

## SOVEREIGN CREDIT DEFAULT SWAP (CDS) SPREADS CHANGES IN VARIOUS ECONOMIC CONJUNCTURES: EVIDENCE FROM TURKEY BY MACHINE LEARNING ALGORITHMS

Assoc. Prof. Mustafa Tevfik KARTAL (Ph.D.) \* 

Assoc. Prof. Serpil KILIÇ DEPREN (Ph.D.) \* 

Özer DEPREN (Ph.D.) \* 

### ABSTRACT

*The study aims to define the sources of Turkey's sovereign CDS spread changes to develop policies that stabilize CDS spreads since they have a volatile and increasing trend, especially in the last two years. In this context, monthly data of 13 factors related to international, macroeconomic, and market between 2011/1 and 2019/12 are used by dividing the dataset into three periods as the full period (2011-2019), the stability period (2011-2017), and the macroeconomic turbulent period (2018-2019) and performing 4 different machine learning algorithms. The empirical results prove that (i) Treasury bond interest rate should be lower than 8% in the stability period and gold prices should be lower than TL 5.500 in the macroeconomic turbulent period to have low-level CDS spreads; (ii) NPL volume has no significant effect on in any period examined; (iii) the significance of factors on sovereign CDS spreads vary over the periods.*

**Keywords:** Sovereign CDS Spreads, Machine Learning Algorithms, eXtreme Gradient Boosting, Turkey

**Jel Kodları:** C40; E44; F30; G15

### 1. INTRODUCTION

Sustainability and development in the financial sector have great importance on financial stability (FS), which is parallel with the economic growth of countries. FS can be affected positively or negatively by a variety of macroeconomic and market (financial) indicators as well as international factors. In this context, inflation, economic growth, foreign exchange rates (FER), and interest rates should be considered and followed up strictly due to their effect on economies. Besides, FS could be monitored via different indicators such as FER denominated deposit/total deposit ratio, loan/deposit ratio, non-

\* Borsa İstanbul Strategic Planning, Financial Reporting, and Investor Relations Directorate, İstanbul/ Turkey. E-mail: [mustafatevfikkartal@gmail.com](mailto:mustafatevfikkartal@gmail.com)

\* Yıldız Technical University, Faculty of Arts & Science, Department of Statistics, İstanbul/ Turkey. E-mail: [serkilig@yildiz.edu.tr](mailto:serkilig@yildiz.edu.tr)

\* Customer Experience Directorate in Yapı Kredi Bank, İstanbul/ Turkey. E-mail: [ozerdepre@gmail.com](mailto:ozerdepre@gmail.com)

#### **Makale Geçmiři/Article History**

Başvuru Tarihi / Date of Application : 21 Ocak / January 2022

Düzeltilme Tarihi / Revision Date : 15 Şubat / February 2022

Kabul Tarihi / Acceptance Date : 27 Şubat / February 2022

performing loans (NPL), and CDS spreads. Each of these indicators reflects the riskiness, soundness, and predictability of countries.

CDS is a financial derivative product to be used for protection against losses (resulting from default) on debts provided via FER denominated securities like bonds and bills (Hibbert & Pavlova, 2017; The Central Bank of the Republic of Turkey (CBRT), 2020a; Kartal, 2020). A CDS contract enables sellers to have annual payments in the case of bond issuers' defaults. When CDS spreads of countries increase, the amount, which should be paid by CDS buyers, will also increase (Hasan et al., 2016). This condition may result in decreasing demand for securities issued by these countries due to increasing CDS spreads. There are two types of CDS, which are sovereign and corporate (Shahzad et al., 2017). Sovereign CDS are related to countries, whereas corporate CDS are related to the companies' economic performance.

Figure 1 presents the development of Turkey's CDS spreads since 2011 which represents a long period after the GFC period.

**Figure 1. The Development of Turkey's Sovereign CDS Spreads**



Source: Bloomberg, 2020.

As can be seen in Figure 1, Turkey's sovereign CDS spreads have been more volatile in recent years concerning previous years. High volatility and high-level of sovereign CDS spreads in Turkey have been shown after 2018 because of financial shocks and deteriorations in the macroeconomic environment. Nevertheless, Turkey still has high-level sovereign CDS spreads among peers (CBRT, 2020a). In this sense, it is thought to research why Turkey has high sovereign CDS spreads and which factors cause this condition.

The level of CDS spreads is essential for foreign investments in countries. Especially, global investors consider sovereign CDS spreads of countries while they allocate their assets, which is a

requirement for benefit in terms of diversification (Dooley & Hutchison, 2009; Yang et al., 2018). For this reason, low-level sovereign CDS spreads are crucial for countries to provide much more foreign investment inflows via securities. However, achieving low-level sovereign CDS spreads is not easy in the globalizing world where countries have been much more inter-dependent. In addition to national (macroeconomic and market) indicators, international factors should be taken into consideration (Galil et al., 2014; Kocsis & Monostori, 2016; Kartal, 2020) to have low-level CDS spreads and stimulate foreign portfolio investment in turn.

This study aims to define the importance of independent factors that have statistically significant effects on sovereign CDS spreads of Turkey. In other words, making a prediction rather than forecasting is aimed in this study. In this context, four machine learning algorithms are performed using a wide range of factors including global, macroeconomic, and market variables with monthly data between 2011/1 and 2019/12. The analysis is applied based on three periods: full period (2011-2019), stability period (2011-2017), and macroeconomic turbulent period (2018-2019). The study focuses solely on Turkey because Turkey has relatively high-level CDS spreads. Another reason is that Turkey is one of the countries that have the highest CDS spreads among. The study defines that the most influential factors on Turkey's CDS spreads and the performance of machine learning algorithms prediction accuracy varies according to the periods. The results also show that the periods (stability or turbulent) change the effect of influential factors on CDS spreads of Turkey. Moreover, NPL volume does not have a significant effect on sovereign CDS spreads in any period.

The main contribution of this study is to reveal the factors and their relative importance as predictors of CDS spreads of Turkey that is a country having the highest sovereign CDS spreads as a leading emerging country. Besides, four different machine learning algorithms with repeated cross-validation method, which has limited usage in explaining CDS spreads in the literature, are applied to a wide range of dataset consisting of both stability and macroeconomic turbulent periods. According to our knowledge, any academic paper has investigated factors that are likely to estimate sovereign CDS spreads through machine learning algorithms at the time the study is prepared. Another significant contribution of this study suggests some policy recommendations based on the optimal thresholds of the factors that are obtained by the analysis.

The rest of this study is organized as follows. Section 2 presents the literature review. Section 3 describes the variables, data, and methodology used in the study. Section 4 includes the modeling results and variable importance of the best algorithm in each period. Section 5 presents concluding remarks.

## **2. LITERATURE REVIEW**

In the literature, factors that have effects on CDS spreads can be divided into three groups: international, macroeconomic, and market factors.

