The effects of epidemics on capital markets volatility: A case study of Borsa Istanbul***

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Abstract

This study examines the effects of epidemics like H1N1, MERS and EBOLA on the volatility of capital markets through the case of Borsa Istanbul. The data set covers the period from 1/2/2009 – 8/11/2020 and consists of daily frequency observations. In the study, first, the appropriate volatility model for BIST 100 Index, which is the main market index of Borsa Istanbul, was determined. ARCH, GARCH, T-GARCH and E-GARCH models were tested to estimate the appropriate volatility model. According to the findings, E-GARCH (1,1) is more suitable for modelling the BIST 100 Index volatility. It was found that the H1N1 pandemic caused an increase in BIST 100 Index volatility, and negative news rather than positive news was effective on BIST 100 volatility. In addition, the effects of COVID-19 pandemic on BIST in the current situation were evaluated. During the pandemic period, the excessive increase in volatility and the negative trend in the return series are remarkable compared to previous periods.

Keywords: H1N1, MERS, Ebola, COVID-19, Stock Market Volatility, Borsa Istanbul

Introduction

Stock markets are the lifeblood of the economy due to their resource allocation function. Transactions carried out within stock markets are under the influence of many factors. Especially since the 2000s, many epidemics began to be considered as a powerful factor affecting the economies and the stock markets. McKibbin and Sidorenko (2006) examined the effects of pandemic influenza on the global economy under different scenarios and reported that GDP losses would be $ 330 million to $ 4.4 trillion. Ma *et al*. (2020) examined the effects of 1968 Flu, SARS, H1N1, MERS, Ebola and Zika health crises on the economy. It was stated that the GDP decreased by 3% in the countries where the crises were experienced, compared to the ones that were not experienced, and it would take about

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five years to return to the previous level. It has been reported that the global economic impacts of COVID-19 will be much greater, and the impact of previous crises can be expressed as the lower limit for COVID-19. Sharif *et al*. (2020) stated that the COVID-19 and oil price shocks had unprecedented effects on geopolitical risk, economic policy uncertainty and stock market volatility.

H1N1, Ebola and MERS occur recently and directly or indirectly affected Turkey due to geographic proximity or first-hand experience. Lastly, at the end of 2019, the world faced the threat of COVID-19. By August 31, COVID-19 spread in over 180 countries, 25.484.767 cases were reached, and 850.535 died due to COVID-19 (John Hopkins University, 2020). Due to COVID-19, countries have started to implement social, economic, psychological precaution and restrictions in a short term (Şenol and Zeren, 2020; Ahmad *et al*., 2020). These precautions and restrictions will continue to be implemented depending on the course of the disease. Long-term effects are predicted to be more than previous outbreaks. It is predicted that long-term effects will be more severe than previous outbreaks (Ceylan and Ozkan, 2020; Ma *et al*., 2020; Zhang *et al*., 2020). This study analyses the effects of previous outbreaks and the current COVID-19 pandemics on Borsa Istanbul (BIST), which is represents capital market of Turkey as developing country. Turkish economy is open structure due to both geographical position and implemented economic policies. In addition, the distribution of domestic and foreign investors and their transaction volume is almost equal within BIST (Dünya, 9/7/2020). Therefore, BIST has the capability to represent the motivation of different geographies for investors.

In this study the effect of outbreaks on BIST volatility is examined. H1N1, MERS, Ebola and COVID-19 outbreaks were included in the study. Augmented Dickey Fuller and Phillips Perron tests were used for the analysis of stationarity. ARCH, GARCH, E-GARCH and T-GARCH were used for modelling volatility. H1N1, MERS and Ebola were added to the model as dummy variables. Since the VIX Index (Volatility Index) generally represents the current and expected reactions of the markets, it is included in the analysis process as a control variable. Lastly, COVID-19 effects on BIST and sectoral indices examined in a separate framework. The rest of the study consists of the relevant literature, data set and methodology, findings, and conclusion, respectively.

1. Literature Review

McKibbin and Sidorenko (2006) examined the effects of pandemic influenza on the global economy under mild, moderate, severe, and ultra-scenarios with the Asia Pacific G-Cubed model. As a result, it reported that deaths would be 1.4 million to 142.2 million, and GDP losses would be $ 330 million to $ 4.4 trillion. Prager *et al*. (2017) examined the effects of influenza outbreak on the US GDP under different scenarios such as the availability of vaccine, seasonal or pandemic form for the period of 2005-2013. Computable general equilibrium model simulations reported that outbreaks could create between $ 19.9 billion and $ 45.3 billion losses in GDP.

Del Giudice and Paltrinieri (2017) investigated the impact of Ebola outbreak and the Arab Spring on investment funds that take African countries as reference for the period 2006-2015. It is concluded that Ebola outbreak and the Arab Spring have greatly affected the fund performance and caused investors to withdraw their savings from the relevant funds. Withdrawals in funds increase as the rate of coverage in the media increases. Ichew and Marinč (2018) examined the effects of the Ebola outbreak on companies in the perspective of the geographical proximity of the company's activities and locations to the disease region and the intensity of media coverage. As a result, it is stated that the effects of the outbreak are closely related to geographical proximity, company size (small companies), industry and media publications. Jalloh (2019) investigated the economic conditions of countries affected by the Ebola outbreak and stated that Ebola negatively affected the economies of the countries where the outbreak occurred. However, the isolation of the countries where the outbreak was experienced greatly contributed to the worsening of the economic conditions. Baker *et al*. (2020) examined stock and commodity markets since 1900 and compared COVID-19 with previous infectious disease outbreaks. It has been reported that COVID-19 has a much larger impact on both the stock and the good markets compared to previous infectious disease outbreaks, and the effect on market volatility is approximately twice as much as the 2008 financial crisis. Zhang *et al*. (2020) examined the interaction of 12 country stock markets under the COVID-19 pandemic. When the data up to March 27, 2020 are evaluated with binary correlation and minimum spanning tree method, it has been stated that the structure of the interaction between stock market has changed greatly. Sharif *et al*. (2020) examined the interaction between COVID-19, oil price shocks, the stock market, geopolitical risk, and economic policy uncertainty for the US. The data for the period of January 21, 2020 - March 30, 2020 were evaluated with the wavelet method and the wavelet-based Granger causality tests. It was stated that the COVID-19 and oil price shocks had unprecedented effects on geopolitical risk, economic policy uncertainty and stock market volatility. It also has been reported that COVID-19 should be interpreted differently in the long and short term, but it can currently be described as an economic crisis. Ruiz Estrada *et al*. (2020) examined the time and spatial patterns of outbreaks and analysed the impact of COVID-19 on financial markets. The findings obtained are that COVID-19 can produce similar results to the 1929 crisis and the current situation may begin to improve at the end of 9-12 months. It has been reported that the stock market performance index created with the data of 10 countries' stock markets was 1.88 at the beginning of the epidemic but reached 0.45 on the 140th day of the epidemic. The bull market view at the beginning of the epidemic turned into a bear market. Rabhi (2020) investigated the reactions of China, India, Indonesia, Malaysia, Philippines and Thailand stock markets to COVID-19. It has been found that fatality affect the stock markets more than the number of cases, and in general, COVID-19 affects the stock markets negatively. In addition, in times of turmoil and uncertainty, it has been observed that the oil price, gold price, exchange rate and US stock markets are the determinants of Asian stock markets. Ma *et al*. (2020) examined the effects of 1968 Flu, SARS, H1N1, MERS, Ebola and Zika health crises on the economy. It was stated that the GDP decreased by 3% in the countries where the crises were experienced, compared to the ones that were not experienced. It would take about five years to return to the previous level. It has been reported that the global economic impacts of COVID-19 will be much greater, and the impact of previous crises can be expressed as the lower limit for COVID-19.

