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Research Article

The Impact of U.S.-China Tensions on Borsa Istanbul Stock Market: Evidence from ARDL Approach

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Abstract: The aim of this study is to examine the impact of United States (U.S.)-China trade war tensions on the Borsa Istanbul (BIST) stock market. The study covers the period between January 2017 and February 2024. The reason for choosing this period is the escalation of U.S.-China trade tensions after Donald Trump took office as the 45th U.S. President in January 2017. In the research model, the BIST-100 Return Index is used as the dependent variable; the U.S.-China Tension Index developed by Roger et al. (2024) to represent the tensions arising from the U.S.-China trade war and the terms of trade, interest rate, inflation and exchange rate are considered as independent variables. The stationarity properties of the variables are analysed with Augmented Dickey and Fuller (ADF), Kwiatkowski et al. (KPSS, 1992), Christopoulos and León-Ledesma (2010) Fourier ADF and Becker et al. (2006) Fourier KPSS tests. Long and short-run relationships are analysed with the Autoregressive Distributed Lag (ARDL) bounds test approach. The results of the study show that increases in the U.S.-China Tension Index have a negative impact on the BIST-100 Return Index in both the long and short run. This finding reveals that Borsa Istanbul is sensitive to global geopolitical risks stemming from the U.S.-China trade war. The results point to the significant effects of global geopolitical risks on capital markets and emphasise that this is an important strategic factor that should be considered especially in terms of portfolio management and global risk management.

Keywords: U.S.-China Tension Index, Borsa Istanbul, ARDL Bounds Approach
Jel Codes: C58, F50, G10

ABD-Çin Geriliminin Borsa İstanbul Hisse Senedi Piyasasına Etkisi: ARDL Yaklaşımından Kanıtlar

Öz: Bu araştırmanın amacı, Amerika Birleşik Devletleri (ABD)-Çin ticaret savaşı kaynaklı gerilimlerin Borsa İstanbul (BİST) hisse senedi piyasası üzerindeki etkisini incelemektir. Araştırma, Ocak 2017 ile Şubat 2024 dönemini kapsamaktadır. Bu dönemin seçilme nedeni, Donald Trump'ın Ocak 2017'de 45. ABD Başkanı olarak göreve başlamasıyla birlikte ABD-Çin ticari gerilimlerinin tırmanışa geçmesidir. Araştırma modelinde, BİST-100 Getiri Endeksi bağımlı değişken olarak kullanılmış; ABD-Çin ticaret savaşı kaynaklı gerilimleri temsilen, Roger vd. (2024) tarafından geliştirilen ABD-Çin Gerilim Endeksi ile dış ticaret haddi, faiz oranı, enflasyon ve döviz kuru bağımsız değişkenler olarak değerlendirilmiştir. Değişkenlerin durağanlık özellikleri, Augmented Dickey ve Fuller (ADF), Kwiatkowski vd. (KPSS, 1992), Christopoulos ve León-Ledesma (2010) Fourier ADF ve Becker vd. (2006) Fourier KPSS testleriyle analiz edilmiştir. Uzun ve kısa vadeli ilişkiler, Otoregresif Dağıtılmış Gecikmeli Sınır Testi (ARDL) yaklaşımıyla analiz edilmiştir. Araştırma sonuçları, ABD-Çin Gerilim Endeksi'ndeki artışların hem uzun hem de kısa dönemde BİST-100 Getiri Endeksi'ni olumsuz etkilediğini göstermiştir. Bu bulgu, Borsa İstanbul'un ABD-Çin ticaret savaşı kaynaklı küresel jeopolitik risklere duyarlı olduğunu ortaya koymaktadır. Sonuçlar, küresel jeopolitik risklerin sermaye piyasaları üzerindeki belirgin etkilerine işaret etmekte; bu durumun, özellikle portföy yönetimi ve küresel risk yönetimi açısından dikkate alınması gereken önemli bir stratejik faktör olduğunu vurgulamaktadır.

Anahtar Kelimeler: ABD-Çin Gerilim Endeksi, Borsa İstanbul, ARDL Sınır Yaklaşımı
Jel Kodları: C58, F50, G10

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1. Introduction

The impact of political tensions on economic relations continues to attract interest in academic circles. According to the neoclassical approach, although international trade provides mutual benefits, inter-state conflicts can weaken trade by hindering firms' profit maximization. Supported by empirical studies, this situation confirms that hostile relations can halt or restrict trade or increase protectionism among countries at peace (Zeng et al., 2022). The increasing protectionism, unilateralism, and interest-driven foreign policy approach of the U.S. have begun to seriously challenge the norm-based liberal world order it established with its Western allies. Particularly after the 2008 Global Economic Crisis, fluctuations in U.S. financial markets, trade difficulties, and a weakening economic power have undermined its hegemonic role in the international system. This uncertainty indicates that the unipolar hegemonic order is beginning to decline and that rising powers are reshaping global governance to align with their own interests. The country that has benefited the most from this shift is China, taking advantage of the U.S.' diminishing influence, China has sought to transform the international system in its favour (Tokatlı, 2023).

The election of Donald Trump as president in 2016 accelerated the tensions between the U.S. and China. The demands of the Trump administration focused on concerns that the U.S. trade deficits with China weakened its competitiveness, China's unfair investment practices disadvantaged foreign firms, and China's goal of becoming a technological superpower posed a threat to the Western economic order (Huang, 2019). From 2017 onwards, China was accused by the U.S. of engaging in unfair trade practices and intellectual property theft. Tensions between the two countries escalated rapidly after Trump signed a memorandum to initiate a case against China at the World Trade Organization, restricted investments in key Chinese technology sectors, and imposed tariffs on Chinese goods. Subsequently, the U.S. implemented the first tariffs on goods imported from China, officially launching the "U.S.-China Trade War." During this period, both sides engaged in negotiations and ultimately reached an agreement on the "Phase One Deal." This agreement was seen as a temporary truce (Moosa et al., 2020).

The U.S.-China tensions continue to generate global impacts across various domains, including economic, trade, technological, financial, social, and demographic areas. These tensions have resulted in wide-ranging consequences, from disruptions in international trade flows to the restructuring of supply chains, redirection of investment flows, and transformations in education and migration dynamics. Steinbock (2018) argued that the U.S.-China trade tensions, particularly with China becoming the primary target of the U.S., have undermined global economic integration and asserted that Trump's policies threaten the international order. Huang (2019) emphasized that these tensions are the result of long-standing issues and highlighted the need for commitments and institutionalized steps to achieve a lasting resolution. Sun (2019), in his study, argued that the technology war initiated by the Trump administration against China would weaken security relations between the two countries and undermine global governance of science and technology. Amiti et al. (2019) noted that the 2018 trade war caused significant economic losses in the U.S. by negatively impacting imports and real incomes. Capie et al. (2020) revealed that the evolution of the trade war into a technology war prioritized national security concerns over economic logic, disrupting global supply chains. While Danso (2020) stated that the U.S.-China tensions had limited short-term effects, he warned of potential adverse developments for the global economy in the long term. Lin (2020) noted that despite China's post-pandemic recovery, the economic impacts of U.S.-China tensions persist. Zeng et al. (2022) identified permanent effects of U.S.-China tensions on specific sectors, while Cai et al. (2022) demonstrated that these tensions have triggered strategic partnerships in the oil market. Özçelik (2022) argued that the U.S. trade sanctions against China have proven ineffective. Wang et al. (2023) reported that U.S.-China tensions reduced air traffic, while Tokatlı (2023) analysed this power struggle through the concept of the Thucydides Trap, suggesting that tensions could lead to a large-scale conflict. Mohsin et al. (2024) characterized these tensions as a "New Cold War," arguing that economic and ideological competition is reshaping the global order. Flynn et al. (2024), examining the impact of these tensions on scientific studies, highlighted their negative effects on scientific collaboration and productivity. Sabala and Devadoss (2019) pointed out that U.S.-China tensions not only caused economic losses for both countries but also directly and indirectly affected the economies of other nations. Jiming and Posen (2019) stated that declining international trade led to unemployment in various countries. Charbonneau (2019) noted that the tensions harmed Canada’s economic performance, while Lemmer (2019) reported declines in commodity exports in South Africa. Yean et al. (2019) highlighted reductions in solar energy exports in Malaysia; Abiad et al. (2018) observed declining car and spare part sales in Japan and Europe; Gunnella and Quaglietti (2019) warned of increasing risks to investor confidence in the long term. Yefremov (2018) noted that lower economic growth in China would reduce raw material demand from other countries, affecting developing nations like Taiwan, Singapore, Vietnam, Thailand, and Malaysia. Finally, Evans (2019) concluded that all nations could suffer losses from this trade war.