The first group of studies in the literature focus on the relationship with global variables and CDS spreads. Oil prices, the volatility index (VIX), and gold prices are examples of international factors affecting CDS spreads. Many scholars determine that CDS spreads are influenced by oil prices (Duffie

et al., 2003; Arouri et al., 2011; Hammoudeh et al., 2013; Lahiani et al., 2016; Pavlova et al., 2018; Yang et al., 2018; Bouri et al., 2020; Wang et al., 2020). Besides, VIX explains changes in CDS spreads which implies the default risk of countries (Che & Kapadia, 2012). Also, there is a strong relationship between CDS spreads and VIX index, and the VIX index is an essential variable in explaining changes of CDS spreads in emerging countries, the US, Turkey, and many different countries (Ertuğrul & Öztürk, 2013; Galil et al., 2014; Hibbert & Pavlova, 2017; Akçelik & Fendoğlu, 2019; Park et al., 2019; CBRT, 2020a; Kartal, 2020). In this sense, gold prices are another critical factor that is positively associated with CDS spreads in BRICS, emerging countries, Euro Area, Frontier countries, G7 countries, and Turkey (Arce et al., 2013; Miyazaki & Hamori, 2013; Bouri et al., 2016; Yang et al., 2018; Kartal, 2020).

The second group of studies in the literature focus on the relationship between macroeconomic variables and CDS spreads. FER, fiscal debt balance, inflation (consumer price index-CPI), non-financial corporate foreign exchange debt (NFCFED), and reserves are factors in this group. Galil et al. (2014) determine a negative relationship between CDS and unexpected inflation in the US. On the other hand, Benbouzid et al. (2017) define a positive relationship between inflation and CDS in selected 30 countries' banks. Similar to the study of Benbouzid et al. (2017), it is revealed that inflation is highly correlated to CDS in Turkey (CBRT, 2020a). Ertuğrul & Öztürk (2013) examine effects of FER on CDS spreads in selected emerging countries while Fontana and Scheicher (2016) study the effects of Euro/USD FER volatility in the Euro area, Hassan et al. (2017) research the relationship between CDS spreads and the value of Turkish Lira (TL) and CDS spreads, and Kartal (2020) study on Turkey. They define that FER is an important variable to be considered in the examination of CDS spreads. Moreover, CBRT examines the effects of fiscal debt balance, NFCFED, and reserves. It is pointed out that fiscal debt balance and NFCFED have positive effects on CDS spreads of Turkey while reserves have negative effects (CBRT, 2020a).

The third group of studies in the literature focus on the relationship with market variables and CDS spreads. The central bank weighted average funding cost (CB WAFC), NPL, stock prices, and Treasury bond interest rate are the factors in the third group. According to Longstaff et al. (1995), there is a negative relation to reinvestment (spot) rate and CDS spreads. Also, Collin-Dufresne et al. (2001) conclude that high spot rates decrease default probability. Besides, Alexander & Kaeck (2008) study the effect of interest rates on CDS spreads and determine that interest rates are significantly effective. Galil & Soffer (2011) demonstrate that more excellent spreads of the US.

Moreover, Galil et al. (2014) examine that lower Treasury bond interest rates and greater stock return consistently decrease CDS spreads of the US. In addition, Benbouzid et al. (2017) consider NPL as a determinant of banks' CDS spreads. Moreover, Lahiani et al. (2016) state that stock prices have a significant effect on CDS. Even, Hibbert & Pavlova (2017) emphasize that there is a positive effect of CB WAFC on CDS spreads in selected 34 countries while modeling the interaction between CB WAFC and CDS spreads.

Collin-Dufresne et al. (2001), Jorion & Zhang (2007), Hassan et al. (2015) conclude that international factors have an important effect whereas country-specific (macroeconomic) factors don't have on sovereign CDS spreads. On the contrary, Fontana & Scheicher (2016) and Hibbert & Pavlova (2017) state that CDS spreads are much more sensitive to country-specific drivers. Besides, Galil et al. (2014) determine that market variables have significant explanatory power in explaining CDS spread changes. Moreover, Akçelik & Fendoğlu (2019) define that leading domestic macroeconomic indicators matter more strongly for country risk premium dynamics. Considering these determinations, the study prefers to include international, macroeconomic, and market variables simultaneously.

As summarized above, a variety of factors are effective on CDS spreads and these are selected to be used in the study. Besides these factors, the literature includes other variables used to examine CDS spreads like credit ratings (Hull et al., 2004; Norden & Weber, 2004; Galil & Soffer, 2011), economic growth (Benbouzid et al., 2017; CBRT, 2020a). Data for these variables are issued at quarterly or irregular times. However, the study aims to focus on monthly data. For this reason, such variables cannot be used in the study.

When evaluating studies in the literature, it can be summarized that the studies employ various statistical and econometric methods such as autoregressive conditional heteroskedastic (ARCH) types, bounding test, causality & cointegration tests, generalized method of moments, impulse-response analysis, regression types, vector autoregressive model (VAR), and vector error correction model (VECM) to examine CDS spreads. In this study, with using international, macroeconomic, and market variables, which are predicted to be influential on CDS spreads according to the literature, with the data including a large period from 2011/1 to 2019/12, and applying machine learning algorithms, which are relatively new methods, have the potential to contribute to the literature.

### **3. VARIABLES, DATA, AND METHODOLOGY**

#### **3.1. Variables**

5-years sovereign CDS spreads are used as a dependent variable because 5-years maturity has the most liquidity sovereign CDS spreads (Hasan et al., 2016; CBRT, 2020a). In light of the literature review, we prefer the final dataset includes 13 independent variables.

Table 1 lists the descriptions, and expected effects of independent variables on sovereign CDS spreads.

**Table 1. Description of Independent Variables**

Variable Group	Variables	Symbol	Description	Expected Effects
International	Gold Prices	GOLD	Gold Prices (TL per Ounce)	+
	Oil Prices	OIL	Crude Oil Prices (US Dollar)	+
	VIX Index	VIX	Chicago Board Options Exchange Volatility Index	+
Macroeconomic	FER	FER	USD/TL FER	+
	Inflation	CPI	CPI (Annual %)	+
	NFCFED	NFCFED	NFCFED (US Dollar)	+
	Reserves	RSRV	CBRT Gross Reserves (US Dollar, Including Gold)	-
Market	BIST 100 Index	BIST 100	Trading Day Closing Value	-
	CBRT WACF	WACF	Weighted Average Funding Cost (%)	+
	Credit Interest Rate	CRINT	Commercial credits interest rate (%)	+
	Deposit Interest Rate	DEPINT	Deposit interest rate (%)	+
	NPL	NPL	NPL volume (TL)	+
	Treasury Bond Interest Rate	TBINT	10-Year Turkish Treasury Bond Interest Rate	+

*Positive (+) effect means that CDS increases when independent variables increase.  
 Negative (-) effect means that CDS decreases when independent variables increase.*

### 3.2. Data Acquisition

The study covers the years 2011/1 and 2019/12, which focuses on the year after the global financial crisis (GFC) period. Data is started in 2011 because there is GFC in 2008 and the effects of the crisis continued in 2009 and 2010, and data for CBRT WACC could not be collected before 2011. It is acknowledged that there is a recent crisis named COVID-19 Pandemic in the world. However, this is an unpretending condition for all countries and indicators. Also, there is not so much data for variables. For this reason, the pandemic period is not included in the study.

Our dataset is acquired from multiple sources including Bloomberg (2020), Banking Regulation and Supervision Agency (BRSA) (2020), and CBRT (2020b).

### 3.3. Model Building

In the study, machine learning algorithms are used to measure whether the factors have a significant effect on Turkey's sovereign CDS spreads in the full period (2011-2019), the stability period (2011-2017), and the macroeconomic turbulent period (2018-2019). Our proposed method explores robust models with high predictive accuracy by applying and comparing 4 popular machine learning algorithms which are the eXtreme Gradient Boosting, Random Forest, Support Vector Machines, and k-Nearest Neighbors.

