSCI stock market index)	Lag order	TB1	TB2	B1(t)	B2(t)	D1(t)	D2(t)	LM test statistic
Panel A: Model C								
Brazil	0	Oct-07	-	0.021(0.298)	-	0.002(0.154)	-	−3.378
Panel B: Model CC								
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
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

TB1 and TB2 stand for the dates of the structural breaks, B1(t) and B2(t) refers to the dummy variables for the structural breaks in the intercept, and while D1(t) and D2(t) represent the dummy variables for the structural breaks in the trend. The statistics in parentheses are t-statistics. Asterisks (*), (**) and (***) denote statistical significance at the 10%, 5% and 1% levels, respectively.

[5]Critical values for Model C and Model CC are presented in the Appendix.

intercept. In Model C, the unit root null hypothesis cannot be rejected for the Brazilian stock market series (The critical values of Model C are presented in Table A1 in the Appendix). In Model CC, the LM test statistic indicates that more than half of the series are stationary except for the South African and the US stock market price indices (The critical values of Model CC are reported in Table A2 in the Appendix). Therefore, we conclude that Chinese, Indian and Russian stock market indices are stationary in level, while all the other series are stationary in first difference.

Discussion of structural breaks

We now turn to the investigation of the locations of breakpoints. The break dates in Table 2 differ from those in Table 1, which is to be expected given that, since the breakpoints are determined endogenously, break dates may differ between methods. Most of the breaks in Table 2 are also linked to global events that have affected the global stock market. It is nevertheless noteworthy that these events can only be treated as possible events[6] associated with structural breaks, but not as evidence of a statistical linkage with the time periods of structural breaks. This is a limitation of our study that requires further investigation.

For half of the countries, the first break appeared in about 2003–2004. This period was associated with the 2003 global economic boom. Before this, the 1997–1999 Asian financial crisis had caused a collapse of demand in most developing economies in Asia. Soon after it came to the IT dot com bubble, the 2000s energy crisis and the global recession of 2001. However, these adverse shocks gave way to a positive shock. In particular, the world experienced unprecedented economic growth between 2003–2008. Even in Sub-Saharan Africa, growth accelerated from 2.4% in the 1990s to 5.5% in 2003.[7] In short, a global boom lifted all boats around, including both the BRICS and the US.

Four countries have second breaks in 2008, which is linked to GFC. Evidently, most developed countries slowed considerably during the GFC. Specifically, stock markets of developed countries fell by more than 40% from the levels prior to GFC while leading economic indicators, including shipping rates, fell significantly.[8] In contrast, two of the five BRICS economies (China and South Africa) were isolated from this global financial turmoil. However, the BRICS economies and their stock markets were still growing strongly, the global financial meltdown leaving their economies unscathed. Unlike developed countries, strong foreign exchange reserves and increasing domestic demand levels allowed the BRICS nations to withstand the crisis and keep growing, thus strengthening their positions as significant consumer markets.

Overall, the structural breaks' locations show that the BRICS and the US economies are sensitive to both internal and external shocks, and this sensitivity is likely to increase as developing countries continue their integration into the world economy. We visualize our empirical findings by superimposing the level and trend break(s) for all series identified by the LM unit root tests and plotting the log of the stock market price index in each country. Linear trends are estimated via ordinary least squares (OLS) regression to connect the structural breakpoints. Figure 3 shows the results and illustrates that the break date(s) for each stock market coincide with the visualization of the series.

Bootstrap full-sample causality test

We adopt the bootstrap full-sample Granger causality test to examine the causal relationship between different stock markets. The critical values are generated using the bootstrap procedure with 1000 replications. We test the null hypothesis that the stock market in the country i does not Granger-cause the stock market in country j by estimating the full-sample bootstrap

[6]Detailed events around the identified break date(s) for each country are reported in Table A3 in the Appendix.

