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Economic policy uncertainty and stock prices in BRIC countries: evidence from asymmetric frequency domain causality approach

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Abstract

Purpose – The aim of this study is to investigate the relationship between economic policy uncertainty (EPU) and stock prices during the period from March 2003 to March 2021.

Design/methodology/approach – The study uses asymmetric and symmetric frequency domain causality tests and focuses on BRIC countries, namely, Brazil, Russia, India and China.

Findings – The findings of the symmetric causality test confirm unidirectional permanent causality from EPU to stock prices for Brazil and India and bidirectional causality for China. However, according to the asymmetric causality test, the findings for China show that there is no causality between the variables. The results for Brazil and India indicate that there is unidirectional permanent causality from positive components of EPU to positive components of stock prices. Moreover, for Brazil, there is unidirectional temporary causality from the negative components of EPU to the negative components of stock prices. For India, there is temporary causality in the opposite direction.

Originality/value – The reactions of financial markets to positive and negative shocks differ. In this context, to the best of the authors' knowledge, this study is the first attempt to examine the causal relationships between stock prices and uncertainty using an asymmetric frequency domain approach. Thus, the study enables the analysis of the effects of positive and negative shocks in the stock market separately.

Keywords Asymmetric causality, BRIC countries, Economic policy uncertainty, Frequency domain analysis, Stock prices

Paper type Research paper

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1. Introduction

Over the past 25 years, information and computer technologies have become increasingly integrated into financial markets. However, technological developments have both expanded stock markets and caused them to become more fragile and uncertain. In addition to technological and financial developments, the economic policies of governments also play an important role in this uncertainty and fragility. Uncertainty about governments' economic policies can affect financial markets (Brogaard and Detzel, 2015). Policymakers can contribute to economic policy uncertainty (EPU) through investment and consumption spending, as well as regulatory, fiscal and monetary policies. Meanwhile, the political news about what governments have done or might do dominate financial markets and affect asset prices (Pastor and Veronesi, 2013).

According to some studies, business decision-makers cannot assess risks, opportunities and tradeoffs of new technologies if they do not have certainty about government policies (Marcus, 1981). Moreover, policy uncertainty causes fluctuations in investment and employment (Bernanke, 1983). Rational investors either stop investing completely or in part until uncertainty disappears. Therefore, uncertainty can negatively affect economic growth and investment (Antonakakis *et al.*, 2013). Uncertainty about government intervention can also affect other macroeconomic indicators. Stock prices are directly related to macroeconomic variables such as economic growth, employment, foreign direct investment and foreign trade. For this reason, changes in EPU are likely to affect stock prices (Chang *et al.*, 2015). The increase in EPU also led to slow economic recoveries, unemployment and a fall in the stock market (Li *et al.*, 2016).

Stock prices, which reflect the future prospects and financial health of firms, are among the most important indicators in portfolio investment decisions and capital budgeting (Chang *et al.*, 2015). As measures of the value of companies, stock prices are extremely sensitive to changes in the markets. Just as the value of a company depends on current economic conditions and projections, the value of publicly traded companies depends on forecasts regarding domestic and global economic conditions. Similarly, stock price changes are associated with current or projected economic conditions (Peiro, 2016).

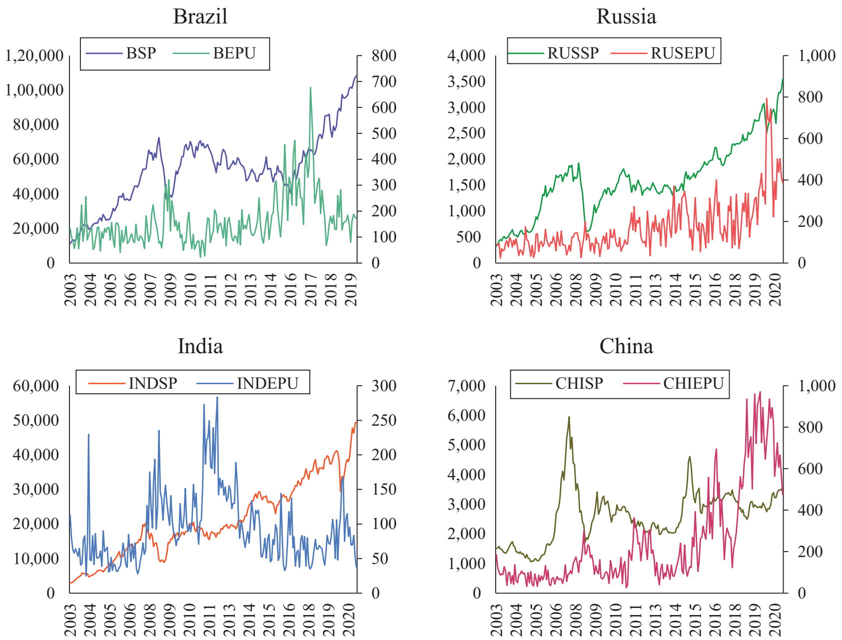
Economic uncertainties can spread across countries for a variety of reasons. Sudden fluctuations in output, employment, interest rates, oil prices and exchange rates indicate that a country has an uncertain and unstable structure. Governments can contribute to the rise of EPU through mismanagement and wrong decisions. Uncertainties due to elections also have a significant impact on markets. Political uncertainty is greater when economic conditions are poor (Ko and Lee, 2015). EPUs are expected to increase during economic and political crises.