#### 3.3.1. eXtreme Gradient Boosting

The eXtreme Gradient Boosting (XGBoost) algorithm, which is an ensemble method to Classification and Regression Tree, is first introduced by Chen & Guestrin in 2016. The algorithm procedure is summarized below (Ayumi, 2016):

- 1) Determine the best cut-point for all independent variables based on the Gini impurity ( $I_G(p) = 1 - \sum_{i=1}^J p_i^2$ ) or Entropy metrics ( $E = - \sum_{i=1}^J p_i \log_2 p_i$ ) to optimize the objective function ( $\text{Information Gain} = E_{\text{ParentNode}} - E_{\text{ChildNode}}$ )
- 2) Repeat Step 1 and 2 until the pre-defined sample size of a node (m) is reached,
- 3) Calculate the score of prediction to each low-performed leaf,
- 4) Repeat Steps from 1 to 4 until the pre-determined number of a tree (k) is reached
- 5) Calculate the basic average for the prediction score to get the final score.

There are two important parameters in this algorithm, which are m and k. The minimum size of a node (m) and the number of the tree created (k) are effective on prediction accuracy.

### 3.3.2. *Random Forest*

Random Forest algorithm is first proposed by Tin Kam Ho in 1995 (Ho, 1995). This algorithm uses a bootstrapping method to improve the prediction performance of a categorical or continuous dependent variable. Thus, the algorithm generally outperforms a single tree algorithm. Basic Random Forest Algorithm is described below (Khun & Johnson, 2013):

- 1) Determine the parameter m, which is the number of models to build,
- 2) Generate bootstrap samples (m) using the original dataset,
- 3) Train a tree-based model using the sample created in Step 2,
- 4) Select the best predictors among the k predictors to split data based on the Gini impurity ( $I_G(p) = 1 - \sum_{i=1}^J p_i^2$ ) or Entropy metrics ( $E = - \sum_{i=1}^J p_i \log_2 p_i$ ) to optimize the objective function ( $\text{Information Gain} = E_{\text{ParentNode}} - E_{\text{ChildNode}}$ )
- 5) Repeat Step 3 and Step 4 for each split for m-times
- 6) Calculate arithmetic average score of m trees.

Generally, it is suggested that the initial value of m is 1000, and then it should be increased until performance levels off based on the performance of the model (Khun & Johnson, 2013).

### 3.3.3. *Support Vector Machines*

Support Vector Machines (SVM) is a nonparametric algorithm that is applied for both classification and regression predictions (Boser, Guyon & Varma, 1992). The basics of the SVM algorithm are based on finding the optimal parallel hyperplanes that are generated for minimization of the distance between two hyperplanes (Delen, Oztekin & Kong, 2010; Zhang et al., 2015). The optimization problem of SVM is described below:

$$\max W(\alpha, \alpha^*) = -\varepsilon \sum_{i=1}^l (\alpha_i^* + \alpha_i) + \sum_{i=1}^l (\alpha_i^* - \alpha_i) y_i - \frac{1}{2} \sum_{i,j=1}^l (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_j) k(x_i, x_j)$$

$$\text{subject to: } \sum_{i,j=1}^l (\alpha_i - \alpha_i^*) = 0, \quad 0 \leq \alpha^{(*)} \leq \frac{C}{l}$$

C is a constant that is used to determine the trade-off between minimization of the errors ( $\epsilon$ ) and maximization of the model complexity parameter ( $\|w^2\|$ ),  $\alpha$ ,  $y$ ,  $x$ , and  $k$  are Lagrange multipliers, dependent variable vector, independent variables matrix, and kernel parameter, respectively.

In SVM, it is crucial to use the most suitable kernel function to have high prediction accuracy.

### **3.3.4. *k*-Nearest Neighbors**

K-nearest neighbor (k\_NN) algorithm is a machine learning technique to predict the categorical or continuous dependent variable (Aha et al., 1991). This technique uses similarity measures between k neighbors for prediction. Algorithm steps are described below:

- 1) Determine the number of neighbors (k),
- 2) Calculate the suitable distance metrics (similarity measures), generally, Euclidean ( $d(x_i, x_j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \dots + (x_{ip} - x_{jp})^2}$ ) or Mahalanobis ( $D_M(x) = \sqrt{(x - \mu)^T S(x - \mu)}$ , where S covariance matrix and  $\mu$  mean vector of x observed variables) distance are used.
- 3) Based on the minimum distance between ( $d(m_i, x) = \min\{d(m_i, x)\}$ ) the data point and k nearest neighbors distance values, assign a predicted value.

In this algorithm, the k parameter and the suitable distance metrics are crucial for high prediction accuracy.

## **4. EMPIRICAL ANALYSIS**

### **4.1. Descriptive Statistics**

According to Figure 1, sovereign CDS spreads are between 115 and 315 levels in the period of 2011-2017 while it is between 165 and 560 levels from 2018 to 2019. Table 2 presents the descriptive statistics of three different periods.



**Table 2. Descriptive Statistics of All Periods**

	Full Period (2011-2019)		Stability Period (2011-2017)		Macroeconomic Turbulent Period (2018-2019)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
<b>CDS</b>	241.6	81.6	214.0	47.2	340.1	98.9
<b>GOLD*</b>	4.0	1.7	3.2	0.7	7.0	1.3
<b>OIL</b>	76.4	25.5	79.5	27.8	64.9	6.3
<b>VIX</b>	16.4	5.0	16.4	5.4	16.1	3.3
<b>FER</b>	3.0	1.4	2.4	0.7	5.3	0.8
<b>CPI</b>	10.0	4.2	8.3	1.8	15.8	5.0
<b>NFCFED**</b>	-173.6	33.8	-166.0	33.5	-200.4	16.8
<b>RSRV**</b>	111.2	14.5	114.4	14.3	99.8	8.6
<b>BIST100*</b>	81.8	16.0	76.7	13.6	101.3	8.6
<b>WACF</b>	10.7	5.5	8.2	2.0	19.5	4.7
<b>CRINT</b>	15.6	5.1	13.5	2.2	22.7	5.8
<b>DEPINT</b>	11.1	4.2	9.3	1.5	17.5	4.4
<b>NPL**</b>	49.8	30.5	36.9	15.5	99.1	26.7
<b>TBINT</b>	10.7	3.2	9.3	1.2	15.6	3.0

\* means multiply with 1.000; \*\* means multiply with 1 billion.

The volatility of CDS values in the 2018-2019 period is two times higher than the period of 2011-2017. Thus, full data are split into two sub-groups to measure the effects of independent variables on sovereign CDS spreads. Also, in addition to the volatility of sovereign CDS values, the volatility of GOLD, FER, CPI, WACF, CRINT, DEPINT, NPL, and TBINT in the macroeconomic turbulent period are significantly higher than the period of 2011-2017.

#### 4.2. The Results of Statistical Analysis

The analysis is applied for each period. In all datasets, the 5-fold with three repeats cross-validation method is used to overcome the overfitting problem.  $R^2$ , Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used for model performance criteria.

Table 3 shows the model performance criteria for the full period.

