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SOURCES OF UNCERTAINTY AND THEIR IMPACT ON STOCK PRICES EVIDENCE FROM EMERGING ECONOMIES

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Abstract

This study investigates the short- and long-term effects of various sources of uncertainty on the share prices of key exchanges in emerging nations. The sample comprises monthly time series data from January 2017 to December 2021 for China, India, Russia, and Brazil. The study contains a version of Autoregressive-Distributive-Lag (ARDL) with error correction as well as other relevant approaches to time series. Economic policy, climate policy, pandemics, and Twitter-based uncertainty may cause a long-term decline in SSE (Shanghai Stock Exchange) composite index and BSE (Bombay Stock Exchange) Sensex index. In China, geopolitical, climatic, and pandemic uncertainty are short-term sources of uncertainty, and in India, economic policy, geopolitical, and pandemic uncertainty. Moreover, no sources of uncertainty have a long-term impact on Russia's Moscow Exchange (MOEX) index. All sources except climate uncertainty are short-term MOEX index contributors. Pandemics and Twitter-based uncertainty are long-term sources, whereas economic policy and Twitter-based uncertainty are short-term sources for Brazilian Stock Exchange (BOVESPA) Index. This research adds to the literature by examining the relationship between distinct sources of uncertainty and an emerging market share prices index. It provides the behavior of leading share price indexes in the presence of uncertainty. The study's conclusions only apply to emerging economies. Future research may take into account a panel dataset consisting of a large number of emerging nations to examine the same set of variables.

JEL classification: C22, C32, C82, D81, E22, E70

Keywords: Economic policy uncertainty, Geopolitical uncertainty, Climate uncertainty, pandemic uncertainty, Twitter-based uncertainty, Share price index

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Introduction

In any economy, share price indexes serve as an indicator of financial performance. The increase in trade volume for any index reflects investors' confidence in the respective economy. However, an unpredictable environment has a significant impact on the investor's decision to purchase shares in the target economy. There are various sources of uncertainty, including economic policy, climate policy, geopolitical, pandemic, and news-based uncertainty (Jurado et al., 2015). Each source of uncertainty may have varying effects on the share price of an economy (Ferguson & Lam, 2016). For instance, economic policy uncertainty refers to the ambiguity surrounding the applicable laws, regulations, and norms for a certain economic action (Aydin et al., 2021). Likewise, climate policy uncertainty shows ambiguity over an economy's climate safety measures (Sumarsan et al., 2021). In addition, geopolitical uncertainty shows the potential for instability involving 2 nations in the form of terrorist attacks or conflicts (Jurado et al., 2015). In addition, the extended pandemic uncertainty has produced a worldwide atmosphere of worry for personal safety and healthcare concerns (Dash & Maitra, 2022). Moreover, news-based uncertainty such as Twitter has prolonged ambiguity regarding the credibility of news from unofficial sources for a target economy (Meshki & Ashrafi, 2014). The governments of various nations have provided monetary and non-monetary reliefs to impacted regions to reduce a target source of uncertainty. It has also produced an inflationary strain in any economy, ultimately affecting share prices on their respective stock markets (Ferguson & Lam, 2016). Economic policy, climate policy, and pandemics affect economies and financial markets, making them major uncertainty indicators. Economic policy uncertainty causes cautious investor behavior and market volatility. Lack of climate policy clarity affects investor decisions in climate-sensitive sectors. Pandemics disrupt global supply lines and economies, bringing market volatility and containment uncertainty. Twitter's real-time information and public opinions help analysts assess investor sentiment, event reactions, and market perceptions in exchange markets. Despite limits, Twitter sentiment analysis helps comprehend market dynamics, predict movements, and assess news impact on stock markets.

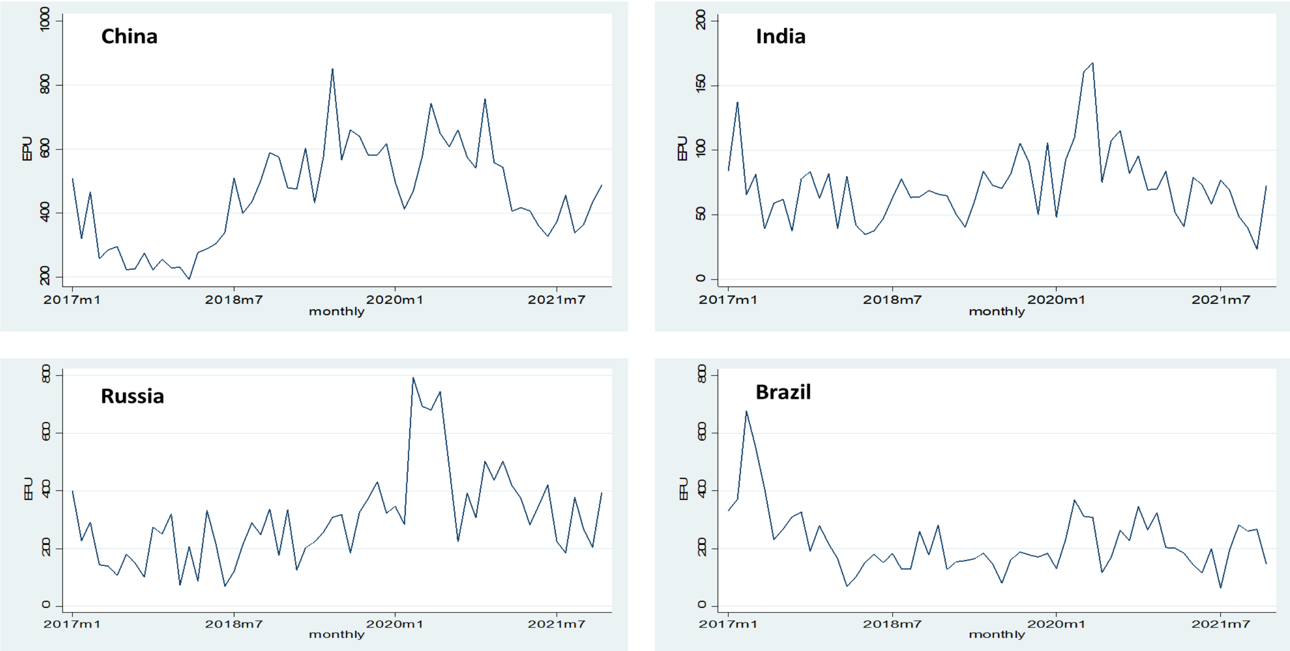
Figure 1 depicts the trend of the average monthly share price index for sampled nations from January 2017 to December 2021. In December 2018, the SSE Composite index reached its lowest level at 2,493.9 points. However, the same index showed an upward trend thereafter, with the maximum point recorded in December 2021 at 3,639.78 points. During the period of research for the BSE Sensex index in India, the average monthly share price index trended upward. The lowest point during the study period was recorded in January 2017 with 27,656 points, while the greatest point was recorded in December 2021 with 58,253 points. The average share price index in Russia for the MOEX index and in Brazil for the BOVESPA index exhibited a similar upward trend.

Figure 1: Share Price Trends

Source: Line trends estimations using STATA 13.

