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KÜRESEL KRİZLERİN GELİŞMEKTE OLAN PİYASALAR ÜZERİNDEKİ ETKİSİ[1]

THE EFFECT OF GLOBAL CRISES ON EMERGING MARKETS

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Öz

Bu çalışma, küresel krizin ortaya çıkışını ve gelişmekte olan piyasaların kriz ortamına tepkisini incelemektedir. Bu amaçla Morgan Stanley tarafından "Kırılgan Beşli" olarak tanımlanan ülkeler (Türkiye, Hindistan, Brezilya, Endonezya ve Güney Afrika) çalışma konusu olarak seçilmiştir. Küresel olumsuzluğun Kırılgan Beşli pazarlara etkisini ölçmek için COVID-19'un etkili olduğu 2 Ocak 2020 ile 21 Temmuz 2022 arasındaki dönem seçilmiştir. Çalışmaya konu olan indeksleri tahmin etmek için TARCH ve EGARCH modelleri kullanılmaktadır. TARCH model kestirimi sonucunda SNSX ve FTSE indeksleri için asimetrik etkiyi gösteren katsayının anlamlı olduğu tespit edilmiştir. EGARCH model tahmini sonucunda BIST100, BVSP ve JKSE endekslerinde asimetrik etkiyi gösteren katsayı negatif ve anlamlıdır. Bu sonuçlara göre çalışma, küresel piyasalarda meydana gelen olumsuz bir şokun oynaklık üzerinde önemli bir etkiye sahip olduğunu savunmaktadır.

Anahtar Kelimeler: Finansal Piyasalarda Oynaklık, COVID-19, Ekonomik ve Siyasi Belirsizlik

JEL Sınıflaması: G10, G15, F30

Abstract

In this study, the emergence of the global crisis and the response of emerging markets to the crisis environment are investigated. For this purpose, the countries defined as the 'Fragile Five' (Turkey, India, Brazil, Indonesia and South Africa) by Morgan Stanley have been selected as the subject of the study. In order to measure the impact of global negativity on the Fragile Five markets, the period between January 2, 2020 and July 21, 2022, when COVID-19 was effective, has been chosen. TARCH and EGARCH models are used for the estimation of the indices subject to the study. As a result of the TARCH model estimation, it is determined that the coefficient showing the asymmetric effect for the SNSX and FTSE indices is significant. As a result of the EGARCH model estimation, the coefficient showing the asymmetric effect in BIST100, BVSP and JKSE indices is negative and significant. According to these results, the study argues that a negative shock in global markets has a significant effect on volatility.

Keywords: Volatility in Financial Markets; COVID-19; Economic and Political Uncertainty

JEL Classification: G10, G15, F30

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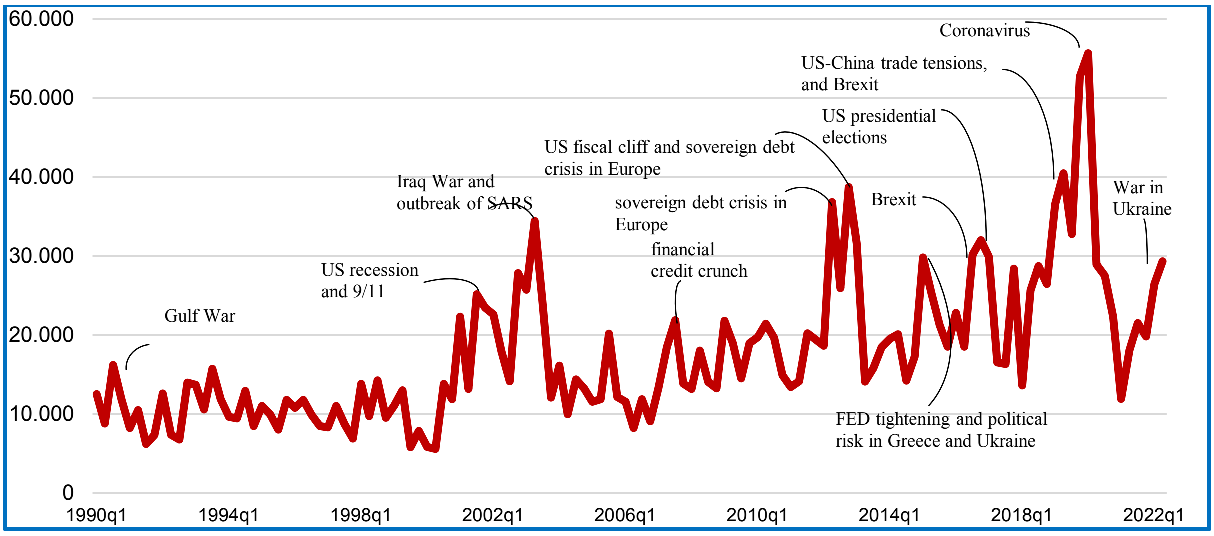
1. Introduction

