Article

Linkages Between the Foreign Exchange Markets of BRIC Countries—Brazil, Russia, India and China—and the USA

Journal of Emerging Market Finance
17(3) 333–353

SAGE Publications
sagepub.in/home.nav
DOI: 10.1177/0972652718800081
http://journals.sagepub.com/home/emf

Ramya Rajajagadeesan Aroul[1]
Peggy E. Swanson[2]

Abstract

The past decade has witnessed increasing trade and capital flow movements between BRIC countries (Brazil, Russia, India and China) and the USA indicating a need for a better understanding of currency linkages between these countries. This article examines long-run and short-run relationships between foreign exchange markets of BRIC countries and the USA. Long-run results indicate that, over a period beginning January 2000 and ending November 2013, the currency markets of China, India and the USA are tied together, implying that from the perspective of the US investor, the markets of Brazil and Russia provide the greater diversification benefits. Further, the USA is found to be the source of the common trend (CT), suggesting that it leads the three (cointegrated) markets towards the long-run equilibrium relationships. Brazil and India share no short-run lead-lag relationship with the USA.

[1] Department of Economics and Finance, Texas A&M University—Commerce, Commerce, Texas, USA.
[2] Department of Finance and Real Estate, University of Texas at Arlington, Arlington, Texas, USA.

Corresponding author:
Ramya Rajajagadeesan Aroul, Department of Economics and Finance, Texas A&M University—Commerce, Commerce, Texas 75429-3011, USA.
E-mail: ramya.aroul@tamuc.edu

JEL Classification: F31, G15

Keywords

BRIC, portfolio diversification, cointegration, structural break, Granger causality, variance decomposition analysis

1. Introduction

Brazil, Russia, India and China, commonly called the BRIC countries, are four economies that are expected to create a transformation in the world economy in the future. There is a growing trend of inward and outward FDI and portfolio investment between these countries and the developed economies in the past few decades. In fact, the BRIC countries' share of world output has doubled to 15 per cent in the past decade. While the developed economies faced severe economic contraction in the past year, China and India have continuously grown although at half the rate as before this financial crisis. Hence, there is an enormous interest in the popular press about these countries, but the popular interest is not reflected in the academic research. Very few studies examine BRIC countries as a block (Aloui, Aissa, & Nguyen, 2011). BRIC countries thus not only provide an interesting sample due to the importance they play at this juncture but also a unique sample considering the lack of studies focusing on these countries.

Interest in foreign currencies as assets has been increasing over time. Current uncertainties and volatilities in global currency markets have caused global investors to look more closely at emerging countries. Emerging economies that have encouraged international investment by removing restrictions on cross-border capital movements, deregulating domestic financial markets and being proactive in offering competitive investment environments (Vo & Daly, 2007) have experienced a rapid increase in capital flows, highlighting the importance of international financial market integration.

Most literature attempts to document linkages between returns of stock indices of major equity markets and, more recently, of several emerging markets (Chan, Gup, & Pan, 1997) and, to a lesser extent, linkages between currency markets. Sweeney (2003) argues that cointegration among asset prices has no inferences by itself for efficiency. Schatz (2010) provides empirical evidence of the dynamic interactions between international macroeconomic determinants and emerging market sector indices. Similar to the capital markets, there can be linkages between the currency markets. Increasing capital flow movements between BRIC countries and the developed economies are affected by currency values and vice versa. Therefore, studying the currency markets and the co-movement of their currencies is indeed a contribution to the extant literature as one attempts to follow the progression of both global financial market and economic integration. This article provides further analysis on the issue of international financial linkages by examining the long-run relationships between the four BRIC-emerging foreign exchange markets—those of Brazil, Russia, India and China and the USA market, using daily data for the period January 2000–November 2013.

Primary findings of the study include, first, the estimation of multivariate cointegration finds two statistically significant cointegrating relationships among the five currency markets. Second, these financial markets have one statistically significant common trend (CT), which drives the system in the long run. Third, the study analyses short-run lead-lag relationships between markets providing information that may help market participants predict future short-run performance of one market based on the performance of another.

If international markets are segmented (not cointegrated), shocks to one market are not propagated to other markets and hence international portfolio diversification benefits can be exploited. On the other hand, if markets are linked together in the long run (cointegrated), the markets are affected by the same economic stimuli that limit long-run diversification opportunities (Gerlach, Wilson, & Zurbruegg, 2006).

The remainder of the article is organised as follows. The next section looks at characteristics of the BRIC countries, followed by a literature review on market linkages. Data are presented next, followed by methodology and empirical results and ending with conclusions.

2. BRICs

Although Brazil, Russia, China and India have been grouped together as a block by many analysts, these four countries are not an obvious set. They are quite different from each other with dissimilar internal politics and economics. Even though all of them are federal states, only India and Brazil are well institutionalised democracies, of which the former is parliamentary and the latter is presidential. China is a Marxist people's republic, and Russia is a declared democracy moving towards authoritarianism. Each of the four countries represents a unique cultural and linguistic background. Each has its own challenges that could bring speedy economic progress to a standstill: China with pollution problems, India with poor physical infrastructure, Brazil's inability to capitalise and grow rapidly despite current high commodity prices and Russia's corruption problems. Thus, they do not share the same strengths and development challenges and are also very different in their culture and language.