Figure 2 depicts the average monthly trend for economic policy uncertainty (EPU) in China, India, Russia, and Brazil for the period of January 2017 through December 2021. During the period between January 2018 and July 2019, the average EPU for China increased. After this period, the EPU began to decline relative to China's average trend. Similarly, the figure indicated that EPU in India increased on average from January 2018 to July 2020. After this period, the EPU began to decline relative to the region's average trend. Nonetheless, the statistic indicates a rising average EPU trend for Russia from July 2017 to January 2020. In later years, the EPU of Russia began to decline.

Figure 2: Economic Policy Uncertainty Trends



Source: Line trends estimations using STATA 13.

Figure 3 displays the average climate policy uncertainty (CPU), geopolitical uncertainty index (GPU), pandemic uncertainty (PDU), and Twitter-based uncertainty (TBU) for the sampled nations from January 2017 to December 2021. The CPU index is a weighted average of declining trends in all four countries. During the study period, however, the GPU suggests a random tendency for the sampled nations. Nevertheless, pandemic uncertainty increased at the end of 2019 and reached its peak in December 2020. After that, the PDU began to decline globally, including in China, India, Russia, and Brazil. The number also indicated Twitter-based uncertainty in the aforementioned four nations during the study period. From July 2017 to July 2020, the average TBU is projected to increase in all four nations. However, the same began to decline thereafter.

Figure 3 supports the prevalent view that climate policy uncertainty (CPU) decreased while geopolitical uncertainty index (GPU) varied among nations. The graph also shows a rise in pandemic uncertainty (PDU) in late 2019, followed by a global fall. Twitter-based uncertainty (TBU) increased in all four nations from July 2017 to July 2020 but declined afterward. These findings confirm that climate policy, pandemics, and Twitter-based issues increase uncertainty, whereas geopolitical uncertainty is inconsistent.

The purpose of the present study is to investigate the effects of various sources of uncertainty on the stock prices of prominent stock markets in emerging nations such as China, India, Russia, and Brazil. The specific research objectives are as follows:

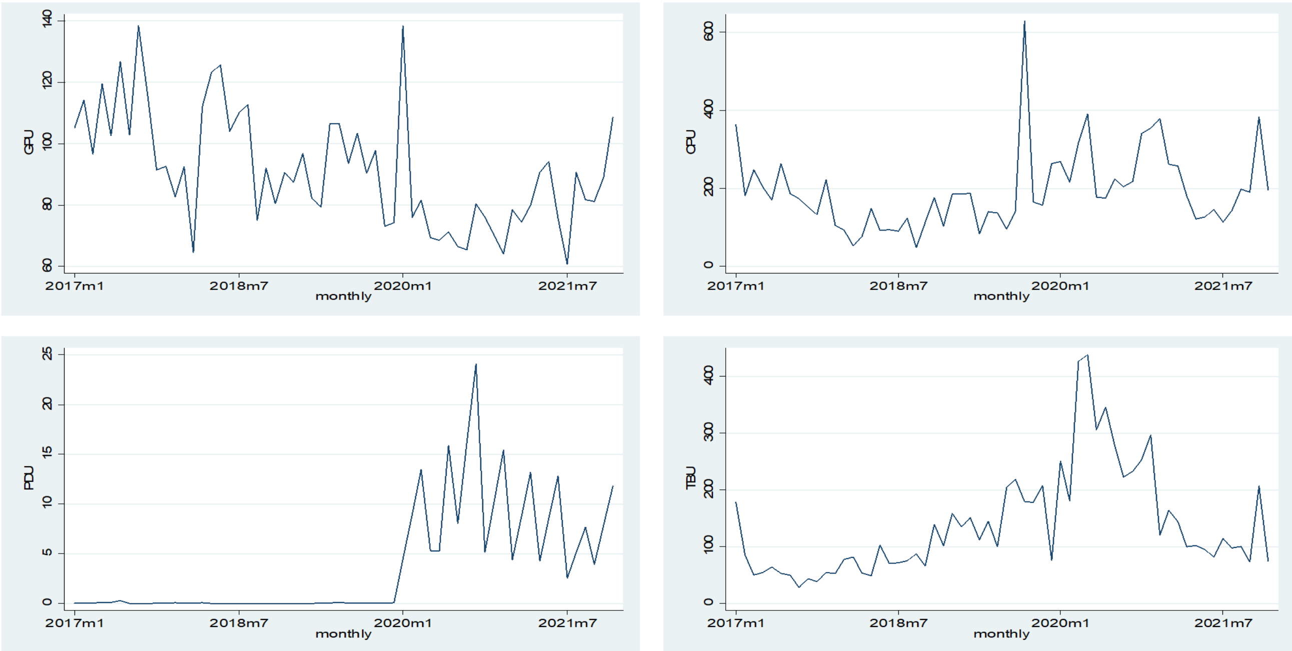
1) Analyze the primary source of uncertainty that may have a major short-term impact on the target population's share price index.
2) Evaluate the source of uncertainty that has a substantial long-term impact on the sample population's share price index.

The aforementioned objectives necessitate answering the following questions using statistical and economic methods.

1) How might various sources of uncertainty affect the share prices of emerging markets in the short term?
2) What is the long-term impact of various sources of uncertainty on the share values of emerging economies?

Additionally, uncertainty influences household's saving and investing choices. It has a significant impact on a government's stock market policies. Moreover, the uncertainty generates a climate of anxiety among governments to take drastic action to stabilize the impacted economy. The remaining portion of the study includes but is not limited to, a literature review and hypotheses, the overall research design and methodology, empirical analysis and discussion, and finally a conclusion along with recommendations, limitations, and implications.

Figure 3: CPU, GPU, PDU, and TBU Trends



Source: Line trends estimations using STATA 13.

Review of literature and hypothesis development

Sources of uncertainty and share price

The research provides evidence for a variety of causes of uncertainty, including economic policy, geopolitics, climate policy, pandemics, and uncertainty based on Twitter, which may affect the share prices of key stock markets. Economic policy uncertainty is the lack of clarity about how and why the government will run a certain economy in the future (Pastor & Veronesi, 2012). In any economy, how well the financial markets do depends on how much investors trust the country's economic policies. Uncertainty makes investors doubtful, which causes the value of their shares to go down. So, most previous studies agree that uncertainty about economic policy has a negative effect on share price indices in different parts of the world (Bahmani-Oskooee & Saha, 2019; Baker et al., 2021; Guenichi & Nejib, 2022; Ko & Lee, 2015; Sánchez-Gabarre, 2020; Sum, 2013). The following hypothesis was created based on the significantly negative findings of the aforementioned studies about the influence of economic policy uncertainty on the share price index:

H_1: EPU strongly decreases the share price index in the long run and short-run.

Geopolitical unpredictability is caused by terrorism, conflicts, and international tensions, which make international trade, investments, and relationships hard to predict (Jurado et al., 2015). Geopolitical uncertainty has a negative impact on both foreign and domestic investors' decisions to invest in the financial sector during political tensions, conflicts, or acts of terrorism. The impact of geopolitical uncertainty on the share price index is still a puzzle. In addition, studies show that geopolitical uncertainty decreases the share price index (Jurado et al., 2015; Sánchez-Gabarre, 2020). Given that geopolitical uncertainty decreases the stock market index, the following is true:

H_2: Geopolitical Uncertainty negatively impacts the Share Price index in the long run and short-run.