[7]Refer to the article 'Mystery of India's economic growth unravelled' by Swaminathan S Anklesria 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

[8]Refer to 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

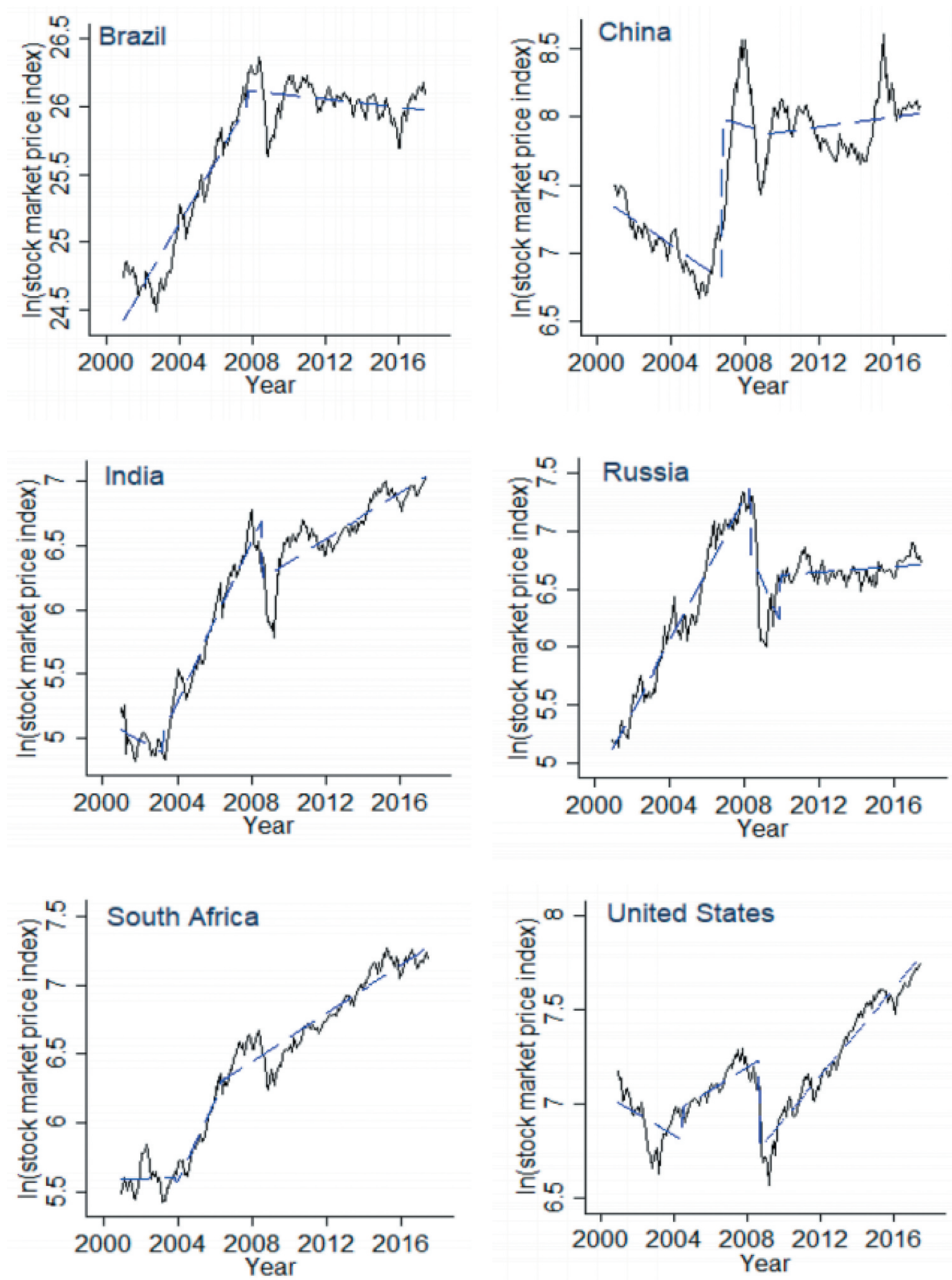

Figure 3. Log of the MSCI stock market price index (Dec 2000-Jun 2017)
Note: These graphs are based on authors' calculations. Linear trends are estimated via OLS regression to connect the structural breakpoints.

