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The effect of the fear index, dollar index and bitcoin on volatility: An example from Borsa Istanbul

Murat Dilmac[1+]
Serpil Sumer[2]
Hilal Mola[3]
Firat Altinkaynak[4]

[1,2,3,4]*Atatürk University, Faculty of Social Sciences and Humanities, Finance and Banking Department, Oltu, Erzurum, Turkey.*
[1]*Email: mdilmac@atauni.edu.tr*
[2]*Email: serpil.sumer@atauni.edu.tr*
[3]*Email: hilal.karatas@atauni.edu.tr*
[4]*Email: afirat@atauni.edu.tr*

(+ Corresponding author)

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ABSTRACT

The effect of the Russia–Ukraine war has fluctuated in Europe and Asia's economic conjuncture by virtue of constant shifting balances. The portfolios of investors who made decisions in uncertain conditions have been affected by these fluctuations that have caused volatility in the stock market's indexes. The aim of this study is to examine the impact of the Fear Index (FI), the Dollar Index, and Bitcoin on the volatility of the Borsa Istanbul 100 Index (BIST). Autoregressive distributed lag (ARDL) time series analysis was used for the study, which revealed that the Dollar Index has no effect on volatility, while the FI was found to have an effect on volatility both in the short and long runs. In addition, Bitcoin was determined to have an effect on volatility only in the long run. When the period of the data used is examined, the outbreak of the Russia–Ukraine war in February 2022 is thought to be the reason for the increase in the FI. It can be assumed that the decisions of investors to invest in the BIST were adversely affected by the war as a natural consequence of this, and investors who ceased investing in the BIST index opted to invest elsewhere.

Contribution/Originality: The component of this study that sets it apart from previous studies in the literature is that it deals with the Dollar Index, Bitcoin, and the Fear Index, as these are assumed to affect stock returns. The analyses of variables were carried out separately in the previous literature.

1. INTRODUCTION

Stock market volatility is an issue that is of ongoing interest to policy makers, academics and investors (Dai, Zhou, Wen, & He, 2020; Wang, 2019). For investors trying to make decisions in an environment of uncertainty, stock market volatility provides important information (Becker, Clements, & McClelland, 2009). In addition, volatility is a key variable used in portfolio selection, hedging, risk management and option pricing (Liang, Li, Ma, & Wei, 2021; Wang, 2019). Accurate estimation of the volatility that will occur in the stock markets is a current issue, and studies (for example, De la Torre-Torres, Venegas-Martínez, and Martínez-Torre-Enciso (2021)) have been carried out for the estimation and modeling of volatility. The disappearance of barriers between countries due to globalization has led to the diversification of investment channels among investors.

Studies on the assessment and modelling of volatility have become more significant and meaningful due to the rapid advancement of globalization. While examining the works on the measurement and modelling of volatility, it is interesting to note that it is frequently linked the Fear Index (FI) (Becker et al., 2009; Lu & Zhu, 2010; Bevilacqua, Morelli, & Uzan, 2020; Chen, Liang, & Umar, 2021; and Li, 2022). The Chicago Board Options

Exchange Volatility Index (VIX), also known as the Fear Index, provides information about the degree of fear in financial markets. The index was created in 1993 and represents investors' fears (Li, 2022). Worldwide financial crises, epidemics, wars, etc., lead to an increase in the FI (Whaley, 2000). An increase in the FI indicates that the risk perceptions of market investors increase, while the opposite situation indicates that the risk perceptions of investors decrease (Yıldırım, 2022) and show a more optimistic attitude toward the future. For this reason, it would be appropriate for people or organizations that are thinking about investing to behave in accordance with the data from the FI. Fear has an impact on an investors' stock returns in addition to their portfolio diversity (Smales, 2017).

While deciding what to do in an economic situation that is changing, investors exercise caution. Global investors, however, have shifted to various financial markets based on the risk-return balance since the financial markets were liberalized. Risk, return on assets, and stock market volatility that are particular to each nation influence how investors' portfolios are constructed (Sarwar & Khan, 2017). Making decisions has become increasingly difficult in the current economic climate due to the unpredictability in the markets. In behavioral economics literature, studies carried out to comprehend the financial decisions made by investors based on the risk-return balance have occupied a significant space (Bekaert & Hoerova, 2014).

