



RESEARCH ARTICLE

## How Vulnerable is the Turkish Stock Market to the Credit Default Swap? Evidence from the Markov Switching GARCH Model

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### ABSTRACT

This study aims to investigate the effect of the credit default swap (CDS) on the Turkish stock market. More specifically, it analyses whether the relationship between CDS and the Turkish stock market has changed during the period of unprecedented stock returns in 2022. The Markov Switching GARCH method is preferred because of its many advantages in the analysis of the return series of the variables. Two different models are estimated for the full sample weekly period of 2010:01-10/2022:12-11 and the subsample weekly period of 2010:01-10/2021:12-05. The subsample period is more optimal than the full sample period. Nevertheless, the findings of both sample periods are included to make a comparison. The effect of CDS on the Turkish stock market is greater in the high-volatility regime than in the low-volatility regime. CDS has a negative impact on the Turkish stock market in both low and high volatility periods. The most striking finding is that CDS affects the Turkish stock market approximately twice as much in the subsample period as in the full sample period in both regimes. Policymakers should follow risk-oriented policies instead of policies against the wind against the risk of a possible boom in financial markets.

**Keywords:** Credit default swap, Turkish stock market, Markov Switching GARCH

**JEL Classification:** C58, E44, G24



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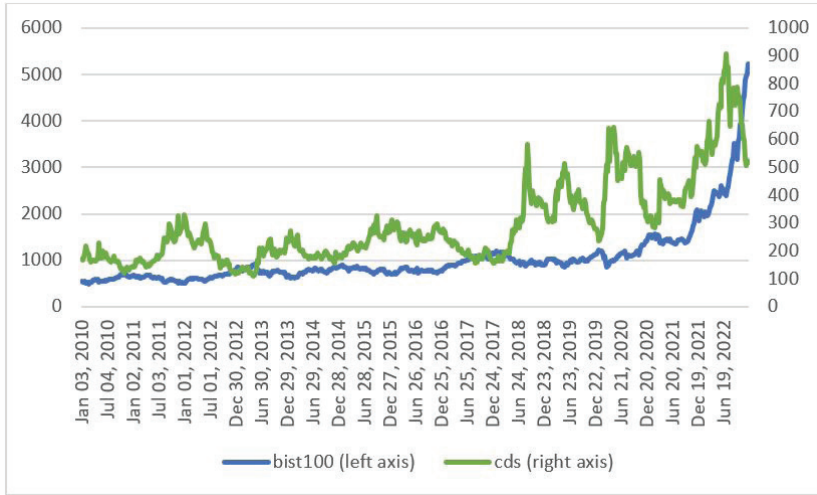
## 1. Introduction

It is known that the main reason for the outbreak of the Global Financial Crisis was the non-repayment of subprime mortgage credits. These credits resulted in the bankruptcy of many large banks and the financial system was in trouble. Since the crisis, there have been many studies dealing with the causes, consequences, and possible effects of the crisis, as well as changing paradigms in general in positive and normative economics. Credit risk, which received limited attention before the crisis, is one of them. Whether the credit risk is priced on time or not has become an important question, especially after this crisis. The three most important markets in terms of credit risk are bond, stock, and credit default swap (CDS) markets. However, according to Longstaff, Mithal, and Neis (2005) and Forte and Peña (2009), bonds lag behind the other two markets in incorporating credit risk information (Chau, Han, and Shi, 2018).