Although all four countries are grouped together, China is leading the race with its GDP almost three times that of Brazil which ranks second. India and Russia are well below these leaders. The GDP of all BRIC countries combined is close to that of the USA, but US GDP is almost twice that of China. The GDP growth rates of all BRIC countries are more than the USA except for Brazil.[1]

Despite their significant differences, they may still form a set because they have a similar type of influence in, or equivalent implications for, international trade. Although the countries are anthropologically, culturally, geographically and economically from different spheres, there are a few facets that bring them together as a group. All four exhibit modern industrial sectors that have access and contribute to the global capitalist economy in a major way. All four countries have changed their political systems to accept global capitalism. China and India are leading suppliers of manufactured goods and services, while Brazil and Russia are principal suppliers of raw materials. Apart from their growth characteristics, the BRIC countries have little in common.

3. Literature Review

Markowitz (1952) in his modern portfolio theory finds that there are likely gains from international portfolio diversification if there is no perfect correlation among returns from these markets. Because of deregulation and financial market liberalisation, the financial markets are becoming more and more integrated, thereby decreasing international portfolio diversification. Previous studies focused on investigating the dynamic interaction among the developed markets and largely ignored the developing markets. Recently with the emergence of Asian capital markets, studies have begun to include them as well (Baharumshah, Sarmidi, & Tan, 2003; Dunis & Shannon, 2005; Phylaktis & Ravazzolo, 2005; Siklos & Ng, 2001; Wong, Penm, Terrell, & Lim, 2004). In addition, the focus of past work has been almost exclusively on equity markets with little attention given to currency markets.

Several alternative econometric methodologies have been employed to analyse international market linkages. Cointegration technique is used to examine the existence of long-run relationships among stationary time series (Engle & Granger, 1987). If international markets are found to be interrelated in the long run (cointegrated), then these markets are affected by similar economic stimuli that bound long-run diversification opportunities (Gerlach et al., 2006; Wilson & Zurbruegg, 2001). Because of deregulation and financial market liberalisation, financial markets are becoming more and more integrated, thereby decreasing international portfolio diversification gains.

Previous studies focused on dynamic interactions among developed markets and largely ignored developing markets. With the emergence of Asian capital markets, studies have begun to include them as well (Phylaktis & Ravazzolo, 2005). Also, past work has dealt almost exclusively with equity market relationships, with little attention given to currency markets. Meese and Singleton (1982) first looked at exchange rates as stationary time series and established that exchange rate systems may exhibit cointegration type of relationships. Baillie and Bollerslev (1989) found that seven different nominal spot and forward exchange rates contain unit roots in their univariate time series representations. Also, they find that the spot exchange rates show a cointegration-type relationship in the long run. This finding created a lot of attention among scholars, and Sephton and Larsen (1991) used the same data set and find evidence that the presence of cointegration is dependent on the time horizon chosen. Baillie and Bollerslev (1994) find that there exists cointegration relationships between exchange rates in the long run, and they term this form of cointegration as 'fractional cointegration'. Diebold, Gardeazabal, and Yilmaz (1994), find that when a trend is explicitly modelled, there exists no evidence of cointegration relationships among exchange rates.

Previous studies examining long-run linkages find that diversification benefits within international stock markets are substantially reduced because the markets are highly correlated in the long run (Fraser & Oyefeso, 2005; Kasa, 1992; Yang, Min, & Li, 2003). Quite a few papers have recommended that global financial market integration can be due to real interest rate convergence (Awad & Goodwin, 1998; Phylaktis, 1999; Zhou, 2003) or interest rate equalisation (Goodwin & Grennes, 1994; Mancuso, Goodwin, & Grennes, 2003). Therefore, the assets of the more developed economies tend to become close substitutes (Buch, 2004; Obstfeld & Taylor, 2004).

Also, a number of past studies have reported the existence of significant linkages both between emerging and developed markets and among emerging markets (Fujii, 2005; Gallo & Otranto, 2005). But little can be said about the BRIC markets which have become a very established economic bloc. This study attempts to fill this gap by examining the long-run relationships and short-run causal linkages between the currency markets of BRIC countries and the USA. This study attempts to answer the following questions. (a) Do the currency markets of BRIC countries and the USA exhibit long-run relationships? (b) If the cointegrating relationships hold, are there any structural breaks? Does the cointegrating relationship hold after the structural break if any? (c) Are there any short-run causal linkages among the currency markets of BRIC countries and the USA?

4. Data

To estimate relationships between the currency markets of BRIC countries and the USA, a common baseline currency exchange rate is needed, and special drawing rights (SDRs) are selected. The SDR price of all five currencies, namely Brazilian Real, Russian Rouble, Indian Rupee, Chinese Yuan and US Dollar is used for the analysis.[2] The daily data set for the study contains SDR prices of five currencies[3] from 1 January 2000 to 30 November 2013 and contains 3,629 observations for each currency, thereby providing adequate scope for the cointegration tests.[4]

Table 1 presents descriptive statistics of daily exchange rate returns of the five currencies in the sample period. All five markets show positive returns. The negative values for skewness in two out of the five currency markets mean that the distribution of the series has a long left tail. Also the Jarque–Bera test statistics show evidence for rejection of the normality hypothesis.

Table 1. Descriptive Statistics of Exchange Rate Returns

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	J–B	Observation
BR	0.04	−0.01	0.09	−0.10	0.01	0.14	2.70	142.51	3,629
CH	0.01	−0.01	0.02	−0.03	0.00	−0.40	2.28	28.61	3,629
IN	0.02	0.00	0.03	−0.04	0.00	−0.27	1.77	91.37	3,629
RU	0.03	−0.01	0.05	−0.03	0.01	0.57	2.87	73.50	3,629
US	0.01	0.00	0.03	−0.02	0.00	0.25	2.11	149.27	3,629

Source: The authors.
Notes: BR: Brazil; CH: China; IN: India; RU: Russia; US: United States; J–B: Jarque–Bera.