On December 31, 2019, the first case of COVID-19 was detected in China. The virus began to spread to all countries of the world and the disease was declared a pandemic by the World Health Organisation (WHO) on March 11, 2020. The rapid spread of the disease affected all areas of socio-economic life with an increasing number of cases and deaths, and the negative effects of the pandemic were felt in the world economies (Takyi and Bentum-Ennin, 2021). The COVID-19 pandemic has affected national economies and financial markets around the world. The continued spread of the virus has led to uncertainties in the capital market and devastating effects resulting in a partial or total lockdown of economic activities (Amewu et al., 2022).

Countries have adopted strict policies to prevent the spread of the pandemic, such as curfews, domestic and international travel bans, and financial incentives, which further harden the global economic and trade environment and affect international trade (Qin et al., 2020; Feng et al., 2021; Narayan, 2021; Takyi and Bentum-Ennin, 2021). These policy reactions have increased the uncertainty for both investors and policymakers, and this environment has affected the decisions of investors, leading to sharp declines in financial markets (Padhan and Prabheesh, 2021; Takyi and Bentum-Ennin, 2021). According to World Trade Organisation (WTO) statistics, the volume of trade in goods decreased by 3% on an annual basis in the first quarter of 2020. Preliminary estimates of global trade in the second quarter of 2020 show that the pandemic and the policies implemented to prevent it affected a large part of the world's population, and the global trade in goods fell by 18.5% on an annual basis (Qin et al., 2020; Feng et al., 2021). In addition to these decreases in the trade volume caused by the COVID-19 pandemic, it is observed that the pandemic has had significant effects on the stock market (SM) and exchange rates in developing countries (Hoshikawa and Yoshimi, 2021). The main reason for this is that increasing uncertainties due to the COVID-19 outbreak affect the volatility in stock prices and exchange rates (Narayan, 2021; Padhan and Prabheesh, 2021). For this reason, with the outbreak of the pandemic, investors withdrew their capital from emerging markets securities, causing stock market volatility to increase and the currencies of these economies to depreciate (Hoshikawa and Yoshimi, 2021). The effects of the COVID-19 pandemic and the crisis created by the global crises in the world SM can be better understood from Chart 1.

Chart 1. Effects of Crises on World Stock Exchanges



Source: worlduncertaintyindex

Chart 1 shows the effects of the crises experienced in the world SM between 1990 and 2022. It can be seen that the Gulf War that started in 1990, the financial crises in 2002 and subsequent years, the Iraq War and the SARS epidemic, as well as other significant financial problems in the USA and the EU specifically, caused sharp downside breaks in the world SM. The hardest downward break in the world SM was experienced due to COVID-19, which started in China and became a pandemic.

This study investigates the effects of global crises on financial markets. It is known that developing countries are particularly and significantly affected by global developments. For this reason, in this study, market volatilities that occurred during the pandemic period in the countries defined as the Fragile Five (Turkey, India, Brazil, Indonesia and South Africa) by the American bank Morgan Stanley are investigated. In particular, it is a matter of interest how the current energy and food crisis and the expectation of an expansion and deepening of the Ukrainian war will affect emerging markets such as the Fragile Five. For this reason, the main objective of this study is to determine the developments in the financial sector of the Fragile Five countries during the pandemic period.

Subsequently, the aim is to predict future reactions that will be experienced in the financial sector in the global crisis environment by the Fragile Five and developing countries. When the study is evaluated in this context, it could make an important contribution to the literature.

2. Literature Review

Since globalisation has increased the pass-through between financial markets, the COVID-19 pandemic has affected global financial markets in the same way as various other severe financial and economic conditions (Al-Awadhi et al., 2020; Ali et al., 2020; Haroon and Rizvi, 2020; Iqbal et al., 2021). Consequently, domestic capital market are more vulnerable to external shocks (Boubaker et al., 2021). For example, those who invest in stocks took a negative position, especially in the early part of the pandemic (Padhan and Prabheesh, 2021; Takyi and Bentum-Ennin, 2021). For this reason, since the COVID-19 outbreak turned into a pandemic, global stock returns have decreased, and volatility has increased. Many investors keep the assets they consider to be 'safe havens' – investments that retain their value and withstand high levels of volatility – in their portfolios in order to reduce risk during periods of uncertainty. This causes SM prices to fall and financial markets to underperform (Takyi and Bentum-Ennin, 2021).