Certainly, the global climate is changing. But there is uncertainty about how big climate change will be and when it will happen, as well as how much it will cost to switch to a low-carbon economy (Pastor & Veronesi, 2012). To reduce the uncertainty of climate policies, stringent policies and processes must be developed (Jurado et al., 2015). Investors may lose faith in an economy if they don't know how well environmental safety will be implemented. This could make them less likely to invest in the financial market of that economy (Chan & Malik, 2022). So, the study must come up with the following hypothesis, which will measure how bad the uncertainty about climate policy is for the target group's share price index.

H_3: Climate Uncertainty plays a strong role in decreasing the share price index in the long run and short-run.

"Pandemic uncertainty" means that there isn't a lot of clear information about how a virus spreads, what its exact symptoms are, how to treat it, etc. (Sumarsan et al., 2021). The emergence of the COVID-19 virus has had a substantial influence on the global environment, especially on the global financial markets (Szczygielski et al., 2021). Increasing pandemic uncertainty has caused investors to either not invest in pandemic-affected economies or remove their capital from the stock market for fear of losing their money (Wang et al., 2021). So, the following hypothesis is made to find out if uncertainty about a pandemic has a big effect on the share price index.

H_4: Pandemic Uncertainty has a substantial role in decreasing the share price index in the long run and short-run.

Twitter-based uncertainty means that people aren't sure if the financial market information they get on Twitter is true (Meshki & Ashrafi, 2014). Uncertainty about a tweet's authenticity may undermine an economy's index performance (Baker et al., 2021). To evaluate if Twitter-based uncertainty affects the study population's share price index, we test the following hypotheses.

H_5: Twitter-based Uncertainty has a negative role in impacting the share price index in the long run and short-run.

Table 1(a) provides a summary of the literature evidence for samples, populations, study period, estimating methodologies, and findings.

Table 1(a): Summary of Literature Evidence (Sources of Uncertainty)

Reference	Population & Sample	Period	Estimation Method	Findings
Sum (2013)	ASEAN nations (5 countries)	1985-2012	Granger Causality and VAR	EPU (-, sig)
Meshki & Ashrafi (2014)	Tehran	1985-1990	GMM and SEM analysis	Good News (+, sig) Bad News (-, sig)
Ko & Lee (2015)	11 Economies	1998-2014	Wavelet Analysis	EPU (-, sig)
Fang-Ming & Chien-Ho (2016)	S&P 500 Index	2003-2013	SEM analysis	Information Uncertainty (-, Insig)
Su et al. (2018)	WTI and Brent Oil	1994-2016	Wavelet Analysis	Information Uncertainty (-, sig)
Bahmani-Oskooee & Saha (2019)	13 Countries	1985-2016	ARDL	EPU (-,sig) short run EPU (-,ins) long run
Sánchez-Gabarre (2020)	Spain and Brazil	2006-2019	ARDL	EPU (-,sig) short run EPU (-, sig) long run GPU (-, ins) long +short
Baker et al. (2021)	USA	2011-2019	Trend/Graph analysis	EPU (-, sig) TBU (-, sig)
Szczygielski et al. (2021)	Asian and Latin American Markets	2019-2020	ARCH/GARCH	PDU (-, weak sig) Asia PDU (-, sig) Latin America
Chan & Malik (2022)	Nasdaq, Amex, and NYSE indexes	2005-2020	OLS	CPU (-,sig)
Guenichi & Nejib (2022)	Tunisia	2020-2021	VAR/DCC/GARCH	EPU (-, sig) PDU (-, sig)

Source: Own work.

Determinants of Share Price index

In addition to uncertainty, other drivers boost or reduce the global share market index. This study's control variables were these drivers. It's worth mentioning their prior impact on share prices. The real growth rate is the leading indicator of an economy's overall performance.

People are more likely to trust the economy as a whole, and especially its financial markets when the growth rate goes up. Most research shows a favorable linkage between GDP growth and the stock market index (Arora & Bhimani, 2016; Demir, 2019; Gregoriou et al., 2015; Hadi et al., 2022; Narayan et al., 2013). The following hypothesis examines the potential impact of real growth on share prices.

H_6: The real growth rate plays an important role in enhancing the stock price index.

The actual interest rate may have an adverse impact on the stock price index (Narayan et al., 2014). For the most part, studies have shown that real interest rates have a positive effect on stock market indices worldwide, as a higher rate provides a larger return on investment (Sheikh et al., 2020; Sumarsan et al., 2021). This historical research finds that an increase in real interest rates causes an increase in the stock market index.

H_7: There is a significant and positive effect of real interest on stock prices.

Inflation describes a scenario in which the general price level is rising (Narayan et al., 2014). Investors may assume that the company's profitability would decline if prices continued to rise (Arora & Bhimani, 2016). Profitability declines may lead to a dip in share price and the whole stock market. Therefore, the negative impact of inflation on the share price index may be assumed. Several studies demonstrate that inflation has a negative impact on share index prices (Antonakakis et al., 2017; Arora & Bhimani, 2016; Narayan et al., 2014). The following hypothesis suggests that inflation has a negative impact on the target population's share price index.

H_8: The inflation rate strongly undermines the index of stock prices.

Many studies indicate that the exchange rate promotes share prices (Narayan et al., 2014). The devaluation of local currencies increases exports, which in turn raises share values (Bahmani-Oskooee & Saha, 2018). Therefore, the exchange rate influences share prices positively (Demir, 2019; Hadi et al., 2022; Sheikh et al., 2020; Sumarsan et al., 2021). It was hypothesized in the study that a favorable exchange rate would have a positive effect on stock market performance.

H_9: The exchange rate plays an important role in boosting the stock price index.

Table 1(b) summarises the literature on the drivers of the share price index, including the sample, demographics, study period, estimation methods, and findings.

Table 1(b): Summary of literature evidence (Determinants)

Reference	Population & sample	Period	Estimation method	Findings
Narayan et al. (2013)	NYSE	1998-2008	Time series regression	RGR (+, sig)
Narayan et al. (2014)	Indian Banking Sector	1998-2008	Panel Regression	RIR (+, sig) EXC(+, sig) RGR (+,sig) INF (-, sig)
Gregoriou et al. (2015)	160 Countries	2000-2011	Panel Regression	RGR (+, Sig)
Arora & Bhimani (2016)	Manufacturing Sector of Singapore	2006-2015	Panel Regression	INF (-, weak sig) RGR (+, weak sig)
Antonakakis et al. (2017)	USA	1791-2015	DCC-GARCH	INF (-, sig)
Bahmani-Oskooee & Saha (2018)	24 Countries	Monthly	Non-linear ARDL	EXC (sig)
Demir (2019)	BIST-100	2003-2017	ARDL	RIR (-,sig) EXC(+,sig) RGR (+,sig)
Sheikh et al. (2020)	KSE-100 Index	2004-2018	Non-linear ARDL	RIR (+, sig) EXC (-, sig)
Sumarsan et al. (2021)	Jakarta Stock Exchange Index	2019-2020	FFT Curve Fitting for Prediction	RIR (+, sig) EXC (-, sig)
Hadi et al. (2022)	USA	1999-2016	VAR and Granger Causality	EXC (+, sig) GR (+,sig)

Source: Own work.