Table 2. Contemporaneous Correlation Matrix of Exchange Rate Returns

	BR	CH	IN	RU	US
BR	1.00	–	–	–	–
CH	0.45	1.00	–	–	–
IN	0.46	0.79	1.00	–	–
RU	0.25	0.52	0.44	1.00	–
US	0.46	0.97	0.80	0.54	1.00

Source: The authors.
Notes: BR: Brazil; CH: China; IN: India; RU: Russia; US: United States.

Table 2 shows the cross-correlation of exchange rate returns between each pair of markets. US currency markets are highly correlated with China and India and weakly correlated with Brazil and Russia.

5. Methodology and Findings

We use RATS for conducting all our statistical analyses. Long-run effects are studied first, and unit root tests determine the order of integration. If and when the time series is nonstationary, Johansen (1991) multivariate cointegration tests are conducted to identify the number of cointegrating vectors (CIVs) (if any) and exclusion tests to identify whether the markets belong in the cointegration space and if they are weakly exogenous. After examining long-run relationships, short-term lead-lag relationships are investigated using causality tests.

Tests for Stationarity

Results of stationarity tests are reported in Table 3.

Examining the unit root properties of the time series becomes a necessary condition in performing cointegration analysis. The augmented Dickey–Fuller (ADF) (Dickey & Fuller, 1981), the Kwiatkowski, Phillips, Schmidt, and Shin (1992) and the Ng and Perron (2001) tests are used to evaluate the stationary properties. To test for stationarity using the ADF test, the following regression in Equation (1) is performed and the coefficient estimated for a_1 is tested for null hypothesis of $a_1 = 0$:

$$\Delta y_t = a_0 + a_1 y_{t-1} + \sum_{i=1}^{p} a_i \Delta y_{t-i} + \varepsilon_i \tag{1}$$

Table 3. Unit Root Tests

	ADF[a]		KPSS[b]		MZ_a[c]		MZ_t[c]	
Country	Level	First Difference	Level	First Difference	Level	First Difference	Level	First Difference
LBR	–1.51	–42.12***	4.09***	0.17	–0.32	–7.20***	–1.24	–2.86***
LCH	–0.13	–58.70***	7.55***	0.14	–1.08	–18.54***	–1.34	–3.03***
LIN	–1.37	–56.24***	2.77***	0.12	–3.77	–34.04***	–1.37	–4.12***
LRU	–1.82	–35.00***	2.33***	0.09	–4.53	–72.45***	–1.75	–6.00***
LUS	–1.32	–60.22***	5.72***	0.07	–1.26	–20.31***	–0.64	–3.18***

LBR: Brazil; LCH: China; LIN: India; LRU: Russia; LUS: United States

Source: The authors.

Notes: [a] For each of the currencies, the lag length of the augmented Dickey-Fuller (ADF) regressions is chosen to make certain that the residuals from each of the equations are devoid of serial correlation as measured by the Ljung-Box Q (LBQ) statistics at the 5% level of significance. The ADF regressions include only a constant for all currencies. The results of the *ADF* regressions (including a constant and a trend), the *KPSS* (trend stationary case) test and the Ng–Perron (demeaned) tests are exactly the same but are not included to conserve space. Details are available on request. The critical value that has been adopted from MacKinnon (1996) is −2.864 at the 5% level of significance.

[b] For the *KPSSμ* test, the lag truncation parameter is set to eight (Schlitzer 1995). The critical value obtained from Kwiatkowski *et al.* (1992) is 0.463 at the 5% level of significance.

[c] For the Ng–Perron *MZt* tests, the data is detrended by the Generalized Least Squares (GLS) procedure, while for the *MZa* the data is demeaned. The lag length is based on the modified information criteria (MIC) developed in Ng and Perron 2001. Critical values for the corresponding *MZa* and *MZt* statistics obtained from Ng and Perron (2001) are −17.30 and −2.91, respectively, at the 5% level.

***denotes 5% level of significance

Unlike the ADF test, the KPSS tests for a null hypothesis of stationarity against the alternate hypothesis of nonstationarity.

$$\mathrm{KPSS} = (\mathrm{T}^{-2} \textstyle\sum_{t=1}^{T} S_t^2)/\lambda^2 \tag{2}$$

In all five currency series, the null hypothesis of a unit root cannot to be rejected when the variables are in levels using ADF but can be rejected when the series are in first differences (as shown in Table 3).[5] The KPSS test is used to complement the results from ADF regressions. The null hypothesis of stationarity in KPSS is rejected when the variables are in levels but not when the series are in first differences for all the five currencies, confirming the findings of the ADF test. For the KPSS test, the lag truncation parameter is set to seven since this is allowed for optimal power and size distortions.

These unit root tests are known to suffer potentially severe finite sample power and size problems. Therefore, we further conduct Ng and Perron (2001) that uses the GLS detrending procedure to create 'efficient' versions of the modified Phillips and Perron (1988) tests, which provide good power and reliable size to reconfirm the results of unit root tests by ADF and KPSS procedures. The relevant variables are MZ and MZt:

$$MZ_\alpha = (T^{-1}y_T^2 - s_{AR}^2)\left(2T^{-2}\sum_{t=1}^{T} y_{t-1}^2\right)^{-1} \tag{3}$$

$$MSB = \left(T^{-2}\sum_{t=1}^{T}\frac{y_{t-1}^2}{s_{AR}^2}\right)^{1/2} \tag{4}$$

Based on these tests, a currency is considered and included for the subsequent cointegration analysis if and only if it is found to be nonstationary and integrated of order 1, I(1). All the five currencies in our data set are included for the cointegration analyses.

