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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

THE EFFECT OF FINANCIAL STRESS ON STOCK MARKETS: AN EXAMPLE OF MINT ECONOMIES

FİNANSAL STRESİN HİSSE SENEDİ PİYASALARI ÜZERİNDEKİ ETKİSİ: MINT EKONOMİLERİ ÖRNEĞİ

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Abstract

Increasing uncertainties due to developments in financial markets lead to uncontrollable financial behaviors. Financial stress indices are created by considering many financial indicators directly related to the financial system. So, examining the impact of financial stress indices on stock markets, which have an important share in financial markets is important. The paper aims to investigate the short and long-term effects of emerging markets' financial stress index (EFSI) and global financial stress indices (GFSI) on the stock markets of MINT (Mexico, Indonesia, Nigeria, and Turkey) economies. For this purpose, analyses are made using the ARDL (Autoregressive Distributed Lag) Bounds Test method using weekly data for 10/01/2014-26/04/2024. It has been determined that EFSI and GFSI negatively affected the benchmark stock market indices of all MINT economies in the short term and that the negative effect continued in the long term. Still, it has been significant for only EFSI in all MINT economies, as an important results of the analysis. It has been determined that following financial stress indices can be a leading indicator for stock market investors. It is hoped that the paper's results may be useful for financial market actors considering investing in these markets.

Keywords: Stock Markets, Financial Stress Index, MINT Economies.
Jel Classification: C32, G15, G32.

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Öz

Finansal piyasalarda yaşanan gelişmeler dolayısıyla artan belirsizlikler kontrol edilemeyen finansal davranışlara yol açmaktadır. Finansal stres endeksleri doğrudan finansal sistem ile ilişkili birçok finansal gösterge dikkate alınarak oluşturulmaktadır. Bu nedenle finansal stres endekslerinin finansal piyasalarda önemli payı olan hisse senedi piyasaları üzerindeki etkisinin incelenmesi önem arz etmektedir. Çalışmada gelişen piyasalar finansal stres endeksi (EFSI) ile küresel finansal stres endekslerinin (GFSI) MINT (Meksika, Endonezya, Nijerya ve Türkiye) ekonomilerine ait hisse senedi piyasaları üzerindeki kısa ve uzun dönemli etkilerinin araştırılması amaçlanmıştır. Bu amaçla 10/01/2014-26/04/2024 dönemine ait haftalık veriler kullanılarak ARDL (Autoregressive Distributed Lag) Sınır Testi metodu ile analizler yapılmıştır. Analizler sonucunda MINT ekonomilerinin tümü için EFSI ve GFSI'nın kısa dönemde ülkelerin gösterge borsa endekslerini negatif etkilediği, uzun dönemde ise bu olumsuz etkinin devam ettiği fakat EFSI için anlamlı olduğu tespit edilmiştir. Finansal stres endekslerini takip etmenin borsa yatırımcıları için öncü bir gösterge olabileceği belirlenmiştir. Çalışma sonuçlarının bu piyasalara yatırım yapma düşüncesindeki piyasa aktörleri için yararlı olabileceği umulmaktadır.

Anahtar Kelimeler: Hisse Senedi Piyasaları, Finansal Stres Endeksi, MINT Ekonomileri.

Jel Sınıflandırması: C32, G15, G32.

1. Introduction

Pressures on financial markets and expectations of possible losses in the markets are the main sources of financial stress. Financial stress, which increases with risk and uncertainty, essentially emerges a fragile financial structure and shocks. A strong financial structure reduces the possibility of any shock resulting in excessive stress and crisis. For this reason, the magnitude of the shocks faced by the financial system and the interaction of these shocks with financial system vulnerabilities determine the level of financial stress. The fact that financial markets are sound does not mean there will be no financial stress in these markets. Internal and external shocks in economies with strong markets can significantly increase financial stress. Financial stress can be the source of both fluctuations in financial markets and economic stagnation. In this regard, measuring financial stress and creating and monitoring financial stress indices (FSI) have become important.

The main purpose of FSI is to reveal the instability situations existing in the financial system and explain this with a single statistical variable (Hollo, Kremer, and Lo Duca, 2012: 2). FSI is used to provide detailed information about the financial situation and to facilitate the detection of hidden vulnerabilities, which are the main cause of the weaknesses that create and transmit stress in financial markets (Illing and Liu, 2003: 2; Monin, 2019: 1-2).

Global Financial Stress Index (GFSI) is an important international financial and economic indicator developed to reflect global financial fragilities and global financial system risks and enable easy financial market monitoring. This index is created based on 18 stress indicators belonging to 3 different financial asset classes: yield spreads, interest rates, and other indicators. It is calculated and published weekly by the Federal Reserve Bank of St. Louis. It is stated that global financial stress indices are much more effective than the VIX fear index in measuring global stress (Liang, Luo, Li, and Huynh, 2023: 2; Bouri, Gupta, Lau, Roubaud and Wang, 2018: 297-298). The Emerging Markets Financial Stress Index (EFSI) is the emerging economies-specific subcategory of the FSI created by the Office of Financial Research (OFR). OFR FSIs are created and published daily. In addition, FSIs specific to the United States (USFSI) and Other Advanced Economies (OAEFSI) are the other subcategories of FSI created by OFR. OFR FSIs consist of 33 indicators of financial stress, which are 5 basic indicators; credit, equity valuation, funding, safe assets, and volatility (Monin, 2019: 9).