Since Donald Trump took office in 2016, polarized policies, a shift away from globalization, and rising geopolitical risks have caused significant turbulence in the global economy and financial markets (Cai et al., 2023). The trade war between the U.S. and China, as the world's two largest economies in terms of trade, foreign direct investment, and capital flows, has not only damaged international trade relations but also continuously had a negative effect on the performance of global financial markets (Huynh and Burggraf, 2020). This tension has notably caused significant fluctuations in stock markets, highlighting the impact of uncertainty. Announcements related to the trade war often triggered sudden spikes in the Chicago Board Options Exchange's Volatility Index (VIX) and led to declines in stock prices. In other words, uncertainties caused by the trade wars have adversely affected stock markets by increasing risk premiums. The trade war events of 2018 and 2019 exposed the vulnerability of financial markets to uncertainty. Furthermore, policy uncertainties associated with the trade war have tightened financial conditions by raising risk premiums, as noted by Bank of England Governor Mark Carney (Ozdagli and Wang, 2022).

As the world's two leading economies, bilateral relations between the U.S. and China have profound impacts on trade, economic development, and capital and commodity markets. Therefore, it is essential to evaluate the effects of U.S.-China political relations on financial markets. However, literature addressing the effects of uncertainties in political relations on financial markets appears to be in its infancy. The primary reason for this underdevelopment is the escalation of U.S.-China political tensions since Donald Trump assumed the presidency in 2017, along with the absence of a comprehensive index to define these trade tensions. Recognizing this gap, Roger et al. (2024) developed an index called the U.S.-China Tension Index (UCT). Based on their study titled "U.S.-China Tension", the index aims to fill this void by quantifying the variable intensity of concerns related to these tensions over time and measuring their economic consequences. The authors claim their study is the first to quantitatively measure the intensity of bilateral tensions between the U.S. and China over time. The approach to constructing the UCT relies on analysing text data from leading U.S. newspapers. The study combines the search-based textual analysis method pioneered by Baker et al. (2016) with machine learning techniques. The analysis searches for keywords frequently used in news discussions about U.S.-China tensions, categorized into three groups; "terms related to the U.S. and China," "terms related to contentious issues in bilateral relations," and "terms evoking tension." Subsequently, the proportion of articles containing these keywords from the three categories is calculated to construct the UCT index.

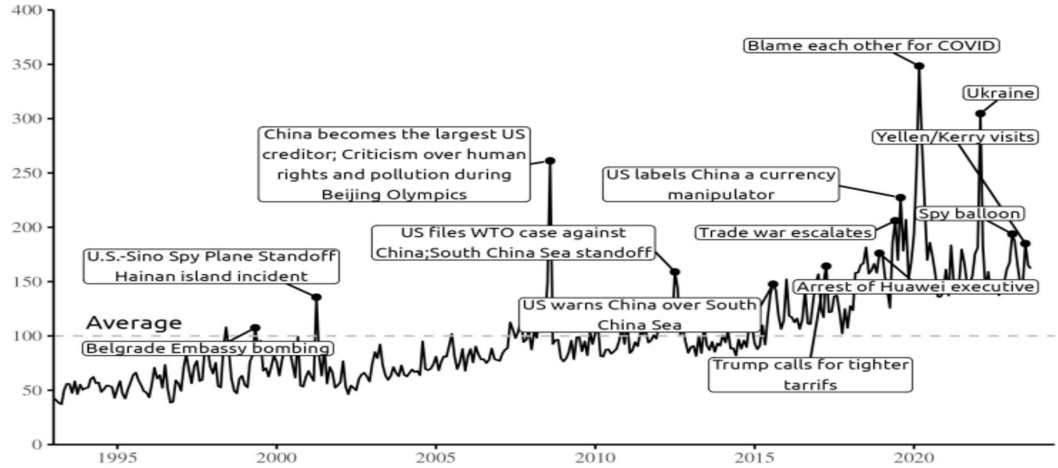

Figure 1. Roger et al. (2024) U.S. Newspaper-Based U.S.-China Tension Index

Figure 1 visualizes the trajectory of the UCT index, which covers the period from the end of 1993 to 2024, along with significant events related to U.S.-China tensions during this period. The index rose due to key incidents such as the bombing of the Belgrade Embassy in 1999, the Hainan Island incident and the U.S.-China spy plane collision in 2001, separatist unrest in Tibet and Xinjiang in 2008, China's rapid military buildup, and its emergence as the largest foreign creditor of the U.S. Additionally, the index increased during events such as the U.S.'s strategic pivot to Asia and the agreement on the Trans-Pacific Partnership in 2011, the escape of a Chinese dissident to the U.S. embassy amid rising trade tensions in 2012, and disputes in the South China Sea in 2015. The index spiked in May and June 2019, when the U.S. imposed steep tariffs on goods imported from China. Moreover, the index reached its highest value in March 2020, when the U.S. administration blamed China for the initial mass outbreak of the coronavirus pandemic, and it rose again in February 2022 following the onset of the war in Ukraine. Overall, tensions between the world's two largest economies have shown a growing trend over time, consistently remaining above average levels since 2015.

Considering the information presented, this study examines the impact of the U.S.-China tension on Türkiye's capital market. The selection of Türkiye as a third party in the context of U.S.-China tensions is thought to be based on several significant factors. First, Türkiye's strategic position as a bridge between Asia and Europe and its location along critical trade routes stand out. As an emerging economy, Türkiye's sensitivity to global capital flows makes it susceptible to the effects of U.S.-China tensions. Additionally, Türkiye maintains strong trade ties with both the U.S. and China, which increases the likelihood of indirect effects of the trade war between these two powers on the Turkish economy. Stock markets, often considered the barometer of national economies, are another key factor highlighted in this study. Stock markets reflect the movements of local and international capital and are highly sensitive to economic uncertainties. In this context, Türkiye's status as an emerging economy and its dependence on external financing make the effects of global trade wars on its capital markets more apparent. Consequently, these dynamics position Türkiye as a critical case study for analysing the effects of U.S.-China tensions. Within this framework, the study seeks to contribute to the literature by examining the impact of the U.S.-China Tension Index (developed by Roger et al., 2024) on the Borsa Istanbul (BIST) stock market. A review of the literature revealed no existing research addressing the impact of this tension on the BIST stock market, motivating the present study. Furthermore, the research aims to serve as a valuable resource for investors, portfolio managers, and other stakeholders by providing insights into portfolio diversification in the face of economic uncertainties to achieve optimal returns and effective risk management. In this study, the BIST-100 Return Index is used as the dependent variable, while the U.S.-China Tension Index and Türkiye's macroeconomic indicators are employed as independent variables. The stationarity characteristics of the variables were analysed using the ADF, KPSS, Fourier ADF, and Fourier KPSS tests. The model developed in the study examines the long-term and short-term relationships using the ARDL bounds testing approach.

The remainder of the paper is organized as follows; the relevant literature on the effects of U.S.-China tensions on financial markets and investment strategies is reviewed, the data set and applied model are explained, the econometric techniques used in the analysis are summarized, the empirical results of the study are presented, and the research concludes with the findings and evaluation section.

