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Stock market volatility and structural breaks: An empirical analysis of fragile five countries using GARCH and EGARCH models

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Abstract

This study aims to investigate the potential effects of structural breaks on volatility permanence and asymmetry in stock exchanges of fragile five countries. The study covers the stock market index of 12 countries that were evaluated as fragile fives by various investment institutions on different dates between January 2013 and November 2019. The GARCH and EGARCH models are used for volatility estimates, and ICSS iteration algorithm is used to detect structural breaks. Results of the study reveals that among the 12 stock exchanges Indonesia, India, Brazil, Russia and Turkey are the top five countries with persistent volatility in their stock market indices. According to the empirical results from the study, volatility models in which structural breaks were not included depicts that the permanence effect is high in Indonesia and India, however, it is relatively lower in Argentina and Egypt. In addition, asymmetric volatility and leverage effect was observed in all country indices except Argentina. While where the response to negative shocks are strongest the indices of Pakistan, Qatar, South Africa and India, the response in Russia is lower. No structural breaks were observed in South Africa, Mexico, Argentina and Qatar exchanges during the period considered in study. In addition, it was found that using structural breaks in volatility estimates increased the predictive performance of the models.

Keywords: Fragile Five, Volatility, Structural Break, GARCH, EGARCH

JEL Classification: G15, C23, C58

1. Introduction

The effect of financial liberalization in developing economies started to appear more intensely in the 80's and 90's. Although the role of capital markets in the financial liberalization trend has been neglected until the 90's (Arestis and Demetriades, 1997), the importance given to the capital markets has increased in the last 30 years. However, increasing capital flows into emerging economies caused financial vulnerability in these economies in the later periods (Demirgüç-Kunt and Detragiache, 1998). Financial breaks are associated with shocks in the economy. Allen and Gale (2004) stated that shocks experienced in the financial system cause volatility in financial asset prices, but the volatility in asset prices is disproportionately larger than the shocks and this indicates the fragility of the financial system in question. While small

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shocks in the economy cause capital flows to change direction, the intensity of these shocks over time results in an economic crisis.

In order to get rid of the global financial crisis in 2008, the FED expanded its monetary policy, and until 2013, there was an abundance of liquidity worldwide. During this period, a large part of cheap capital flowed to emerging economies with higher return rates leading to an expansion in the financial and capital markets of these economies. In May 2013, FED announced that it ended its expansion policy and switched to an asset purchase program. This decision had a shock effect on developing economies and financial markets as well changed dramatically. During the period until the end of 2013, foreign portfolio investments in emerging economies decreased significantly and the currencies of emerging countries as well as stocks prices depreciated, while government bond market rates and CDS premiums increased significantly. During this period, Morgan Stanley explained that some of the developing country economies, which diverged from the FED's decision, became more fragile and classified Turkey, Brazil, Indonesia, India and South Africa as Fragile Five countries. Morgan Stanley made such a classification considering that factors such as inflation, current account deficit, uncertainty in capital flows and instability in growth performances would be effective on the value of a country's currency (Lord, 2013). In addition, in a report published in December of 2013 by Morgan Stanley, they stated that the election in these 5 countries especially in 2014 would cause fragility of their respective economies to persist in these countries. The currencies of these countries lost 14% to 24% of their value in the year 2014 as compared to 2013. Similarly, Turkey (-12%), Indonesia (-12%) and Brazil (-8%) depreciated in their stock market index. The stock market index of the Fragile fives countries has become more volatile than other developing countries.

In 2016, Morgan Stanley's Asian economist Chetan Ahya updated his Fragile five countries by adding Mexico and Colombia instead of Brazil and India, with the expectation that the FED will increase interest rates three times in 2017. In this classification, six basic factors namely current account balance, foreing exchange reserves to external debt ratio, foreign holdings of government bonds, U.S. dollar debt, inflation and real rate differential were used (Ren, 2016). In 2017, Standard & Poors calssified Turkey, Argentina, Pakistan, Egypt, and Qatar as the new fragile fives economies in their research on 19 economies with the highest country risk (sovering risk) profiles, with the expectation that the FED will increase its interest rates by tightening monetary policy. In determining these economies, they used seven variables that showed sovereign's external financial risks. These variables are: current account balance as percentage (%) of GDP, current account balance as percentage (%) of current account receipts (CAR), usable reserves, gross external financing requirement as percentage (%) of usable reserves and CAR, narrow net external debt as percentage (%) of CAR, short-term external debt by remaining maturity as percentage (%) of CAR and government foreign currency debt as percentage (%) of total debt. While determining the fragile fives countries, S&P has determined the five most vulnerable economies according to each criterion and according to the variables and the 5 countries that are among the most vulnerable groups are considered as fragile fives countries (Kraemer, 2017). In addition to some economic difficulties, Danske Bank made a new fragile fives classification consisting of Turkey, Argentina, Russia, Brazil and South Africa in their August 2018 report on the grounds that it will be effective on the geopolitical risks of the country due to America's sanction and trade disputes. (Christensen, 2018).

This study focuses on the impact of structural breaks on volatility permanence and asymmetry in fragile five-country stock market indices. In this context, the volatility of returns in the fragile five country indices were estimated in the first stage with the GARCH and E-GARCH models, investigating the permanence and asymmetry effect on the country indices and the predictive powers of the models were compared. In the second stage, structural break periods were included in the model and the volatility modeling was repeated. The reason for the study to be carried out in two stages is to present new evidence to the literature by comparing the effect of permanence and asymmetry of models with structural breaks to models that do not include structural breaks. Estimation results of the study, demonstrate that the permanence in volatility was high in all of the countries in the fragile five categories, that the indices were under asymmetrical reaction and the leverage effect appeared against positive and negative shocks. It could also be seen that the predictive powers of the models are stronger. In addition, Indonesia, India, Brazil, Russia and Turkey were observed, in terms of persistence in the volatility index, to be among the five most vulnerable countries. The rest of the study is designed as follows: Firstly, literature related to the study has been examined. The following section includes the GARCH, EGARCH and ICSS iteration algorithm econometric methodology. Comparative summary of estimation results is presented in the last section

2. Literature Review

In the financial literature, many empirical studies have been conducted on volatility behavior of stock markets. While most of these studies try to explain the relationship between stock returns and stock volatility, some research has examined the permanence and spillovers effect of shocks experienced in the markets. In earlier studies by Mandelbrot (1963) and Fama (1965), they found that positive or negative big changes in asset prices generally followed by large changes, while small changes followed by small changes. A thorough review of the available financial literature reveals that emerging markets are more volatile than developed markets. Studies by Divecha et al. (1992), Stone (1992) and Ferson and Harvey (1993) found evidence of high volatility in developing countries.