MINT economies are one of the emerging economies comprising Mexico, Indonesia, Nigeria, and Turkey. MINT economies are a group of countries that operate as major economic powers following the BRICS economies. However, although MINT economies are smaller than BRICS economies, they have favorable demographic characteristics, a dense young workforce, and positive economic prospects. One of the common features of MINT economies is that they are among the emerging market economies with high growth potential.

The background of global financial markets shows that financial stress can be a more prominent leading indicator in periods of financial uncertainty and crises. It can be stated that financial stress can have a much greater impact on stock prices than classical economic factors since the variables used to measure financial stress are directly related to systematic risk and the financial system (Xu, Liang, and Wang, 2023: 1). Although financial stress is linked to general financial and economic conditions, its relationship with stock market indices has not been confirmed in emerging stock markets.

The paper aims to determine how the benchmark stock market indices of MINT countries, one of the emerging economy groups, are affected by global (GFSI) and emerging markets financial stress indices (EFSI). MINT countries are a relatively new definition, and no previous studies have focused on the relevant sample. The paper differs from its counterparts in the literature in terms of both the applied country group and the comparison of the effects of the financial stress indices considered. The fact that whether the stock markets of MINT economies are sensitive to EFSI and GFSI and whether these countries are compared accordingly makes the study important. In this regard, it can be stated that the study will contribute to the literature. The following parts of the paper consist of a literature review, data set and method, findings, and conclusion.

2. Literature Review

Related studies generally focus on calculating the FSI of countries, predicting financial crises with the FSI, and examining the relationships between the FSI and macroeconomic factors, when the literature on financial stress is scanned. The papers investigating the effects of financial stress on financial markets are summarized below in this section.

Illing and Liu (2006) created a macroeconomic FSI for Canada based on the 1980-2002 period. This index; is created by aggregating stress indicators in foreign exchange, stock, debt, and banking markets using the principal components method. The study found that high levels of financial stress not only affect the financial system but also cause significant losses in the real economy. Hakkio and Keeton (2009) created a monthly FSI-Kansas City FSI (KCFSI) for the United States in the period 1990-2009, weighted by the principal component method with 11 variables. It is found that high stress affects economic activity in the paper which examines the relationship between economic activity and financial stress. Gupta, Hammoudeh, Modise, and Nguyen (2014) investigated whether the FSI created for the US in the 1990-2011 period could be used to predict US stock returns. While creating the FSI, they also used variables such as US economic policy, stock market uncertainty, consumer sentiment index, and KCFSI. As a result, it was determined that these variables did not create a significant statistical difference in the prediction of stock returns. Park and Mercado (2014) discussed the period 1992-2011 in their study where they researched the determinants of FSI in emerging countries. It was found that the domestic FSIs of 25 emerging countries were increased by the FSIs of emerging economies and regional and non-regional emerging countries by using panel regression estimation. Although a significant part of the change in domestic FSI is due to domestic shocks, it has been determined that regional shocks are significantly effective in emerging Asian countries. Das, Kumar, Tiwari, Shahbaz, and Hasim (2018) investigated the relationship between S&P 500 stock returns, as well as gold and crude oil prices, and GFSI, examined the period 1993-2017. Non-parametric quantitative causality analysis was applied. In conclusion, it has been observed that there is a unidirectional causality from stocks to FSI and a bidirectional causality between oil and gold and FSI. Das, Kannadhasan, and Bhattacharyya (2019) investigated whether economic policy uncertainty, geopolitical risk, and financial stress similarly affected the economies of emerging countries in the 1997-2018 period with a non-parametric causality test. As a result, it was determined that these shocks affected the markets of countries significantly, but the effects of the shocks varied according to the markets. In addition, it was concluded that economic policy uncertainty has a more significant effect on developing country stock markets than the other two indicators. Fu, Chen, Sharif, and Razi (2022) investigated the impact of global financial stress and commodity prices on global clean energy stocks (Quantive autoregressive distributed lag (QARDL) method) in the 2008-2021 period. A negative relationship was detected between the clean energy stocks and financial stress in the short and long term. Zhang and Li (2022) investigated the forecasting performance of FSI on S&P500 returns in the period 1927-2016. The FSI index, which was developed for the USA and has data until 2016, was used in the paper. As a result of the analysis, it was found that the FSI index increased the predictive power of S&P500 returns, especially in the short term. Armah, Bossman, and Amewu (2023) investigated the impact of global financial stress on African stock markets by using the transfer entropy method. FSIs of the USA and Other Developed Economies, published by OFR and thought to better reflect global financial stress, were used in the paper. Analysis results have shown that African stock markets are affected by these financial stress indices in the medium term and they are risky markets. Günay, Öner, and Aybars (2023) examined the return spread between the financial stress of emerging markets and BRIC-T stock markets with the Quantil Vector Autoregression method for the period 2000-2023. According to the findings, it has been determined that there is a positive or negative return spread from the Russian and Brazilian stock markets to EFSI, depending on the periods. Liang et al. (2023) investigated the predictive power of GFSI, fear index-VIX, US Economic Policy Uncertainty, global economic policy uncertainty, and geopolitical risk factors on 21 international stock market volatilities. It has been determined that GFSI has a better performance than other factors in the long-term forecast of the stock market indices. Xu et al. (2023) investigated the relationship and predictability of FSI of China (CNFSI) with China's stock returns for the 2008-2020 period. A predictive regression model was used in the study, and according to the findings, it was determined that CNFSI was negatively related to the next stock returns and its predictive power was higher, especially in bull markets.

