Journal of Applied Economics and Business Research
JAEBR, 11(2): 80-89 (2021)

Cross-Country Analysis of the Impact of Covid-19 on Share Markets

Rahman Aydın[1]
Atatürk University, Turkey, email: rahman.aydin@atauni.edu.tr

Serhat Alpagut
Ağri İbrahim Çeçen University, Turkey

İbrahim Halil Polat
Hakkari University, Turkey

Anıl Lögün
Atatürk University, Turkey

Abstract
The negative effects on the macroeconomic indicators of the countries during the pandemic process that started with the Covid 19 epidemic made it necessary for individuals, investors, institutions, and governments to create a new policy. To determine the right policies, the effects of Covid 19 on the country's economy have been the subject of research by scientists. This study, it is aimed to investigate the effect of the pandemic on the stock market together with its sub-sectors. For this reason, in this study, the volatility of BIST100, known as the Turkish Stock Exchange, and its sub-indices, finance, service, and industry indices during the pandemic process were investigated. Working day data obtained from the Central Bank of the Republic of Turkey between 1/02/2020 - 10/11/2020 periods were used in the study. First, logarithmic transformation of the data was provided. Then, it was converted into a return series and included in the analysis.In order to obtain a consistent estimate, the series should not contain unit-roots. For this purpose, using the ADF unit root test, it was investigated whether the series contain unit root or not. According to the findings obtained from the study, it was determined that the most suitable variance model for BIST100 and Industrial indexes was the GARCH (1,1) model. It was found that the most suitable variance model in financial and services indices was the TARCH (1,1) model. In addition, while it is estimated that there is symmetrical volatility in BIST100 and Industrial indices, it is concluded that there are asymmetric and leverage effects in financial and services indices.

Keywords: Stock Market, Pandemia, GARCH, TARCH

JEL Classification: C58, E44, F65, I19

1.Introduction

A disease similar to pneumonia cases started to appear in Wuhan City, Hubei Province, in China in December 2019 (Atalan, 2020). With the emergence of these cases, the high rate of spread among people and the rapid increase in the number of cases from day to day have created a

[1] Correspondence to Rahman Aydın, E-mail: rahman.aydin@atauni.edu.tr

ripple effect in all areas of human life and have shown a compelling effect on current global health systems (Nicola et al., 2020). Due to the epidemic declared as a global emergency by the World Health Organization on January 30, 2020, many restrictive measures were implemented by governments, and the economic effects of the epidemic began to be seen (Zhu et al., 2020). For example, measures that lead to changes in the consumption and investment levels in the society, such as travel restrictions and bans to leave the house within the scope of pandemic measures, have caused changes in the total demand and total supply levels the national economies. Therefore, these changes have created negative effects on countries' economies both on macro and micro levels. So much so that the Covid-19 epidemic is estimated to have caused an economic loss of more than 280 billion dollars to the world economy (Ayittey et al., 2020). The demand shock caused by the restrictions imposed because of the epidemic decreasing the expenditures in transportation, tourism, and foreign trade sectors in all economies is increasing gradually, and the consequences of this affect all economies. Increasing demand shocks affect production levels and cause supply shocks. In addition, in an environment of concern arising from uncertainties, financial investors are The inability to make a decision, and the possibility of financial shocks have raised the expectations of recession in the economies (Fernandes, 2020). Within the scope of the mentioned uncertainties; Some countries have implemented expansionary monetary policies to overcome the bottleneck in production due to reduced labor demand and expansionary fiscal policies to increase aggregate demand. Japan announced that it entered recession in May 2020. Japanese Prime Minister Shinzo Abe stood out as the largest support package globally with $ 2.2 trillion, doubling the total support with $ 1.1 trillion in April 2020 and $ 1.1 trillion on May 27, 2020. US President Donald Trump approved the largest economic stimulus package in US history of $ 2 trillion in late March 2020, and at the beginning of May 2020, the US Treasury announced that it plans to borrow 3 trillion dollars in the second quarter of the year within the scope of the economy packages announced after the Covid-19 virus outbreak. Germany 750 billion euros, England 350 billion sterling, France 110 billion euros, India 265 billion dollars and Turkey for 100 billion support package for prevention of declining growth and reducing unemployment assistance for the payment of credit support and wages for companies and a grant has been submitted (BBC, 2020). In addition, during the pandemic process, it was thought that this process could be overcome more easily with the monetary expansion policies of the central banks, which are planning to go through a difficult period by providing easy access to financing, companies not having difficulties in loan payments and expansion in the monetary base. The European Central Bank has stated that it will implement a monetary policy against the external shock to protect the functioning of the market in combating the Covid-19 epidemic. European Central Bank announced a support package of 870 Billion Euros within Pandemic Emergency Purchase Program scope. It also emphasized that it could expand the scope of asset purchases and put 3 Trillion-euro funding sources into use for financing transactions. (Cavallino and Fiore, 2020).