LR statistic. The results of the full-sample Granger causality test are provided in Table 3. As is evident, the null hypothesis that BRICS stock markets do not Granger-cause the US stock market cannot be rejected at the 10% significance level or better. Our findings suggest that although the BRICS countries have taken some positive steps that are responsible for the substantial improvements in their stock markets, thus far they may not have been sufficient for the market to become mature – developed (Bouri et al. 2018), and therefore the markets have not yet become integrated with the US market (Abid, Kaabia, and Guesmi 2014).

On the other hand, the null hypothesis that the US stock market does not Granger-cause Chinese stock market is rejected at the 10% significance level, indicating that the US stock market has

Table 3. Results of the bootstrap full-sample Granger causality test.

Direction of causality	Bootstrap LR-statistic	p
Panel A: BRICS as the independent variable (Y)		
Brazil → United States	0.491	1
China → United States	0.815	5
India → United States	6.595	4
Russia → United States	−0.863	1
South Africa → United States	−0.688	1
Panel B: US as the independent variable (Y)		
United States → Brazil	0.676	1
United States → China	5.823*	5
United States → India	−0.618	4
United States → Russia	−0.475	1
United States → South Africa	3.785	1

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. Asterisk(*) denotes statistically significant at the 10% level.

predictive power for Chinese stock market. Furthermore, we cannot find causality running from the US stock market to the rest of the BRICS stock markets. Overall, the findings imply that there are diversification benefits for US investors in BRICS stock markets. However, as the world's single largest economy, developments in the US stock market are bound to have significant effects on other countries' stock markets. Thus, the full-sample test results are misleading due to structural breaks in the data series, which may cause parameter non-constancy in the whole VAR system.

Table 4. Results of the parameter stability tests.

Bivariate VAR(p) systems		Long-run stability tests		Short-run stability test	
Dependent variables	Independent variables	Lc	Lcfor system	Sup-LR	Sup-Wald
Panel A: BRICS as the dependent variable					
Brazil	United States	4.981***	10.307***	4.312	12.937
China	United States	5.454***	8.688***	2.776*	30.537*
India	United States	4.008***	11.280***	4.360*	39.243*
Russia	United States	6.316***	11.514***	10.542**	31.627**
South Africa	United States	5.060***	10.992***	3.109	9.326
Panel B: US as the dependent variable					
United States	Brazil	6.933***	-	8.676	26.028
United States	China	1.442***	-	5.901***	64.908***
United States	India	6.087***	-	3.691	33.220
United States	Russia	7.887***	-	20.521***	61.563***
United States	South Africa	4.025***	-	1.887	5.661

The Hansen-Nyblom long-run parameter stability test is conducted on each equation separately and on the VAR system as a whole. The Sup-LR and Sup-Wald tests statistics are appropriate for examining a swift regime shift. The p-values are obtained from a bootstrap approximation to the null distribution of the test statistic, conducted by Monte Carlo simulation using 1000 samples generated from a VAR model with constant parameters. Asterisks (*), (**) and (***) denote statistical significance at the 10%, 5% and 1% levels, respectively.

Parameter non-constancy

As argued in Balcilar, Ozdemir, and Arslanturk (2010) and Balcilar and Ozdemir (2013), parameter non-constancy can lead to biased causal inference based on the VAR model in Equation (2). To be more specific, the parameter non-constancy can lead to non-rejection of the null hypothesis of Granger non-causality. Therefore, the Granger causality test of the full sample VAR model will show sensitivity to temporally unstable parameters and changes in the sample period selected. The temporally unstable parameters are examined through the L_c test for the long-run parameter stability. Furthermore, the Sup-LR and Sup-Wald tests are used to examine the short-run parameter constancy. Table 4 reports the results of the parameter stability tests. The L_c test estimates indicate that the 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 are inconsistent at the 1% significance level for all stock market pairs. In Panel A, the Sup-LR and Sup-Wald test results imply significant evidence of short-run parameter instability in most of the BRICS stock markets equations.

