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Predicting Stock Returns and Volatility in BRICS Countries during a Pandemic: Evidence from the Novel Wild Bootstrap Likelihood Ratio Approach

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Abstract

In this study, we examine how attention to different pandemics leads returns and volatility of BRICS stock markets, while controlling for economic policy uncertainty. The attention is measured via the newly developed daily infectious disease equity market volatility tracker (EMV-ID). To achieve the study objective, the wild bootstrap likelihood ratio test is employed in analysing time-series data covering the period November 1997 – May 2021. The estimations confirm a time-varying predictive performance of the EMV-ID on both stock returns and volatility series of BRICS, which increases significantly during the months marked by pandemics. The predictive power of the EMV-ID on stock market volatility is however relatively stronger than its predictive power on stock market returns. Our results are robust to alternative specification of volatility based on a Generalized Autoregressive Conditional Heteroskedasticity model.

1. Introduction

This study examines whether attention to infectious disease pandemics is a predictor of stock market performance in BRICS—Brazil, Russia, India, China and South Africa. We further investigate to see whether there is any significant difference in the reaction of stock returns and volatility to the different periods of pandemics witnessed over the years. We also consider whether markets can become so inefficient during crisis periods that monthly returns would become predictable. The efficient market hypothesis (EMH) asserts that asset prices are the reflections of all available information (Fama, 2021). Thus, we test whether the stock market performance among the BRICS countries also reflects the historical information about pandemics. It is important to test this hypothesis because of the unprecedented pressure observed in the major financial markets across the globe between February and March 2020, following the declaration of COVID-19 as a pandemic by the World Health Organization (WHO) (See Li *et al.,* 2019; Bai *et al.,* 2020; Baker *et al.,* 2020; Mazur, Dang & Vega, 2020). The reactions of stock markets during this period have drawn out some inferences widely supported by empirical evidence, that

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pandemics are important when analysing the movements in financial markets and stock market performance (Al-Awadhi *et al.*, 2020; Goodell, 2020, Liu *et al.*, 2020; Padhan & Prabheesh, 2021; Sansa, 2020; Zeren & Hizarci, 2020).

This position comes from the assumption that new information diffuses swiftly within equity markets and they are thus efficient in reflecting new information quickly and accurately (Malkiel, 2003). New information is immediately incorporated into stock prices as the news spreads very quickly (Malkiel, 2003). Such movements in stock market prices would result from investors' reactions to new information which depends on investors' sentiments and their levels of risk aversion (Salisu, Sikiru & Vo, 2020; Van Hoang & Syed, 2021).

According to the adaptive market hypothesis, financial markets do not function in a vacuum; they possess dynamic characteristics that vary over time as market conditions change (Lo, 2004, 2005; Ozkan, 2020). Just as economic cycles do not respond in the same way to changes in macroeconomic fundamentals over time, certain time periods will shape the trends in financial market performance (Bekiros *et al.,* 2018). For instance, time variations in asset returns and prices may arise from changing costs of transaction, difference in the level of uncertainty per time, investors' risk profiles and herding behaviour (Ozkan, 2020). For this reason, it is necessary to investigate the time-varying reactions of stock markets to historical information on pandemics to see how this type of information shapes the individual stocks over time.

Devpura, Narayan and Sharma (2018) test whether the prediction of US stock market returns are time-varying, using a wide range of predictors which have historical time series. In the same vein, this study has also been inspired by the historical time series data on the EMV-ID tracker provided by Baker *et al.* (2020). Li *et al.* (2020) test the predictive power of the EMV-ID data on the European stock market realised volatility. However, there is the need to further test whether the time variation in the prediction of stock markets is country-specific (Devpura *et al.,* 2018). This study therefore deviates from the earlier approaches of Devpura *et al.* (2018) and Li *et al.* (2020) as it now finds evidence of time-varying predictability of each of the BRICS stock market indices.

As the five largest emerging markets, the BRICS economies are significant to the global economy, and are by implication significant to the global financial markets. These countries currently jointly account for 33% of global GDP and are projected to surpass the United States and European countries combined, in terms of global GDP share by 2030 (Larionova, 2020). Therefore, economic downturns in the BRICS countries do not only have serious implications for these countries now but also for global economic conditions in the nearest future. Stock market is particularly dependent on the performance of macroeconomic variables such as economic growth. The BRICS stock markets are not expected to respond to pandemics the same way because of the different impacts of the pandemics and the different policy responses in each country. Therefore, to account for cross-country differences, this study carries out country-specific time-series analyses using the novel wild bootstrap likelihood ratio (WBLR) approach for predicting asset returns developed by Kim and Shamsuddin (2020). This approach is especially useful for studying financial assets with unknown forms of conditional heteroscedasticity and non-normality.

The study contributes to two strands of literatures. First, on the efficient predictability of stock market returns and volatility, the study finds evidence that historical variables related to disease pandemics—in this case, the EMV-ID tracker—can be sufficiently used as a predictor of stock market indices. Second, on the relationship between pandemics and BRICS stock market performance, it also provides evidence that pandemics have a heterogeneous effect on market returns and volatility across the countries at different times. The implication is that these markets are very efficient, because according to the efficient market hypothesis, stock market responds to information on pandemics. This study result further implies that according to the adaptive market hypothesis, how pandemics affect the stock market returns and volatility is not the same over time. It can be concluded that the market characteristics have varied over time, which is expected as the macroeconomic features of these countries have continuously changed over time. These have implications for market participants who are likely to re-evaluate their investment strategies and options of portfolio diversification in favour of good safe havens. It also has implications for policymakers who would need to evaluate the economic consequences of efforts to contain infectious diseases.

Against this background, the rest of this paper is sectioned in the following manner; section 2 is a review of literature, section 3 presents the data and methodological approach employed, section 4 reports the results, section 5 focuses on the robustness analysis, while the final section provides the conclusion and policy implications of the findings.

2. Literature Review

There are prototype studies which show that stock returns and volatility are predictable. They include Patelis (1997), Avramov (2002), Cremers (2002), Rapach, Wohar and Rangvid (2005), Campbell and Yogo (2006), Ang and Bekaert (2007), Aye *et al.* (2014), Balcilar *et al.* (2019), and Iyke and Ho (2020). Bekiros *et al.* (2018) emphasise the importance of analysing the nonlinear behaviour of the financial market in response to business cycles, affirming that stock market returns and volatility respond differently to shocks at different stages of business cycles. Prior to the outbreak of the COVID-19 pandemic, efficient predictability of stock market returns and volatility was often buttressed by researchers (Wen, Gong & Cai, 2016; Hong & Lee, 2017; Ma *et al.,* 2019; Wei *et al.,* 2019; Li *et al.,* 2020; Liang, Wei & Zhang, 2020; Liang *et al.,* 2020; Zhang, Ma & Liao, 2020). The global health crisis has opened up new possible predictors of the financial market, which are now being included in the model of financial markets in order to understand investor behaviour at such a time. Some of the new explanatory variables include fear index for COVID-19 (Liu, Huynh & Dai, 2021), pandemic-induced fear and uncertainty (Salisu & Adediran, 2020; Salisu & Akanni, 2020; Salisu, Sikiru & Vo, 2020), Google-based anxiety on COVID-19 and Google trend synthetic index (Papadamou *et al.,* 2020), confirmed cases of COVID-19 and deaths due to COVID-19 (Erdem, 2020; Just & Echaust, 2020; Chang, Feng & Zheng, 2021), COVID-19 reproductive number (Díaz, Henríquez & Winkelried, 2022), government responses to the pandemic (Chang *et al.,* 2021; Díaz *et al.,* 2022) and pandemic announcement (Liu, Choo & Lee, 2020). These have shown that in addition to the traditional determinants of financial markets, there can be more variables from crises related to human health which convey information that affect market sentiment.