Uncertainty is a central principle of finance. Many costly investment decisions are made in an uncertain environment (Dixit, 1989). Investors who do not have perfect information about macro-level variables and stock dividends often try to make intelligent predictions by using available information (Ozoguz, 2009). Conditions in financial markets can change within seconds. Therefore, investors closely follow news about the stock market. Understanding the origins of stock market, volatility is important for policymakers and market practitioners. The dividend discount model and arbitrage pricing theory suggest that the effect of new or unexpected information on various macroeconomic variables will result also impact stock prices by influencing expected dividends and discount rates. Since future corporate earnings and hence cash flows depend on macroeconomic stability, it is not surprising that uncertainty about the future behavior of macroeconomic fundamentals triggers proportional responses by current stock returns (Chinzara, 2011). According to basic financial theory, price decreases due to increased policy uncertainty stem from negative expectations regarding future income flows and increases in discount rates

(Brogaard and Detzel, 2015). Uncertainty about future government actions can affect market prices in two ways. On the one hand, uncertainty can have a positive effect on prices if governments respond appropriately to unexpected shocks, in which governments often intervene, leading investors to believe that prices will be maintained. On the other hand, discount rates may increase due to non-diversifiable risk, and in this case, EPU may adversely affect asset prices (Pastor and Veronesi, 2013). From an economic perspective, high uncertainty about policy changes leads to an increase in risk premia, which discourages firms from making new investments and make credit more expensive for households, thereby reducing stock prices (Badshah, 2019).

Based on the above discussion of the relationship between EPU and stock prices, we investigate the causality between the two macroeconomic indicators in Brazil, Russia, India and China (i.e. the BRIC countries). We chose the BRIC countries because they receive a large share of global investment flows and are economically important. According to the World Development Indicators (World Bank, 2019), the BRIC countries accounted for 21% of global gross domestic product in 2018. At the same time, these countries are home to 41% of the world's population. Thus, BRIC countries dominate other developing market economies.

Figure 1 shows the stock prices and EPUs in BRIC countries for the period of analysis. The values on the left vertical axis are the stock prices and the values on the right vertical axis are the EPU values. As can be seen in the figure, the 2008 financial crisis affected both uncertainty and stock prices in these four countries. During the crisis, EPU reached unprecedented levels and stock prices plummeted. Since the crisis, the stock market has



Source: Prepared by the UKP using data from investing.com

Figure 1.
Stock prices (SP) and EPU in BRIC countries (2003m3-2021m3)

recovered, and the EPU has declined. The highest EPU value for India was reached in 2012, and the highest values for Russia and Brazil were reached in 2017. Since 2017, EPU has been decreasing in Brazil and India, whereas it has been increasing in China. In China, the EPU reached its highest value in 2019. High EPU could be the reason for low stock prices in China. In the remaining countries, stock prices peaked in 2019.

Especially in financial markets, the reactions of individuals and firms to negative and positive shocks can vary widely. Therefore, it is important to consider the effects of negative and positive shocks in causal relationships between EPUs and stock prices. Most recent studies in the literature are based on rolling-window or time-varying causality tests. These tests neglect the effects of positive and negative shocks on the variables. Moreover, a limited number of studies have examined the relationship between EPU and stock prices in the BRIC countries. We aim to fill these two gaps in the literature by using a recently developed asymmetric frequency domain test. With this test, we examined whether the asymmetric causal relationship between EPU and stock prices is permanent or temporary. We believe that our study will contribute to the current literature by providing strong policy recommendations.

In Section 1, we present the relationship between stock prices and EPU and provide information on EPU and stock prices in BRIC countries. The remainder of this paper is structured as follows. Section 2 reviews the studies that empirically test the relationship between the two variables. Section 3 describes the data set and model used in this paper. Section 4 presents the empirical findings, and Section 5 provides a conclusion and summary of the study.

2. Literature review

There are numerous studies in the literature that investigate the adverse effects of policy uncertainty on investment (Rodrik, 1991; Gulen and Ion, 2015; and Bahmani-Oskooee and Maki-Nayeri, 2019), employment (Julio and Yook, 2012) and economic growth (Bhagat *et al.*, 2013; Fernández-Villaverde, 2015). Similarly, EPU can affect stock prices. Although the impact of EPU on various macroeconomic variables has been analyzed in many studies, studies on the relationship between EPU and stock prices or stock returns emerged only after the 2008 global financial crisis (Li *et al.*, 2016). Baker *et al.* (2013, 2016) can be considered as a turning point in the literature. The authors made an important contribution by developing an EPU index, which has been used in many recent empirical studies. The EPU index consists of the average of three main indicators of uncertainty: major news on EPU, expiring tax provisions and forecasters' disagreements about government purchases and inflation. Recently, the effects of EPU on the stock market have attracted great interest among investors, policymakers and academics (Jin *et al.*, 2019).

Uncertainty in one country may affect stock prices in another country. Mensi *et al.* (2014) investigate this possibility by performing quantile regressions for the BRICS countries (i.e. the BRIC countries and South Africa) with data from September 1997 to September 2013; they found that US EPU has no effect on the BRICS stock markets. Momin and Masih (2015) investigated the impact of US EPU on the BRICS countries' stock returns using an autoregressive distributed lag model for the period January 2000 to March 2015. The authors found that only the Indian stock market was affected by the US EPU. Dakhlaoui and Aloui (2016) investigated the impact of EPU in the USA on the stock returns of the BRIC countries using daily data from July 4, 1997, to July 27, 2011. They found that the relationship between BRIC stock indices and EPU in the USA is negative, but the volatility distribution varies between negative and positive values. Another result is that the correlation between uncertainty and stock returns is quite variable during global economic crisis periods.

