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# ANALYSIS OF THE RELATIONSHIP BETWEEN CREDIT DEFAULT SWAPS (CDS), THE FEAR INDEX (VIX), AND BIST 100 USING THE WAVELET COHERENCE MODEL

Emine KARAÇAYIR<sup>1</sup>

#### Abstract

High levels of volatility, which reflect fluctuations in the price of a financial asset or instrument, lead investors to monitor global markets more closely. The VIX index, closely followed by global investors, signals expectations of increased market volatility when it is at high levels and decreased volatility when it is at low levels. Increases in the VIX index lead to an increase in CDS premiums, which represent a country's risk premium. The relationship between the VIX index, which is a global risk indicator, and the BIST 100 index is highly significant for investors operating in Türkiye's capital markets. This study examines the relationships between CDS premiums, the VIX index, and the BIST 100 index using the Wavelet Coherence Analysis method. The analysis results reveal that the relationship between VIX and CDS varies in intensity and direction over time. Furthermore, it can be seen that the relationship between the VIX and BIST variables is very strong in both the short and long term, with a negative direction from the VIX variable to the BIST variable. Moreover, the CDS variable was found to negatively impact the BIST index during the short-term period of 2019-2021.

Keywords: VIX Fear Index, Cds Credit Default Swaps, Wavelet Coherence Analysis

JEL Codes: G20, G28

<sup>&</sup>lt;sup>1</sup> Assist. Prof., University of Karamanoğlu Mehmetbey, Faculty of Economics and Administrative Sciences, <u>eminekalayci@kmu.edu.tr</u>, <u>https://orcid.org/0000-0003-0512-9084</u>



## INTRODUCTION

Volatility of financial products is among the most critical factors influencing investment decisions. During periods of high market volatility, investors may become apprehensive and refrain from making investment decisions. Investors generally monitor not only local markets but also global market volatility. In this context, the VIX volatility index is one of the key indices tracked by investors. The VIX volatility index, which was developed by Whaley in years 1993 and is based on the S&P 500 index, is derived from Black and Scholes' Nobel Prize-winning study carried out in 1973 and is frequently referred to in the literature as the "fear index". Calculated by the Chicago Board Options Exchange (CBOE), this index reflects the expected market volatility for the next 30 days. Its calculation is based on the price differences of call and put options of stocks included in the S&P 500 index. The VIX index rises when the price differences between options are high, and the index decreases when these differences are low. A high index value indicates expectations of increased market volatility, whereas a low index value suggests decreased volatility expectations. Increasing VIX levels reflect expectations of future volatility increases in S&P 500 index options prices. As the VIX value increases, the level of concern among market participants also grows (Whaley, 2000, p.12). The VIX index is widely used as an indicator of risk management, risk appetite, derivative product management, and market uncertainty (Aksoylu & Görmüs, 2018). For investors making investments in capital markets in Türkiye, the relationship between the globally recognized VIX index and the BIST 100 index is an important area of analysis. Moreover, an increase in the VIX index is expected to lead to higher CDS (Credit Default Swaps) premiums.

CDS premiums serve as an indicator of country risk premiums and are used to measure credit risk, evaluate investors' risk perception toward a specific country, and present an overall framework for local economic risks (Bektaş & Babuşcu, 2019). CDSs are considered derivative instruments that have high liquidity and offer early warning signals for changes in credit risk (Gümrah, 2009). The supply and demand for these derivatives are shaped by investors' risk perceptions, and the intersection of the supply and demand curves determines the CDS premium (Bozkurt, 2015). CDSs can be associated not only with internal factors but also with external factors, including the VIX index. Considering their quick response to market fluctuations, CDS premiums have drawn significant attention from market participants. Therefore, the VIX index and CDS premiums are two of the most widely used concepts.

Reviewing the previous studies, it can be seen that there is a strong focus on the relationship between CDS premiums and macroeconomic indicators. The present study, on the other hand, aims to examine the relationship between CDS premiums, the VIX index, and the BIST 100 index using Wavelet Coherence Analysis, a dynamic method that allows the investigation of variable relationships across both time and



frequency dimensions. Wavelet Coherence Analysis is preferred because it provides detailed findings for each time segment rather than being confined to a specific time interval. Within this scope, analyzing the relationship between the VIX index, CDS premiums, and the BIST 100 index will provide a valuable information resource, particularly for investors and other stakeholders. The second section of this study reviews the literature, summarizing domestic and international studies and their findings. The third section details the dataset and methodology used, while the fourth section presents the application and analysis results. The final section discusses the results and provides a general evaluation of the conclusions drawn.

### LITERATURE REVIEW

In the literature, there are many studies carried out on various variables related with CDS premiums. When evaluating studies examining exchange rates, which is one of the factors considered to significantly impact CDSs, it can be seen that those carried out by Longstaff, Jun, Pedersen, and Singleton (2011), Liu and Morley (2012), Omachel and Rudolf (2015), Çonkar and Vergili (2017), Hassan, Kayhan, and Bayat (2017), Bayhan, Kömür, and Yıldız (2021), Durgun-Kaygısız and İşcan (2021), Özman, Özpınar, and Doru (2018), and Açcı, Kayhan, and Bayat (2018) concluded that there is a causal relationship from exchange rates to CDS premiums in the long run.