Previously, stock market performance was linked to previous disease outbreaks. Nippani and Washer (2004) examine the effect of the SARS outbreak on the stock market performance of several countries. The results from the conventional *t*-tests and the non-parametric Mann–Whitney test employed show that the disease outbreak negatively affects the stock markets in China and Vietnam. Chen, Jang and Kim (2007) study the response of Taiwanese hotel stock returns to the outbreak of the SARS epidemic using an event-study analysis, and report steep declines in the stock returns as a result of the epidemic. Chen *et al.* (2009), through an event-study analysis with the GARCH process, examine the effect of the SARS outbreak on the Taiwanese stock market. The authors find that the disease outbreak negatively affected wholesale and retail, as well as the tourism sector of the economy. According to Ichev and Marinč (2018), during the Ebola outbreak, stock prices of some US companies with linkages to West African countries where Ebola was prevalent were also affected negatively. Wang, Yang and Chen (2013) focus on the impact of major outbreaks of infectious diseases such as Enterovirus 71, Dengue fever SARS and HINI on Taiwanese biotechnology stocks. The empirical findings lead to the conclusion that disease outbreaks trigger abnormal stock returns.

There is a fast-growing body of literature on the reactions of various stock markets to the outbreak of COVID-19. Al-Awadhi *et al.* (2020), through a panel analysis, examine the impact of contagious infections on stock market returns in China, using COVID-19 as a case study. The study outcomes show that stock returns are negatively impacted by the growing number of COVID-19 infections and deaths. As the total confirmed COVID-19 cases increase, Apergis and Apergis (2020) show how the Chinese stock market returns are significantly and negatively affected. The negative impact becomes worse with an increase in the number of total deaths. Using an event-study approach, Liu *et al.* (2020) analyse the short-term effect of the COVID-19 pandemic on 21 major stock markets across several countries. Zeren and Hizarci (2020) examine the presence of co-movements between COVID-19 spread and several stock markets using Maki cointegration, and find a pandemic-stock market nexus. Baek, Mohanty and Mina (2020) explore a Markov-switching AR model for an industry-level analysis. The results show that the US stock market volatility is significantly affected by COVID-19 (see also Bora & Basistha, 2020; Chaudhary, Bakhshi & Gupta, 2020; Endri, Aipama & Septiano, 2021). The authors conclude that the reactions of stock markets to pandemic outbreaks are both negative and rapid. There are confirmed heterogenous reactions of equity values from different sectors, such that some sectors are adversely affected, while others remain resilient to the pandemic (He *et al.,* 2020; Mazur *et al.*, 2020; Narayan, Gong & Ahmed, 2021). Although these studies vary in their choice of financial markets, countries/regions and the period covered, they all similarly conclude that stock markets experience great shocks during pandemics.

Growth in the number of reported COVID-19 cases by itself has the ability to increase stock market crash risk; this ability becomes even more pronounced when fear sentiment of the pandemic is high (Liu *et al.,* 2021). Surveys of literature by Goodell (2020), Narayan (2021) and Padhan and Prabheesh (2021) show that the COVID-19 pandemic increases stock market volatility and negatively affects stock market returns. This is due to increased herding behaviour and delay in investment decisions by market participants. However, government intervention and stimulus packages have resulted in good news for the markets (Sha & Sharma, 2020; Sharma & Sha, 2020). A panel-VAR model and a panel logit model analysis prove that the chances of recording negative returns are significantly increased during the COVID-19 pandemic due to the amplification of uncertainty (Salisu, Ebuh & Usman, 2020). A statistical analysis also provides evidence that uncertainty associated with the pandemic outbreak, along with the economic losses recorded as a result of the outbreak, greatly raise the level of volatility in the markets (Zhang, Hu & Ji, 2020). News about the state of the pandemic—that is, how COVID-19 replicates itself—significantly increase stock market volatility across the world (Díaz *et al.,* 2022). The effect of global official announcements on stock market volatility is more than the effect of domestic official reports (Albulescu, 2021). Evidence from a panel data analysis of 13 stock markets across four continents proves that anxiety created by COVID-19 elevates risk-aversion in stock markets and consequently raises volatility (Papadamou *et al.*, 2020). The level of volatility in individual stock markets is related to how much a country is affected by the pandemic (Zhang *et al.,* 2020). While pandemic announcement serves as a negative shock across the global stock market, there are differences in the response of stock markets in different countries to this shock (Liu, Choo & Lee, 2020). The stock markets in higher-income countries react briskly at the beginning of the crisis, while stock markets in low-income countries react less; however, the stock markets of the rich countries bounce back quicker than those of the poorer countries (Liu, Choo & Lee, 2020). Emerging stock market returns are more negatively affected than developed market returns by pandemic-induced fear and uncertainty (Salisu, Sikiru & Vo, 2020).

Zhang, Sha and Xu (2021) find that risks spill over from the G7 countries to the BRIC. Volatility spill over is enhanced after the risk events including the COVID-19 pandemic. Malik, Sharma and Kaur (2021) also find volatility spillover of stock indices among the BRIC during the COVID-19 pandemic. Shi (2021) studies the spillovers of stock markets among the BRICS before and during the COVID-19 pandemic. While comparing the impact of COVID-19 on stock markets with the impact of the 2008 global financial crisis, Kumar *et al.* (2021) find evidence of negative impacts of COVID-19 on the BRICS stock markets. In terms of volatility, while the stock markets of India and Russia are more volatile during the global financial crisis, the stock markets of China, Brazil and South Africa are more volatile during the COVID-19 pandemic. Kharbanda and Jain (2021) show how COVID-19 confirmed cases and deaths adversely affect stock market returns and volatility index. Even though the BRICS stock markets are acclimatised to infectious disease, the predictability of their stock returns and volatility during the pandemic is yet to be explored.

Bal and Mohanty (2021) test the predictability of stock market returns by the growth rate of COVID-19 daily cases, using both linear and non-linear Granger causality tests. The linear and non-linear bidirectional causal relationships between these two variables show that each contains useful information that can help to predict the other. Alfaro *et al.* (2020) also predict US stock returns and report that markets may rebound if the curve of the disease becomes flatter. Salisu and Vo (2020) also predict stock returns using health news from 20 countries during the

COVID-19 pandemic. Using a pandemic/epidemic-induced uncertainty index, Salisu and Sikiru (2020) predict the Asia-Pacific Islamic stock market returns and confirm its resilience. Huynh *et al.* (2021) draw on media coverage, fake news, panic, sentiment, media hype and infodemic as behavioural indicators of financial markets which make up the feverish sentiment index. This index is found to persistently predict stock market returns and volatility in the 17 largest economies. The results validate the predictability of stock returns based on information linked to COVID-19 infections and deaths.