In contrast, the Panel B results suggest that the parameters in more than half of the US stock market equations are constant. Overall, we conclude that the VAR systems under consideration have undergone structural and regime changes and the VAR model parameters are not constant over time. Hence, the estimations based on the bootstrap full-sample Granger causality test are bias and not reliable.

Bootstrap sub-sample rolling-window Granger causality test

Due to the parameter instability, the equations ($y_{i,t}$ and $y_{j,t}$) in the VAR model are re-estimated using a rolling-window technique. The rolling estimators, also known as fixed-window estimators, are obtained by changing sequentially the sub-sample of a fixed length that moves from the beginning to the end of the sample. In each step, first 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 causality test. First, the fixed-window rolling estimation procedure allows the system to evolve over time. Second, the approach conveniently addresses the sub-sample instability issue, using a sequence of different sub-samples.

As was argued by Balcilar, Ozdemir, and Arslanturk (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 estimates based on a large window size more precise. However, such estimates will not represent the true parameters, due to fewer windows of estimates. On the other hand, smaller windows will provide larger numbers of estimates but can increase the estimates' variance. Following Koutris, Heracleous, and Spanos (2008), we estimate the tests with a higher accuracy level by adopting a small rolling window and applying the bootstrap technique to each window.

Nevertheless, there is no strict rule for selecting the window size for rolling-window estimation. Pesaran and Timmermann (2005) investigated the window size under a structural change in terms of the root mean square error. Their Monte Carlo simulation results suggested that the bias in the autoregressive parameters is minimized with a window size of around 10–20 in the presence of frequent breaks. Pesaran and Timmermann (2005) highlighted two conflicting demands when deciding on the optimal window size. The degrees of freedom of estimation (potential for multiple structural breaks) require a larger (smaller) sample size to accurately estimate the parameters. Following the suggestions based on Pesaran and Timmermann (2005) simulation results, 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 the US stock market are plotted in Figure 4. In all the plots, 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 plotted in Figure 4 point to two standard features. First, the causality among the BRICS and the US stock markets does not exist over most of the sample period. Second, we observe an increase in causality during crisis periods. Specifically, most of the country pairs show a stronger causality in the periods of GFC (2007–2008), chronic sovereign debt crises in the Eurozone (2010–2012), and Britain exiting the European Union ('Brexit' in 2016). Overall, our findings suggest that most times, US investors could diversify their portfolio risks in BRICS stock market. Investment decisions, however, should be made by considering the dynamics of stock markets' relationships and with due caution, knowing that these relationships are subject to change. Moreover, the findings of rising causality between the BRICS and the US stock markets in volatile periods suggest that there are limited diversification possibilities for US investors during those periods.

In the context of portfolio investment in BRICS countries, another critical issue is market segmentation. Market segmentation is due to barriers that are difficult for investors to overcome. In

