THE RELEVANCE OF CBOE VOLATILITY INDEX TO STOCK MARKETS IN EMERGING ECONOMIES

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Abstract. *We examine the capability of CBOE S&P500 Volatility index (VIX) to determine returns of emerging stock market indices as compared to local stock markets volatility indicators. Our study considers CBOE S&P500 VIX, local BRIC stock market volatility indices and BRIC stock market MSCI indices daily returns in the period from January 1, 2009 to September 30, 2014. Research is conducted in two steps. First, we perform Spearman correlation analysis between daily changes in CBOE S&P500 VIX, local BRIC stock market VIX and MSCI BRIC stock market indices returns. Second, we perform multiple regression analysis with ARCH effects to estimate the relevance of CBOE S&P500 VIX and local VIX in determining BRIC stock market returns. Research reports weak correlation between CBOE S&P500 VIX and local VIX (except for Brazil). Furthermore, results challenge the assumption of CBOE S&P500 VIX being an indicator of global risk aversion. We conclude that commonly documented trends of rising globalization and stock markets co-integration are not yet present in emerging economies, therefore the usage of CBOE S&P500 VIX alone in determining BRIC stock market returns should be considered cautiously, and local volatility indices should be accounted for in analysis. Furthermore, the data confirms the presence of safe haven properties in Chinese stock market index.*

Key words*: CBOE VIX, BRIC, implied volatility, emerging economy*

1. Introduction

Apparently, increase in globalization, countries liberalization and openness has rendered a strong interdependence between financial market dynamics across the globe. Additionally, recently undersigned treaties like General Agreement on Tariffs and Trade agreements (GATT), European Community (EC), North American Free Trade Agreement (NAFTA), and Association of Southeast Asian Nations (ASAN) significantly supported worldwide economic integration (Cavaglia et al., 2000).

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Recent financial crisis and its aftermath of volatility spillover effects evoked growing interest in market sentiment indicators measured by stock market volatility indices (VIX). As outlined by Gemmil et al. (1997), shocks in stock markets implied VIX across financial markets are interrelated and may be employed as indicators of the rise in volatility in other markets. As summarized by Hu (2006), "*markets are more likely to crash together than to boom together*". (Hu, 2006, p. 729). The latter summary of market turmoil contagion effect encourages investors to be more sensitive to market distortions and highly look up for market sentiment parameters and their transmission when considering portfolio diversification alternatives (Shiller, 2013). The extent to which stock price indices in developed and emerging countries are affected by volatility indicators "*is important to the individual investor, the policy maker and forecaster, the researcher and more recently the investment banks that are specializing in new financial innovations to minimize risk*" (Natarajan et al., 2013, p. 56).

The context of globalization has fostered surging discussions about the choice of market sentiment indicators while constructing investment strategies. As outlined by Whaley (2009), CBOE S&P 500 VIX (thereafter $VIX_{S\&P}$) index has proven its applicability in regime-switching, threshold and transition models due to its property of forward-looking indication of market risk perception.

A stream of academic research has proven that *implied* volatility outperforms *realized* volatility in terms of forecasting power (for more details, see Christensen & Prabhala (1998), Szakmary et al. (2003), Corrado & Miller (2005) and Carr & Wu (2006). The plausibility of $VIX_{S\&P}$ to serve as a proxy for market turmoil, risk aversion and benchmark of future volatility measure (Fassas & Siriopoulos, 2012) can be summarized by Carr & Wu (2009), who outlined two major components combined within a single index, specifically, the *quantity* and the *price* of perceived risk.

Some scholars like Fassas & Siriopoulos (2012) refer $VIX_{S\&P}$ to a global volatility indicator and argue that it alone may reflect market shocks worldwide in the context of recent markets co-integration trends, which diminishes significance of local stock market volatility indices (thereafter VIX_{local}). The rationale behind such statements stems from arguments similar to those expressed by Nelson & Mossavar-Rahmani (2014), who claims that volatility of S&P 500 index is highly relative to the US economic cycle, capable to reflect the global cycle and is in line with volatility observed during global recession periods.

Nonetheless, evident asymmetries in volatility transmission foster contradicting stream of research which aims at challenging the "one size fits all" approach to volatility indicators. Aggarwal et al. (1999) report shifts in emerging stock markets volatility being explained solely by local market shocks (Mexican Peso crisis, Latin America hyperinflation, and Marcos-Aquino conflict in the Philippines) in the period of 1985-1995. Furthermore, Bailey & Chung (1995) report that sudden changes in volatility of emerging stock markets is highly related to contemporaneous local political events.