2. Empirical Literature Review

In this literature review, the impact of U.S.-China tensions on financial markets, particularly stock markets, and the investment world is assessed. Among these studies, Ing and Vadila (2019) examined the direct and indirect effects of U.S.-China trade tensions on Indonesia's trade and investments. The analysis using 2018 data found that while the tensions created short-term opportunities for Indonesia, they would suppress the global economy. Öztürk and Altınöz (2019) investigated the impact of U.S. import tariffs on Chinese goods and Chinese tariffs on U.S. imports on the Shanghai Stock Exchange Composite Index using data from 1991 to 2016. In their research model, China's macroeconomic indicators were used as control variables. The empirical results revealed that U.S. tariffs negatively affected the Shanghai stock index in the long term. Egger and Zhu (2020) aimed to analyse the effects of the U.S.-China trade war, which began in 2018, on the stocks of publicly traded companies during the period when tariffs were announced and implemented. Using an event study methodology, 38 countries were included as third parties, in addition to the direct parties of the trade war. The study's results showed that tariffs harmed firms in the target country as well as third-party countries not involved in the trade war. De Nicola et al. (2020) examined the effects of U.S.-China trade tensions on 10 East Asian stock market indices using an event study methodology. According to the research findings, the trade war escalations in the first eight months of 2018 led to a 50-60% decline in the 10 major stock market indices in East Asia, particularly in the two large Chinese stock markets; without the trade war, these losses would have been halved, or the stock markets would have gained. Setiawan (2020) applied an event study methodology to assess the impact of the U.S.-China trade war on ASEAN countries' stock prices. The analysis considered three periods; the normal period (January 2009-November 2017), the pre-event period (December 2017-February 2018), and the event period (March 2018-June 2018). The results revealed that ASEAN stock markets saw positive abnormal returns in the pre-event period but experienced negative abnormal returns during the event period. This suggests the trade war negatively affected the capital markets of six ASEAN countries. Similarly, Huynh and Burggraf (2020) explored the co-movement of global stock markets amid the U.S.-China trade tensions, focusing on indices from G7 countries, including the S&P 500 (U.S.), MSCI China (China), Nikkei (Japan), DAX (Germany), FTSE (UK), TSX (Canada), CAC (France), and MIB (Italy). The analysis covered the period from June 2016 to June 2019. The findings obtained from copula methods revealed that, prior to the trade war, the stock market indices moved symmetrically together; however, during the trade war, negative downward movements were detected in the stock markets. Burggraf et al. (2020) analysed over 3,200 tweets from Trump's Twitter account to investigate how political news affects stock price movements. The findings showed that tweets regarding U.S.-China tensions negatively impacted the S&P 500 returns and positively affected the VIX. Additionally, a one-way Granger causality relationship was found from Trump's tweets to returns and the VIX. Blanchard et al. (2021) analysed the effects of rising trade barriers on global foreign direct investment (FDI) using data from the period 2018-2022. The results of the analysis indicated that while investments showed a tendency to move towards Southeast Asia on a sectoral basis, the role of global value chains in investment decisions had a limited or negative impact on total investments in China and Southeast Asia. Wang et al. (2021) examined the stock market responses of 2,754 Chinese companies listed on the Shanghai and Shenzhen stock exchanges to the U.S.-China trade war. Based on the research findings from the period March 2018-May 2019, the trade war led to significant and negative impacts on the markets, with this effect being stronger among companies exporting to the U.S. and non-state-owned companies. He et al. (2021) examined the effects of U.S. and Chinese trade policy uncertainty on stock markets. Using data from 2000 to 2019, they employed a time-varying parameter stochastic volatility VAR (TVP-SV-VAR) model to investigate the changing effects of trade uncertainty indices over time. The analysis found that U.S. trade uncertainty had strong effects on both U.S. and Chinese stock indices, and that U.S.-China tensions had a positive impact on the U.S. stock market while negatively affecting the Chinese stock market.

Ferrari Minesso et al. (2022), who used text analysis and machine learning algorithms to create an index measuring U.S.-China trade tensions, examined the effects of this tension on financial markets using this index. According to the analysis findings, trade tension did not generally affect U.S. markets, but companies more exposed to China saw a negative impact on their stock prices, as did emerging market stock indices. On the other hand, during this period, the U.S. dollar appreciated, while the currencies of emerging markets depreciated. Chen and Pantelous (2022) studied the effects of the U.S.-China trade conflict on the stock markets of China and the U.S. at the industry level, using a sample of 56 Chinese and 49 American companies. Based on the research findings, using a transfer entropy-based technique, it was found that Chinese industries were more exposed to trade tensions compared to U.S. industries. Chengying et al. (2022) examined the effects of the U.S.-China trade war on the Chinese stock market. The study analysed the impact of the trade war on various sectors at different periods using an event study method. It was observed that there was a larger market decline at the beginning of the trade war, but in the long term, the impact of the trade war became a systemic risk. Ozdagli and Wang (2022), in their study, used the U.S.-China trade war as a natural experiment to examine the effects of policy uncertainty shocks on financial markets. The findings showed that firms with a heavy reliance on bank debt responded less negatively to uncertainty shocks in terms of stock prices; this effect was particularly strong among zombie firms, and bank debt played a protective role in poor economic conditions. Carlomagno and Albagli (2022) examined the effects of U.S.-China trade tensions on international asset markets, using an event study method and daily indicators related to trade war news, covering a sample of 36 developed and developing economies. The analysis findings showed that the tension significantly reduced long-term bond yields in the U.S. and other developed economies, weakened stock markets, and led to currency depreciations in emerging economies.

Cai et al. (2023) analysed the link between U.S.-China political relations and Chinese stock market returns using a time-varying Granger causality method. The Shanghai Composite Index was used to represent Chinese stock market returns, and the U.S.-China political relations index was sourced from the International Relations Institute of Tsinghua University. Covering the period from January 1990 to September 2021, the study found that changes in U.S.-China relations had long-term causal effects on stock market fluctuations, whereas the reverse effects were short-lived. Huang et al. (2023) examined the financial impacts of the U.S.-China trade war (2018-2019) on firms in global supply chains. Their research revealed that U.S. firms with higher export and import volumes to China saw greater declines in stock values and higher default risks on days when high tariffs were announced. Chen et al. (2023) used a structural vector autoregressive model to assess the impact of the U.S.-China trade war on U.S. financial markets. Analysing 49 key event days between March 2018 and January 2020, the study found that trade war shocks led to significant changes in stock prices and Treasury bond yields, explaining over 30% of the changes, with firms highly exposed to the Chinese market being particularly affected. Zhang and Liu (2024) used an event study method to analyse the impact of the U.S.-China trade war on stock market movements among Mainland China, Hong Kong, the U.S., Japan, and Singapore during the period from January 3, 2017, to February 3, 2023. The findings revealed that, after July 6, 2018, stock market movements in the Asia-Pacific economies, particularly in the communications services and industrial sectors, became more sensitive to news related to the U.S.-China trade war, and the stock market movements between the U.S. and Mainland China declined to lower levels due to the war. Jung and Park (2024) examined the effects of U.S.-China trade disputes on multinational companies' foreign direct investment decisions. Based on research findings from 2003 to 2020, European firms increased their investments to deepen market penetration in China, while American multinational companies pulled back from the Chinese market and redirected their resources to Southeast Asia to reduce their dependence on China. Roger et al. (2024) created a newspaper-based index to represent U.S.-China tensions and analysed its impact on company investments, supply chain relationships, stock returns, and macroeconomic data. The analysis results showed that this index has a negative relationship with U.S. companies' investment expenditures, with a larger effect on companies more exposed to China. Additionally, as tensions escalated, the worsening economic expectations were reflected in the stock returns of U.S. companies. In conclusion, the study highlighted the negative economic consequences of U.S.-China tensions on company investments, supply chain relationships, stock returns, and macroeconomic data.

The research on the effects of U.S.-China trade tensions on stock markets is limited, with many studies focusing on Asian markets, which have been adversely affected by these tensions. These studies generally conclude that U.S.-China tensions negatively influence stock market indices. However, there is a lack of research specifically analyzing the impact of these tensions on the BIST stock market. Hence, this study provides a valuable contribution to understanding market dynamics in Türkiye.

3. Data Set and Model

This study aims to explore the effect of U.S.-China tensions on the BIST stock market. For this purpose, the U.S.-China Tension Index, developed by Rogers et al. (2024), was used to capture tensions between the two countries, while the BIST-100 Return Index represented the BIST market. Control variables, such as terms of trade, interest rates, inflation, and exchange rates, were chosen based on relevant literature. The research spans from January 2017 to February 2024, with January 2017 selected as the starting point due to Donald Trump’s election as the 45th U.S. President in November 2016 and his inauguration in January 2017. Trump's presidency marked a pivotal shift in U.S.-China relations, characterized by a more adversarial and competitive approach towards China, influencing various aspects of bilateral relations. Hence, the study period begins in January 2017 and ends in February 2024, the most recent date available for the U.S.-China Tension Index. This research uses monthly data, comprising 86 observations. Rather than using monthly closing prices of the BIST-100 Index, the total return index is applied, which accounts for both price changes and dividend reinvestment, offering a more accurate measure of market performance for investors. A total return index is thus more suitable for analyzing the impact of external shocks, like U.S.-China tensions, on the market. By focusing on returns, the analysis can highlight how the market responds to changes in the tension index, how risk perceptions evolve, and how investor behaviour shifts. Unlike closing prices, the total return index offers a more dynamic and comprehensive view, enhancing the analysis of the BIST market’s sensitivity to U.S.-China tensions. To account for scale differences and variability, a natural logarithmic transformation was applied to the variables. A summary of the variables used is provided in Table 1.

Table 1. Summary Information of Variables

Variable	Short Code	Variable Definition
BIST-100 Return Index	BIST	(Return) BIST 100 Index (XU100_CFNNTLTL), Based on Closing Prices (27-12-1996=9.76)
U.S.-China Tension Index	UCT	U.S.-China Tension Index
Terms of Trade	TOT	Terms of Trade = (Export Price Index / Import Price Index) x 100
Interest Rate	INT	Weighted Average Interest Rate Applied to Commercial Credits Extended by Banks (Current Data, %) (Turkish lira Based)
Inflation	INF	Price Index (Domestic Producer Prices) (2003=100)
Foreign Exchange Rate	EXC	Domestic Producer Price Index Based Real Effective Exchange Rate (2003=100)

Note: BIST, INT, INF, and EXC variables were sourced from the Central Bank of the Republic of Türkiye's Data Delivery System; TOT variable was retrieved from the Turkish Statistical Institute, and UCT variable was obtained from https://www.policyuncertainty.com/US_China_Tension.html.