Domestic political uncertainty in a country can affect stock prices and returns in the same country. Ozoguz (2009) used Markov switching and intertemporal capital asset pricing models to examine the relationships between these variables in the USA from January 1961 to December 2001 and found a negative relationship between uncertainty and stock values. Sum (2012) used ordinary least squares (OLS) method to investigate the data from February 1993 to April 2012 and concluded that EPU negatively affects stock market returns in the European Union, Turkey, Ukraine, Switzerland, Russia and Norway. Antonakakis *et al.* (2013) used a dynamic conditional correlation model for the USA from January 1985 to January 2013 and found that S&P500 returns and EPU are negatively correlated. Bijsterbosch and Guérin (2013) used a Markov regime-switching model for the US variables from January 1986 to January 2012 and concluded that high EPU episodes decrease stock prices and bond returns. Kang and Ratti (2013) used a vector autoregression (VAR) model and found that a positive oil demand shock against US oil demand increased concerns about future oil supply and triggered EPU, which reduced stock returns. They also determined that EPU significantly affected stock returns in Europe and Canada. Brogaard and Detzel (2015) used the generalized method of moments to test the relationship between stock market returns and EPU in the USA. The authors used monthly data from May 1985 to December 2012 and found a negative contemporaneous correlation between changes in EPU and stock market returns. Chang *et al.* (2015) utilized a bootstrap panel causality test for seven Organisation for Economic Co-operation and Development countries from January 2001 to April 2013 and concluded that stock price indices cause government policy uncertainty in Italy and Spain, whereas government policy uncertainty causes stock price uncertainty in the USA and the UK. They also argued that there is no causality between the variables in Canada, Germany and France. Ko and Lee (2015) performed a wavelet analysis for 11 countries in Asia, Europe and North America over the period from January 1998 to December 2012 and found that stock prices decrease after an increase in EPU.

Arouri *et al.* (2016) used the Markov regime-switching regression for the USA from 1900 to 2014 and found that an increase in EPU negatively affects stock returns. Li *et al.* (2016) used bootstrap full-sample and sub-sample rolling-window causality tests using data from China for the period from February 1995 to February 2012 and India for the period from February 2003 to February 2013. They found bidirectional causality in some sub-periods and reported that there is a weak negative relationship between EPU and stock returns in the two countries. Chen *et al.* (2017) used OLS and a VAR model to investigate Chinese data over the period from January 1996 to 2013 and found that an increase in EPU lead to a decrease in future stock market returns over different horizons. Christou *et al.* (2017) used a panel VAR model for Australia, Canada, China, Japan, South Korea and the USA from January 1998 to December 2014. The results revealed that increased policy uncertainty negatively affects stock market returns. Demir and Ersan (2018) investigated the relationship between EPU and stock returns of tourism companies listed on the Borsa Istanbul. They used multiple regression approaches from January 2002 to December 2013 and revealed that the performance of the tourism sector is affected by uncertainty regarding domestic and foreign economic policies. It was also determined that EPU had a negative impact on the stock returns of Turkish tourism companies. Xiong *et al.* (2018) used the dynamic conditional correlation-bivariate generalized autoregressive conditional heteroskedasticity model from January 1995 to December 2016 and concluded that absolute changes in EPU had a greater impact on Shanghai stock market returns than on Shenzhen stock market returns. The authors also found that fluctuations in stock returns are greater during financial crises.

Guo *et al.* (2018) used quantitative regression to analyze the relationship between EPU and stock returns in the group of seven (G7) and BRIC countries from February 1985 to August 2015. The results for the ten countries revealed important details. According to the results, EPU has an asymmetric relationship with the stock markets of the USA and Italy, while EPU negatively affected the stock markets of Germany, Japan, India and China. Moreover, the impact of uncertainty on the Canadian and Russian stock exchanges was moderate, while there was no relationship between EPU and stock prices in the UK and France. Chiang (2019) examined the relationships among EPU, risk and excess stock returns in G7 countries over the period January 1997 to June 2016, using a generalized error distribution GARCH model. The results showed that an increase in EPU reduces excess stock returns. Gao *et al.* (2019) investigated the relationships among stock prices, EPU and global oil prices in China for the period from January 2005 to December 2017. They used a rolling window Toda-Yamamoto causality test and concluded that the bidirectional causality between the variables was mainly associated with the 1997 Asian crisis, the 2008 financial crisis and China's economic structural reform.

In contrast to previous studies, Jin *et al.* (2019) investigated the relationship between EPU and stock price crash risk. They used OLS to estimate the relationship for China over the period from January 2009 to December 2017 and concluded that EPU has a positive impact on crash risk. As seen in the literature discussion, there are relationships between EPU and stock prices and returns that vary by country. However, none of the studies in the literature have considered the impact of positive and negative shocks on this relationship. More reliable results are obtained by separating the effects of positive and negative situations in financial markets. In this context, our study explains the causality relationships between the stock market and EPU by distinguishing period and shock, thus contributing to the existing literature.

3. Methodology

In the empirical analysis part of this study, we use symmetric and asymmetric frequency–domain causality tests to investigate the nexus between EPU and stock prices. The frequency-based causality tests offer significant advantages over conventional tests. Time domain causality tests can be run to determine the causal relationship between variables at time zero (Breitung and Candelon, 2006). In other words, an analysis based on a conventional time domain test can lead to ignoring the different frequency components of the series. This type of information loss in series can cause deviating results. To overcome this problem, frequency domain causality tests can be used to examine causality at different time points considering different frequency components. Thus, using all the information in the series can provide policymakers with more comprehensive insights into economic activities.