Behavioral economics specifies the deficiencies and flaws of the traditional economy and also deals with the psychological, social, cultural, mental and emotional factors that affect the preferences of the decision units in economic terms (Teitelbaum & Zeiler, 2018). In addition, according to behavioral economics, individuals may exhibit irrational or emotionless behaviors while making decisions (Loewenstein, Weber, Hsee, & Welch, 2001). Decision makers believe that by weighing the desirable outcomes and possibilities of their choices, they can make an informed decision between conflicting options. A desirable outcome from an economics point of view is the advantage attained as a result of the decision. In other words, decision making is seen as a condition of maximum utility. Even so, this goal-oriented strategy does not imply that people lack feeling when making judgements (Rick & Loewenstein, 2008).

In addition to the FI, volatility is linked to Bitcoin in the literature that analyzes stock price variations. Investors view Bitcoin, a popular virtual currency in recent years, as a financial asset rather than a medium of exchange (Kang, Yoon, Bekiros, & Uddin, 2020; Katsiampa, 2017). Stock price variations are thought to be caused by people using Bitcoin as a substitute for stocks as a financial instrument.

The dollar index is an additional factor connected to stock market swings. Investors consider changes in the dollar index to be related to risk (Chakraborty, Tang, & Wu, 2015). Investors make their choices under the presumption that changes in the dollar index have an influence on stock returns (Hughen & Beyer, 2015). Investors commonly use the dollar index as a type of financial indicator (Bruno, Shim, & Shin, 2022). In the literature, the interrelation between stocks, the FI, the dollar index and bitcoin has been examined with various combinations. Akkaya (2021) looked at the influence of stock, the FI and the dollar index on the volatility of bitcoin; Su, Xi, Tao, and Umar (2022) examined the FI and bitcoin volatility; Wu, Pandey, and Dba (2014) investigated the interrelation between stocks and bitcoin; Shilov and Zubarev (2021) looked at the interrelation between financial assets, such as dollars and stocks, and bitcoin volatility; Baba and Sakurai (2011) examined the interrelation between the FI and macroeconomic variables; and Kliger and Kudryavtsev (2013); Emna and Myriam (2017) and Badshah (2018) studied the interrelation between the FI and stock volatility.

The dollar index, the volatility of stocks, and Bitcoin are all related to the FI in the literature (Alexander & Imeraj, 2021; Chow, Jiang, Li, & Li, 2020; Erik, Lombardi, Mihaljek, & Shin, 2020). Similarly, the stock price is influenced by how investors evaluate the dollar and Bitcoin as financial assets. When the study's model was created, it was decided to investigate whether the volatility of the BIST 100 index was influenced by Bitcoin or the dollar or fear indices. The underlying reason for choosing the BIST 100 index as the dependent variable is that investors see Bitcoin and dollars as financial assets to invest in. Additionally, the FI was added to the study as an independent variable because it has been noted in studies in the literature how the FI affects investors' assessments. The component of the study that sets it apart from previous studies in the literature is that it deals with variables that are assumed to affect stock returns and that the literature as a whole endeavored to analyze the interrelation among them in various combinations. The interrelation among the variables in the study and their impact on one another can be compared to links in a chain.

2. METHOD, DATA AND MODEL

The data used in the study was obtained from Matriks Information Distribution Services. The time series data covers 251 days' worth of closing values between January 3, 2022, and December 30, 2022. In the study, the cointegration relationship between the volatility of the Borsa Istanbul 100 index (BIST) and the changes in the fear index (FI), the dollar index (DXY) and the value of Bitcoin (BTC) in the specified period was examined. In addition, it was added to the model as a dummy variable in order to examine the short and long-term effects of the Russia–Ukraine war, which started in February 2022, on the volatility of Borsa Istanbul. The descriptive statistics of the variables and the correlation data between the variables are presented in Table 1.