The formal model used in the study is represented by Equation (1) and was developed by following the approach of Öztürk and Altınöz (2019). In their research on the effect of the U.S.-China trade wars on the Shanghai Stock Exchange Composite Index, Öztürk and Altınöz (2019) used key macroeconomic variables of China as control factors. Similarly, in this study, interest rate, inflation, and exchange rate are used as main macroeconomic indicators. For the interest rate variable, commercial loan rates were selected. This choice was based on the consideration that these rates, determined directly by credit demand in the trade and industrial sectors, better reflect the actual state of the economy, including supply-demand dynamics and financial costs. Producer Price Index (PPI) was chosen as the inflation indicator. Producer prices encompass changes in raw material, energy, and other production costs, directly reflecting the cost pressures faced by companies. Increases in production costs can create downward pressure on profitability, thereby affecting stock returns. PPI was preferred due to its suitability for analysing these cost dynamics. For the exchange rate variable, PPI-based real effective exchange rate was used. This exchange rate is adjusted for inflation and reflects the relative values of the currencies of the country’s trading partners. It provides a more accurate representation of the competitiveness of local producers. Changes in competitiveness, particularly those affecting export-oriented companies, can influence profitability and consequently stock returns. Therefore, PPI-based real effective exchange rate was chosen for its ability to comprehensively analysed the competitiveness, cost structures, and exchange rate sensitivities of firms. Finally, terms of trade, defined as the ratio of export prices to import prices, were included as a control variable in the study. The price fluctuations and demand changes caused by trade wars in global markets are reflected in Türkiye’s export and import prices. This, in turn, indirectly affects the global competitiveness and profitability of Turkish companies, thereby influencing stock returns. For these reasons, terms of trade, which can reflect the country’s trade conditions, were included as a variable.

$$BIST_t = a_0 + a_1 UCT_t + a_2\, TOT_t + a_3\, INT_t + a_4\, INF_t + a_5\, EXC_t + \varepsilon_{1t} \tag{1}$$

Descriptive statistics are presented in Table 2. It is observed that the mean and median values of the research variables are quite close to each other. BIST and INF variables have higher standard deviations compared to the other variables. This indicates that they are more volatile and fluctuate over a wider range. However, the lower standard deviations of the other variables suggest a more stable trend. BIST, UCT, INT, and INF variables exhibit positive skewness. This indicates that the data are right-skewed and may include some extremely high values. Conversely, the negative skewness of TOT and EXC variables indicates left-skewed distributions. This suggests that most of the values in these variables are concentrated above the mean, with a tail extending toward lower values. The kurtosis value of UCT variable is 5.88, which is significantly higher than that of the other variables. This shows that the distribution of UCT is more peaked, with outliers occurring more frequently. The Jarque-Bera test results show that the normality assumption is rejected at the 5% significance level for BIST, UCT, TOT, INT, and INF variables, while EXC variable is normally distributed.

Table 2. Descriptive Statistics

	BIST	UCT	TOT	INT	INF	EXC
Mean	7.9752	5.0307	4.5100	2.9894	6.5632	4.4106
Median	7.5731	5.0013	4.5395	2.9698	6.2066	4.4162
Maximum	9.7571	5.8577	4.6500	3.9881	8.0548	4.5619
Minimum	7.1860	4.6102	4.2813	2.2764	5.6524	4.2026
Standard Deviation	0.7696	0.2098	0.0930	0.3769	0.7659	0.0801
Skewness	1.0782	1.3042	-0.8813	0.7538	0.6541	-0.2385
Kurtosis	2.7319	5.8844	2.8229	3.7090	1.9553	2.5896
Jarque-Bera (JB) Statistic	16.9213	54.1960	11.2453	9.9466	10.0433	1.4189
JB Probability	0.0002	0.0000	0.0036	0.0069	0.0065	0.4919

Figure 2 shows the graphs of the study variables. Upon examining the graphs, it is observed that BIST and INF variables exhibit an upward trend over time. In contrast, the graphs of UCT, TOT, INT, and EXC variables display a more fluctuating pattern. This fluctuating behaviour indicates that these variables tend to increase at certain times and decrease at others.

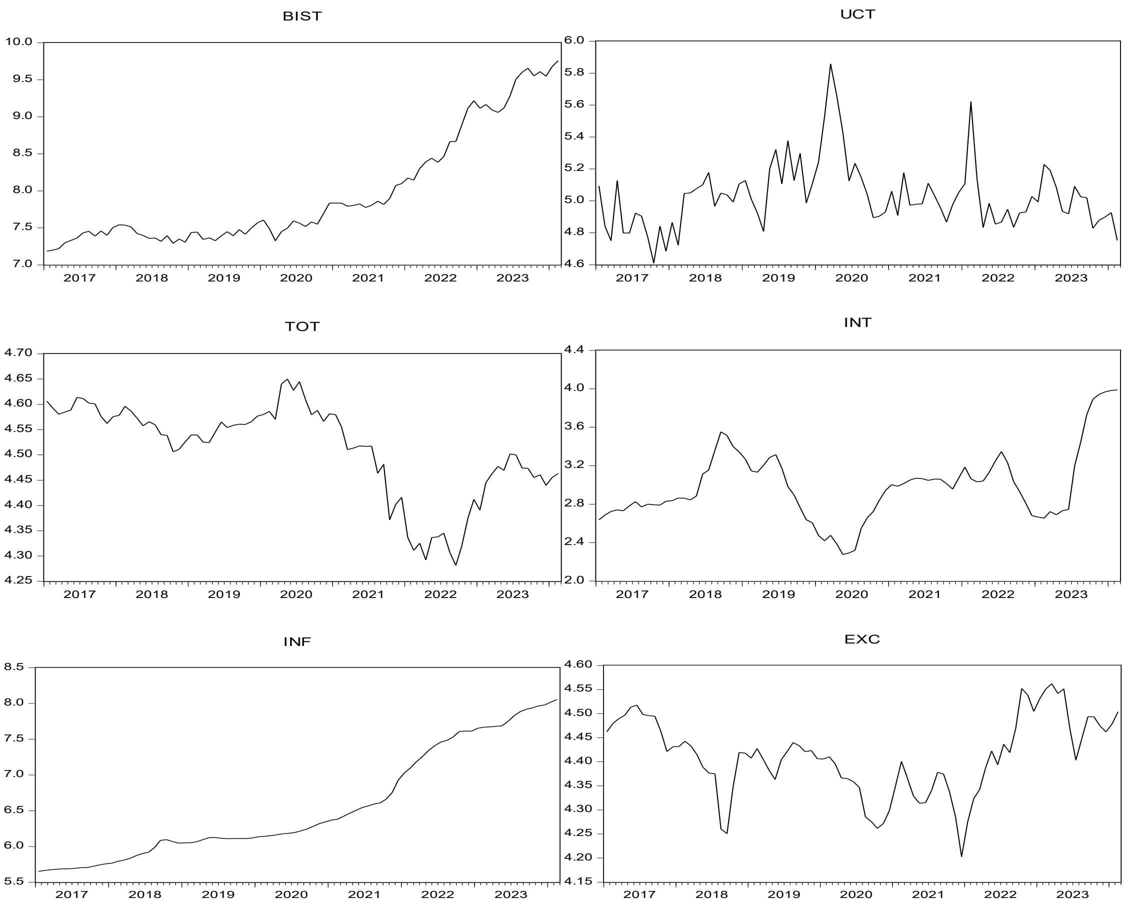

Figure 2. Graphs of Variables

4. Econometric Method

In time series analysis, stationarity signifies that a series maintains a constant mean and variance over time, a critical property for ensuring reliable analysis (Hamilton, 1994). Non-stationary series are unreliable for forecasting due to their time-varying mean or variance, potentially leading to erroneous results (Enders, 2014). In time series analysis, identifying the stationarity characteristics of the variables used in the study can influence the choice of subsequent tests, such as cointegration, causality, or other econometric methods. In this context, the stationarity properties of the variables in this study were assessed using the ADF, KPSS, Fourier ADF and Fourier KPSS unit root tests. The long-term and short-term relationships in the research model are examined using the ARDL bounds testing approach. The econometric techniques employed in the study are briefly outlined below.

The unit root test method developed by Dickey and Fuller (1979) evaluates whether a series contains a unit root. If autocorrelation is present in the error terms, this issue is addressed by incorporating lagged values of the series. In the ADF test, the lagged value of the dependent variable is added as an independent variable. The ADF test, derived from Dickey and Fuller's (1979, 1981) research, tests the stationarity of the series using constant and constant/trend models, as presented in Equations (2) and (3). In the following model equations, Δ represents the difference operator, t denotes time, and p represents the lag length. In the test, the null hypothesis H_0: $\gamma=0$ suggests that the series has a unit root, while the alternative hypothesis H_1: $\gamma\neq0$ indicates that the series is stationary.