Additionally, in some studies where emerging markets and developed markets are compared, it is concluded that stock returns have different characteristics. For example, Harvey (1995) and Bekaert and Harvey (2002) show that emerging market returns have higher volatility, longer tail length and better predictive power than developed markets. Bekaert and Harvey (1997) argued that fluctuations in emerging markets were primarily determined by local information variables. Aggarwal et al. (1999) claimed that volatility in emerging markets showed sudden and large changes, and these sudden changes were mostly related to local events. In addition, results of the study showed that most emerging market returns exhibit positive skewness in contrast to negative skewness experienced in developed markets. In a related study, De Santis and Imrohoroglu (1997) found that volatility and permanence were higher in emerging markets compared to developed markets, while the leverage effect was also low.

To summarize the studies on volatility persistence, asymmetry and leverage effect in various stock exchanges; Duppati et al. (2017) using five-minute intraday data on India, China, Japan, Korea and Singapore tested long memory volatility and found that there was a persistence effect in all countries for volatility. In the study conducted by Gutiérrez et al. (2017) on the Latin American stock markets in the period from 1992 to 2014, it was found that volatility asymmetry was significant both in the long term and short term. Mallikarjuna and Rao (2019) conducted a study covering 24 stock exchanges in developed, emerging and frontier markets and found that there is a high level of permanence in all markets in their volatility estimates with GARCH, EGARCH and TGARCH models for the period of 2000-2018. Also, they pointed out that developed markets have higher volatility asymmetry and leverage effect compared to emerging and frontier markets. In his study on volatility asymmetry and permanence in 20 stock market index, Baur and Dimpfl (2018) stated that the persistence in volatility is high and the leverage effect is stronger in high volatility indices. Horpestad et al. (2019) investigated the effect of asymmetric volatility on 19 stock indexes from North America, Latin America, Europe, Asia and Australia, and asymmetric volatility effect was observed in all stock market indexes. They argued that the impact was stronger in the US and European

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stock indexes. Conditional variance models are widely used in the measurement of volatility on returns. ARCH model introduced by Engle (1982) showed that it is possible to model the conditional mean and variance of a series separately simultaneously. The Generalized ARCH (GARCH) model was developed by Bollerslev (1986) due to the difficulties experienced in making the prediction of the error term in the model and requiring the estimation of many parameters in ARCH models.

However, due to the fact that ARCH and GARCH models react symmetrically to shocks on volatility, wide distributional nature of financial data, in addition, their volatility changes over time and have an autocorrelated structure, sound results could no longer be obtained from researches based on these models. In order to overcome these problems, researchers have developed different variance models. To eliminate these problems, the EGARCH model was developed by Nelson (1991). It has been determined that the EGARCH model has a different effect on volatility in the face of positive and negative news relative to the GARCH model and is more sensitive to important news. Although the ARCH, GARCH and EGARCH models are useful in modeling the volatility cluster, they do not take into account the structural changes in the volatility process. To solve this problem and explain sudden changes in volatility, Inclan and Tiao (1994) developed the iterated cumulative sums of squares (ICSS) algorithm. Using the ICSS algorithm, Aggarwal et al. (1999), in their study on developed and emerging markets, found that local events such as the Mexican Peso Crisis, the hyper-inflation period in Latin America, and the stock market scandal in India coincided with the breaks detected. Again, in an emerging market context, studies by Kasman (2009), Todea and Petrescu (2012), Çağli et al. (2012) found that structural breaks coincided with local and political important events and the permanence decreased in the structural break volatility models. Ni et al. (2016) stated that government policies had a major impact on structural breakdown periods on the Chinese stock market indices, and that adding structural breaks to the model predicted permanence in volatility better. Tsuji (2018) conducted a similar study on the US and UK stock exchanges, and found that the permanence in both GARCH and E-GARCH with structural break model estimates is relatively reduced compared to models without taking into account structural breaks.

3. Econometric Model and Data

When estimating with financial time series, ignoring the characteristics of the series causes significant deviations in the model results. To circumvent this problem, Engle (1982) developed the autoregressive conditional heteroskedasticity (ARCH) model to model the volatility cluster in financial time series. Bollerslev (1986) added the conditional variance to the volatility model and brought the generalized autoregressive conditional heteroskedasticity (GARCH) model into the literature. The GARCH model developed by Bollerslev (1986) is expressed as follows:

$$\begin{gathered} r_t = \mu_t + \varepsilon_t , \\ \varepsilon_t \setminus (\varepsilon_{t-1}, \varepsilon_{t-2}, ..., r_{t-1}, r_{t-2}, ...) \sim GED(0, h_t) \\ h_t = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)h_t^2 \end{gathered} \tag{1}$$

In this equation, r_t shows return, μ_t is conditional mean of r_t, h_t volatility, L lag processor and is in the form $\omega > 0$, α_i, $\beta_i \geq 0$. In cases where the conditional error of the return series does not show a normal distribution, it can be assumed that the conditional error of the GARCH model shows a generalized error distribution (GED). In the GARCH model, the sum of α_i and β_i gives the permanence in volatility in the face of a shock. If the summation of α_i and β_i is equal to 1, then the GARCH model is called the integrated generalized autoregressive conditional heteroskedasticity (IGARCH) model.