The paper is different from its counterparts in the literature in terms of both comparing the impact of the examined financial stress indices on stock markets and in terms of the country group examined. It can be stated that the paper will contribute to the literature in terms of whether the stock markets of MINT countries are sensitive to EFSI and GFSI with current data and their comparison in this direction has not been made.

3. Dataset and Methodology

3.1. Dataset

The relationships between the benchmark stock market indices of MINT countries and the global (GFSI) and emerging markets financial stress indices (EFSI) are investigated in this paper. St. Louis Financial Stress Index which is calculated weekly is used as the GFSI variable. As the EFSI variable, the Emerging economies-specific subcategory of the OFR FSI is used. This index is calculated daily. The weekly averages of the index are taken and included in the analysis to make a comparison with the GFSI index in the paper. Since financial stress indices contain negative values, they are included in the analysis without applying logarithmic transformation. The closing prices of the benchmark stock market index of these countries are used to represent the stock markets of MINT economies. Logarithmic transformation is applied to stock market index data. The paper uses weekly data for the period 10/01/2014-26/04/2024. The variable abbreviations, descriptions, and sources used in the paper are presented in Table 1.

Table 1: Dataset and Sources

Variable Abbreviation	Description	Sources
IPC	Mexico Stock Market Prices	Investing[1]
IDXCOMP	Indonesia Stock Market Prices	Investing
NSEALL	Nigeria Stock Market Prices	Investing
ISE100	Türkiye Stock Market Prices	Investing
GFSI	Global Financial Stress Index	Federal Reserve Economic Data[2]
EFSI	Financial Stress Index of Emerging Economies	Office of Financial Research Data[3]

Source: Author's organization of the data sources

Figure 1 shows the time-dependent oscillation graphs of the variables.

1 Investing, https://tr.investing.com

2 FRED, Federal Reserve Economic Data. St. Louis Fed Financial Stress Index. https://fred.stlouisfed.org/series/STLFSI4

3 OFR, Office of Financial Research. OFR Financial Stress Index. https://www.financialresearch.gov/financial-stress-index/