**Table 3. Model Performance Criteria of Different Machine Learning Algorithms for each Period**

Period	Model	$R^2$	RMSE	MAE
2011 – 2019 Full Period	eXtreme Gradient Boosting	90.9%	27.263	19.207
	Random Forest	89.4%	29.237	20.945
	Support Vector Machine (Radial)	88.3%	29.795	18.366
	k-NN	82.8%	35.033	23.882
2011 – 2017 Stability Period	Support Vector Machine (Radial)	87.6%	17.310	12.925
	eXtreme Gradient Boosting	81.7%	20.652	16.327
	Random Forest	81.5%	21.277	16.657
2018 – 2019 Macroeconomic Turbulent Period	k-NN	80.6%	21.520	17.103
	eXtreme Gradient Boosting	84.4%	47.577	37.305
	Random Forest	79.4%	51.785	42.042
	Support Vector Machine (Radial)	76.9%	54.204	42.352
	k-NN	61.9%	64.201	53.025

According to Table 3, it is shown that the eXtreme Gradient Boosting algorithm has the highest  $R^2$  and the lowest RMSE values in the full period and the macroeconomic turbulent period. For these periods, the MAE value of the eXtreme Gradient Boosting algorithm is relatively lower than the other algorithms. Thus, the eXtreme Gradient Boosting is the most accurate classification algorithm to

determine the factors affecting CDS in the full period and the macroeconomic turbulent period. On contrary to the results of the full period and the macroeconomic turbulent period, the Support Vector Machines algorithm is the best performing algorithm in the stability period.  $R^2$  of the model is 87.6% and it has the lowest RMSE and MAE values. Besides,  $R^2$  values of all machine learning algorithms used in this research, except for k-NN in the macroeconomic turbulent period, are above 80%, which is high enough to be able to interpret the model.

As a result of this analysis, it is suggested to use the Support Vector Machines algorithm for a non-volatile dataset such as the stability period to measure the effects of independent variables on the dependent variable. On the other hand, it is obtained that the eXtreme Gradient Boosting algorithm is suitable for the data that has high volatility such as the macroeconomic turbulent period to predict the potential impact of the factors on sovereign CDS spreads.

Table 4 summarizes the rank of variable importance for the best performer algorithm in each period.

**Table 4. Variable Importance of the Best Performing Models in each Period**

	Full Period	Stability Period	Macroeconomic Turbulent Period
	eXtreme Gradient Boosting	Support Vector Machine	eXtreme Gradient Boosting
<b>FER</b>	1	8	4
<b>GOLD</b>	2	9	1
<b>WACF</b>	3	4	5
<b>TBINT</b>	4	1	6
<b>BIST100</b>	5	2	3
<b>VIX</b>	6	5	9
<b>NFCFED</b>	7	10	8
<b>CRINT</b>	8	12	12
<b>OIL</b>	9	7	10
<b>RSRV</b>	10	6	2
<b>CPI</b>	11	3	7
<b>DEPINT</b>	12	11	11
<b>NPL</b>	not significant	not significant	not significant

*Variables that are ranked 1 (the most important) to 12 (the least important).*

As shown in the Table 4, the ranking of the variable importance partially differs for all periods. The most important variables affecting sovereign CDS spreads are USD/TL foreign exchange rates, gold prices, and weighted average funding cost in the full period.

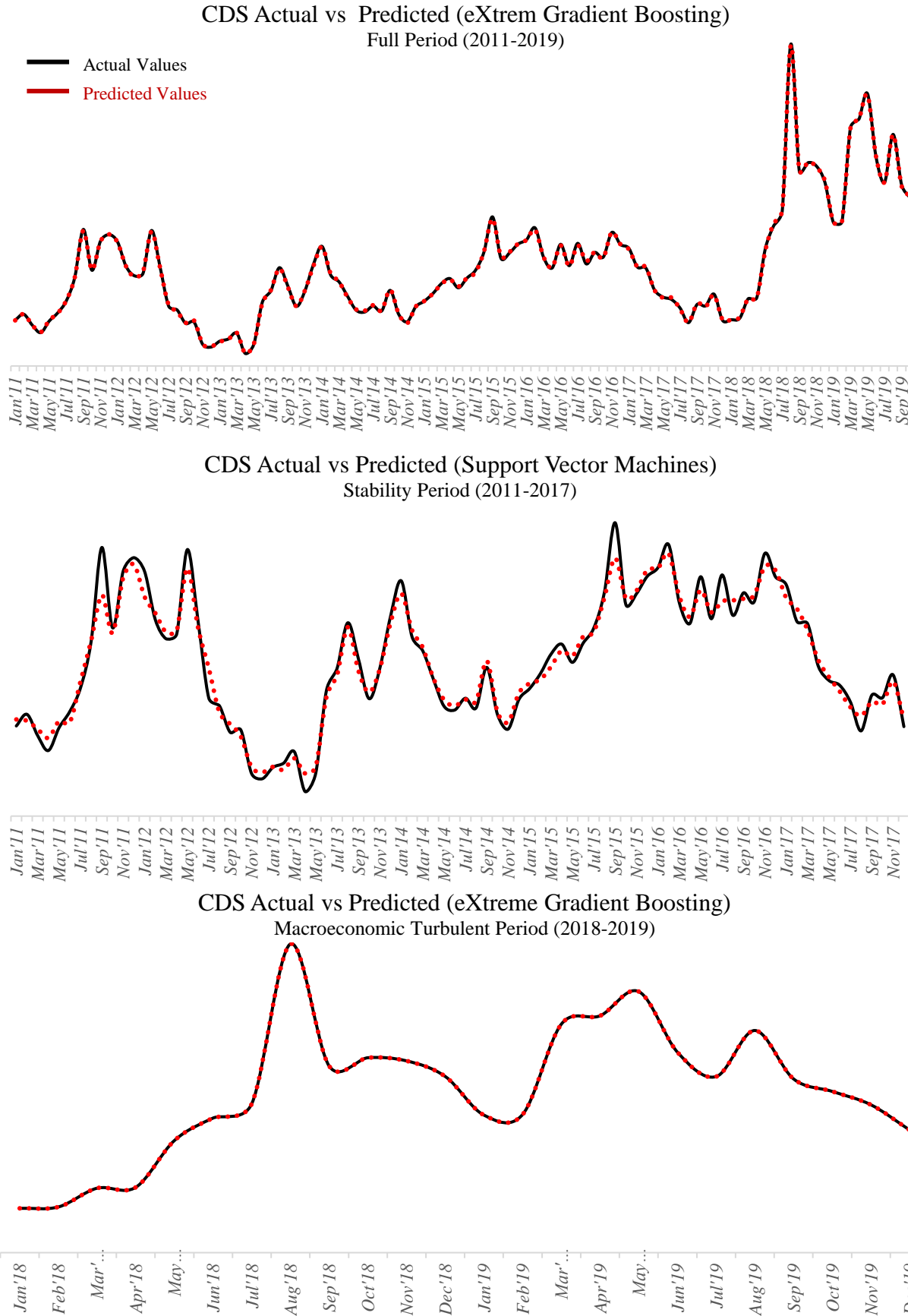
Also, the Treasury bond interest rate, BIST 100 index, and inflation are the most critical factors that have statistically significant effects on sovereign CDS spreads for the stability period. Moreover, our results point out a marginal predictive contribution of gold prices, gross reserves, and BIST 100 index on sovereign CDS spreads in the macroeconomic turbulent period is relatively higher than the other variables. On the other hand, NPL volume (TL) does not have a statistically significant influence on CDS in any period.

Although this analysis shows that the order of influential factors varies depending on the period, weighted average funding cost and BIST 100 index are essential in all periods. Besides, foreign

exchange rates, gold prices, Treasury bond interest rates, inflation, and the VIX index have importance in at least two sub-periods. These results indicate that Turkish authorities should always take care of these factors to decrease Turkey's sovereign CDS spreads and hence to stimulate foreign investment inflows to the country.