The COVID-19 pandemic has been the subject of many studies due to its impact on global economies. During the pandemic, some investment instruments such as gold were seen as a 'safe haven' and their demand increased. However, the overall impact of the pandemic on financial markets has been negative (Liu et al., 2020; Ali et al., 2020; Baker et al., 2020; Ramelli and Wagner, 2020; Takyi and Bentum-Ennin, 2021; Salisu et al., 2021; Heyden et al., 2021; Udeaja and Isah, 2022; Guven et al., 2022). The COVID-19 pandemic has caused volatility, especially in the SM (Bakas and Triantafyllou, 2020; Ashraf, 2020; Zaremba et al., 2020; Dong et al., 2021; Bai et al., 2021; Albulescu, 2021; Díaz et al., 2022). In response to these results, other studies have stated that vaccine studies and vaccination news have a positive effect on SM and stock prices, and that the number of recovered patients has a stronger effect on the SM index than death cases (Gormsen and Koijen, 2020; Ding et al., 2021; Li et al., 2021; Smales, 2021; Chan et al., 2022). Additionally, it has been noted by Onali (2020) and Zhang et al. (2020) that the effect of the pandemic on financial markets is negative or positive depending on the country and time period.

The effects of terrorist attacks, trade wars, and tensions between countries that develop into war on SM indices and financial markets attract great attention from researchers, and diverse studies have been conducted on these subjects. A number of these studies refer to the effect of terrorist incidents on the SM index (Charles and Darné, 2006; Nikkinen and Vähämaa, 2010) and how this is reflected in stock and bond prices (Goel et al., 2017). Similarly, the trade war between the USA and China affected the SM return and SM volatility (He et al., 2021; Bissoondoyal-Bheenick et al., 2022), increased uncertainty in financial markets (Xia et al., 2019) and the risk of spillover effect (Li et al., 2020), and there is evidence that it increased risk spreads across exchanges (Shi et al., 2021). In addition, several studies in the literature discuss the effect of wars on financial markets, SM indices and volatility. For example, World War II caused volatility in stock returns (Choudhry, 2010; Akhtar et al., 2011; Hudson and Urquhart, 2015) and affected government bond prices (Frey and Kucher, 2000, 2001). In addition to these studies, the effect of the ongoing war between Russia and Ukraine on financial markets has been examined, and this research makes an important contribution to the literature. According to these studies, the Russia–Ukraine war negatively affects global SM indices (Boubaker et al., 2022; Boungou and Yatié, 2022), it affects financial markets and increases instability by decreasing stock returns (Lo et al., 2022; Yousaf et al., 2022) and it affects European financial markets and global commodity markets (Umar et al., 2022; Ahmed et al., 2022). Furthermore, the onset of the war caused shock transfer on the SM (Alam et al., 2022).

3. Methodology and Results

This study examines the volatility of the SM indices of the countries known as the Fragile Five during the pandemic period. For this purpose, daily day data between January 2, 2020 and July 21, 2022 are used. The data of the indices used in the study were obtained from the investing.com base. First, natural logarithmic transformation of the data was performed. Subsequently, the return series of the BIST100, FTSE, BVSP, SNSX and JKSE stock indices belonging to the Fragile Five were obtained. The formula $R = 100 * (\ln P_t - lnP_{t-1})$ was used to calculate the return series. After the return series was calculated, the indices used in the study are expressed as RBIST100, RFTSE, RBVSP, RSNSX and RJKSE, respectively. The data used in the study and referred to in the rest of this section is presented in Table 1.

Table 1. Stock Market Indices

Country	Description	Code
Turkey	Borsa Istanbul 100 Index	BIST100
South Africa	Johannesburg Stock Market Index	FTSE
Brazil	Sao Paulo Stock Exchange Index	BVSP
India	S&P Mumbai Stock Exchange Index	SNSX
Indonesia	Jakarta Stock Exchange Composite Index	JKSE

Table 1 presents the RBIST100, RFTSE, RBVSP, RSNSX and RJKSE indices. In the continuation of the study, the optimal autoregressive–moving-average (p, q) model (ARMA) is estimated with the help of the least squares method. The ARCH model was developed by Engle (1982) in order to predict the changing variance in the indices. The ARCH model is depicted as follows:

$$h_t = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 k \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (1)$$