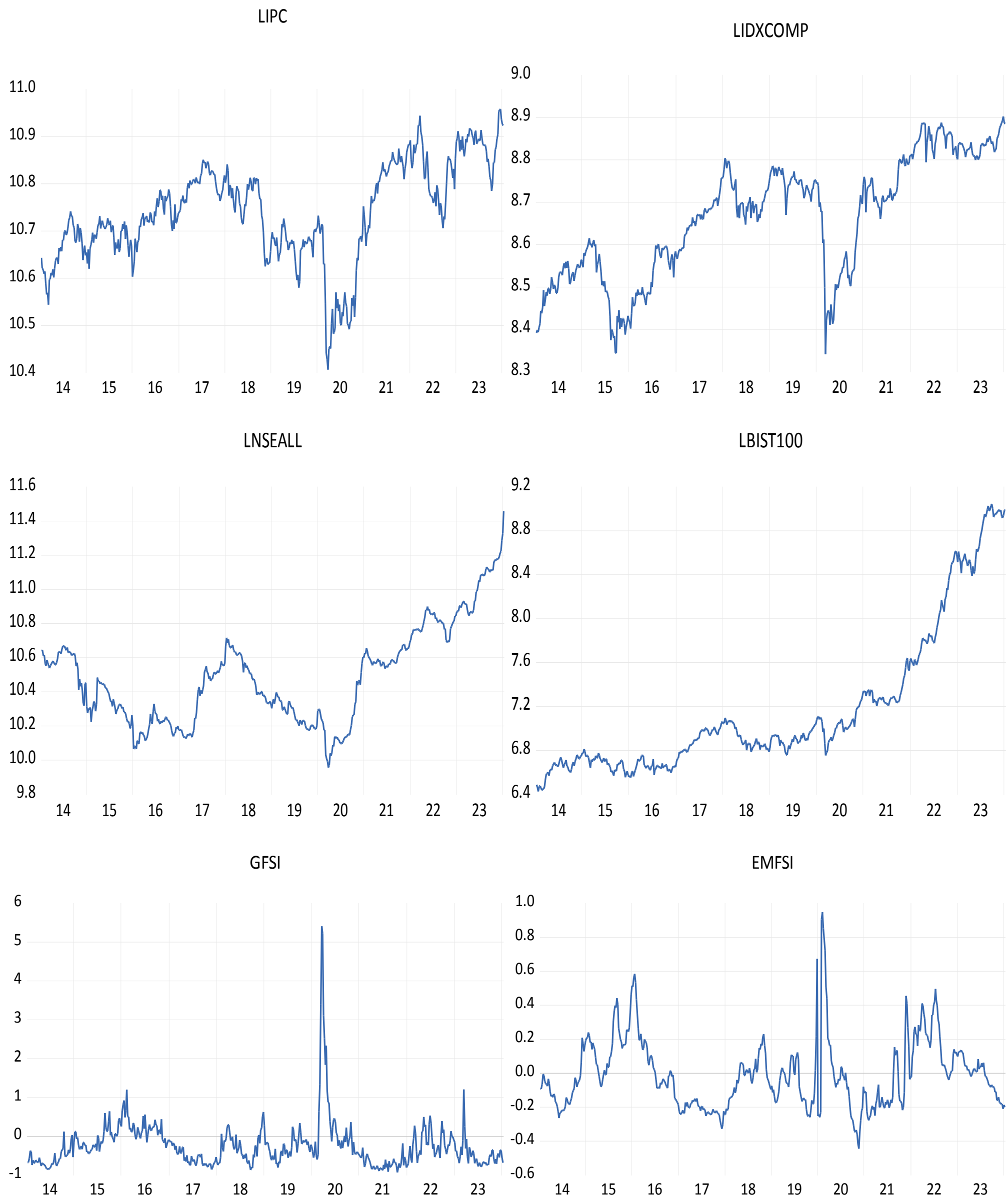


Figure 1. Time-Dependent Oscillation Graphs of Variables

Source: Author's calculations by the data

As seen in Figure 1; Although the stock markets of MINT economies showed fluctuating movements between 2014 and 2019, they experienced sharp declines in 2019 and then a significant rise and peaked. The developments in the course of global and emerging economies' FSIs are also shown in the lower part of Figure 1. Here, the sharp rise and subsequent decline in both financial stress indices, especially during Covid-19, are noteworthy.

The models established in line with the aim of the paper are presented below, there are 8 models:

Model 1a: $IPC_{it} = \alpha_t + EFSI_{it} + \mu_t$

Model 1b: $IPC_t = \alpha_t + GFSI_t + \mu_t$

Model 2a: $IDXCOMP_t = \alpha_t + EFSI_t + \mu_t$

Model 2b: $IDXCOMP_t = \alpha_t + GFSI_t + \mu_t$

Model 3a: $NSEALL_t = \alpha_t + EFSI_t + \mu_t$

Model 3b: $NSEALL_t = \alpha_t + GFSI_t + \mu_t$

Model 4a: $ISE100_t = \alpha_t + EFSI_t + \mu_t$

Model 4b: $ISE100_t = GFSI_t + \mu_t$

3.2. Methodology

Stationarity analyses of the series are carried out to prevent spurious regressions in the first established models following the establishment of the models used in the paper. Stationarity testing is carried out with the Augmented Dickey-Fuller-ADF (1981) unit root tests, which are based on the null hypothesis that the series have unit roots, and the Kwiatkowski-Phillips-Schmidt-Shin-KPSS (1992) unit root tests, which are based on the stationarity null hypothesis. In addition to these standard unit root tests, Zivot-Andrews's (1992) unit root test with structural break is used due to the structure with breaks in the variables. Zivot-Andrews (1992) unit root test is a stationarity test in which the structural breakpoint is estimated internally. This test is performed by establishing 3 structural break models. Model A tests the break occurring in the constant, Model B tests the break occurring in the trend, and Model C tests the break occurring in both the constant and trend. In this test, the null hypothesis is that there is a unit root in the series, and the alternative hypothesis is that the series is stationary. If the obtained t statistics are smaller in absolute value than the critical values, the alternative hypothesis that the series is stationary is rejected. Autoregressive Distributed Lag (ARDL) bound test method, introduced by Pesaran and Shin (1995) and later developed by Pesaran, Shin, and Smith (2001), is used to determine the relationship between series that are stationary at different orders. The ARDL model has some advantages over classical cointegration tests. The first and most important is that it gives consistent results about the relationship between the variables of different orders. In other words, the ARDL model can be applied to I(0) and I(1) levels, which are the stationarity level values of the variables. The second advantage is that it gives consistent results with smaller data. The third advantage is that in the ARDL model, the optimal lag levels at the stationary levels of the variables are considered.

The unrestricted error correction model is first estimated while determining the cointegration relationship with the ARDL bounds test. The unrestricted error correction model equation is shown in Equation (1). Equation (1) is a general model, and in the equation; y is the dependent variable, x is the independent variable, d is the first difference of the series, and m and n are the lag lengths.

$$dy = \alpha_0 + \sum_{i=1}^{m} \beta_1 dy_{t-i} + \sum_{i=0}^{n} \beta_2 dx_{t-i} + \delta_1\, y_{t-1} + \delta_2\, x_{t-1} + \varepsilon_t \tag{1}$$

The F_{BDS} statistic of the model is calculated using the Wald test to investigate the cointegration relationship. The hypotheses established to investigate the cointegration between the variables are as follows: H_0: (There is no cointegration) H_1: (There is cointegration). The calculated F_{BDS} statistics are based on the Pesaran et al. (2001) study, if the calculated FBDS statistic is higher than the table's upper critical value, H_0 is rejected and H_1 is accepted. Equation (2) is used to analyze the long-term relationship between the variables following the determination of a cointegration relationship between the variables.