The actual and predicted values of CDS spreads, which are obtained from the best performing algorithm in each period, are shown in Figure 2.

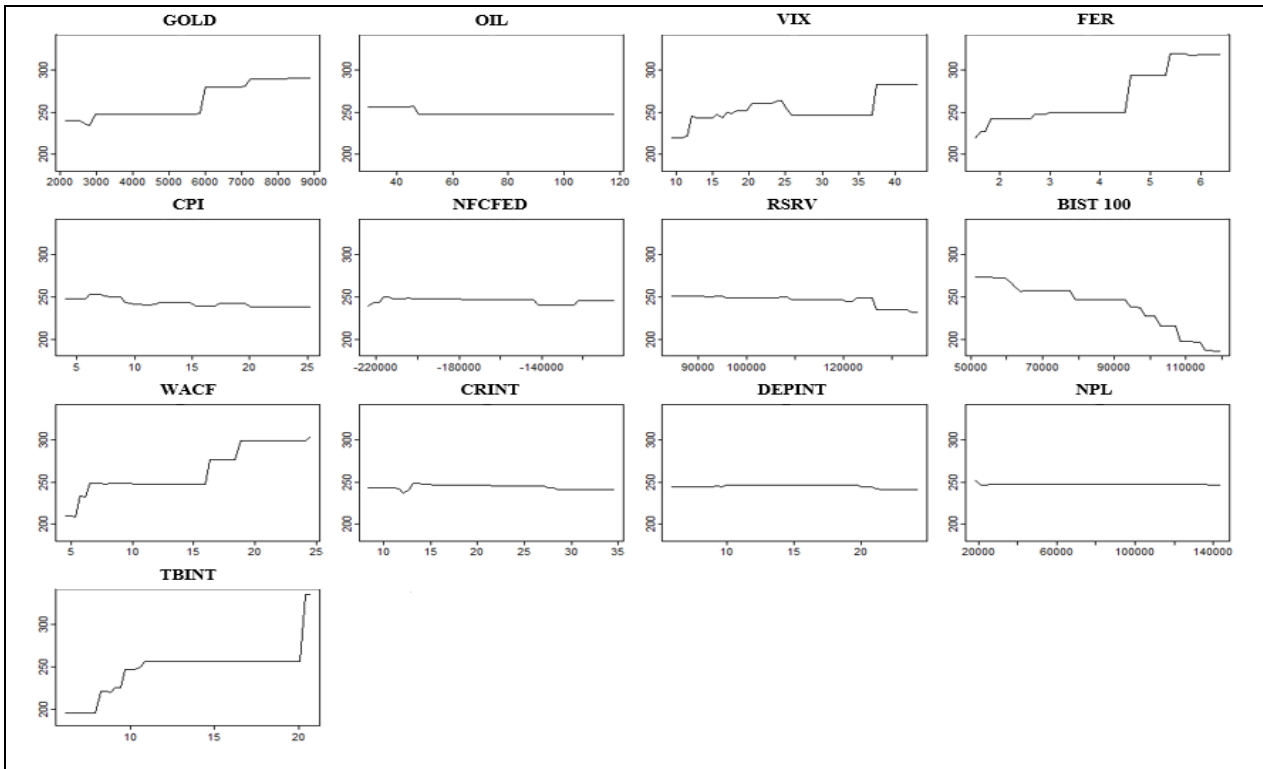
**Figure 2. The Comparison of Actual and Predicted CDS Spread Values of the Best Performing Algorithms in the Related Period**



The straight line in Figure 2 represents the actual value of CDS and the dotted line represents the predicted values obtained from the related algorithm. Based on Figure 2, predicted values are very close to the actual values of CDS spreads, which means that models are valid and interpretable in terms of understanding the factors affecting CDS.

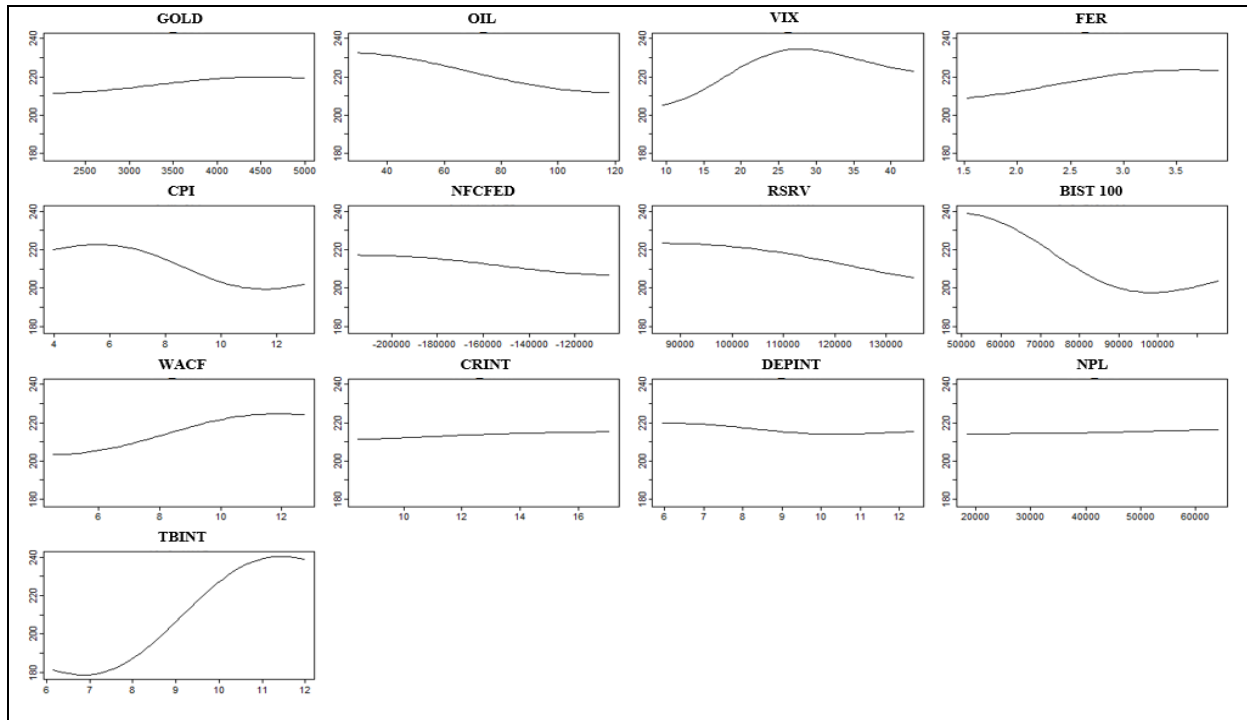
In the full period, critical thresholds of independent variables affecting CDS are given in Figure 3. To keep sovereign CDS spreads under 250, gold prices, USD/TL foreign exchange rate, weighted average funding cost, and Treasury bond interest rate should be lower than TL 6,000, 3.0, 6%, and 8%, respectively. In addition to this, the BIST 100 index should be higher than 100,000.