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In order to model the leverage effect in stock returns in this study, the Exponential GARCH (EGARCH) model developed by Nelson (1991) is used. The mathematical representation of the EGARCH model is as follows:

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t , \\ \varepsilon_t \backslash (\varepsilon_{t-1}, \varepsilon_{t-2}, ..., r_{t-1}, r_{t-2}, ...) &\sim GED(0, h_t) \\ \ln h_t &= \omega + \alpha(L) \frac{\varepsilon_t}{\sqrt{h_t}} + \beta(L) \ln h_t + f \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| \end{aligned} \tag{2}$$

The EGARCH model has several advantages over the GARCH model. The first of these is that the conditional variance is modeled in log-linear form, the non-negative constraint on GARCH parameters disappears, and even if the estimated GARCH parameters are negative, the conditional variance is always positive since logarithmic transformation is made. Second, the use of standardized errors instead of the past value of the error term in the EGARCH model provides the opportunity to make a more natural explanation about the magnitude and permanence of the shock. Finally, in the EGARCH model, the asymmetry effect is measured by the f volatility parameter. If $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ in Equation (2) is positive, the effect of shock on conditional variance will be equal to the sum of $\alpha+f$, and if negative, it is equal to the sum of $-\alpha+ f$. In addition, if the predicted f parameter is statistically significant, then the presence of leverage effect is accepted (Enders, 2008).

In this study, the iterated cumulative sums of squares (ICSS) algorithm, which was introduced by Inclan and Tiao (1994) and developed by Sansó et al. (2004), was used to detect breaks in variance. Sansó et al. (2004) stated that the test statistic, which also takes into account the conditional variance situation, should be as follows:

$$K_2 = \sup_k \left| T^{-1/2} G_k \right| \tag{3}$$

where $G_k = \hat{\omega}_4^{-1/2} \left(C_k - \frac{k}{T} C_T \right), C_k = \sum_{t-1}^{k} r_t^2$ and shows the sum of cumulative squares for the r_t return series. $\hat{\omega}_4$, ω_4 is a consistent estimator of, and the ω_4 non-parametric estimator of is as follows:

$$\hat{\omega}_4 = \frac{1}{T} \sum_{t=1}^{T} (\alpha_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T} \sum_{l=1}^{m} \omega(1,m) \sum_{t=l+1}^{T} (\alpha_t^2 - \hat{\sigma}^2)(\alpha_t^2 - \hat{\sigma}^2) \tag{4}$$

where $\omega(1,m)$ is a lag interval like Barlett and $\omega(1,m) = 1 - l/(m+1)$ is defined as its shape or quadratic spectral. This estimator m is based on the choice of bandwidth. Sansó et al. (2004) suggested using the bandwidth method developed by Newey and West (1994). Thus, K_2 statistics give more sensitive results compared to the distribution feature of the series and showing conditional variance.

The study covers the period of January 2003–November 2019. Volatility modeling was carried out on stock market indices of 12 developing countries, which were included in the fragile fives classification by different investment institutions. The countries included in the study and the selected indices are presented in Table 1.

Table 1: Fragile five country classifications of investment institutions

Morgan Stanley Classification (2013)	*Morgan Stanley Classification (2016)*	*Standard&Poors Classification (2017)*	*Danske Bank Classification (2018)*
Turkey (BIST 100)	Turkey (BIST 100)	Turkey (BIST 100)	Turkey (BIST 100)
Brazil (BOVESPA)	Mexico (IPC)	Pakistan (KARACHI)	Brazil (BOVESPA)
Indonesia (IDX)	Indonesia (IDX)	Argentina (MERVAL)	Argentina (MERVAL)
India (NIFTY 50)	Colombia (COLCAB)	Egypt (EGX 30)	Russia (MOEX)
South Africa (JSE)	South Africa (JSE)	Katar (DOHA)	South Africa (JSE)

In this study, daily market prices of stock market indexes were used. The return series of the mentioned variables were created with the formula $r_t = \ln(p_t / p_{t-1})x100$ and return series were used in the estimation of volatility models. The data used in the study were obtained from the Matrix Data Terminal program. Matrix Data Terminal is a capital market data monitoring and processing platforms for the financial markets in Turkey. It brings together in a single program the ability to monitor, analyze and process data. Eviews 10 and Gauss 10 programs were used in the analysis of the data.

4. Empirical Results

In this study, firstly, the presence of autocorrelation in the data was investigated to establish the volatility model related to the country indices, and the ARMA processes was estimated on the series to remove any linear dependency. Estimated ARMA models for the index to be compared are as follows: ARMA (5,3) for Turkey, ARMA (5.5) for the Brazilian index, ARMA (5,2) for Indonesia, ARMA (1,1) in the case of South Africa, ARMA (4 , 4) for India, ARMA (4.2) for Mexico, ARMA (2.4) for Colombia, ARMA (5.5) for Argentina, ARMA (3.2) for Pakistan, ARMA (5.2) for Egypt, for Qatar it was calculated as ARMA (2,5) and for Russia as ARMA (4,5).

Descriptive statistics of index returns are given in Table 2. Analysis of the results shown in the table shows that the average returns of all indices except Mexico and Colombia are positive. The indices with the highest daily average return are Argentina (0.14%), Egypt (0.053%) and Pakistan (0.047%). Again a look at index standard deviations depicts that country index with the highest volatility is Argentina (2.52%), followed by Turkey (1.40%) and then Brazil (1.40%). The index with the lowest standard deviation is the Colombian index (0.842). When the kurtosis and skewness values of the return series are analyzed, it is seen that the series differ significantly from the normal distribution. In parallel with this result, the return series are normally distributed according to the Jarque-Bera (JB) test, which measures whether the distribution of the return series conform to the normal distribution. When Box-Pierce Q statistics, which measure the presence of autocorrelation in the mean and variance of the return series, are examined, it is concluded that there is no autocorrelation in the average and variance of the return series. In addition, the ARCH LM test shows that the return series exhibit conditional variance heteroskedasticity features. Finally, ADF and KPSS unit root tests were conducted to determine whether the return series are stationary or not and the result of two unit root tests reveal stationarity.