Model with constant term:

$$\Delta y_t = \alpha + \gamma\, y_{t-1} + \sum_{j=1}^{p} \delta_j\ \Delta y_{t-j} + \epsilon_t \tag{2}$$

Model with constant term and trend:

$$\Delta y_t = \alpha + \gamma\, y_{t-1} + \beta_t + \sum_{j=1}^{p} \delta_j\ \Delta y_{t-j} + \epsilon_t \tag{3}$$

Another conventional test applied in this study is test developed by Kwiatkowski et al. (KPSS, 1992). The KPSS (1992) test uses Lagrange Multiplier (LM) statistics to test the null hypothesis of stationarity against the alternative hypothesis of non-stationarity. The objective of this test is to achieve stationarity by removing the deterministic trend from the observed series. In the KPSS (1992) test, the series is modelled as the sum of the deterministic trend, random walk, and stationary error, and the LM test is used to test the hypothesis that the random walk has zero variance. Let y_t, t=1, 2, 3,...,T be the series whose stationarity is to be determined.

$$y_t = \xi_t + r_t + \varepsilon_t \tag{4}$$

$$r_t = r_{t-1} + u_t \tag{5}$$

In Equation 4, r_t denotes the random walk process, β_t denotes the deterministic trend and $u_t \sim IID(0, \sigma_u^2)$. In the KPSS (1992) test, the hypotheses are formulated as Equation (6). In the hypotheses, σ_u^2 indicates the variance of the error term. If the null hypothesis is accepted, r_t and y_t will be stationary.

$$\begin{aligned} &H_o: \sigma_u^2 = 0 \ \text{(Series is stationary)} \\ &H_o: \sigma_u^2 \neq 0 \ \text{(Series is not stationary)} \end{aligned} \tag{6}$$

Where e_t is the error terms from the regression of y on the constant and trend, the variance of the error terms is defined as σ_ε^2. The partial sums of the error terms S_t and the LM test statistic used to test the null hypothesis are calculated using Equation (7).

$$S_t = \sum_{i=1}^{t} e_i \, , t = 1,2,3, \dots . T$$
$$LM = \sum_{t=1}^{T} S_t^2 \Big/ \sigma_\varepsilon^2 \tag{7}$$

Perron (1989) introduced the first unit root process in the literature that accounts for structural breaks in time series. In his study, Perron (1989) explored how a one-time change in the constant or slope of the trend would affect the null and alternative hypotheses regarding the presence of a unit root. Structural breaks are assumed to be sudden and are modelled using shadow variables. Leybourne et al. (1998) and Harvey and Mills (2002) developed unit root tests based on the assumption of slower, smooth transitions for structural breaks. However, in these tests, the number of structural breaks is determined by the number of logistic smooth transition functions employed (Hepsağ, 2022). To address this, Becker et al. (2004, 2006) developed the Fourier KPSS stationarity test, which accounts for Fourier functions, enabling analyses without specifying the number, location, or form of structural breaks. Additionally, the Fourier ADF test developed by Christopoulos and León-Ledesma (2010), based on Becker et al. (2006), incorporates Fourier functions into the ADF unit root test. This test consists of two stages, with the first stage focusing on the regression model in Equation (8).

$$y_t = \delta_0 + \delta_1 \sin\left(\frac{2\pi kt}{T}\right) + \delta_2 \cos\left(\frac{2\pi kt}{T}\right) + v_t \tag{8}$$

Here, t is the deterministic trend, k is the number of frequencies and T is the number of observations. The main hypothesis of the test is presented in Equation (9). It is assumed that h_t follows a stationary process with zero mean. A three-step procedure is required to calculate the test statistic.

$$H_0 : v_t = \mu_t, \quad \mu_t = \mu_{t-1} + h_t \tag{9}$$

In the first step of the procedure, the appropriate k value should be found. This k value is the value that minimises the sum of residual squares. In the next process, the residuals of the model are obtained by Equation (10).

$$\widehat{v_t} = y_t - [\hat{\delta}_0 + \hat{\delta}_1 \sin\left(\frac{2\pi\hat{k}t}{T}\right) + \delta_2 \cos\left(\frac{2\pi\hat{k}t}{T}\right)] \tag{10}$$

The unit root test is applied to the residuals obtained by Equation (9). The Fourier ADF test is applied by applying the model in Equation (11) below to the residuals.

$$\Delta v_t = \alpha_1 v_{t-1} + \sum_{j=1}^{p} \beta_j \Delta v_{t-j} + \mu_t \tag{11}$$

The null and alternative hypothesis of the Fourier ADF test is expressed in Equation (12).

$$H_0 : \alpha_1 = 0, \quad H_1 : \alpha_1 < 0 \tag{12}$$

In the last step, the significance of the trigonometric terms is tested with the tests in Equation (13) through the F test. The critical values required for the F test are calculated in Becker et al. (2006). If the null hypothesis indicating the insignificance of the trigonometric terms is accepted, the conventional ADF test is applied instead of the FADF test.

$$H_0\colon \delta_1 = \delta_2 = 0, \quad H_1\colon \delta_1 \neq \delta_2 \neq 0 \tag{13}$$

Another test based on Fourier approximations used in the study is the Fourier KPSS unit root test. Becker et al. (2006) developed a KPSS-type stationarity test by including Fourier functions in unit root tests. Thus, by using the Fourier function, the number of refractions whether the break is sudden or not is no longer important in the determination. According to Becker et al. (2006), the data creation process is presented in Equation (14).

$$\begin{aligned} y_t &= X_t'\beta + Z_t'\gamma + r_t + \varepsilon_t \\ r_t &= r_{t-1} + u_t \end{aligned} \tag{14}$$

Here, ε_t is the stationary error term and u_t is the independent identically distributed error term with variance σ_u^2. $X_t = [1]$ denotes the stationarity process of y_t in level and $X_t = [1, t]'$ denotes the stationarity process in trend. The deterministic component Z_t is expressed as Equation (15).

$$Z_t = [\sin\left(\frac{2\pi kt}{T}\right), \cos\left(\frac{2\pi kt}{T}\right)]' \tag{15}$$

In Equation (14), k is the number of frequencies, T is the number of samples and t is the trend component. Considering the assumption that Z_t and $\sigma_u^2 = 0$, the regression equation in Equation (14), which follows a stationary process, is expanded and expressed as Equation (16).

$$y_t = \alpha + \beta t + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + e_t \tag{16}$$

In this case, whether the series is stationary or not will depend on the number of frequencies and sample size. In the FKPSS test, the null hypothesis that the series is stationary ($H_o\colon \sigma_u^2 = 0$) is tested against the alternative hypothesis. If the FKPSS test statistic is less than the critical values, the null hypothesis cannot be rejected. The significance of the trigonometric terms is also tested using a process like the Fourier ADF test.

The ARDL approach is employed in this study due to its advantages in identifying both short and long-run relationships within the model. Traditional cointegration approaches require all variables to be stationary of the same degree. However, the ARDL method, developed by Pesaran and Shin (1995) and Pesaran et al. (2001), removes this restriction, allowing the analysis of variables that are I(0) or I(1). The ARDL method can estimate both long-run and short-run relationships, but it is not applicable if any variable is I(2) or higher. Another benefit of the ARDL model over classical cointegration tests is its applicability to small sample sizes (Narayan, 2005). This method involves two main stages. The first stage involves testing for the presence of a long-run relationship. If cointegration exists, the long-run coefficient is estimated, and the error correction term is included in the short-run error correction model (Narayan & Smyth, 2005). In this context, assuming Y is the dependent variable, and Z represents the independent variables, the long-run relationship is expressed in Equation (17). Pesaran et al. (2001) developed a bounds testing approach to analyse the long-run relationship in Equation (17).

$$Y_t = \phi + \beta Z_t + \epsilon_t \tag{17}$$

The ARDL method is based on estimating the long-run relationship between variables through an unconstrained error correction model. This model is then transformed into an Error Correction Model (ECM) to estimate the short-run coefficients. Equation (18) shows a linear ARDL model with distributed lags.

$$\Delta Y_t = \mu + \rho_y Y_{t-1} + \rho_x Z_{t-1} + \sum_{i=1}^{p-1} a_i \, \Delta Y_{t-i} + \sum_{i=0}^{q-1} \beta_i \, \Delta Z_{t-1} + \epsilon_t \tag{18}$$

5. Findings

The finding process in the study started with the reporting of ADF and FADF unit root tests with constant term and trend presented in Table 3.