Increases in interest rates in the USA impact global liquidity conditions, thereby increasing global risk perceptions. This situation causes an increase in CDS premiums. Studies examining the relationship between CDS premiums and government bond yields - such as Blanco et al. (2005), Arslan (2006), Forte and Pena (2009), Zhu (2006), Pollege and Posch (2013), Zinna (2013), Ertunga and Çakar (2016), Ergenç and Genç (2020), and Özman, Özpınar, and Doru (2018) - revealed that bond prices and CDS premiums move in parallel with each other.

In the literature, there are numerous studies examining the effects of macroeconomic indicators such as external debt, current account deficits, inflation, and growth on CDS premiums and prices. Prominent ones among those studies include those carried out by Brandorf and Holmberg (2010), Çiftçi and Çeviş (2012), Kargı (2014), Baltacı and Akyol (2016), Basher and Sadorsky (2016), Öner (2018), Akyol and Baltacı (2018), Bektaş and Babuşcu (2019), Altunöz (2021), and Gareyev et al. (2021). Even though some of these studies identified statistically significant relationships among the variables, others reported no such linkages.

Pan and Singleton (2008) examined CDS premiums, the VIX Index, 10-year U.S. Treasury yields, and exchange rate volatility across South Korea, Mexico, and Türkiye for the period between 2001 and



2006. Using a single-factor lognormal model estimated by maximum likelihood, they analyzed the term structure of CDS spreads to capture the dynamics of credit event arrival rates and loss rates. The results they achieved revealed a significant relationship between the VIX Index and CDS premiums in the analyzed countries.

Similarly, Fontana and Scheicher (2016) analyzed the determinants of CDS premiums and government bond yields in eight countries for the period between 2006 and 2010 by using four variables, including the VIX Index, and found a significant relationship between the VIX Index and CDS premiums. In their analysis, they employed panel regression models with time and country fixed effects, supported by principal component analysis (PCA) to identify common patterns across countries. Their findings emphasize the importance of both global risk factors and market frictions in explaining the CDS-bond basis dynamics during periods of financial distress.

Hancı (2014) investigated the relationship between CDS premiums and BIST-100 returns in Türkiye for the period between 2008 and 2012 by using the GARCH method and found a negative relationship between CDS premiums and BIST-100 returns.

Heinz and Sun (2014) analyzed CDS premiums, the VIX Index, and macroeconomic conditions in 24 European countries by making use of panel data for the period between 2007 and 2012 and concluded that CDS premiums are significantly associated with the VIX Index.

Akkaya (2017) analyzed the relationship between bond yields, CDS premiums, the Borsa Istanbul return index, and gold prices for the period between 2008 and 2016 and identified causality from the Borsa Istanbul return index to CDS premiums. In the study, both multiple regression and VAR (Vector Autoregressive) analyses were applied. The results of the Granger causality test revealed that changes in the Borsa Istanbul return index and gold prices were significant predictors of the movements in CDS premiums.

Kadooğlu, Hazar, and Cütçü (2016) examined the relationship between CDS premiums and stock index closing prices in developed and developing countries, finding that the relationship was most sensitive in Ireland and weakest in Türkiye. In their study, various curve estimation regression models were applied to identify the most suitable functional form for each country, and the models with the highest explanatory power ( $R^2$ ) were selected.

Bektur and Malcioğlu (2017) studied the relationship between CDS premiums and the BIST-100 index in Türkiye for the period between 2000 and 2017 and concluded that changes in the BIST-100 index

cause fluctuations in CDS premiums. In the study, symmetric and asymmetric causality analyses were applied. While the Hacker–Hatemi-J (2006) bootstrap causality test revealed a one-way causality from CDS to BIST-100, the Hatemi-J (2012) asymmetric causality test indicated that the direction and strength of the relationship differ depending on whether the shocks are positive or negative.

Yüksel and Yüksel (2017) analyzed the relationship between CDS premiums and the VIX Index across 21 countries, including Türkiye, for the period between 2009 and 2013 by using the GARCH model and found a positive relationship between CDS premiums and the VIX Index.

Şahin and Özkan (2018) examined the relationship between CDS premiums, exchange rates, and the BIST-100 index for the period between 2012 and 2017. Their results indicated bidirectional causality between the BIST-100 index and CDS premiums, whereas no causality was found between exchange rates and the BIST-100 index. In the study, unit root tests (ADF and PP) were conducted, and the cointegration relationship among variables was analyzed using the Engle-Granger method. Based on the presence of cointegration, an error correction model (ECM) was estimated, and causality was examined through the Granger test within this framework.

Bektaş and Babuşcu (2019) investigated the relationship between growth, exchange rates, the VIX Index, and CDS premiums for the period between 2008 and 2018 and found unidirectional causality between the VIX Index and growth. However, there was no relationship between exchange rates and CDS premiums. In their study, the Augmented Dickey-Fuller (ADF) test was used to check the stationarity of the variables, and then Granger causality tests were conducted within a VAR framework to analyze the short- and longterm dynamics among the variables.