**Figure 3. Critical Thresholds of Independent Variables Affecting CDS in the Full Period**



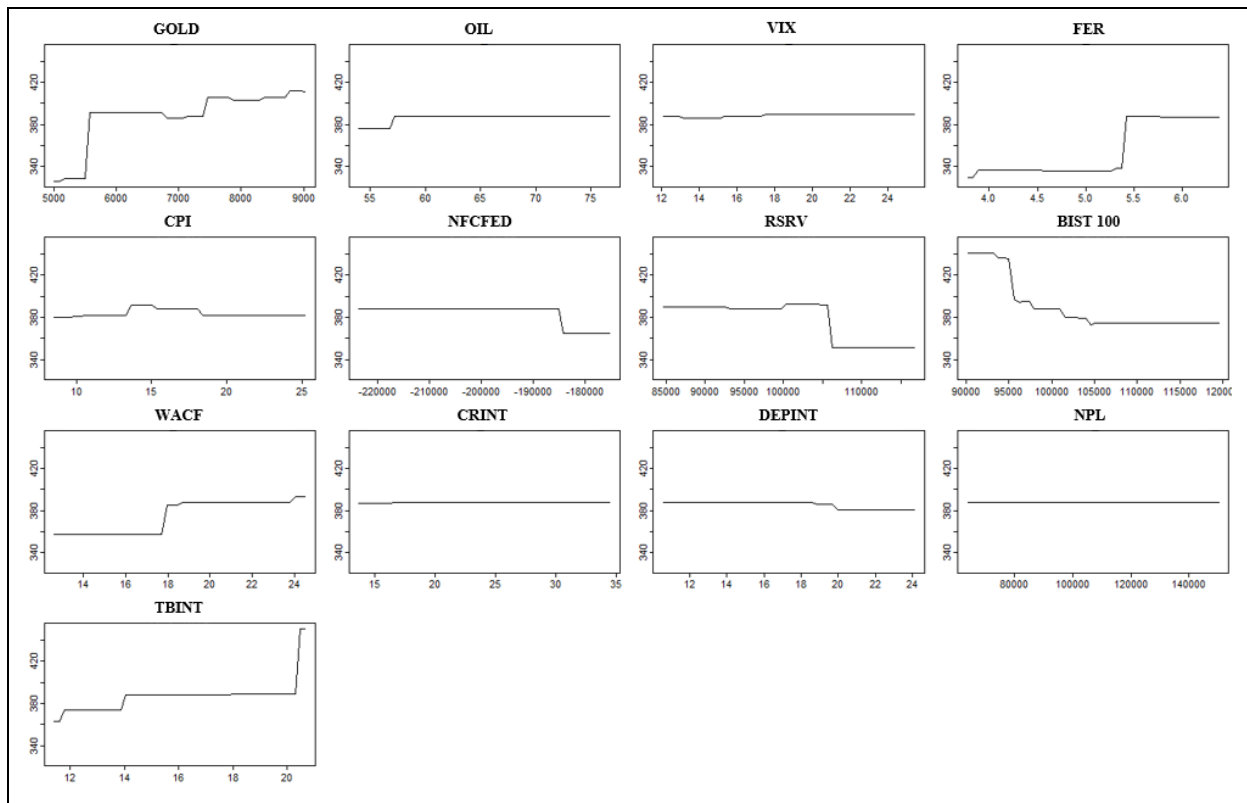
In the stability period, critical thresholds of independent variables affecting CDS are given in Figure 4. To maintain sovereign CDS spreads under 250, the Treasury bond interest rate, weighted average funding cost, volatility index, and USD/TL foreign exchange rate should be lower than %8, 10%, 25, and 3.0, respectively. On the other hand, inflation, BIST100 index, and oil prices should be higher than 10%, 90,000, and USD 80.

**Figure 4. Critical Thresholds of Independent Variables Affecting CDS in the Stability Period**



In the macroeconomic turbulent period, critical thresholds of influential factors in defining the sovereign CDS spreads are indicated in Figure 5.

**Figure 5. Critical Thresholds of Independent Variables Affecting CDS in the Macroeconomic Turbulent Period**



The gold price should be lower than 5,500, USD/TL foreign exchange rate should be lower than 5.5, weighted average funding cost should be lower than 16%, treasury bond interest rate should be lower than 14% while gross reserves should be higher than USD 105 billion and BIST 100 index should be higher than 110,000 to keep sovereign CDS spreads under 350.

### **4.3. Discussion on the Analysis Results**

The results of the analysis indicate that sovereign CDS spreads of Turkey are affected by international (gold prices, volatility index), macroeconomic (foreign exchange rates, inflation, non-financial corporate foreign exchange debt, reserves), and market (BIST 100 index, weighted average funding cost, treasury bond interest rate) factors. On the contrary to the literature, NPL volume does not have a significant impact on Turkey's sovereign CDS spreads at any period.

As indicated by the analysis, our results are consistent with previous studies in the literature that suggests the influence of the gold prices on Turkey's sovereign CDS spreads. For example, authors like Arce et al. (2013), Miyazaki & Hamori (2013), Bouri et al. (2016), and Yang et al. (2018) infer that an increase in the gold prices causes an increase in sovereign CDS spreads. Also, a positive relationship between volatility index and sovereign CDS spreads is determined, which is compliant with the studies of Che & Kapadia (2012), Galil et al. (2014), Hibbert & Pavlova (2017), Akçelik & Fendoğlu (2019, and CBRT (2020a). On the other hand, oil prices do not have a significant effect on Turkey's sovereign CDS spreads. In line with the analysis results, there has been evidence highlighting the positive impact of the foreign exchange rate on sovereign CDS spreads in Turkey. Besides, reserves are determined as negatively related to CDS as harmonious with CBRT (2020a). Non-financial corporate foreign exchange debt is another negatively associated with CDS spreads defined by CBRT (2020a). In contrast with the results of these studies (Galil et al., 2014; Benbouzid et al., 2017; CBRT, 2020a), higher inflation results in lower CDS spreads in the stability period.

As expected, the BIST 100 index is negatively related to CDS spreads (Lahiani et al., 2016). Also, the weighted average funding cost is positively related to CDS spreads and similar results are found by Hibbert & Pavlova (2017). Besides, it is pointed out that the greater the Treasury bond interest rate increases CDS spreads in the study. This result is consistent with numerous studies of the relationship between the Treasury bond interest rate and CDS spreads (Longstaff et al., 1995; Collin-Dufresne et al., 2001; Galil & Soffer, 2011; Galil et al., 2014). On the other hand, credit interest rates, deposit interest rates, and NPL volume do not have a significant effect on Turkey's sovereign CDS spreads.

According to the results, it is beneficial to recommended policy proposals to provide a decrease in sovereign CDS spreads of Turkey. In this sense, firstly, the authorities should position the level of sovereign CDS spreads as a macro-prudential concern and should take into account this new reality in all policy-making processes. Secondly, the authorities should take into consideration the negative effects of macroeconomic and market determinants and try to stabilize and/or decrease them because these factors are mainly under the control of Turkish authorities. Finally, they should focus on the relationships between determinants on sovereign CDS spreads from the ranking of the variable

importance in each period. In addition to these proposals, the authorities should work on decreasing the harmful effects of global factors such as volatility index and gold prices via the FER channel. Moreover, the authorities should work on developing new regulations to provide decreases in inflation, which affects all variables, respectively.

To compete with financial markets, the Turkish real sector should continue low-level sovereign CDS spreads in the medium and long term. That said, it is worth mentioning that some national evaluation is considered to decrease the national risk level. These actions should be an increase in national credit rating notes, which are given by international credit rating agencies such as S&P, Moody's, and Fitch. Other actions could be decreasing the current account deficit and sustaining the balance, decreasing dependence on foreign liquidity inflows both direct and portfolio investments, and keeping fiscal deficit at minimum levels.