3.1 Symmetric frequency domain Granger causality

Breitung and Candelon (2006) proposed the frequency domain causality test based on Geweke (1982) and Hosoya (1991). They used a bivariate finite-order VAR model as follows:

$$\begin{pmatrix} Q_{11}(L) & Q_{12}(L) \\ Q_{21}(L) & Q_{22}(L) \end{pmatrix} \begin{pmatrix} X_t \\ Y_t \end{pmatrix} = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{1}$$

In equation (1), $Q(L)$ is an autoregressive polynomial that is defined as $1-\sum_{i=1}^{p} Q_i L^{\mathrm{I}}$. Breitung and Candelon used equation (2) to measure frequency causality as suggested by Geweke (1982) and Hosoya (1991):

$$M_{y\to x}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right] = \log\left[1+\frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{2}$$

where $M_{y\to x}(\omega) = 0$ is the test of the null hypothesis that Y does not cause X. Breitung and Candelon (2006) proposed the following VAR(p) model to investigate frequency causality:

$$X_t = \sum_{k=1}^{p} \theta_{11,k} X_{t-k} + \sum_{k=1}^{p} \theta_{12,k} Y_{t-k} + \varepsilon_t \tag{3}$$

The $M_{y\to x}(\omega) = 0$ linear restriction is used to test the null hypothesis of $R(\omega)\theta_{12} = 0$ (Bahmani-Oskooee *et al.*, 2016), where θ_{12} and $R(\omega)$ are defined as $[\theta_{12,1}, \theta_{12,2}, \ldots \theta_{12,p}]$' and $\begin{bmatrix} \cos(\omega)\cos(2\omega)\ldots\ldots\cos(p\omega) \\ \sin(\omega)\sin(2\omega)\ldots\ldots.\sin(p\omega) \end{bmatrix}$, respectively. For the Granger non-causality null hypothesis at w frequency, one can use a chi-square distribution with two degrees of freedom.

3.2 Asymmetric frequency domain Granger causality

Conventional causality tests based on the symmetry assumption assume that the effects of positive and negative shocks are not separated (Bahmani-Oskooee *et al.*, 2016). In other words, it is assumed that the effects of positive and negative shocks are the same. However, investors, firms and traders show different reactions to these shocks. Apergis and Miller (2006) argued that negative news in financial markets is an important factor that influences consumption decisions. According to Hatemi-J (2019), market participants react more to negative news in financial markets than to positive news. In addition, Wen *et al.* (2019) stated that the main reason for the decline in stock prices, which is an important problem for financial markets, is bad news. In this case, it is a very restrictive assumption to assume a symmetric relationship that economic agents respond equally to negative and positive shocks in financial markets (Hatemi-J, 2012).

Positive and negative shocks can have different effects in time series, and they may bias the results of conventional tests. To overcome this issue, Hatemi-J (2012) obtained negative and positive shocks as in equations (4) and (5):

$$y_t = y_{t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{T} \varepsilon_{1i} \tag{4}$$

$$x_t = x_{t-1} + \varepsilon_{2t} = x_{10} + \sum_{i=1}^{T} \varepsilon_{2i} \tag{5}$$

With these equations, positive and negative shocks are defined as in equation (6):

$$\varepsilon^+_{1t} = \max(\varepsilon_{1t}, 0), \varepsilon^+_{2t} = \max(\varepsilon_{2t}, 0), \varepsilon^-_{1t} = \min(\varepsilon_{1t}, 0), \varepsilon^-_{2t} = \min(\varepsilon_{2t}, 0) \tag{6}$$

We can rewrite equations (4) and (5) with restrictions $\varepsilon_{1t} = \varepsilon^+_{1t} + \varepsilon^-_{1t}$ and $\varepsilon_{2t} = \varepsilon^+_{2t} + \varepsilon^-_{2t}$ as follows (Bahmani-Oskooee *et al.*, 2016):

$$y_t = y_{t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{t} \varepsilon^+_{1i} + \sum_{i=1}^{t} \varepsilon^-_{1i} \tag{7}$$

$$x_t = x_{t-1} + \varepsilon_{2t} = x_{10} + \sum_{i=1}^{T} \varepsilon^+_{2i} + \sum_{i=1}^{T} \varepsilon^-_{2i} \tag{8}$$

Hatemi-J (2012) assumes that the relationship between negative and positive shocks is similar at all frequencies. However, Granger (1969) stated that the relationship between two variables might differ at different frequencies. Therefore, Bahmani-Oskooee *et al.* (2016) transformed the Hatemi-J (2012)'s asymmetric causality test from the time dimension to the frequency dimension. They focused on two combinations, (y^+_t, x^+_t) and (y^-_t, x^-_t), for causal relationships and proposed the following model for the asymmetric causality test in the frequency domain:

$$\begin{pmatrix} Q_{11}(L) & Q_{12}(L) \\ Q_{21}(L) & Q_{22}(L) \end{pmatrix} \begin{pmatrix} y^+_t \\ x^+_t \end{pmatrix} = \begin{pmatrix} \upsilon_{1t} \\ \upsilon_{2t} \end{pmatrix} \tag{9}$$

where $Q(L)$ denote an autoregressive polynomial that is defined as $1 - \sum_{i=1}^{p} Q_i L^{\ddagger}$. They used equation (9) to measure asymmetric frequency causality as suggested by Geweke (1982) and Hosoya (1991). In equation (10), $M_{x^+_t \to y^+_t}(\omega)$ tests the null hypothesis that x^+_t does not cause y^+_t:

$$M_{x^+_t \to y^+_t}(\omega) = \log\left[\frac{2\pi f_{EX}(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right] = \log\left[1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{10}$$

Furthermore, Bahmani-Oskooee *et al.* (2016) proposed the following VAR(p) model to test frequency causality for positive components:

$$y^+_t = \sum_{k=1}^{p} \theta_{11,k} y^+_{t-k} + \sum_{k=1}^{p} \theta_{12,k} x^+_{t-k} + \varpi_t \tag{11}$$

The $M_{x^+_t \to y^+_t}(\omega)$ linear restriction is used to test the null hypothesis of $R(\omega)\theta_{12} = 0$ (Bahmani-Oskooee *et al.*, 2016), where θ_{12} and $R(\omega)$ are defined as $[\theta_{12,1}, \theta_{12,2}, \ldots \theta_{12,p}]$' and $\begin{bmatrix} \cos(\omega)\cos(2\omega)\ldots\ldots\cos(p\omega) \\ \sin(\omega)\sin(2\omega)\ldots\ldots\ldots\sin(p\omega) \end{bmatrix}$, respectively. The null hypothesis is tested using a Wald statistic.