Topaloğlu and Ege (2020) studied the relationship between CDS premiums and BIST-100 index returns for the period between 2010 and 2019, concluding that a negative relationship exists between the two variables. In their study, they employed a variety of time series analysis methods, including structural break unit root tests, cointegration tests, the error correction model (ECM), Granger causality analysis, impulse-response functions, and variance decomposition. Long-term relationships were estimated using FMOLS, DOLS, and CCR approaches.

Sarıgül and Şengelen (2020) examined the relationship between the Borsa Istanbul and CDS premiums for the period between 2014 and 2019 and reported a bidirectional causality. In their study, the Johansen cointegration test was employed to determine long-term relationships, and the FMOLS method



was used to estimate long-run coefficients. In addition, the error correction model (VECM) and Granger causality analysis were applied to reveal short-term dynamics between variables.

Pazarcı, Kar, Kılıç, and Umut (2022) analyzed the relationship between CDS premiums, exchange rates, stock indices, and the VIX Index in Türkiye for the period between 2002 and 2022 by using the ARDL method. They found that stock indices are influenced by exchange rates, CDS premiums, and the VIX Index. In their study, unit root tests (ADF and PP) were conducted to examine the stationarity of the variables, followed by the application of the ARDL bounds testing approach to investigate long-run relationships. The results confirmed the presence of cointegration, and both long-run coefficients and short-run dynamics were estimated through an error correction model.

Güzel and İltaş (2022) examined the relationship between the VIX Index and BRICS-T country stock markets for the period between 2015 and 2021 and identified unidirectional causality for all BRICS-T countries except India. In their study, the Breitung and Candelon (2006) frequency domain causality test was employed to analyze the direction and strength of causality across different time horizons.

Topaloğlu, Şahin, and Görgel (2024) studied the relationship between CDS premiums, which is considered a tool for measuring country risk, and inflation, the BIST-100 index, and the volatility fear index for the period between 2008 and 2024 using the ARDL estimation method. Granger causality tests indicated a positive long-term relationship between CDS premiums, inflation, and the VIX Index, whereas a negative relationship was found with the BIST-100 variable. Moreover, inflation and the BIST-100 index were identified as causes of CDS premiums.

In recent years, as an alternative to traditional time series analyses, the wavelet coherence method which considers both time and frequency components—has provided a deeper understanding of the complex relationships among financial variables. Although the number of studies analyzing the interaction between CDS premiums, the VIX Index, and the BIST-100 index using the wavelet method is limited, the existing research presents noteworthy findings.

Güngör ve Eyüboğlu (2024) investigated the dynamic interaction between Türkiye's sovereign CDS spreads and major financial indicators, including bond yields, stock index, and exchange rates. By employing the wavelet coherence method, the study revealed significant time-frequency co-movements between CDS spreads and these variables, especially during periods of financial stress. The results confirmed that the interaction patterns vary across different time horizons and are stronger during global volatility episodes such as the COVID-19 pandemic.

Yıldırım and Erdoğan (2020) analyzed the co-movement between the BIST-100 index and macroeconomic variables such as gold prices, exchange rates, and interest rates by using the wavelet coherence approach. The findings revealed a negative relationship between the BIST-100 index and exchange rate basket and gold prices, while a positive relationship was observed between CDS premiums and gold prices at specific frequencies. The study demonstrated the advantage of wavelet methods in capturing time-varying causality across different scales.

Özdemir and Kaya (2021) examined the behavior of Türkiye's CDS spreads by incorporating variables such as the VIX Index, MSCI Turkey Index, USD/TRY exchange rate, and the BIST-100 index. The study applied wavelet coherence analysis to explore the co-movement structure across time and frequency domains. The results indicated a strong and persistent coherence between the VIX Index and CDS premiums, particularly during periods of global uncertainty, highlighting the sensitivity of Türkiye's credit risk perception to external shocks. The literature review highlights the limited number of studies examining CDS premiums, the VIX Index, and the BIST-100 index together. Furthermore, previous studies predominantly focused on investigating the existence of relationships between these variables. The present study, however, distinguishes itself by providing a comprehensive analysis of these relationships and employing a methodology that delivers detailed findings for each time frame, thereby offering a unique contribution to the literature.

Koncak and Nazlıoğlu (2024) examined the relationship between global uncertainty indicators (VIX and GEPU) and the Turkish stock market, represented by the BIST 100 index, using monthly data from January 1997 to December 2023 through a continuous wavelet coherence analysis. The study focused on the time-varying structure of the relationships among the variables over short, medium, and long terms, revealing significant increases in uncertainty indicators and fluctuations in the BIST 100 during crisis periods (2001, 2008, COVID-19). The findings indicate a strong long-term negative relationship between the VIX and BIST 100, while the relationship between GEPU and BIST 100 is more volatile and predominantly observed in the short and medium terms. Partial wavelet coherence analysis further enabled a more accurate interpretation of these relationships by isolating the effects of a third variable.

