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The interactive relationship between the US economic policy uncertainty and BRIC stock markets

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ABSTRACT

The purpose of this paper is to investigate the dynamics of volatility spillovers between the US economic policy uncertainty and the BRIC equity markets. To do so, we perform the cross correlation function suggested by Cheung–Ng (1996) within a rolling approach. Although the mean return spillover between the BRIC stock indices and US uncertainty is negative, the volatility spillover is found to oscillate between negative and positive values. Therefore, it is highly risky for investors to invest in the US and BRIC stock markets simultaneously. In addition, we find that there is strong evidence of a time-varying correlation between US economic uncertainty and stock market volatility. Furthermore, the correlation is found to be highly volatile during periods of global economic instability. So, market participants in the BRIC stock markets do closely monitor the US economic policy conditions.

1. Introduction

The economic and financial system disturbances in one country could be significantly transmitted to other countries in the world, whether directly or indirectly. Besides, the effect magnitude becomes significant when it is originating from one of the world's leading economies (Forbes and Chinn, 2004; Sum, 2012c). The recent economic downturn and the US economic recession lead to the most

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complex financial crisis to date because of its rapid contagion effect. Indeed, the complexity of the crisis stems from its rapid spread from the US housing market to the US financial market, which then impacts on the rest of the world, specifically the emerging and frontier economies and their financial markets (Bianconi et al., 2013). For instance, the Brazil, Russia, India and China (BRIC) developing economies are middle-income countries with a relatively large size that could enhance the global economic growth.

Since the global financial crisis of 2007, an intensive debate emerged about the response of the emerging economies. A number of existing studies emphasize the inability of the developing countries to deal with the US financial turmoil (see, among others, Eichengreen and Park, 2008 and Eichengreen et al., 2009), whereas some other authors, are more concerned with the delayed impact of the global financial turbulence on the BRIC markets. Dooley and Hutchinson (2009) and Llaudes et al. (2010) claim that the response of the emerging economies to the subprime mortgage crisis varies and depends on different phases of the crisis. In fact, the response of the BRIC countries is found to be relatively limited at the beginning of the global financial crisis (hereafter, GFC).

In parallel, an extensive literature emerged concerning the economic policy uncertainty (hereafter, EPU). Indeed, the policies resulting from the lack of agreement or the frequent changes of economic policies by the policy-makers could be transmitted into a significant economic policy uncertainty. Hence, the EPU may cost the economy as a whole many jobs, dampen the economic recovery or lead to the collapse of stock markets. Specifically, the stock price dependence of corporate investment is found to be weak in election years (see, Durnev, 2011). Given that investors make and review their predictions about future macroeconomic policies, times of high volatility in the US stock market correspond to the times of high probability of electing the potential winner (see, Goodell and Vähämaa, 2013).

In the existent literature, it is clearly perceived that there is a long-term negative relationship between equity returns and the economic policy uncertainty (see Bansal et al., 2005). More precisely, during bad economic periods, a high economic policy uncertainty is highly linked to stock market volatility (see, among others, Pastor and Veronesi, 2013). Although many studies explore the links of returns between the economic policy uncertainty and stock price indices, only few studies examine the links of volatility between the two variables. For instance, Ulrich (2012) showed positive volatility spillovers between economic policy uncertainty and equity returns. On another side, there is a strong evidence of negative connectedness between the EPU and equity returns (see Ozoguz, 2009; Dzielinski, 2011; Sum, 2012a, 2012b, 2012c, 2012d; Bhagat et al., 2013). Moreover, the short and long-term associations between EPU and stock returns are found to be unstable. Using a rolling window approach, Li et al. (2013) show the existence of a causality linkage running in a bidirectional way between the EPU index and stock price returns. In sum, it is shown that the US EPU index is an increasing function of the US stock return volatility, whereas the US stock returns are a decreasing function of the US EPU index changes (see Antonakakis et al., 2013). Brogaard and Detzel (2015) provide evidence showing that the impact of a high degree of economic policy uncertainty is higher on the future stock returns than on the contemporaneous returns

Although few studies focus on the influence of the EPU index returns in the US on the stock market returns in Brazil, Russia, India and China (such as Sum, 2012c), the volatility spillover between the US EPU and the BRIC stock markets is disregarded in the existing literature. Given the growing integration of the BRIC economies into the advanced economies especially the US, shocks originating from the US are significantly transmitted to the BRIC economies (Sum, 2012c) and have a particular effect on the performance of the BRIC stock markets (Bansal et al., 2005; Dzielinski, 2011; Ozoguz, 2009).

In this paper, our attention is focused on the volatility shocks transmissions between the economic policy uncertainty in the United States and the BRIC stock markets. At least three main are motivating our research. First, the market participants can predict the BRIC stock markets' declines by observing the economic policy changes in the United States. In fact, they can determine whether the BRIC economies are insulated from the global financial stress. Second, the investors can check whether this group of emerging markets provides portfolios' diversification opportunities. Third, one can determine whether the four emerging economies can be viewed as a locomotive force for maintaining the US and the world economic growth.

The aim of this paper is to analyze the nonlinear causality linkages and the time-varying patterns of the correlations between the US economic policy uncertainty and the BRIC stock markets. Specifically, we attempt to answer two main questions. First, how do the return and volatility spillovers vary between the EPU and the BRIC stock markets? Second, how do the correlations between the EPU in the US and the stock markets in the BRICs evolve over time?

What characterizes the empirical corpus of this study is the use of two alternative methodologies, namely the two-stage methodology suggested by Cheung and Ng (1996) and the rolling correlation method. We deem that the Cheung–Ng methodology is a promise tool because it detects the contemporaneous and delayed relationships between the variables under investigation, whereas, the rolling correlation methodology shows how the correlation between the two sets of variables evolves over time, mainly during the critical periods.

The remainder of this paper is structured as follows. Section 2 provides some theoretical background of the connectedness between equity returns and EPU. Section 3 discusses the methodology. Empirical results are reported in Section 4 while the main policy implications are wrapped in Section 5. Section 6 concludes.

2. Some theoretical arguments

The study of the policy uncertainty effects on the economy is dating back to the eighties with Marcus (1981), Bernanke (1983), Aizenman and Marion (1991), and Rodrik (1991). The interest of such effect has reemerged since the onset of the global financial crisis on 2008. For instance, Antonakakis et al. (2013), investigate the impact of macro policy uncertainty on the economy, focusing their interest on the dynamic interaction between the uncertainty and the performance of the stock market. The authors found that the latest financial crisis makes positive the dynamic correlation between the macroeconomic policy uncertainty and the stock market returns. Besides, the rise in the volatility of both stock market and economic policy uncertainty weakens the stock returns and augments the uncertainty.