Hatemi-J (2012) noted that the analyzed series are not normally distributed because there may be the autoregressive conditional heteroscedasticity (ARCH) effect in financial data. For this reason, the Wald statistics may deviate from the asymptotic distribution. Therefore, Bahmani-Oskooee *et al.* (2016) obtained critical values using the bootstrapping simulation technique.

4. Data and empirical results

We investigate the relationship between EPU and stock prices for the BRIC countries over the period from March 2003 to March 2021. The EPU index and stock prices (SP) data were obtained from Baker *et al.* (2013) [1] and Investing (2021), respectively. All variables used in the study are transformed into logarithmic form.

In the first part of the empirical analysis, we perform augmented Dickey–Fuller (Dickey and Fuller, 1981) and Phillips–Perron (Phillips and Perron, 1988) unit root tests to determine the degree of integration of the series. Table 1 shows the results of the unit root tests for each country. According to the results, EPU is stationary at level I(0), while stock prices contain a unit root for all countries except Brazil [2]. Stock prices are stationary at the first difference I(1) in Brazil, China and Russia.

After determining the stationary properties of the series, we check multivariate normality and ARCH effects for the symmetric and asymmetric causality tests [3]. Table 2 presents the results of the multivariate normality and multivariate ARCH effects tests for symmetric causality. As can be seen in the table, the residuals do not follow a normal distribution for all countries, and ARCH effects are present for Brazil and China.

Table 3 provides the results of the multivariate normality and multivariate ARCH tests for asymmetric causality. The results show that residuals of the negative and positive components do not follow a normal distribution for all countries. Moreover, ARCH effects are present in both components for Brazil and China.

Countries	Variables	ADF Test stat. I(0)	ADF Test stat. I(1)	p I(0)/I(1)	PP Test stat. I(0)	PP Test stat. I(1)	Bandwidth I(0)/I(1)
Brazil	EPU	−3.503*	–	3	−8.202*	–	8
	SP	−1.774	−6.192*	9/8	−2.891**	–	0
China	EPU	−1.565	−18.980*	2/1	−3.464*	–	6
	SP	−1.724	−12.909*	0/0	−2.239	−13.352*	8/7
India	EPU	−3.067**	–	2	−6.171*	–	6
	SP	−2.479	−13.689*	0/0	−2.406	−13.772*	6/6
Russia	EPU	−3.325**	–	2	−7.736*	–	8
	SP	−2.084	−11.637*	1/0	−2.389	−11.712*	5/4

Table 1. Results of the unit root tests

Countries	Multivariate ARCH	Multivariate Normality
Brazil	0.285	0.000*
China	0.121	0.011**
India	0.018**	0.000*
Russia	0.000*	0.000*

Note: * and ** denote the significance of the test statistic at 1% and 5% levels, respectively

Table 2. Normality and ARCH effects for symmetric causality

Countries	The positive components Multivariate ARCH	The positive components Multivariate Normality	The negative components Multivariate ARCH	The negative components Multivariate Normality
Brazil	0.796	0.000*	0.315	0.000*
China	0.155	0.000*	0.577	0.000*
India	0.016**	0.000*	0.163	0.000*
Russia	0.001*	0.000*	0.000*	0.000*

Notes: The null of the normality test is residuals follow a normal distribution. The null of the ARCH test is ARCH effects present. * denotes the significance of the test statistic at 1% level

Table 3. Normality and ARCH effects for asymmetric causality

Financial series do not generally follow a normal distribution. We find that the residuals in both symmetric and asymmetric causality tests are not normally distributed and exhibit ARCH effects. In this case, standard time series approaches based on normality and constant variance may not provide accurate results (Hatemi-J, 2012). Therefore, we use the bootstrap method to avoid these problems.

The results of the symmetric causality tests causality tests in the frequency domain are shown in Table 4. The frequency lengths for the long and short periods are 0.5 and 2.5, respectively. In other words, 0.5 indicates permanent causality, whereas 2.5 represents a temporary causal relationship. The long term refers to periods longer than 1 year ([2 × 3.14/0.5]), whereas the short term refers to periods of about 3 months ([2 × 3.14]/2.5). According to the symmetric causality results, there is unidirectional permanent causality from EPU to stock prices for Brazil, China and India. For China, there is also unidirectional temporary causality from stock prices to EPU.

Table 5 shows the results of the asymmetric frequency domain causality test for the positive components. The results indicate that there is unidirectional permanent causality from the positive components of EPU to the positive components of stock prices for Brazil. For India, there are permanent and temporary causality relations in the same direction.