The first effects of the Covid-19 outbreak on financial markets began with the negative impact of the China Shanghai Composite Index, Hong Kong Hang Seng Index, and South Korea KOSPI Index in Asian markets after the virus's emergence. As of March 2020, since its inception in 1987, the US stock exchange has witnessed a significant drop for the second time after the drop in 1997. With the USA's negative impact, Europe and Asia's stock markets were also adversely affected. The UK's main index FTSE fell more than 10% on March 12, 2020. In Japan, the stock market decreased by more than 20% compared to its highest position in December 2019 (Nicola et al., 2020). On February 19, 2020, the S&P 500 and S&P Europe 350 indices were also at their all-time highs, while only 30 days later, both indices lost more than a third of their value. A single-day decrease of 12% was experienced in mid-March 2020 (Heyden, J. and Heyden, T. 2020). Within the scope of combating the adversities experienced, central banks and governments aimed to weaken negative situation's effects by introducing monetary policy instruments to the market in this process. For example, on March 15, 2020, the

 ISSN 1927-033X

Federal Reserve (FED) announced a zero percent interest policy and a mitigation (QE) program of at least $ 700 billion. The S&P 500, the Dow Jones Industrial Average, and Nasdaq, a stock market index that measures 500 large companies' stock performance on the US stock market depreciated significantly until the US government announced the Covid-19 aid package. Following the aid, these indices increased by 7.3%, 7.73%, and 7.33%, respectively. Apart from this, the same situation was observed in other indices. Increases were seen in the Shanghai Composite Index, the Hong Kong Hang Seng Index and the South Korea KOSPI Index, and the Japanese Nikkei indexes after the aid. In addition, although Germany's DAX, Britain's FTSE 100, and Euro Stoxx 50 fell until March, a significant improvement was observed after the EU's bailout package was accepted. Although many stock exchanges have started to recover recently, there is still great uncertainty in these markets as the pandemic continues (Zhang et al., 2020, p.1).

2.Literature Review

The relationship between the volatility created by the pandemic in the financial markets and the stock returns, the unexpected increase in the pandemic cases has been stated to negatively affect 4% to 11% on the US stock movements. (Alfaro et al., 2020). In addition, when all the shares of both the Hang Seng Index and the Shanghai Stock Exchange Composite Index are examined, it is seen that this epidemic had a negative impact on stock returns (Al-Awadhi et al., 2020), and the impact on Japanese stock returns compared to the pre-Covid-19 period. Was stronger in the Covid-19 era (Narayan et al., 2020), where stock returns in Chinese markets, which were already contracting before Covid-19, worsened with the pandemic (Liu et al., 2020; Liu et al., 2020), US stock markets. There was a negative impact on liquidity and volatility (Baig et al., 2020), there was a significant deterioration in the stock market between March 2020 and June 2020 in India (Kumar and Kumara, 2020), and the reported daily growth of Covid-19 confirmed cases. It draws attention to the relevant literature that the triggering fear about news about death negatively affects the performance of Asian stock markets (Rabhi, 2020). Contrary to these studies, Samadi et al. (2020) concluded that Covid-19 in Iran has no negative impact on the stock market.