Recent studies by Chulia et al. (2009) estimate volatility transmission from the US to Euro zone (EZ) stock markets after the September 11 attack, but not from EZ to the US stock market after terrorist attacks in Madrid and London on March 11 and July 7, 2009 respectively. As confirmed by studies of Bekaert & Harvey (1997) and Susmel & Thompson (1998), the explanatory power of global events is weak when considering emerging markets volatility shocks.

The importance of emerging markets is significantly increasing as they have become integrated part of the global equity portfolio allocation with market capitalization of emerging countries hiking from only 1% in 1988 to 11% in 2014 (MSCI, 2014). Currently, BRIC countries account for 41% of the world's population, hold USD 4.4 trillion of foreign reserves and create one-fifth of global domestic products at relatively low costs (MSCI, 2014). Establishment of joint BRIC and South Africa Bank in the mid-2014 aimed at providing money for infrastructure and development projects, higher BRIC co-integration after the recent Crimean crisis and economic sanctions targeted at Russian Federation, and the established BRICS exchanges alliance in order to "*expose international investors to their dynamic economies*" (BRICS Exchanges Alliance, 2014) with the future perspectives to incline towards the development of Energy Association of BRICS altogether signify growing importance of the block.

In this paper we aim at estimating the capability of $VIX_{S\&P}$ in determining emerging stock market returns as compared to that of local volatility indices. Our results document the empirical significance of BRIC stock market *local* volatility indices in determining stock market returns. We argue that even in the context of recent financial markets globalization, openness and subsequent co-integration, stock markets in emerging economies do not fully reflect and absorb the effects of global market turmoil measured by $VIX_{S\&P}$, but rather are sensitive to local events. Furthermore, we argue that the level of relevance of volatility indices in determining BRIC stock market returns is idiosyncratic and should be further individually explored. Therefore, investors should not solely rely on $VIX_{S\&P}$, but also account for VIX_{local} dynamics when considering emerging stock markets in portfolio allocation strategies.

The paper continues as follows. Section 2 discusses data used in the research. Section 3 elaborates on methodology. Section 4 presents results, and the last Section concludes.

2. Data

In this study, we use daily log-changes in $VIX_{S\&P}$ and VIX_{local} of Brazil, Russia, India and China stock markets, and daily log-returns of Brazil, Russia, India and China MSCI stock market indices 01.01.2009 to 30.09.2014. Our sample consists of 1412 daily observations after excluding weekends and bank holidays. We selected this period as it is not contaminated by recent global financial crisis dynamics, and is representative in terms of market shocks (summarized in Table 1 below) and resurgence periods amid.

TABLE 1. **Summary of the major market shocks during 2009–2014**

Date	Event
May, 2010	„Flash Crash" led by Greek sovereign debt concerns
21 July 2010	Dodd Frank Wall Street Reform and Consumer Protection Act (DFA)
January 2011	Civil uprising in Syria and Lybia
March 2011	The earthquake and tsunami in Japan
6 August 2011	USA credit rating downgrade from AAA to AA+ (by S&P)
August 2011	Possibility of transmission of European sovereign debt crisis to Italy and Spain (I)
January 2012	France, Austria, Spain, Italy and Portugal credit ratings downgrade (S&P)
Mid of 2012	Possibility of transmission of European sovereign debt crisis to Italy and Spain (II)
February 2014	Ukrainian Revolution
March 2014	Bazil credit rating downgrade, Crimean Crisis and the first sanctions to Russian Federation

Note. Prepared by the authors, 2015

In our study, we set $VIX_{S\&P}$ as a proxy for global market uncertainty and risk aversion. Our choice of *implied* volatility measure is supported by its capability to serve as a forward-looking indicator as opposed to alternative historical volatility (HV) measure. The main flaw of HV is its consideration of close-to-close prices of the stock without capturing the magnitude of intraday price movements, while $VIX_{S\&P}$ measures implied volatility of 30-day period options on the S&P 500 index. In other words, it provides estimates of expected *future* realized volatility for 30 calendar days ahead suggesting that higher VIX indicates higher implied volatility in the S&P 500 index (Whaley, 2000). Figure 1 exhibits dynamics of $VIX_{S\&P}$ and S&P 500 index. Market shocks, illustrated by plummeting stock market index returns, are captured by corresponding spikes in $VIX_{S\&P}$ index. Furthermore, diverging trends after 2012 signify diminishing market "fear gauge" and increasing economic resurgence of S&P 500 companies.