Table 6 presents the asymmetric frequency domain causality test results for the negative components. For Brazil, there is unidirectional temporary causality from the negative

			H0: EPU does not cause SP					
Countries	w = 0.5	1%	5%	10%	w = 2.5	1%	5%	10%
Brazil	14.549*	9.499	6.089	4.698	5.485	8.706	5.776	4.455
China	5.272***	8.768	5.635	4.097	0.827	8.050	5.695	4.353
India	6.800**	8.828	6.147	4.793	2.833	8.853	5.545	4.467
Russia	2.269	10.711	6.221	4.544	0.352	8.730	5.861	4.424
H0: SP do not cause EPU								
Brazil	4.432	9.160	5.762	4.460	1.336	9.883	5.831	4.615
China	3.096	9.251	5.929	4.612	4.654***	8.782	5.967	4.567
India	1.238	8.815	6.110	4.623	2.375	9.942	6.001	4.600
Russia	0.884	8.890	6.029	4.593	0.472	9.250	5.551	4.491

Notes: w denotes the frequency length. *, **, and *** denote the significance of the test statistic 1%, 5%, and 10% levels, respectively

Table 4. The results of symmetric frequency domain causality test

Countries	w = 0.5	1%	5%	10%	w = 2.5	1%	5%	10%
H0: positive components of EPU do not cause positive components of SP								
Brazil	9.194**	9.724	6.153	4.305	4.708	10.409	7.032	5.165
China	0.767	9.571	6.088	4.707	1.077	9.356	5.837	4.350
India	8.219**	8.578	5.903	4.556	4.588***	9.693	6.086	4.479
Russia	0.862	9.046	6.174	5.571	1.344	8.912	5.895	4.305
H0: positive components of SP do not cause positive components of EPU								
Brazil	0.030	8.767	5.406	4.402	1.242	9.342	6.377	4.912
China	0.456	9.601	5.805	4.352	2.448	9.452	5.923	4.443
India	0.835	9.228	6.161	4.758	0.201	9.547	6.026	4.640
Russia	2.901	9.472	5.999	4.438	0.752	9.307	5.641	4.600

Notes: w denotes the frequency length. ** and *** denote the significance of the test statistic level at 5% and 10%, respectively

Table 5. The results of asymmetric frequency domain causality test for positive components

Table 6.
The results of asymmetric frequency domain causality for negative components

Countries	w = 0.5	1%	5%	10%	w = 2.5	1%	5%	10%
H0: negative components of EPU do not cause negative components of SP								
Brazil	3.334	8.854	5.440	4.217	4.973***	8.575	5.442	4.165
China	0.488	8.477	5.853	4.403	1.646	9.189	5.896	4.402
India	1.818	8.891	5.934	4.586	0.408	10.070	5.901	4.467
Russia	1.769	9.435	6.287	4.714	0.973	9.415	6.128	4.742
H0: negative components of SP do not cause negative components of EPU								
Brazil	2.138	9.328	6.044	4.452	3.241	10.322	5.665	4.170
China	0.638	11.155	6.240	4.788	1.556	9.991	6.221	4.575
India	2.349	10.001	5.993	4.548	8.087**	9.210	5.404	4.243
Russia	2.239	10.861	5.980	4.390	0.582	9.244	5.816	4.397

Notes: w denotes the frequency length. ** and *** denote the significance of the test statistic at 5% and 10% levels, respectively

components of EPU to the negative components of stock prices. For India, there is a temporary causality in the opposite direction.

The symmetric and asymmetric frequency domain causality graphical test results for all frequencies are shown in Figures A1 to A3 (Appendix). In the figures, the Wald statistics are represented by a solid line, and there is a causal relationship between the frequencies with a solid line above the dashed lines. As can be seen in detail in the figures, symmetrical and asymmetrical causality findings are different for China. Asymmetric causality findings show that there is no relationship between stock prices and EPU in China. In this case, the volatility in the Chinese stock market may be due to different macroeconomic indicators such as economic growth, exchange rate, foreign trade, financial development and energy consumption. The overall results of the study show that there is a strong relationship between EPU and stock prices for India and Brazil.

5. Conclusions

This study examined the relationship between EPU and stock prices for BRIC countries during the period from March 2003 to September 2019 using symmetric and asymmetric frequency domain causality tests. The main contribution of this study was the separate consideration of positive and negative shocks in examining the asymmetric causal relationship between EPU and stock prices.

Using a symmetric causality test, we found permanent bidirectional causality between EPU and stock prices for China. There is also unidirectional causality from EPU to stock prices for Brazil and India. Li *et al.* (2016), Christou (2017) and Guo *et al.* (2018) determined that Chinese EPU reduces stock prices and returns. We have also determined that Chinese stock prices affect EPU. However, the results of the asymmetric causality test show that there is no causality between variables for China. For this reason, the findings of our study do not coincide with previous studies. Chinese EPU has increased in recent years (shown in Figure 1). Stock prices have remained at the level of the 2009 financial crisis. In order to revive the stock market, the Chinese Government should focus on other macroeconomic indicators besides the EPU.

According to the asymmetric causality results, positive EPU shocks positively affected stock prices in Brazil. Moreover, unidirectional causality from EPU to stock prices is found in this country for negative shocks. The removal of economic uncertainty in Brazil stimulates investment, which has a positive effect on the stock market. The negative shocks in EPU postpone investment decisions, undermine confidence in the stock market and thus reduce stock prices.

For India, we found unidirectional permanent and temporary causality from positive EPU shocks to positive stock price shocks. This result is in line with the findings of Li *et al.* (2016) and Guo *et al.* (2018). As India's EPU has declined, fluctuations in employment and investment have also decreased, and the Indian stock market has been supported by increasing investment. Moreover, unidirectional causality from stock prices to EPU is found for negative shocks in India. In this case, negative stock price shocks in India increased EPU by reducing the value of firms and household wealth. Stock price fluctuations caused by positive and negative shocks lead to policy changes. A rapid outflow of money from the stock market leads to an increase in the exchange rate and the debt burden. According to our findings, this is the case for India. During the global crisis of 2008, the National Stock Exchange of India suffered a major shock, and at the same time, the Indian rupee depreciated significantly. To overcome this problem, the Indian Government implemented expansionary policies such as credit expansion and tax cuts.