Table 2: Descriptive statistics of index returns

Summary statistics	*Turkey (BIST 100)*	*Brazil (BOVESPA)*	*Indonesia (IDX Comp.)*	*South Africa (JSE)*	*India (NIFTY 50)*	*Mexico (BMV IPC)*
Observations	1734	1737	1690	1725	1703	1735
Mean	0.017	0.031	0.019	0.019	0.041	-0.001
Std. Dev.	1.401	1.401	0.950	1.008	0.900	0.867
Skewness	-0.547	-0.101	-0.416	-0.180	-0.199	-0.371
Kurtosis	7.104	4.808	6.292	4.348	6.032	6.148
Jarque-Bera (*p*-value)	1303.6***	239.8***	811.9***	140.1***	663.8***	756.6***
Q(40)	27.364 (0.70)	26.897(0.62)	46.029(0.06)	39.178(0.41)	32.442(0.44)	38.025(0.29)
LM(5)	9.6***	5.4***	28.8***	10.4***	7.6***	21.8***
ADF	-42.3***	-42.1***	-26.1***	-42.7***	-37.8***	-37.8***
KPSS	0.05***	0.30***	0.04***	0.06***	0.03***	0.05***
Summary statistics	*Colombia (COLCAP)*	*Argentine (MERVAL)*	*Pakistan (Karachi100)*	*Egypt (EGX30)*	*Qatar (DOHA)*	*Russia (MOEX)*
Observations	1682	1685	1708	1681	1718	1737
Mean	-0.008	0.144	0.047	0.053	0.011	0.039
Std. Dev.	0.842	2.521	0.986	1.305	1.034	1.086
Skewness	-0.217	-4.242	-0.290	-0.182	-0.315	-0.839
Kurtosis	5.513	80.441	5.119	6.261	11.198	13.194
Jarque-Bera (*p*-value)	455.9 ***	426103***	343.6***	754.3 ***	4840.2***	7725.5***
Q(40)	29.934(0.66)	25.057(0.72)	28.694(0.76)	31.656(0.53)	37.700(0.26)	32.444(0.39)
LM(5)	35.1***	5.0**	22.3***	26.7***	28.3***	11.4***
ADF	-35.2***	-42.3***	-34.9***	32.9***	-37.5***	-41.4***
KPSS	0.21***	0.14***	0.03***	0.08***	0.10***	0.01***

NB: Returns are defined as 100 times the log-differences of the stock price indices.The JB statistic refers to the Jarque-Bera normality test in which the null hypothesis is established that the series are normally distributed. Q(.) statistic refers to the Box-Pierce autocorrelation test for different lag values where the null hypothesis is setup that all autocorrelation coefficients are equal to zero. The LM(.) statistic refers to the ARCH test for different lag values where the null hypothesis is set to be conditionally varying variance. *** shows that the series are stationary at 1% significance level.

In the second stage of the study, the volatility of the Fragile Five country indexes was estimated by GARCH and EGARCH models. The model was created with Generalized Error Distribution (GED), taking into account the maximum likelihood function.

When the volatility estimates calculated using the GARCH (1,1) model as presented in Table 3 are examined, it is observed that all the models established have no problems with autocorrelation and all models except that for Argentina have no ARCH effect. In addition, all of the GED parameters expressed in v in the table are less than 2, and it is determined that the models show normal distribution. It was observed that ARCH (α) and GARCH (β) coefficients were significant in all models. The sum of the ARCH and GARCH coefficients in the models ($\alpha + \beta$) shows the permanence effect of the shocks on returns, and the permanence effect in the models is high in all country indices ($\alpha + \beta$ >0,933) except Egypt (0.884).

Table 3: Estimation results for GARCH (1,1) models

GARCH	*Turkey (BIST 100)*	*Brazil (BOVESPA)*	*Indonesia (IDX Comp.)*	*South Africa (JSE)*	*India (NIFTY 50)*	*Mexico (BMV IPC)*
μ	0.068**	0.043	0.064***	0.042**	0.067***	0.014
ω	0.061**	0.055***	0.014***	0.025***	0.020**	0.027***
α	0.047***	0.045***	0.067***	0.077***	0.064***	0.091***
β	0.920***	0.926***	0.915***	0.899***	0.910***	0.872***
v	1.309***	1.461***	1.307***	1.554***	1.347***	1.511***
Q(40)	31.765[0.47]	32.789[0.33]	35.078[0.37]	48.057[0.12]	32.910[0.42]	33.513[0.49]
$Q_s(40)$	35.328[0.68]	28.376[0.91]	26.704[0.94]	38.183[0.55]	19.395[0.99]	34.582[0.71]
LM(5)	2.146[0.06]	0.422[0.83]	0.768[0.57]	0.419[0.83]	0.343[0.88]	1.262[0.27]
Ln(L)	-2927.3	-2959.4	-2094.5	-2352.3	-2103.6	-2073.0
AIC	3.401	3.434	2.500	2.743	2.493	2.409
SIC	3.442	3.481	2.539	2.765	2.534	2.443
GARCH	*Colombia (COLCAP)*	*Argentine (MERVAL)*	*Pakistan (Karachi100)*	*Egypt (EGX30)*	*Qatar (DOHA)*	*Russia (MOEX)*
μ	0.012	0.222***	0.072***	0.083***	0.021	0.042***
ω	0.034***	0.445***	0.058***	0.188***	0.067***	0.032***
α	0.151***	0.224***	0.143***	0.169***	0.146***	0.058***
β	0.805***	0.714***	0.800***	0.715***	0.787***	0.913***
v	1.357***	1.228***	1.328***	1.318***	1.133***	1.276***
Q(40)	23.287[0.91]	21.419[0.87]	39.955[0.25]	47.694[0.05]	44.484[0.09]	23.923[0.81]
$Q_s(40)$	27.520[0.93]	32.435[0.79]	32.057[0.81]	38.395[0.51]	13.382[0.99]	6.178[1.00]
LM(5)	0.288[0.91]	3.747[0.00]	0.711[0.61]	1.718[0.12]	0.543[0.74]	0.084[0.99]
Ln(L)	-1895.7	-3587.6	-2222.0	-2631.8	-2189.2	-2434.9
AIC	2.274	4.288	2.621	3.154	2.570	2.827
SIC	2.309	4.337	2.653	3.193	2.608	2.871

Note: signs and abbreviations presented in the table are explained as follows. μ*;* constant term for the mean equation; ω; constant term for the conditional variance equation; α ; ARCH coefficient; β*;* GARCH coefficient, *f;* asymmetric volatility and leverage effect, v; shows the generalized error distribution (GED) parameter estimate, the Box-Pierce autocorrelation test for the Q(40) ve $Q_s(40)$ error terms and the square of the error terms, and the LM(5) shows conditionally variance test. Ln(L) shows log-Likelihood values. The ***, ** and * marks represent statistically significant predictive values at the significance level of 1%, 5% and 10%, respectively.