We set MSCI local (VIX_{local}) implied volatility indices of BRIC countries and corresponding stock market indices as summarized in Table 2 below.

TABLE 2. MSCI Emerging Stock Market Indices and VIX_{local}

	Brazil	Russia	India	China
MSCI Stock Market Index	EWZSO	RTSI	NIFTY	HSI
VIX_{local}	VXEWZ	RTSVX	INVIXN	ASCNCHIX

Note. Prepared by the authors, 2015

Figure 2 exhibits dynamics of implied volatility indices of $VIX_{S\&P}$, VIX_{local} of corresponding BRIC and developed (Australia, Germany, Japan and United Kingdom) countries, which we include for graphical comparison. Apparent though lagging co-movement between market uncertainty indices in emerging and developed economies illustrates interdependence and transmission of volatility.

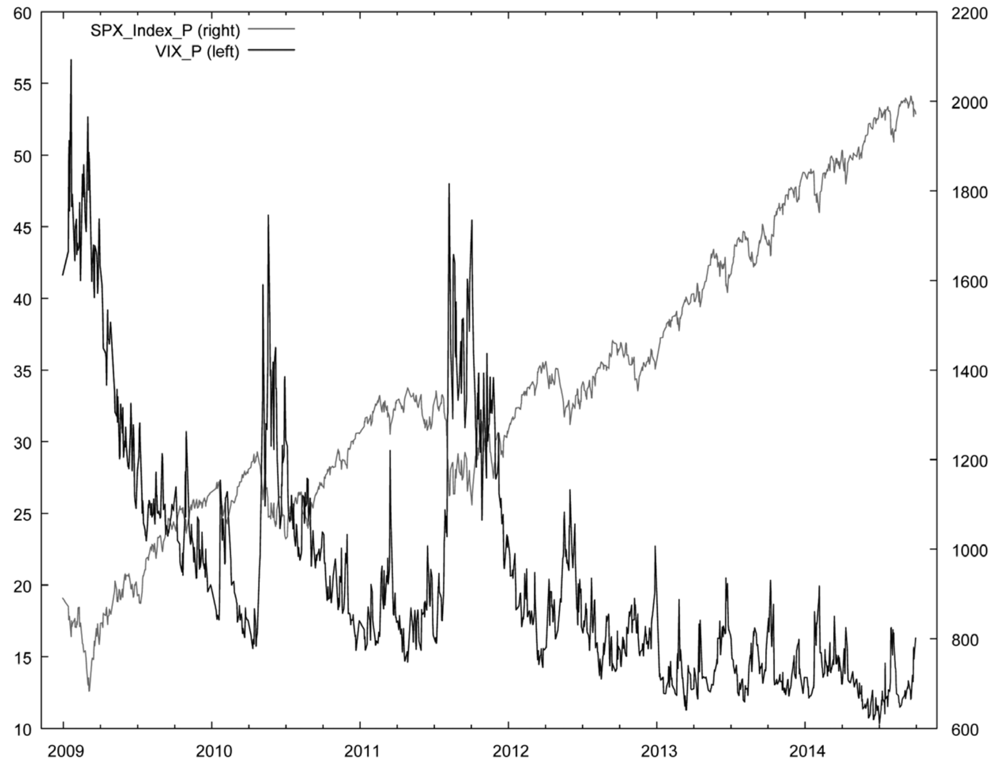

FIG. 1. **$VIX_{S\&P}$ and S&P 500 indices dynamics, 2009-2014.**

Note. Prepared by the authors, 2015

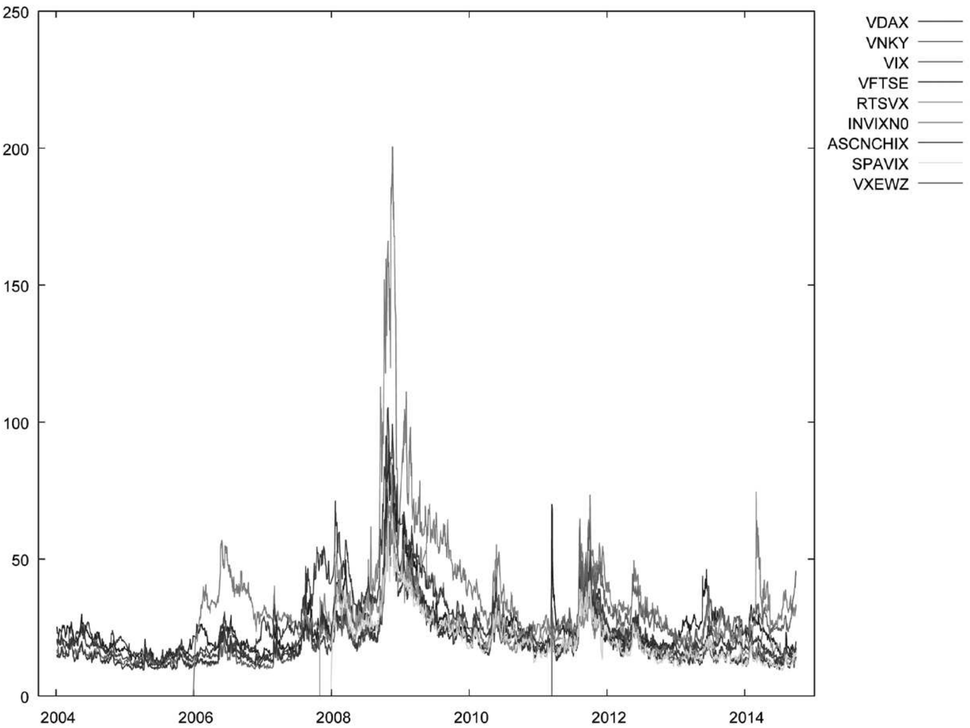

FIG. 2. **Implied Volatility Indices Dynamics in Developed and BRIC Markets, 2004-2014.**

Note. Prepared by the authors, 2015

Growing global interest in emerging markets is exhibited in Table 3, which illustrates the structure of investment portfolio held by overseas investors in corresponding BRIC markets. In Brazil, India and China, most part of investment portfolio is comprised of equities, while in Russia, 93% of foreign investment is concentrated in debt securities. The table highlights percentage of US investment in the corresponding country economy, which implies that $VIX_{S\&P}$ may be more relevant in determining Brazilian stock market returns (42% of US share in total Brazil portfolio investment assets), as contrasted to Russia, where US investments account for less than 5%.

TABLE 3. **Investment portfolio composition held by overseas investors in BRIC, 2013**

	BR	IN	RU	CN
Equities	67%	98%	7%	61%
Debt Securities	33%	2%	93%	39%