Şenol and Zeren (2020) examined the impact of COVID-19 on stock markets within the framework of MSCI Global, Emerging Markets, Europe and G7. According to the Fourier cointegration results, the existence of a cointegration relationship between COVID-19 and indices was determined. Ashraf (2020) measured the response of 64 countries' stock market to COVID-19 for the period between January 22, 2020 and April 17, 2020. It has been concluded that COVID-19 negatively affects the markets, and the markets take the number of cases into account compared to the fatality number. In addition, it has been stated that the markets react quickly to the outbreak and the response changes over time depending on the outbreak stage. Ali *et al*. (2020) examined the impact of COVID-19 on China, USA, UK, Italy, Spain, France, Germany, Switzerland, South Korea stock markets, corporate bond index (S&P 500), US treasury bond core index (ICE core), Bitcoin, Oil (WTI) and gold prices. It has been reported that stock markets and financial instrument returns were negative during the outbreak period, volatility increased and the current situation worsened during the moving from epidemic to pandemic. Ngwakwe (2020) examined the change of Shanghai Stock Exchange Composite Index, Euronext 100, S&P 500 and DJIA Indices with reference to 50 days before and after the COVID-19 outbreak. It was stated that the indices reacted differently to the outbreak. While DJIA decreased and SSE increased in the period before the outbreak, the S&P 500 and Euronext 100 did not show a significant change. It was reported that only the average of the SSI Index increased in the period after the outbreak. Al-Awadhi *et al*. (2020) investigated the effects of COVID-19 on the Hang Seng Index and the SSE Composite Index. It was stated that the outbreak negatively affected the markets, and there was a strong negative relationship between the number of cases and fatality and indices.

2. Data Set

BIST 100 Index, which is an indicator of Borsa Istanbul, was used in the study as a dependent variable. The VIX Index was taken as the control variable. MERS, H1N1 and Ebola outbreaks were taken as dummy variables. As a whole MERS, H1N1, Ebola and VIX are explanatory variables in the equation. The data were obtained from BIST Data Store and the CBOE official website. The date of dummy variables are the periods when the spread of epidemics peaked. The relevant dates have been created by considering the publications and notifications of the World Health Organization (WHO). The effects of COVID-19 were evaluated for the period December 31, 2019 and August 11, 2020. The data set covers the period between January 02, 2009 and August 11, 2020. The series are converted into return series with the formula $(\mathrm{r} = \ln{(P_t/P_{t-1})} * 100)$. Descriptive information about the series is included in Table 1.

Table 1. Information on Variables

Variable	Symbol	Period
BIST 100	BIST 100	1/2/2009 – 8/11/2020
VIX	VIX	1/2/2009 - 8/11/2020
Influenza A	H1N1	4/27/2009 – 8/9/2010
Ebola	Ebola	3/10/2014 – 3/28/2016
MERS	MERS	3/24/2014 – 10/30/2015
COVID-19	COVID-19	12/31/2019 – 8/11/2020

There are two selection criteria for epidemics; it must occur recently and directly or indirectly affected Turkey. The H1N1 pandemic was effective between 2009 and 2010 (WHO, 2009; WHO, 2010b). The number of deaths announced by WHO is 18.449 (WHO, 2010a), and the estimated number of deaths is between 151.700-575.400 (Dawood *et al*., 2012, p. 690). Ebola emerged in Africa in 1976 and 1.590 people died of Ebola by 2012 (WHO, 2017). The Ebola outbreak started in 2014 and 11.310 people died between 2014 and 2016 due to Ebola, the PHEIC (Public Health Emergency of International Concern) status for Ebola was lifted by WHO on March 29, 2016 (WHO, 2016a; CDC, 2016). MERS first appeared in Saudi Arabia in 2012 and peaked in 2014 and 2015. It was reported by WHO that 858 people died due to MERS (WHO, 2019; WHO, 2016b). COVID-19 emerged in China on December 31, 2019 and was described as a pandemic by WHO on March 11, 2020. The number of cases was 20.405.695 on August 13, 2020 (WHO, 2020).

3. Methodology

In the study, Augmented Dickey Fuller and Phillips Perron tests were used for the analysis of stationarity. ARCH, GARCH, E-GARCH and T-GARCH (ARCH family models for short) were used for modelling volatility. Since the VIX Index generally represents the current and expected reactions of the markets, it is included in the analysis as a control variable.