Although Sum (2012) argued that EPU negatively affects stock prices in Russia, our results from symmetric and asymmetric causality tests show that there is no relationship between the two variables for this country. In Russia, stock prices have increased since 2014. Although the EPU reached its highest value in 2017, the Russian stock market continues to rise. However, Russia still has a high level of economic uncertainty.

The overall results show that economic policies of governments have a causal relationship with stock prices in Brazil and India. Effective and strong economic policies implemented by governments in these countries support the performance of their stock markets. However, uncertainty about economic policies has a detrimental effect on stock markets.

Finally, this study offers some research opportunities. The effects of EPU on the prices of other assets in BRIC countries, such as oil and gold, should be examined. In addition, future research should investigate the asymmetric causal relationship between EPU and stock prices in developed country groups such as the G7. Furthermore, the impact of positive or negative EPU shocks in the USA on the stock markets in other countries can be analyzed using the asymmetric frequency domain causality test.

Notes

1. www.policyuncertainty.com/
2. The unit root test results for the positive and negative shocks available upon request from the authors.
3. We use Hacker and Hatemi-J (2005) and Doornik and Hansen (2008) tests to check multivariate ARCH and multivariate normality, respectively.

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Appendix

A: SP do not cause EPU *B: EPU does not cause SP*

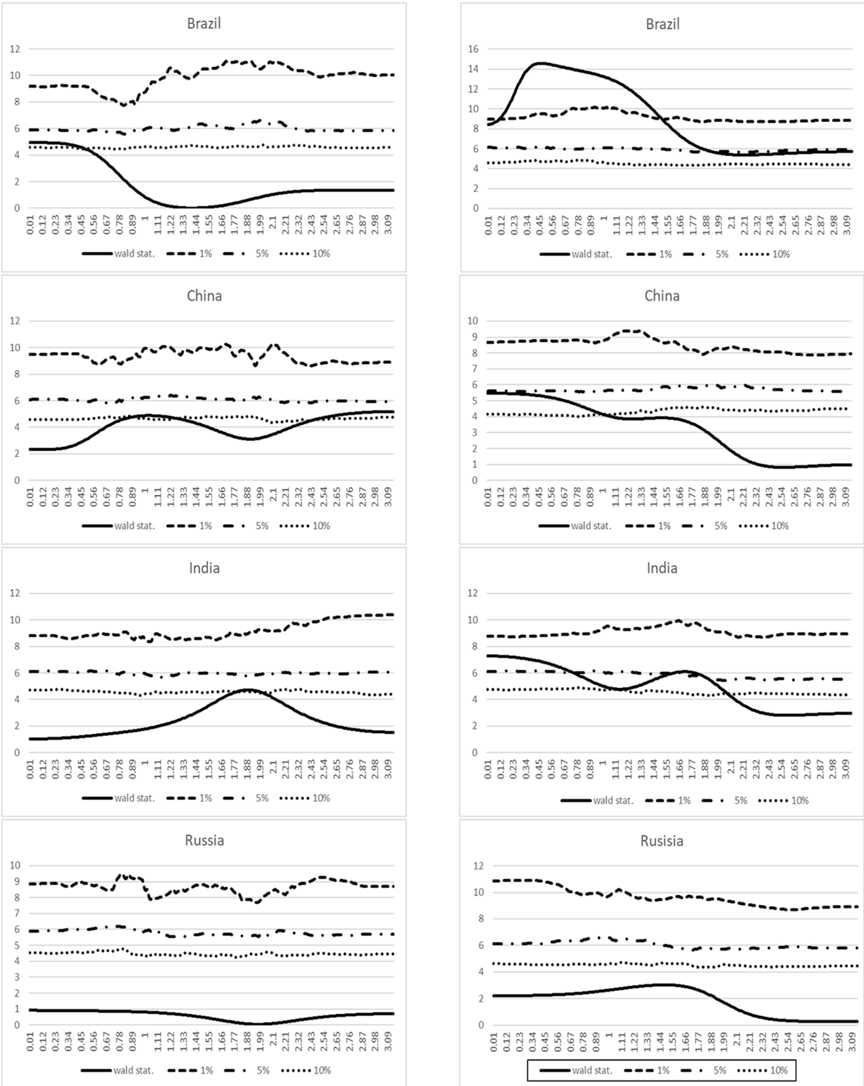

Figure A1.
Symmetric frequency domain causality test resultsA: SP do not cause EPU B: EPU does not cause SP