#### **DATASET AND METHOD**

This study examines the relationships between the VIX Index, Türkiye's CDS premium, and the BIST100 Index across both time and frequency domains using the wavelet coherence analysis, which is a dynamic analytical method that allows for the investigation of variable interactions. The analysis not only identifies the relationships during the study period but also captures how they change over time and across



different frequency bands. The variables were selected based on prior studies in the academic literature, and monthly data covering the period from January 1, 2010, to December 1, 2024, were employed. All data were obtained from the "investing.com" database. The closing price of the CBOE VIX Index is denoted as VIX, the Credit Default Swaps variable as CDS, and the closing price of the BIST 100 Index as BIST100. The analysis was conducted using the logarithmic return series of all variables. Descriptive statistics for the raw data are presented in Table 1.

|          | CDS     | VIX     | BIST     |  |
|----------|---------|---------|----------|--|
| Median   | 261.150 | 16.770  | 909.3    |  |
| S.D      | 150.258 | 6.756   | 2574.721 |  |
| Kurtosis | 4.274   | 7.321   | 6.626    |  |
| Skewness | 1.301   | 1.756   | 2.248    |  |
| J.B      | 62.168  | 231.10  | 247.753  |  |
| p-value  | (0.000) | (0.000) | (0.000)  |  |

**Table 1:** Descriptive analysis and unit root test of variable

As shown in Table 1, the standard deviation of the BIST (2574.721) is notably high, indicating significant fluctuations in the index. In contrast, the lower standard deviations of CDS and VIX suggest relatively low volatility. Financial time series are typically characterized by leptokurtic distributions, meaning they do not follow a normal distribution. Therefore, they require more sophisticated modeling approaches. Analyzing the kurtosis and skewness coefficients of the logarithmic return series confirms this non-normality. Both VIX (7.321) and BIST (6.626) exhibit high kurtosis, reflecting the presence of outliers and pronounced extreme fluctuations. Additionally, the positive skewness values greater than 1 for CDS, VIX, and BIST indicate a tendency toward large positive returns, meaning that extremely high values occur more frequently. Regarding stationarity, the results reveal that the level values of all series are non-stationary at the 1% significance level. Overall, the findings from the descriptive statistics and stationarity analysis suggest that the examined financial time series are well-suited for further analysis using advanced econometric models.