$$y = \alpha_0 + \sum_{i=1}^{m} \alpha_{1i} y_{t-i} + \sum_{i=0}^{n} \alpha_{2i} x_{t-i} + \varepsilon_t \tag{2}$$

While analyzing the long-term relationship, diagnostic tests for the models are performed to test the suitability of the established model after the long-term elasticity coefficients are determined. The cumulative sum of consecutive residuals (CUSUM) test introduced by Brown, Durbin, and Evans (1975) is performed to test the stability of the determined long-term coefficients. The short-term relationship between variables is examined by creating an error correction model. The error correction model equation is given in Equation (3). When analyzing the short-term relationship, the error correction term (ECM_{t-1}), which expresses the one-lagged value of the residuals of the long-term relationship model, is added to the long-term ARDL model. The error correction term coefficient (μ) means how much of a deviation occurring in the short term can be corrected in the long term. At the same time, this coefficient is expected to be statistically significant and have a negative sign.

$$dy = \alpha_0 + \sum_{i=1}^{m} \mu_{1i} dy_{t-i} + \sum_{i=0}^{n} \mu_{2i} dx_{t-i} + \mu \mathrm{ECM}_{t-1} + \varepsilon_t \tag{3}$$

4. Findings

The variables have a fractal structure when the time-dependent oscillation graphs of the variables used in the study are examined in Figure 1. Therefore, in addition to standard unit root tests, applying unit root tests that allow structural breaks will allow more consistent analyses.

First, ADF and KPSS unit root tests, which are called standard unit root tests are applied to all variables to test the stationarity of the series, and the results are presented in Table 2, before moving on to model estimations.

Table 2: ADF and KPSS Unit Root Tests

Variables	**ADF-t_{stats}**		**KPSS-LM_{stats}**	
Dependent Variables	**Level C&T**	**1th Difference C&T**	**Level C&T**	**1th Difference C&T**
IPC	-2.529723	-22.89321*	0.277352	0.037727*
IDXCOMP	-2.740738	-23.91613*	0.226887	0.029537*
NSEALL	1.963286	-17.19757*	0.492236	0.133271**
ISE100	0.212324	-6.451293*	0.51190	0.149483*
Independent Variables				

EFSI	-3.509104**		0.109164*	
GFSI	-6.181018*		0.096123*	
Critical Values	1% – 3.975734 5% – 3.418453 10% – 3.131728		1% 0.216000 5% 0.146000 10% 0.119000	

Source: Author's estimate

Note: *, and **respectively denote 1%, and 5%; C&T denotes Costant&Trend.

The ADF and KPSS unit root tests with the reverse hypothesis gave parallel results. According to Table 2, when the first differences of the IPC, IDXCOMP, NSEALL, and ISE100 variables are taken, these variables are stationary in difference since the ADF-t_{stats} are greater than the critical values. In addition, since the ADF-t_{stats} of the EFSI and GFSI variables are greater than the critical values in absolute terms, it has been concluded that these variables are stationary at the level. When the first differences of the IPC, IDXCOMP, NSEALL, and ISE100 variables are taken, these variables are stationary at the difference since the KPSS-LM_{stats} are less than the critical values. In addition, since the KPSS-LM_{stats} of the EFSI and GFSI variables are less than the critical values, it has been concluded that these variables are stationary at the level.

The Zivot-Andrews unit root test results are presented in Table 3. The first part of the table includes the unit root test results at the level, and the lower part includes the unit root test results at the first differences for variables that are not stationary at the level.

Table 3: Zivot-Andrews Unit Root Test

Variable/Model	**Model A (Break in the intercept)**		**Model B (Break in the trend)**		**Model A (Break in both)**	
	t_{stats}	**Breaking**	**t_{stats}**	**Breaking**	**t_{stats}**	**Breaking**
IPC	-4.048028	9/28/2018	-3.290109	3/20/2020	-4.293808	9/28/2018
IDXCOMP	-3.553693	1/03/2020	-2.934622	6/26/2020	-4.052176	1/17/2020
NSEALL	-1.633257	9/18/2020	-2.378586	3/13/2020	-2.668356	5/31/2019
ISE100	-3.408467	7/15/2022	-4.418939	3/26/2021	-4.445372	3/12/2021
EFSI	-3.943584	4/15/2016	-3.575911	6/09/2017	-4.630562	2/05/2016
GFSI	-6.632107	11/06/2020	-6.417057	8/28/2015	-6.635507	2/21/2020
Critical Values	1% – 5.34 5% – 4.93 10% – 4.58		1% – 4.80 5% – 4.42 10% – 4.11		1% – 5.57 5% – 5.08 10% – 4.82	
ΔIPC	-23.20392	4/03/2020	-22.89975	11/02/2018	-23.18942	4/03/2020
ΔIDXCOMP	-9.493821	5/15/2020	-9.137337	1/31/2020	-9.510072	10/02/2015
ΔNSEALL	-8.422425	2/02/2018	-8.080467	7/08/2022	-8.406955	2/02/2018
ΔISE100	-10.37584	10/08/2021	-10.20589	7/13/2018	-10.46778	10/15/2021
ΔEFSI	-12.72963	3/06/2020	-12.53441	2/04/2022	-12.72748	3/06/2020