In the ARCH (p) model, the conditional variance of ε_t depends on the realised values of the $\varepsilon_{t-i}^2{}'$s. In ARCH models, long-term delays are required for conditional variance. To overcome this limitation, the Bollerslev (1986) GARCH equation was developed. The GARCH equation is presented in equation (2) below (Aydin et al., 2021).

$$h_t = a_0 + \sum_{n=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

In addition to the ARCH and GARCH models, the TARCH model is also used to predict indices. In the TARCH model, the effects of positive and negative shocks on volatility occur separately from each other. The conditional variance of the model is presented in equation (3) below (Nelson, 1991; Ali, 2013; Aydin et al., 2021).

$$h_t = a_0 + \sum_{i=1}^{q} a_i \mu_{t-i}^2 + \sum_{i=1}^{p} \gamma_i \mu_{t-i}^2 \theta_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The shadow variable (θ_t) represents positive and negative shocks. In the model, μ_t is the random error term with zero mean and unit variance. Where $\mu_{t-i} > 0$ represents positive news, $\mu_{t-i} < 0$ represents negative news. Finally, while the a_i parameter in the model represents positive news, the sum of, $a_i + \gamma_i$ parameters represents negative news (Zakoian, 1994; Sabiruzzaman et al., 2010; Aydin et al., 2021).

Another model that considers the asymmetric volatility situation is the EGARCH model, which was introduced to the literature with the contributions of Engle and Ng (1993). In the EGARCH model, positive and negative shocks on volatility show their effects on the news curve (Nelson, 1991; Ali, 2013; Aydin et al., 2021). The EGARCH model, which is an asymmetrical model, is shown in equation (4) below.

$$\log(h_t) = \alpha_0 + \sum_{k=1}^{r} \vartheta_1 \frac{\varepsilon_{t-1}}{h_{t-i}} + \sum_{k=1}^{r} \gamma_1 \left|\frac{\varepsilon_{t-1}}{h_{t-i}}\right| + \sum_{k=1}^{r} \beta_1 \log(h_{t-i}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

In the case of the ϑ_1 parameter in equation (4) being less than zero, this refers to the situation where negative news is more effective than positive news on volatility (Dhamija, 2010). Thus, with the EGARCH model, it is possible to understand that the effects of positive and negative news on volatility are different.

Following this presentation of the theoretical information about the models used in the study, descriptive statistics of the data will be presented. Descriptive statistics of the data are presented in Table 2 below.

Table 2. Descriptive Statistics of Returns of Stock Indices

	Mean	Maximum	Minimum	Standard Deviation	Skew	Kurtosis
BIST100	3.1664	3.4229	2.9255	0.1219	0.4471	2.3337
FTSE	6.3521	6.9038	5.6487	0.3981	-0.2234	1.5265
BVSP	11.5829	11.7812	11.0599	0.1273	-1.3112	4.9848
SNSX	10.7697	11.0311	10.1651	0.2067	-0.7512	2.4737
JKSE	8.6973	8.8923	8.2783	0.1333	-0.6784	2.5843

According to Table 2, the BVSP index has the highest mean and the FTSE index has the highest standard deviation. Looking at the skewness values, FTSE, BVSP, SNSX and JKSE indices have negative values. That is to say, these indices are skewed to the left. However, since the BIST100 index has a positive value, it is determined to be skewed to the right. When the kurtosis values are examined, it is seen that all indices have positive values. Thus, it can be concluded that the middle part of all indices is more pointed than normal, in other words, it has a pointed (leptokurtic) structure. Before examining the volatility of the indices, the study will investigate whether they are stationary or not. ADF and PP unit root tests are used for the stationarity test. ADF and PP unit root test results are presented in Table 3.

Table 3. Unit Root Test

	ADF Unit Root Test		PP Unit Root Test		
	Fixed Model	**Fixed + Trend Model**	**Fixed Model**	**Fixed + Trend Model**	
BIST100	-0.084	-2.354	0.054	-2.489	I(0)
RBIST100	-15.477***	-15.502***	-25.811***	-25.812***	I(1)
BVSP	-2.385	-2.732	-1.868	-2.196	I(0)
RBVSP	-7.937***	-7.941***	-31.355***	-31.344***	I(1)
SNSX	-1.937	-2.486	-0.725	-2.159	I(0)
RSNSX	-8.291***	-8.292***	-27.578***	-27.564***	I(1)
FTSE	-0.752	-2.181	-0.723	-2.121	I(0)
RFTSE	-24.734***	-24.716***	-24.486***	-24.468***	I(1)
JKSE	-1.021	-3.577**	-1.003	-3.447**	I(0)
RJKSE	-12.725***	-12.779***	-24.912***	-24.929***	I(1)
- *** indicates stationarity at the 1% level. - ( ) denotes probability values.					