Li *et al.* (2020) employ the standard HAR-RV model estimated with OLS to investigate the predictive power of the Infectious Disease EMV tracker on three European stock markets— France, UK and Germany. It is found that France and UK stock markets volatilities are predicted by the EMV-ID during the global pandemic. This finding is however limited to its scope which is Europe; there is a need to test the validity of the predictive power of the EMV-ID beyond this market region. Bai *et al.* (2020), while controlling for the potential impact of global economic policy uncertainty (GEPU), use the EMV-ID to examine stock market volatility in Japan, US, UK and China between January 2005 and April 2020. The authors find that the EMV-ID has a significant positive impact on the volatility of stock markets in the selected countries. The use of the EMV-ID does not explore the long-term effects of pandemic outbreaks on stock markets returns and volatility. Salisu and Adediran (2020) also prove that the EMV-ID is efficient in predicting energy market volatility. The current study presents a different approach from these lines of research as it explores the long-term predictive power of attention to pandemics on the BRICS stock markets returns and volatility

3. Methodology and Data

3.1 Methodology

The WBLR test of Kim and Shamsuddin (2020) is employed in examining the long-term ability of attention to pandemics to predict stock market returns and volatility in the BRICS countries. The WBLR test is based on the LR test in a restricted vector autoregression (VAR) form of predictive regression, and it is robust to non-normality, persistency, small sample bias, endogeneity and conditional heteroscedasticity, all typical features of the financial time series (for details, see Kim & Shamsuddin, 2020; Olasehinde-Williams, Olanipekun & Özkan, 2021). The predictive regression model with a persistent predictor and control variable employed in predicting stock returns and volatility during periods of pandemics is stated as follows:

$$D_t = \alpha_0 + \beta_1 P_{t-1} + \beta_2 C_{t-1} + \varepsilon_t \quad (1)$$

Where D_t denotes stock market returns or volatility, P the EMV-ID (the measure of the magnitude of pandemic outbreaks), and C the GEPU.

Existing literature establishes the importance of economic policy uncertainty as a key factor driving stock market returns and volatility (Liu & Zhang, 2015; Christou *et al.,* 2017; Demir & Ersan, 2018; Fang *et al.,* 2019; Li *et al.,* 2019; Bai *et al.,* 2020). Moreover, periods of outbreaks of infectious diseases are generally characterised by heightened uncertainty; for example, in terms of contagiousness and lethality, the speed of development and distribution of vaccines, the possibility of more waves of the pandemic, the socio-economic effect of the disease outbreak, and policy responses/interventions (see Altig *et al.,* 2020). This study therefore adopts GEPU as a control variable.

To take endogeneity into account, the regressors (predictors) are expressed in the following manner:

$$P_t = \alpha_1 + \theta_1 P_{t-1} + \gamma_{1t} \tag{2}$$

$$C_t = \alpha_2 + \theta_2 C_{t-1} + \gamma_{2t} \tag{3}$$

In eqs. (2) and (3), it is assumed that P and C are weakly stationary, θ measures the persistence of the regressors and the null of unpredictability is given as $H_0\colon \beta_i = 0$.

Eqs. (1) to (3) are treated as a restricted VAR. The estimated generalised least squares (EGLS) method is used to estimate the restricted VAR model since the EGLS estimator has certain advantages over the least-squares (LS) estimator. First, the LS estimator does not take into account endogeneity that often arises from contemporaneous correlations between the error terms in the predictive model, while the EGLS estimator does. Second, the EGLS estimator is unbiased in the context of a highly persistent predictor. Third, due to smaller asymptotic variance, the EGLS estimator shows greater efficiency than the LS estimator particularly when linear parameter restrictions are imposed on a VAR model. The null hypothesis, $H_0\colon \beta_i = 0$, implying that the independent variables do not have the ability to predict the dependent variable, is tested with the LR test specified as follows:

$$LR = T[log(det(\Sigma(H_0))) - log(det(\Sigma(H_1)))] \tag{4}$$

Here, T refers to the sample size, $det()$ stands for the matrix determinant, while $\Sigma(H_i)$ represents the EGLS residual covariance matrix for $H_i (i = 0\ or\ 1)$. To guard against undesirable small sample properties which the conventional LR test is subject to, as well as (conditional) heteroscedasticity, the wild bootstrap (Mammen, 1993) LR test which is robust to these problems is applied. For a sample $\{(D_t,\ P_t, C_t)\}_{t=1}^{T}$, the WBLR test is performed in 3 stages as follows:

Stage 1: In this stage, parameters are estimated through EGLS under $H_0\colon \beta_1 = 0$ in eqs. (1) to (3). The restricted parameter estimators are given as: $\hat{\alpha}_0, \hat{\alpha}_1, \hat{\alpha}_2, 0, \hat{\beta}_2, \hat{\theta}_1, \hat{\theta}_2$, while $\hat{\varepsilon}_t, \hat{\gamma}_{1t}, \hat{\gamma}_{2t}$ represent the residuals under H_0.[1]

Stage 2: Artificial data generation through residual resampling under H_0 is carried out as follows:

$$D_t^* = \hat{\alpha}_0 + \hat{\beta}_2 C_{t-1}^* + \hat{\varepsilon}_t^* \tag{5}$$

$$P_t^* = \hat{\alpha}_1 + \hat{\theta}_1 P_{t-1}^* + \hat{\gamma}_{1t}^* \tag{6}$$

[1] Note that $\hat{\beta}_1 = 0$ under H_0.

$$C_t^* = \hat{\alpha}_2 + \hat{\theta}_2 P_{t-1}^* + \hat{\gamma}_{2t}^* \tag{7}$$

Where $(\hat{\varepsilon}_t^*, \hat{\gamma}_{1t}^*, \hat{\gamma}_{2t}^*)$ represents a random resample obtained from $\left\{(\hat{\varepsilon}_t, \hat{\gamma}_{1t,} \hat{\gamma}_{2t}\ )\right\}_{t=1}^{T}$. Thus, in this stage, $\left\{(D_t^*, P_{t,}^*\ C_t^*)\right\}_{t=1}^{T}$ is generated recursively from the resampled residuals in a process that takes D_1, P_1, C_1 as the starting values. The vector of all residuals is resampled in order to preserve cross-sectional dependence.

Stage 3: As a final step, the WBLR test statistic is calculated in this stage using the formula:

$$LR^* = T[log(det(\Sigma^*(H_0))) - log(det(\Sigma^*(H_1)))] \tag{8}$$

Here, $\Sigma^*(H_i)$ stands for the EGLS residual covariance matrix obtained from $\left\{(D_t^*, P_{t,}^* C_t^*)\right\}_{t=1}^{T}$ under $H_i (i = 0\ or\ 1)$. Both the restricted and unrestricted models are estimated using data from step 2 (i.e. residual based bootstrap data under the null hypothesis).

The second and third stages are repeated G times to generate the bootstrap distribution $\{LR^*(i)\}_{i=1}^{G}$. Bootstrap p-values are then generated as the part of $\{LR^*(i)\}_{i=1}^{G}$ higher than the LR value calculated in eq. (4). The H_0 is rejected at a particular significance level (α) if p-value obtained is lower than α.

3.2 Data

3.2.1 Response Variables and Summary Statistics

Following extant literature, monthly returns and realized volatility (RV) data of the stock markets indices of Brazil, Russia, India, China and South Africa (BVSP, MOEX, NSEI, SSEC and JTOPI respectively) are used as dependent variables (see Giot, Laurent & Petitjean, 2010; Andersen, Bollerslev & Meddahi, 2011; Dutta, 2017; Wang *et al.,* 2018; Dai *et al.,* 2020). To obtain the monthly returns series, the first differences of the monthly natural logarithmic values of the various indices are computed as percentages, whereas, monthly RV series are calculated as the monthly summation of daily squared returns for each index. Monthly and daily values of the BRICS stock market indices are available at www.investing.com. The sample period covers November 1997-May 2021 (283 observations).[2]