Most of the existing studies pointed out negative mean return spillovers and positive volatility transmissions between the economic policy uncertainty and the stock market indices. The focus of many authors goes on studying the impact of the economic policy uncertainty index on the three macroeconomic indicators; namely, the economic growth, firm investments and the inflation (see, among others, Bloom, 2009; Baum et al., 2010; Bachmann et al., 2010; Jones and Olson, 2013). Given, the importance of oil shocks in the economy, also important is the question of the response of policy makers. Hence, a high firm uncertainty is interrelated with an increased oil price volatility (for more details see Lee et al., 2011; Yoon and Ratti, 2011). In fact, it is commonly argued that the macro policy uncertainty affects negatively the investment and the growth level. While awaiting the removal of the uncertainty, rational agents withhold their investment decision dealing with the investments that are either partly or completely irreversible.

The corporate investment is generally irreversible and costly. In fact, the uncertainty for firms mainly arising from political or economic shocks will significantly affect their profits, sales and costs. Hence, changes of policies will change the business environment conditions in which the firms operate as well as their investment behaviors (Wang et al., 2014). According to Baker et al. (2013), the economic policy uncertainty has an effect on business investment by influencing the business cycle intensity. In finance, it is well documented that the decision-making process is generally made in a context of uncertainty. Given the prompt adjustment in the prices of assets to new information, the variance of investors' beliefs is influenced by the information available to investors, considering that such information vary over time. For instance, Bekaert et al. (2009) claim that the uncertainty has a direct effect on the term structure, which has in turn a major effect on the countercyclical volatility of stock returns.

From a theoretical point of view, investors build their expectations about the current economic state by linking asset prices to the economic uncertainty. Hence, a high level of uncertainty results in higher variability of asset prices. In an environment of high uncertainty, investors who are risk averse, require a high return of compensation (or risk premium) (see, David, 1997; Veronesi, 1999). Following, Bird and Yeung (2012), the protection level of investors increases with the market uncertainty. Indeed, in times of a high level of uncertainty in the market, investors have a tendency to ignore good news, while they have tendency to dismiss bad news in times of low level of uncertainty.

Second, according to Jones and Olson (2013), the uncertainty effect on inflation is still unclear since it is dependent on international shocks, notably the oil shocks. In this way, aggregate demand oil shocks are found to dampen the dynamic co-movement between the policy uncertainty and stock market returns (see, among others, Antonakakis et al., 2013).

On a theoretical side, oil prices and economic policy uncertainty are closely connected and affecting real stock returns via canals of the expected discount rate and/or cash flows (see, Kang and Ratti, 2013). Specifically, stock prices are the discounted values of future cash flows. In fact, the expected discount rate consists of the expected inflation and the expected real interest rate. Both of them are simultaneously affected by expected oil prices (see, Huang et al., 1996). Because of the prominence of oil price changes for the economy, the economic policy uncertainty is affected by structural oil shocks. More precisely, oil price shocks affect relative prices, involve the income redistribution and have an impact on the expectations of both real interest rate and inflation (see, Kang and Ratti, 2013). Moreover, the oil price increase resulting from the rise in global demand for commodities could be related to a weak economic policy uncertainty, whereas, the rise in oil prices as a result of the rise in oil demand for precautionary purposes,[1] could be related to a high economic policy uncertainty (see, Kang and Ratti, 2013).

3. Methodology

As noted earlier, the cross correlation function (CCF) of Cheung and Ng (1996) is performed to analyze the lead/lag relationships between the US EPU and the BRIC equity markets. Shortly, the approach suggested by Cheung and Ng (1996) is founded on the residuals obtained from estimating the CCF methodology, which avoids the problems of omitted variables. In addition, it is robust against changes of the distributional assumptions. Furthermore, its asymptotic distribution is well-defined and not normal. Another main feature of the CCF approach is that it does not require simultaneous modeling of intra- and inter-variable dynamics, which makes its implementation relatively simple, compared to other multivariate models.

The first stage is to estimate the appropriate univariate model in order to allow for time variation in the conditional mean and the conditional variance. The second stage is to construct the residuals and squared residuals standardized by conditional variances. Their cross-correlation functions are then employed to identify causality patterns in the mean and the variance, respectively.

In the first step, an estimation of nonlinear ARCH-type models needs to be performed to describe the time-varying volatility. Following the standard Box and Jenkins (1970) approach, ARMA type processes are estimated to analyze the stationary series and to estimate the mean equation. The ARCH test of Engle (1982) is used to test the null hypotheses of no conditional heteroscedasticity. Once the alternative of no conditional Heteroscedasticity is rejected, the mean and the variance equations are estimated simultaneously using the maximum likelihood technique. In our study, five models are estimated; namely (i) the GARCH(1,1), (ii) the EGARCH(1,1) (exponential GARCH model) of Nelson (1991), (iii) the T-GARCH(1,1) (Threshold GARCH model) of Zakoian (1991), (iv) the TS-GARCH(1,1), and (v) the P-GARCH(1,1). The use of the ARCH-family models for describing the time varying of volatility of time-series data is interesting insofar as it permits to estimate with accuracy the parameters by correcting for outliers. Specifically, if no corrections are made, the problem of spurious regression may occur. Ding et al. (1993) developed the general power ARCH model, α_i and β_i represent the standard ARCH and GARCH parameters, γ_i the leverage parameter and δ is the power parameter. The power term is not imposed, it is rather estimated within the model.[2]

[1] The rise in oil demand may occur for fear of a possible scarcity of crude oil in the future.

[2] "Rather than imposing a structure on the data, the PARCH model allows a power transformation term inclusive of any positive value and so permits a virtually infinite range of transformations" (McKenzie et al., 2001, p. 3).

Table 1
Summary of nested ARCH model specifications.
Sources: McKenzie and Mitchell (1998).

Model	d	α_i	β_i	γ_i
ARCH	2	Not restricted	0	0
GARCH	2	Not restricted	Not restricted	0
Taylor ARCH	1	Not restricted	0	0
Taylor GARCH	1	Not restricted	0	0
TARCH	1	Not restricted	Not restricted	$\lvert\gamma_i\rvert \le 1$
Generalized TARCH	1	Not restricted	Not restricted	$\lvert\gamma_i\rvert \le 1$
Power GARCH	Not restricted	Not restricted	Not restricted	0
Asymmetric PARCH	Not restricted	Not restricted	0	$\lvert\gamma_i\rvert \le 1$
Asymmetric PGARCH	Not restricted	Not restricted	0	$\lvert\gamma_i\rvert \le 1$

Notes: The table displays necessary restrictions on the A-PARCH model proposed by Ding et al. (1993), in order to nest some ARCH-family models.

The power terms capture volatility clustering by amplifying the outliers in the time series. The leverage parameter is useful to consider for the asymmetric effect of both negative and positive shocks on the conditional variance. The asymmetric effect permits negative shocks to respond in a different way from positive shocks.