In the time series analysis, first, the stationarity test is performed to eliminate the spurious regression problem. In the case of spurious regression, the high correlation detected between variables is erroneous and the regression established does not reflect the real relationship (Granger and Newbold, 1974, p. 111). The results of the stationarity tests also affect the subsequent analysis process. For the analysing stationarity, mostly unit root tests are used. Augmented Dickey Fuller (ADF) (1981) and Phillips Perron (PP) (1988) tests are among the commonly used unit root tests. ADF and PP tests were applied for stationarity in the study. ADF and PP are testing the presence of unit root in the null hypothesis. If the test statistic is greater than the critical values, it means that the null hypothesis is rejected. In this case, the series are stationary (see Table 3).

Variance, one of the criteria of stationarity in time series, changes over time and Autoregressive Conditional Heteroscedasticity (ARCH) models are used in the modelling of time series. The first model that provides a systematic framework for volatility modelling is Engle's (1982) ARCH model. Due to reasons such as the method of determining the number of lags of the error squares to be included in the model is not clear, the high number of lags reduces the efficiency of the model, the existence of very strict restrictive criteria for the coefficients, and the asymmetry effect of shocks is not considered (Brooks, 2014, p. 428; Tsay, 2010, p. 119), ARCH models leaved its place to the improved versions. By adding the conditional variance's own lag values to the ARCH model, a Generalized ARCH (GARCH) model was created by Bollerslev (1986). ARCH and GARCH models assume that shocks have the same effect on volatility. Therefore, they are regarded as symmetrical models. Investors' different responses to positive and negative shocks have led to the development of asymmetric models suggesting different effects of positive and negative shocks in volatility modeling. Asymmetric volatility models are considered extensions of the GARCH model, and among these models, E-GARCH and T-GARCH are frequently used.

The GARCH model is good at capturing the thick tail and volatility cluster. However, since the error terms are defined as a function of their magnitude in the GARCH model, they fail to capture the asymmetry in the variance structure (Songül, 2010, p. 18). Nelson (1991) developed the Exponential GARCH (E-GARCH) model that considers the magnitude and effect aspects of lagged error terms.

The E-GARCH model formulates the conditional variance equation instead of the variance itself. It allows the coefficients to be negative since it uses logarithmic values. The model provides an advantage in that the coefficients are not constrained to be negative and allows asymmetric peaks of conditional variance with exponentiation (Alexander, 2008, p. 151). Another model that considers asymmetry in volatility modelling is the Threshold GARCH (T-GARCH) model proposed by Zakoian (1994). T-GARCH model, which indicates that the effect of positive and negative shocks is not symmetrical, is obtained by adding the leverage parameter to the GARCH model (Baykut and Kula, 2018, p. 286). Table 2 contains information on ARCH, GARCH, T-GARCH and E-GARCH models (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Zakoian, 1994).

Table 2. Overview of ARCH Family Models Used in the Study

Model	**Equation**	**Model Specification**
ARCH	$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$	$\alpha_0 > 0, \alpha_1 \geq 0$
GARCH	$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$	$\alpha_0 > 0, \alpha_1 \geq 0, \beta_1 \geq 0, \alpha_1 + \beta_1 \leq 1$
E-GARCH	$\log(h_t) = \alpha_0 + \sum_{i=1}^{q} \beta_i \log(h_{t-i}) + \sum_{i=1}^{p} \alpha_i \left\lvert \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right\rvert + \sum_{i=1}^{r} \gamma_i \frac{\varepsilon_{t-i}}{h_{t-i}}$	$\gamma \neq 0 \Rightarrow$ asymmetry effect exists, $\gamma < 0 \Rightarrow$ leverage effect exists
T-GARCH	$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 d_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i}$	$\gamma \neq 0 \Rightarrow$ asymmetry effect exists, $\gamma < 0 \Rightarrow$ leverage effect exists, $d_{t-i} = \begin{cases} 1, \varepsilon_{t-i} < 0, & negative\ effect \\ 0, \varepsilon_{t-i} \geq 0, & positive\ effect \end{cases}$

The parameters in the equations are; h_t is conditional variance, α_i and β_i are ARCH and GARCH effects respectively, ε_{t-i}^2 error term, γ leverage effect, and d is the dummy variable for positive and negative shocks.

4. Findings

For BIST 100 Index and VIX Index, the stationary test was first performed. ADF and PP unit root tests were used to determine stationarity. Results are reported in Table 3.

Table 3. Unit Root Test Results for BIST 100 and VIX Index Return Series

Unit Root Test	ADF	PP
	Level	Level
BIST 100	-51.875***	-51.877***
VIX	-54.997***	-65.432***

Notes: Critical values are taken from MacKinnon (1996). ***, **, and * show statistical significance at 1%, 5% and 10% significance level, respectively. Critical values for ADF and PP tests are -2.567, -2.863 and -3.433 at the 10%, 5% and 1% significance level, respectively.

ADF and PP unit root tests produced results that support each other. The test statistics of BIST 100 and VIX Index return series are statistically significant at 1% significance level. In other words, the H_0 hypothesis stating that the series have unit root at level value was rejected. Series are zero degree integrated or stationary at level.

The appropriate ARMA (p, q) model should be determined after the stationary test for the BIST 100 return series. The Schwarz Bayesian Information Criteria (SIC) was taken as reference. Combinations up to the 4th lag number were created for ARCH and GARCH effects and 25 models in total were tested. Table 4 shows the ARMA model results.

Table 4. BIST 100 Return Series ARMA (p, q) Model Selection According to SIC

Model p / q	0	1	2	3	4
0	1.924888	1.927826	1.929973	1.930113	1.933271
1	1.927826	1.930557	1.932293	1.931921	1.933271
2	1.930056	1.932479	1.93227	1.933747	1.935414
3	1.930513	1.931901	1.933628	1.937729	1.93704
4	1.931316	1.932871	1.935193	1.936791	1.937871

When Table 4 is examined, it is seen that the model with the lowest coefficient according to SIC is ARMA (0, 0). ARMA (0, 0) has the lowest coefficient value with 1.924888 coefficient It is the model decided to be used for analysis. After choosing the ARMA model, ARCH-LM test was applied to determine whether the model has heteroscedasticity problem in error terms. Detecting heteroscedasticity is required to use the ARCH family model. ARCH-LM test results applied for BIST 100 ARMA (0, 0) are shown in Table 5.