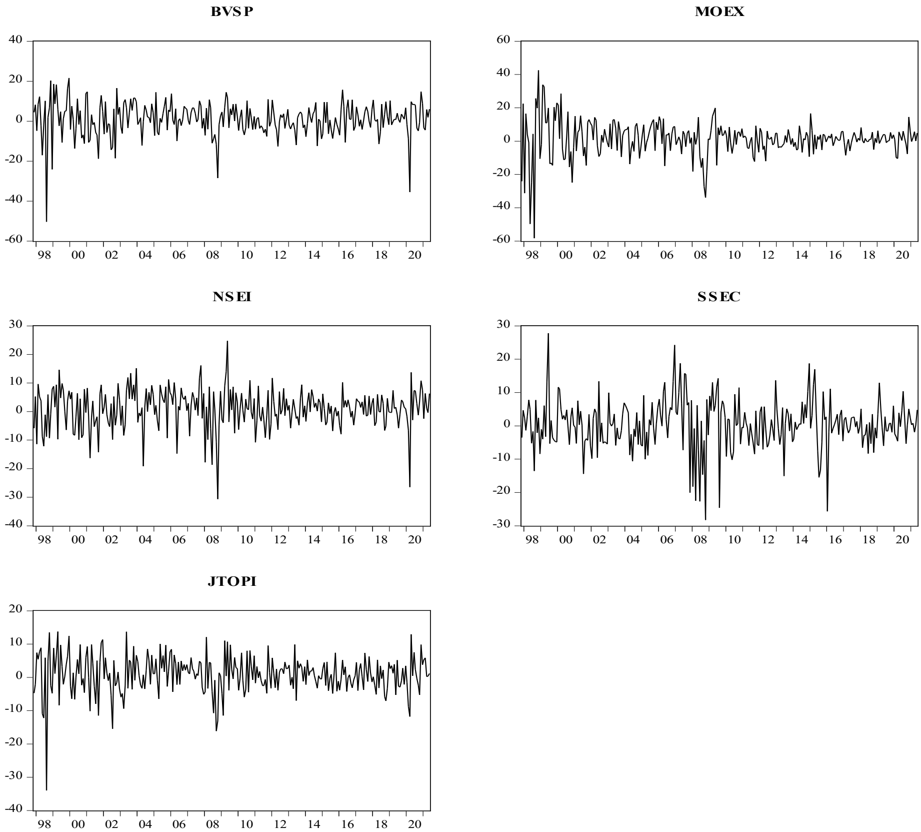
Fig. 1 shows time series plots of monthly returns and RV series, and Table 1 reports the descriptive statistics for both returns and volatility series. From the table, it is evident that all the BRICS stock market indices have positive average returns. Judging from the mean values of the return series, the MOEX index of Russia has the biggest mean returns (1.33%), while the SSEC index of China has the smallest mean returns (0.39%). In terms of mean values of volatility series, average volatility for the MOEX index of Russia is the largest among the BRICS stock market indices, while the JTOPI index of South Africa is the smallest among the BRICS stock market indices. As observed in Table 1, all returns (volatility) series are not normally distributed with negative (positive) skewness and excess kurtosis. Furthermore, the

[2] Note that the start date is dictated by MOEX index, while both end date and frequency are dictated by GEPU index.

non-normality of the returns and volatility series is confirmed by the rejection of the null of normality under the Jarque-Bera test. The augmented Dickey-Fuller (1979) unit root test outcomes show that all returns and volatility series are stationary during the sample period. Results from the ARCH-LM test of Engle (1982) show evidence of statistically significant conditional heteroscedasticity for all the time-series except volatility series of BVSP, MOEX and SSEC.

Figure 1 Graphical Presentation of Returns and RV Series

Panel A: Graphical Presentation of Returns Series



Panel B: Graphical Presentation of Realized Volatility Series

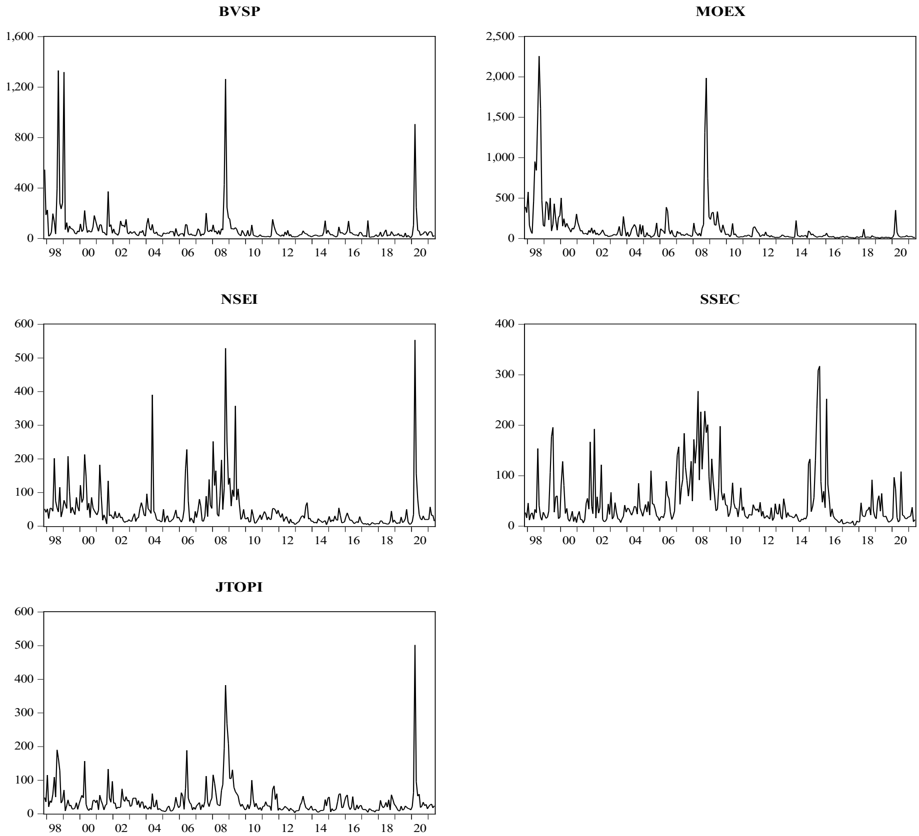


Table 1 Summary Statistics

Series	*Indices*	*Mean*	*Min.*	*Max.*	*Skew.*	*Kurt.*	*Jarque-Bera*	*ADF*	*ARCH-LM*
Return	*BVSP*	0.93	-50.34	21.54	-1.27	8.85	479.22***	-15.99***	23.84***
	MOEX	1.33	-58.25	42.55	-0.87	9.04	465.92***	-14.88***	148.66***
	NSEI	0.94	-30.66	24.73	-0.72	5.39	91.78***	-16.44***	22.79**
	SSEC	0.39	-28.27	27.80	-0.32	5.25	64.58***	-15.03***	42.62***
	JTOPI	0.86	-33.97	13.76	-0.93	7.61	291.42***	-17.93***	52.19***
Volatility	*BVSP*	75.32	6.09	1330.85	6.43	49.32	27256.67***	-12.10***	34.01***
	MOEX	119.66	4.53	2257.60	5.38	36.77	14814.08***	-5.73***	128.86***
	NSEI	46.13	2.44	552.81	4.43	28.22	8425.86***	-11.32***	8.62
	SSEC	47.79	1.58	316.96	2.39	9.15	716.77***	-3.55***	90.79***
	JTOPI	37.86	2.99	501.69	5.14	39.22	16710.83***	-9.53***	8.12

Notes: (1) *** and ** denote statistical significance at 1% and 5% respectively. (2) Min., Max., Skew., Kurt., ADF and ARCH-LM indicate minimum, maximum, skewness, kurtosis, the Augmented Dickey-Fuller (1979) test statistics for the null hypothesis of a unit root and the empirical statistics of the Lagrange Multiplier test for conditional heteroscedasticity of Engle (1982), respectively.