Many studies including Ding et al. (1993), Hentschel (1995), Brooks et al. (1997) and Brooks and McKenzie (2003) implemented the power ARCH (PARCH) model for stock return data. The TARCH (threshold ARCH) and the EGARCH models are frequently used for modeling and forecasting financial time series (see among others, Tully and Lucey, 2007). These asymmetric models permit to positive shocks to react differently from negative shocks. In particular, the EGARCH model is widely used in modeling the equity indices and the stock exchange market volatility (see, among others, McMillan et al., 2000; Ebeid and Bedeir, 2004; Balaban et al., 2006). Curto and Pinto (2012) found that the EGARCH and APARCH models are more prone to correctly detect the excessive volatility of major stock indices in 2008. While the results generated using these two models are very close, the EGARCH model is found to be the most dominant in forecasting the volatility among other asymmetric models.

Morales and Gassie (2011) use the GARCH and TGARCH models in order to examine the patterns of volatility in the stock markets of BRIC economies. Hence, the BRIC stock markets share some common characteristics but they don't share common volatility patterns. Although the Indian, Brazilian and Chinese stock markets show a volatility persistence, the TGARCH model is the most appropriate estimation technique only for the Indian stock market. Therefore, positive and negative news have an asymmetric impact on the Indian market. Furthermore, the economic uncertainty index is investigated in the literature using GARCH-type models (see Atta-Mensah, 2004; Lim et al., 2013).

In this study, several standard ARCH and GARCH models are nested[3] within the asymmetric power GARCH (APGARCH) model. Table 1 reports diverse restrictions for these nested models and the APGARCH model. Table 1 also specifies the permissible values for (α), (β), (γ) and (δ) parameters corresponding to the ARCH, GARCH, leverage effect and power terms, respectively. These parameters vary depending on the required model.

$$U_t = \left[\frac{(r_t - \mu_{r,t})^2}{\sigma_{r,t}^2}\right] = \varepsilon_t^2 \tag{1a}$$

$$V_t = \left[\frac{(r_t - \mu_{r,t})^2}{\sigma_{r,t}^2}\right] = \xi_t^2 \tag{1b}$$

[3] "Following the approach of Ding et al. (1993) and Hentschel (1995), it is possible to nest a number of the more standard ARCH and GARCH formulations" (McKenzie and Mitchell, 1998, p. 6).

McKenzie and Mitchell (1998) consider a number of nested ARCH models proposed by Ding et al. (1993), including the standard ARCH model of Engle (1982) and the GARCH model of Bollerslev (1986). There are more exotic variants for instance the Taylor ARCH and GARCH models,[4] the TARCH model introduced by Zakoian (1991), the generalized TARCH, power GARCH, asymmetric power ARCH (A-PARCH) and asymmetric power GARCH (A-PGARCH) models.[5] Table 1 reports a summary of the nested ARCH models.

In the second step, the CCF methodology involves constructing the standardized residuals for each selected variable. They are specified, as follows: where εt and ζt are the standardized residuals for the economic policy uncertainty and the stock market index returns, respectively. Moreover, at lag k, the sample cross-correlation coefficients of the standardized residuals and the squared standardized residuals are given respectively by: $\hat{r}\varepsilon\zeta(k)$ and $\hat{r}UV(k)$. $r\varepsilon\zeta(k)$ and $rUV(k)$ are used as causality in mean and causality in variance tests, respectively. Therefore, the null of no causality in variance (in mean) against the alternative of causality in variance (in mean) for a specified lag (k) is tested independently. Their corresponding CCF test statistics are given respectively by

$$CCF\ statistic = \sqrt{T}r_{UV}(k) \tag{2a}$$

$$CCF\ statistic = \sqrt{T}r_{\varepsilon\xi}(k) \tag{2b}$$

"Lag" indicates the number of periods that the daily index of EPU lags behind the daily stock indices whereas the term "lead" is the number of days that the US economic policy uncertainty leads the BRIC stock returns. If the CCF test statistic in the "lead" line is not significant, this means that BRIC equity markets do not cause the US EPU index. The non-significant CCF statistic in the "lag" line indicates that the US EPU does not cause BRIC stock returns. The standardized residual "levels" and squared standardized residuals are used to test the causality in mean and the causality in variance, respectively. The CCF test statistics are computed for 15 "leads" and 15 "lags".

4. Data and empirical findings

4.1. Data and preliminary analysis

The data set for this analysis consists of daily US EPU[6] (EPU_US) indexes and daily stock market indexes for the BRIC countries, namely Bovespa Index (BI_Brazil); Moscow Times Index (MTI_Russia); Bombay Sensex Index (BSI_India) and Shanghai Composite Index (SCI_China). The data are running from July 4, 1997 to July 27, 2011 and yielding 2898 observations. We start our empirical investigation by analyzing the stochastic properties of EPU indexes and stock indices. One of the specific features of a high frequency financial time series is that they are level and/or non-stationary. Therefore, it is required to use the first order differentiation of data (or higher order). In this respect, the two unit root tests: the augmented Dickey–Fuller (1979) (ADF) and the Phillips–Perron (1988) (PP) are performed.[7] Considering the preliminary analysis results, we adopt the first differences for all the series under investigation using the form below:

$$r_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3}$$

Table 2 reports the descriptive statistics for the BRIC stock returns and EPU indexes. As we can perceive, the BRIC stock returns are more volatile than the changes of the EPU_US. In fact, the changes of the EPU index have the largest standard deviation compared to the stock returns. The Russian

[4] "Taylor (1986) and Schwert (1989) have suggested that it is the conditional standard deviation which should be the focus of an ARCH model. This model is also nested in the conditional variance equation where α_i and β_i are free, $\delta=1$ and $\gamma=0$" (McKenzie and Mitchell, 1998, p. 6).

[5] It should be noted that the APARCH model nests approximately (not strictly) the EGARCH model when $\delta \to 0$.

[6] The data for the economic policy uncertainty index are extracted from http://www.policyuncertainty.com/.

[7] One merit of the PP test is that it is robust to both autocorrelation and heteroscedasticity in the error terms.

Table 2
Descriptive statistics.

	BI_Brazil	MTI_Russia	BSI_India	SCI_China	EPU_US
Mean	0.000505	0.001063	0.000501	0.000295	0.000624
Std. dev.	0.023986	0.033230	0.018809	0.018033	0.693974
Skewness	0.174647	−0.390649	−0.041950	−0.070157	0.038386
Kurtosis	15.03561	19.15420	8.391506	6.547116	3.479891
J–B	17,500.05	31,573.50	3509.640	1521.132	28.51002
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000001)
$\mathbf{Q}(10)$	480,171	194,286	256,008	427,925	4,999,519
$\mathbf{Q}^2(10)$	4,089,326	6,732,940	3,340,686	3,068,018	2,620,541
N	2897	2897	2897	2897	2897

Notes: For N time series observations we consider, Std. dev., which is the standard deviation. J–B is the Jarque–Béra test statistics of normality. $Q(10)$, the Ljung–Box statistic for serial correlation; $Q^2(10)$, the Ljung–Box statistic for serial correlation of the squared series. The values in parentheses are the actual probability values. The sample period is from July 4, 1997 to July 27, 2011.

equity returns have the largest mean value. The EPU and the Brazilian stock index (BI_Brazil) exhibit positive skewness, while the others are left skewed showing non-symmetric distributions. The "peakedness" of a distribution is measured by Kurtosis statistics. These are found to be higher than the normal values, indicating departures from normality for all the return series under consideration. Following the Jarque–Béra (1979) test statistics, the null hypothesis of normality is strongly rejected for all the series.