Table 5. ARCH-LM Test Results for BIST 100 ARMA (0, 0)

Lag Lengths	χ^2 Table Value	Observed R^2	F Statistic
1	3.84146	29.16304***	29.46120***
2	5.99146	52.15006***	26.56180***
4	9.48773	105.7473***	27.47026***
8	15.50731	114.4853***	14.89930***
12	21.02607	121.9724***	10.59822***

Notes: ***, **, and * show statistical significance at 1%, 5% and 10% significance level, respectively. H_0: There is no ARCH effect up to q in the residuals. $a_i = 0\ far\ all\ i = 1, \ldots, q$.

When Table 5 is examined, it is seen that the R^2 values obtained as a result of the ARCH-LM test performed for different lag lengths are greater than the χ^2 table values. In addition, the significance of the R^2 values confirm that there is ARCH effect in the residuals and thus the series face heteroscedasticity. In this case, ARCH family models can be used to eliminate the heteroscedasticity problem and to make volatility calculations. Four different ARCH family models are used for volatility estimation for the BIST 100 Index return series. ARCH and GARCH models are used as symmetric models. E-GARCH and T-GARCH models are used as asymmetric models. In the models created, the problem of negativity (negative coefficient), stability (coefficients bigger than 1) and heteroscedasticity were checked again, and it was decided that the appropriate model was E-GARCH (1, 1). The rankings of the models are shown in Table 6. The best fit model was chosen by highest log-likelihood and lowest information criteria. ARCH model has autocorrelation and heteroscedasticity, so ARCH model is not taking place in Table 6.

Table 6. Ranking of Appropriate Models

Rankings	Model	Log likelihood	AIC	SIC
1.	E-GARCH (1,1)	9926.768	-7.385	-7.374
2.	T-GARCH (1,1)	9926.131	-7.384	-7.373
3.	GARCH (1,1)	9909.291	-7.373	-7.364

After determining the appropriate volatility model for the BIST 100 Index return series, three dummy variables were added to the model, taking as reference the H1N1, Ebola and MERS outbreaks. Later, the VIX Index was added to the model as a control variable, and it was tested whether the effects of dummy variables were caused by other factors. In Table 7, Panel A contains the effect of outbreaks[2] on the stock market index volatility and Panel B contains the results of the model in which the VIX Index is added to the main model as a control variable

When the diagnostic tests of both models are examined, it is seen that there is no autocorrelation in the standardized error ($LB-Q(36)$) and standardized error squares ($LB-\ Q^2(36)$). The ARCH effect disappears. The validity of the models is thus also confirmed by the autocorrelation test results. When the effects of the dummy variables were analyzed, it was determined that the MERS and Ebola outbreaks did not have a significant effect on the BIST 100 Index volatility. That the results indicate that the effectiveness of H1N1 on BIST 100 Index volatility was significant at 5% level and increased the volatility by 1.7%. According to the E-GARCH (1, 1) model, the coefficient is negative (-0.079)

[2] The reason why we could not include the COVID 19 pandemic as a dummy variable in the equation is that, unlike previous epidemics, the pandemic is still ongoing and even has not completed its peak period during analysis. As a result, its impact on BIST is likely to change.

and significant at 1% level. Therefore, this result suggests that negative news has more impact on volatility than positive news.

Table 7. The Effect of H1N1, Ebola and MERS Outbreaks on BIST 100 Index Volatility

Period: 2/1/2009 – 31/12/2019						
	Panel A			Panel B		
	Mean Equation			Mean Equation		
	Coefficient	Standard error	z Statistics	Coefficient	Standard error	z Statistics
φ	0.026**	0.011	2.382	0.024**	0.011	2.217
ν	-	-	-	-0.040***	0.003	-13.017
	Variance Equation			Variance Equation		
	Coefficient	Standard error	z Statistics	Coefficient	Standard error	z Statistics
ω	-0.166***	0.016	-10.182	-0.169***	0.019	-9.103
α_1	0.145***	0.016	9.246	0.138***	0.016	8.468
β_1	0.948***	0.007	134.551	0.941***	0.009	105.662
D_{H1N1}	0.016**	0.008	2.172	0.017**	0.008	2.131
D_{Ebola}	-0.004	0.013	-0.321	-0.012	0.014	-0.866
D_{MERS}	0.000	0.014	0.016	0.005	0.015	0.345
γ	-0.078***	0.007	-10.613	-0.079***	0.008	-10.367
$LB-Q(36)$		22.651			26.166	
$LB-\ Q^2(36)$		38.858			32.823	
$ARCH-LM(12)$		0.815			0.822324	

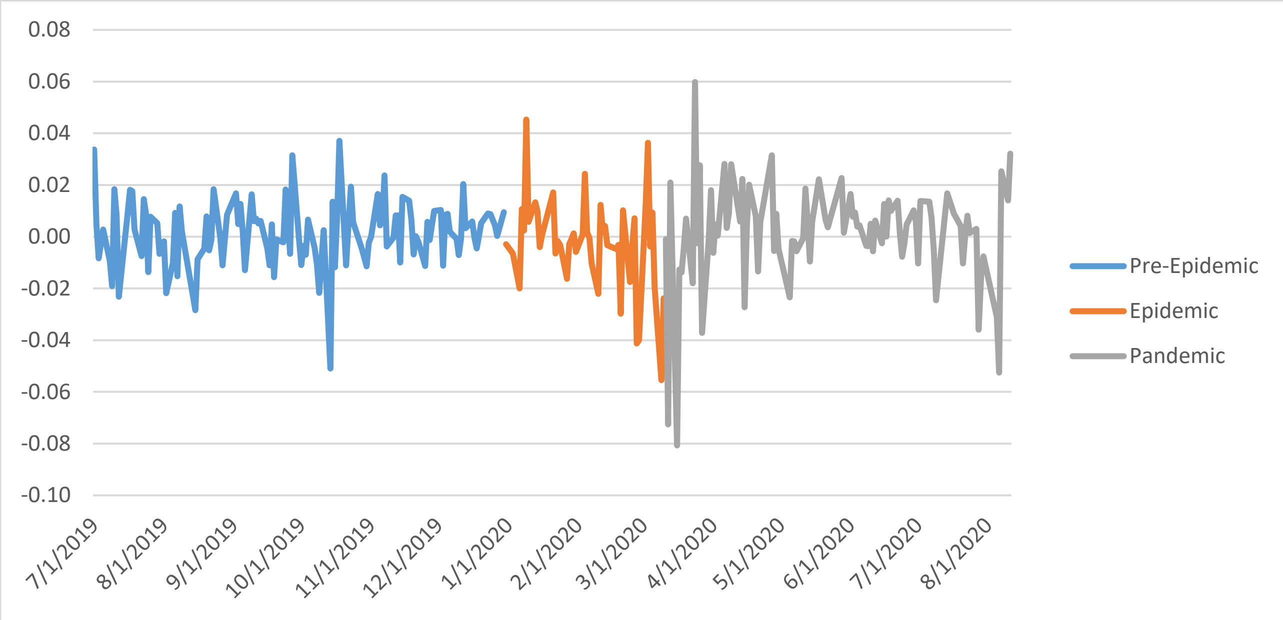
Notes: ***, **, and * show statistical significance at 1%, 5% and 10% significance level, respectively. φ and ω are the constant terms in the mean and variance equation, α_1 is ARCH effect, β_1 is GARCH effect and ν is VIX Index. D_{H1N1},D_{Ebola}, D_{MERS} are dummy variables for H1N1, Ebola and MERS, respectively.