Cointegration Tests

This article employs multiple cointegration tests using the maximum likelihood procedure developed by Johansen (1988) and Johansen and Juselius (1990). Previous studies have shown that the Johansen's (1991) cointegration test procedure is the most suitable for systems of higher numbers of variables (Lajaunie, McManis, & Naka, 1996). The test statistics used are the trace statistic (λ-trace) and maximal eigenvalue (λ-max) test. The null hypothesis states that there are at most *r* co-integrating relationships. The tests of cointegration are performed sequentially, starting with the hypothesis of zero CIVs.

We start our cointegration analyses (Johansen, 1988; Johansen & Juselius, 1990) by considering an n variable first-order vector autoregression (VAR) given by the following equation:

$$x_t = A_1 x_{t-1} + \cdots + A_k x_{t-k} + \mu + \varepsilon_t, \tag{5}$$

where x_t is an n-dimensional vector. Johansen's cointegration procedure also requires choosing the optimal lag for the VAR estimation. The optimum lag length of the VAR chosen is the minimum to eliminate serial correlation in the residuals as measured by the Ljung–Box Q statistics (at the 5% level of significance). Additionally, the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) are employed to compute the lag length. The information criteria provide different lag lengths (AIC indicates seven lags, while SBC indicates three lags), with the likelihood ratio procedure indicating 30 lags.[6] After subtracting x_{t-1} from both sides of the equation in (5), the VAR is transformed to the following error-correction model.

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \cdots + \Gamma_{k-1} \Delta x_{t-k+1} + \Pi x_{t-1} + \mu + \varepsilon_t, \tag{6}$$

where Δ is the difference operator, Γi represents the n X n coefficient matrix equal to $-(I - A_1 - \ldots - A_i)$ for ($I = 1,\ldots k-1$), and Π is an n X n matrix equal to $-(I - A_1 - \ldots - A_k)$ the rank of which decides the CIVs. The two test statistics that help us determine the CIVs are λ_{Trace} and λ_{max}. The λ_{Trace} tests the null hypothesis that the number of CIVs is less than or equal to r against a general alternative. λ_{max} tests the null hypothesis that the number of CIVs is equal to r against an alternative of r+1 CIVs. The statistics are defined as follows:

$$\lambda_{Trace}(r) = -T \times \sum_{i=r+1}^{n} ln(1 - \hat{\lambda}_i) \tag{7}$$

$$\lambda_{Max}(r, r+1) = -T \times ln(1 - \hat{\lambda}_{r+1}) \tag{8}$$

The most suitable deterministic component is the model that contains only an intercept in the cointegrating relationship based on the $G(r)$ statistics. The cointegration results presented in Table 4 support two CIVs among the currency markets under consideration. Both the λ_{Trace} and λ_{Max} test statistics are compared to their corresponding critical values as tabulated in Osterwald-Lenum (1992).

Table 4. Johansen's λ Trace and λ Max Summary Table

H0: r ≤	λ trace	H0: r =	λ max
0	81.40***	0	69.82***
1	48.67**	1	47.86**
2	21.93	2	29.80
3	8.46	3	15.49
4	0.06	4	3.84

Source: The authors.
Notes: The null hypothesis is *H*0, which tests for the number of cointegrating vectors (CIVs) (designated by *r*) given by both the λ Trace and λ Max test statistics. Critical values have been obtained from Osterwald-Lenum (1992), Table 1. For each period the lag length used in the VAR is chosen to eliminate serial correlation in the residuals at the 5% significance level. The cointegration tests are for the full sample: 1/1/2000 to 11/29/2013.
*** denotes significance at the 1% level
** denotes significance at the 5% level.

Exclusion Tests and Tests of Weak Exogeneity

Even if there are two CIVs among the five currency markets, there is a possibility that some of them are excluded in the cointegrating relationship allowing for long-term diversification benefits. Exclusion of a currency from the CIV implies that the currency does not belong to the cointegration space in maintaining the long-run relationship, thereby the potential for diversification benefits may not be reduced for these markets.

In a system consisting of n variables, there can be at most $n - 1$ CIVs (Gonzalo & Granger, 1995). When the number of CIVs is equal to $n-1$, each of the markets is driven by a single common stochastic trend, implying that diversification benefits from investing within these markets are considerably reduced. Results of the exclusion tests help to identify excludable markets.