Fig. 1 displays time series of the BRIC stock returns and the EPU changes. As we can see, the two variables display volatility "clustering" or volatility "pooling" (i.e. time series exhibit periods of a high volatility interspersed by fairly stable periods). Statistically, these changes in variance through time indicate strong heteroskedasticity. The portmanteau test is performed to test for first and second-moment dependencies in the distribution of each return series. The Ljung–Box statistics Q and Q^2 (for squared series) are also used to test for autocorrelation. Q-statistics detect significant autocorrelation for up to 10 lags in all cases. Furthermore, the Q-statistics, based on squared returns, provide evidence of conditional heteroskedasticity. Based on the above results, a conditional variance equation is estimated with the conditional mean equation.

4.2. Cheung–Ng' approach and the rolling correlation method

4.2.1. ARCH type model estimation

In this section, the non linear ARCH-type models are employed for modeling the time varying volatility. So, the mean equation is estimated using the ARMA(p,q)[8] type processes. Subsequently, ARMA(p,q) processes are compared with the following conditional variance models, namely (1) the GARCH(1,1), (2) the EGARCH(1,1), (3) the T-GARCH(1,1), (4) the TS-GARCH(1,1), and (5) the P-GARCH (1,1). The appropriate model for each time series is chosen using diagnostic statistics and both Schwarz and Akaike information criteria. The maximum likelihood estimates for the EPU and the stock return series are displayed in Table 3. We estimate an asymmetric power GARCH model for the EPU index and for both Brazilian and Russian stock return series, while for Indian and Chinese stock markets, we select an EGARCH model.

Table 3 relates the estimation results of EGARCH and APGARCH models. As we see, the ARCH and GARCH coefficients are positive and statistically significant in all cases. Moreover, the sum of the coefficients ($\sum(\alpha+\beta)$) equals unity for Indian and Chinese stock returns. The estimated parameter of the EPU index, reveals that shocks of the volatility have a permanent effect on the conditional

[8] The lag truncation lengths, (p) and (q), are specified using the Box–Jenkins approach (Box and Jenkins, 1970). According to the Akaike and Schwarz information criteria, for the stock return indexes, our results reveal that an MA(1) is chosen for MTI and BSI stock returns, whereas ARMA(3,4) is chosen for BI stock return. In addition, for stock market returns, we found that an ARMA(4,2) is preferred for SCI. MA(2) is chosen for the US economic policy uncertainty index.

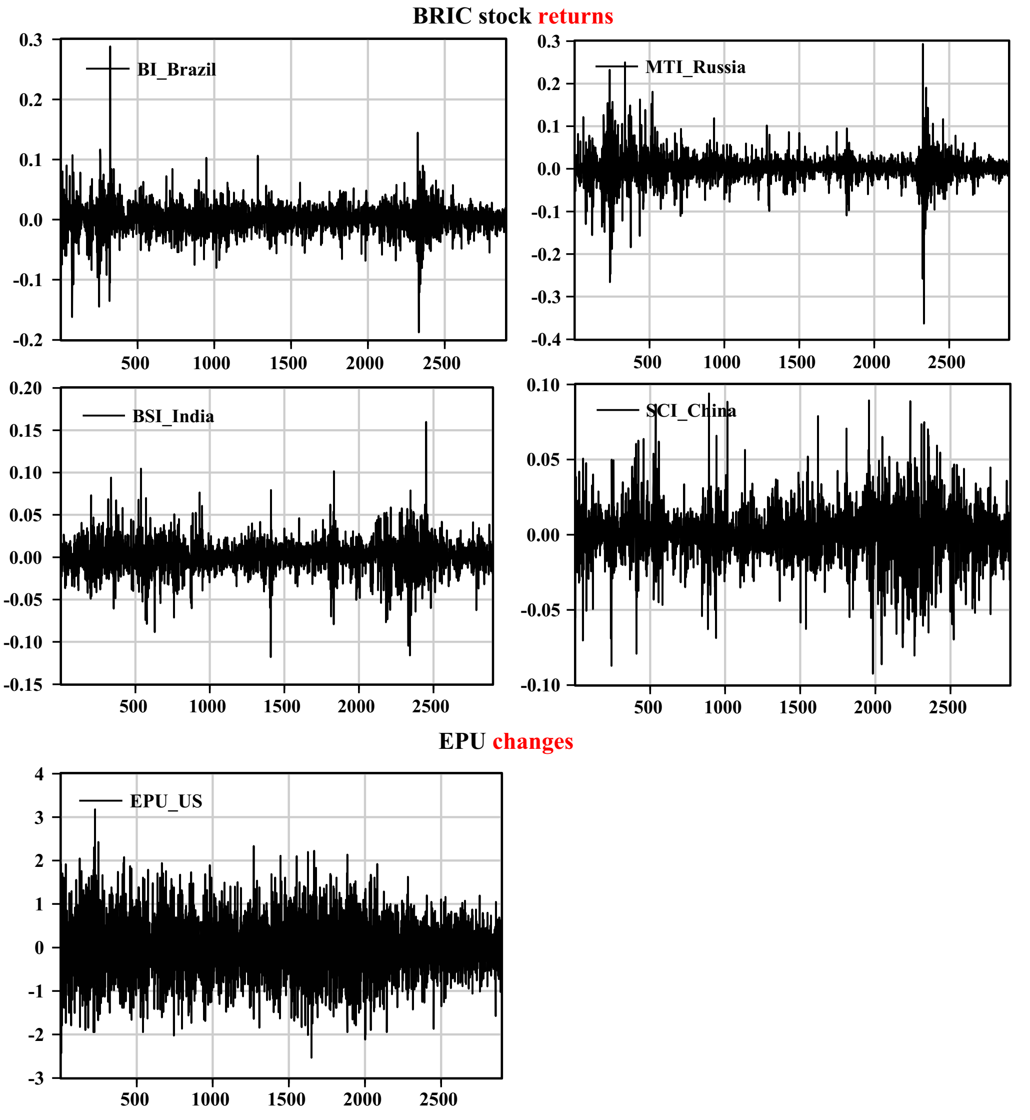

Fig. 1. BRIC stock markets and the US EPU changes.

variance. However, the estimated models for Brazil and Russia have the sum of the ARCH and GARCH coefficients less than one suggesting that shocks are transitory. All the *t*-distribution parameters (except for EPU_US) are significantly higher than one, thus reflecting a finite variance.