3.2.2 Predictor Variable, Control Variable, Persistence of Independent Variables and Contemporaneous Correlation between Error Terms

Two independent variables are used, namely: EMV-ID and GEPU. The EMV-ID was developed by Baker *et al.* (2020) as a newspaper-based index. The GEPU index, created by Davis (2016), is a GDP-weighted mean of the country-specific EPU indices introduced by Baker, Bloom and Davis (2016). EMV-ID serves as the predictor variable, and GEPU serves as a control variable. The monthly data of these variables are obtained from www.policyuncertainty.com and plotted in Fig. 2.

Figure 2 Graphical Presentation of EMV-ID and GEPU

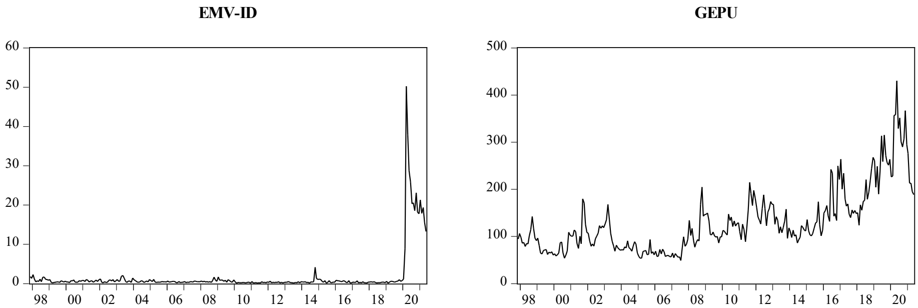


Table 2 Persistence Measure and Contemporaneous Correlation

		Independent variables	
		Predictor variable (EMV-ID)	*Control variable (GEPU)*
Persistence measure			
AR(1) coefficient		0.828^{***}	0.917^{***}
Contemporaneous correlation			
Return series	*BVSP*	-0.106^{*}	-0.216^{***}
	MOEX	-0.139^{**}	-0.158^{***}
	NSEI	-0.145^{**}	-0.207^{***}
	SSEC	-0.058	-0.140^{**}
	JTOPI	-0.191^{***}	-0.287^{***}
Volatility series	*BVSP*	0.223^{***}	0.231^{***}
	MOEX	0.140^{**}	0.083
	NSEI	0.221^{***}	0.208^{***}
	SSEC	0.113^{*}	0.078
	JTOPI	0.278^{***}	0.288^{***}

Notes: (1) ***, ** and * refer to statistical significance at 1%, 5% and 10% respectively. (2) AR(1) denotes the first-order autoregressive coefficients

According to Ang and Bekaert (2007), the persistence property of independent variables is particularly important for determining the finite sample performance of predictive test statistics. Thus, to assess the persistence of the independent variables, the magnitude of the first-order autoregressive (AR(1)) coefficient is used. The results in Table 2 demonstrate that AR(1) coefficients of independent variables are very close to one. The AR(1) coefficients clearly show that independent variables are highly persistent. To investigate endogeneity, the contemporaneous correlation coefficient between the residuals of the predictive regression model stated in eq. (1) and the AR(1) models in eqs. (2) and (3) are calculated for each country and the results presented in Table 2. The contemporaneous correlation outcomes reported in Table 2 show a negative (positive) and statistically significant correlation between the residual terms for returns (volatility) series.

The key findings in Tables 1 and 2 (such as non-normality, high degree of persistence, endogeneity and conditional heteroscedasticity) justify the use of the WBLR test based on EGLS estimation.

4. Empirical Results

A static approach is first used to investigate whether attention to pandemics is a useful predictor of stock market returns and volatility in the BRICS countries. The static approach applies the WBLR test on the entire sample period.[3] The p-values of the WBLR test for the null hypothesis that attention to pandemics does not have the ability to predict stock market returns ($H_0\colon \beta_1 = 0$) are 0.648 for Brazil, 0.190 for Russia, 0.284 for India, 0.195 for China and 0.304 for South Africa, while those for the null hypothesis that attention to pandemics does not have the ability to predict stock market volatility ($H_0\colon \beta_1 = 0$) are 0.004 for Brazil, 0.011 for Russia, 0.001 for India, 0.516 for China and 0.004 for South Africa. These results indicate that the EMV-ID is not a good predictor of stock market returns for all the BRICS countries. It is however a good predictor of stock market volatility for all the countries, except China.

The static approach however often produces unreliable estimates, especially when the data series experience structural instability. In the presence of structural instability, the analysis results can exhibit changes across different periods (Balcilar, Ozdemir & Arslanturk, 2010). Therefore, the ability of attention to pandemics to predict stock market returns and volatility of the BRICS countries is further examined with a dynamic approach. This dynamic approach adopts the WBLR test with rolling sub-sample windows. The rolling sub-sample windows method gives the opportunity to detect the dynamic (or time-varying) predictive ability of the predictor (in this paper, attention to pandemics). Besides, the rolling sub-sample windows method adequately prevents data snooping bias (Hsu & Kuan, 2005) and is robust to possible structural instabilities in the time series (Lazăr, Todea & Filip, 2012). The length of the sub-sample window is determined as 5 years (60 monthly observations), which is adequate for capturing the impacts of variations in market conditions (Charles, Darné & Kim, 2017).[4] This sub-sample window length is also sufficient to ensure desirable size and power properties of the test used (Charles *et al.,* 2011). November 1997 to October 2002 serves as the first sub-sample period. After the WBLR test is applied on the first sub-sample period, the window moves forward by

[3] The R package "VAR.etp" developed by Kim (2014) is used for the WBLR test.
[4] Kim, Shamsuddin and Lim (2011), Charles et al. (2017), Khuntia and Pattanayak (2018), and Kim and Shamsuddin (2020) empirically show that the test results are not sensitive to different choices of window length, therefore, different window lengths are not used in the paper.

one month and the test is reapplied. This process is continued till the end of the sample period, and the WBLR test p-values for each sub-sample (a total of 224 sub-samples) are obtained as a measure of dynamic predictive ability of attention to pandemics for stock market returns and volatility. This process enables episodes of high degree of predictability (statistically significant) to be recognised.

Fig. 3 plots the p-values of the WBLR test applied on returns series for $H_0\colon \beta_1 = 0$, whereas, Fig. 4 plots the p-values of the WBLR test applied on volatility series for $H_0\colon \beta_1 = 0$.[5] The p-value below the horizontal line indicates the rejection of the null of unpredictability at 10% significance level i.e. returns or volatility are statistically predicted with the EMV-ID in that period. The graphical plots in Figs. 3 and 4 clearly show that the null hypothesis that attention to pandemics does not have the ability to predict stock market returns and volatility cannot be rejected at 10% significance level in most of the periods. However, in some of the periods, the null hypothesis can be rejected. The result shows two things; first, the predictive performance of the EMV-ID on all the stock market returns and volatility is time-varying. Second, the EMV-ID predicts stock market volatility better than stock market returns; hence, attention to pandemics predict volatility in stock markets better than they predict stock market returns in the BRICS countries.