# Table 2: Unit root test results

|  |        | BIST                  | CDS                 | VIX               |                                |        | BIST                | CDS                 | VIX                 |  |
|--|--------|-----------------------|---------------------|-------------------|--------------------------------|--------|---------------------|---------------------|---------------------|--|
| ADF I(0)-<br>costant   | t stat | 1.603173              | -2.21696            | -4.141            | ADF I(1)-<br>costant           | 4 -4-4 | -12.3668            | -13.3686            |                     |  |
|  | t-stat | (0.9995)              | (0.201)             | (0.001)           |                                | t-stat | (0.000)             | (0.000)             | -                   |  |
|  | 1%     | -3.466994             | -3.46699            | -3.467            |                                | 1%     | -3.46721            | -3.46721            | -                   |  |
|  | 5%     | -2.877544             | -2.87754            | -2.878            |                                | 5%     | -2.87764            | -2.87764            | -                   |  |
|  | 10%    | -2.575381             | -2.57538            | -2.575            |                                | 10%    | -2.57543            | -2.57543            | -                   |  |
| ADF I(0)-<br>costant+trend   | t-stat | -0.464393<br>(0.9844) | -2.85119<br>(0.181) | -4.130<br>(0.007) | ADF I(1)-<br>costant+trend     | t-stat | -12.5919<br>(0.000) | -13.3432<br>(0.000) | -                   |  |
|  | 1%     | -4.010143             | -4.01014            | -4.010            |                                | 1%     | -4.01044            | -4.01044            | _                   |  |
|  | 5%     | -3.435125             | -3.43513            | -3.435            |                                | 5%     | -3.43527            | -3.43527            | _                   |  |
|  | 10%    | -3.141565             | -3.14157            | -3.142            |                                | 10%    | -3.14165            | -3.14165            | _                   |  |
|  | 1070   | 3.072825              | -0.0252             | -0.512            |                                | 1070   | -11.8485            | -13.4047            | -18.1365            |  |
| none   | t-stat | (0.995)               | (0.673)             | -0.312<br>(0.494) | ADF I(1)-none                  | t-stat | (0.000)             | (0.000)             | (0.000)             |  |
| ADF I(0)-none  | 1%     | -2.577945             | -2.57795            | -2.578            |                                | 1%     | -2.57802            | -2.57802            | -2.57802            |  |
|  | 5%     | -1.942614             | -1.94261            | -1.943            |                                | 5%     | -1.94262            | -1.94262            | -1.94262            |  |
|  | 10%    | -1.615522             | -1.61552            | -1.616            | AD                             | 10%    | -1.61552            | -1.61552            | -1.61552            |  |
|  | , -    | 1.6365                | -2.18666            | -5.253            |                                |        | -12.3973            | -13.4608            |                     |  |
| - 1  | t-stat | (0.9996)              | (0.212)             | (0.000)           | it )                           | t-stat | (0.000)             | (0.000)             | -                   |  |
| PP I(0)<br>constant  | 1%     | -3.466994             | -3.46699            | -3.467            | PP I(1)<br>constant            | 1%     | -3.46721            | -3.46721            | -                   |  |
|  | 5%     | -2.877544             | -2.87754            | -2.878            | PP<br>con                      | 5%     | -2.87764            | -2.87764            | -                   |  |
|  | 10%    | -2.575381             | -2.57538            | -2.575            |                                | 10%    | -2.57543            | -2.57543            | -                   |  |
| PP I(0)<br>constant+tren<br>d  | t-stat | -0.478988             | -2.94869            | -5.236            | PP I(1)<br>constant+tren<br>d  |        | -12.5778            | -13.4419            |                     |  |
|  |        | (0.9837)              | (0.150)             | (0.000)           |                                | t-stat | (0.000)             | (0.000)             | -                   |  |
|  | 1%     | -4.010143             | -4.01014            | -4.010            |                                | 1%     | -4.01044            | -4.01044            | -                   |  |
|  | 5%     | -3.435125             | -3.43513            | -3.435            |                                | 5%     | -3.43527            | -3.43527            | -                   |  |
|  | 10%    | -3.141565             | -3.14157            | -3.142            |                                | 10%    | -3.14165            | -3.14165            | -                   |  |
| PP I(0) none   | t-stat | 2.966672<br>(0.9993)  | 0.011981<br>(0.685) | -0.532<br>(0.485) | PP I(1) none                   | t-stat | -11.8849<br>(0.000) | -13.4996<br>(0.000) | -29.0816<br>(0.000) |  |
|  | 1%     | -2.577945             | -2.57795            | -2.578            |                                | 1%     | -2.57802            | -2.57802            | -2.57802            |  |
|  | 5%     | -1.942614             | -1.94261            | -1.943            |                                | 5%     | -1.94262            | -1.94262            | -1.94262            |  |
|  | 10%    | -1.615522             | -1.61552            | -1.616            |                                | 10%    | -1.61552            | -1.61552            | -1.61552            |  |
| KPSS<br>I(0)constan<br>t   | t-stat | 1.312841              | 1.177855            | 0.188             | KPSS<br>I(1)constan<br>t       | t-stat | 0.5519              | 0.070056            | 0.171594            |  |
|  | 1%     | 0.739                 | 0.739               | 0,739             |                                | 1%     | 0.739               | 0.739               | 0.739               |  |
|  | 5%     | 0.463                 | 0.463               | 0.463             |                                | 5%     | 0.463               | 0.463               | 0.463               |  |
|  | 10%    | 0.347                 | 0.347               | 0.347             | I(1                            | 10%    | 0.347               | 0.347               | 0.347               |  |
| KPSS I(0)<br>constant+tr<br>end  | t-stat | 0.334944              | 0.099801            | 0.190             | a                              | t-stat | 0.092189            | 0.058988            | 0.14799             |  |
|  | 1%     | 0.216                 | 0.216               | 0.216             | KPSS<br>I(1)constan<br>t+trend | 1%     | 0.216               | 0.216               | 0.216               |  |
|  | 5%     | 0.146                 | 0.146               | 0.146             |                                | 5%     | 0.146               | 0.146               | 0.146               |  |
|  | 10%    | 0.119                 | 0.119               | 0.119             | I(1<br>t                       | 10%    | 0.119               | 0.119               | 0.119               |  |
| The series were tested using the SIC information criterion, with a maximum lag length of 13. |        |                       |                     |                   |                                |        |                     |                     |                     |  |



In the stationarity tests of the series, ADF, PP, and KPSS unit root tests were used. The hypotheses for ADF and PP tests are as follows:

For the ADF and PP tests, the hypotheses are as follows:

H<sub>0</sub>: The series is not stationary.

H<sub>1</sub>: The series is stationary.

For the KPSS test, the hypotheses are as follows:

H<sub>0</sub>: The series is stationary.

H<sub>1</sub>: The series is not stationary.

The BIST and CDS variables are found to be non-stationary at level according to the ADF, PP, and KPSS unit root tests. In other words, the null hypothesis (H<sub>0</sub>) of the ADF, PP, and KPSS tests cannot be rejected for the level values of BIST and CDS, indicating that these series contain a unit root. However, when the first differences of these series are examined, it is observed that the variables become stationary in both models with constant and with constant and trend, according to the ADF, PP, and KPSS tests. Therefore, the analysis proceeded with the first differenced values of the series. In contrast, the unit root test results for the VIX variable show that the series is stationary at level in both constant and trend models according to the ADF and PP tests. Since the null hypothesis is rejected for the level values of VIX in the ADF and PP tests, the analysis continued with the level values of the VIX series. As a result, the wavelet analysis was conducted using BIST as an I(1), CDS as an I(1), and VIX as an I(0) variable.

Wavelet analysis, also referred to as "wavelet transform", is a mathematical method used to examine the time-dependent variation of frequencies within a dataset. This analysis is highly effective in distinguishing signals and patterns at various scales within time series data. Similar to the Fourier analysis, the wavelet analysis investigates frequency components; however, it provides time information as well, offering a more comprehensive and multidimensional analysis. As a result, wavelet analysis was used to detect both general relationships (across entire cross-sections) and intra-section variations among variables. This analysis is based on Fourier cycles and wavelets.