The asymmetric parameter of the APGARCH model (γ) allows the negative and positive shocks of a same magnitude to trigger an asymmetrical reaction from the market. Furthermore, the reported results show that the asymmetry terms are significant for the five selected models. Further, the EGARCH model is selected for BSI-India and SCI-China time series. The GARCH coefficients for these stock returns are respectively equal to 0.962932 and 0.971732, and their corresponding *t*-statistics exceed 2, implying substantial persistence. The Ljung–Box (1978) *Q*-statistics ($Q(15)$ and $Q^2(15)$) for standardized residuals and their squares, respectively, fail to reject the null hypothesis of no autocorrelation up to order 15 for all series, indicating the adequacy of the selected specifications.

Table 3
ARMA-EGARCH/APGARCH models for the BRIC stock returns and the US EPU changes.

	BI_Brazil	MTI_Russia	BSI_India	SCI_China	EPU_US
C	5.16E−05 (0.092754)	0.001493 (3.428352)	0.000703 (2.381017)	4.51E−05 (0.164648)	−6.53E−05 (−0.057297)
C	_	1.85E−06 (1.863510)	−0.456059 (−11.66637)	−0.381678 (−10.25240)	0.000802 (1.602260)
$\mathbf{\Phi_1}$	0.031332 (0.156673)	_	_	0.818790 (3.907406)	
$\mathbf{\Phi_2}$	0.090509 (0.457415)	_	_	−0.633739 (−4.136655)	
$\mathbf{\Phi_3}$	0.744076 (4.613004)	_	_	0.110452 (4.157430)	
$\mathbf{\Phi_4}$	_	_	_	−0.034997 (−1.302898)	
$\mathbf{\Theta_1}$	0.007775 (0.038782)	0.028407 (1.419718)	0.080455 (4.137129)	−0.780803 (−3.734220)	−0.724736 (−38.59550)
$\mathbf{\Theta_2}$	−0.098327 (−0.501806)	_	_	0.571277 (3.813277)	−0.159980 (−8.412838)
$\mathbf{\Theta_3}$	−0.723307 (−4.494051)	_	_	_	
$\mathbf{\Theta_4}$	−0.000919 (−0.035870)	_	_	_	
$\boldsymbol{\alpha}$	_	_	0.204311 (16.31807)	0.203848 (15.84550)	
$\boldsymbol{\alpha_1}$	0.079431 (8.083077)	0.064846 (11.21372)	_	_	0.016892 (4.696555)
$\boldsymbol{\gamma}$	0.818010 (7.145935)	0.146162 (6.401276)	−0.082068 (−10.06109)	−0.032672	0.484011 (2.519762)
$\boldsymbol{\beta}$	_	_	0.962932 (230.9292)	0.971732 (250.6000)	
$\boldsymbol{\beta_1}$	0.893546 (111.7395)	0.914192 (199.8717)	_	_	0.984140 (287.1252)
$\boldsymbol{\delta}$	1.286555 (10.26300)	2.381247 (17.37640)	_	_	1.231190 (4.232290)
$\sum(\alpha+\beta)$	**0.972977**	**0.979038**	**1.167243**	**1.17558**	**1.001032**
***t*-Distribution parameter**	7.082321 {0.781531}	4.292038 {0.326175}	_	_	12.85362 {3.103313}
Log likelihood	7133.849	6518.161	7739.433	7812.249	−2326.856
$\overline{\boldsymbol{R}^2}$	−0.003579	−0.000914	−0.000760	0.008322	0.358750
AIC	−4.921112	−4.495106	−5.338925	−5.393190	1.611913
SIC	−4.894293	−4.480677	−5.326558	−5.370490	1.628403
$\boldsymbol{Q}(15)$	15.132 [0.057]	14.651 [0.402]	15.191 [0.365]	16.754 [0.053]	24.111 [0.030]
$\boldsymbol{Q}^2(15)$	16.432 [0.037]	7.4219 [0.917]	6.7145 [0.945]	9.7392 [0.372]	5.3500 [0.967]
LM	4.828016	0.333779	0.356665	0.350118	0.096273

Notes: Numbers in parentheses are *t*-Student statistic. Numbers in brackets are *p*-values. *Q*(15) and *Q*2(15) are the Ljung–Box statistics for the first 15 autocorrelations of the standardized residuals and squared standardized residuals, respectively. $\overline{R^2}$, AIC and SIC are the Adjusted *R*-squared, Akaike criterion and Schwarz criterion, respectively. The *t*-distribution parameter indicates the estimated parameter and the standard error {.} for *t*-distribution assumed for the data.

Table 4
Mean causality and variance causality tests: cross correlation between standardized residuals and squared standardized residuals, respectively.

K	**Causality in mean EPU_US**				**causality in variance EPU_US**			
	BI_Brazil	**MTI_Russia**	**BSI_India**	**SCI_China**	**BI_Brazil**	**MTI_Russia**	**BSI_India**	**SCI_China**
−15	−0.0220	−0.0068	0.0049	0.0055	0.0084	−0.0005	−0.0092	−0.0023
−14	−0.0197	−0.0263	−0.0037	−0.0124	−0.0196	**0.0380****	0.0050	0.0280
−13	−0.0084	−0.0055	0.0004	−0.0199	−0.0136	−0.0154	−0.0151	−0.0036
−12	−0.0001	−0.0037	−0.0161	0.0055	−0.0076	−0.0248	−**0.0346***	−0.0015
−11	0.0002	0.0068	0.0223	−0.0028	0.0033	0.0279	−0.0182	0.0112
−10	−0.0183	0.0015	0.0147	0.0261	−0.0202	−0.0189	−0.0042	−0.0221
−9	−**0.0406****	−0.0159	−0.0068	−0.0099	−0.0006	−0.0232	−0.0031	−0.0092
−8	0.0248	−0.0267	−0.0087	0.0036	−0.0168	−**0.0410****	−0.0122	0.0273
−7	−0.0164	0.0038	−0.0001	−0.0010	−0.0063	−0.0030	−0.0039	0.0155
−6	−0.0122	−**0.0373****	−**0.0337***	0.0289	−0.0267	−0.0012	−0.0011	−0.0008
−5	−**0.0583*****	−**0.0536*****	−0.0290	−**0.0512*****	−0.0027	0.0180	0.0150	0.0176
−4	−**0.0392****	−**0.0438****	−0.0278	0.0141	0.0165	0.0015	**0.0413****	**0.0494*****
−3	−**0.0388****	−0.0261	−0.0169	−0.0189	0.0028	0.0023	−0.0013	−0.0124
−2	−**0.0454****	−0.0242	−**0.0389****	−**0.0328***	−0.0102	0.0076	0.0059	−0.0143
−1	−0.0253	−**0.0400****	−**0.0673*****	−0.0152	−0.0083	**0.0397****	0.0247	−0.0159
0	0.0181	−0.0128	−0.0280	0.0095	0.0084	0.0164	**0.0330***	0,0016
1	0.0043	**0.0369****	0.0153	−0.0119	0.0007	−0.0155	0.0290	0.0067
2	−0.0210	−0.0010	−**0.0366****	0.0090	0.0086	0.0136	−0.0152	0.0032
3	0.0079	0.0076	−0.0304	−0.0042	0.0036	0.0163	0.0027	0.0074
4	−0.0020	−0.0287	0.0067	−**0.0333***	−0.0239	−0.0064	−0.0098	−**0.0323***
5	0.0051	0.0021	0.0191	0.0011	−0.0129	−0.0217	0.0032	−0.0117
6	−**0.0334***	−0.0112	0.0028	0.0296	0.0195	0.0066	−0.0112	−0.0147
7	−**0.0323***	−**0.0410****	−0.0220	−0.0232	0.0135	−0.0070	0.0102	0.0244
8	0.0051	0.0203	0.0154	0.0133	−0.0013	0.0255	0.0191	0.0092
9	−0.0055	−**0.0330***	0.0009	−0.0054	−0.0168	0.0035	−0.0222	−0.0164
10	0.0217	0.0023	−0.0089	−**0.0360***	0.0022	0.0166	0.0173	−0.0079
11	−0.0174	0.0096	0.0149	−0.0008	−0.0096	−0.0011	0.0017	0.0273
12	0.0231	0.0182	0.0157	0.0246	−0.0053	−0.0077	0.0011	0.0014
13	0.0116	−**0.0499*****	−0.0259	−0.0130	0.0075	−0.0101	−0.0194	−0.0041
14	0.0063	0.0122	−0.0262	0.0015	0.0057	0.0162	−0.0097	0.0217
15	0.0018	0.0051	0.0002	0.0163	0.0305	**0.0363***	0.0197	0.0164