Besides, providing and sustaining harmonization between fiscal and monetary policies are crucial to prevent the occurrence of negative developments resulting from macroeconomic and market variables which cause the increase of sovereign CDS spreads. Therefore, necessary precautions must be taken on time without causing any delays so that they could provide positive effects. Also, the effects of changes in determinants should be analyzed continuously. This is necessary according to analysis results. That is why variable importance varies according to periods whether the economy is in the stability or turbulent period.

Also, the provided and maintained harmonization between fiscal and monetary policies are strictly crucial to prevent the occurrence of negative developments resulting from macroeconomic and market variables which cause the increase of sovereign CDS spreads. Therefore, the necessity of preventing the negative effects on CDS spreads should be taken timely. The impacts of changes in determinants should be followed up in further periods.

Taking into consideration the importance of sovereign CDS spreads in reflecting the country risk and financial stability of Turkey, an authority such as CBRT, BRSA, etc., should be appointed to follow up strictly and prevent sudden increase on the determinants not to cause the increasing of CDS spreads.

## **5. CONCLUSION**

The study examines the determinants of Turkey's sovereign CDS spreads change which is the primary indicator of country risk and financial stability, especially when foreign investors tend to make investments via securities. The dataset has 108 observations for monthly periods between 2011/1 and 2019/12. The machine learning algorithms, which are k-Nearest Neighbour, Support Vector Machines, Random Forest, and eXtreme Gradient Boosting, are used to analyze the relationships between sovereign CDS spreads and 13 independent factors. Generally, the performance of all algorithms is not differentiated from each other, except the k-NN algorithm in the macroeconomic turbulent period. Here, the eXtreme Gradient Boosting, the Random Forest, and the Support Vector Machine algorithms are used to validate the results obtained. Since the k-NN algorithm is underperformed in volatile data such as the macroeconomic turbulent period, the model performance is lower than other models. Algorithms



used in this study allow us to address the importance level of each variable on sovereign CDS spreads. Based on the analysis results, it is revealed that the impacts of variables vary over the periods in which the Turkish economy has been. Also, machine learning algorithms show that independent determinants, that have a positive or negative impact on sovereign CDS spread, are mainly macroeconomic factors. Thus, some policy recommendations by determining influential factors, which Turkey can sustain economic growth by ensuring financial stability, are presented.

The study has some limitations. For example, the data is drawn from Turkey as an emerging country, which has been faced with increasing sovereign CDS spreads, recently. However, there are some other emerging countries having high-level CDS spreads such as, Venezuela, Argentina, Ukraine, Pakistan, Egypt, and South Africa. Especially, CDS spreads of Venezuela and Argentina are quite higher than all other emerging countries. In this sense, future research including a different bundle of these countries would be applied through machine learning techniques. As a limitation, the other variables that may have influential on sovereign CDS spreads in this research, may need to be included. Predicting the sovereign CDS spreads trend by the most prevailing machine learning algorithms used for this research may be important guidance for government administrators and policy-makers to keep the key factors, which are influential on CDS spreads, stable. Moreover, the COVID-19 pandemic should be considered in forthcoming studies that could effect sovereign CDS spreads.

## KAYNAKÇA

- Aha, D., Kibler, D.W., & Albert, M.K. (1991). Instance-based learning algorithms. *Machine Learning*, 6, 37–66.
- Akçelik, F., & Fendoğlu, S. (2019). Country Risk Premium and Domestic Macroeconomic Fundamentals When Global Risk Appetite Slides. *CBRT Research and Monetary Policy Department*, No. 2019-04.
- Alexander, C., & Kaeck, A. (2008). Regime Dependent Determinants of Credit Default Swap Spreads. *Journal of Banking & Finance*, 32(6), 1008-1021.
- Arce, O., Mayordomo, S., & Peña, J. I. (2013). Credit-Risk Valuation in the Sovereign CDS and Bonds Markets: Evidence from the Euro Area Crisis. *Journal of International Money and Finance*, 35, 124-145.
- Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility Spillovers between Oil Prices and Stock Sector Returns: Implications for Portfolio Management. *Journal of International Money and Finance*, 30(7), 1387-1405.
- Ayumi, V. (2016). Pose-based Human Action Recognition with Extreme Gradient Boosting. *IEEE Student Conference on Research and Development (SCORED)*, Kuala Lumpur, 1-5.

- Banking Regulation and Supervision Agency (BRSA). (2020). Monthly Data, <https://www.bddk.org.tr/BultenAylık>, 20.02.2020.
- Benbouzid, N., Mallick, S. K., & Sousa, R. M. (2017). An International Forensic Perspective of the Determinants of Bank CDS Spreads. *Journal of Financial Stability*, 33, 60-70.
- Bloomberg. (2020). Bloomberg Terminal, 20.02.2020.
- Boser, B. E., Guyon, I. M. & Vapnik, V. N. (1992). A Training Algorithm for Optimal Margin Classifiers. In D. Haussler (ed.), *Proceedings of the 5th Annual Workshop on Computational Learning Theory (COLT'92)* (pp. 144-152), July, Pittsburgh, PA, USA: ACM Press.
- Bouri, E., de Boyrie, M. E., & Pavlova, I. (2016). Volatility Transmission from Commodity Markets to Sovereign CDS Spreads in Emerging and Frontier Countries. *International Review of Financial Analysis*, 49, 155-165.
- Bouri, E., Kachacha, I., & Roubaud, D. (2020). Oil Market Conditions and Sovereign Risk in MENA Oil Exporters and Importers. *Energy Policy*, 137, 111073.
- CBRT. (2020a). Inflation Report 2020-I, <https://www.tcmb.gov.tr/wps/wcm/connect/EN/TCMB+EN/Main+Menu/Publications/Reports/Inflation+Report>, 16.02.2020.
- CBRT. (2020b). Electronic Data Distribution System (EVDS), <https://evds2.tcmb.gov.tr/index.php?/evds/serieMarket>, 20.02.2020.
- Che, X., & Kapadia, N. (2012). Can credit risk be hedged in equity markets? SSRN Electronic Journal. <https://doi.org/10.2139/ssrn.2024611>.
- Collin-Dufresne, P., Goldstein, R. S., & Martin, J. S. (2001). The Determinants of Credit Spread Changes. *Journal of Finance*, 56(6), 2177-2207.
- Delen, D., Oztekin, A., & Kong, Z.J. (2010). A machine learning-based approach to prognostic analysis of thoracic transplantations. *Artificial Intelligence in Medicine*, 49(1), 33-42.
- Dooley, M., & Hutchison, M. (2009). Transmission of the US Subprime Crisis to Emerging Markets: Evidence on the Decoupling–Recoupling Hypothesis. *Journal of International Money and Finance*, 28(8), 1331-1349.
- Duffie, D., Pedersen, L. H., & Singleton, K. J. (2003). Modeling Sovereign Yield Spreads: A Case Study of Russian Debt. *The journal of Finance*, 58(1), 119-159.
- Ertuğrul, H. M., & Öztürk, H. (2013). The Drivers of Credit Swap Prices: Evidence from Selected Emerging Market Countries. *Emerging Markets Finance & Trade*, 49, 228-249.