5. The Effects of COVID-19 on Borsa Istanbul

The COVID-19 pandemic continues as of January 2021. In Turkey, along with June, the travel ban, the restrictions that apply, such as curfew has been lifted in a large part, and economic and social life flows in a controlled manner. Although the pandemic has not yet ended, it is observed that the general trend in BIST 100 Index followed a horizontal course, especially as of June, when some of the restrictions were lifted (Ministry of Internal Affairs, 2020). Therefore, in order to examine the effects of COVID-19 on BIST under current conditions, BIST 100 Index data are interpreted over three periods; 6 months before the outbreak (as of 7/11/2019), the epidemic period between 12/31/2019 and 3/10/2020 and the pandemic period covering current data from 3/11/2020 to 8/11/2020.

First, the effects of COVID-19 outbreak on the return series of the BIST 100 Index for the period examined were considered. Two series, both unitary and cumulative[3], were created for the index's return series. Figure 1 includes the return series of the BIST 100 Index.

Figure 1. Return Series of the BIST 100 Index



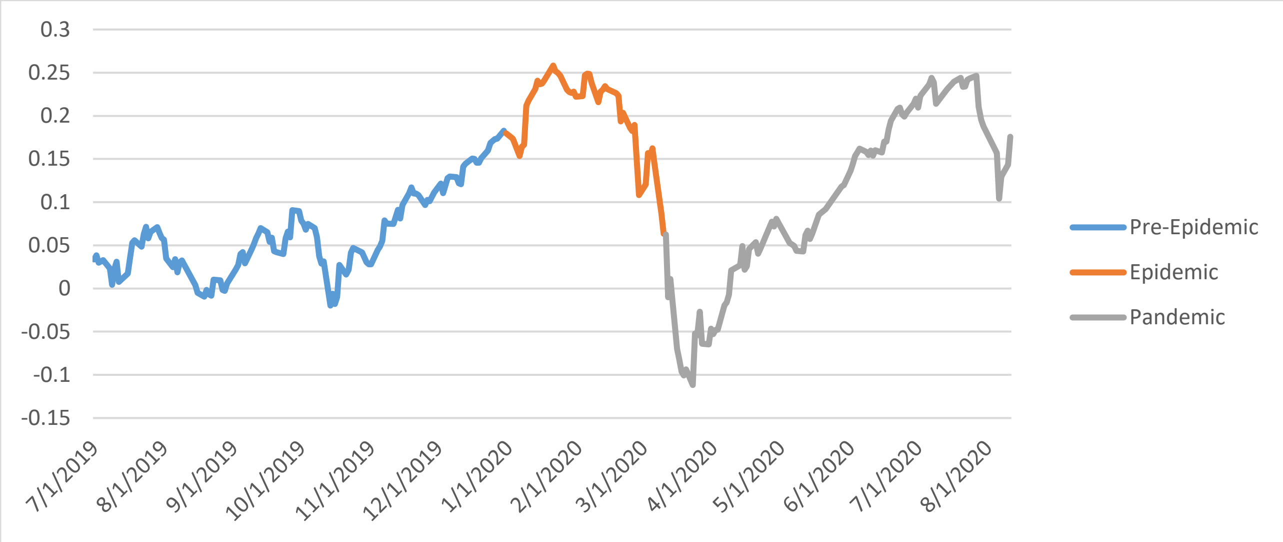
Source: own representation

When Figure 1 is analysed, it is seen that the return series showed an intense movement especially during the epidemic and pandemic period. The return series reached its highest and lowest levels in the period under review. On 3/11/2020 outbreak is declared as a pandemic and the date pose a particular importance for Turkey. The first case detected on 3/11/2020 in Turkey. In the pre-epidemic period, the highest daily returns and losses were 3.7% and 5%, respectively. This situation reached 4.5% and 5.5% in the epidemic period and 6% and 8.1% in the pandemic period. The pandemic has presented opportunities along with risks.

When the change in the return series is compared in terms of periodic return, it is 18% in the pre-epidemic period, - 12% in the epidemic period and 11% in the pandemic period up to 8/11/2020. The process can be monitored within Figure 2. While the BIST 100 Index was at 1147.54 on 12/30/2019 before the onset of the outbreak, it was at the level of 1110.05 as of 8/11/2020. In the relevant period, huge losses were experienced and the index fell to 842.46 (26% loss). However, losses in the index were largely compensated.

[3] Unitary return series refers to individual change in the variable. Cumulative return series refers to total change in the variable over a period.

Figure 2. Cumulative Return Series of the BIST 100 Index



Source: own representation

In Table 8, market movements in the period examined are given quantitatively. The period of 2/4/2009-8.11.2020 was divided into two parts as before and after COVID-19 as of 12/31/2019. Market movements in both periods were calculated. In the period before COVID-19, market movements above 2.5% were 200 and their share in the total was 7.5%. In the COVID-19 period (a period of 1/20 of the previous period), the market movements realized above 2.5% were 20 and their share in the total was 13.2%. Although the outbreak contains many threats, it has also offered opportunities compared to previous periods. Considering the period after 2009, it is understood that COVID-19 has had a great impact on the BIST 100. When the COVID-19 period compared with previous epidemics peak periods, the comments will be made on Ebola, since Ebola and MERS cover the same dates and the effects of Ebola are broader. The number of observations analyzed is half of the H1N1 period and one third of Ebola. Compared to the H1N1 period, the index movements' share in total by 20% more. Compared to the Ebola period, the index movements' share in total 2.5% by 140% more.