Yang et al. (2020) conclude that the pandemic outbreak has caused a sharp increase in risks in the financial sector, transmitted to other industries. Even though governments tried to reduce their effects on the sectors with the financial policies they implemented during the pandemic period, some sectors in the countries suffered more. He et al. (2020) examined how Covid-19 affects different Chinese stock market sectors. They show that while some sectors have been adversely affected by the pandemic, others (such as manufacturing, information technology, education, and healthcare) survive the crisis. Some studies examining the relationship between the stock market and Covid-19 have carried out examinations with stock market index values. Mazur et al. (2020) concluded that the US stock market was significantly adversely affected, causing the US GDP to shrink 4.8 percent in the first quarter. Baker et al. (2020) compared the impact of the Spanish virus with the Covid-19 virus on US stocks that occurred earlier. They stated that Covid-19 has a more negative impact on the US stock market. Sharif et al. (2020); The relationship between the Covid-19 virus and US stocks were examined with Granger causality analysis. According to the study results, a one-way negative causality relationship was obtained between the Covid-19 virus and stock prices. Ahmar and De Val (2020) found that stocks' price was negatively affected by the increase in the number of cases of the Covid-19 virus in Spain. Chittineni (2020) revealed that Nifty 50 returns and market volatility moved independently from each other during the pandemic period. Al-Awadhi et al. (2020) found that it has a significant negative impact on the Chinese stocks market.

GARCH type models can be used to examine the pandemic's effect on estimating the volatility of stock markets. Panyagometh (2020) found that most of the Thai stock market shares were negatively affected by the Covid-19 outbreak compared to the absence of the epidemic. Verma and Sinha (2020) found that the Indian stock market was not affected by the number of Covid-19 cases. On the other hand, Bora and Basistha (2020) showed that the NSE Nifty Index's volatility significantly affected the pandemic period due to the GJR - GARCH model estimation. The results of Lee et al., (2020) revealed that the Covid-19 case numbers significantly affected the sectors in the Malaysian stock market. Apergis and Apergis (2020) examined the impact of the Covid-19 outbreak on the volatility of Chinese stock markets. As a result of the GARCHX forecast, it was concluded that the Covid-19 epidemic had a positive effect on the volatility of stock returns. Liu (2021) examined the volatility of Chinese stock markets within the EGARCH model. According to the study findings, it was observed that the uncertainty caused by the Covid-19 outbreak caused the Chinese stock markets to decline. Sector-based analysis results concluded that sectors such as transportation and industry were negatively affected by the epidemic and that the sector such as information systems was positively affected by the epidemic. Some researchers have conducted multi-country panel studies. Bahrini and Filfilan (2020) aimed to investigate the Covid-19 outbreak's impact on GCC countries' stock markets returns. The study results using fixed-effect and random-effect panel data approaches show that there is no clear evidence of how GCC stock markets responded to the increase in deaths from the Covid-19 outbreak. Chaudhary et al. (2020) aimed to reveal the differences between the US, China, Japan, Germany, India, the United Kingdom, France, Italy, Brazil, and Canada stock markets before and after the Covid-19 pandemic period. As a result of the GARCH (1,1) model estimation, it was seen that the impact of the Covid-19 outbreak increased the volatility in the indices of countries.

In the literature, there are studies on BIST100. Ozturk et al. (2020) examined whether the outbreak of Covid-19 had an impact on 28 sectors and indicator indices traded on Borsa Istanbul (BIST). As a result of the study, the epidemic's negative economic effects are mostly seen in metal products and machinery sectors. Sports, banking, and insurance sectors follow these industries. Despite the economic recession, the food and beverage, wholesale-retail, and real estate investment sectors were the least affected by the epidemic. Cetin (2020), pandemic period BIST100 index closing of overseas travel restrictions imposed on Turkey, the opening has reached the conclusion that positively associated with the highest and lowest rates. Ozdemir (2020) examined the relationship between Covid-19 case and death numbers and BIST100 industry indices. As a result of the study, the positive shock in the number of deaths causes a negative shock in the Service index, in some periods it causes positive shock in some periods on the Industrial index, causes a positive shock in the Technology index. While it affects the financial sector index negatively, it has been concluded that technology affects the sector index positively. The pandemic in the world shows itself as an area where more research should be done due to these deep effects both economically and financial markets. In this sense, this study investigated the volatility in BIST100 and its sub-indices, financial, services, and industry indices. This study makes important contributions to the literature on researching the volatility occurring in the BIST100 and its sub-indexes during the pandemic process. In the next part of the study, the theory of models to be used in the analysis, and the findings will be presented.