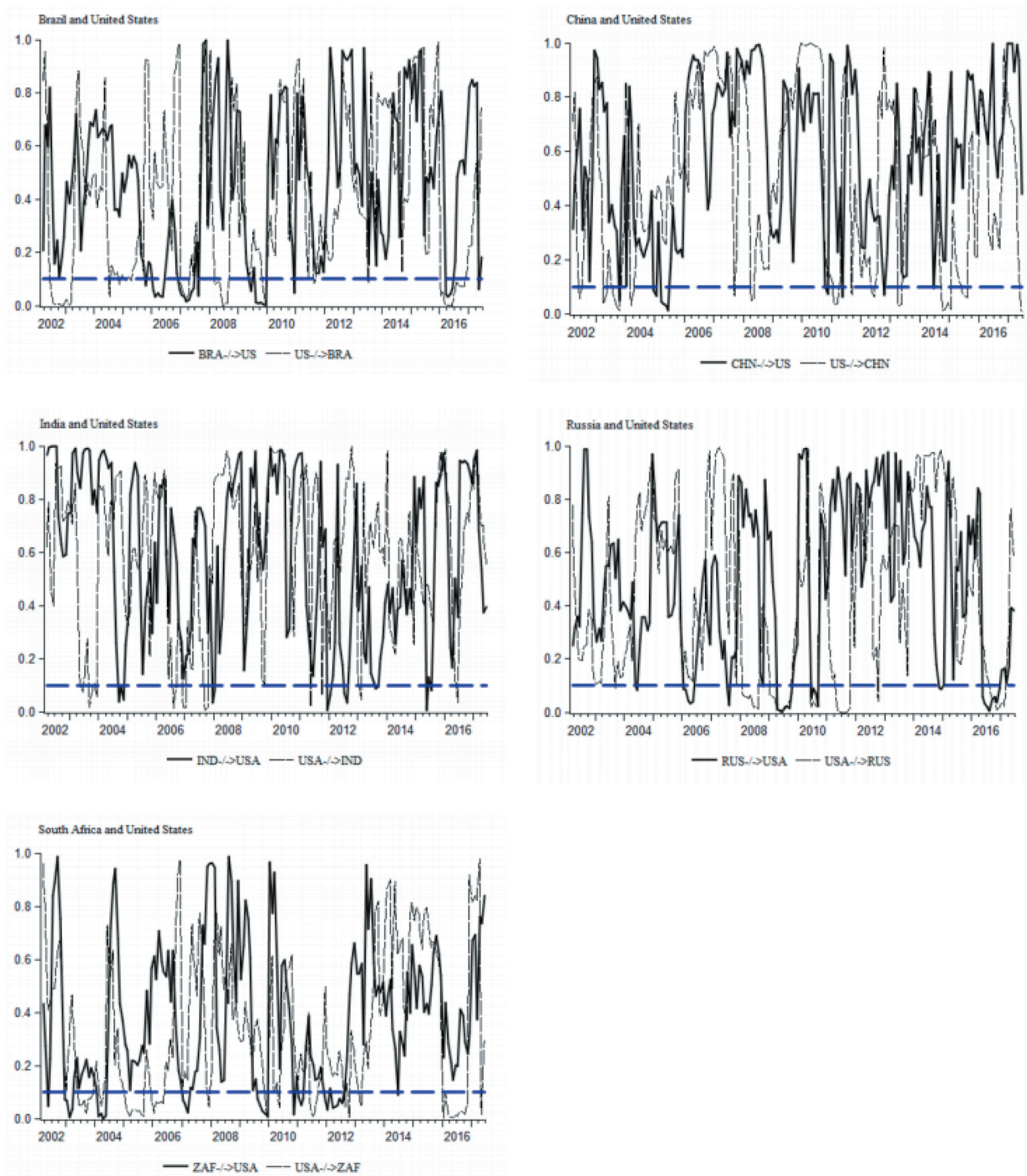

Figure 4. Rolling-window estimates of Granger non-causality between the BRICS and the US stock markets
Note: The blue lines indicates the 10% significance level. The relationship y \nrightarrow x stands for "y does not Granger-cause x". The p-values are generated using a bootstrap procedure with 1000 repetitions.