Total investment portfolio, Billions, USD	25	1	54	1 120
US % of total portfolio investment assets	42%	10%	less than 5%	7%
US % of equities share of portfolio investment assets	42%	11%	9%	less than 5%

Note. International Monetary Fund, 2013. Retrieved from: http://cpis.imf.org/

3. Methodology

First, we obtain and discuss summary statistics. After that, Jarque-Bera test for data normality, Augmented Dickey-Fuller (ADF) test for stationarity and tests for ARCH effects are implemented prior to analysis. Subsequently, correlation analysis between $VIX_{S\&P}$ and VIX_{local} of the corresponding BRIC stock markets is performed according to the classification of relative correlation strength provided below:

0.00-0.19 very weak
0.20-0.39 weak
0.40-0.59 moderate
0.60-0.79 strong
0.80-1.00 very strong

Presence of relatively strong correlation between $VIX_{S\&P}$ and VIX_{local} would imply that $VIX_{S\&P}$ alone might be relevant for representing BRIC stock markets risk aversion, given strong correlation between volatility and corresponding stock market indices. Similarly, correlation analysis between $VIX_{S\&P}$ and BRIC stock market returns is performed.

Multiple regression analysis with ARCH effects is performed by

$$R_{i,t} = c_{i,0} + c_{i,1}(\mathrm{VIX}_{S\&P})_{t-1} + c_{i,2}(VIX_{i,local})_{t-1} + c_{i,3}(V_m)_{t-1} + c_{i,4}D1 + c_{i,5}D2 + c_{i,6}(D1{*}VIX_{S\&P})_{t-1} + c_{i,7}(D2{*}\,VIX_{i,local})_{t-1} + e_{i,t} \qquad (1)$$

$R_{i,t}$ – i stock market log return at time t;
$c_{i,0}$ – constant;

$c_{i,n}$ – coefficients of volatility indicators;
e_t – error term,
$V_{m,i}$ – interaction term which is strictly positive and defined by:

$$V_{m,i} = (VIX_{S\&P} - \min(VIX_{S\&P}) + 1) * (VIX_{i,\,local} - \min(VIX_{i,\,local}) + 1) \quad (2)$$

Dummy variables are defined by:

$D1 = 1$ if $VIX_{S\&P} > 0$. 0 otherwise;
$D2 = 1$ if $VIX_{i,\,local} > 0$. 0 otherwise.