Source: Author's estimate

According to Table 3, Models A, B, and C gave similar results. The hypothesis that they are stationary at the level is rejected, and the null hypothesis showing the existence of a structural break unit root in the variables is accepted since the t statistics for the other variables except GFSI are smaller than the critical values. When the first differences of these variables are taken, it is seen that they are stationary. Since the t statistics for the GFSI variable are larger than the critical values, the hypothesis that they are stationary at the level is accepted. The findings obtained from the unit root tests show that the variables are I(1) and/or I(0). Therefore, it can be stated that the precondition for the ARDL bounds test is met.

Lag lengths and bounds test results of 8 different ARDL models established to determine short – and long-term relationships between variables determined to be stationary of different orders are presented in Table 4. In addition, while estimating these models, some diagnostic tests are performed to ensure that the models gave consistent results and the results are presented in Table 5. The Breusch-Godfrey LM test tested whether there is an autocorrelation problem in the model, the Ramsey-Reset test tested whether there is a model-building error, and the White test tested whether there is a heteroscedasticity problem. CUSUM graphs, the results of which are presented in Graph 1, give an idea about the stability of the long-term coefficients calculated for the models at 5%. The most appropriate models for the study are tried to be estimated by making the necessary changes in the model predictions, in the light of the findings obtained in these tests.

Table 4: ARDL Bounds Test

Models	Lag	F_{bds}
1a: IPC-EFSI	(1,0)	7.854235[a]
1b: IPC-GFSI	(1,1)	2.484042
2a: IDXCOMP-EFSI	(1,0)	5.818399[c]
2b: IDXCOMP-GFSI	(3,1)	1.823209
3a: NSEALL-EFSI	(2,1)	5.906702[c]
3b: NSEALL-GFSI	(2,1)	0.689465
4a: ISE100-EFSI	(1,0)	6.240597[c]
4b: ISE100-GFSI	(1,1)	5.782094[c]
Critical Values (k*=1)	I(0)	I(1)
10%	4.04	4.78
5%	4.94	5.73
2.5%	5.77	6.68
1%	6.84	7.84

Source: Author's estimate

Note: *k denotes the independent variable number in the model. [a], [b], [c] and [d] respectively denote 1%, 2.5%, 5%, and 10%.

The F statistics for the model established between the Mexican stock exchange IPC and EFSI is significant at 1%; For the models established between the Indonesian stock exchange IDXCOMP, the Nigerian stock exchange NSEALL, and the Turkish stock exchange ISE100 and EFSI, the F statistic is found to be significant at 5%, according to the Bounds Test results in Table 4. In addition, it has been determined that the F statistic is significant at 5% for the model established between the Turkish stock exchange ISE100 and GFSI. Thus, it has been determined that there is a long-term relationship (cointegration) between the stock markets of MINT economies and the EFSI. In addition, it has been determined that there is a cointegration between the Turkish stock exchange ISE100 and the GFSI, but there is no cointegration between the Mexican, Indonesian, and Nigerian stock markets and the GFSI.

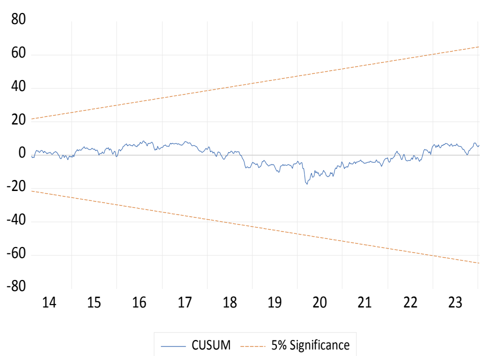
Table 5: Diagnostic Tests

Models	p-value (Breusch-Godfrey LM)	p-value (Ramsey Reset)	p-value (White)
1a: IPC-EFSI	0.7719	0.5027	0.1814
1b: IPC-GFSI	0.3484	0.5932	0.0926
2a: IDXCOMP-EFSI	0.1343	0.3827	0.0725
2b: IDXCOMP-GFSI	0.6576	0.1386	0.2308
3a: NSEALL-EFSI	0.6861	0.3911	0.1946
3b: NSEALL-GFSI	0.4376	0.3517	0.1559
4a: ISE100-EFSI	0.8765	0.4528	0.1029
4b: ISE100-GFSI	0.9958	0.4453	0.1226

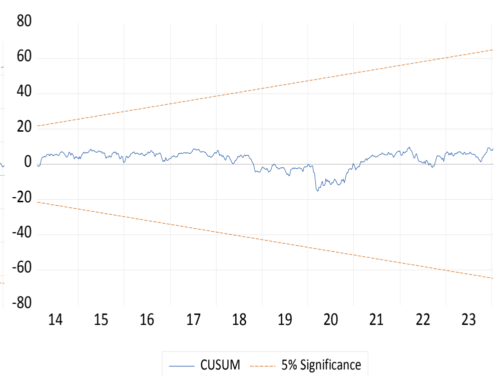
Source: Author's estimate

According to Table 5; the Breusch-Godfrey LM test, Ramsey-Reset test, and White test results showed no autocorrelation, model-building errors, and heteroscedasticity problems in the established models, respectively.