Research design and methodology

The study examines the long- and short-term effects of uncertainty on the stock price indices of China, India, Russia, and Brazil. The study's general research design is secondary data derived from quantitative data. The sources of uncertainty include economic policy, geopolitical, pandemic, and Twitter-based uncertainties. The analysis includes monthly data from January 2013 through December 2021. The study looked at four different sets of data for each country: one for China, one for India, one for Russia, and one for Brazil. The study used data from multiple sources, including: www.investing.com, www.policyuncertainty.com, www.matteoacoviello.com, and www.worlduncertaintyindex.com. The study also used WDI data on real growth, the exchange rate, the interest rate, and the WDI data on real growth, the exchange rate, the interest rate, and the inflation rate. The share price index is the study's predicted variable. The independent variables, on the other hand, are different sources of uncertainty. Table 2 gives a complete description of the variables, how they are used, and the research that they are based on.

Table 2: Operationalization of variables

Variable Title and Symbol	Measurement	Reference
Share Price Index (SPI)	Monthly Share Price Index	(Basu, 2022; Oyewole et al., 2022; Sánchez-Gabarre, 2020; D. Yuan et al., 2022)
Sources of Uncertainty		
Economic Policy Uncertainty (EPU)	Economic Policy Uncertainty Index Value	(Basu, 2022; Oyewole et al., 2022; M. Yuan et al., 2022)
Geopolitical Uncertainty (GPU)	Geopolitical Uncertainty Index Value	(Apaitan et al., 2022; Mumtaz & Musso, 2021)
Climate Policy Uncertainty (CPU)	Climate Policy Uncertainty Index Value	(Chan & Malik, 2022)
Pandemic Uncertainty (PDU)	Pandemic Uncertainty Index Value	(Dash & Maitra, 2022; Szczygielski et al., 2021; Wang et al., 2021)
Twitter-based Uncertainty (TBU)	Twitter-based Uncertainty Index Value	(Adeosun et al., 2022; Baker et al., 2021; Ferracuti, 2022)
Macroeconomic determinants of share price index		
Real Growth Rate (RGR)	GDP Growth (%)	(Arora & Bhimani, 2016; Demir, 2019; Hadi et al., 2022)
Real Interest Rate (RIR)	Real Interest Rate (% of GDP)	(Sheikh et al., 2020; Sumarsan et al., 2021)
Inflation Rate (INFR)	CPI (% of GDP)	(Antonakakis et al., 2017; Arora & Bhimani, 2016)
Exchange Rate (EXR)	Official Exchange Rate (In terms of US$, an average of the period)	(Hadi et al., 2022; Sheikh et al., 2020; Sumarsan et al., 2021)

Source: Own work.

The study must measure the impact of uncertainty on share price indices in China, India, Russia, and Brazil. Due to the time series nature of the data and the research objectives, the study requires several time series procedures. These include descriptive statistics, stationarity testing, lag selection, co-integration, regression estimation through the autoregressive distributive lag (ARDL) model and its diagnostics, or Cochrane-Orcutt AR (1) regression.

The following is the economic model of this study.

$$Share\ \ price\ index = f\,(Sources\ of\ \ Uncertainty) \quad (1)$$

Where, sources of uncertainty include uncertainty through economic policy (EPU), geopolitical (GPU), climate policy (CPU), pandemic (PDU), and twitter-based (TBU).

The basic model of the study as per the economic model is given as follows as equation 2:

$$SPI_t = \beta_0 + \beta_1 Uncer + \beta_2 RGR + \beta_3 RIR + \beta_4 INFR + \beta_5 EXR + \varepsilon_t \quad (2)$$

The next process is to transform the basic model into the log-linear model to ensure uniformity for the variables' measurement. The 2nd model, therefore, is transformed by adding a natural log (LN) with all the variables into the following 3rd equation.

$$LnSPI_t = \beta_0 + \beta_1 LnUncer + \beta_2 LnRGR + \beta_3 LnRIR + \beta_4 LnINFR_t + \beta_5 LnEXR + \varepsilon_t \quad (3)$$

The basic Time series equation of the study

$$LnSPI_t = \beta_0 + \beta_1 LnUncer_t + \beta_2 LnRGR + \beta_3 LnRIR + \beta_4 LnINFR + \beta_5 LnEXR_t + \varepsilon_t \quad (4)$$

The long-run equilibrium of the ARDL model is depicted in the following 5th equation.

$$LnSPI_t = \alpha_0 + \beta_1 LnSPI_{t-i} + \beta_2 LnUncer_{t-i} + \beta_3 LnRGR_{t-i} + \beta_4 LnRIR_{t-i} + \beta_5 LnINFR_{t-i} + \beta_6 LnEXR_{t-i} + \varepsilon_t \quad (5)$$

An error correction-based short-run estimation of the ARDL model is depicted as the 6th equation as follows.

$$\Delta LnSPI_t = \alpha_0 + \sum_{i=1}^{n} \alpha_1 \Delta LnSPI_{t-i} + \sum_{i=1}^{n} \alpha_2 \Delta LnUncer_{t-i} + \sum_{i=1}^{n} \alpha_3 \Delta LnRGR_{t-i} + \sum_{i=1}^{n} \alpha_4 \Delta LnRIR_{t-i} + \sum_{i=1}^{n} \alpha_5 \Delta LnINFR_{t-i} + \sum_{i=1}^{n} \alpha_6 \Delta LnEXR_{t-i} + \omega ECT_{t-1} + \varepsilon_t \quad (6)$$

The ARDL model requires assumption and diagnostic testing. It includes the RESET (Ramsey) test for the variable omission, model misspecification testing with Hatsq, and heteroscedasticity testing with Breusch-Pagan. Additionally, it also includes normality testing with Jarque-Bera and serial correlation testing with the Breusch-Godfrey LM test. Violating the first 4 assumptions needs data manipulation, while serial correlation requires Cochrane-Orcutt AR(1) regression (Vougas, 2021). This econometric model uses AR(1) to adjust for autocorrelation.

$$LnSPI_t = \beta_1 LnUncer_t + \beta_2 LnRGR_t + \beta_3 LnRIR_t + \beta_4 LnINFR_t + \beta_5 LnEXR_t + \mu_t \quad (7)$$

Where: $\mu_t = \rho\mu_{t-1} + e_t$

Empirical Results and analysis

The study examines the short- and long-term effects of different sources of uncertainty on the share price indexes of the top four rising economies. The study requires time series analysis, including descriptive statistics, stationarity testing, lag selection, ARDL bound testing, and ARDL estimations. The study estimates ARDL diagnostic tests and Cochrane-Orcutt, Praise & Winston AR(1) regression model. Table 3 compares the mean and standard deviations for the major emerging nations. Below the table is a concise description of its contents.