3. Methodology

In this study, BIST100, Services, Financial, and Industry indices' volatility during the pandemic period was examined. For this, business day data between 1/02/2020 - 11/10/2020 was used. The data used were obtained from the Central Bank of the Republic of Turkey. First of all, the return series was obtained by providing the natural logarithmic transformation of the data. $R= p_t / p_{t-1}$ equation was used for the payoff series. The indices converted into return series are expressed as RBIST100, RServices, RFinancial, and RIndustrial, respectively. In this section, ARCH-GARCH models will be introduced, and then the most suitable ARCH-GARCH model will be estimated for the estimation of the return series.

To determine the most suitable ARCH and GARCH models for BIST100, Financial, Service, and Industry indices, the return series of the indices was created. The most suitable ARMA (p, q) model is estimated by using the generalized least squares method by looking at the stationarity of the earnings series obtained. In this context, the ARCH model was developed by Engle (1982) in order to predict the varying variance in financial assets. ARCH model is shown below;

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 \tag{1}$$

h_t represents the conditional variance of the ARCH model. p is the degree of the ARCH process, and α denotes the unknown parameter vector. The conditional variance of ε_t in the ARCH (p) model depends on the realized values of ε_{t-i}^2. Long-term delays are required for conditional variance in ARCH models. Engle's studies were developed by Bollerslev (1986) to have a more appropriate delay and better reflect its past effects. Thus, the GARCH model containing the delay values of conditional variance was defined. GARCH model is shown below;

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \, h_{t-i} = \alpha_0 + A(L)\varepsilon_t^2 + \beta(L)h_t \tag{2}$$

As can be seen, the conditional variance h_t depends on both the previous period values of the error term and its past period values. In addition, the model must satisfy the conditions $q \geq 0$, $p > 0$, $a_0 > 0$, $a_i \geq 0$, $i = 1,\ldots, Q$, $\beta_i \geq 0$, $i = 1,\ldots, P$. Because stationarity is an important condition in the estimation of GARCH model. For the predicted model to satisfy the stationary condition, it must satisfy the condition $a_i + \beta_i < 1$. In more general terms;

$$\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i < 1 \tag{3}$$

It expresses the stationary condition in the form. TARCH model is also used to estimate the indices. The most important feature of the TARCH model is that it takes into account the asymmetry in volatility. In the TARCH model, the effects of positive and negative shocks on volatility occur differently. The conditional variance of the model is expressed as follows.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \mu_{t-i}^2 + \sum_{i=1}^{p} \gamma_i \, \mu_{t-i}^2 \theta_{t-i} + \sum_{i=1}^{p} \beta_i \, h_{t-i} \tag{4}$$

In the model, the term t represents a shadow variable. Shadow refers to the positive and negative shocks created by variable shocks. In the model, μ_t is the random error term with zero mean and unit variance. If the error term is greater than zero, it indicates the presence of positive news, and a lower than zero indicates the presence of negative news. While a_i represents the effect of positive news in the model, $a_i + \gamma_i$ represents the effect of negative news (Sabiruzzaman et al., 2010).

4. Results and Discussion

Table 1 shows the stability test results of BIST100, Services, Financial and Industrial indices. It is seen that each index is not stable in level value. However, it is seen that there are RBIST100, RServices, RFinancial, and RIndustrial indices expressed as return series. After deciding that the yield series are stable, the most suitable ARMA model estimation is presented in Table 2.