Table 3. ADF and FADF Test Results

Variable	ADF	k	FADF	F Statistics	Min SSR
BIST	-0.5442 (0.9795)	1	-3.8336	461.4102	0.8791
UCT	-4.1890 (0.0070)	1	-4.4072	14.6057	2.7560
TOT	-1.6828 (0.7505)	2	-3.2797	59.9067	0.1587
INT	-2.2866 (0.4363)	3	-2.8220	25.9923	6.4944
INF	-1.4967 (0.8232)	1	-1.3886	242.3076	0.6575
EXC	-2.7819 (0.2081)	1	-2.9796	38.9456	0.2787
ΔBIST	-8.6772 (0.0000)	1	-9.1139	1.5444	0.5227
ΔUCT	-	4	-8.2451	0.7803	2.6851
ΔTOT	-9.7181 (0.0000)	2	-10.9250	3.8077	0.0539
ΔINT	-4.8516 (0.0009)	3	-5.3831	6.2954	0.8345
ΔINF	-4.2443 (0.0060)	2	-5.4239	16.6445	0.0505
ΔEXC	-7.5501 (0.0000)	4	-7.4138	2.7916	0.1004

Note: "Δ" denotes the first-difference notation. The critical values for the ADF unit root test at the 5% significance level are -3.4635. For the FADF unit root test, the critical values at the 5% significance level are -4.46 for frequency k=1, -4.16 for k=2, -3.83 for k=3, -3.70 for k=4, and -3.63 for k=5. The critical value for testing the significance of trigonometric terms at the 5% significance level is 4.972.

The results of the ADF unit root test in Table 3 indicate that, at the 5% significance level, the null hypothesis of no unit root cannot be rejected for the BIST, TOT, INT, INF, and EXC variables. These variables exhibit a unit root at the level but become stationary after taking first differences. However, for the UCT variable, the null hypothesis of no unit root is rejected at the 5% significance level, and it is found to be stationary at the level.

According to the FADF test results in the same table, the calculated FADF test statistics for the BIST, TOT, INT, INF, EXC, and UCT variables are lower than the critical values at the 5% significance level based on frequency numbers. Therefore, the null hypothesis of a unit root cannot be rejected. These results suggest that all variables are unit root at the level but become stationary after the first differences.

The significance of the trigonometric terms is also assessed. The F-statistic values at the level exceed the 5% significance threshold of 4.972 (Becker et al., 2006), so the null hypothesis of their insignificance is rejected. This implies that the trigonometric terms are significant at the level, and thus, the FADF unit root test is applicable.

Table 4. KPSS and FKPSS Test Results

Variable	KPSS	k	FKPSS	F Statistics	Min SSR
BIST	0.2861	1	0.0604	461.4102	0.8791
UCT	0.2008	1	0.0748	14.6057	2.7560
TOT	0.1073	2	0.1127	59.9067	0.1587
INT	0.1079	3	0.1143	25.9923	6.4944
INF	0.2668	1	0.0594	242.3076	0.6575
EXC	0.2265	1	0.0630	38.9456	0.2787
ΔBIST	0.0978	1	0.0812	1.5444	0.5227
ΔUCT	0.1058	4	0.0857	0.7803	2.6851
ΔTOT	-	2	0.1020	3.8077	0.0539
ΔINT	-	3	0.1261	6.2954	0.8345
ΔINF	0.0969	2	0.1150	16.6445	0.0505
ΔEXC	0.0490	4	0.0790	2.7916	0.1004

Note: Note: "Δ" denotes the first-difference notation. The critical value for the KPSS test at the 5% significance level is 0.1460. For the FKPSS stationarity test, the critical values are as follows: 0.054 for frequency k=1, 0.1321 for k=2, 0.1423 for k=3, 0.1478 for k=4, and 0.1484 for k=5. The critical value for testing the significance of trigonometric terms at the 5% significance level is 4.972.

The constant term and trend models for the KPSS and FKPSS stationarity tests are shown in Table 4. In the KPSS test, if the calculated test statistics exceed the critical values, the null hypothesis of the variables being stationary at the level is rejected. At the 5% significance level, the BIST, UCT, INF, and EXC variables show unit roots at the level, while the TOT and INT variables are stationary. The variables with unit roots at level become stationary after taking the first differences.

According to the FKPSS test results in the same table, the test statistics for BIST, UCT, INF, and EXC are greater than the critical values at the 5% level, so the null hypothesis of these variables being stationary at the level is rejected. These variables are unit root at level and become stationary after first differencing. The TOT and INT variables are stationary at level. The F-statistic values for the series are greater than the 5% significance value of 4.972 from Becker et al. (2006), rejecting the null hypothesis of the insignificance of the trigonometric terms. This suggests that the trigonometric terms are significant at the level. Therefore, the FKPSS unit root test is applicable and can be reported.

Based on the test results, the dependent variable BIST was found to have a unit root at level and becomes stationary at the first difference, indicating it is I(1). The independent variables showed mixed results, with most being I(0) or I(1). Since the dependent variable is I(1) and no variables are I(2), the ARDL approach was deemed appropriate. The ARDL model was determined by selecting the specification that minimizes the relevant criterion, and as shown in Figure 3, the ARDL (3, 8, 0, 8, 7, 8) model was chosen based on the Akaike Information Criterion.

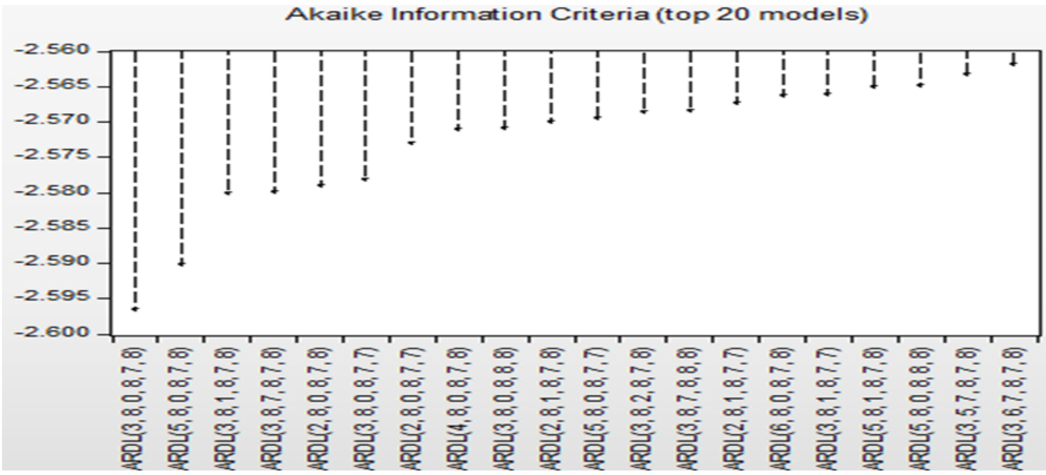

Figure 3. Model Selection

In the ARDL (3, 8, 0, 8, 7, 8) model, the cointegration relationship is tested using the Unrestricted Error Correction Model (UECM), which is presented in Equation (19):

$$\Delta BIST_t = \beta_0 + \sum_{i=1}^{p=3} \beta_{1i}\,\Delta BIST_{t-i} + \sum_{i=0}^{r=8} \beta_{2i}\,\Delta UCT_{t-i} + \sum_{i=0}^{s=0} \beta_{3i}\,\Delta TOT_{t-i} + \sum_{i=0}^{k=8} \beta_{4i}\,\Delta INT_{k-i} + \sum_{i=0}^{l=7} \beta_{5i}\,\Delta INF_{l-i} + \sum_{i=0}^{m=8} \beta_{6i}\,\Delta EXC_{l-i} + a_1 BIST_{\,t-1} + a_2 UCT_{t-1} + a_3 TOT_{t-1} + a_4 INT_{t-1} + a_5 INF_{t-1} + a_6 EXC_{t-1} + \varepsilon_t \quad (19)$$

The notation Δ in Equation (19) represents the difference operator, ε_t is the error term, β_0 is the constant, and $\beta_{1,2,3,4,5,6}$ represent the short-term coefficients. The long-term coefficients are denoted by $a_{1,2,3,4,5,6}$ while p, r, s, k, l, and m indicate the lag lengths determined by the information criterion. In the ARDL approach, the F bounds test is used to check for cointegration. The test evaluates the alternative hypothesis $H_1: a_1 \neq a_2 \neq a_3 \neq a_4 \neq a_5 \neq a_6 \neq 0$ against the null hypothesis $H_0: a_1 = a_2 = a_3 = a_4 = a_5 = a_6 = 0$. If the F bound test statistic exceeds the upper bound critical value, the null hypothesis H_0, which assumes no cointegration, is rejected, confirming the presence of a cointegration relationship. After determining the long-term coefficients of the ARDL model, the Error Correction Model (ECM) is formulated to analyse the short-term dynamics. For this mechanism to function effectively, the error correction term (λ) must be negative and statistically significant. The ECM model is expressed in Equation (20).