CDS is a creditor's insurance of its credits by paying a certain fee. A firm may transfer the risk of its credit to third parties or institutions by making a CDS contract. If the firm cannot repay the credit, the party or institution undertaking the risk is obliged to pay back the amount specified in the swap agreement to the bank (Altınok and Akça, 2021). In this sense, a CDS agreement has shared the load of the financial sector. However, the higher the political and economic risks, the higher the CDS for a country. This situation will mean that the country will have to pay more risk premiums for the credits it will use, and it will also cause the behaviour of investors within the country and who are considering coming to the country to change. Therefore, the relationship between stock markets, where investor behaviour is an essential driver, and CDS becomes important. So, does the stock market lead the CDS or does the CDS lead the stock market? The literature on this question is quite extensive. Many studies provide evidence that these two markets affect each other (Celik and Koc, 2016; Bildirici, Sonüstün, and Gökmenoğlu, 2019; Mateev, 2019; Sun, Wang, Yao, Li, and Li, 2020; Ballester, Escrivá, and González-Urteaga, 2021; Ustaoglu, 2022) and there is mostly a negative correlation between them (Fei, Fuertes, and Kalotychou, 2017; Topaloğlu and Ege, 2020; Saritaş, Kiliç, and Nazlioğlu, 2021). Positive trends in stock markets

cause a decrease in CDS, while increases in CDS cause a decrease in stock market returns.

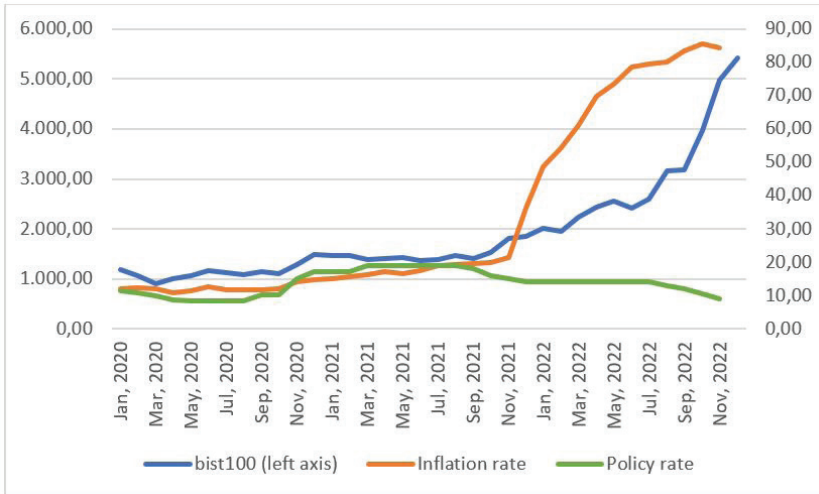
**Graph 1. BIST100 Index and Turkey's CDS**



Source: [www.investing.com](http://www.investing.com)

As a developing country, the relationship between credit risks and financial markets is noteworthy for Turkey. Since 2018, Turkey's CDS has been following an increasing trend. It is thought that this increasing trend has important effects, especially on the behaviour of foreign investors. Graph 1 presents the Istanbul Stock Exchange 100 Index (BIST100), which is an important indicator of the Turkish stock market and Turkey's CDS for the period 2010-2022. It is clearly seen that the direction of the relationship between these indicators, which followed a relatively stable course until 2018, is negative. In company with a serious increasing trend of CDS after 2018, the negative relationship between BIST100 and CDS continued until 2022. However, it is clear that this relationship has become erratic since the end of 2021. But why?

**Graph 2. BIST100, Inflation and Policy Rate in Turkey**



Source: CBRT.

The obvious answer to the above question is shown in Graph 2. Graph 2 presents BIST100, the annual rate of inflation, and the CBRT policy rate simultaneously for Turkey in the 2020-2022 period. These variables, which followed a relatively constant course until December 2021, took a different turn in 2022. Although the inflation rate has increased, the Central Bank of the Republic of Türkiye (CBRT) policy rate has been reduced. Meanwhile, as will be remembered from Graph 1, the unprecedented increases in the BIST100 index continue despite the increases in CDS. This is where other dynamics come into play. Despite the price stability target, the CBRT lowered the policy rate on the grounds of supporting the acceleration in industrial production and the increase in employment. In addition to the low policy rate and the seeking for returns stemming from high inflation, high profits on corporate and bank balance sheets have led investors to turn to the stock market. Ozsoy (2022) stated that investors in Turkey flocked to stocks to avoid inflation and that the Turkish stock market provided the world's largest profit of 80%.