Table 1. ADF Unit Root Test

	Constant	Constant + Trend	
BIST100	-1.108 (0.712)	-1.358 (0.870)	I(0)
RBIST100	-8.171 (0.000)*	-8.203 (0.000)*	I(1)
Services Index	-0.843 (0.804)	-1.732 (0.733)	I(0)
RServices Index	-8.187 (0.000)*	-8.165 (0.000)*	I(1)
Financial Index	-1.527 (0.517)	-1.201 (0.907)	I(0)
RFinancial Index	-14.639 (0.000)*	-14.702 (0.000)*	I(1)
Industrial Index	-0.434 (0.899)	-1.540 (0.812)	I(0)
RIndustrial Index	-7.716 (0.000)*	-7.791 (0.000)*	I(1)

*Note: * indicates stability at 1% level. - () refers to probability values.*

Table 2. ARMA (p,q) Model

	Variables	Parameter	t-Statistic Value	Prob- Value
RBIST100 Index	C	0.001	0.221	0.825
	AR(2)	0.218	3.228	0.001*
RServices Index	C	0.001	0.712	0.477
	AR(2)	0.202	2.993	0.003*
	MA(8)	-0.160	-2.316	0.021**
RFinancial Index	C	-0.001	-0.091	0.891
	AR(5)	0.169	2.468	0.014**
	MA(8)	-0.128	-1.738	0.068***
RIndustrial Index	C	0.001	0.909	0.364
	AR(2)	0.255	3.829	0.001*

*Note: *, **, *** indicate stagnation at 1%, 5%, 10% significance level, respectively.*

In Table 2, the homogeneous part of the ARMA model (p, q) autoregressive moving average process, which is made to select the most suitable volatility model, is expressed with p lags and the moving average part with q lags. Accordingly, the most appropriate lag model for the RBIST100 index is estimated as ARMA (2, 0), for the services index ARMA (2, 8), for the financial index ARMA (5, 8), and finally for the industrial index ARMA (2, 0). has been. After the ARMA models were estimated, it was investigated whether there was an ARCH effect. ARCH-LM test was used to test the H0 hypothesis, which was established as no ARCH effect. ARCH-LM test results are presented in Table 3.

Table 3. ARCH-LM Test

	F Statistic Value	F Prob Value	Observation*R^2	Probability Chi-Square Value	Lag Length	Hypothesis
RBIST100 Index	6.438	0.000*	33.531	0.000*	6	H_0 Red
RServices Index	10.041	0.000*	54.032	0.000*	7	H_0 Red
RFinancial Index	3.742	0.001*	20.899	0.001*	6	H_0 Red
RIndustrial Index	8.875	0.001*	49.249	0.000*	7	H_0 Red

*Note: *, **, *** indicate stagnation at 1%, 5%, 10% significance level, respectively.*

ARCH-LM results are shown in Table 3. H_0 hypothesis stating that there is no ARCH effect for RBIST100, RServices, RFinancial, and RIndustrial indices was rejected. Thus, it is concluded that there is an ARCH effect in all series of returns. In the next part of the study, the most appropriate ARCH, GARCH, EGARCH, and TARCH variance model to explain the volatility will be estimated for the models that are accepted to have an ARCH effect. Table 4 shows the most suitable model estimated for the services revenue series.

Table 4. RServices Index

	ARCH (1)	GARCH (1, 1)	EGARCH(1,1)	TGARCH(1,1)
C	0.001 (0.432)	0.002 (0.054)**	0.001 (0.071)***	0.001 (0.067)***
AR(2)	0.246 (0.000)*	0.117 (0.056)**	0.102 (0.157)	0.113 (0.141)
MA(8)	-0.139 (0.112)	-0.106 (0.071)***	-0.117 (0.112)	-0.135 (0.074)***
$\boldsymbol{\alpha_0}$	0.001 (0.000)*	5.431 (0.048)**	-0.851 (0.001)*	2.491 (0.008)***
$\boldsymbol{\alpha_1}$	0.171 (0.038)**	0.149 (0.036)**	-	-0.049 (0.160)
$\boldsymbol{\beta_1}$	-	0.599 (0.001)*	0.909 (0.001)*	0.805 (0.001)*
$\boldsymbol{\gamma_1}$	-	-	0.112 (0.143)	-
$\boldsymbol{\vartheta_1}$	-	-	-0.228 (0.001)*	-
$\boldsymbol{\theta_1}$	-	-	-	0.247 (0.001)
AIC	-5.331	-5.467	-5.543	-5.544
SIC	-5.251	-5.372	-5.432	-5.433