Table 3: Comparative Summary Statistics

		China		India		Russia		Brazil	
	N	μ	σ	μ	σ	μ	σ	μ	σ
SPI	60	3149.18	295.16	39401.84	8234.03	2729.22	619.42	93061.58	18021.57
EPU	60	453.58	153.70	72.44	28.19	304.28	157.65	222.75	108.45
GPU	60	91.59	18.98	91.59	18.98	91.59	18.98	91.59	18.98
CPU	60	192.69	101.47	192.69	101.47	192.69	101.47	192.69	101.47
PDU	60	3.75	5.61	3.75	5.61	3.75	5.61	3.75	5.61
TBU	60	138.37	93.37	138.37	93.37	138.37	93.37	138.37	93.37
RGR	60	6.00	2.02	3.87	5.53	1.79	2.49	1.01	2.77
RIR	60	1.56	1.59	4.03	2.70	1.43	5.50	29.30	8.66
INFR	60	1.99	0.67	4.55	1.21	4.22	1.35	4.47	1.94
EXC	60	6.73	0.18	70.39	3.43	66.30	5.82	4.27	0.87

Where: SPI = Share price index, EPU = Economic Policy uncertainty, GPU = Geo-political uncertainty, CPU = Climate policy uncertainty, PDU = Pandemic Uncertainty, TBU = Twitter based Uncertainty, RGR = Real growth rate, RIR = Real interest rate, INFR = Inflation rate, and EXC = Official Exchange rate. Additionally, N = Number of observations, μ = Mean value, σ = Standard Deviation

Source: Own work.

Table 3 compares 4 developing leading nations' mean and standard deviation. During the study period, China's share price index averaged 3,149.18, India's 39,401.84, Russia's 2,729.22, and Brazil's 93,061.58. Brazil has contributed the most to the Share price index over the study period. In addition, the average EPU in China is 453.58, in India it is 72.44, in Russia it is 304.28, and in Brazil, it is 222.75.

China has a greater average EPU than the other 3 countries, whereas India has a lower average. GPU, CPU, PDU, and TBU averaged 91.59, 192.69, 3.75, and 138.37 respectively over the study period.

The analysis discovered discrepancies in SPI's macroeconomic drivers' averages. The table lists China, India, Russia, and Brazil's average real growth rates as 6%, 3.87, 1.79, and 1.01%. During the study period, China had a greater average real growth rate than other countries. The table also included China, India, Russia, and Brazil's average real interest rates as 1.56%, 4.03%, 1.43%, and 29.30%. Brazil's economy boasts a higher real interest rate' than Russia's. During the study period, China's inflation rate averaged 2%, India's 4.55, Russia's 4.22, and Brazil's 4.47. Inflation was highest in India and lowest in China during the study period. The table shows the average official exchange rate for China, India, Russia, and Brazil. Thus, India's exchange rate was greater than Brazil's.

The study estimated stationarity using Dickey and Fuller (1979), and Phillips and Perron (1988). Both tests assume a unit root, but the alternative confirms stationarity. Table 4 shows the level and initial differential stationarity of the top 4 emerging economies. The table below explains stationarity testing.

Table 4: Comparative Unit Root Testing

	At Level							
	China		India		Russia		Brazil	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
SPI	-1.77	-1.66	-1.82	-2.02	-2.65	-3.84**	-2.98	-2.92
EPU	-1.79	-2.75	-3.46**	-4.94***	-3.74**	-5.89***	-3.40*	-4.21***
GPU	-3.17*	-5.75***	-3.17*	-5.75***	-3.17*	-5.75***	-3.17*	-5.75***
CPU	-2.55	-4.83***	-2.55	-4.83***	-2.55	-4.83***	-2.55	-4.83***
PDU	-2.93	-2.84	-2.93	-2.84	-2.93	-2.84	-2.93	-2.84
TBU	-1.44	-2.81	-1.44	-3.39*	-1.44	-3.39*	-1.44	-3.39*
RGR	-1.58	-1.65	-1.53	-1.54	-1.95	-2.01	-1.50	-1.54
RIR	-1.11	-1.11	-1.63	-1.66	-2.17	-2.15	-2.82	-2.90
INF	-1.24	-1.25	-1.96	-1.99	-2.11	-2.11	-1.66	-1.69
EXR	-1.41	-1.44	-2.01	-2.12	-2.75	-2.84	-2.67	-2.75
First Difference								
SPI	-5.40***	-7.23***	-5.64***	-8.22***	-4.22***	-7.49***	-5.41***	-6.39***
EPU	-7.03***	-11.38***	-7.44***	-12.19***	-6.84***	-13.57***	-6.87***	-10.30***
GPU	-6.21***	-13.36***	-6.21***	-13.36***	-6.21***	-13.36***	-6.21***	-13.36***
CPU	-4.13***	-12.34***	-4.13***	-12.34***	-4.13***	-12.34***	-4.13***	-12.34***
PDU	-6.30***	-7.36***	-6.30***	-7.36***	-6.30***	-7.36***	-6.30***	-7.36***
TBU	-5.59***	-13.18***	-5.59***	-13.18***	-5.59***	-13.18***	-5.59***	-13.18***
RGR	-5.22***	-7.48***	-5.28***	-7.54***	-5.38***	-7.64***	-5.33***	-7.59***
RIR	-5.60***	-7.80***	-5.55***	-7.78***	-5.21***	-7.47***	-5.65***	-7.87***
INF	-5.48***	-7.72***	-5.23***	-7.49***	-5.30***	-7.56***	-5.38***	-7.64***
EXR	-5.28***	-7.54***	-5.65***	-7.86***	-5.62***	-7.84***	-5.58***	-7.81***

Source: Own work.

EPU, CPU, and GPU are stationarity using ADF and PP unit root testing. The remaining variables, including the share price index, are not stationary. All variables are stationary at the first difference using ADF and PP. Mixed stationarity confirms ARDL model estimation. Initial ARDL application requires 1^{st} difference stationarity of the dependent variable and mixed stationarity of other variables (Shrestha & Bhatta, 2018).

Before estimating ARDL, Emerson (2007) advised estimating optimal lag with AIC, HQIC, and SBIC. The optimal lag selection determines the appropriate number of lags for ARDL (Wooldridge, 2018). Table 5 shows the optimal lags for each country, including Mode, which confirms the maximum lags for individual variables.

Table 5: Comparative Optimal Lag Selection

	China				India			
	AIC	HQIC	SBIC	Mode	AIC	HQIC	SBIC	Mode
SPI	1	1	1	1	1	1	1	1
EPU	1	1	1	1	1	1	1	1
GPU	2	2	1	2	2	2	1	2
CPU	3	3	2	3	3	3	2	3
PDU	1	1	1	1	1	1	1	1
TBU	2	2	1	2	2	2	1	2

	China				India			
	AIC	HQIC	SBIC	Mode	AIC	HQIC	SBIC	Mode
RGR	1	1	1	1	1	1	1	1
RIR	1	1	1	1	1	1	1	1
INF	1	1	1	1	1	1	1	1
EXR	1	1	1	1	1	1	1	1
	Russia				Brazil			
	AIC	HQIC	SBIC	Mode	AIC	HQIC	SBIC	Mode
SPI	3	3	2	3	2	1	1	1
EPU	2	2	1	2	1	1	1	1
GPU	2	2	1	2	2	2	1	2
CPU	3	3	2	3	3	3	1	3
PDU	1	1	1	1	1	1	1	1
TBU	2	2	1	2	2	2	2	2
RGR	1	1	1	1	1	1	1	1
RIR	1	1	1	1	1	1	1	1
INF	1	1	1	1	1	1	1	1
EXR	1	1	1	1	1	1	1	1

Source: Own work.