In Table 3, unit root test results of BIST100, BVSP, SNSX, FTSE and JKSE indices are presented. Accordingly, it can be seen that the level value of each index is not stationary. In contrast, the RBIST100, RBVSP, RSNSX, RFTSE and RJKSE indices, which are expressed as return series, do not contain unit roots, that is, they have a stationary process.

Table 4. ARMA (p, q) Model

	Variables	Coefficient	Statistics Value	Probability Value
RBIST100 Index	C	0.001	1.508	0.131
	AR(2)	0.151	3.802	0.001***
RBVSP Index	C	-0.001	-0.275	0.782
	AR(1)	2.108	15.392	0.000***
	AR(2)	-2.246	-7.714	0.000***
	AR(3)	1.485	5.378	0.000***
	AR(4)	-0.524	-4.621	0.000***
	MA(1)	-2.211	-19.37	0.000***
	MA(2)	2.502	9.971	0.000***
	MA(3)	-1.775	-7.382	0.000***
	MA(4)	0.683	6.994	0.000***
RSNSX Index	C	0.001	0.939	0.3478
	AR(1)	-1.524	-50.301	0.0000***
	AR(2)	-0.934	-32.863	0.0000***
	MA(1)	1.456	43.862	0.0000***
	MA(2)	0.912	28.912	0.0000***
RFTSE Index	C	0.001	1.941	0.052*
	AR(3)	-0.068	-1.771	0.0077*
RJKSE Index	C	0.001	0.458	0.646
	AR(1)	-1.393	-18.72	0.0000***
	AR(2)	-0.793	-10.94	0.0000***
	MA(1)	1.441	17.764	0.0000***

	MA(2)	0.762	28.912	0.0000***
- *** and * indicate stationarity at 1% and 10% significance levels, respectively.				

In Table 4, the ARMA (p, q) model is used to select the most appropriate volatility model. The most suitable models estimated for indices are ARMA (2, 0) for the RBIST100 index, ARMA (4, 4) for the RBVSP index, ARMA (2, 2) for the RSNSX index, ARMA (3, 0) for the RFTSE index and finally ARMA (2, 2) for the RJKSE index. Following this estimation of the ARMA models, the next point to investigate is whether there is an ARCH effect. The probability values of the parameters and AIC-SIC information criteria were considered for the best fit model.

Table 5. ARCH-LM Test

	F Statistics Value	F - Probability Value	Observation * R^2	Chi-Square Probability Value	Lag Length	Hypothesis
RBIST100 Index	5.525	0.000***	41.835	0.000***	8	H_0 Reject
RBVSP Index	30.508	0.000***	179.535	0.000***	8	H_0 Reject
RSNSX Index	37.091	0.000***	206.354	0.000***	8	H_0 Reject
RFTSE Index	4.021	0.000***	31.081	0.000***	8	H_0 Reject
RJKSE Index	29.671	0.001***	174.941	0.000***	8	H_0 Reject
- ***, **, * indicate stationarity at 1%, 5% and 10% significance levels, respectively.						

Table 5 shows ARCH-LM. For the indices RBIST100, RBVSP, RSNSX, RFTSE and RJSE, ARCH effect is expressed as an example. The content of serial deliveries in ARCH effect content has been reached. ARCH, GARCH, EGARCH and TARCH models will be estimated. As shown in Table 6, RBIST100 appeared to be the most suitable model to be applied for recovery.

Table 6. RBIST100 Index

	ARCH (1)	GARCH (1, 1)	EGARCH(1,1)	TGARCH(1,1)
C	0.001 (0.0246)**	0.001 (0.488)	**0.001 (0.046)****	0.001 (0.022)**
AR(2)	0.186 (0.000)***	0.162 (0.051)**	**0.142 (0.002)*****	0.121 (0.011)**
$\boldsymbol{\alpha_0}$	0.001 (0.000)***	0.003 (0.0396)**	**-0.864 (0.000)*****	0.001 (0.000)***
$\boldsymbol{\alpha_1}$	0.171 (0.000)***	0.151 (0.041)**		0.092 (0.000)***
$\boldsymbol{\beta_1}$		0.599 (0.001)***	**0.927 (0.000)*****	0.562 (0.000)***
$\boldsymbol{\gamma_1}$			**0.201 (0.000)*****	
$\boldsymbol{\vartheta_1}$			**-0.046 (0.000)*****	
$\boldsymbol{\theta_1}$				0.217 (0.000)***
AIC	-7.044	-6.881	**-7.161**	-7.156
SIC	-7.016	-6.846	**-7.117**	-7.113
- ***, **, * denote 1%, 5% and 10% significance level, respectively. - ( ) indicates probability value.				