We include dummy variables in regression analysis in order to capture the effect of $VIX_{S\&P}$ and VIX_{local} on intercept (terms $c_{i,4}D1$and $c_{i,5}D2$, respectively) and on slope (terms $c_{i,6}(D1*VIX_{S\&P})_{t-1}$ and $c_{i,7}(D2*VIX_{i,local})_{t-1}$). Interaction term $V_{m,i}$ is included in regression analysis in order to test for possible indirect (moderation) effect of $VIX_{S\&P}$ on relation between $VIX_{i,\,local}$ and the corresponding stock market indices, $R_{i,t}$.

4. Empirical Results

4.1. Summary Statistics and Statistical Testing

Summary statistics is outlined in Table 4. The lowest daily return of 0.01% was generated by Brazilian stock market index (EWZSO) which was also the least resilient. The returns of Russian stock market (RTSI) were the most volatile with standard deviation of 1.97% attributing it to the least attractive of all BRIC for risk averse investors. Additionally, Russian stock market returns were negatively biased due to negative skewness in the period of consideration, as opposed to the rest of indices. Furthermore, Brazil and China generate the highest excess kurtosis (16.9 and 25.9 respectively), which may indicate possible overestimation of mean returns probability.

TABLE 4. **Summary statistics of BRIC stock market indices**

Index	Country	Mean	Median	Min	Max	Std. Dev.	CV	Skewness	Ex.Kurt.
EWZSO	Brazil	0.0001	0.0000	-0.0618	0.0700	0.0073	72.6	2.007	25.928
RTSI	Russia	0.0004	0.0007	-0.1280	0.0967	0.0197	48.1	-0.176	3.559
NIFTY	India	0.0007	0.0008	-0.0638	0.1633	0.0132	19.1	1.191	16.899
HSI	China	0.0003	0.0004	-0.0583	0.0715	0.0137	40.9	0.050	2.225

Note. Prepared by the authors, 2015

As illustrated in Appendix 1, Jarque-Bera test results violate normality assumption for all data time series, which implies the relevance of Spearman test for correlation analysis. ADF test rejected the null hypothesis of unit root, therefore no further data transformation is needed. Due to the presence of autocorrelation in error terms (Appendix 2), regression with ARCH effects is estimated.

4.2. Correlation Analysis Results

Spearman correlation analysis results summarized in Table 5 report weak correlation estimates between local volatility indices of BRIC stock markets, which implies weak (or absent) volatility transmission effects between emerging economies under study, despite their recent growing interdependence discussed in Section 1. Similarly, correlation estimates between $VIX_{S\&P}$ and Russian, Indian and Chinese stock markets appear to be low, entailing the absence of contagion effect in risk aversion stemming from US stock market. However, relatively high correlation estimate between $VIX_{S\&P}$ and Brazilian VIX_{local} (0.71) is anticipated as it is in line with relatively high share of US investments (42%) in Brazil economy, as depicted in Table 3 and is suggested by geographic proximity.

TABLE 5. **Spearman Correlation Estimates between VIXS&P and VIXlocal of BRIC**

Implied volatility indices	$VIX_{S\&P}$	VXEWZ (Brazil)	RTSVX (Russia)	INVIXN (India)
VXEWZ (Brazil)	0.71			
RTSVX (Russia)	0.26	0.34		
INVIXN (India)	0.18	0.29	0.27	
ASCNCHIX (China)	0.48	0.54	0.32	0.34

Note. Prepared by the authors, 2015

Spearman correlation estimates between volatility indices and BRIC stock market returns are summarised in Table 6. As anticipated, all correlation estimates are negative implying diverging dynamics between stock market daily returns and corresponding changes in volatility indices. $VIX_{S\&P}$ correlation with BRIC stock market returns is reported to be very weak. Slightly higher, but still weak correlation is observed between $VIX_{S\&P}$ and Russian stock market index. Furthermore, local volatility indices report weak/moderate correlation estimates with the corresponding local stock market indices.

TABLE 6. **Spearman Correlation Estimates between VIXS&P, VIXlocal and BRIC Stock Market Indices**

Index	Country	$VIX_{S\&P}$	VXEWZ (Brazil)	RTSVX (Russia)	INVIXN (India)	ASCNCHIX (China)
EWZSO	Brazil	-0.01	-0.06	-0.01	-0.05	-0.01
RTSI	Russia	-0.36	-0.41	-0.47	-0.29	-0.36
NIFTY	India	-0.18	-0.26	-0.19	-0.51	-0.33
HSI	China	-0.15	-0.25	-0.23	-0.32	-0.46

Note. Prepared by the authors, 2015

4.3. Regression Analysis Results

Regression analysis with ARCH effects is performed following methodology discussed in Section 2. Regression coefficient estimates are summarized in Table 7, while explicit regression results are presented in Appendix 3.