particular, Brazil has a long history of controls on capital outflows. In 1991, the real interest rates in Brazil were increased significantly to avoid capital flight. With the prevailing low rates in the US, capital started flowing into the country. In 1993, controls on capital inflows were enacted. Unlike the Chilean and Colombian capital controls, which took the form of unremunerated reserve requirements, Brazil's capital controls were based on exchange rate transaction tax. India also uses capital controls extensively as a macroeconomic management tool. Although India has been gradually reducing capital controls over the past two decades, it continues to have strict international capital controls. According to the Fernandez et al. (2016, updated online June 2019) data set on capital control restrictiveness using the IMF Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) as underlying data source, India obtained 0.93 in 2017 (The range is from 0 with no restrictions to 1 as entirely closed). When markets are segmented, the optimal portfolio may not include all international securities. Simultaneously, since it is usually costly and risky to overcome barriers to international portfolio investment, investors may receive benefits that have nothing to do with diversification of unsystematic risk. Therefore, it is noteworthy that the net realized return may not be sufficient to justify foreign stocks' holding even if the special benefits of segmented markets are further enhanced by diversification benefits that arise when these assets are less than perfectly correlated with the domestic portfolio. This phenomenon is further fostered by investors' portfolio natural bias towards their home market due to differences in the consumption patterns that limit their demand for foreign stocks.

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 analyse the determinants of that causality. For this purpose, the dependent variable (y) takes the value of one if the Granger causality is significant at 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 the BRICS and the US stock markets (i.e. the probability of occurrence of this event (y)). In doing so, the probability of observing a value of one is modelled as

Table 5. Explanatory variables in the probit model.

Name	Variables	Source
diff_BCI	Absolute value of the difference in the Business Confidence Index between country i and j	OECD data website[a]
diff-(Rm-Rf)	Abosulte value of the difference in excess return on the market between country i and j	Stefano Marmi website[b]
diff_SMB	Absolute value of the difference of Small Minus Big between country i and j	Stefano Marmi website
diff_HML	Absolute value of the difference of High Minus Low between country i and j	Stefano Marmi website
DM1	Dummy variable for the 2008 Global Financial Crises	Takes the value 1 in the crisis period and o otherwise
DM2	Dummy variable for the Euro Area recession (2010–2012)	Takes the value 1 in the crisis period and o otherwise

Due to data availability, these variables are for Brazil, China and the US. The excess return on the market refers to the difference between the market return and the risk-free rate of return. The market returns for Brazil, China, and the US are the value-weighted returns for all stocks on the Sao Paulo, Shanghai and Shenzhen, New York, Amex and Nasdaq stock exchanges. The risk-free rates of return for Brazil, China and the US are the Brazil Treasury bill rate as well as the US / China 91-day Treasury bill rate. 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.

a https://data.oecd.org/leadind/business-confidence-index-bci.htm

b http://homepage.sns.it/marmi/Data_Library.html#datalibrary

$$Pr(y = 1)X, \beta) = 1 - \Phi(-X'\beta) = \Phi(X'\beta) \quad (3)$$

where Φ is the cumulative distribution function of the standard normal distribution. We follow the standard convention by assuming that the index specification is linear in the parameters and has the form $X'\beta$.

The independent variables in our model are known to affect a country pair's stock markets. Hence, we hypothesize that these variables may explain the causal relationships between these markets. Our model includes the absolute value of the difference in the general business conditions as proxied by the business confidence index and the Fama-French factor between countries i and j as the explanatory variables. We take the absolute value of the differences in variables 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). We reflect the impact of these changes by using dummy variables for the times of these crises as explanatory variables in the model. The definitions, sources and related references are provided in Table 5.

Table 6. Results of probit models.

Dependent variables	US to Brazil	US to China	Brazil to US	China to US
	(1)	(2)	(3)	(4)
diff_BCI	0.766***	0.837	−1.022***	−1.229
	(0.251)	(0.522)	(0.254)	(0.788)
	[0.153]	[0.007]	[−0.107]	[−0.016]
diff_-(Rm-Rf)	-	-	−0.106*	−0.124*
			(0.056)	(0.074)
			[−0.011]	[−0.002]
diff_SMB	-	−0.215*	-	-
		(0.121)		
		[−0.002]		
diff_HML	-	-	-	−0.225
				(0.164)
				[−0.003]
DM1	-	5.677***	-	-
		(0.919)		
		[0.048]		
DM2	-	6.333***	−2.010***	-
		(1.274)	(0.599)	
		[0.054]	[−0.211]	
R2	0.207	0.274	0.352	0.209
non-missing obs.	63	63	63	63