$$\log(h_t) = \alpha_0 + \sum_{k=1}^{r} \vartheta_1 \frac{\varepsilon_{t-1}}{h_{t-i}} + \sum_{k=1}^{r} \gamma_1 \left|\frac{\varepsilon_{t-1}}{h_{t-i}}\right| + \sum_{k=1}^{r} \beta_1 \log(h_{t-i})$$

In the model, α_0= -0.864, β_1 = 0.927, γ_1 = 0.201 and ϑ_1= -0.046 were estimated, and the parameters were found to be significant. It can be seen that the coefficient of the GARCH term is less than 1 and the stationarity condition is satisfied. The ϑ_1 parameter represents the asymmetric effect in the EGARCH (1, 1) model. If this parameter is significant, it indicates the asymmetric effect, while its negative value indicates the presence of the leverage effect. Since the coefficient of the ϑ_1 parameter in the EGARCH (1, 1) model is -0.046, there is both an asymmetrical effect and a leverage effect in the BIST100 index. It can be seen that the effect of a negative shock on returns causes more volatility than positive shocks.

Table 7. RBVSP Index

	ARCH (1)	GARCH (1, 1)	EGARCH(1,1)	TGARCH(1,1)
C	0.001 (0.724)	0.001 (0.712)	-0.001 (0.671)	**-0.001 (782)**
AR(1)	-0.228 (0.214)	0.421 (0.000)***	-0.106 (0.711)	**2.108 (0.000)*****
AR(2)	-0.181 (0.175)	0.382 (0.001)***	-0.292 (0.101)	**-2.246 (0.000)*****
AR(3)	0.679 (0.000)***	0.445 (0.000)***	0.569 (0.000)***	**1.485 (0.000)*****
AR(4)	0.401 (0.031)**	-0.721 (0.000)***	0.412 (0.126)	**-0.524 (0.000)*****

MA(1)	0.202 (0.341)	-0.501 (0.000)***	0.048 (0.871)	**-2.211 (0.000)*** **
MA(2)	0.224 (0.107)	-0.341 (0.002)***	0.365 (0.053)**	**2.502 (0.000)*** **
MA(3)	-0.707 (0.000)***	-0.464 (0.000)***	-0.556 (0.001)***	**-1.775 (0.000)*** **
MA(4)	-0.292 (0.168)	0.793 (0.000)***	-0.309 (0.276)	**0.683 (0.000)*** **
$\boldsymbol{\alpha_0}$	0.001 (0.000)***	0.001 (0.001)***	-0.409 (0.000)***	**0.001 (0.000)*** **
$\boldsymbol{\alpha_1}$	0.171 (0.000)***	0.149 (0.000)***		**0.011 (0.657)**
$\boldsymbol{\beta_1}$		0.599 (0.000)***	0.966 (0.000)***	**0.866 (0.000)*** **
$\boldsymbol{\gamma_1}$			0.161 (0.000)***	
$\boldsymbol{\vartheta_1}$			-0.127 (0.000)***	
$\boldsymbol{\theta_1}$				**0.139 (0.000)*** **
AIC	-5.377	-5.445	-5.565	**-5.576**
SIC	-5.303	-5.364	-5.476	**-5.488**
- ***, **, * denote 1%, 5% and 10% significance levels, respectively. - ( ) indicates probability value.				

$$h_t = \alpha_0 + \sum_{j}^{q} \beta_1 h_{t-j} + \sum_{i}^{r} \alpha_1 \varepsilon_{t-i} + \sum_{k}^{p} \alpha_1 \varepsilon_{t-k}^2 \ \theta_{t-k}$$

In the TARCH (1,1) model, the stationarity conditions are met in the mean and variance equations. The variance equation of the model was estimated as α_0= 0.001, α_1 = 0.011, β_1 = 0.866 and θ_1= 0.139, and it was determined that the parameters were significant at the 1% level. In this case, it was concluded that there is both asymmetric and leverage effect in the RSNSX index.