Table 5 shows that for China, the ideal lag (using mode) is 1123121111. For India's ARDL model, the ideal lag (using mode) is 1123121111. ARDL model estimation for Russia requires an optimal lag of 3223121111. For Brazil, the ideal ARDL lag is 1123121111.

Engle and Granger (1987) advised investigating co-integration for the study's long-run connection. Pesaran et al. (2001) recommended a bound test for ARDL co-integration testing. Table 6 shows bound testing estimates for China, India, Russia, and Brazil. The interpretations of these estimates are summarised in the table presented below.

Table 6: Comparative Co-integration Estimates (ARDL Bound Test)

	Critical Levels				Criteria	Decision
China						
F-value = 3.66	10.00%	5.00%	2.50%	1.00%	F -value > Upper Bound Critical F = H0 Rejected	Co-integration Exists
Lower Bounds	2.12	2.45	2.75	3.15		
Upper Bounds	3.23	3.61	3.99	4.43		
India						
F-value = 3.72	10.00%	5.00%	2.50%	1.00%	F-value > Upper Bound Critical F = H0 Rejected	Co-integration Exists
Lower Bounds	2.12	2.45	2.75	3.15		
Upper Bounds	3.23	3.61	3.99	4.43		
Russia						
F-value = 1.66	10.00%	5.00%	2.50%	1.00%	F-value < Upper Bound Critical F = Failed to reject H0	Co-integration does not exist
Lower Bounds	2.12	2.45	2.75	3.15		
Upper Bounds	3.23	3.61	3.99	4.43		

	Critical Levels				Criteria	Decision
Brazil						
F-value = 2.308	10.00%	5.00%	2.50%	1.00%	F-value < Upper Bound Critical F = Failed to Reject H0	Co-integration does not exist
Lower Bounds	2.12	2.45	2.75	3.15		
Upper Bounds	3.23	3.61	3.99	4.43		

Source: Own work.

Table 6 shows long-run ARDL bound test estimates. Null hypothesis: No long-term association. China and India only have long-term strong ties because H_0 is refused co-integration estimates of Russia and Brazil fail to reject H_0, hence they do not confirm long-run relationships between study variables.

Nkoro and Uko (2016) stated that an ARDL model is an ordinary least squares (OLS) model that uses a mixed version of stationarity for predictor variables including stationarity at the first difference for the response variable to estimate the long and the short run linkages. Furthermore, McNown et al., (2018) suggested using an 'error correction model' (ECM) for estimating the ARDL. To account for the erroneous relationships brought on by the non-stationarity of time series, this model blends the equilibrium of long-run with short-run trends. Table 7 reports the comparative error-corrected ARDL model estimates for sampled nations. The estimated results are summarized below the table.

Table 7: Comparative ARDL Estimations

	China	India	Russia	Brazil
	ARDL (4, 1, 3, 3, 3, 0)	ARDL (3, 4, 3, 0, 3, 4)	ARDL (3, 2, 1, 0, 3, 2)	ARDL (3, 0, 0, 0, 3, 3)
Adjustment				
L.SPI	-0.22700**	-0.16600**	0.00208	0.22200
	(0.08680)	(0.06300)	(0.04230)	(0.55500)
Long Run				
EPU	-0.19100*	-5.34700**	-18.84000	-0.30800**
	(0.10600)	(1.90000)	(386.20000)	(0.12300)
GPU	-0.22600	-12.55000	-46.34000	-0.23000
	(0.24700)	(43.45000)	(940.30000)	(0.26300)
CPU	-0.29500**	-0.86300*	-10.58000	-0.11100
	(0.11700)	(0.42400)	(214.50000)	(0.10600)
PDU	-0.00930***	-0.00448**	-1.31900	-0.00820
	(0.00230)	(0.00220)	(27.65000)	(0.02200)
TBU	-0.00193**	-0.49200***	-0.78100	-0.08220*
	(0.00090)	(0.11500)	(18.31000)	(0.04970)
Short Run				
SPI				
LD	0.13400	-0.19700	-0.28500	0.05220
	(0.14000)	(0.15600)	(0.17400)	(0.12500)
L2D	-0.12200	-0.28100*	-0.48700***	-0.23900*
	(0.13700)	(0.19700)	(0.16000)	(0.12700)
L3D	-0.35100**	-	-	-
	(0.14700)	-	-	-
EPU				
D	-0.05350	-0.13500**	-0.05000**	-
	(0.03400)	(0.06490)	(0.02460)	-
LD	-	-0.12700**	-0.02140	-
		(0.06110)	(0.01770)	-
L2D	-	-0.13600***	-	-
		(0.04770)	-	-

	China	India	Russia	Brazil
	ARDL (4, 1, 3, 3, 3, 0)	ARDL (3, 4, 3, 0, 3, 4)	ARDL (3, 2, 1, 0, 3, 2)	ARDL (3, 0, 0, 0, 3, 3)
		EPU		
L3D	-	-0.07150**	-	-
		(0.03140)	-	-
		GPU		
D	-0.11000**	-0.20100**	-0.09420*	-
	(0.05380)	(0.09750)	(0.05030)	-
LD	-0.11600**	-0.04340	-	-
	(0.04850)	(0.07200)	-	-
L2D	-0.07050**	-0.09120*	-	-
	(0.03420)	(0.05210)	-	-
		CPU		
D	-0.04770***	-	-	-
	(0.01740)	-	-	-
LD	-0.03350**	-	-	-
	(0.01650)	-	-	-
L2D	-0.04130***	-	-	-
	(0.01390)	-	-	-
		PDU		
D	-0.01370**	-0.01960**	-0.00849	-0.00424
	(0.00580)	(0.00754)	(0.00678)	(0.00854)
LD	-0.00575	-0.02080**	-0.01440**	-0.01040
	(0.00595)	(0.00765)	(0.00622)	(0.00717)
L2D	-0.01110*	-0.02360***	-0.01240*	-0.02490***
	(0.00604)	(0.00799)	(0.00637)	(0.00782)
		TBU		
D	-	-0.04350	-0.02780	-0.06420**
	-	(0.02720)	(0.02390)	(0.02840)
LD	-	-0.03730	-0.06340**	-0.06360*
	-	(0.03100)	(0.02450)	(0.03310)
L2D	-	-0.01360	-	-0.04960*
	-	(0.02900)	-	(0.02730)
L3D	-	0.03570	-	-
	-	(0.02210)	-	-
Constant	1.98900**	-1.43200***	-0.52000	2.92400***
	(0.91000)	(1.02700)	(0.49700)	(0.74100)
Sample	2017m5 - 2021m12	2017m5 - 2021m12	2017m5 - 2021m12	2017m5 - 2021m12
Log Likelihood	119.60856	110.62748	105.41537	89.48010
Observations	56.00000	56.00000	56.00000	56.00000
R^2	0.50620	0.65150	0.39570	0.25260

Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Source: Own work.