Table 1. Descriptive statistics and correlation of variables.

Variable	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque–Bera	Probability
BIST	0.346	0.325	0.932	0.167	0.121	1.553	8.066	369.285	0.000
FI	25.624	25.47	36.45	16.6	4.215	0.229	2.182	9.206	0.010
DXY	103.988	104.465	114.13	94.79	5.258	-0.073	1.995	10.781	0.005
BTC	28119.94	23156	47945	15778	10261.88	0.468	1.586	30.074	0.000
Correlation coefficients									
BIST	1								
FI	0.055	1							
DXY	0.022	0.192	1						
BTC	-0.086	-0.061	-0.851	1					

The time series approach was used for the econometric method in the study. First, the stationarity analyses of the variables were made in this context. The autoregressive distributed leg (ARDL) approach was employed based on the stagnation analysis findings. This cointegration approach proposed by Pesaran, Shin, and Smith (2001) removes the constraint put forward by Engle and Granger (1987); Phillips and Hansen (1990); Johansen (1988); Johansen (1995) and Johansen and Juselius (1990) that the variables in the cointegration techniques are at the same stationarity level (Bölük & Mert, 2015). The ARDL model is a single overarching equation model, so even if the variables are stationary at I(0) or I(1), it can still be used (Laurenceson & Chai, 1998; Nasrullah et al., 2021). However, the model will not be valid if the variables are stationary at the I(2) level (Acaroğlu & Güllü, 2022).

The ARDL approach first investigates whether there is a long- or short-term relationship between the dependent variable and independent variables. For this purpose, in order to determine the existence of cointegration between variables, an unconstrained error correction model should be established. Equation 1 shows the unconstrained error correction model adapted to the variables of this study.

$$\Delta lnXu100v = \beta_0 + \sum_{i=1}^{m} \alpha_{1i}\, lnBIST_{t-i} + \sum_{i=0}^{m} \alpha_{2i}\, lnFI_{t-i} + \sum_{i=0}^{m} \alpha_{3i}\, lnDXY_{t-i} + \sum_{i=0}^{m} \alpha_{4i}\, lnBTC_{t-i} + \beta_1 lnBIST_{t-i} + \beta_2 lnFI_{t-i} + \beta_3 lnDXY_{t-i} + \beta_4 lnBTC_{t-i} + \beta_4 Dummy_{t-i} + \varepsilon_t \quad (1)$$

Here, BIST stands for the volatility value of Borsa İstanbul Inc.'s national 100 index, FI is the daily closing values of the Chicago Board Options Exchange Volatility Index, DXY is the daily closing values of the dollar index, BTC is Bitcoin's daily closing values, the Dummy is the Russia–Ukraine war, Δ represents first difference, ln is the natural logarithm, α and β are the prediction coefficients, m is the appropriate delay coefficient for the variable, and ε is the error term.

In the ARDL approach, the hypothesis (H0) that the long-run coefficients are equal to zero is tested. The F test is used to accept or reject H0. For the F test statistic, Pesaran, Shin, and Smith (2001) and the crucial values developed by Narayan and Narayan (2005) are used. At significance levels of 10%, 5%, and 1%, the F test statistic is required to stay below the crucial value for I(0) in order for H0 to be accepted and conclude that cointegration is absent. H0 is rejected and cointegration is inferred if the F test statistic is higher than the crucial value for I(1). Additionally, the outcome is ambiguous if the F test result falls between the two limits (Acaroğlu & Güllü, 2022).

If cointegration is detected between the variables, an ARDL model, as in Equation 2, is used to identify whether it is a short- or long-run relationship.

$$\Delta lnXu100v = \beta_0 + \sum_{i=1}^{a} \beta_{1i}\, \Delta lnXu100v_{t-i} + \sum_{i=0}^{b} \beta_{2i}\, \Delta lnFI_{t-i} + \sum_{i=0}^{c} \beta_{3i}\, \Delta lnDXY_{t-i} + \sum_{i=0}^{d} \beta_{4i}\, \Delta lnBTC_{t-i} + \sum_{i=0}^{e} \beta_{5i}\, \Delta Dummy_{t-i} + \varepsilon_t \quad (2)$$

Equation 2 has been adapted to suit the variables of the study; a, b, c, d and e stand for the appropriate lag numbers, Δ is the first difference, ln is the natural logarithm, α and β are the prediction coefficients, and ε_t is the error term. At this stage, the long-term coefficients are determined.