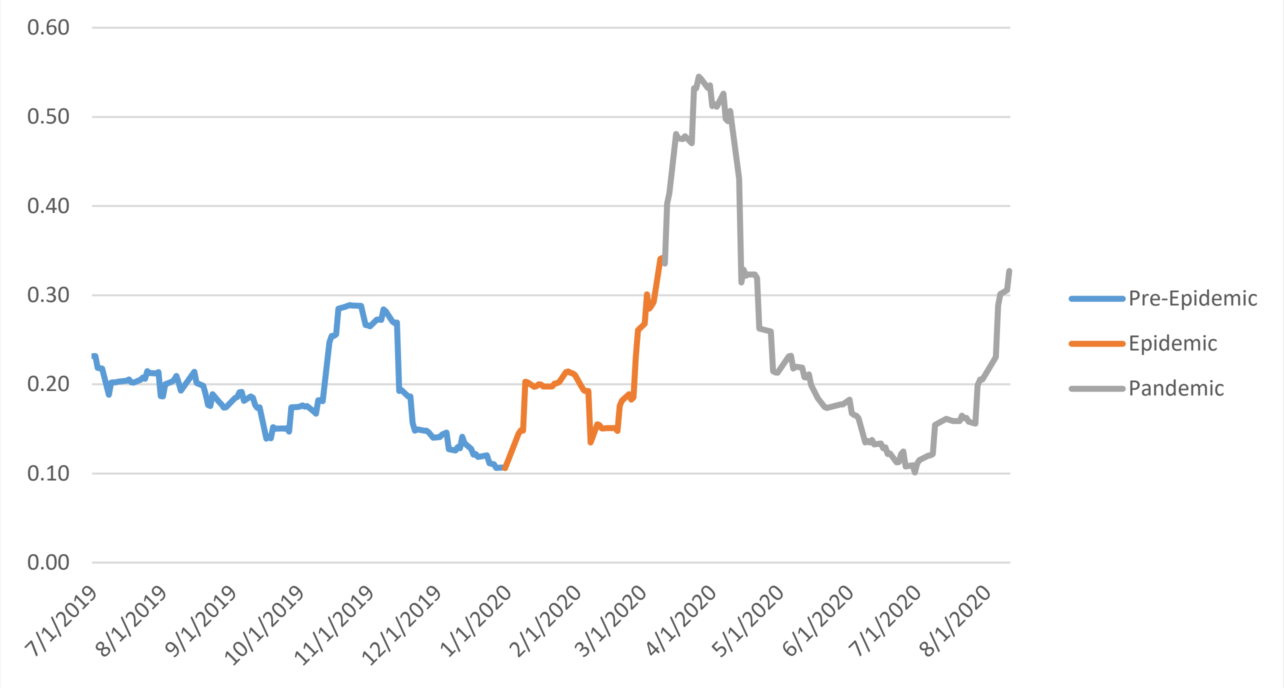
Table 8. Classification of the BIST 100 Return Index Movements

Period		A	B	C	D	E
Number of Observations		2664	318	495	404	151
Movement of	+2.5%	100	21	16	11	9
BIST 100 return	-2.5%	100	14	14	10	11
Share in Total		7.5%	11%	6%	5.2%	13.2%

A: Before COVID-19 period covers the dates 2/4/2009-12/30/2019.
B: H1N1 period covers the dates 4/27/2009 – 8/9/2010.
C: Ebola period covers the dates 3/10/2014 – 3/28/2016.
D: MERS period covers the dates 3/24/2014 – 10/30/2015.
E: COVID-19 period covers the dates 12/31/2019-08/11/2020.

Figure 3 shows that market volatility reached its highest levels especially during the pandemic period. Generally, COVID-19 has increased market volatility. Volatility is a cumulative measure and is created based on historical data. Therefore, it expresses the previous period response of the index. Based on the volatility change, it can be said that the index has an intense response from the beginning of the outbreak.

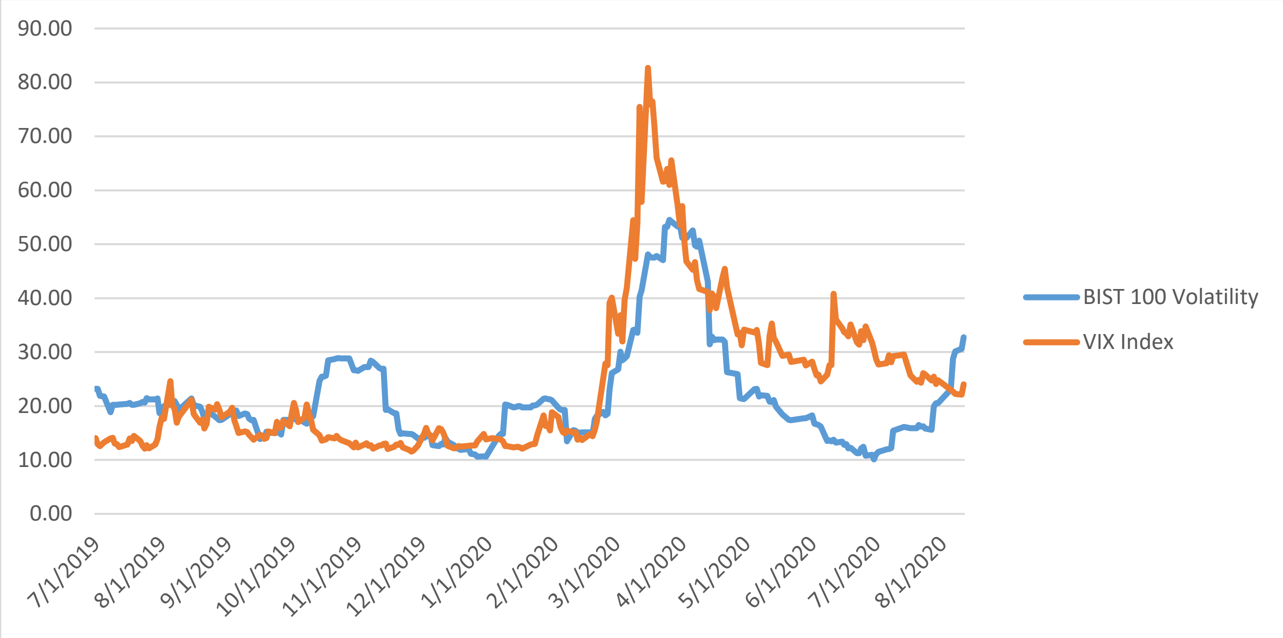
Figure 3. Volatility of the BIST 100 Index