When the volatility estimates calculated using the E-GARCH (1,1) model in Table 4 are examined, it is observed that all the models established have no autocorrelation problems and no ARCH effect exists in all models except Argentina at 1% significance level. In addition, all of the GED parameters expressed in v in the table are less than 2, and it is determined that the models depict normal distribution. Estimation results reveals that both ARCH (α) and GARCH (β) coefficients were significant in all models. The *f* coefficient representing the leverage effect is statistically significant in all models except in models for Argentina and indicate that positive and negative shocks on volatility are asymmetrical. In addition, the fact that the *f* coefficient is negative in all models except for Argentina shows that there is a leverage effect, that is, negative shocks experienced in the stock markets of these countries cause more volatility than positive shocks. Among the fragile five-country stock market indices, the most strong indices are Pakistan (-0.178), Qatar (-0.135), South Africa (-0.126) and India (-0.125), while the weakest is Russia (-0.049). When the AIC and SIC information criteria of GARCH and EGARCH models are analyzed, the log-Likelihood values expressed with Ln(L) are examined, the results are consistent with other studies in the literature, and the explanatory power of the EGARCH model is found to be better than the GARCH model.

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Table 4: Estimation results for E-GARCH (1,1) models

E-GARCH	*Turkey (BIST 100)*	*Brazil (BOVESPA)*	*Indonesia (IDX Comp.)*	*South Africa (JSE)*	*India (NIFTY 50)*	*Mexico (BMV IPC)*
μ	0.045	0.024	0.055***	0.009	0.048**	-0.001
ω	-0.038**	-0.049***	-0.101***	-0.066***	-0.089***	-0.080***
α	0.078***	0.094***	0.124***	0.081***	0.099***	0.087***
β	0.961***	0.963***	0.979***	0.971***	0.964***	0.970***
f	-0.083***	-0.060***	-0.053***	-0.126***	-0.125***	-0.094***
v	1.345***	1.450***	1.306***	1.650***	1.430***	1.551***
Q(40)	30.378[0.54]	33.927[0.28]	32.552[0.49]	45.223[0.19]	36.831[0.25]	31.887[0.57]
$Q_s(40)$	39.164[0.50]	28.907[0.90]	28.156[0.92]	34.876[0.70]	27.372[0.93]	38.586[0.53]
LM(5)	2.236[0.05]	0.522[0.75]	0.520[0.76]	0.290[0.91]	0.569[0.72]	2.062[0.07]
Ln(L)	-2914.9	-2956.1	-2088.0	-2325.1	-2081.2	-2057.9
AIC	3.388	3.432	2.493	2.712	2.467	2.393
SIC	3.432	3.482	2.535	2.738	2.512	2.430
E-GARCH	*Colombia (COLCAP)*	*Argentine (MERVAL)*	*Pakistan (Karachi100)*	*Egypt (EGX30)*	*Qatar (DOHA)*	*Russia (MOEX)*
μ	0.003	0.205***	0.035	0.066**	-0.001	0.042***
ω	-0.234***	-0.158***	-0.200***	-0.181***	-0.184***	-0.105***
α	0.258***	0.491***	0.236***	0.287***	0.228***	0.139***
β	0.929***	0.862***	0.920***	0.896***	0.929***	0.961***
f	-0.094***	-0.029	-0.178***	-0.083***	-0.135***	-0.049***
v	1.398***	1.242***	1.482***	1.327***	1.194***	1.318***
Q(40)	21.513[0.95]	20.644[0.89]	39.832[0.26]	48.130[0.04]	45.220[0.07]	25.290[0.75]
$Q_s(40)$	24.423[0.97]	35.332[0.68]	45.876[0.24]	42.744[0.35]	16.191[1.00]	9.352[1.00]
LM(5)	0.260[0.93]	3.685[0.002]	1.593[0.15]	2.489[0.03]	0.416[0.83]	0.139[0.98]
Ln(L)	-1891.3	-3584.6	-2184.6	-2628.0	-2171.9	-2426.9
AIC	2.269	4.286	2.578	3.151	2.550	2.819
SIC	2.308	4.338	2.613	3.193	2.592	2.867

Note: signs and abbreviations presented in the table are explained as follows. μ; constant term for the mean equation; ω*;* constant term for the conditional variance equation; α ARCH coefficient; β GARCH coefficient, *f;* asymmetric volatility and leverage effect, v; shows the generalized error distribution (GED) parameter estimate, the Box-Pierce autocorrelation test for the Q (40) and Qs (40) error terms and the square of the error terms, and the LM (5) conditionally variance test. Ln(L) shows log-Likelihood values. The ***, ** and * marks represent statistically significant predictive values at the significance level of 1%, 5% and 10%, respectively.

Since volatility models do not take into account structural breaks, the permanence parameter can be high in the model estimations. To reduce this effect, the iteration algorithm (ICSS) developed by Inclan and Tiao (1994) and as updated by Sansó et al. (2004) was used. The breaks detected in the Fragile Five Country indices following the execution of the algorithm are as shown in Table 5.

When Table 5 is examined, it could be seen that the market with the most breaks is the Colombian market with 3 breaks. Also, the Brazilian, Indonesian and Indian markets experienced 2 breaks. A single structural break was detected in the market index of Turkey, Pakistan, Egypt. No structural breaks were detected in the market indexes of Russia, South Africa, Mexico, Argentina and Qatar. In Chart 1, volatility series covering structural break periods of stock market indices where structural breaks are detected are shown. When the volatility levels in the dates of Table 5 and Chart 1 are analyzed, the effects of local events in the country in the said periods are observed. When the volatility graphs and structural break dates in the country indexes are analyzed, we can evaluate the exchanges in three categories based on volatility behavior. First, Indonesia, Turkey and India are observed to exhibit similar structural break points in market indexes. Along with the bond purchase tender implemented by the FED, the uncertainty due to the elections that were held in these countries in 2014 made their market riskier. Of course, local events experienced during this period also increased the risk levels. Gezi Park Events (27 May-16 June 2013) that started in mid-2013 up to March 2014 against the incumbent government in Turkey and the Judicial Coup Attempts (17 to 25 December 2013) events before the local elections made the Turkish stock market fragile. From 30th March 2014, uncertainty in the markets decreased as the sitting government won the elections. On the other hand, the increase in oil prices in the middle of 2018 followed by the depreciation in the value of the country's currency together with the trade sanctions betweenthe US and China caused the Indian stock market to be highly volatile.