Table 8. RSNSX Index

	ARCH (1)	**GARCH (1, 1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
C	0.001 (0.383)	0.001 (0.513)	0.001 (0.205)	**0.001 (0.095)***
AR(1)	-1.327 (0.000)*	0.861 (0.442)	0.551 (0.000)***	**0.002 (0.987)**
AR(2)	-0.835 (0.000)*	-0.565 (0.521)	-0.966 (0.000)***	**-0.749 (0.000)*** **
MA(1)	1.394 (0.000)*	-0.903 (0.421)	-0.534 (0.000)***	**0.092 (0.549)**
MA(2)	0.921 (0.000)*	0.575 (0.521)	0.954 (0.000)***	**0.718 (0.000)*** **
$\boldsymbol{\alpha_0}$	0.001 (0.000)*	0.001 (0.067)*	-0.416 (0.000)***	**0.001 (0.000)*** **
$\boldsymbol{\alpha_1}$	0.171 (0.000)*	0.149 (0.118)		**-0.049 (0.001)*** **
$\boldsymbol{\beta_1}$		0.599 (0.005)***	0.965 (0.000)***	**0.884 (0.000)*** **
$\boldsymbol{\gamma_1}$			0.146 (0.000)***	
$\boldsymbol{\vartheta_1}$			-0.145 (0.000)***	
$\boldsymbol{\theta_1}$				**0.246 (0.000)*** **
AIC	-5.761	-5.535	-6.093	**-6.106**
SIC	-5.741	-5.471	-6.032	**-6.045**
- ***, **, * denote 1%, 5% and 10% significance levels, respectively. - ( ) indicates probability value.				

$$h_t = \alpha_0 + \sum_{j}^{q} \beta_1 h_{t-j} + \sum_{i}^{r} \alpha_1 \varepsilon_{t-i} + \sum_{k}^{p} \alpha_1 \varepsilon_{t-k}^2 \ \theta_{t-k}$$

In the TARCH (1,1) model, the stationarity conditions are met in the mean and variance equations. The variance equation of the model was estimated as α_0= 0.001, α_1 = -0.049, β_1 = 0.884 and θ_1= 0.246, and it was determined that the parameters were significant at the 1% level. In this case, it was concluded that there is both asymmetric and leverage effect in the RSNSX index.

Table 9. RFTSE Index

	ARCH (1)	**GARCH (1, 1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
C	0.001 (0.127)	0.001 (0.411)	0.001 (0.078)*	**0.001 (0.11)**
AR(3)	-0.059 (0.051)*	-0.011 (0.891)	-0.068 (0.089)*	**-0.066 (0.101)**
$\boldsymbol{\alpha_0}$	0.001(0.000)***	0.001 (0.201)	-3.568 (0.002)***	**0.001 (0.003)*** **
$\boldsymbol{\alpha_1}$	0.171 (0.000)***	0.151 (0.092)*		**0.204 (0.001)*** **
$\boldsymbol{\beta_1}$		0.599 (0.031)**	0.569 (0.000)***	**0.381 (0.042)***

$\boldsymbol{\gamma_1}$			0.258 (0.001)***	
$\boldsymbol{\vartheta_1}$			0.091 (0.028)**	
$\boldsymbol{\theta_1}$				**-0.165 (0.004)*** **
AIC	-4.934	-4.768	-4.975	**-4.979**
SIC	-4.907	-4.755	-4.934	**-4.938**
- ***, **, * denote 1%, 5% and 10% significance levels, respectively. - ( ) indicates probability value.				

$$h_t = \alpha_0 + \sum_{j}^{q} \beta_1 h_{t-j} + \sum_{i}^{r} \alpha_1 \varepsilon_{t-i} + \sum_{k}^{p} \alpha_1 \varepsilon_{t-k}^2 \; \theta_{t-k}$$

In the TARCH (1,1) model, the stationarity conditions are met in the mean and variance equations. The variance equation of the model was estimated as α_0= 0.001, α_1 = 0.204, β_1 = 0.381 and θ_1= -0.165, and it was determined that the parameters were significant at the 1% level. In this case, it is understood that there is an asymmetric effect in the SNSX index. However, when the coefficient of the shadow variable was -0.165, it was determined that there was no leverage effect.