Notes: (−1.−2. …. −15) are time "Lags" and refer to causality in mean and causality in variance from the US economic policy uncertainty to BRIC stock market indices. (+1.+2. …. +15) are time "Leads" and refer to causality in mean and causality in variance from BRIC stock market indices to the US economic policy uncertainty. "***", "**", "*" indicate significance at 1%, 5% and 10% levels, respectively.

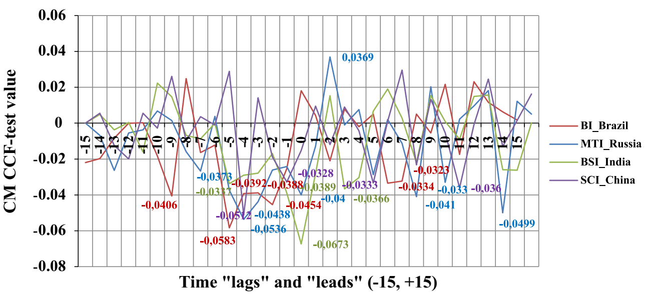

Fig. 2. Causality in the mean between the US EPU changes and the BRIC stock returns.

4.2.2. The CCF methodology results

The CCF test statistics are computed for 15 lags and 15 leads. The results are conveyed in Table 4. From the CCF statistic results, the relationship between the US EPU and BRIC stock markets appears to be dynamic and intricate. With regard to the causality in mean hypothesis, results indicate no evidence of instantaneous causality in mean (for time lag 0) between the two variables. The CCF statistics show strong evidence of feedback in the mean of the BRIC equity markets and the index of the EPU_US within 15 days. This means that the uncertainty about economic policy causes the Brazilian stock returns in mean at lags 2, 3, 4, 5 and 9 whereas, the BI_Brazil stock index causes the economic uncertainty at lags 6 and 7. Also, we identify a causality-in-mean running from EPU_US to MTI_Russia index returns up to lag 6. Inversely, the Russian stock market index causes the policy uncertainty in mean up to lag 13. The results provide evidence of a causality-in-mean that runs from the economic policy uncertainty to Indian and Chinese stock indexes up to lags 6 and 5, respectively. Reversely, BSI_India and SCI_China stock market indexes respectively cause the index of EPU_US at lags 2 and 10.

Fig. 2 shows the lead/lag structure of the causality in mean between the changes in the US EPU and BRIC stock returns. We perceive a strong evidence of negative mean return spillovers between each BRIC stock index and the variations of economic policy uncertainty in the US economy.

Turning to the causality in the variance, the estimation results show no evidence of instantaneous causality (i.e. for time lag 0) between the variations of the US EPU and the three BRIC stock returns, namely BI_Brazil, MTI_Russia and SCI_China. However, a contemporaneous and significant correlation coefficient for EPU_US and BSI_India is evidenced.

According to the CCF statistic estimations, there exists some evidence of feedback in the variance of the two sets of time-series. Specifically, the US EPU causes Russian stock returns in variance at lags 1, 8 and 14 whereas MTI_Russia index returns cause EPU_US index at lag 15. Moreover, there exists some evidence of volatility transmission running in a bidirectional way between the returns of the US EPU and the Chinese stock index at lag 4. Although there is no evidence of feedback, the US EPU causes Indian stock market returns in variance at lags 4 and 12. However, no evidence of volatility spillovers between EPU_US and BI_Brazil stock indices is detected.

The reported results indicate that in the short term, the US EPU is an exporter of causality to the BRIC stock returns. The index of US EPU is also considered as an importer of causality from the stock returns of BRIC.

Although changes in the Indian stock returns do not create any volatility effect on the US EPU within fifteen days, the changes of the US economic uncertainty are transmitted to Indian stock returns. Specifically, there is no evidence of volatility transmissions between Brazilian stock returns and the US EPU index, particularly in the short-run.

Regarding the time horizons during which EPU and stock returns interact with each other, our results show that this interaction does not only reflect a long term relationship, as proved by Bansal et al. (2005), but it also reflects a short term relationship. Furthermore, contrarily to Brogaard and Detzel (2015), we find no significant contemporaneous impact of EPU index on stock market returns. In addition, our findings are in line with the existing results including Antonakakis et al. (2013). Specifically, we find that the relationship between the US EPU and the BRIC stock market does not only reflect linkages between returns but it also reflects connectedness of volatility.