Table 5: Structural breaks in variance test results

Countries (Index)	*Number of break(s)*	*Date of break*		
Turkey (BIST 100)	1	28.03.2014		
Brazil (BOVESPA)	2	24.09.2014	29.06.2016	
Indonesia (IDX Comp.)	2	5.06.2013	24.09.2013	
South Africa (JSE)	0			
India (NIFTY 50)	2	28.05.2013	07.09.2018	
Mexico (BMV IPC)	0			
Colombia (COLCAP)	3	25.11.2014	10.05.2016	15.01.2018
Argentine (MERVAL)	0			
Pakistan (KARACHI 100)	1	18.04.2017		
Egypt (EGX30)	1	05.03.2017		
Qatar (DOHA)	0			
Russia (MOEX)	1	24.02.2016		

While the effects of these events continued during this period, some of the subsidiaries of India’s leading infrastructure development and financial services company, Infrastructure Leasing & Financial Services Limited (IL&FS), faced the risk of default by mid-2018 due to the failure to meet multiple debt obligations. The liquidity risk of this company, whose market value is greater than 10% of the banking sector, caused a great panic in the Indian debt market and had a negative impact on the non-banking finance companies and other businesses operating in the financial sector. Ultimately, the Indian government stepped in quickly to save the company by taking over the company (Roy, 2019).

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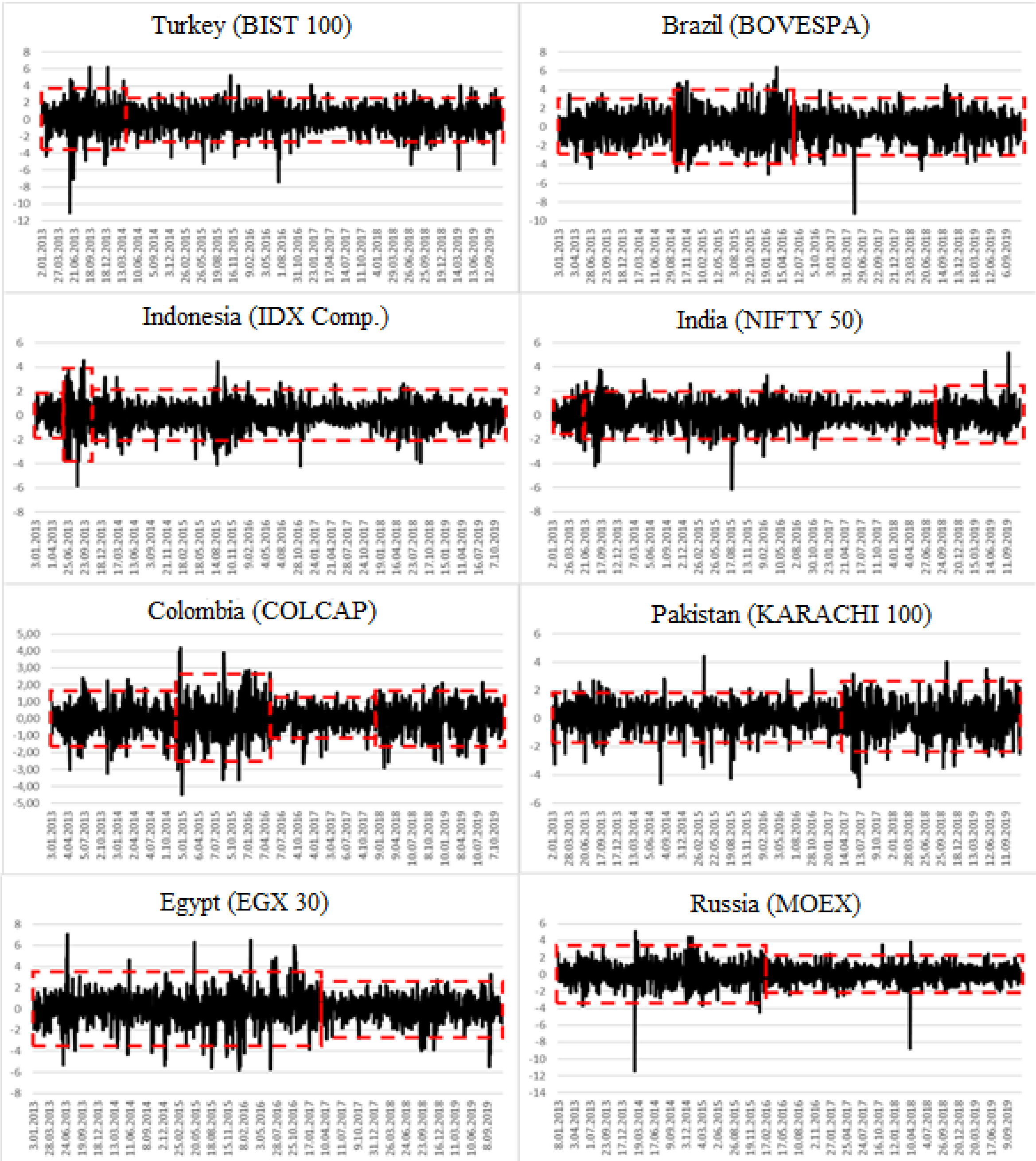

Figure 1: Breaking periods in the return series

The breaks in Colombia, Russia, Brazil and Egypt are identical. The common feature of these countries is that they are seriously affected by the oil crisis that spanned the period from 2014-2016, as they are oil exporting countries. The near 50% decrease in oil prices after the second half of 2014 caused significant destruction in the economies of oil exporting countries. In addition to the oil crisis, the political tensions in Brazil between 2014 and 2016 were effective in causing volatility increase in the Brazilian stock market index. Analysis of the volatility of returns in Pakistan stock market index shows that volatility increased in the second half of 2017. This situation shows the period of dismissal of the Pakistani prime minister due to the allegations of corruption in the country. In addition, terrorist incidents experienced in 2017 increased the political risk in the country.