Table 10. RJKSE Index

	ARCH (1)	GARCH (1, 1)	EGARCH(1,1)	TGARCH(1,1)
C	0.001 (0.051)	0.001 (0.271)	**0.001 (0.315)**	0.001 (0.361)
AR(1)	-1.448 (0.000)***	-1.475 (0.000)***	**0.336 (0.000)*** **	-0.508 (0.241)
AR(2)	-0.872 (0.000)***	-0.941 (0.000)***	**-0.979 (0.000)*** **	0.026 (0.945)
MA(1)	1.408 (0.000)***	1.489 (0.000)***	**-0.353 (0.000)*** **	0.461 (0.282)
MA(2)	0.783 (0.000)***	0.932 (0.000)***	**0.995 (0.000)*** **	-0.107 (0.772)
$\boldsymbol{\alpha_0}$	0.001 (0.000)***	0.001 (0.001)***	**-0.941 (0.000)*** **	0.001 (0.000)***
$\boldsymbol{\alpha_1}$	0.171 (0.000)***	0.149 (0.001)***		0.071 (0.021)**
$\boldsymbol{\beta_1}$		0.599 (0.000)***	**0.921 (0.000)*** **	0.738 (0.000)***
$\boldsymbol{\gamma_1}$			**0.281 (0.000)*** **	
$\boldsymbol{\vartheta_1}$			**-0.122 (0.000)*** **	
$\boldsymbol{\theta_1}$				0.179 (0.000)***
AIC	-6.093	-6.232	**-6.339**	-6.337
SIC	-6.044	-6.211	**-6.277**	-6.275
- ***, **, * denote 1%, 5% and 10% significance levels, respectively. - ( ) indicates probability value.				

$$\log(h_t) = \alpha_0 + \sum_{k=1}^{r} \vartheta_1 \frac{\varepsilon_{t-1}}{h_{t-i}} + \sum_{k=1}^{r} \gamma_1 \left|\frac{\varepsilon_{t-1}}{h_{t-i}}\right| + \sum_{k=1}^{r} \beta_1 \log(h_{t-i})$$

The decision was taken to select the EGARCH (1, 1) model since the coefficients in the significance of the parameters and the mean equation are less than 1 and satisfy the stationarity condition. In the model, α_0= -0.941, β_1 =0.921, γ_1 = 0.281 and ϑ_1= -0.122 were estimated, and the parameters were found to be significant. In addition, since the coefficient of the GARCH term is less than 1, the stationarity conditions of the variance equation are met. The ϑ_1 parameter represents the asymmetric effect in the EGARCH (1, 1) model. If this parameter is significant, it indicates the asymmetric effect, while its negative value means that there is a leverage effect. Since the coefficient of the ϑ_1 parameter is -0.122 in the EGARCH (1, 1) model, there is both an asymmetrical effect and a leverage effect in the RJKSE index. In summary, the effect of a negative shock on returns creates more volatility than positive shocks. When the literature is examined, it is argued that a negative economic or political shock in global markets significantly affects volatility. Russia and Ukraine on financial markets have been discussed, and this research contributes to the literature. According to these studies, Russia–Ukraine war negatively affects global SM indices (Boubaker et al., 2022; Boungou and Yatié, 2022), it affects financial markets and increases instability by decreasing stock returns (Lo et al., 2022; Yousaf et al., 2022) and it affects European financial markets and global commodity markets (Umar et al., 2022; Ahmed et al., 2022). Furthermore, the onset of the war caused shock transfer on the SM (Alam et al., 2022).

4. Conclusion

In this study, the effect of the COVID-19 epidemic on the SM in the Fragile Five countries has been investigated. The pandemic period was chosen in order to investigate the reaction to global crises in the Fragile Five financial markets. For this purpose, Turkey, India, Brazil, Indonesia and South Africa, those countries defined as the Fragile Five by Morgan Stanley, have been the subject of the study. TARCH and EGARCH models have been used to estimate the volatility experienced in the SM indices of the countries studied. An estimation of the TARCH model determined that the coefficient showing the asymmetric effect for the SNSX, BVSP and FTSE indices was significant. An estimation of the EGARCH model determined that the coefficient showing the asymmetric effect in BIST100 and JKSE indices was negative and significant. Thus, it has been concluded that a negative economic or political shock in global markets has a greater impact on volatility. When considering the Fragile Five of Turkey, South Africa, Brazil, India and Indonesia, it can be seen that a global negative shock causes volatility in the financial markets of these countries.

Considering the increasing global uncertainty due to the ongoing Ukraine War, with crises in the energy and food sectors, it is predicted that developing countries such as the Fragile Five will create more volatility in the SM. For this reason, international fund owners who are considering investing in the financial markets of developing countries should be cautious, as considering the existence of global economic and political uncertainty and the likelihood that this uncertainty will increase, it is thought that negative shocks in emerging markets will create increased volatility. In addition, it is strongly recommended that policymakers in the relevant countries develop economic policies that promote an environment of confidence to protect against negative shocks, and to raise the confidence of international funder owners faced with increasing global economic and political uncertainty. In this way, these countries can ensure they achieve increased demand in the financial markets.

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