Next, the Breusch–Godfrey test for serial correlation using the Lagrange multiplier (LM) test, the Breusch and Pagan (1979) heteroscedasticity test, the Ramsey RESET test, and the normality test are performed to investigate the suitability of the model. The CUSUM and CUSUMQ tests are additionally utilized to assess the model's stability, or the stationarity of the variables' coefficients and to detect whether a structural break has occurred.

3. FINDINGS

In the first stage, the stationarity analysis of the series was performed. In the ARDL approach, the series of the variables are stationary at I(0) and I(1), which does not prevent the analysis from being carried out. For this purpose, the series of all variables were subjected to the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. In addition, the series were also subjected to the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) unit root test. In the unit root tests, the lag lengths were determined by the Akaike Information Criterion (AIC). In the ADF and PP unit root tests, the null hypothesis indicates that the series has a unit root. Therefore, if the test results are statistically insignificant, it is assumed that the series are not stationary and contain a unit root. Table 2 presents the ADF and PP test findings of the variables used in the study.

Table 2. ADF and PP unit root tests.

Variable	ADF				PP			
	Constant		Constant and trend		Constant		Constant and trend	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
BIST	-2.623*	-5.655***	-2.934	-5.744***	-4.943***	**-12.413*** **	-4.995***	**-12.578*** **
FI	-3,658***	**-12.447*** **	-3.727**	**-12.455*** **	-3.630***	**-15.962*** **	-3.689**	**-15.988*** **
DXY	-1.520	-12.231***	-0.351	-12.368***	-1.523	-14.451***	-0.553	-14.538***
BTC	-1.506	-14.081***	-2.444	-14.073***	-1.423	-14.012***	-2.275	-14.003***

Note: ***,** and * represent 1%, 5% and 10% respectively.

According to the findings in Table 1, BIST, DXY and BTC are not stationary at the I(0) level in the ADF unit root test, but they are stationary at the I(1) level, and the FI variable is stationary at the I(0) level. In the PP unit root test, BIST and FI were found to be stationary at the I(0) level, while DXY and BTC were found to be stationary at the I(1) level. In the KPSS unit root test, the findings of which are presented in Table 3, the null hypothesis shows that the series does not have a unit root and is stationary. Therefore, unlike the ADF and PP tests, if the KPSS test results are statistically insignificant, it is assumed that the series are stationary and do not contain a unit root.

Table 3. KPSS unit root tests of variables.

Variable	KPSS			
	Constant		Constant and trend	
	I(0)	I(1)	I(0)	I(1)
BIST	0.269	0.283	0.263***	0.105
FI	0.111	**0.096**	0.0924	**0.035**
DXY	1.599***	0.315	0.310***	0.095
BTC	1.822***	0.073	0.242***	0.042

Note: *** represents the 10% level of significance.

According to the KPSS test findings in Table 3, it was determined that the FI variable was stationary at the I(0) level, and the BIST, DXY and BTC variables were stationary at the I(1) level. The findings are similar to those of the ADF and PP tests. According to the findings obtained from the ADF, PP and KPSS unit root tests, it was decided that the ARDL approach was appropriate to investigate the existence of cointegration among the variables. For this purpose, the bounds test was performed to detect the existence of cointegration between the variables. According to the F statistic value obtained by the bounds test in Table 4, since the upper limit at the 1% significance level is higher than the critical value, cointegration was found between the series.

Table 4. Bounds test statistics and critical values.