The volatility of the Fragile Five Country indices has been re-estimated using the GARCH and EGARCH models, taking into account the effect of structural breaks. The model was created with Generalized Error Distribution (GED) and taking into account the maximum likelihood function. While predicting models with structural breaks, dummy variables were created for structural break periods. Dummy variables in the models are shown with the parameter Y_i. In order to avoid falling into the dummy variable trap, the first break period was not included in the model. Estimated models output as presented in Table 6 demonstrates that all of the established models do not have autocorrelation problems and ARCH effect does not remain in all models. In addition, all of the GED parameters expressed in v in the table are less than 2 and it has been found to be statistically significant at 1% significance level. The ARCH (α) parameter which shows the effect of short-term shocks on index returns in structural break-down GARCH models presented in Table 6 was statistically significant in all countries studied. The impact of shocks on volatility in Egypt (0.163), Colombia (0.157) and Pakistan (0.142) were shown to be higher than the other countries. When the total ($\alpha + \beta$) of the ARCH and GARCH coefficients showing the permanence effect in the shocks is analyzed, it is seen that the shocks have a high permanence effect, but when the structural breakage is not included, the permanence effect decreases as seen in Table 3 above.

The indices with the highest volatility persistence are India (0.975) and Indonesia (0.962), while the lowest index is Egypt (0.827). When Y_i coefficients showing structural break periods are analyzed, Y_1 and Y_2 parameters of Brazil and India and Indonesia Y_2, Colombia Y_3 parameters were found to be statistically insignificant. Structural break parameters of other models are statistically significant. When the first break period before the reference period as the accepted model results are analyzed, Egypt (-0.154), Turkey (-0.098) and Russia (-0.045) decrease compared to the reference period in the stock index volatility, Indonesia (0.165), Colombia (0.097) and Pakistan (an increase was observed in 0.086).

When the results of E-GARCH model with structural break were examined, it was observed that the coefficient f representing the leverage effect with the ARCH (α) and GARCH (β) coefficients was statistically significant in all models. It is observed that the β coefficient showing the permanence on volatility is higher in Indonesia (0.978) and India (0.966). In the case where the f coefficient representing the leverage effect in all models is found to be statistical significance indicates that the positive and negative shocks on volatility are asymmetric, and negative f coefficient depicts the presence of leverage effect, that is, the negative shocks experienced in this country's stock exchanges cause more volatility than positive shocks. In this context, it was determined that the leverage effect in indices was higher in Pakistan (-0.182) and India (-0.123). When the Y_i coefficients showing the breaking periods are analyzed, similar results were observed with the GARCH model outputs. When the AIC and SIC information criteria of the GARCH and EGARCH models with structural breaks, the log-Likelihood values expressed in Ln(L) were examined, the EGARCH model's explanatory power was found to be better than the GARCH model. In addition, when estimated results from the models with structural breaks and models without structural breaks were compared, it was observed to be consistent with the results found in the literature.

Table 6: Estimation results for structural break using GARCH and E-GARCH models

GARCH	*Turkey (BIST 100)*	*Brazil (BOVESPA)*	*Indonesia (IDX Comp.)*	*India (NIFTY 50)*	*Colombia (COLCAP)*	*Pakistan (Karachi100)*	*Egypt (EGX30)*	*Russia (MOEX)*
μ	0.068**	0.045	0.054***	0.066***	0.018	0.075***	0.079***	0.042***
ω	0.211**	0.087**	0.037*	0.028**	0.070***	0.075***	0.335***	0.091***
α	0.051***	0.042***	0.080***	0.058***	0.157***	0.142***	0.163***	0.054***
β	0.880***	0.907***	0.882***	0.917***	0.714***	0.749***	0.664***	0.886***
Y_1	-0.098**	0.054	0.165*	-0.010	0.097**	0.086***	-0.154***	-0.045***
Y_2		-0.006	-0.010	-0.003	-0.022*			
Y_3					0.024			
v	1.332***	1.469***	1.302***	1.344***	1.363***	1.342***	1.341***	1.309***
$Q(40)$	32.051[0.46]	32.263[0.35]	37.543[0.26]	32.031[0.46]	21.119[0.95]	39.031[0.29]	45.585[0.07]	26.251[0.70]
$Q_s(40)$	37.853[0.56]	28.308[0.91]	30.317[0.86]	22.836[0.98]	25.085[0.96]	33.055[0.77]	36.965[0.60]	8.653[1.00]
$LM(5)$	1.732[0.12]	0.318[0.90]	0.598[0.70]	0.269[0.93]	0.251[0.94]	1.055[0.383]	2.175[0.05]	0.139[0.98]
$Ln(L)$	-2.922.6	-2958.0	-2093.0	-2103.2	-1892.2	-2213.3	-2622.8	-2425.0
AIC	3.396	3.435	2.500	2.494	2.273	2.612	3.145	2.817
SIC	3.441	3.488	2.546	2.543	2.318	2.642	3.187	2.864
E-GARCH	*Turkey (BIST 100)*	*Brazil (BOVESPA)*	*Indonesia (IDX Comp.)*	*India (NIFTY 50)*	*Colombia (COLCAP)*	*Pakistan (Karachi100)*	*Egypt (EGX30)*	*Russia (MOEX)*
μ	0.046*	0.023	0.054***	0.051***	0.005	0.049**	0.071**	0.044***
ω	0.030	-0.039	-0.051**	-0.068***	-0.280***	-0.238***	-0.120***	-0.068***
α	0.072**	0.097***	0.094***	0.094***	0.253***	0.240***	0.271***	0.122***
β	0.918***	0.923***	0.978***	0.966***	0.871***	0.885***	0.856***	0.939***
f	-0.100***	-0.080***	-0.058***	-0.123***	-0.101***	-0.182***	-0.097***	-0.0540***
Y_1	-0.050***	0.042**	-0.0003	-0.018	0.098**	0.065**	-0.097***	-0.043***
Y_2		-0.0006	-0.031**	-0.021	-0.054*			
Y_3					0.029			
v	1.371***	1.486***	1.314***	1.439***	1.416***	1.488***	1.361***	1.348***
$Q(40)$	29.928[0.57]	28.675[0.53]	33.343[0.45]	36.861[0.25]	20.955[0.96]	41.577[0.20]	45.975[0.06]	25.677[0.73]
$Q_s(40)$	35.844[0.65]	30.533[0.86]	34.825[0.70]	25.459[0.96]	25.032[0.96]	43.771[0.31]	42.251[0.37]	10.469[1.00]
$LM(5)$	1.500[0.18]	0.442[0.81]	0.456[0.80]	0.486[0.78]	0.242[0.94]	1.612[0.15]	2.680[0.02]	0.231[0.94]
$Ln(L)$	-2911.7	-2946.3	-2082.6	-2080.3	-1880.4	-2180.5	-2618.4	-2418.4
AIC	3.385	3.422	2.489	2.469	2.260	2.574	3.141	2.811
SIC	3.432	3.479	2.538	2.520	2.308	2.613	3.186	2.861