Table 5, Row 1 of Panels A and B repeats the Johansen λ_{Trace} and λ_{Max} statistics, respectively, and shows existence of two CIVs when all the five markets are incorporated in the system. In addition, the joint exclusion test in Panel D suggests that the null hypothesis $\beta_{BR} = \beta_{RU} = 0$ cannot be rejected. This provides supplementary evidence that the markets of Brazil and Russia are not part of the two CIVs and implies that only the currency markets of the USA, India and China are part of the long-run cointegrating relationships. Overall, the results show that the currency markets of the

Table 5. Tests for the Exclusion of a Currency from the Long-run Relationship

Panel A	**λ trace**				
All markets	H0	H1	H2	H3	H4
Excluding LBR and	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$
LRU	81.40***	48.67**	21.93	8.46	0.06
	60.73**	30.43**	0.08	–	–
Panel B	**λ max**				
All markets	H0	H1	H2	H3	H4
Excluding LBR and	$r = 0$	$r = 1$	$r = 2$	$r = 3$	$r = 4$
LRU	69.82**	47.86**	29.8	15.49	3.84
	30.30**	18.27**	0.08	–	–
Panel C	**Exclusion**				
$\beta i = 0$a	LBR	LRU	LIN	LCH	LUS
All markets	2.76	1.45	33.61**	22.53**	15.84**
Excluding LBR and LRU	–	–	28.09**	19.95**	13.76**
Panel D	**Test statistic**				
$\beta_{LBR} = \beta_{LRU} = 0$b	2.86				
Panel E	**Exogeneity**				
$\alpha i = 0$c	LIN	LCH	LUS		
Non excludable markets	16.77**	12.21**	1.47		

Source: The authors.

Notes: LBR: Brazil; LCH: China; LIN: India; LRU: Russia; LUS: United States

(a) Currency *i* can be excluded from the cointegration space. The test statistic is $\chi 2(r) * [n - (n - m),]$ where *n* is the number of variables in the vector autoregression (VAR) and *m* is the number of restrictions in the system.

(b) LBR and LRU are jointly excludable. The test statistic is $\chi 2(r) * [n - (n - m)]$, where *n* is the number of variables in the VAR and *m* is the number of restrictions in the system.

(c) Currency *i* is weakly exogenous. The test statistic is $\chi 2(r) * [n - (n - m)]$, where *n* is the number of variables in the VAR and *m* is the number of restrictions in the system.

The double asterisk ** denotes significance at the 5% level.

USA, China and India are linked and that their joint diversification benefits are reduced. Greater benefits are possible from Brazil and Russia because these markets are not trending long term with the other markets.

Subsequently, tests of weak exogeneity are performed to examine which of the markets do not respond to the deviations from the long-run equilibrium relationship and contribute to the CTs. Because there are two CIVs among three markets, there must be $n - r - 1$ source of common stochastic trends. Results shown in Panel E indicate that the currency

Table 6. CIV and CT Stationarity Tests

	ADF_a	$KPSS_b$	MZa_c	MZt_c
CIV 1	–3.59**	0.41	–19.28***	–3.09***
CIV 2	–3.49**	0.39	–24.71***	–4.27***
CT1	–2.28	0.89*	–5.23	–1.26

Source: The authors.

Notes: CIV1: Cointegrating Vector 1; CIV2: Cointegrating Vector 2; CT1: Common Trend 1
(a) Under the null hypothesis of a unit root. The critical value for the *ADF* (constant but not trend) obtained from MacKinnon (1996) is −2.86 at the 5% level.
(b) Under the null hypothesis of stationarity. The critical values obtained from Kwiatkowski *et al.* (1992) are 0.739 and 0.46 and at the 1 and 5% levels, respectively.
(c) Under the null hypothesis of a unit root. For the Ng–Perron tests, the data have been demeaned by the GLS procedure. The lag length is based on the modified information criteria (MIC). Critical values for the corresponding *MZa* and *MZt* statistics are −8.10 and −1.98, respectively, at the 5% level.
The triple asterisk *** denotes significance at the 5% level.

market of the USA is weakly exogenous, and that the null hypothesis cannot be rejected at the conventional level of significance. In other words, the US currency market is the source of the common stochastic trend, and it drives the three cointegrated markets towards the long-run equilibrium relationships. These currency market findings are in line with findings from previous stock market integration studies in which the USA is found to lead other international markets (Bessler & Yang, 2003).

Diagnostic Tests

Under certain conditions, the Johansen's VAR maximum likelihood estimation procedure can lead to ambiguous conclusions regarding the number of CIVs (Gonzalo & Lee, 2000). The statistical properties of the CIVs and the CTs are examined with ADF, KPSS and Ng−Perron unit root tests on the CIVs and CTs. CIVs should be stationary and show no statistical evidence of nonstationarity, while the CTs should be non-stationary and should have unit roots. Results are presented in Table 6. Conditional on the limitations that $\beta_{BR} = \beta_{RU} = 0$ and $\alpha_{US} = 0$, the two CIVs shared by the three non-excludable markets show no signs of non-stationarity, while the single CT shows no evidence of stationarity, no matter which unit root testing procedure is employed. These results verify the statistical properties of the CIVs and CTs.

Recursive Tests

Next, we examine the degree of convergence among the currency markets over time using the recursive cointegration technique (Hansen & Johansen, 1999). The recursive trace statistic is normalised by the 10 per cent critical value, and the number of trace statistics greater than 1.0 shows the number of CIVs in the system. Figure 1 reveals that two CIVs are shared among the five currency markets of Brazil, Russia, China, India and the USA. The first CIV is statistically significant throughout the entire sample period (2000–2013), while the second one is significant until the beginning of 2005, and it drops out after that. It then re-emerges during 2010. Finally, the two-CIV specification ($r = 2$) is appropriate for the system under consideration.

Causality Tests

After examining the long-run relationships among the currency markets of the BRIC countries and the USA using cointegration techniques, short-term lead-lag relationships are studied using causality tests. Granger causality (1969) measures whether or not the explanation of a variable can be improved by lagged values of another variable. Bivariate causality tests ignore interactions among the variables in the system, and therefore a multivariate VAR causality test (Granger, 1988) is employed.