Model	F	k	Level	Critical values		
				1%	5%	10%
ARDL(3, 3, 0, 0, 1)	6.0778***	4	I(0)	3.74	2.86	2.45
			I(1)	5.06	4.01	3.52

Note: F test indicates the probability value. *** represents the 10% level of significance. The bounds test's critical values were obtained from Pesaran et al. (2001). Table Case 3: Constant (k = 4). The number of lags is determined by the AIC.

For the long-run and short-run associations, the variables are looked at in the ARDL bounds test approach when a cointegration between the variables is found. Table 5 displays the estimation results. The R-squared, adjusted R-squared and F-statistic values demonstrate that the model has a high explanatory power and is statistically significant.

Table 5. ARDL (3, 3, 0, 0, 1) models.

Variable	Coefficient	Std. error	t-statistic	Prob.
LBIST(-1)	1.07	0.062	17.362	0.000***
LBIST(-2)	0.001	0.091	0.009	0.993
LBIST(-3)	-0.167	0.059	-2.802	0.006***
LFI	0.024	0.069	0.350	0.727
LFI(-1)	0.097	0.093	1.046	0.297
LFI(-2)	0.071	0.093	0.767	0.444
LFI(-3)	-0.132	0.067	-1.958	0.052*
LDXY	-0.148	0.191	-0.774	0.439
LBTC	-0.075	0.026	-2.896	0.004***
DMMY	0.245	0.071	3.455	0.001***
DMMY(-1)	-0.278	0.070	-3.959	0.000***
C	1.164	1.057	1.102	0.272
R-squared: 0.953 Adjusted R-squared: 0.951 F-statistic (Prob): 433.701*** DW stat: 2.024				

Note: *** and * represent the 1% and 10% levels of significance, respectively.

In the ARDL approach, the Akaike information criterion (AIC), Bayes information criterion (BIC) or Hannan–Quinn information criterion (HQ) can be used to determine the optimal model. In this study, the ARDL model was estimated according to the AIC.

To determine the optimal ARDL model, it was decided that the ARDL (3, 3, 0, 0, 1) model with the lowest AIC value was the most optimal. Table 6 shows the findings of the five models with the lowest AIC values. Since Model 1 has the lowest AIC value, it has been determined as the optimum model.

Table 6. Model selection criteria.

Model	Logl	AIC*	BIC	HQ	Adj. R-sq	Specification
1	316.097	-2.472	-2.301	-2.404	0.949	ARDL(3, 3, 0, 0, 1)
2	313.048	-2.472	-2.344	-2.420	0.948	ARDL(3, 0, 0, 0, 1)
3	316.963	-2.471	-2.286	-2.370	0.949	ARDL(3, 3, 0, 1, 1)
4	313.806	-2.470	-2.328	-2.413	0.948	ARDL(3, 0, 0, 1, 1)
5	316.764	-2.470	-2.284	-2.395	0.949	ARDL(3, 4, 0, 0, 1)

Note: * represents the 1% level of significance.

The diagnostic tests results of the ARDL model are displayed in Table 7. The Ramsey RESET test demonstrates that the regression has no model-building errors. Also, the Breusch–Godfrey serial correlation test demonstrates that the model has no autocorrelation problems, and the Breusch–Pagan–Godfrey test does not have problems with variable variance. The findings of the Jarque–Bera (JB) test demonstrate that the model lacks a normal distribution.

The t-test, which affects the outcomes in models with large-scale observations, is considered to be unaffected by deviations from the normality assumption, according to Montgomery (2001); Schmidt and Finan (2018) and Tsagris, Alenazi, Verrou, and Pandis (2020). As a result, it would be more accurate to concentrate on identifying flawed model assumptions that may skew the outcome, such as outliers, high leverage, varying variance, associated errors, non-linearity, and interactions.

For this reason, deviation in the assumption of normality for the model used in the study was ignored based on the results of the other diagnostic tests and the number of observations.

Table 7. ARDL model diagnostic tests results.

Diagnostic test	Test statistic	Prob.
χ^2_{BGSC}	0.364	0.695
χ^2_{BPGh}	0.306	0.984
χ^2_{Ramsey}	0.496	0.482
χ^2_{JB}	1116.06	0.000***

Note: *** represents the 10% level of significance.