Note: signs and abbreviations presented in the table are explained as follows. μ ; constant term for the mean equation; ω ; constant term for the conditional variance equation; α ; ARCH coefficient; β ; GARCH coefficient, *f;* asymmetric volatility and leverage effect, Y_i coefficients of dummy variables created for structural breaks, ν; The generalized error distribution (GED) shows the parameter estimate, the Box-Pierce autocorrelation test for the Q(40) and $Q_s(40)$ error terms and the square of the error terms, and the LM(5) conditionally variance test. Ln(L) shows log-Likelihood values. ***, **, and * marks represent statistically significant predictive values at 1%, 5% and 10% significance levels, respectively.

5. Conclusion

Increased capital flows from developed markets to emerging markets with financial liberalization caused fragility in developing country markets. Economic, political etc adverse events experienced in these countries caused shocks in their markets, and the increase in the severity of these shocks dragged the countries into economic crises. Of course, the shocks that can be experienced in the financial system of countries are common regardless of developed or underdeveloped countries, however, the degree of the reaction to the shocks by the market players causes fragility in the relevant markets. As a result, high volatility was observed in asset prices, which made the markets more prone to speculative transactions. Investors want to make a profit from emerging markets, where returns are high, and they are hesitant to avoid long-term investments in the same markets, where uncertainty is high. In such cases, the permanence level of shocks experienced in a particular market and the impact of negative news on the markets are variables that affect investors investment decisions. In this study, the existence of permanence and asymmetry effect in volatility on the fragile five country stock exchange indices, the effects of structural breaks on volatility permanence and asymmetry were investigated. GARCH and EGARCH models were used for volatility estimates in the study. In addition, the models were tested individually with and without taking into account structural breaks and the predictive powers of the models were also tested. The data set of the study covers the indicator stock indexes of 12 developing countries classified as fragile fives countries by different investment institutions between 2013-2018. Daily data covering the period January 2013-November 2019 were used in the study.

According to the empirical results from the study, volatility models in which structural breaks were not included depicts that the permanence effect is high in Indonesia and India, however, it is relatively lower in Argentina and Egypt. In addition, asymmetric volatility and leverage effect was observed in all country indices except Argentina. While where the response to negative shocks are strongest the indices of Pakistan, Qatar, South Africa and India, the response in Russia is lower. No structural breaks were observed in South Africa, Mexico, Argentina and Qatar exchanges during the period considered in study. When the volatility models with structural breaks are examined, it is seen that volatility is high in all countries in the Fragile Five Category, especially in Indonesia and India. However, following the structural break model predictions, we can say that the vulnerable groups of five in terms of persistence of volatility in index are Indonesia, India, Brazil, Russia and Turkey. In addition, it is observed that the effect of positive and negative news on volatility in all country indices is asymmetric, and negative shocks are more effective on volatility than positive shocks. These results coincides with the findings by Baur and Dimpfl (2018) and Horpestad et al. (2019). Moreover, the study also provides evidence of the predictive performance of volatility models. According to the results of the study, it is seen that the structural break periods overlap with the local and political events in the country concerned and support results from studies by Aggarwal et al. (1999), Kasman (2009) and Çağli et al. (2012). Again, models with structural breaks have better predictive powers, and incorporating structural breaks into models reduces the permanence in volatility relatively, and this result is in line with results obtained by Todea and Petrescu (2012), Ni et al. (2016) and Tsuji (2018). Additionally, in all volatility models established in the study, EGARCH models are compared with GARCH models following the claim that EGARCH models have better predictive power. The reason for this claim is due to the asymmetric properties and leverage effect as put forward by Black (1976).

The results of this study show that although the study covers the same period, the shocks experienced in the various countries are not of similar characteristics. While the impact of volatility fluctuations was based on local and political shock in some economies (Turkey, Brazil, India, Pakistan), it is observed that in some economies oil crisis, global shocks like the

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Fed decisions were more effective impact of volatility fluctuations. For these reasons, the study provides information to individual and corporate portfolio investors who plan to invest in international markets about the duration of shocks and recovery periods. Investors can diversify their portfolios according to the volatility characteristics of the country exchanges and determine strategic plans to be applied during shocks. Portfolio insurance can be used as an alternative strategy, especially during periods of high volatility. Despite their similarities, there are significant differences between regime-switching models and structural break models. Structural breaks do not allow for the behavior about mean and volatility in previous period, whereas regime-switching is applicable for structural change. Along these lines, further studies, that may perform markov regime switching model (MR-GARCH) and structural break models, simultaneously for volatility estimation of fragile five countries, may contribute to the existing literature. The significant impact of COVID-19 pandemic on further policies should be also considered in future studies as stock market volatility and market breaks might be impacted (Karabag, 2020) due to COVID-19 (market volatility might possibly increase in several countries) pandemic or this new normal.

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