Although the literature on the relationship between the stock market and CDS is rich, the recent developments in the Turkish economy have been a motivation to re-examine the relationship between the two markets in light of the above-

mentioned events. This study has two aims: The first is to investigate how CDS affects the Turkish stock market. The second is to reveal whether the relationship between CDS and the Turkish stock market has changed with the experiences of 2022. For these purposes, the relationship between the two variables was determined with two models obtained by the Markov Switching - Generalized Autoregressive Conditional Heteroskedasticity (MS-GARCH) method, which allows regime-switching. Models contain different sample periods. The reason for this is to seek an answer to whether the relationship between CDS and the Turkish stock market has changed. It is hoped that investigating the periodically changing relationship between CDS and stock markets with different samples and the regime-switching method will contribute to the current literature. In addition, the results of the study will indirectly point to some potential consequences of policies like high inflation and low policy rate.

The rest of the study is organised as follows: Section 2 describes the literature. Then, section 3 presents the methodology. Section 4 introduces the data and preliminary analysis. Section 5 discusses the empirical results. Section 6 finalises the study with the conclusion.

## **2. Literature**

Merton (1974) was one of the first studies investigating the effect of the risk structure of interest rates on pricing. This study analysed the pricing of corporate debt using the Modigliani-Miller (1958) theorem. The risk structures of interest rates were determined by risky discounted bonds in the analysis. However, the popularity of CDS has been more recent. CDS was designed by J. P. Morgan in 1994 to transfer credit risk exposure from the balance sheet in order to protect sellers (Augustin, Subrahmanyam, Tang, and Wang, 2016). Especially before the 2008 Global Financial Crisis, the literature on CDS spreads was limited. The reason for this was both the limited amount of data and the uncertainty of the social costs in the pre-crisis period. (Hammoudeh and Sari, 2011). However, the literature on CDS spreads and the relationship between these spreads and stock markets has been enriched in the post-crisis period. Evidence points to strong spillover effects

from CDS spread to stock returns (Hammoudeh and Sari, 2011; Mateev, 2019; Sun et al., 2020; Ballester et al., 2021). Sun et al. (2020) found that the average spillovers from CDS to stock market returns are greater in developing countries than in developed countries. On the contrary, average spillovers from stock market returns to CDS are larger in developed countries. Similarly, Mateev (2019) and Ballester et al. (2021) have provided evidence that the relationship between CDS spreads and stock returns is bidirectional. Asandului, Lupu, Mursa, and Musetescu (2015) noted that the stock market has been significantly affected by CDS. Fei et al. (2017) found a negative and significant relationship between CDS and stock markets. In addition, Esen, Zeren, and Şimdi (2015) stated that positive stock market trends increase investors' confidence and cause CDSs to decrease. Also, Fei et al. (2017) and Anton and Nucu (2020) emphasised that the relationship between CDS and stock returns is time-varying and non-linear and therefore includes regime shifts.

It is thought that studies investigating the relationship between CDS and stock returns in Turkey should be emphasised separately, so much so that in recent years, quite a lot of studies have been done on this issue and continue to be done. Celik and Koc (2016), Bildirici et al. (2019), and Ustaoglu (2022) found that there is bidirectional causality between the two variables. A change in CDS affects the performance of stock markets and vice versa. Ustaoglu (2022) determined a strong causality relationship from CDS to the Turkish stock market in the short and medium term, and from the Turkish stock market to CDS in the short, medium, and long term. Bolaman Avci (2020) emphasised that the direction of causality between the two variables is only from the stock market to CDS, whereas Topaloglu and Ege (2020) and Kandemir, Vurur, and Gokgoz (2022) found that there is unidirectional causality from CDS to the stock market. There is also a negative and long-term cointegration relationship between CDS and the Turkish stock market (Sovbetov and Saka, 2018; Topaloglu and Ege, 2020; Saritas et al., 2021). On the other hand, Ceylan, Tuzun, and Ekinci (2018) emphasised that the negative relationship between the two variables is also valid for different regime periods.