The CUSUM and CUSUMQ graphs were created (see Figure 1) to assess the consistency of the coefficients and to look for structural breaks in the ARDL model. If the graphs are within the crucial limits at the 5% significance level, it can be said that the estimated long-run coefficients are consistent. According to the CUSUM and CUSUMQ graphic data in Figure 1, it can be said that there is no structural break at the 5% significance level and the long-run coefficients of the model calculated within the scope of the ARDL bounds test are stable.

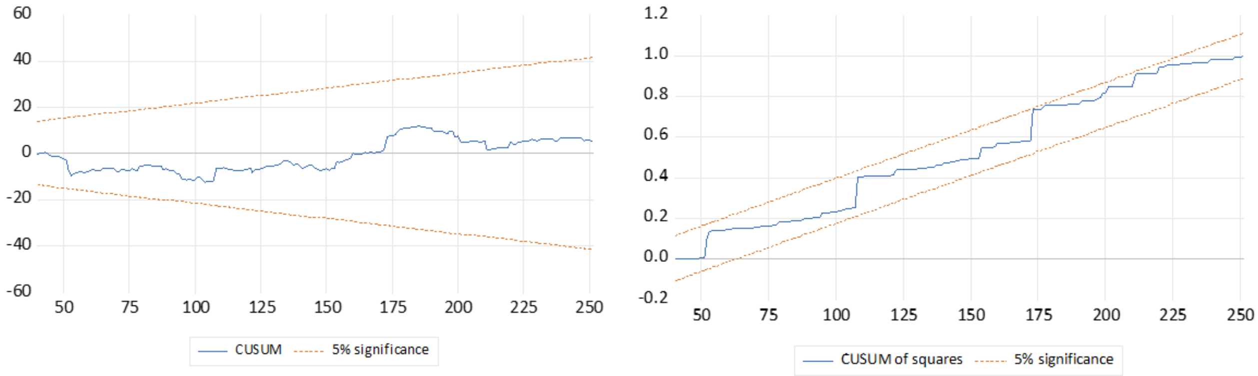

Figure 1. CUSUM and CUSUMSQ statistics for stability test.

Table 8 presents the estimation results for the long-run interrelation between FI, DXY, BTC and DMMY (Russia–Ukraine war) and the volatility of the XU100 index. The findings show that there is a significant and positive interrelation at the level of 1% between the volatility of the FI and XU100, a negative interrelation at the 10% level of significance with BTC, and at the 10% significance level with the DMMY variable used to examine the effects of the war between Russia and Ukraine. In other words, every 0.63 unit increase in the FI increases the volatility of XU100 by one unit (or vice versa), while every 0.78 unit increase in BTC decreases the volatility of XU100 by one unit. The Russia–Ukraine war, on the other hand, has a reducing effect on the volatility of the XU100 in the long run. No statistically significant interrelation was found on the XU100 volatility of the dollar index.

Table 8. Long-run coefficients.

Variable	Coefficient	Std. error	t-statistic	Prob.
LFI	0.638	0.320	1.992	0.048**
LDXY	-1.548	2.019	-0.767	0.444
LBTC	-0.781	0.251	-3.110	0.002***
DMMY	-0.343	0.189	-1.820	0.070*

Note: ***, ** and * represent the 1%, 5% and 10% levels of significance, respectively.

Table 9 shows the short-term coefficient estimation findings of the ARDL model. According to the results, the volatility of XU100 has a positive and significant interrelation at the level of 1% with the volatility of the previous two days. A one-unit increase in the volatility of the last two days of XU100 causes an increase of approximately 0.16 units on the trading day volatility of the XU100. Another finding is that there is a 5% positive and significant interrelation between the closing values of the two previous days in FI and the volatility of XU100. A one-unit increase in FI can cause an increase in XU100's volatility of 0.13 units after two business days. The dummy variable, unlike the long-run estimation, was found to increase the volatility of XU100 in the short term at a significance level of 1%.