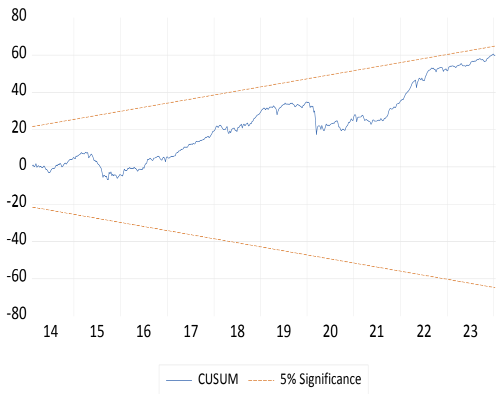
Graph 1: CUSUM Graphics



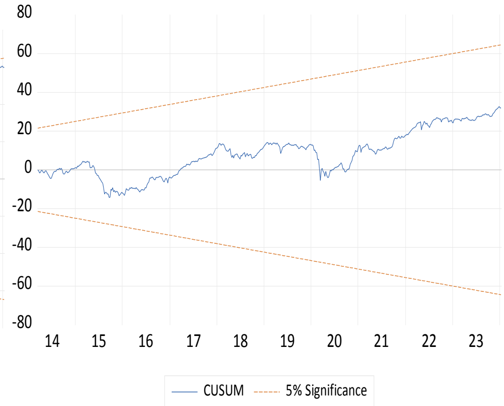
IPC-EFSI



IPC-GFSI



IDXCOMP-EFSI



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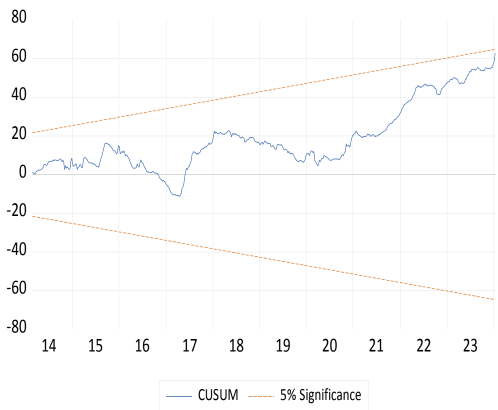
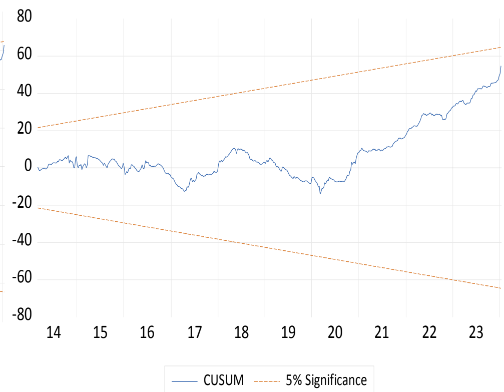
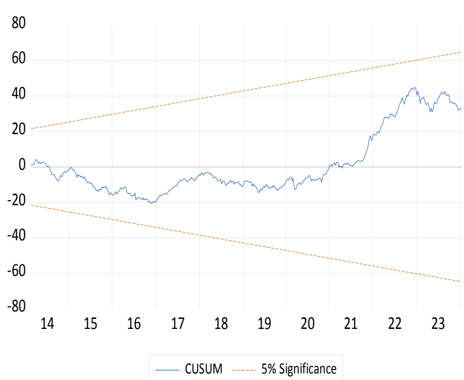


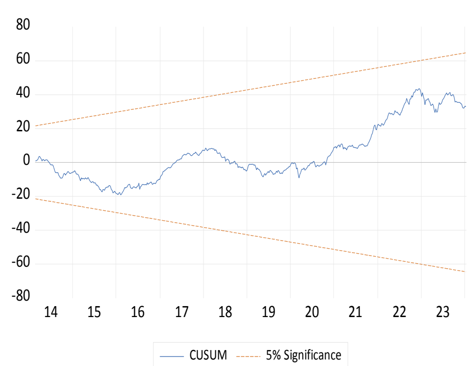
NSEALL-EFSI



NSEALL-GFSI



ISE100-EFSI



ISE100-GFSI

Source: Author's estimate

When the CUSUM graphs in Graph 1 are examined, it is concluded that the consecutive residuals do not deviate from the 5% confidence interval limits, there is no structural change regarding the variables used in the analysis, and therefore the long-term coefficients are stable.

The coefficients showing the long – and short-term relationships of the ARDL models, estimated after the significant cointegration relationships are obtained, are presented in Table 6.