Long run estimates

In China, India, and Brazil, ARDL estimates show a strong negative long-run link between EPU and SPI. Nonetheless, the same adverse link is not significant in Russia during the research period. A one-unit increase in economic policy uncertainty would significantly lower the Shanghai SE composite index in China, the BSE Sensex index in India, and the BOVESPA index in Brazil. The negative impact of EPU on SPI in China, India, and Brazil supports the first long-term hypothesis. Much research confirms EPU's negative impact on SPI (Baker et al., 2021; Guenichi & Nejib, 2022; Sánchez-Gabarre, 2020). According to the literature, economic policy uncertainty is low in China but high in India and Brazil, creating ambiguity for local and foreign investors and causing a decline in stock exchange points. Estimates showed a negative but minor impact of GPU on SPI in China, India, and Brazil. The negative and insignificant influence of GPU on SPI accepts the 2nd hypothesis for the long-run relation for target populations during the research period. Additionally, the result is consistent with certain literature evidence (Sánchez-Gabarre, 2020). In China, India, Russia, and Brazil, geopolitical uncertainty is not a key source of share price decline.

ARDL long-run estimations show a negative impact of CPU on SPI for China and India. In Russia and Brazil, this is not significant over the research period. A one-point rise in climate policy uncertainty would down the SSE Composite Index by 0.295%. A one-point increase in climate policy uncertainty will lower India's BSE Sensex by 0.863%. China and India's negative CPU impact on SPI support the 3rd hypothesis. However, the same hypothesis cannot be accepted for Russia and Brazil. Much research confirms CPU's negative impact on China and India's SPI (Chan & Malik, 2022). The negative and significant impact of CPU for SPI implies that climate policy uncertainties affect China's Shanghai SE composite index. However, the weak negative contribution of CPU for SPI suggests that climate policy uncertainty in India has a small impact on the BSE Sensex index. Climate policy uncertainty doesn't affect Russia's MOEX or Brazil's BOVESPA. The table also shows a highly significant negative impact of PDU on the SSE composite index and the BSE Sensex index over the study period. Long-term PDU effects on SPI in Russia and Brazil were not found. One point of pandemic uncertainty would reduce SSE composite index by 0.0093 points. An increase in pandemic uncertainty would lower the BSE Sensex by 0.00448 points. The results support the fourth hypothesis for China and India but reject it for Russia and Brazil during the research period. Several studies support the negative and statistically significant findings regarding PDU and SPI (Guenichi & Nejib, 2022; Szczygielski et al., 2021). The study found that the COVID-19 pandemic had a negative impact on China and India's leading stock exchanges.

In India, TBU has a large negative influence on SPI, but in China and Brazil, it has a weak negative impact. In contrast, the same is not significant for Russia over the study period. Twitter-based uncertainty produces a 0.00193-point drop in the SSE composite index. In addition, a one-unit increase in the same would precipitate a 0.492-point drop in the BSE Sensex index. A unit rise in TBU causes a 0.0822-point drop in BOVESPA. The negative and significant effect of TBU for SPI is supported by China, India, and Brazil, but not Russia. The negative and substantial finding is consistent with several studies (Baker et al., 2021). The study found that news-based uncertainty (Twitter) decreases the SPI in India, China, and Brazil. In the case of Russia, the same does not play a significant role.

Short run estimates

Table 7 shows ARDL short-term estimates for error corrective adjustment. China and India have statistically significant negative error correction coefficients. In contrast, the same is neither negative nor significant for Russia and Brazil. The research shows Co-integration only for China and India. The short-run estimations of the error correction version of ARDL show that EPU has no short-term impact on China's and Brazil's SPI. The same is diminishing India's SPI at all 3 lag differences and Russia's at the first. These findings accept 1st hypothesis for India and Russia. China and Brazil's share price indexes reject the short-term impact hypothesis of EPU. Geopolitical uncertainty has a short-term negative influence on China, India, and Russia's share price indexes. Geopolitical uncertainty has no short-term influence on Brazil's share index, estimates indicate. The strong and negative short-term effect of GPU on the share price index in China, India, and Russia supports the second hypothesis, but Brazil contradicts it. Short-run estimates of the error-correction version of ARDL show the CPU's negative impact on China's share price index. Therefore, the finding accepts the 3rd hypothesis for the share market of China only. Pandemic uncertainty has a significant negative influence on the Chinese share price index and a strong negative impact on the Indian share price index. Similar to Russia, Brazil's share price index shows a strong negative impact of PDU at 1st lag difference and a strong negative impact at 2nd lag difference. The findings accept the 4th hypothesis. Twitter-based uncertainty has a little short-term impact on China, India, or Russia. The finding rejects the 5th hypothesis. TBU has a negative and significant impact on Brazil's share price index, which accepts the 5th hypothesis for this country. There are many assumptions for ARDL estimations which include variable omission (Ramsey-RESET), Functional misspecification (Hatsq), Heteroscedasticity (Breusch-pagan), Serial correlation (Breusch-Godfrey), and Normality (Jarque-Bera). Table 8 reports the estimates of all these assumptions as diagnostics tests.

Table 8 shows no variable omission, functional misspecification, heteroscedasticity, and normal residuals for sampled nations. The table shows the serial correlation in each time series. The existence of serial correlation in any sample of time series data necessitates the use of the Cochrane-Orcutt AR(1) regression model for estimation (Thornton, 1987). Cochrane and Orcutt (1949) set the basis for employing the AR(1) method for linear regression. However, Prais and Winsten (1954) transformed the basic method into AR (1). A more efficient version for this purpose was developed by Vougas (2021) using AR(2).

Table 8: Comparative Diagnostic Tests

Diagnostic Tests		P-values			
		China	India	Russia	Brazil
Variable Omission	'RESET (Ramsey')	0.128	0.099	0.066	0.632
Functional Misspecification	'Hatsq'	0.114	0.591	0.792	0.060
Heteroscedasticity	'Breusch-Pagan / Cook-Weisberg test for heteroscedasticity'	0.067	0.492	0.191	0.940
Serial Correlation	'Breusch-Godfrey LM test'	0.000	0.001	0.000	0.001
Normality	'Jarque-Bera normality test'	0.052	0.757	1.950	0.129

Source: Own work.

Table 9 shows Cochran-Orcutt regression values from Prais and Winsten AR(1). It covers the macroeconomic indicators; "real growth rate, real interest rate, inflation rate, and 'official exchange rate" as well as sources of uncertainty. According to the estimations, the real growth rate significantly boosts the share price index in China and Brazil, confirming the 6^{th} hypothesis. Nevertheless, the real growth rate has no effect on the Indian and Russian share price indexes over the study period, rejecting the 6^{th} hypothesis. Consistent with the findings of certain research, RGR has a significant positive impact on the share price index (Demir, 2019; Hadi et al., 2022). Estimates also showed a positive impact of the real interest rate on China, Russia, and Brazil's share price index. The finding accepts the 7^{th} hypothesis. However, this does not have a major impact on the Indian share price index, rejecting the 7^{th} hypothesis. Some research confirms RIR's positive impact on stock prices (Sheikh et al., 2020; Sumarsan et al., 2021).