Fourier analysis, which was developed by Joseph Fourier, is a mathematical method for decomposing a signal or time series into its constituent frequency components. It lays the foundation of wavelet analysis.

Wavelet analysis, further developed by Morlet, Grossman, and Meyer, transforms a variable into wavelet coefficients by incorporating the time dimension (Combes & Grossmann, 1987, p.126-132).

Wavelet transformation is based on two primary wavelet base functions: father wavelets, which handle low-frequency trend components, and mother wavelets, which capture high-frequency detail components. Father wavelets ( $\phi$ ) and mother wavelets ( $\psi$ ) are represented through specific parameters. Wavelet functions are constructed based on location, scale parameters, and the mother wavelet function. The mother wavelet function is expressed as follows (Cai et al., 2017):

$$\psi \in L^2(\mathbb{R}), \, \psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}} \, \psi \left( \frac{t-\tau}{s} \right), s, \tau \in \mathbb{R}, s \neq 0 \tag{1}$$

where,  $\frac{1}{\sqrt{|s|}}$  represents the normalization factor ensuring unit variance of the wavelet, while s is the scaling factor controlling the wavelet's width. Scale and frequency are inversely related, meaning a higher scale corresponds to an extended wavelet suitable for detecting lower frequencies. Additionally,  $\tau$  represents the translation parameter controlling the wavelet's position (Cai et al., 2017). The mother wavelet functions can be represented using different mathematical expressions depending on their specific applications. For instance, mother wavelets such as the "Haar" wavelet, "Daubechies" wavelets, and the "Morlet" wavelet are defined by distinct mathematical formulations.

The Morlet wavelet, for example, is a widely used mother wavelet function, particularly in the analysis of time-series data. As a complex-valued wavelet, the Morlet wavelet is highly regarded in the fields of signal processing and time-series analysis due to its ability to achieve an optimal balance between time and frequency localization. It is characterized by its Gaussian shape in the time domain and sinusoidal oscillation in the frequency domain. This combination enables the Morlet wavelet to effectively capture both high-frequency and low-frequency components of a signal, making it a versatile tool for analyzing complex data models (Cohen & Walden, 2010). Moreover, the Morlet wavelet is particularly useful for analyzing non-stationary data (Cohen, 2019). According to the results given in Table 1, it is seen that the time series data used in this study are not normally distributed and non-stationary, for this reason the Morlet wavelet method was chosen for the wavelet transform. The transformation process, which involves adding a time dimension to the wavelets, consists of several steps. The wavelet function is constructed as follows (Vacha & Barunik, 2012, p. 242-243):

$$\psi_{1,m} = \frac{1}{\sqrt{m}} \psi\left(\frac{t-1}{m}\right), 1, m \qquad \in R, m \neq 0$$
<sup>(2)</sup>



In the function, the scale dimension "m" represents the time dimension "i".

The Morlet wavelet function was defined, and the functions for two different time series were as follows:

$$W_{(x,y)} = W_x(1,m)W_y(1,m) \rightarrow XY$$

$$R^{2}(\mathfrak{l},m) = \frac{IS(m^{-1}W_{xy}(\mathfrak{l},m))I^{2}}{S(m^{-1}IW_{x}(\mathfrak{l},m)I^{2})S(m^{-1}IW_{y}(\mathfrak{l},m)I^{2})} \sim for all \ R^{2}(\mathfrak{l},m)for \ 0 \le R^{2}(\mathfrak{l},m) \le 1$$
(3)

S= Wave smoothing coefficient

 $R^2 = (i,m)$  The proximity of the value (i,m) to 1 indicates the dependence of the variables in the time series, whereas its proximity to 0 suggests no relationship between the variables in the time series.

The functions containing negative values are expressed as follows:

$$\varphi_{xy}(\mathfrak{l},m)\tan^{-1}\left(\frac{\aleph\{S((m^{-1}W_{xy}(\mathfrak{l},m))\}}{\rho\{S((m^{-1}W_{xy}(\mathfrak{l},m))\}}\right) \to XY$$

$$\tag{4}$$

The hypotheses tested in the study are as follows:

 $H_{1,0}$ : There is no relationship between the CDS premium and the BIST100 index.

 $H_{1,1}$ : There is a relationship between the CDS premium and the BIST100 index.

 $H_{2,0}$ : There is no relationship between the VIX index and the BIST100 index.

 $H_{2,1}$ : There is a relationship between the VIX index and the BIST100 index.

H<sub>3,0</sub>: There is no relationship between the VIX index and the CDS premium.

 $H_{3,1}$ : There is a relationship between the VIX index and the CDS premium.