TABLE 7. **Regression Coefficients**

	EWZSO (Brazil)		RTSE (Russia)		NFTY (India)		HIS (China)	
	coef.	sig.	coef.	sig.	coef.	sig.	coef.	sig.
const	-0.100		-0.124		-0.246	*	0.317	**
c_1 (Effect of $VIX_{S\&P}$)	-0.068		-0.095		-0.201	*	0.186	**
c_2 (Effect of $VIX_{i.local}$)	-0.095		-0.120		-0.185	*	0.255	**
c_3 (Moderation effect of $VIX_{S\&P}$)	0.065		0.074		0.129	*	-0.198	**
c_4 (Effect of $VIX_{S\&P}$ on intercept)	0.000		-0.003	**	-0.001		-0.001	
c_5 (Effect of $VIX_{i.local}$ on intercept)	0.001		0.001		0.000		0.000	
c_6 (Effect of $VIX_{S\&P}$ on slope)	-0.024		-0.033		-0.016		0.005	
c_7 (Effect of $VIX_{i.local}$ on slope)	0.014		0.021		0.039	**	0.019	

** Statistically significant coefficient with 0.05 confidence interval

* Statistically significant coefficient with 0.1 confidence interval

Note. Prepared by the authors, 2015

Regression results illustrate evident idiosyncrasies in relationship between $VIX_{S\&P}$, VIX_{local} and the corresponding BRIC stock market returns dynamics. In the case of Brazil, insignificant coefficient estimates suggest that neither $VIX_{S\&P}$ nor VIX_{local} (VXEWZ) explain EWZSO returns. However, it is an anticipated result due to relatively low Spearman correlation between EWZSO and $VIX_{S\&P}$ (Table 5) and between EWZSO and VXEWZ (Table 6): -0.01 and -0.06, respectively. Regression coefficients of Russian stock market index returns are insignificant except for D1 dummy variable coefficient c_4, which implies that daily returns of RTSE are negatively affected by (and only in the case of) increase in $VIX_{S\&P}$, and are not explained by regression variables otherwise. Indian stock market returns are explained by both $VIX_{S\&P}$ and VIX_{local}. Furthermore, significant interaction term c_3 suggests the presence of moderation effect of $VIX_{S\&P}$ on the relationship between NIFTY and local volatility indicator, INVIXN. Regression analysis of Chinese stock market HIS index reports unanticipated results. $VIX_{S\&P}$, VIX_{local} and interaction term coefficients are significant at 0.05 significance level and are of positive sign (except for interaction term). Positive c_1 and c_2 coefficients illustrate converging dynamics between Chinese stock market index and indicators of global and local risk aversion. In other words, in periods of rising $VIX_{S\&P}$ and VIX_{local}, HIS index exhibits safe haven properties by rising in value.

ARCH effects, i.e. residual serial correlation, are present in all time series and are controlled in our study. ARCH effects suggest volatility clustering together with possibility of omitted variables in estimated regressions. The latter, together with relatively poor explanatory power of $VIX_{S\&P}$ and VIX_{local} in Brazilian and Russian stock market cases indicate the need of further study of the given phenomenon together with consideration of additional factors.

5. Conclusion

In this paper we challenge the commonly accepted notion of $VIX_{S\&P}$ as a global "fear gauge" indicator and argue that stock markets of emerging economies are idiosyncratic in their patterns of risk perception. We claim that BRIC stock markets are still too slow to absorb global risk aversion and therefore contagion effect caused by financial markets globalization, co-integration and speed of information transmission does not (yet) have significant effect on BRIC stock market returns. Due to this fact, allocating investments in BRIC stock markets can be a viable diversification tool because of BRIC peculiar response to shocks in global and local volatility indicators. Furthermore, our study contradicts prevailing attitude to emerging markets as volatile and solely risky. Data indicates the presence of safe haven properties in Chinese stock market index supported by statistically significant regression coefficients.

As implied by our research results, $VIX_{S\&P}$ does not explain changes in Brazil and Russian stock market returns and is relevant in determining Indian and Chinese stock market returns only when considered together with VIX_{local}. Therefore, considering $VIX_{S\&P}$ as an indicator of global stock market risk aversion should be treated cautiously when evaluating investment opportunities in emerging stock markets. Furthermore, relatively poor explanatory power of volatility indices in Indian and Russian cases, and no explanatory power in the Brazil case call for further research in the field.