Table 9: Comparative Cochrane-Orcutt (Praise & Winsten - AR(1)) regression

	China	India	Russia	Brazil
EPU	-0.001430*	-0.063700**	0.012100	-0.054200**
	(0.000759)	(0.029900)	(0.023700)	(0.022300)
GPU	-0.000443	-0.067300	-0.043800	-0.019100
	(0.000983)	(0.058500)	(0.062700)	(0.047000)
CPU	0.000364	0.038500*	0.018800	0.007400
	(0.000467)	(0.021900)	(0.024000)	(0.022800)
PDU	-0.000380***	-0.007910	-0.011200	-0.000137
	(0.000140)	(0.007870)	(0.007170)	(0.009960)
TBU	-0.001710***	-0.119000***	-0.042500	-0.077400***
	(0.000539)	(0.031700)	(0.036300)	(0.024100)
RGR	0.001830**	0.126000	-0.167000	7.477000**
	(0.000890)	(0.210000)	(0.137000)	(3.088000)
RIR	0.001370***	0.036000	0.103000**	44.240000**
	(0.000297)	(0.086900)	(0.043500)	(17.820000)
INFR	-0.009460***	-0.596000**	-0.458000***	-1.485000*
	(0.001340)	(0.276000)	(0.109000)	(0.749000)
EXC	0.052200***	6.139000***	2.621000***	61.050000**
	(0.019400)	(1.842000)	(0.577000)	(24.300000)
Constant	0.426000***	-13.910000*	-3.188000	-224.400000**
	(0.036400)	(8.059000)	(2.263000)	(94.720000)
Prob > F	0.000000	0.000000	0.000000	0.000200
Observations	60.000000	60.000000	60.000000	60.000000
R-squared	0.724000	0.892000	0.726000	0.652000
DW-state (original)	1.067723	1.197374	1.037761	1.143914
DW-state (Transformed)	1.891378	2.024861	1.631390	1.609178

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: Own work.

Estimates show inflation has a negative influence on China and Russia's share prices. Brazil's inflation has a lower negative impact than India's. In all the cases, the findings accept the 8th hypothesis. The negative impact of inflation on the share price index confirms prior studies (Antonakakis et al., 2017; Arora & Bhimani, 2016). The estimate shows a positive long-term influence of the exchange rate on all four nations' share price indexes. The finding accepts the 9th hypothesis and concludes that the exchange rate boosts the target populations' share price index. The result is consistent with several historical studies (Bahmani-Oskooee & Saha, 2018; Demir, 2019; Hadi et al., 2022).

Conclusion

The study examined the long-term and short-term influence of numerous sources of uncertainty on the leading share price index of China, India, Russia, and Brazil from January 2017 to December 2021. The dependent variable was the share price index, which shows the monthly prices of China's Shanghai SE Composite Index, India's BSE Sensex, Russia's MOEX, and Brazil's BOVESPA. Economic policy uncertainty, geopolitical uncertainty, climate uncertainty, pandemic uncertainty, and Twitter-based uncertainty are independent variables. The study also assesses the impact of controlled variables on the share price index: GDP, RIR, INFR, and EXC. Monthly time series datasets were utilized for each country sampled. The comparative analysis comprises descriptive, stationarity, optimal lag, cointegration, ARDL estimates, diagnostic tests (ARDL post estimations), and Cochrane-Orcutt AR(1) model utilizing Prais & Wintsen technique. EPU, CPU, PDU, TBU as a source of uncertainty, and INFR as a macroeconomic determinant affect SSE composite index in China long-term. Real growth rate, real interest rate, and exchange rate are also important for boosting the share price index. GPU, CPU, and PDU have a negative and significant impact on the SSE composite index in China in the short term. EPU, CPU, PDU, and TBU as sources of uncertainty and INFR as macroeconomic factors affect the BSE Sensex index in India in the long run. The exchange rate is the single factor that affects the share price index. EPU, GPU, and PDU are sources of short-term uncertainty for the same share price index. In the long term, all sources of money don't affect Russia's MOEX index.

EPU, GPU, PDU, and TBU negatively impact the target population's short-term index. EPU and TBU were identified as sources of long-term uncertainty for Brazil's BOVESPA index. PDU and TBU are short-term uncertainties that negatively affect the index. The analysis suggests that EPU, CPU, PDU, and TBU are accountable for a likely long-term drop in the SSE composite index and the BSE Sensex. However, GPU, CPU, and PDU in China and EPU, GPU, and PDU in India are the sources of short-term uncertainty for both indices. In contrast, no sources of uncertainty have a long-term effect on the MOEX index in Russia. Short-term sources of index uncertainty are EPU, GPU, PDU, and TBU. EPU and TBU are the long-term sources of uncertainty declining the BOVESPA, while PDU and TBU are the short-term sources. A summarized conclusion is provided in Table 10 for a bird's eye view in this regard.

Limitations of the study

First, uncertainty only affects China, India, Russia, and Brazil's share price indexes. These growing nations have substantial economies, but the conclusions may not apply to other countries or regions. Future studies should analyze characteristics across geographies and economies to better understand how uncertainty influences share prices. Second, the study examines the long-term and short-term effects of uncertainty on share prices, but not the processes. Future study could investigate how investor opinions, market reactions, and investor behavior affect share prices.

Research suggestions

To better understand how uncertainty affects share prices in different markets and economies, one should include more emerging nations in the sample. Explore investor emotions, market reactions, and investor behavior as mediators between uncertainty and share prices to better understand how uncertainty impacts share prices. Daily or intraday data might reveal uncertainty dynamics and their immediate consequences on share prices. To comprehend share prices and uncertainties, include macroeconomic statistics, business earnings, market liquidity, and industry-specific data.

Explore the interconnections and feedback effects of uncertainty sources to better understand how they affect share prices. Future study should address these constraints by expanding sample size, researching mechanisms, using higher-frequency data, adding components, and investigating uncertainty interactions. This will help investors and policymakers comprehend emerging market share values and risks.

Table 10: A Summarized Conclusion

Hypothesis	Result Obtained					Conclusion
	Time Horizon	China	India	Russia	Brazil	
H_1: EPU strongly decreases the share price index in the long-run, and short -run.	Short-Run	(-)	(-)***	(-)**	N/A	EPU strongly decreases SPI in India and China in the short-run.
	Long-Run	(-)*	(-)**	(-)	(-)**	EPU strongly decreases SPI in China, India, and Brazil in the long-run.
H_2: Geopolitical Uncertainty negatively impacts the Share Price index in the long-run, and short-run.	Short-Run	(-)**	(-)**	(-)*	N/A	GPU strongly decreases SPI in China, India, and Russia in the short run.
	Long-Run	(-)	(-)	(-)	(-)	The negative impact of GPU on SPI is insignificant for target population in the long run.
H_3: Climate Policy Uncertainty plays a strong role in decreasing the share price index in the long-run, and short-run.	Short-Run	(-)***	N/A	N/A	N/A	CPU strongly decreases SPI in China only in short run.
	Long-Run	(-)**	(-)*	(-)	(-)	CPU strongly decreases SPI in China and India in the long run.
H_4: Pandemic Uncertainty has a substantial role in decreasing the share price index in the long-run, and short-run.	Short-Run	(-)**	(-)**	(-)**	(-)***	PDU strongly decreases SPI for the target population in the short run.
	Long-Run	(-)***	(-)**	(-)	(-)	PDU strongly decreases SPI in the long run in China and India only.
H_5: Twitter-based Uncertainty has a negative role in impacting the share price index in the long-run, and short-run.	Short-Run	N/A	(-)	(-)**	(-)**	TBU strongly decreases SPI in short run for Russia and Brazil only.
	Long-Run	(-)***	(-)***	(-)	(-)*	TBU strongly decrease SPI in China, India, and Brazil for long run.

Source: Own work.

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