$$\Delta BIST_t = \beta_0 + \sum_{i=1}^{p=3} \beta_{1i}\,\Delta BIST_{t-i} + \sum_{i=0}^{r=8} \beta_{2i}\,\Delta UCT_{t-i} + \sum_{i=0}^{s=0} \beta_{3i}\,\Delta TOT_{t-i} + \sum_{i=0}^{k=8} \beta_{4i}\,\Delta INT_{k-i} + \sum_{i=0}^{l=7} \beta_{5i}\,\Delta INF_{l-i} + \sum_{i=0}^{l=8} \beta_{6i}\,\Delta EXC_{l-i} + \lambda\, ECT_{t-1} + \varepsilon_t \tag{20}$$

The robustness of the ARDL (3, 8, 0, 8, 7, 8) model was evaluated through diagnostic tests. The Jarque-Bera test confirmed the normality of error terms with p=0.5543>0.05, indicating a normal distribution. The Breusch-Godfrey LM test showed no serial correlation up to 8 lags (p=0.1897>0.05). Heteroscedasticity was examined using the Breusch-Pagan-Godfrey test, and the result (p=0.3396>0.05) supported the assumption of constant variance. Lastly, the Ramsey RESET test indicated no specification error in the model (p=0.7855>0.05). These tests collectively confirm the model's reliability.

Table 5. Diagnostic Test Results

Diagnostic Tests	Test Statistic	P. Value
Breusch-Pagan-Godfrey Test	1.1442	0.3396
Breusch-Godfrey LM Test	1.5268	0.1897
Jarqua-Bera Test	1.1797	0.5543
Ramsey Reset Test	0.2742	0.7855

The findings of the ARDL bounds test are reported in Table 6. The F-statistic for the bounds test was calculated as 9.4954. Since this value exceeds the upper critical values at all significance levels for I(1), the null hypothesis of no cointegration in the model was rejected. Therefore, the series included in the ARDL (3, 8, 0, 8, 7, 8) model are cointegrated. In other words, there is a long-term equilibrium relationship in the model.

Table 6. F Test Result

Test Statistic	Value	Significant	I (0)	I (1)
F Statistic	9.4954	10%	2.355	3.5
k	5	5%	2.787	4.015
		1%	3.725	5.163

Table 7 presents the long-term parameter estimates of the ARDL model. According to these estimates, all variables, except for the terms of trade (TOT), are statistically significant at various levels. The coefficient of the U.S.-China Tension Index (UCT) variable is negative and significant (-0.3577), while the coefficient for the terms of trade (0.6381) is positive but not significant. The interest rate coefficient (-0.1427) is negative and significant, the inflation coefficient (1.0423) is positive and significant, and the exchange rate coefficient (1.8142) is also positive and significant. The long-term estimates suggest that a 1% increase in the U.S.-China Tension Index leads to a 0.3577% decrease in the BIST-100 Return Index, implying that tensions between the U.S. and China have a negative impact on Türkiye's stock market. Conversely, increases in terms of trade, inflation, and exchange rates positively influence the stock market return index, though the effect of terms of trade is not statistically significant. Higher commercial loan interest rates, however, are found to negatively affect the stock market return index.

Table 7. Long-Term Results

Variable	Coefficient	Standard Error	T Statistic	P. Value
UCT	-0.3577	0.1351	-2.6468	0.0118**
TOT	0.6381	0.4267	1.4953	0.1431
INT	-0.1427	0.0582	-2.4510	0.0190**
INF	1.0423	0.0364	28.6102	0.0000***
EXC	1.8142	0.3441	5.2709	0.0000***

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

Table 8 presents the short-term estimates of the error correction model. For the stock market return index, its own lagged values up to two periods have a positive effect, but only the first lag is statistically significant. This indicates that the index is influenced by its past values in the short term, with the effect diminishing over time. The first lag being positive and significant shows that the previous period's performance positively impacts the current period, making this relationship statistically reliable. In contrast, the second lag is positive but insignificant, suggesting that the effect of returns from two periods ago is weak and not measurable with confidence. Thus, the short-term dynamics of the stock market return index are mainly influenced by the previous period, but this effect fades quickly. Overall, the influence of past values on the short-term dynamics of the stock market return index decreases rapidly, indicating the market adapts quickly to new information or that the effects of other variables become more prominent. In the short term, the U.S.-China Tension Index negatively affects the stock market return index, showing the market's sensitivity to global geopolitical risks, which hurt Türkiye's stock market. However, the mixed results across seven lags suggest the effect weakens over time or is offset by other variables. The effects of interest rates, inflation, and exchange rates on the stock market return index are also mixed, indicating that their impact may vary with market conditions. The negative and significant error correction coefficient (CointEq(-1) = -0.8034) confirms the operation of the error correction mechanism, suggesting that around 80% of short-term disruptions are corrected in the next period, with imbalances returning to long-term equilibrium in approximately 1.24 months (1/0.8034).

Table 8. Short-Term Results

Variable	Coefficient	Standard Error	T Statistic	P. Value
C	-6.0322	0.7517	-8.0239	0.0000***
D(BIST(-1))	0.2446	0.0914	2.6745	0.0110**
D(BIST(-2))	0.1546	0.1004	1.5383	0.1323
D(UCT)	-0.1519	0.0453	-3.3487	0.0018***
D(UCT(-1))	0.1349	0.0594	2.2689	0.0290**
D(UCT(-2))	0.0872	0.0530	1.6451	0.1082
D(UCT(-3))	0.0042	0.0503	0.0836	0.9338
D(UCT(-4))	0.0052	0.0518	0.1002	0.9207
D(UCT(-5))	-0.1275	0.0504	-2.5289	0.0157**
D(UCT(-6))	-0.0792	0.0530	-1.4939	0.1434
D(UCT(-7))	-0.1271	0.0478	-2.6565	0.0115**
D(INT)	-0.0155	0.1027	-0.1518	0.8801
D(INT(-1))	0.0718	0.1078	0.6656	0.5096
D(INT(-2))	-0.0292	0.1105	-0.2647	0.7927
D(INT(-3))	-0.0460	0.1129	-0.4074	0.6860
D(INT(-4))	0.1565	0.1051	1.4888	0.1448
D(INT(-5))	0.0855	0.1059	0.8077	0.4243
D(INT(-6))	0.3734	0.1068	3.4959	0.0012***
D(INT(-7))	0.2450	0.1136	2.1554	0.0375**
D(INF)	0.3983	0.4265	0.9338	0.3563
D(INF(-1))	0.1988	0.4726	0.4207	0.6763
D(INF(-2))	0.2848	0.4851	0.5870	0.5606
D(INF(-3))	-0.1694	0.5009	-0.3382	0.7370
D(INF(-4))	0.0071	0.5152	0.0138	0.9890
D(INF(-5))	0.8739	0.4730	1.8474	0.0725*
D(INF(-6))	-1.5889	0.4491	-3.5378	0.0011***
D(EXC)	-0.2894	0.3174	-0.9115	0.3677
D(EXC(-1))	-1.5132	0.3362	-4.5000	0.0001***
D(EXC(-2))	-1.1466	0.3497	-3.2787	0.0022***
D(EXC(-3))	-1.3493	0.3377	-3.9950	0.0003***
D(EXC(-4))	-0.8757	0.3367	-2.6005	0.0132**
D(EXC(-5))	-0.7828	0.3083	-2.5388	0.0153**
D(EXC(-6))	-0.4146	0.2861	-1.4491	0.1555
D(EXC(-7))	-0.4015	0.2638	-1.5217	0.1364
CointEq(-1)*	-0.8034	0.1000	-8.0292	0.0000***

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

The significance of the error correction coefficient can also be tested using the t-bound test reported in Table 9. Since the absolute value of the t-bound test statistic exceeds the upper critical values provided for all significance levels, it can be confirmed that the error correction coefficient is significant.

Table 9. T-Boundary Test Results

Test Statistic	Value	Significant	I (0)	I (1)
T Statistic	-6.7979	%10	-2.57	-3.86
		%5	-2.86	-4.19
		%2,5	-3.13	-4.46
		%1	-3.43	-4.79

The CUSUM and CUSUM² specification tests shown in Figure 4 are used to assess structural breaks and the stability of the long-term coefficients in the model. In these tests, if the boundary value on the graphs is surpassed, it indicates the presence of a structural issue in the model. It is observed that the parameter estimates remain within the acceptable limits at the 95% confidence level, suggesting that the model is stable.