The standard errors (in parentheses) are robust to arbitrary heteroscedasticity, while the associated marginal effects are provided in square brackets. R^2(McFadden) measures the goodness of fit and mirrors the R^2in OLS. Values between 0.2 and 0.4 (according to McFadden) indicate an excellent model fit. The sample period is from January 2008 to March 2013. Asterisks (*) and (***) denote statistical significance at the 10% and 1% levels, respectively.

The probit model's estimation is conducted by adopting the general-to-specific approach based on the reduction theory (Hendry 1995, Ch. 9). Initially, we analyse a general statistical model with all explanatory variables; then we eliminate the statistically insignificant ones. We first estimate the probit model for the case where the US stock market Granger-cause the Brazilian and Chinese stock markets, with results presented in columns (1) and (2) of Table 6. The *z*-statistics and robust standard errors are calculated using the Huber-White quasi-maximum likelihood method. The probit regressions' coefficients are not a direct interpretation of an independent variable's effect on a dependent variable. We are interested in the *ceteris paribus* impacts of changes in the explanatory variables on causality probability. In doing this, we also calculate the marginal effects and report them in square brackets below the probit regression coefficients for each predictive variable. These marginal effects can be interpreted as the effect of a unit change in a given regressor on the probability that country *i*'s stock market Granger-causes country *j*'s stock market or vice versa, keeping all of the other regressors constant. The results are calculated using the average values of the variables,[9] and the distinction in the coefficient signs is indicated by shading the relevant table cells (that is, the negative coefficients are shaded a light grey). We find that SMB portfolio returns (size premium) decrease the probability of causality running from the US market to the Chinese market. Notably, the dummy variables used to reflect the GFC (2008) and the European debt crisis (2010–2012) increase the chances of causality flows from the US stock market to the Chinese stock markets. Our findings suggest that under volatile market conditions, the US stock market reflects the market information much more quickly than the Chinese stock market. Columns (3) and (4) report the results of the determinants of cross-country stock market causality running from Brazilian and Chinese stock markets to the US stock market. We can see that an increase in the difference in business conditions decreases the probability of causality flows from the Brazil to the US stock market. The difference in excess returns is another crucial factor driving the causality flows from the Brazilian and Chinese stock markets to the US stock market. Specifically, an increase in the difference of excess returns would decrease the probability of Brazilian and Chinese stock markets, causing the US stock market.

Overall, differences in business conditions, the excess return and the size premium are the main drivers of causality between the BRICS and the US stock markets. Our findings that business conditions are a determinant of cross-country stock market causality is in line with Masson's (1998) results, among other studies on stock market contagion. Masson (1998) considered stock market integration to be associated with changes in investors' expectations (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 the size premium as strong determinants is also highlighted by Pritsker (2001), who summarized four separate financial market contagion channels. The former factor can be explained by the cross-market hedging channel (Calvo and Mendoza 2000; Kodres and Pritsker 2002).

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

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 purchasing one asset and another asset's sale. It occurs when new information that affects returns in one market makes investors want to change their portfolio holdings in that market. This change can cause changes in portfolio holdings in other markets, even though there are 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[10] (Saçhs, Tornell, and Velasco 1996). Specifically, if an observed negative real shock attacks country *i*, this shock is transmitted to the real sector of country *j* through real linkages, and the stock markets of both countries will respond to the real shocks. This usually happens between countries that are trade partners. If country *i* suffers from a crisis, this will reduce its import demand, which leads to a contraction of the outputs of enterprises in country *j* that rely on exports. When output of a country decreases, unemployment rate rises, resulting in further sizable appreciation of its currency. Thus, the crisis spreads to country *j* because its products become non-competitive in the export market.