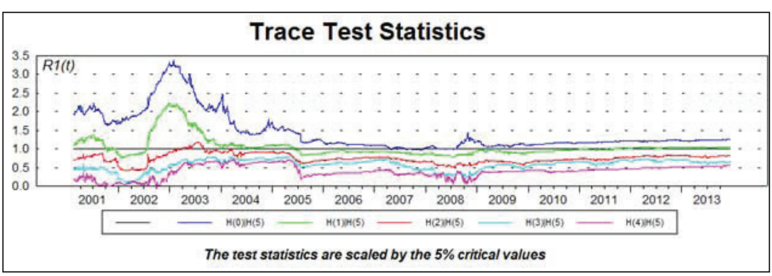

Figure 1. Recursive Trace Tests Under the 'R-Representation'
Source: The authors.
Disclaimer: This image is for representational purposes only. It may not appear well in print.

Table 7. Multivariate Causality Test

	Independent Variables				
Dependent	LBR	LRU	LIN	LCH	LUS
LBR	–	2.91*	46.12***	2.13	3.38**
LRU	23.15***	–	3.17**	20.83***	25.89***
LIN	2.77*	2.07	–	19.34***	0.40
LCH	1.60	0.40	1.56	–	3.93**
LUS	1.16	1.46	0.81	0.26	–

Source: The authors.
Notes: LBR: Brazil; LCH: China; LIN: India; LRU: Russia; LUS: United States *** and ** denotes significance at 1% and 5% respectively

As per Granger (1988), short-term linkages among the variables are investigated by means of the vector error correction model (VECM).

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \cdots + \Gamma_{k-1} \Delta x_{t-k+1} + \lambda e_{t-1} + \varepsilon_t, \tag{9}$$

Where λe_{t-1} denotes the error correction term that captures the adjustment to deviations from the long-run equilibrium. The multivariate causality method results are shown in Table 7. Russia is impacted by all four other markets, Brazil, India, China and the USA; Russia and India Granger cause Brazil; China Granger causes India; and the US Granger causes China.

While previous cointegration tests indicate that Russia and Brazil do not participate in the cointegration relationship (share long-term trends), the multivariate Granger causality test results reflect short-term causal associations between many of the BRIC markets including Russia and Brazil. Also, it should be noted that there exists a short-run linkage between the USA and Russian currency markets although there is no statistically significant long-run relationship. There is potential scope for short-term diversification opportunities between the USA and India implied by their non-significant granger causal relationship. Brazil and the US currency markets are not linked in either short term or long term. The only bidirectional causality is between Russia and Brazil. The presence of short-term lead-lag relationships indicates that the markets are short-term dependent.

Variance Decomposition and Impulse Response Function

Impulse response functions (IRFs) allow visual inspections of the rate at which a one standard deviation shock in one market is transmitted to the

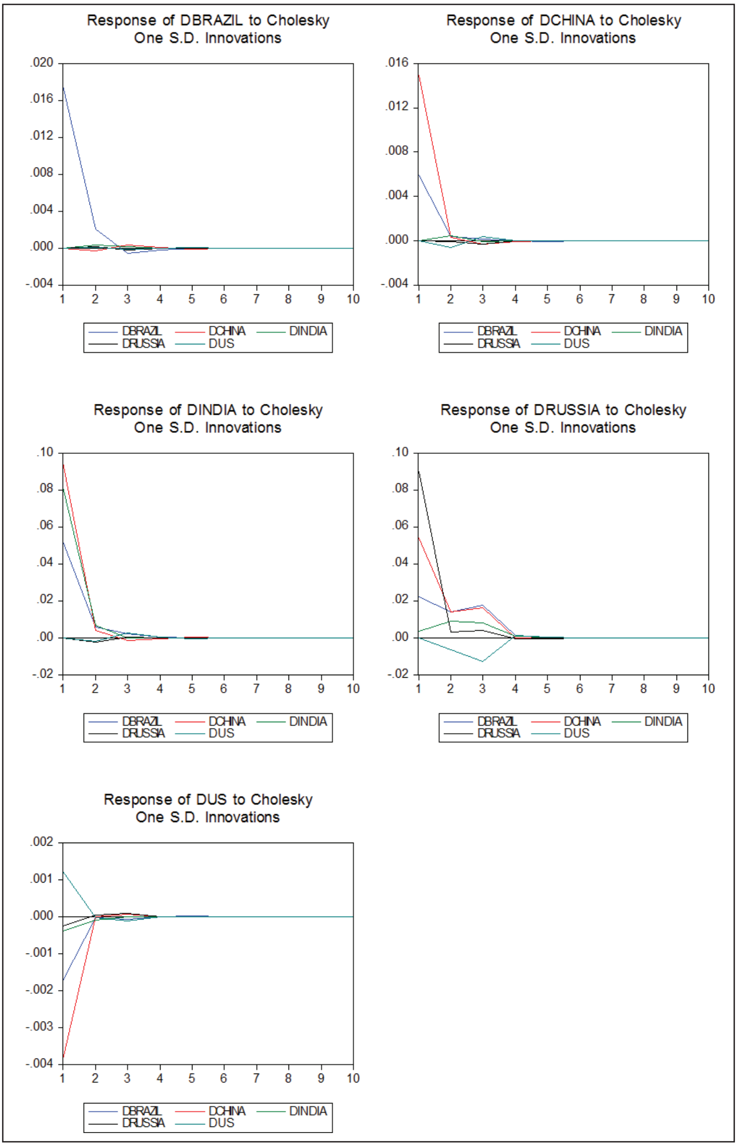

Figure 2. Impulse Response Functions

Source: The authors.

other markets (Phylaktis, 1999). The results are presented in Figure 2. It is apparent that each of the BRIC currencies responds significantly to shocks from the USA.