Our empirical study carries certain limitations which should be kept in mind when assessing results. First, we have considered only four stock market indices in our analysis, therefore implications regarding emerging economies risk aversion should be solely considered within the context of BRIC stock markets. Second, we assume that each stock market's returns are explained only by two factors, $VIX_{S\&P}$ and VIX_{local}. We ruled out macroeconomic, social and political factors as well as other market sentiment indicators, such as ZEW economic indicator, Consumer Confidence Index (CCI), and others which may have impact on stock market returns, albeit these are not the focus of this particular study. Third, we employed parsimonious multiple regression model with ARCH effects. Alternatively, more complex threshold and regime-switching models should be considered to capture shifts in stock market returns dynamics. Finally, we looked at a relatively short time period covering past 5 years and used daily return data as we aimed at studying most recent trends in volatility transmission to emerging markets. Considering longer time span and less frequent data might report less noisy results.

To conclude, our results imply that investors should revisit their attitude towards emerging economies and consider them as a potential source of a different type of risk to be added to their investment portfolio.

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Appendices

APPENDIX 1. **Jarque-Bera and ADF test results**

	Jarque-Bera	ADF without constant	ADF with constant	ADF with constant and trend
VIX_V	1.57E-214	9.28E-26	6.43E-27	3.26E-30
SPX_Index_V	2.94E-283	3.61E-23	6.83E-24	4.75E-26
RTSVX_V	0.00E+00	1.05E-16	3.67E-16	4.11E-16
RTSI_Index_V	4.31E-166	1.10E-19	1.39E-19	1.37E-21
INVIXN1_V	7.31E-257	9.47E-16	4.84E-15	9.56E-15
NIFTY_Index_V	0.00E+00	1.64E-14	3.85E-14	5.32E-14
ASCNCHIX_V	9.83E-240	3.05E-19	3.31E-19	6.59E-20
HSI_Index_V	1.87E-64	2.36E-25	1.64E-26	6.88E-30
VXEWZ_V	3.35E-127	1.02E-11	1.73E-10	1.21E-09
EWZSO_Index_V	0.00E+00	1.80E-07	3.72E-06	3.47E-05

Note. Prepared by authors, 2015

APPENDIX 2. Test Results for ARCH Effects, Order 5

EWZSO_Index

	coefficient	std. error	t-ratio	p-value	
alpha(0)	4.14287e-05	8.84032e-06	4.686	3.22e-06	***
alpha(1)	0.203755	0.0337016	6.046	2.19e-09	***
alpha(2)	-0.00278074	0.0343937	-0.08085	0.9356	
alpha(3)	-0.00282363	0.0343970	-0.08209	0.9346	
alpha(4)	-0.00910124	0.0344082	-0.2645	0.7915	
alpha(5)	0.0228841	0.0337796	0.6775	0.4983	

Null hypothesis: no ARCH effect is present
Test statistic: LM = 36.9801
with p-value = P(Chi-square(5) > 36.9801) = 6.04474e-007

HSI_Index

	coefficient	std. error	t-ratio	p-value	
alpha(0)	7.27047e-05	1.10372e-05	6.587	6.37e-011	***
alpha(1)	0.0832789	0.0266074	3.130	0.0018	***
alpha(2)	0.0594980	0.0265781	2.239	0.0253	**
alpha(3)	0.144670	0.0262201	5.518	4.11e-08	***
alpha(4)	0.0905665	0.0264452	3.425	0.0006	***
alpha(5)	0.173852	0.0264363	6.576	6.85e-011	***

Null hypothesis: no ARCH effect is present
Test statistic: LM = 151.352
with p-value = P(Chi-square(5) > 151.352) = 6.88057e-031

NIFTY_Index

	coefficient	std. error	t-ratio	p-value	
alpha(0)	0.000141433	2.31921e-05	6.098	1.39e-09	***
alpha(1)	0.00847897	0.0270104	0.3139	0.7536	
alpha(2)	0.0161419	0.0269810	0.5983	0.5498	
alpha(3)	0.0204499	0.0267416	0.7647	0.4446	
alpha(4)	0.0469445	0.0267396	1.756	0.0794	*
alpha(5)	0.0509864	0.0267689	1.905	0.0570	*

Null hypothesis: no ARCH effect is present
Test statistic: LM = 8.16708
with p-value = P(Chi-square(5) > 8.16708) = 0.147265