V. Concluding remarks

This paper investigates diversification possibilities between the BRICS and the US stock markets. Using the time series techniques, the results of unit root tests with structural breaks suggest that the BRICS and the US stock markets are vulnerable to both internal and external shocks. This vulnerability may increase in the near future due to increasing economic integration between developing countries and the rest of the world. Bootstrap full-sample Granger causality tests indicate that the US stock market only has predictive power for the Chinese stock market. This may be attributed to parameter non-constancy, which leads to bias causal inference. Hence, a battery of tests is employed to test the parameter stability. Based on the results of parameter non-constancy tests, the VAR system's estimations may not be reliable. The bootstrap rolling-window technique is therefore adopted to tackle this issue. We examine the causality for each sub-sample and find that most of the time causality does not exist between BRICS and the US stock markets.

Nevertheless, the causality strengthens, especially during crises. In sum, our causality analysis suggests that BRICS stock markets are desired portfolio diversification areas for US investors, such benefits are limited during volatile periods . This study investigates some of the possible determinants of cross-country stock market causality though the probit model. The results imply that differences in business conditions, excess returns and premium size are significant determinants of the causality.

There are several avenues for future research. First, future research could investigate moderate variable effects, such as innovation and trust, which could be linked with other theories (e.g. institutional theory, knowledge-based view or transaction cost theory). Second, future studies could focus on multiple-level analyses of independent variables, such as the industrial, market or regional level.

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[10]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 instead an 'Asian mirage', which made them reassesses the creditworthiness of Hong Kong, Indonesia, Korea, Malaysia and Singapore.

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Appendix

Table A1 Critical values of the LM unit root tests (Model C).

Location of breakm, 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

Table A2 Critical values of the LM unit root tests (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

The critical values depend on the location of the breaks. λ_j denotes the break locations.

Table A3 Major events in the BRICS and the US for periods of the breaks.

Countries	Break dates	Major events
Brazil	Oct-07	Oct-07: In South Africa, the leaders of Brazil, India and South Africa vowed to push the interests of developing countries installed international trade talks and said that 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.[a] Apr-2009: China announced a$10 billion infrastructure fund and $15 billion in credits and loans to help Southeast Asian countries combat during the GFC.
India	Apr-03, Aug-08	Apr-2003: India's prime minister acknowledged that the government had manipulated elections in the 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) was held in Sri Lanka, amid extraordinary security.[b] A draft summit declaration called for collective action to combat all forms of terrorist violence 'that were threatening peace, stability and security'. The leaders also agreed to implement a regional trade pact, which was signed in 1995 but had never been fully implemented.
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 signalled a departure from his predecessor's heavy-handed tactics. Dec-09: The prime minister of Russia, Vladimir Putin, declared that Russia would build new weapons to set the planned US missile defence, resulting in Washington sharing 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 wishes to conduct business with the government. Jun-06: In South Africa, a one-day national strike, organized by the main trade union to protest against poverty and unemployment, affected production in the mining and car-manufacturing industries and had a patchy response in other sectors.
United States	Jul-04, Sep-08	Jun-04: The US returned sovereignty to an interim government in Iraq, but kept roughly 135,000 troops in the country to battle against the increasing number of insurgencies. Sep-08: Major Wall Street investment bank Lehman Brothers collapsed and other big US financial players faced growing trouble due to the 'credit crunch'. Billions of dollars were wiped out in bad loans, and there was a prolonged property slump. The US faced its most severe financial crisis since the Great Depression.

The break dates reported in this table are based on the significant breaks identified by Models C and CC of the LM unit root tests.
aThe previous IPO record was raised by NIT DoCoMo for $18.4 billion in 1998
bThe leaders of Afghanistan, Bangladesh, Bhutan, India, and the Maldives, Nepal, Pakistan and Sri Lanka attended the summit.