#### RESULTS

To investigate the relationship between the VIX Index, CDS premiums, and the BIST 100 Index in Türkiye using monthly data for the period between 1 January 2010 and 1 December 2024, the Morlet Wavelet Coherence model, a type of wavelet coherence analysis, was employed. The present study classified



the analysis periods into short-term (4-month), medium-term (8- and 16-month), and long-term (32-month) intervals. Considering the correlation heat map, the intensity of the relationship increases as the color transitions from blue to red. Specifically, blue (cold colors) represents a lower correlation coefficient, while red (warm colors) indicates a stronger correlation (ranging from 0 to 1). The wavelet analysis results were processed using R Studio, and the results are summarized as follows:

Figure 1: The relationship between CDS premiums and the BIST 100 Index



**CDS vs BIST** 

When examining Figure 1, the null hypothesis claiming no relationship between the CDS and BIST variables was rejected (p < 0.05). The relationship between CDS premiums and the BIST 100 Index exhibits a dynamic, time-varying nature. As shown in Figure 1, the correlation between CDS premiums and the BIST 100 Index was very strong, with coefficients in the range of 0.8–1, during the 0- to 4-month periods in 2018–2019. During the 4- to 8-month periods in 2019–2021, the relationship remained strong, with coefficients between 0.6 and 0.8. This period coincides with the 2018 currency crisis and the time when CDS premiums in Türkiye surged rapidly. This period was characterized by economic instability, fluctuations in interest rates, changes in risk perception, and especially the emergence of the COVID-19 pandemic in 2020, all of which contributed to the persistence of high CDS levels. In the medium-term periods between 0.6 and 0.8. This phase aligns with ongoing economic instability, interest rate fluctuations, and risk perception shifts, which contributed to sustained high CDS levels. The direction of this relationship was negative, running from CDS



to BIST. The direction of this relationship was negative, running from CDS to BIST. Negative relationship ∧>: Positive relationship, Colors show power of correlation. And of course, Causality: ∧ X to Y,  $\checkmark$  X to Y,  $\land$  Y to X,  $\checkmark$ : Y to X (X first and Y second variable.  $\downarrow\uparrow\rightarrow\leftarrow$ : No causality or relation.) Therefore, it was determined that the CDS variable negatively affected the BIST Index during the short term (0- to 8month periods) in the period between 2019 and 2021. While the direction of the relationship did not change over time, the intensity of the relationship decreased. In conclusion, it was accepted that an upward change in CDS premiums may cause a downward change in the BIST Index in the short run. Furthermore, the time intervals highlighted in Figure 1 coincide with a series of significant financial, political, and social crises both in Türkiye and globally, which likely intensified the observed dynamics between CDS premiums and the BIST 100 Index. For instance, the 2018 Turkish currency crisis, triggered by geopolitical tensions, credit rating downgrades, and structural economic vulnerabilities, led to a sharp depreciation of the Turkish lira and a surge in CDS levels. Similarly, the COVID-19 pandemic that began in early 2020 caused unprecedented volatility in global markets, driving the VIX Index to record highs and increasing global risk aversion. In Türkiye, the pandemic exacerbated existing macroeconomic imbalances, further elevating country risk perceptions. Additionally, political uncertainties such as the 2016 coup attempt and recurring tensions in international relations may have contributed to heightened risk premiums. These events collectively offer a contextual explanation for the strong and persistent negative relationship between CDS premiums and the BIST Index observed particularly between 2018 and 2021.

Figure 2: The Relationship Between VIX Index and the BIST 100 Index



VIX vs BIST



As seen in Figure 2, the null hypothesis asserting no relationship between the VIX and BIST variables was rejected. A relationship was observed between the two variables across all time intervals and frequency domains during the study period. The direction of the relationship was found to run from the VIX Index to the BIST 100 Index. Thus, the VIX Index can be considered a leading indicator for the BIST Index. The intensity of the relationship remained within the 0.8-1 range across all periods. In other words, the VIX Index had a strong impact on the BIST Index across all time periods (ranging between 4 and 32 months). The direction of the relationship, however, varied over time. From 2013 to 2016, the VIX variable negatively affected the BIST variable. In other words, an upward movement in the VIX Index during this period negatively influenced the BIST Index. Considering that the VIX is commonly referred to as a "fear index", an upward movement in the VIX reflects heightened fear, which could lead to investors withdrawing from the market. Under such circumstances, a downward movement in the BIST Index is an expected outcome. This negative relationship persisted during the period between 2018 and 2020. Overall, as can be seen in Figure 2, it can be concluded that the relationship between the VIX and BIST variables is very strong in both the short and long term, and the direction of the relationship is negative and from the VIX Index to the BIST 100 Index. The strong and persistent relationship observed between the VIX Index and the BIST 100 Index, particularly during the periods of 2013–2016 and 2018–2020, coincides with various domestic and global crises that significantly affected investor sentiment. During the 2013–2016 period, political tensions in Türkiye—such as the Gezi Park protests (2013), corruption investigations (2013), and the attempted coup on July 15, 2016-increased uncertainty and market volatility. In the 2018-2020 period, the Turkish currency crisis and the outbreak of the COVID-19 pandemic emerged as major sources of global financial stress and heightened investor fear. These developments led to sharp spikes in the VIX Index and triggered strong investor reactions in the Turkish stock market. Therefore, the negative relationship between the VIX and the BIST Index during these periods reflects the sensitivity of Türkiye's equity market to global fear and uncertainty.