Table 9. Short-run coefficients.

Variable	Coefficient	Std. error	t-statistic	Prob.
C	1.164	0.210	5.539	0.000***
D(LBIST(-1))	0.166	0.058	2.855	0.005***
D(LBIST(-2))	0.167	0.058	2.873	0.004***
D(LFI)	0.0241	0.066	0.363	0.717
D(LFI(-1))	0.060	0.065	0.933	0.352
D(LFI(-2))	0.132	0.065	2.019	0.045**
D(DMMY)	0.245	0.069	3.563	0.000***
ECT(-1)	-0.095	0.017	-5.559	0.000***

Note: *** and ** represent 1% and 10% significance levels, respectively.

The Russia–Ukraine war causes an increase in the volatility of the XU100 in the short term. In this model, in which short-term coefficients are calculated, the error correction term (ECT) is also included. According to the ECT findings, the error correction coefficient is -0.0953 and has 1% significance. This finding has two meanings. The ECT finding confirms that the error correction model works, and the shocks that will occur in the short term will approach equilibrium again in the long term.

4. DISCUSSION

There is a positive and significant interrelation between the Borsa Istanbul Index (BIST) and the FI both in the long and short terms, and there is a negative and significant interrelation with BTC in the long run. Considering that Bitcoin has grown in popularity and has attracted the attention of investors, this result is not surprising. It is thought that investors moved away from the Borsa Istanbul Index with the expectation of earning more income by investing in Bitcoin. Özdemir and Coşkun (2023), who obtained similar results to those obtained from this study, stated that the BIST and Bitcoin can be alternatives to each other. Finally, there is an insignificant interrelation with DXY in both the long run and the short run. The result regarding the effect of the FI on volatility is consistent with the literature (Chow et al., 2020; Whaley, 2000). An increase in the FI increases the volatility in the Borsa Istanbul index. The study's results are consistent with those of earlier investigations. It was emphasized by Kula and Baykut (2017) that the BIST and the FI have a long-term interrelation. They stated that with the rise of the FI index, the risk perceptions of investors will increase, and with the decrease of the FI index, the investors will be optimistic about the future. Başarır (2018), who examined the causality of the interrelation between the FI and the BIST 100, found a causal interrelation from the FI index to the BIST 100 and concluded that investors can make predictions for the BIST 100 index by making use of the FI index. Önem (2021), on the other hand, stated that the volatility in the FI index partially increases the volatility of the BIST index. Münyas (2022), who examined the interrelation between the FI and the stock markets of developing countries, revealed that the BIST was most affected by changes in the FI. He also stated that while the effect of the FI on stock markets was higher in the short term, it continued to decrease in the long term. However, this study's findings differ from some studies in the literature; Sarıtaş and Nazlıoğlu (2019) concluded that FI shocks have a negative effect on the BIST index.

5. CONCLUSION

This research investigated the effects of selected variables on the volatility of the Borsa Istanbul Index (BIST). The long- and short-run associations of the variables were examined by the ARDL analysis for this purpose. It was revealed that the dollar index has no effect on volatility, while the FI affects volatility both in the short and long runs as a result of the analysis made within the scope of the research. In addition, Bitcoin was determined to affect volatility only in the long run. When the period of the data used is examined in the research, the outbreak of the Russia–Ukraine war in February 2022 is thought to be the reason for the increase in the FI.

The time frame within the scope of the research was specially chosen so that the change in the FI can be seen more apparently in this context. Based on the period selected within the scope of research, it can be expressed that the decision of investors to invest in the BIST was adversely affected by the war as a natural consequence. It is also thought that an underlying reason for the bad effect of the war is Turkey's geopolitical location. Turkey may have led investors to believe that the war would worsen by virtue of its proximity to both nations, which may have led them to diversify their holdings in foreign stock markets. For future studies, the data should include a larger temporal dimension to see the influence of conflict on the FI. Based on the results obtained in the study, the Dollar Index does not have any effect on volatility, and the Fear Index affects volatility in both the short and long terms, which will serve as a guide for future academic studies.

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