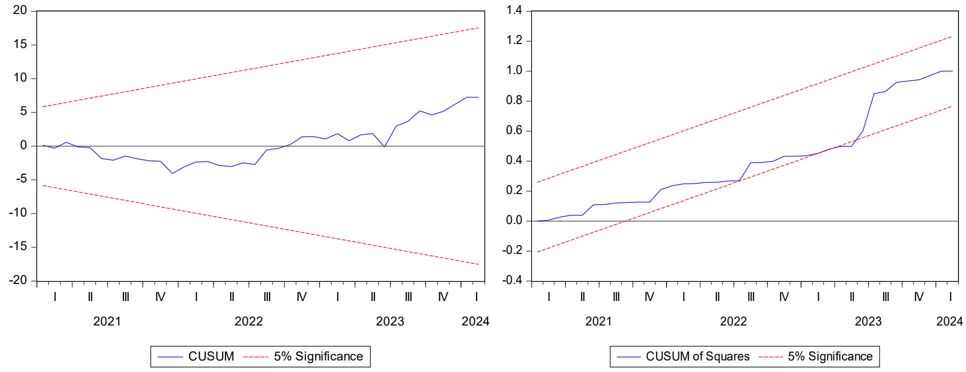

Figure 4. CUSUM and CUSUM² Graphs

6. Conclusion and Discussion

The ongoing tension between the U.S. and China continues to have profound effects on businesses and policymakers, both in terms of rhetoric and tangible actions. In recent years, as markets have become more globalized, trade and political uncertainties have amplified market volatility, influencing investor behaviour. Specifically, the effects of trade wars have led to significant fluctuations in capital markets, raising risk premiums, lowering stock prices, and causing delays in investment decisions. In times of heightened geopolitical risks and uncertainty, companies and investors have been compelled to take proactive steps to manage weaknesses in global supply chains and market volatility, while policymakers have worked to establish more predictable trade policies to promote sustainable growth. This study aims to explore the effects of U.S.-China trade war tensions on the BIST stock market. The data used spans from January 2017 to February 2024, a period marked by escalating U.S.-China trade tensions following Donald Trump's inauguration in January 2017. The research model uses the BIST Return Index as the dependent variable, with the U.S.-China Tension Index (developed by Roger et al., 2024), foreign trade terms, interest rates, inflation, and exchange rates as independent variables to represent trade war-related tensions. The stationarity of the variables was analysed using the ADF, KPSS, Fourier ADF, and Fourier KPSS tests. The unit root tests show that the dependent variable is stationary at the first difference, while the independent variables are stationary at either level or first difference, allowing the use of the ARDL bounds approach. The long-run ARDL estimates indicate that increases in the U.S.-China Tension Index negatively affect the BIST Return Index. In contrast, higher foreign trade terms, inflation, and exchange rates positively impact the stock return index, although the effect of foreign trade terms was not statistically significant. Rising commercial loan interest rates were found to negatively influence the stock return index. Short-term ARDL estimates show that the BIST Return Index is positively affected by its lagged values up to two periods, with only the first lag being statistically significant. The U.S.-China Tension Index also has a significant negative impact on the stock return index in the short run. The effects of interest rates, inflation, and exchange rates on the stock return index in the short-term yield mixed results. Finally, the negative and statistically significant error correction coefficient confirms the presence of an error correction mechanism in the model.

In this study, the effect of the U.S.–China trade war on the BIST-100 return index has been examined, and it was determined that this effect is negative. Several studies in the literature (Öztürk and Altınöz (2019), De Nicola et al. (2020), Setiawan (2020), Huynh and Burggraf (2020), Burggraf et al. (2020), Wang et al. (2021), He et al. (2021), Ferrari Minesso et al. (2022), Carlomagno and Albagli (2022), Huang et al. (2023), Chen et al. (2023), Zhang and Liu (2024)) have investigated the general impact of U.S.–China trade tensions on financial markets and reached similarly negative conclusions. Regarding the sample, a general assessment shows that the present study focuses on Türkiye's BIST-100 index over the period from January 2017 to February 2024, while the studies in the literature include samples from different countries and regions. For example, Öztürk and Altınöz (2019) analyzed China's Shanghai Composite Index, and De Nicola et al. (2020) examined 10 major stock market indices in East Asia. Similarly, while Setiawan (2020) studied ASEAN countries, Huynh and Burggraf (2020) focused on the stock market movements of the G7 countries. These varied sample selections provide diverse perspectives in understanding the regional effects of the U.S.–China trade war. In terms of the variables used, the current study employs the BIST-100 return index as the dependent variable, with independent variables including macroeconomic factors such as the U.S.–China Trade Tension Index, terms of trade, interest rate, inflation, and exchange rate. Other studies in the literature also use stock indices as the dependent variable but have adopted different approaches in selecting independent variables. For instance, while Wang et al. (2021) examined the stock returns of 2,754 companies in China, Burggraf et al. (2020) investigated the impact of Trump's tweets related to the trade war. Additionally, Ferrari Minesso et al. (2022) constructed an index by analyzing news texts related to the trade war using machine learning. Regarding statistical methods, the present study employs the ARDL bounds testing approach to analyze long- and short-run relationships. In contrast, various methodologies have been adopted in the literature. For example, He et al. (2021) used a TVP-SV-VAR model to examine the time-varying effects of trade policy uncertainty, while De Nicola et al. (2020) and Setiawan (2020) utilized event study methodologies to measure the short-term reactions of financial markets to trade war news. Furthermore, Zhang and Liu (2024) adopted an event study approach to analyze the impact of the trade war on Asia-Pacific markets, and Huynh and Burggraf (2020) assessed the movement between markets using copula methods. The use of different methods allows for a multidimensional examination of the effects of the trade war on financial markets. When it comes to the findings, the primary result of the current study is that U.S.–China trade tensions have a negative effect on the BIST-100 index. This finding largely parallels the results of the aforementioned studies. For example, Öztürk and Altınöz (2019) found that the tariffs imposed by the U.S. on China negatively affected the Shanghai index in the long run. Similarly, Wang et al. (2021) detected negative effects in the Chinese stock market, and Setiawan (2020) demonstrated that trade war events led to a decline in stock returns in ASEAN countries. Moreover, Huynh and Burggraf (2020) observed that global stock markets moved downward together during the trade war. However, some studies suggest that the trade war can have different effects on specific markets or sectors. For example, He et al. (2021) found that the increase in uncertainty in the U.S. harmed the Chinese market while having a positive effect on the U.S. market, and Ferrari Minesso et al. (2022) showed that the trade war did not generally affect the U.S. market, but companies with high trade volumes with China were negatively impacted. In conclusion, while most studies have focused on the U.S., China, and Asia-Pacific markets, this research provides new insights into the Turkish market by analyzing the effects of U.S.–China trade war tensions on the BIST. Furthermore, differences in sample selection, variables used, and methodologies offer opportunities to evaluate the effects of the trade war from different perspectives. This study demonstrates that the global geopolitical tensions resulting from the U.S.–China trade war significantly affect not only the direct parties but also emerging markets like Türkiye, thereby confirming that trade wars increase risks in international capital markets.

The negative short- and long-term effects of U.S.-China tensions on the BIST Return Index highlight the sensitivity of capital markets to global geopolitical risks. This situation holds significant implications for both investors and policymakers. Considering the impact of global uncertainties on capital markets, portfolio management and risk management strategies must focus on balancing such geopolitical risks. For investors, the fluctuations caused by the U.S.-China trade wars suggest that, rather than concentrating portfolios on a single country or region, increasing geographical diversification is essential. Ensuring a balanced distribution across different regions in portfolios could reduce the impact of global risks. Additionally, the use of derivative instruments, particularly futures and options, can be an effective strategy to limit potential losses and balance stock volatility. Furthermore, focusing on sustainable investment strategies is crucial for reducing investment risks in the long term. From a global risk management perspective, it highlights that Türkiye needs to reduce its dependence on foreign markets and build a more resilient economic structure against global risks. Increasing foreign exchange reserves and strengthening macroeconomic stability can serve as an important buffer against external shocks. Moreover, diversifying Türkiye's trade partnerships, rather than remaining dependent on just the U.S. and China, would be a critical step in protecting the economy from global trade tensions. Opening to new trade markets and seizing potential opportunities in the process can help Türkiye minimize risks arising from geopolitical uncertainties.

The uncertainties created by geopolitical risks in financial markets carry important messages for policymakers as well. The U.S.-China trade wars once again highlight the importance of establishing balanced foreign relations and developing strategic foresight. To avoid negative impacts from these tensions, Türkiye should manage its economic relations more balanced and strengthen its ties with different trade blocs. Additionally, increasing local production capacity and supporting strategic sectors can reduce dependence on foreign markets and enhance Türkiye's economic resilience. As a result, a wide range of measures, from investment strategies to macroeconomic policies, are required to protect against the effects of such geopolitical risks and uncertainties on financial markets. While this study provides a better understanding of how investments in emerging markets such as Türkiye are affected by global trade tensions, it also highlights the need for more in-depth analyses of macroeconomic conditions, market sentiment and methodologies used for future research.

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