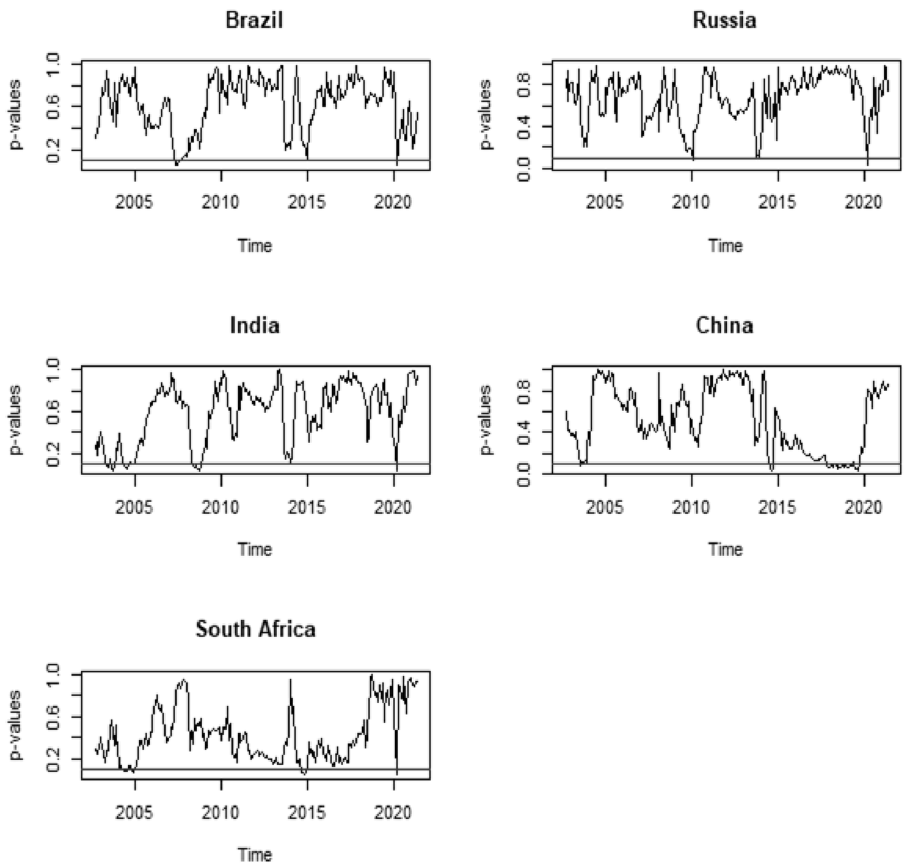
In Fig. 3, as reflected by the amplitudes of the graphs, the predictive power of the EMV-ID on stock market returns in the BRICS countries increases significantly in periods characterised by the outbreak of diseases in each country. In Brazil, the p-value falls below the 10% line in periods corresponding with the outbreak of Dengue haemorrhagic fever in 2008, and also in periods around the outbreak of COVID-19 in 2020. In Russia, similar changes can be seen during the period of the COVID-19 pandemic. In India, the graph crosses the 10% line in periods associated with the outbreaks of SARS (2002/04), the swine influenza pandemic (2009), and the COVID-19 pandemic (2020). In China, the line is crossed in periods associated with the outbreaks of SARS (2003/04), avian influenza (2014/15), and COVID-19 (2019/20). With regards to South Africa, heightened stock market sensitivity is visible in periods corresponding to the outbreaks of the highly pathogenic avian influenza (2004), Ebola (2014/15) and COVID-19 (2020).

Fig. 4 likewise shows that the predictive power of the EMV-ID on stock market volatility in the BRICS countries is significantly enhanced in periods associated with disease outbreaks. In Brazil, the 10% line is crossed in periods associated with the outbreaks of SARS (2003/04), Dengue haemorrhagic fever outbreak (2008), and also in periods around the outbreaks of the West Nile virus (2014), avian influenza (2011), Ebola (2012), Middle East respiratory syndrome coronavirus (2013), yellow fever (2017) and COVID-19 (2020). In Russia, the 10% line is crossed during the SARS outbreak (2003), and in periods following the outbreaks of Ebola (2012) and Middle East respiratory syndrome coronavirus (2013). The line is also crossed around the period of the COVID-19 pandemic. In India, the graph crosses the 10% line in periods associated with the outbreaks of swine influenza, Ebola, Middle East respiratory syndrome coronavirus (MERS-CoV) and COVID-19 pandemic. In China, the p-values are significant in periods corresponding

[5] The plots of the p-values of the WBLR test applied for the null hypothesis that GEPU does not have the ability to predict returns and volatility are reported in the appendix.

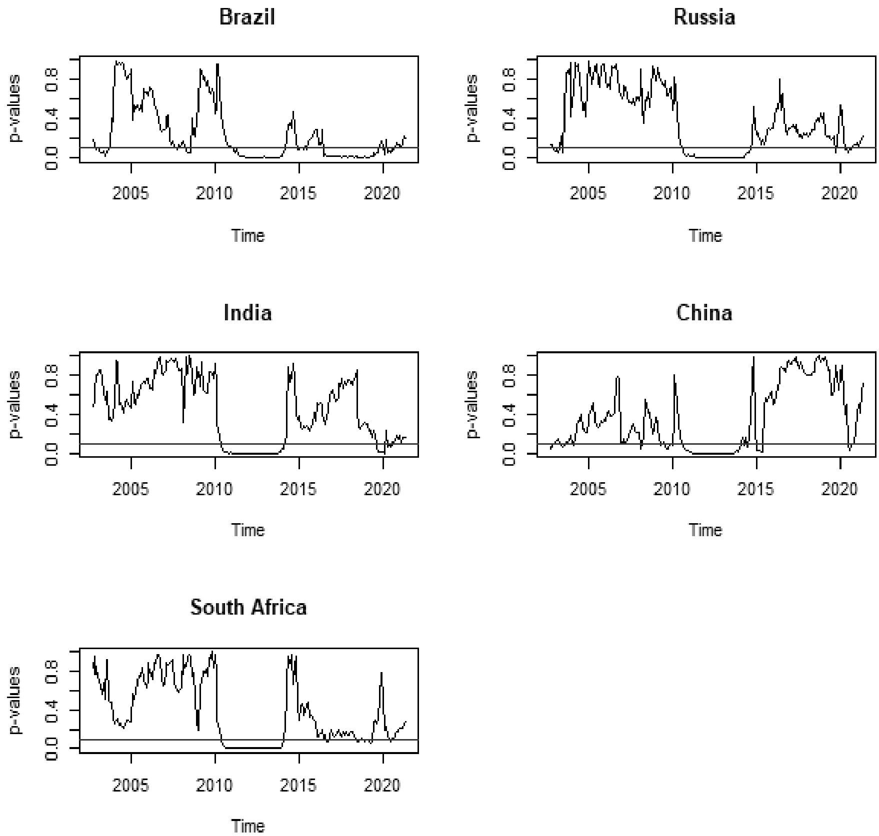
to the outbreaks of SARS (2003-2004), avian influenza (2007-2010, 2014) and the periods following Ebola and MERS-CoV outbreaks. The p-values are also significant in periods associated with the outbreaks of avian influenza (2015/2016) and COVID-19 (2019/20). As for South Africa, significance occurs in periods linked to the outbreaks of Ebola, MERS-CoV and COVID-19. In summary, both static and dynamic analyses results demonstrate that the predictive power of attention to pandemics on stock market volatility is relatively stronger than its predictive power on stock market returns. It is worthy of mention that the stock markets of all the BRICS countries respond uniformly to the outbreaks of both Ebola and MERS-CoV between 2011 and 2015.

Figure 3 WBLR Test p-Values for the Null Hypothesis that EMV-ID Does Not Have the ability to predict stock market returns



Notes: Horizontal gray line represents the 10% significance level.