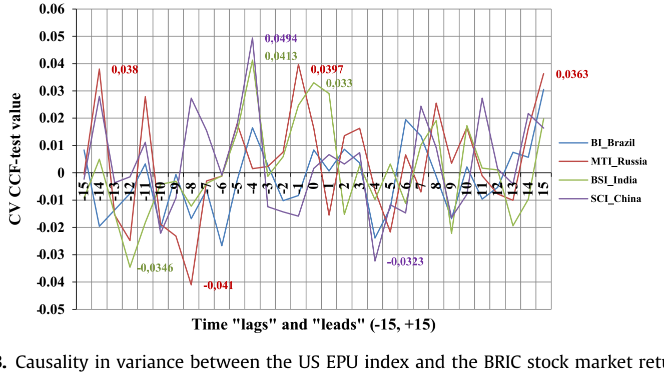

Fig. 3. Causality in variance between the US EPU index and the BRIC stock market returns

More precisely, similarly to Ozoguz (2009), Dzielinski (2011), Pastor and Veronesi (2012), Sum (2012c), Bhagat et al. (2013), and Antonakakis et al. (2013), we find that the BRIC stock returns are a decreasing function of EPU index returns. This result can be explained by the fact that the protection level of investors augments with the market uncertainty (see, Bird and Yeung, 2012). Accordingly, during periods of high (low) level of uncertainty, investors have a tendency to ignore good (bad) news. Contrarily to the existing findings (see, among others, Ulrich, 2012; Antonakakis et al., 2013), the volatility spillover between the BRIC stock market and the EPU index is found to oscillate between negative and positive values.

In Fig. 3, we plot the volatility spillovers between the US EPU changes and the BRIC stock indexes. As we can see, the cross correlation coefficients oscillate between negative and positive values. The finding indicates that it is highly risky for investors to invest in the US and BRIC stock markets simultaneously. To assess the robustness of the CCF statistic results, an alternative method relying on the rolling correlation method is performed.

4.2.3. *The rolling correlation results*

While the Cheung and Ng approach is useful to specify the directions of the interaction in the inter-temporal causality between the EPU and the stock returns, it does not specify how the nonlinear correlation between the two sets of variables evolves over the sample period. Thus, the rolling correlation approach is distinguishable by at least two main reasons. First, it allows for a time-varying connection between the variables. Second, it permits to distinguish the different sub-periods of high correlations as well as times of negative and positive correlations during the study period.

In the existent literature, the causality linkage between the EPU and the stock returns is found to be unstable (see, Li et al., 2013). The aim of this part is to analyze the time-varying nonlinear linkage between the US EPU index and the BRIC stock indices. To do so, we investigate how the correlation between the two sets of filtered data (see, Cajueiro and Tabak, 2004) evolves through time, the rolling correlation method is then performed to the standardized residuals from GARCH-type models. This method computes the correlation coefficient for the first window of a fixed-length (50 trading-days). Then, the sample is rolled in order to calculate the second coefficient for the second window, and so forth. In our case, the second window is obtained by eliminating the first observation and taking the observations ranging from the second day until day 51. This procedure continues up to the last window. This latter includes the last fifty observations. Hence, new time series are then obtained. Interestingly, compared to the single correlation coefficients, the rolling correlation method is useful because it shows how the correlation between the EPU_US and the BRIC stock indices evolves over the long run horizon.

The single correlation coefficients and their corresponding medians of the rolling correlation results are displayed in Table 5. The correlation coefficients indicate a strong negative correlation between EPU_US index and BI_Brazil returns. However, there is a week negative correlation between EPU index and the remaining stock returns. The single correlation coefficients are not sufficient to differentiate between negative and positive correlations. Then, the medians of the rolling results show a positive correlation between the EPU and the Brazilian stock index but they show a negative correlation between the EPU and the rest of the BRIC stock indices.

Fig. 4 illustrates the evolution of the correlation between the US EPU and each BRIC returns. As can be seen from the figure, the correlation is found to be highly volatile during the sample period. Furthermore, the sign of the rolling correlation coefficients is changing over time. Indeed, there is a strong evidence of a time-varying correlation between the EPU_US index and the BRIC stock indexes.

Table 5
The correlation coefficients and the medians of the rolling correlation results.

	BI_Brazil	**MTI_Russia**	**BSI_India**	**SCI_China**
EPU_US	−0.274887 (0.002334)	−0.020760 (−0.020314)	−0.066959 (−0.038420)	−0.037736 (−0.044869)

Notes: The values in parenthesis (.) are the medians of the rolling correlation coefficients.

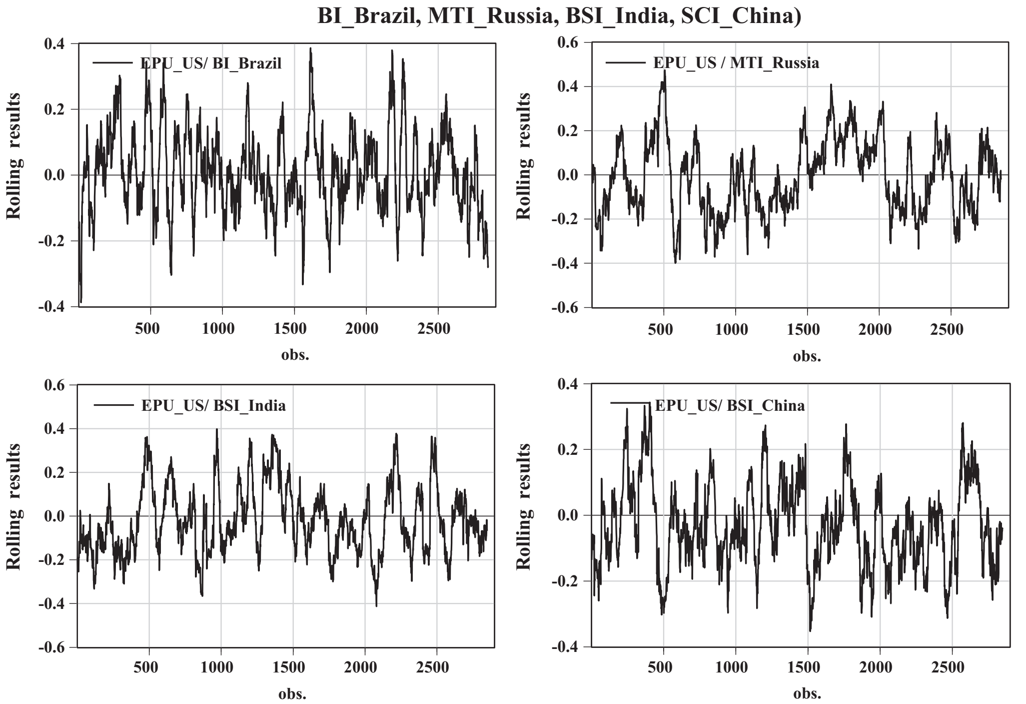

Fig. 4. The rolling correlation result plots. (EPU_US / BI_Brazil, MTI_Russia, BSI_India, SCI_China)

Table 6
Descriptive statistics for rolling correlations over time.