- Fontana, A., & Scheicher, M. (2016). An Analysis of Euro Area Sovereign CDS and Their Relation with Government Bonds. *Journal of Banking & Finance*, 62, 126-140.
- Galil, K., Shapir, O. M., Amiram, D., & Ben-Zion, U. (2014). The Determinants of CDS Spreads. *Journal of Banking & Finance*, 41, 271-282.
- Galil, K., & Soffer, G. (2011). Good News, Bad News and Rating Announcements: An Empirical Investigation. *Journal of Banking & Finance*, 35(11), 3101-3119.
- Hammoudeh, S., Liu, T., Chang, C. L., & McAleer, M. (2013). Risk Spillovers in Oil-Related CDS, Stock and Credit Markets. *Energy Economics*, 36, 526-535.
- Hasan, I., Liu, L., & Zhang, G. (2016). The Determinants of Global Bank Credit-Default-Swap Spreads. *Journal of Financial Services Research*, 50(3), 275-309.
- Hassan, M. K., Ngene, G. M., & Yu, J. S. (2015). Credit Default Swaps and Sovereign Debt Markets. *Economic Systems*, 39(2), 240-252.
- Hassan, M. K., Kayhan, S., & Bayat, T. (2017). Does Credit Default Swap Spread Affect the Value of the Turkish Lira Against the US Dollar? *Borsa Istanbul Review*, 17(1), 1-9.
- Hibbert, A. M., & Pavlova, I. (2017). The Drivers of Sovereign CDS Spread Changes: Local Versus Global Factors. *Financial Review*, 52(3), 435-457.
- Ho, Tin Kam (1995). Random Decision Forests. *Proceedings of the 3rd International Conference on Document Analysis and Recognition*, Montreal, QC, 14-16 August, 278-282.
- Hull, J., Predescu, M., & White, A. (2004). The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements. *Journal of Banking & Finance*, 28(11), 2789-2811.
- Jorion, P., & Zhang, G. (2007). Good and Bad Credit Contagion, Evidence from Credit Defaults Swaps. *Journal of Financial Economics*, 84(3), 860-883.
- Kartal, Mustafa Tevfik (2020). The Behavior of Sovereign Credit Default Swaps (CDS) Spread: Evidence from Turkey with the Effect of COVID-19 Pandemic. *Quantitative Finance and Economics*, 4(3), 489-502.
- Khun, M., & Johnson, K. (2013). *Applied Predictive Modeling*. Springer.
- Kocsis, Z., & Monostori, Z. (2016). The Role of Country-Specific Fundamentals in Sovereign CDS Spreads: Eastern European Experiences. *Emerging Markets Review*, 27, 140-168.
- Lahiani, A., Hammoudeh, S., & Gupta, R. (2016). Linkages between Financial Sector CDS Spreads and Macroeconomic Influence in a Nonlinear Setting. *International Review of Economics & Finance*, 43, 443-456.

- Longstaff, F. A., & Schwartz, E. S. (1995). A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. *The Journal of Finance*, 50(3), 789-819.
- Miyazaki, T., & Hamori, S. (2013). Testing for Causality between the Gold Return and Stock Market Performance: Evidence for Gold Investment in Case of Emergency. *Applied Financial Economics*, 23(1), 27-40.
- Norden, L., & Weber, M. (2004). Informational Efficiency of Credit Default Swap and Stock Markets: The Impact of Credit Rating Announcements. *Journal of Banking & Finance*, 28(11), 2813-2843.
- Park, Y. J., Kutan, A. M., & Ryu, D. (2019). The Impacts of Overseas Market Shocks on the CDS-Option Basis. *The North American Journal of Economics and Finance*, 47, 622-636.
- Pavlova, I., De Boyrie, M. E., & Parhizgari, A. M. (2018). A Dynamic Spillover Analysis of Crude Oil Effects on the Sovereign Credit Risk of Exporting Countries. *The Quarterly Review of Economics and Finance*, 68, 10-22.
- Shahzad, S. J. H., Nor, S. M., Ferrer, R., & Hammoudeh, S. (2017). Asymmetric Determinants of CDS Spreads: US Industry-Level Evidence through the NARDL Approach. *Economic Modelling*, 60, 211-230.
- Wang, J., Sun, X., & Li, J. (2020). How Do Sovereign Credit Default Swap Spreads Behave Under Extreme Oil Price Movements? Evidence from G7 and BRICS Countries. *Finance Research Letters*, 101350.
- Yang, L., Yang, L., & Hamori, S. (2018). Determinants of Dependence Structures of Sovereign Credit Default Swap Spreads between G7 and BRICS Countries. *International Review of Financial Analysis*, 59, 19-34.
- Zhang, Y., Dong, Z., Liu, A., Wang, S., Ji, G., Zhang, Z., & Yang, J. (2015). Magnetic resonance brain image classification via stationary wavelet transform and generalized eigenvalue proximal support vector machine. *Journal of Medical Imaging and Health Informatics*, 5, 1395-1403. <https://doi.org/10.1166/jmihi/2015.1542>.

<b>KATKI ORANI / CONTRIBUTION RATE</b>	<b>AÇIKLAMA / EXPLANATION</b>	<b>KATKIDA BULUNANLAR / CONTRIBUTORS</b>
Fikir veya Kavram / <i>Idea or Notion</i>	Araştırma hipotezini veya fikirini oluşturmak / <i>Form the research hypothesis or idea</i>	Assoc. Prof. Mustafa Tevfik KARTAL (Ph.D.) Assoc. Prof. Serpil KILIÇ DEPREN (Ph.D.) Özer DEPREN (Ph.D.)
Tasarım / <i>Design</i>	Yöntemi, ölçeği ve deseni tasarlamak / <i>Designing method, scale and pattern</i>	Assoc. Prof. Mustafa Tevfik KARTAL (Ph.D.) Assoc. Prof. Serpil KILIÇ DEPREN (Ph.D.) Özer DEPREN (Ph.D.)
Veri Toplama ve İşleme / <i>Data Collecting and Processing</i>	Verileri toplamak, düzenlenmek ve raporlamak / <i>Collecting, organizing and reporting data</i>	Assoc. Prof. Mustafa Tevfik KARTAL (Ph.D.) Assoc. Prof. Serpil KILIÇ DEPREN (Ph.D.) Özer DEPREN (Ph.D.)
Tartışma ve Yorum / <i>Discussion and Interpretation</i>	Bulguların değerlendirilmesinde ve sonuçlandırılmasında sorumluluk almak / <i>Taking responsibility in evaluating and finalizing the findings</i>	Assoc. Prof. Mustafa Tevfik KARTAL (Ph.D.) Assoc. Prof. Serpil KILIÇ DEPREN (Ph.D.) Özer DEPREN (Ph.D.)
Literatür Taraması / <i>Literature Review</i>	Çalışma için gerekli literatürü taramak / <i>Review the literature required for the study</i>	Assoc. Prof. Mustafa Tevfik KARTAL (Ph.D.) Assoc. Prof. Serpil KILIÇ DEPREN (Ph.D.) Özer DEPREN (Ph.D.)

**Hakem Değerlendirmesi:** Dış bağımsız.

**Çıkar Çatışması:** Yazarlar çıkar çatışması bildirmemiştir.

**Finansal Destek:** Yazarlar bu çalışma için finansal destek almadığını beyan etmiştir.

**Teşekkür:** -

**Peer-review:** Externally peer-reviewed.

**Conflict of Interest:** The authors have no conflict of interest to declare.

**Grant Support:** The authors declared that this study has received no financial support.

**Acknowledgement:** -