Figure 4 WBLR Test p-Values for the Null Hypothesis that EMV-ID Does Not Have the Ability to Predict Stock Market Volatility

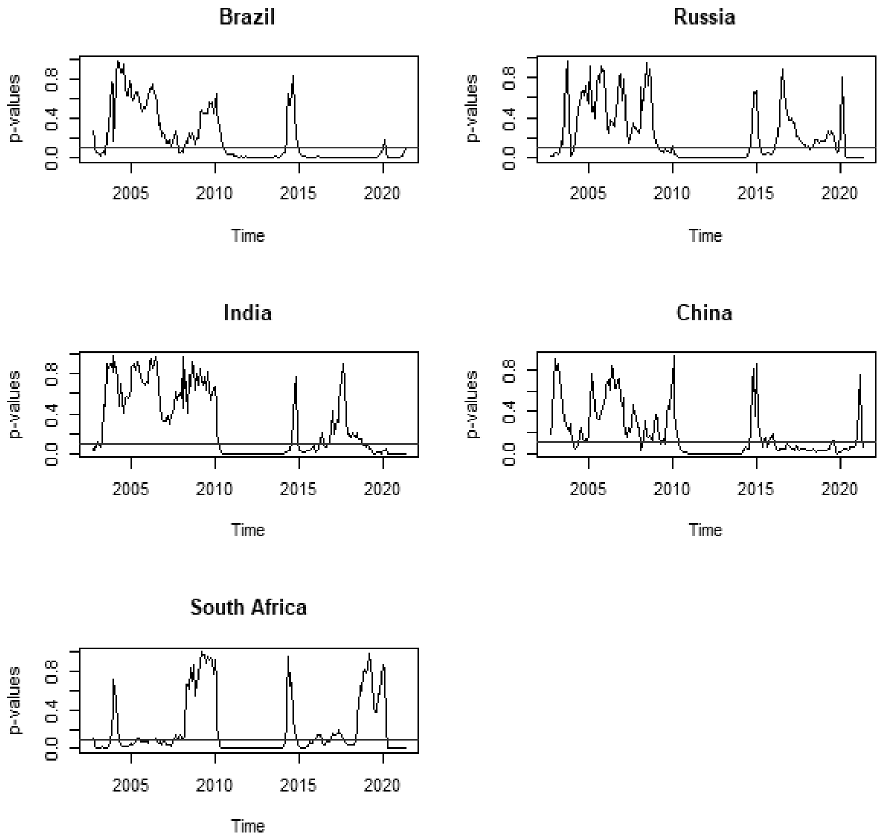


Notes: Horizontal gray line represents the 10% significance level.

5. Robustness Test

To check whether the results in the previous section are robust to the choice of the volatility measure, we repeat our analysis using another measure of volatility that is widely used in the literature, namely: generalised autoregressive conditional heteroscedasticity (GARCH)-based volatility (see Arouri *et al.,* 2012; Hung *et al.,* 2013; Demirer *et al.,* 2018; Gupta & Yoon, 2018; Behera & Rath, 2021). The p-values of the WBLR test applied on GARCH-based volatility series for $H_0: \beta_1 = 0$ are plotted in Fig. 5. Comparing the outcomes in Fig. 4 and Fig. 5, it appears that our findings are quite robust to the different volatility measures as the results from both approaches are relatively similar.

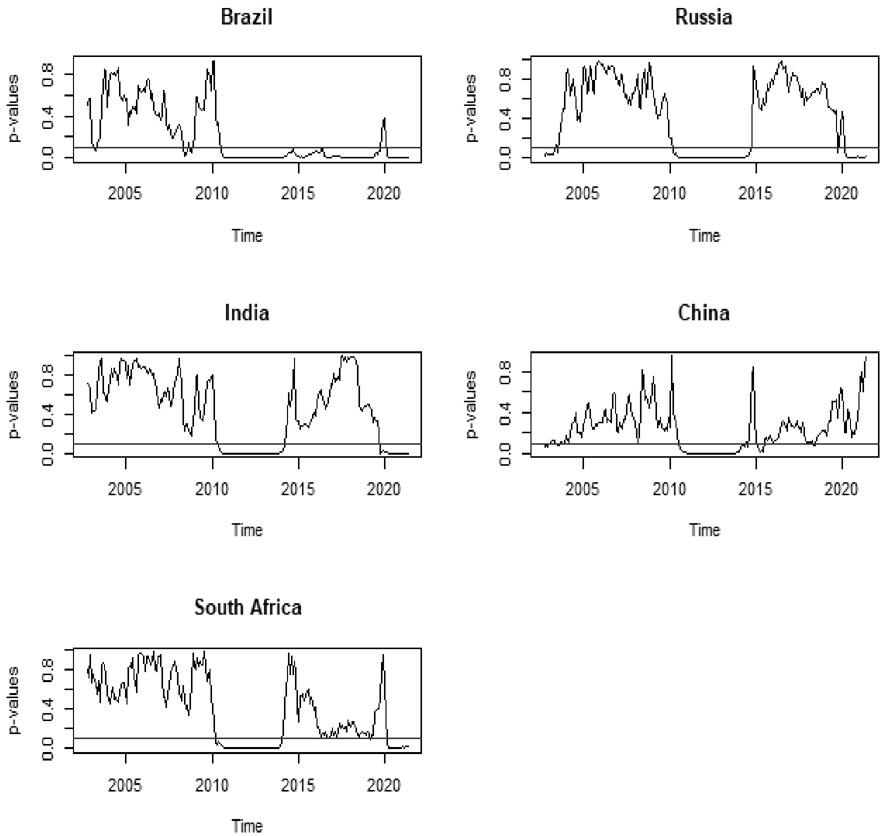
Figure 5 WBLR Test p-Values for the Null Hypothesis that EMV-ID Does Not Have the Ability to Predict Stock Market GARCH-Based Volatility



Notes: Horizontal gray line represents the 10% significance level.

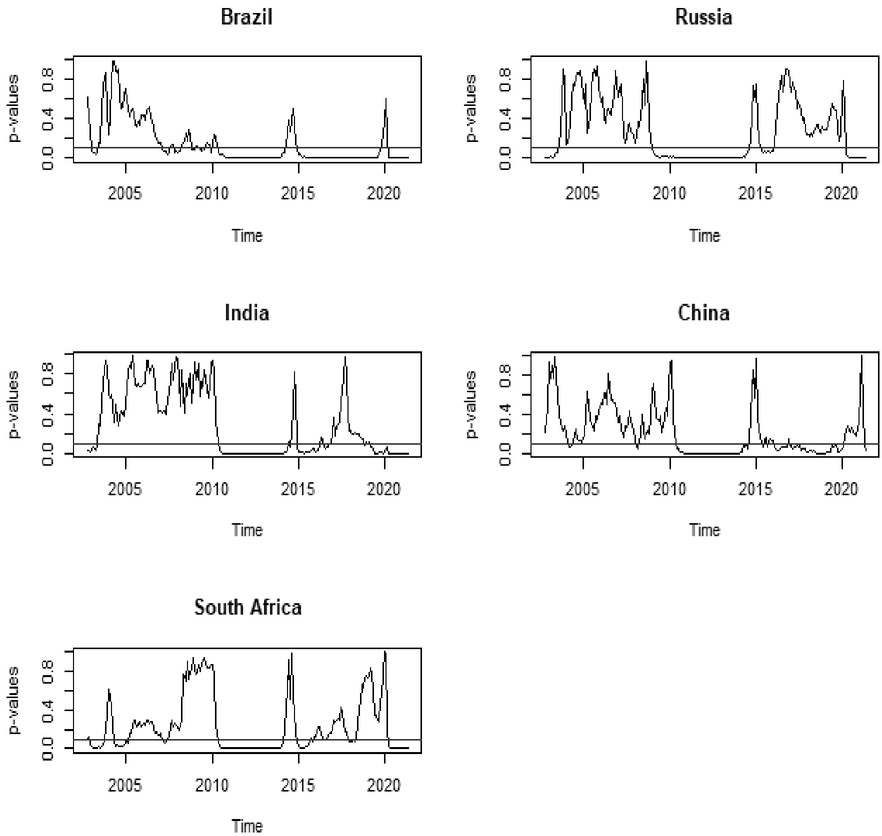
As an additional robustness test, we reapply the WBLR test on the log transformed series of EMV-ID, GEPU and volatility (both RV and GARCH-based volatility) and plot the results in Figs. 6 and 7. The results are again not too different from those earlier obtained.