Table 6: ARDL Estimations

Models	Long-Term Coeff.	Short-Term Coeff.	ECM(-1)	t_{stats}
1a: IPC-EFSI	-0.750163**	-0.15325*	-0.20107*	-3.96720*
1b: IPC-GFSI	-0.037242	-0.11514*	-0.21982**	-2.23107
2a: IDXCOMP-EFSI	-0.928163**	-0.12521*	-0.13444**	-3.41456**
2b: IDXCOMP-GFSI	-0.122035	-0.12601*	-0.13199***	-1.91141
3a: NSEALL-EFSI	-1.493867 **	-0.46605*	-0.89678*	-3.35188**
3b: NSEALL-GFSI	-0.458088	-0.11669*	-0.03812	-1.17541
4a: ISE100-EFSI	-0.751609**	-0.11076**	-0.04750*	-3.97270*
4b: ISE100-GFSI	-0.355768	-0.08463**	-0.04855*	-3.79495*
Critical Values (t_{stats})			I(0)	I(1)
10%			-2.57	-2.91
5%			-2.86	-3.22
2.5%			-3.13	-3.50
1%			-3.43	-3.82

Source: Author's estimate

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

There are negative and significant relationships at 5% between stock prices and financial stress of emerging economies in all MINT economies when long-term coefficients are examined. The long-term coefficients between the stock prices of MINT economies and the global financial stress index are also negative but not significant. Based on this result, it can be stated that the increase in financial stress of emerging economies in the long term puts pressure on the stock prices of MINT economies, but the global financial stress index does not have such an effect in the long term. Short-term relationship coefficients and error correction term coefficients based on the error correction model are also presented in Table 6. The error correction term coefficients are expected to be negative and statistically significant for the models to be significant. The significance of t statistics of ECM(-1)s is also taken into account while evaluating significance. Accordingly, it is determined that ECM(-1) is negative and significant in all models except the relationship model between the Nigerian stock market and the global financial stress index. ECM(-1) gives the percentage of improvement in the imbalance between the short and long term in the next period. When the short-term coefficients are examined, it is determined that the coefficients in all models are negative, but the coefficients are significant except for the models established only for Turkey. Thus, it has been determined that both developing economies and the global financial stress index put pressure on MINT stock markets in the short term.

5. Conclusion

In this paper, the short – and long-term effects of EFSI and GFSI on the benchmark stock market indices of MINT economies are examined comparatively. In the study, weekly data for the period 10/01/2014-26/04/2024 are examined. ARDL Bounds Test approach is used in the analysis.

The cointegrations seen between MINT stock exchanges and EFSI, and between the Turkish stock exchange and GFSI in the examined period, in the analysis by using the ARDL method. It has been determined that the emerging markets financial stress index hurts the stock prices of MINT economies in both the short and long term. In addition, it has been concluded that the global financial stress index hurts the stock prices of MINT economies in the short and long term, but this effect is significant in the short term and insignificant in the long term. Based on the findings, it can be stated that the stock markets of MINT economies are negatively affected by both financial stress indices, but the source of this negative effect is more the emerging markets stress index. In summary, increases in financial stress put pressure on the stock markets of MINT economies in both the short and long term. However, it can be said that the increase in the global financial stress index does not significantly affect the stock markets of MINT economies in the long term and the pressure on the stock markets of MINT economies is due to the emerging markets financial stress index in the long term. The negative relationship finding between financial stress and stock markets obtained in the paper is consistent with Das et al. (2019), Fu et al. (2022), Liang et al. (2023), and Xu et al. (2023). Das et al (2018) found that there is one-way causality from the stock market to the FSI and, unlike this paper, found that stock markets are not affected by financial stress. Zhang and Li (2022) also concluded in their study that there is a significant relationship between the GFSI and S&P500 returns in the short term, and this is a similar finding to this paper. In light of the results obtained in the paper, it is thought that the reason why the Nigerian stock market has been more negatively affected by the EFSI is that Nigeria is the most underdeveloped country among the MINT countries in terms of financial development. Although the sharp increases in the Nigerian and Turkish stock markets, especially after 2019, are similar, it can be stated that the difference in the financial development of these two countries differentiates the degree of impact from the financial stress index. In addition, the reason why the Mexican stock market is less negatively affected by financial stress than the Indonesian stock market for Mexico and Indonesia, whose stock market prices exhibit a more volatile structure, can be attributed to the fact that the Mexican stock market is one of the leading stock markets among the American stock markets. In this regard, it can be said that the findings obtained from the paper are generally compatible with the literature. In line with the findings, it can be stated that the financial stress of both the emerging economies and the high level of global financial stress in the MINT economies, which are among the emerging economies, may cause great fluctuations and pressures in the capital markets of these economies and may damage their financial and economic system. For this reason, financial actors who want to invest in emerging country markets, especially MINT economies' markets, can increase the efficiency of their portfolios by making investment decisions by following the movements of both EFSI and GFSI for the short term and by following the movements of EFSI for the long term.

This paper emphasizes that financial stress indices are a leading indicator for stock markets. In particular, the long-term pressure created by the FSI of emerging economies on the stock markets of emerging economies comes to the fore. It can be stated that financial stress indices provide important information about capturing the dynamics in financial markets and changes in investors' demands. At the same time, the paper also shows how important it is to capture capital market dynamics, which are very important for researchers, investors, and policymakers. In future studies, a comparative analysis can be made for emerging and advanced economies, as well as the relationships between each country's FSI and equity markets can be investigated separately.

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