### 3. Methodology

ARCH/GARCH models are often used in modelling financial series. Bollerslev (1986) developed the GARCH Model, which allows the provision of a longer memory and a more flexible lag structure compared to ARCH models. The GARCH (1,1) model can be represented in the following format (Bauwens, Preminger, and Rombouts, 2009):

$$y_t = \mu_t + \sigma_t u_t \quad (1)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (2)$$

In Equation 1,  $\mu_t$  and  $\sigma_t$  are measurable functions of  $y_{t-\tau}$  for  $\tau \leq t-1$ ,  $\varepsilon_t = y_t - \mu_t$  for and the error term  $u_t$  is independent and identically distributed with zero mean and unit variance. In addition, the GARCH model must fulfil some criteria. The constraints  $\omega > 0, \alpha \geq 0, \beta \geq 0$  are necessary for the positivity of the conditional variance.  $\alpha + \beta < 1$  gives the conditional variance resistance to a shock. However, some findings pointing to artificially high persistence in empirical studies using the standard GARCH (1,1) specification have brought along discussions on the development of GARCH parameters (Wee, Chen, and Dunsmuir, 2020). Studies such as Diebold (1986), Schwert (1989) and Lamoureux and Lastrapes (1990) explain the reason for this with regime shifts in the GARCH parameters. Diebold (1986) stated that not including nonlinearity in financial series in the model can cause biases in parameter estimates. Schwert (1989), on the other hand, found that the expansion and contraction phases have different characteristics while investigating the cycle in stock returns. Regime-switching models that separate periods of low and high volatility are often recommended for these problems. Moreover, Bildirici and Ersin (2014) emphasise that the financial series show important regime switching over time due to depression, recession, bankruptcies, natural disasters, panics, changes in government policies, investor expectations, and political instability. Such changes in financial series have caused the analysis methods to be updated over time. One of these methods is Markov Switching. Hamilton (1989) states that the world consists of a finite set of regimes and each regime has its own characteristic. Thus, the specific model parameters of each

regime should be calculated, and the model should be evaluated accordingly. The proposed method is called Markov Switching because it uses the Markov chain to model is described regime switching. An ergodic homogeneous Markov chain on a finite set  $S = \{1, \dots, n\}$ , with transition matrix  $P$  defined by the probabilities  $\{\mu_{ij} = P(s_t = i | s_{t-1} = j)\}$  and invariant probability measure  $\pi = \{\pi_i\}$ . So, the MS-GARCH (1,1) model is described below (Bauwens et al., 2009):

$$y_t = \mu_{s_t} + \sigma_t u_t \tag{3}$$

$$\sigma_t^2 = \omega_{s_t} + \alpha_{s_t} \varepsilon_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2 \tag{4}$$

The assumptions of the model are that:  $\omega_{s_t} > 0, \alpha_{s_t} \geq 0, \beta_{s_t} \geq 0$  for  $s_t \in \{1, \dots, n\}$ , and  $\varepsilon_t = y_t - \mu_{s_t}$ . These assumptions make  $\sigma_t^2$  positive.

Ang and Timmermann (2011) explain the advantages of regime-switching models such as MS-GARCH as follows:

- The cyclical nature of economic variables makes regime-switching common.
- Regime-switching models capture the behaviour of financial return series that are not normally distributed, have ARCH effects, and have time-varying correlations.
- Regime-switching models tend to capture nonlinear behaviour in any series.

#### 4. Data and Preliminary Analysis

In this study, the relationship between the Turkish stock market and Turkey's CDS is analysed for the period 2010:01-10/2022:12-11. Borsa Istanbul 100 index (*bist100*), which represents the Turkish Stock Market, and *cds* (five years USD bond yield) are used for this analysis. Both variables were obtained from the website *www.investing.com*. Despite the availability of previous daily and weekly data, the reason for choosing weekly data for the years 2010-2022 is the irregularities in the *cds* data. First of all, the variables were seasonally adjusted with the Tramo/Seats method. Then, the return series of these variables were calculated by the following formula:



$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{5}$$

*rbist100* and *rcds*, respectively, represent the return series of *bist100* and *cds* obtained by the formula in Equation 5.