*Note: *, **, *** indicate stagnation at 1%, 5%, 10% significance level, respectively.*

$$\mathrm{h_t} = 5.431 + 0.149\varepsilon_{t-1}^2 + 0.599(\mathrm{h_{t-1}})$$
$$(0.048) \quad (0.036) \qquad (0.001)$$

Table 4 contains the estimation results of the RServices Index with the GARCH (1,1) model. In the model, it was estimated as p = 1, q = 1, α_0= 5.431, $\alpha_1 \geq$ 0.149 and β_1 = 0.599 and the parameters were found to be significant. In addition, it is seen that the stationary condition 0.149 + 0.599 < 1 is achieved. Considering the significance of the parameters and the AIC-SIC information criteria, it has been determined that the most suitable model to estimate the volatility of the services index is GARCH (1,1). According to the GARCH (1,1) model, it is concluded that positive and negative shocks have the same effect on volatility in the services index.

Table 5 shows the estimation results of the RFinancial index with the GARCH (1,1) model. In the model, it was estimated as p = 1, q = 1, α_0 = 6.181, $\alpha_1 \geq$ 0.149 and β_1 = 0.599 and it is seen that the parameters are significant. Besides, the stationary condition of 0.149 + 0.599 < 1 is provided. Considering the significance of the parameters and the AIC-SIC information criteria, it was determined that the most suitable model to estimate the financial index is GARCH (1,1). In this case, it is concluded that positive and negative shocks in the financial index have the same effect on volatility.

Table 5. RFinancial Index

	ARCH (1)	GARCH (1, 1)	EGARCH(1,1)	TGARCH(1,1)
C	0.001 (0.893)	0.001 (0.135)	0.001(0.356)	0.001 (0.443)
AR(5)	0.133 (0.003)*	0.079 (0.063)**	0.067 (0.320)	0.084 (0.217)
MA(8)	-0.201 (0.001)*	-0.142 (0.015)**	-0.140 (0.098)***	-0.111 (0.199)
$\boldsymbol{\alpha_0}$	0.001 (0.000)*	6.181 (0.002)*	-0.762 (0.00)*	2.171 (0.000)*
$\boldsymbol{\alpha_1}$	0.171 (0.010)*	0.149 (0.002)*	-	-0.034 (0.481)
$\boldsymbol{\beta_1}$	-	0.599 (0.000)*	0.920 (0.000)*	0.848 (0.000)*
$\boldsymbol{\gamma_1}$	-	-	0.151 (0.017)**	-
$\boldsymbol{\vartheta_1}$	-	-	-0.184 (0.000)**	-
$\boldsymbol{\theta_1}$	-	-	-	0.215 (0.001)*
AIC	-5.004	-5.090	-5.217	-5.206
SIC	-4.924	-4.994	-5.105	-5.161

*Note: *, **, *** indicate stagnation at 1%, 5%, 10% significance level, respectively.*

$$\mathrm{h_t} = 6.181 + 0.149\varepsilon_{t-1}^2 + 0.599(\mathrm{h_{t-1}})$$
$$(0.002) \quad (0.002) \qquad (0.001)$$

Table 6 shows that the most suitable model for the RBIST100 index is the TARCH (1,1) model, considering the AIC-SIC information criteria and the significance of the parameters.

The fact that the coefficient AR (2) is less than 1 indicates that the stationary condition is met. When the variance equation is examined, it is significant at the 1% level of the shadow variable, and its coefficient is positive. In this case, it is concluded that there is both asymmetric and leverage effect in the RBIST100 index.