## Figure 3: The relationship between VIX Index and CDS premiums

Examining Figure 3, it can be seen that the relationship between the VIX and CDS varies in intensity and direction over time. Consequently, the null hypothesis suggesting no relationship between the variables is rejected. The direction of the relationship shifts depending on the time period and frequency intervals. A bidirectional causality between the variables is observed; specifically, during the period between 2011 and 2014 within a 0-4 frequency band, the CDS variable is found to influence the VIX. Conversely, in the 2014– 2015 period within the same frequency band, the VIX is identified as influencing the CDS. In the more recent 16-period frequency band, the relationship between the two variables appears to have reached a critical level. Notably, the post-2019 relationship between the variables intensifies, with a coefficient strength of 0.8-1 in the 16-32 frequency band. This suggests that the economic uncertainties surrounding COVID-19 and its aftermath may have reinforced the bidirectional relationship between these two variables. Overall, while the relationship between the variables serve as leading indicators for each other. In summary, despite the strong correlation between the variables, the fluctuating direction of the correlation, oscillating between negative and positive values over time, makes it challenging to forecast CDS values



based on VIX fluctuations or vice versa. The bidirectional and time-varying relationship observed between the VIX Index and CDS premiums aligns with various global and domestic crises that have shaped risk perception and market behavior. For example, the period between 2011 and 2014 includes the post-global financial crisis recovery, the Eurozone sovereign debt crisis, and the 2013 "Taper Tantrum." These events significantly increased global market volatility and investor caution. Such developments may have strengthened the interdependence between the VIX, a global risk indicator, and CDS premiums, which reflect country-specific credit risk. Similarly, the outbreak of the COVID-19 pandemic during the 2019– 2021 period and its unprecedented economic consequences created an environment of extreme uncertainty in both global and local markets. The simultaneous rise in both VIX and CDS levels during this period may help explain why the coherence between the two variables reached critical levels.

## CONCLUSION

For investors trading in capital markets in Türkiye, the relationship between the VIX Index, a global risk indicator, and the BIST100 Index is very important. Moreover, it is known that an increase in the VIX Index leads to changes in CDS (Credit Default Swaps) premiums. This study examines the relationships between the VIX Index, Türkiye's CDS premium, and the BIST100 Index using monthly data from 1 January 2010 to 1 December 2024. The analysis employs Wavelet Coherence Analysis, a dynamic method that enables the exploration of relationships between variables across both time and frequency domains. The results achieved in this study revealed that the relationship between the CDS and BIST variables changes over time and is predominantly negative. This result is consistent with the results reported by Hanci (2014), Bektur and Malcioğlu (2017), and Topaloğlu and Ege (2020). Specifically, the CDS variable negatively influenced the BIST variable in the short term (2019-2021). Furthermore, the analysis identifies a relationship between the VIX and BIST variables across the entire period and all frequency domains, with the direction of the relationship flowing from the VIX to the BIST. Therefore, the VIX Index can be considered a leading indicator for the BIST. During the 2013–2016 period, the VIX variable negatively influenced the BIST variable, suggesting that upward movements in the VIX Index could heighten investor fear, prompting market withdrawal. In general, the relationship between the VIX and BIST variables is observed to be strong and negative in both the short and long term. This result aligns with those reported by Güzel and İltaş (2022). Lastly, the relationship between the VIX and CDS variables was found to vary in intensity and direction over time. The direction of the relationship changes depending on the time period and frequency intervals. When interpreted broadly, the relationship between the VIX variable and the CDS variable can exhibit both negative and positive directions across time-frequency domains. As a result, these variables are unlikely to provide financial information users with predictive insights as leading indicators



for one another. These results are consistent with those reported by Pan and Singleton (2008) and Fontana and Scheicher (2016). Wavelet coherence analysis reveals that the interaction between CDS premiums and the BIST 100 Index was particularly strong during the 2018 currency crisis and the COVID-19 pandemic. These findings confirm the time-varying nature of the relationship and the short-term vulnerability of the Turkish stock market to credit risk perceptions. Considering the periods covered in the study, it is evident that they coincide with various financial, political, and social crises in both Türkiye and the world, which have intensified the relationships among CDS premiums, the VIX Index, and the BIST 100 Index. The 2018 Turkish currency crisis and the COVID-19 pandemic in 2020 significantly affected Türkiye's country risk perception and investor reactions. The negative relationship between the VIX and the BIST Index reflects the sensitivity of Türkiye's stock market to global fear and uncertainty. Political events during the 2013–2016 period also increased market volatility and reinforced this relationship. Moreover, the bidirectional and time-varying relationship observed between the VIX and CDS premiums became more pronounced due to global crises, the "Taper Tantrum" episode, and the impact of the pandemic. These developments indicate a strong co-movement between global risk perception and Türkiye's credit risk.

This study is among the few that concurrently examine the relationship between CDS, BIST100, and VIX indices. By addressing these relationships across both time and frequency domains and employing a unique methodology, it distinguishes itself from existing literature. In this context, the results achieved in this study regarding the Fear Index are thought to serve as a guiding resource for firms, investors, and policymakers.

### **AUTHOR STATEMENT**

Researcher declared that all contributions to the article were his own. Researcher have not declared any conflict of interest.

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