Figure 6 WBLR Test p-Values for the Null Hypothesis that LNEMV-ID Does Not Have the Ability to Predict Stock Market LNRV



Notes: Horizontal gray line represents the 10% significance level.

Figure 7 WBLR Test p-Values for the Null Hypothesis that LNEMV-ID Does Not Have the Ability to Predict Stock Market LNGARCH-Based Volatility



Notes: Horizontal gray line represents the 10% significance level.

6. Conclusions

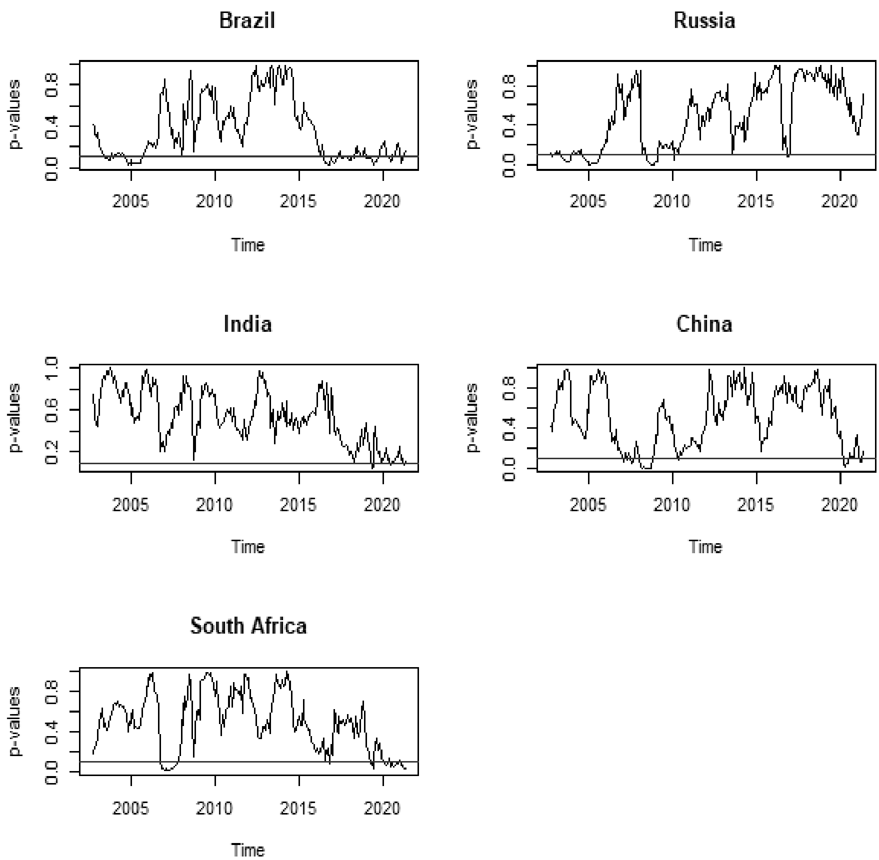
The performance of stock markets during the recent outbreak of COVID-19 has drawn attention to the premise that human health-related crises are some of the drivers of stock market returns and volatility. In this study, the predictability of stock returns and volatility was investigated using the EMV-ID data for the BRICS countries, while controlling for economic policy uncertainty. To achieve the study objective, the novel WBLR test developed by Kim and Shamsuddin (2020) was employed in analysing time-series data covering the period November 1997 – May 2021. The estimations confirmed a time-varying predictive performance of the EMV-ID on both stock returns and volatility series of the BRICS, which increased significantly during the years marked by pandemics. The predictive power of the EMV-ID on stock market volatility is however relatively stronger than its predictive power on stock market returns.

The identified link between attention to pandemics and stock market performance may be attributed to certain factors. As a black swan event, pandemic outbreaks are not only unpredictable but also disruptive. This makes them difficult to properly prepare for. Also, since heightened fear and uncertainty caused by the announcement of disease outbreaks generally trigger downturns in stock markets due to their speculative nature, policy responses designed to contain disease outbreaks such as social distancing, travel bans and stay-at-home orders are also capable of amplifying the negative reaction of stock markets.

This study has shown that good business foresight and timely policy response at the beginning of a pandemic would help cushion the volatility effects on stock markets, hence maintaining stock market stability should form a part of macroeconomic policies towards alleviating the negative effects of pandemics. Regular stress testing, scenario planning and supply chain evaluation are some of the useful techniques that can be adopted to build resilience. Efforts should also be put into ensuring that policy responses designed to address the challenges posed by pandemics do not in themselves amplify the negative economic impact of the disease outbreaks.

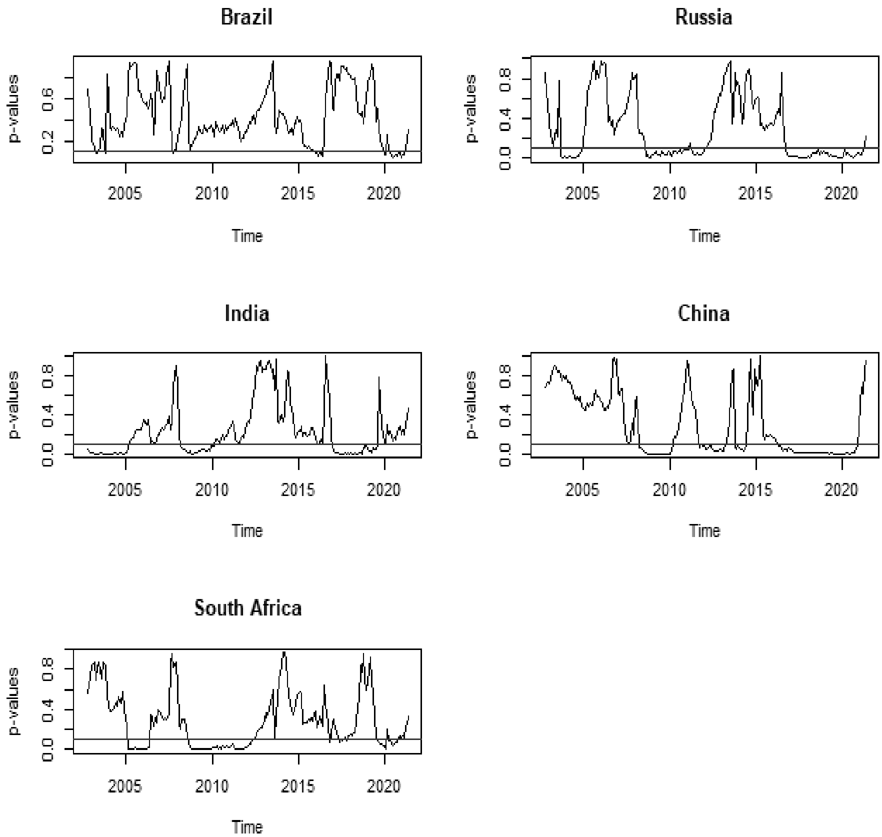
APPENDIX

Figure A1 WBLR Test p-Values for the Null Hypothesis that the GEPU Index Does Not Have the Ability to Predict Stock Market Returns



Notes: Horizontal gray line represents the 10% significance level.

Figure A2 WBLR Test p-Values for the Null Hypothesis that the GEPU Index Does Not Have the Ability to Predict Stock Market Volatility



Notes: Horizontal gray line represents the 10% significance level.

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