RTSI_Index
Test for ARCH of order 5

	coefficient	std. error	t-ratio	p-value	
alpha(0)	0.000228190	3.04258e-05	7.500	1.15e-013	***
alpha(1)	0.0888601	0.0270106	3.290	0.0010	***
alpha(2)	0.0444045	0.0270760	1.640	0.1012	
alpha(3)	0.0974085	0.0269681	3.612	0.0003	***
alpha(4)	0.0547905	0.0270028	2.029	0.0426	**
alpha(5)	0.111992	0.0269340	4.158	3.41e-05	***

Null hypothesis: no ARCH effect is present
Test statistic: LM = 65.2304
with p-value = P(Chi-square(5) > 65.2304) = 1.00396e-012

APPENDIX 3. **Regression with ARCH Effects Results**

M o d e l 2 : GARCH, using observations 13/01/2009:30/09/2014
Dependent variable: **RTSI_Index_V (Russia)**
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0.12388	0.143896	-0.8609	0.38929	
VIX_V_1	-0.0951257	0.111326	-0.8545	0.39284	
RTSVX_V_1	-0.119858	0.110055	-1.0891	0.27612	
VIX_SPAVIX_1	0.0737908	0.0844456	0.8738	0.38221	
D1_1	-0.00283465	0.00132003	-2.1474	0.03176	**
D2_1	0.000570955	0.00133036	0.4292	0.6678	
D1_VIX_1	-0.0329362	0.0210904	-1.5617	0.11837	
D2_RTSVX_1	0.0209698	0.0237159	0.8842	0.37658	
alpha(0)	6.86E-06	1.90E-06	3.6199	0.00029	***
alpha(1)	0.0622856	0.0112066	5.5579	<0.00001	***
beta(1)	0.919284	0.0129653	70.9035	<0.00001	***
Mean dependent var	0.000412		S.D. dependent var	0.019921	
Log-likelihood	3548.838		Akaike criterion	-7073.676	
Schwarz criterion	-7011.058		Hannan-Quinn	-7050.237	

Unconditional error variance = 0.00037245

Model 3 : GARCH, using observations 05/01/2009:30/09/2014 (T = 1376)
Dependent variable: **NIFTY_Index_V (India)**
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0.245831	0.14705	-1.6717	0.09457	*
VIX_V_1	-0.200631	0.109458	-1.8329	0.06681	*
INVIXN1_V_1	-0.184811	0.102834	-1.7972	0.07231	*
VIX_INVIXN1_1	0.129083	0.0770027	1.6763	0.09367	*
D1_1	-0.00075421	0.00080021	-0.9425	0.34593	
D2_1	-0.00026336	0.00080929	-0.3254	0.74487	
D1_VIX_1	-0.015792	0.0120491	-1.3106	0.18998	
D2_INVIXN1_1	0.0390542	0.016768	2.3291	0.01985	**
alpha(0)	1.35E-06	5.55E-07	2.433	0.01497	**
alpha(1)	0.0622628	0.0117199	5.3126	<0.00001	***
beta(1)	0.929891	0.0123902	75.0503	<0.00001	***
Mean dependent var	0.000603		S.D. dependent var	0.013319	
Log-likelihood	4187.927		Akaike criterion	-8351.855	
Schwarz criterion	-8289.132		Hannan-Quinn	-8328.387	

Unconditional error variance = 0.000172144

Model 4 : GARCH, using observations 05/01/2009:30/09/2014 (T = 1379)
Dependent variable: **HSI_Index_V (China)**
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.317292	0.123752	2.5639	0.01035	**
VIX_V_1	0.186277	0.0907925	2.0517	0.0402	**
ASCNCHIX_V_1	0.255297	0.10173	2.5096	0.01209	**
VIX_ASCNCHIX_1	-0.197948	0.0774389	-2.5562	0.01058	**
D1_1	-0.00088754	0.00082093	-1.0811	0.27964	
D2_1	-0.00045355	0.00084868	-0.5344	0.59305	
D1_VIX_1	0.00510783	0.0141005	0.3622	0.71717	
D2_ASCNCHIX_1	0.0187849	0.0238654	0.7871	0.43121	
alpha(0)	1.67E-06	6.38E-07	2.6244	0.00868	***
alpha(1)	0.056044	0.0101394	5.5273	<0.00001	***
beta(1)	0.93178	0.0118662	78.524	<0.00001	***
Mean dependent var	0.000276		S.D. dependent var	0.013755	
Log-likelihood	4197.66		Akaike criterion	-8371.321	
Schwarz criterion	-8308.571		Hannan-Quinn	-8347.846	

Unconditional error variance = 0.000137517