Variance decomposition or forecast error variance decomposition reveals the amount of information each currency contributes to the other currencies in VAR models. Variance decomposition determines how much of the forecast error variance of each currency variable can be explained by exogenous shocks to the other currency variables. The results including the horizons (in days) at which forecast errors are calculated are shown in Table 8. The variance decomposition shows minimal response to the USA due to shocks from other markets. China is heavily influenced by the USA. India has the next higher impact followed by Russia and Brazil. The three countries included in the cointegrating relationship are the ones whose shocks are related to each other.

Table 8. Variance Decomposition of Exchange Rate Innovations between 1 January 2000 and 29 November 2013

Markets	Horizon	LUS	LCHINA	LINDIA	LBRAZIL	LRUSSIA
LUS	1	100.00	0.00	0.00	0.00	0.00
	6	99.93	0.00	0.04	0.00	0.02
	12	99.88	0.00	0.06	0.00	0.05
	24	99.75	0.00	0.11	0.04	0.11
LCHINA	1	90.98	8.91	0.11	0.00	0.00
	6	92.67	7.10	0.21	0.00	0.02
	12	92.65	7.06	0.27	0.01	0.02
	24	92.33	7.22	0.38	0.04	0.03
LINDIA	1	65.57	0.00	34.42	0.00	0.01
	6	65.18	0.02	34.68	0.02	0.10
	12	65.44	0.03	34.37	0.02	0.15
	24	66.06	0.03	33.65	0.02	0.25
LBRAZIL	1	14.98	0.04	1.35	83.59	0.04
	6	14.49	0.08	1.81	83.55	0.07
	12	14.81	0.09	2.00	82.98	0.13
	24	15.54	0.09	2.34	81.74	0.29
LRUSSIA	1	29.89	0.00	0.00	0.00	70.11
	6	40.79	0.02	0.69	0.45	58.04
	12	44.23	0.04	0.92	0.61	54.20
	24	49.66	0.07	1.31	0.87	48.10

Source: The authors.

6. Conclusion

Brazil, Russia, India and China, famously called the BRICs, are gaining popularity because of their progressive economic advancement. Despite the evidence of their increasing importance in world trade and capital flows, the linkages of currency markets of BRIC countries have remained largely unexplored. This study investigates the degree of interdependence among the currency markets of BRIC countries and the USA.

Over the period of study, the BRIC and the US markets are found to be cointegrated, sharing two long-run relationships (two CIVs). Nevertheless, exclusion tests reveal that only the currency markets of the USA, China and India are contributing to the cointegrating relationships, implying that there still exist important potential long-run diversification opportunities for US investors in the markets of Russia and Brazil. The short-run causality tests also reveal some evidence of short-term lead-lag relationships between the USA and India and Brazil.

These findings should benefit portfolio managers, pension fund managers and other institutional investors in the USA and abroad who are considering adding developing country foreign currency asset positions to their portfolios.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

Notes

1. See www.tradingeconomics.com
2. Because the SDR prices of all currencies are not available in DataStream, the US Dollar price of all currencies and the SDR price of the US Dollar are collected and cross rates computed to arrive at the SDR price of the remaining currencies.
3. In order to account for the time zone differences, we use the end-of-day prices of Russia, India and China, while using the beginning-of-day prices for Brazil and the USA.
4. Diebold et al. (1994) find that if daily data are used, then time periods longer than 1 year are appropriate to examine long-run behaviour of daily exchange rates.

5. Because ADF is sensitive to the choice of lag length as the serial correlations may alter test statistics and alterations can occur due to heteroskedasticity, the Ljung−Box Q statistics is employed to find the optimum lag length.
6. Irrespective of the difference in the lags, results and inferences from the VAR estimation are exactly the same. After the choice of lags, the residuals in each equation are tested for serial correlation as measured by the Ljiung−Box Q statistic at the 5 per cent significance level (Crowder & Wohar, 1998).

References

Aloui, R., Aissa, M. S. B., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking & Finance*, *35*(1), 1–11.

Awad, M. A., & Goodwin, B. K. (1998). Dynamic linkages among real interest rates in international capital markets. *Journal of International Money and Finance*, *17*(6), 881–907.

Baharumshah, A. Z., Sarmidi, T., & Tan, H. B. (2003). Dynamic linkages of Asian stock markets: An analysis of pre-liberalization and post-liberalization eras. *Journal of Asia Pacific Economy*, *8*(2), 180–209.

Baillie, R. T., & Bollerslev, T. (1989). Common stochastic trends in a system of exchange rates. *The Journal of Finance*, *44*(1), 167–181.

———. (1994). Cointegration, fractional cointegration and exchange rate dynamics. *Journal of Finance*, *49*(2), 737–745.

Bessler, D. A., & Yang, J. (2003). The structure of interdependence in international stock markets. *Journal of International Money and Finance*, *22*(2), 261–287.

Buch, M. C. (2004). *Globalization of financial markets: Causes of incomplete integration and consequences for economic policy*. Berlin, Germany: Springer-Verlag.

Chan, K., Gup, B., & Pan, M. (1997). International stock market efficiency and integration: A study of 18 countries. *Journal of Business, Finance and Accounting*, *24*(6), 803–813.