A: SP⁺ do not cause EPU⁺ *B: EPU⁺ does not cause SP⁺*

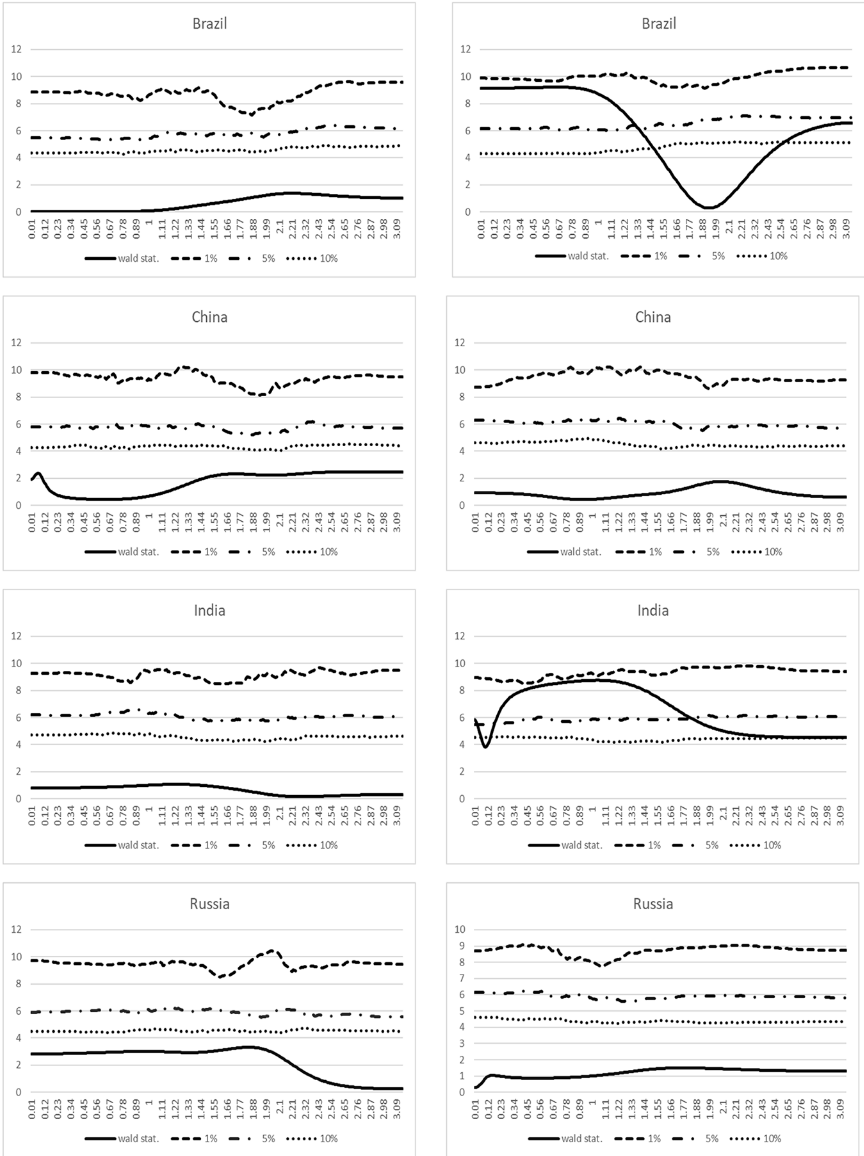

Figure A2.
Asymmetric frequency domain causality test results for positive componentsA: SP^{+} do not cause EPU^{+} B: EPU^{+} does not cause SP^{+}

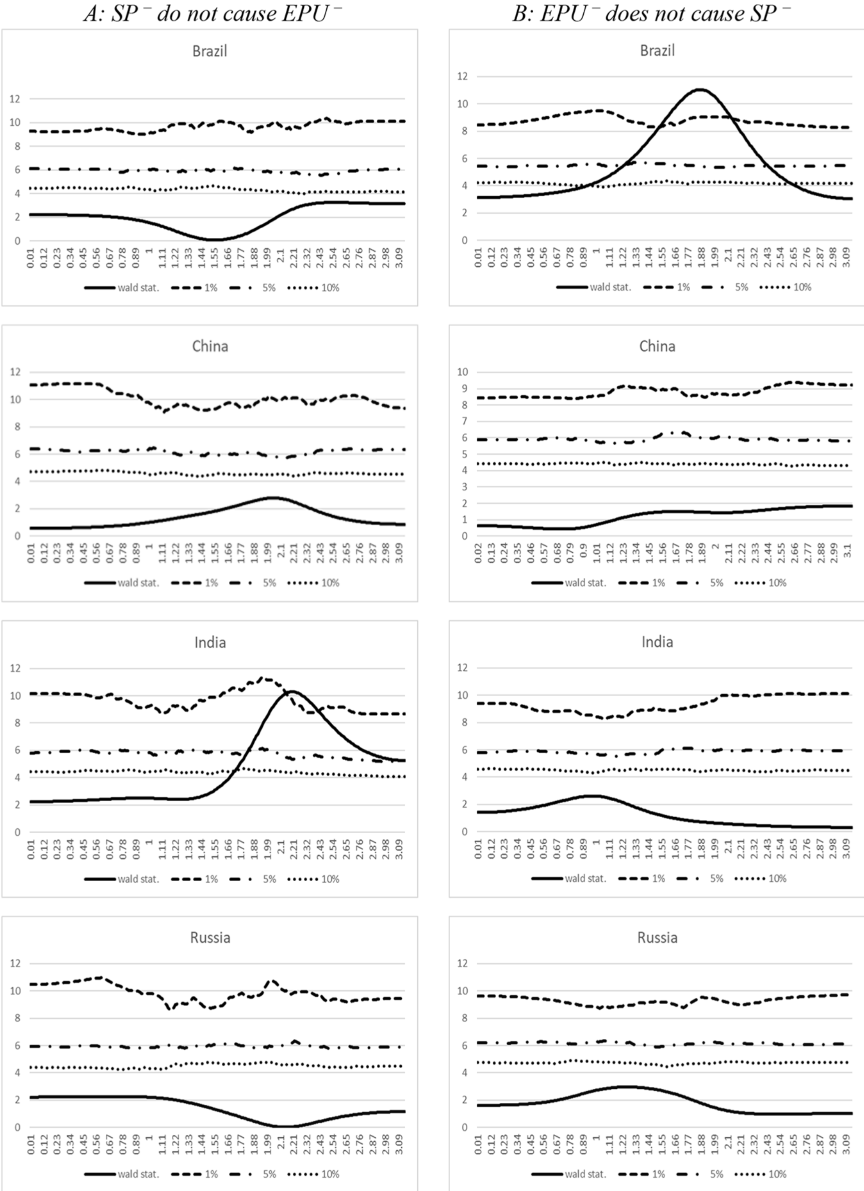

Figure A3.
Asymmetric frequency domain causality test results for negative components
A: SP^- do not cause EPU^-
B: EPU^- does not cause SP^-