Source: own representation

In Figure 4, the VIX Index and the BIST 100 Index volatility are seen together. The VIX Index measures the implied volatility by taking the relationship of option prices to market volatility as a reference. Hence, the VIX Index is a forward indicator. As indicated in Figure 4, it is seen that the VIX Index exhibits leading movements. With the help of the established regression, there was a 71% correlation between the two indices. When only the outbreak period is taken as reference, the correlation increases to 77%. From this point of view, it can be said that the BIST 100 Index gives similar reactions to the developments in the world and is greatly affected by the COVID-19.

Figure 4. Volatility of the VIX and the BIST 100 Index



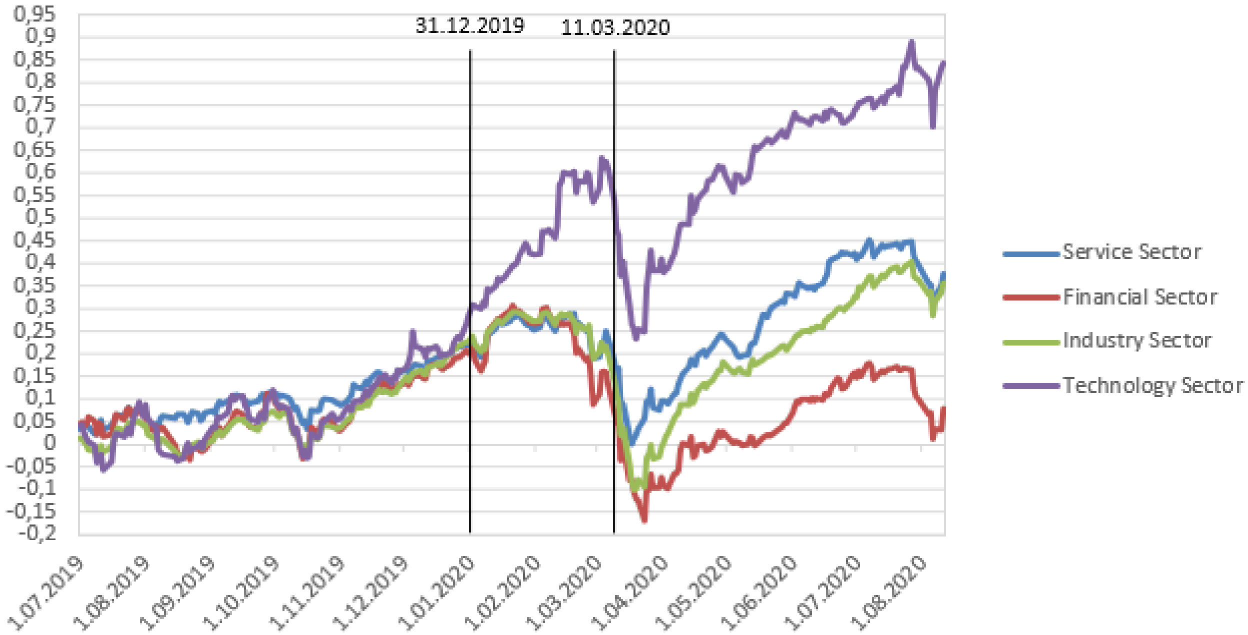
Source: own representation

The COVID-19 pandemic has not yet ended. It has created a more devastating effect than previous outbreaks. By August 31, COVID-19 spread in over 180 countries. 25.484.767 cases were reached, and 850.535 people died due to COVID-19 (John Hopkins University, 2020). Factors such as the spread of the virus, the fatality rate, the general course of the outbreak, the experience of recent outbreaks, the development of the information network, liberalization and the intensity of cross-border trade in modern economies (Baker *et al*., 2020) makes COVID-19 a greater pressure element on financial markets compared to previous outbreaks. As a matter of fact, the same situation is predicted for the BIST.

5.1. The Effects of COVID-19 on BIST Sectoral Indices

Companies quoted on BIST can be grouped under four sectors. These are service, financial, industry and technology sectors. When the change in the return series for the relevant sectors is compared in terms of periodic return, it is 22%, 23%, 26% and 38% in the before COVID-19 period; - 11%, -22%, -16% and 5% in the epidemic period and 23%, 2%, 24% and 37% respectively in the pandemic period up to 8/11/2020. The process can be monitored within Figure 5. The service, financial, industrial and technology sector indices were at 90422.28, 144555.49, 145390.04 and 116989.96 on 12/30/2019 before the onset of the outbreak. The relevant indices were at the level of 99509.00, 115142.00, 154132.00 and 167986.00 as of 8/11/2020. In the relevant period, service, industrial and technology sector indices increased by 10%, 6% and 44% respectively. But financial sector indices decreased by -20%. At the perspective of cumulative returns from highest to lowest, technology sector has 42%, service sector has 12%, industry sector has 8% and financial sector has -19% return. Losses in the service, industry and technology indices were largely compensated. However financial sector index returns neutralized and nearly zero.