Crowder, W. J., & Wohar, M. E. (1998). Cointegration, forecasting and international stock prices. *Global Finance Journal*, *9*(2), 181–204.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*(4), 1057–1072.

Diebold, F. X., Gardeazabal, J., & Yilmaz, K. (1994). On cointegration and exchange rate dynamics. *Journal of Finance*, *49*(2), 727–735.

Dunis, C., & Shannon, G. (2005). Emerging markets of south-east and central Asia: Do they still offer a diversification benefit? *Journal of Asset Management*, *6*(3), 168–190.

Engle, R., & Granger, C. (1987). Cointegration and error correction representation estimation and testing. *Econometrica*, *55*(2), 251–276.

Fraser, P., & Oyefeso, O. (2005). US, UK and European stock market integration. *Journal of Business Finance and Accounting*, *32*(1–2), 161–181.

Fujii, E. (2005). Intra and inter-regional causal linkages of emerging stock markets: Evidence from Asia and Latin America in and out of crises. *Journal of International Financial Markets, Institutions and Money*, *15*(4), 315–342.
Gallo, G. M., & Otranto, E. (2005). Volatility spillovers, interdependence and comovements: A Markov switching approach. *Computational Statistics and Data Analysis*, *52*(6), 3011–3026.
Gerlach, R., Wilson, P., & Zurbruegg, R. (2006). Structural breaks and diversification: The impact of the 1997 Asian financial crisis on the integration of Asia-Pacific real estate markets. *Journal of International Money and Finance*, *25*(6), 974–991.
Gonzalo, J., & Granger, C. W. J. (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business and Economic Statistics*, *13*(1), 27–35.
Gonzalo, J., & Lee, T. H. (2000). On the robustness of cointegration tests when series are fractionally integrated. *Journal of Applied Statistics*, *27*(7), 821–827.
Goodwin, K. B., & Grennes, J. T. (1994). Real interest rate equalization and the integration of international financial markets. *Journal of International Money and Finance*, *13*(1), 107–124.
Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424–438.
———. (1988). Some recent developments in the concept of causality. *Journal of Econometrics*, *39*(1–2), 199–211.
Hansen, H., & Johansen, S. (1999). Some tests for parameter constancy in cointegrated VAR models. *Econometrics Journal*, *2*(2), 306–333.
Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2–3), 231–254.
———. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, *59*(6), 1551–1580.
Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*(2), 169–210.
Kasa, K. (1992). Common stochastic trends in international stock markets. *Journal of Monetary Economics*, *29*(1), 95–124.
Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationary against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1–3), 159–178.
Lajaunie, J., McManis, B., & Naka, A. (1996). Further evidence on foreign exchange market efficiency: An application of cointegration tests. *Financial Review*, *31*(3), 553–564.
Mancuso, A. J., Goodwin, B. K., & Grennes, T. J. (2003). Nonlinear aspects of capital market integration and real interest rate equalization. *International Review of Economics and Finance*, *12*(3), 283–303.

Markowitz, H. M. (1952). Portfolio selection. *Journal of Finance*, *7*(1), 77–91.
Meese, R. A., & Singleton, K. J. (1982). On unit roots and the empirical modeling of exchange rates. *The Journal of Finance*, *37*(4), 1029–1035.
Ng, S., & Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, *69*(6), 1519–1554.
Obstfeld, M., & Taylor, A. M. (2004). *Global capital markets: Integration, crisis, and growth*. London, UK: Cambridge University Press.
Osterwald-Lenum, M. (1992). A note with quartiles as the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Economics and Statistics*, *54*(3), 461–472.
Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346.
Phylaktis, K. (1999). Capital market integration in the Pacific basin region: An impulse response analysis. *Journal of International Money and Finance*, *18*(2), 267–287.
Phylaktis, K., & Ravazzolo, F. (2005). Stock market linkages in emerging markets: Implications for international portfolio diversification. *Journal of International Financial Markets, Institutions and Money*, *15*(2), 91–106.
Schatz, A. (2010). Macroeconomic effects on emerging market sector indices. *Journal of Emerging Market Finance*, *9*(2), 131–169.
Sephton, P. S., & Larsen, H. K. (1991). Tests of exchange market efficiency: Fragile evidence from cointegration tests. *Journal of International Money and Finance*, *10*(4), 561–570.
Siklos, L., & Ng, P. (2001). Integration among Asia-Pacific and international stock markets: Common stochastic trends and regime shift. *Pacific Economic Review*, *6*(1), 89–110.
Sweeney, R. J. (2003). Cointegration and market efficiency. *Journal of Emerging Market Finance*, *2*(1), 41–56.
Vo, X. V., & Daly, K. J. (2007). The determinants of international financial integration. *Global Finance Journal*, *18*(2), 228–250.
Wilson, P., & Zurbruegg, R. (2001). Structural breaks, diversification and international real estate markets: Some new evidence. *Briefings in Real Estate Finance*, *1*(4), 348–366.
Wong, W. K., Penm, J., Terrell, R. D., & Lim, K. Y. C. (2004). The relationship between stock markets of developed countries and Asian emerging markets. *Journal of Applied Mathematics and Decision Sciences*, *8*(4), 201–218.
Yang, J., Min, I., & Li, Q. (2003). European stock market integration: Does EMU matter? *Journal of Business Finance and Accounting*, *30*(9–10), 1253–1276.
Zhou, S. (2003). Interest rate linkages within the European monetary system: New evidence incorporating long-run trends. *Journal of International Money and Finance*, *22*(4), 571–590.