	EPU_US			
	BI_Brazil	**MTI_Russia**	**BSI_India**	**SCI_China**
Mean	0.011273	−0.011765	−0.019452	−0.031194
Median	0.002334	−0.020314	−0.038420	−0.044869
Maximum	0.386497	0.473811	0.398105	0.343323
Minimum	−0.387496	−0.399130	−0.413062	−0.353131
Std. dev.	0.124301	0.164551	0.154616	0.128110
Skewness	0.188249	0.212513	0.453184	0.284463
Kurtosis	3.021318	2.458499	2.676327	2.659770
J–B	16.87497	56.23255	109.9171	52.14620
Probability	0.000217	0.000000	0.000000	0.000000
N	2848	2848	2848	2848

Notes: For *N* time series observations we consider, Std. dev., which is the standard deviation. J–B is the Jarque–Béra test statistics of normality.

Contrarily to the existing studies including, among others, Antonakakis et al. (2013), we uncover that the relationship between the US economic policy index and the BRIC markets of BRIC nations evolves over time. Therefore, in order to be sure that the variation of the correlation over time is not affected by the presence of white noise, we refer to the descriptive statistics of the rolling correlation, which are displayed in Table 6. The reported statistics show that the series are found to be left-skewed, and platykurtic, except for Brazil. According to the Jarque–Béra (1979) test, the null hypothesis of normality is rejected. Based on the reported findings, it can be concluded that the correlation between the BRIC stock returns and the changes of the US EPU is time varying.

Our findings are in line with Pastor and Veronesi' (2013) conclusions. The authors claim that the correlation between the EPU and the stock market volatility becomes increasingly significant during periods of bad economic conditions. In the present study, the choice of the sample period is of great importance because it covers the periods of a number of extreme events weighing on the global economic scale, namely the Asian financial crisis in 1997; the events of September 11th, 2001 in the US; the invasion of Iraq by the USA from March 20th to May 1st, 2003; the Tsunami of December 26th, 2004; the Hurricane Katrina in August 29th, 2005; the subprime crisis in 2007 and the global financial and economic crisis that started in 2008 and is set to last until 2010 in some countries (such as the speculative stock market and real estate price bubbles in China, etc). Therefore, our results suggest that the BRIC stock market performance and the economic policy conditions are interconnected. Hence, investors and stock market operators should monitor the US EPU as well as the global economic instability. Our results also suggest that it is highly risky for investors to simultaneously invest in the US and other emerging markets.

5. Discussion of policy implications

Our findings pave the way for a large discussion and offer several economic and policy implications. In concordance with previous studies including Brogaard and Detzel (2015), Johnson and Lee (2014) and Lam and Zhang (2014), we uncover that the linkage between the changes of the US EPU index and the BRIC' stock markets does not only reflect links of returns but it also reflects transmission of volatilities. Specifically, the BRIC stock returns are found to be a decreasing function of changes in the EPU index. This result can be explained by the fact that the protection level of investors augments with the market uncertainty (see, among other, Bird and Yeung, 2012). Indeed, during episodes of a high (low) level of uncertainty, investors have a tendency to ignore good (bad) news. Furthermore, the volatility spillovers between the two sets of variables are oscillating between positive and negative values which indicates a significant changing pattern in the connectedness between BRIC' equity returns and the changes of economic policies in the US. From a portfolio management perspective, this result implies that investing in the US and BRIC stock markets simultaneously results in high levels of risk. Our findings are intrinsically consistent with those of Ko and Lee (2015), who show that, in general, there is a negative association between the economic policy uncertainty and stock market returns which is changing during high and low frequency cycles. On another side, the rolling correlation method shows that the correlation between the US EPU and the BRIC stock markets evolves over time. Our result is in line with Li et al. (2015) conclusions for China and India. Overall, our findings imply that the changes in economic policy uncertainty in the US economy have a significant effect on BRIC stock market return behavior and volatility. We clearly support the time varying pattern of the linkages between the two time series for all the BRIC countries. Therefore, our findings are supporting the main idea that the effect of EPU on the volatility of the four BRIC stock indexes suggests that the policy uncertainty contributes moderately to the prediction of the economic recessions (see, among others, Karnizova and Li (2014) and Liu and Zhang (2015)). Following, Rapach and Zhou (2013), Pastor and Veronesi (2012), and Liu and Zhang (2015), the business cycle changes are among the main drivers of the stock market behavior. For instance, Pastor and Veronesi (2012) suggest that the launch of new policies with uncertain effects augments the discount factor volatility, which in turn rises the risk premia. Subsequently, the increase in the risk premia leads to increase the stock market volatility (Liu and Zhang, 2015). In addition, the BRIC stock market performance and the economic policy conditions in the US are interrelated and thus investors and stock market participants are invited to monitor the US economic policy conditions as well as the global economic instability when allocating their portfolios and designing their hedging strategies.

It is well documented that the policy uncertainty has a significant influence on economic activities. In fact, the policy uncertainty is linked to unexpected variations that influence the economic environment. In the existing literature, different EPU indexes are developed in order to measure the policy uncertainty effects on the economy. For example, the index developed by Baker et al. (2013), is considered as a good proxy of real economic policy uncertainty in many studies (e.g. Wang et al., 2015). So, it is important to note that given the multiplicity of the economic policy uncertainty measures, the results do obviously depend on the construction of the EPU index.

6. Summary and concluding remarks

In this paper, we perform the Cheung–Ng (1996) framework to analyze the mean return and volatility spillovers between the economic policy uncertainty in the US and the stock market returns in the BRIC economies. The present paper also uses the rolling correlation method to investigate the time-varying correlation between the economic uncertainty and equity returns. The sample covers many sub-periods of the global economic instability ranging from July 4, 1997 to July 27, 2011.

Our study supplements prior works on the global spillovers of economic and financial shocks. In addition to the bidirectional interactive relationships between the US EPU index returns and the four BRIC stock market returns. Our findings indicate a strong evidence of volatility transmissions between the US economic uncertainty and the three stock returns of Russia, India and China, in the short-run. In the long run, we detect a strong evidence of a time-varying correlation between the US EPU and all of the BRIC stock indices. Therefore, the results show that the US EPU index is able to predict the volatility of the stock market even partially. Our results are similar to the existing findings in the sense that there is a negative mean return spillover between the economic uncertainty and the BRICs' stock returns. However, our findings contradict the findings in the existing literature and suggest that the volatility spillovers between the two sets of variables oscillate between negative and positive values. In addition, the rolling correlation approach results confirm the recent results in the literature and show that during periods of bad economic conditions, the US EPU index is highly correlated with the BRIC stock market volatility.

These findings suggest that the BRIC stock market dynamics and the economic policy conditions are strongly interconnected. Indeed, investors and stock market participants should monitor the US economic policy conditions as well as the global economic instability. Our results also suggest that it is highly risky for hedge funds to jointly investing in the US, Brazil, Russia, India and China stock markets. It is important to note that given the multiplicity of the economic policy uncertainty measures, the results do obviously depend on the construction of the EPU index.

Overall, our study highlights the complementarity between the economic and financial perspectives. It also emphasizes the volatility persistence over time. This is interesting insofar as a high degree of economic and financial integration allows for a better understanding of the opportunities associated with short and long-term investment horizons by considering the degree of instability.

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