Table 6. RBIST100 Index

	ARCH (1)	GARCH (1, 1)	EGARCH(1,1)	TGARCH(1,1)
C	0.001 (0.793)	0.001 (0.736)	0.001 (0.264)	0.001 (0.395)
AR(2)	0.204 (0.001)*	0.223 (0.123)	0.145 (0.055)**	0.163 (0.009)**
α_0	0.001 (0.001)*	0.001 (0.324	-0.660 (0.000)*	1.441 (0.000)*
α_1	0.171 (0.127)	0.150 (0.437)	-	-0.107 (0.001)*
β_1	-	0.559 (0.116)	0.929 (0.000)*	0.882 (0.000)*
γ_1	-	-	0.071 (0.268)	-
ϑ_1	-	-	-0.264 (0.000)*	-
θ_1	-	-	-	0.279 (0.000)*
AIC	-5.295	-5.127	-5.594	-5.608
SIC	-5.232	-5.047	-5.499	-5.513

*Note: *, **, *** indicate stagnation at 1%, 5%, 10% significance level, respectively.*

$$h_t = 1.441 - 0.107\mu_{t-1}^2 + 0.279\gamma_i\mu_{t-1}^2 + 0.882(h_{t-1})$$

$$(0.000) \quad (0.001) \quad (0.000) \quad (0.000)$$

Table 7 shows that the most suitable model for the RIndustrial index is the TARCH (1,1) model, considering the AIC-SIC information criteria and the significance of the parameters. The fact that AR (5) coefficient is less than 1 indicates that the stationary condition is met. When the variance equation is examined, it is significant at the 1% level of the shadow variable, and its coefficient is positive. It is concluded that this situation has both asymmetric and leverage effects on the RIndustrial index.

Table 7. RIndustrial Index

	ARCH (1)	GARCH (1, 1)	EGARCH(1,1)	TGARCH(1,1)
C	0.002 (0.255)	0.002 (0.537)	0.002 (0.062)***	0.002 (0.017)**
AR(5)	0.240 (0.000)*	0.228 (0.128)	0.161 (0.029)**	0.132 (0.032)**
α_0	0.001 (0.000)*	0.000 (0.365)	-0.836 (0.000)*	2.261 (0.000)*
α_1	0.171 (0.150)	0.150 (0.475)	-	-0.146 (0.000)*
β_1	-	0.599 (0.153)	0.909 (0.000)*	0.848 (0.000)*
γ_1	-	-	0.085 (0.179)	-
ϑ_1	-	-	-0.251 (0.000)*	-
θ_1	-	-	-	0.327 (0.000)*
AIC	-5.316	-5.139	-5.614	-5.641
SIC	-5.253	-5.060	-5.519	-5.546

*Note: *, **, *** indicate stagnation at 1%, 5%, 10% significance level, respectively.*

$$h_t = 2.261 - 0.146\mu_{t-1}^2 + 0.327\gamma_i\mu_{t-1}^2 + 0.848(h_{t-1})$$

$$(0.000) \quad (0.001) \quad (0.000) \quad (0.000)$$

5. Conclusion

In this study, the effect on the stock market of Turkey Covid-19 outbreaks was investigated. For this purpose, BIST100, Services, Financial and Industrial indices were examined between 1/02/2020 - 11/10/2020. According to the findings, it was determined that there is a symmetrical effect in services and financial index. In this case, positive and negative news to be experienced causes the same volatility in the services and financial index. It was determined that both asymmetric and leverage effects were found in RBIST100 and Rlndustrial indexes. In this case, the positive and negative shocks of the RBIST100 index cause a different type of volatility. At the same time, negative shocks on RBIST100 and RIndustrial indices create more volatility than positive shocks. This shows that BIST100 and RIndustrial indices have a fragile structure. The pandemic period was examined in the study. However, according to the results obtained, it is predicted that a possible financial crisis in the country subject to the study will cause a sharp reaction in BIST100 and RIndustrial indices. It is emphasized that the recovery in these indices will take time with the arrival of positive news. In other words, it is estimated that the short-term adverse effects of a shock in RBIST100 and RIndustrial indices can only be compensated in the long run.

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 ISSN 1927-033X