Figure 5. Cumulative Return Change of the BIST Sub-Indices Throughout COVID-19



Source: own representation

In Table 9 market movements in the period examined are given quantitatively. The period of 2/4/2009-8/11/2020 was divided into three parts as before COVID-19 (2/4/2009-12/30/2019), epidemic period (12/31/2019-3/10/2019) and pandemic period (3/11/2019-8/11/2020). Market movements in all periods were calculated. In the period before COVID-19, market movements above 2.5% were 134, 355, 131 and 331, and 20. Their share in the total was 5%, 13.3%, 4.9% and 12.4% for service, financial, industry and technology sector, respectively. In the COVID-19 epidemic period, which is a period of 0.9/50 of the previous period, the market movements above 2.5% were 7, 10, 6 and 12. Their share in the total was 14%, 20%, 12% and 24% for service, financial, industry and technology sector, respectively. In the COVID-19 pandemic period, which is a period of 1.7/50 of the before COVID-19 period), the market movements above 2.5% were 14, 18, 11 and 28. Their share in the total was 14%, 18%, 11% and 28% for service, financial, industry and technology sector, respectively. In the COVID-19 full period, which is a period of 2.8/50 of the before COVID-19 period, the market movements above 2.5% were 21, 28, 17 and 40. Their share in the total was 14%, 19%, 11% and 26.5% for service, financial, industry and technology sector, respectively.

Table 9. Classification of the BIST Sectoral Indices' Movements

	Period		A	B	C	D	E	F	G
	No of Observations		2664	318	495	404	151	50	101
Service Sector	Movement of BIST 100 return	+2.5%	64	12	5	2	10	3	7
		-2.5%	70	10	13	9	11	4	7
	Share in Total		5%	6.9%	3.6%	2.7%	14%	14%	14%
Financial Sector	Movement of BIST 100 return	+2.5%	187	34	31	25	11	3	8
		-2.5%	168	25	27	21	17	7	10
	Share in Total		13.3%	18.5%	11.7%	11.4%	19%	20%	18%
Industry Sector	Movement of BIST 100 return	+2.5%	57	9	7	5	5	1	4
		-2.5%	74	14	9	7	12	5	7
	Share in Total		4.9%	7.2%	3.2%	3%	11%	12%	11%
Technology Sector	Movement of BIST 100 return	+2.5%	192	35	29	20	26	8	18
		-2.5%	139	13	13	9	14	4	10
	Share in Total		12.4%	15.1%	8.5%	7.2%	26.5%	24%	28%

A: Before COVID-19 period covers the dates 2/4/2009-12/30/2019.
B: H1N1 period covers the dates 4/27/2009 – 8/9/2010.
C: Ebola period covers the dates 3/10/2014 – 3/28/2016.
D: MERS period covers the dates 3/24/2014 – 10/30/2015.
E COVID-19 total period covers the dates 12/31/2019-8/11/2020.
F: COVID-19 epidemic period covers the dates 12/31/2019-3/10/2019.
G: COVID-19 pandemic period covers the dates 3/11/2020-8/11/2020.

Although the outbreak contains many threats, it has also offered opportunities compared to previous periods. Considering the period after 2009, it is understood that COVID-19 has had a great impact on the BIST sub-indices. When COVID-19 period and before were compared, price changes in the service sector remained stable. Negative price changes in the industrial sector became more dominant. The majority of price changes in the financial sector turned from positive to negative. Positive price changes became more dominant in the technology sector.

When the COVID-19 period is compared with the H1N1 period, it is seen that the excessive market movements (±2.5%) in all sectors has increased the excessive movements in the service and technology sector are also increased more than twice. When the COVID-19 period is compared with the Ebola period, it is seen that the excessive market movements in all sectors has increased. The excessive movements in the service, industry and technology sector are also increased tree times more. It is seen that there is only a dramatic change in the rate of positive and negative market movements of the financial sector compared to previous epidemic periods.

Conclusions

In this study, the effects of recent outbreaks on the Borsa Istanbul were investigated. First, the effects of H1N1, Ebola and MERS outbreaks on BIST 100 Index volatility were examined. ARCH family models were used for analysis and it was decided that the appropriate model was E-GARCH (1, 1). The results suggest that only the H1N1 pandemic had a significant effect on BIST 100 Index volatility. Particularly, the H1N1 pandemic caused the increase of BIST 100 Index volatility by 1.7%. However, positive news had more impact on volatility than negative news.

It was also aimed to evaluate the current situation of COVID. H1N1, Ebola and MERS outbreaks have arisen in nearby geography of Turkey. They have influenced the rest of the world intensively. However, Turkey has not heavily or directly affected from relevant outbreaks. COVID-19 is in a very different position. H1N1 caused the most fatality among the other outbreaks. But COVID-19 caused 40 times more fatality than H1N1 (WHO, 2010a). The number of cases has exceeded 25 million. 270.133 cases and 6.370 fatality are already reached in Turkey (John Hopkins University, 2020). Turkey gives a successful test by the means of numerically when assessing the overall situation of the world. However, the markets are under great pressure and the pandemic has negatively affected the markets. When the current process is evaluated, it has been determined that the service and industry sector has caught the acceleration of before COVID-19. The technology sector is positively separated and provides surplus value. The financial sector is negatively separated and its cumulative return is zero. In addition, there are many studies in the literature like Rabhi, 2020; Ashraf, 2020; Awadhi *et al*., 2020; Ali *et al*., 2020; Sharif *et al*., 2002; Şenol and Zeren, 2020; Jalloh, 2019 etc. which report that the impact of epidemics on the markets increases with the number of cases and fatality. The COVID-19 pandemic is particularly devastating for some sectors and is unlike any previous crisis (IMF, 2020). COVID-19 recession has the worst scenario and forecast among global recessions since 1990 (World Bank, 2020). Stock markets experienced double-digit percentage declines. The VIX Index exceeded 80 level. The volatility of financial markets has reached extraordinary levels since 2008. (Ma *et al*., 2020). No epidemic in the last century has had such an impact on stock markets, including the Spanish flu (Baker *et al*., 2020; Goodell, 2020).

The COVID-19 outbreak has already created a global impact and pressure in social, psychological, political, economic and many other aspects. The same effects are also seen in Turkey.

However, restrictions have devastating effects on the financial sector. However, this situation is a double-edged sword. The easing of restrictions also makes it difficult to control the pandemic. Restrictions should be directed to the social life rather than the working environment. Societies, on the other hand, must obey the rules in terms of both health and economic well-being. The date when the pandemic will end is a mystery. However, history is repetitive. Throughout history, epidemics have destroyed the entire population and societies. But paradoxically paved the way for innovations and advances in the sciences, economics and political systems (Huremović, 2019, p. 7).

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