**Graph 3. Return Series of Data**



Graph 3 shows the return series of *rbist100* and *rcds*. The high volatility in the series is remarkable. When the return series are examined, it is seen that high volatility and negative returns are dominant in political instability, the 2016 and 2018 crises, and the Covid-19 Pandemic period.

**Table 1: Summary Statistics and Normality Test**

	<b>RBIST100</b>	<b>RCDS</b>
Mean	0.001451	0.000709
Median	0.002407	-0.001480
Maximum	0.049950	0.177695
Minimum	-0.062412	-0.118829
Std. Dev.	0.014446	0.031853
Skewness	-0.553687	0.634453
Kurtosis	4.521224	6.173150
Jarque-Bera	99.57368	328.4720
Probability	0.000000	0.000000
Sum	0.979114	0.478370
Sum Sq. Dev.	0.140654	0.683864
Observations	675	675

The summary statistics of the return series of the variables and the normality test are described in Table 1. *rbist100* has higher mean and median values than *rcds*. The skewness value for *rbist100* is negative, indicating the series is long left-tailed, whereas *rcds* display positive skewness, which shows *rcds* are long right-tailed. The kurtosis values of the series indicate that they exhibit a leptokurtic (fat-tailed) property. In addition to this picture, the Jarque-Bera test statistics also indicate that the series are not normally distributed.

## 5. Empirical Results

One of the primary steps of time series analysis is to apply the unit root test to variables. In this study, Augmented Dickey-Fuller (1981) and Phillips-Perron (1988) unit root tests, which are widely used, were applied to test whether the return series of variables contain a unit root. The ADF test is an augmented version of Dickey-Fuller and allows higher correlation in residual terms. The PP test also takes into account the moving average process, unlike ADF. These two tests contain the same hypotheses and use the t-statistic. Here, the null hypothesis is that the series contains a unit root, that is, it is not stationary. Accordingly, if the calculated t-statistic is greater than the critical value, the null hypothesis is rejected, and it is concluded that the series do not contain a unit root and are stationary.

**Table 2: Standard Unit Root Tests**

Variables	Include in Test Equation	ADF	PP
RBIST100	With constant	-25.802* (0.000)	-25.831* (0.000)
	Without constant and trend	-25.562* (0.000)	-25.686* (0.000)
RCDS	With constant	-28.815* (0.000)	-28.707* (0.000)
	Without constant and trend	-28.820* (0.000)	-28.710* (0.000)

Note: \* It indicates stationarity  $I(0)$  at a 5% significance level according to Schwarz Information Criteria (SIC).

Table 2 presents the results of the ADF and PP standard unit root tests. In the cases with constant and without constant and trend of both tests, it is found that the variables do not contain a unit root. Therefore, it can be said that the variables are stationary.

To detect possible structural breaks in the variance of the return series, the test that allows multiple breaks, based on the Iterative Cumulative Sum of Squares method proposed by Inclan and Tiao (1994), was used. This test was later modified by Sansó, Carrion, and Aragó (2004) taking into account the conditional variance with Monte Carlo simulations. According to the  $\kappa_1$  and  $\kappa_2$  statistics obtained from the test, no structural break was detected in the return series of the variables.

The ARMA/ARIMA (Autoregressive Integrated Moving Average) structure of the model needs to be determined. As a result of unit root tests, the series being determined as  $I(0)$  means that the series does not contain an integrated process, and therefore the appropriate model testing should be done through ARMA, not ARIMA.

**Table 3: ARMA (p/q) Selection**

AR / MA	0.000000	1.000000	2.000000	3.000000	4.000000	5.000000
0.000000	-5.627310*	-5.607901	-5.602116	-5.593069	-5.587326	-5.579601
1.000000	-5.607903	-5.600010	-5.593761	-5.584197	-5.578377	-5.571397
2.000000	-5.602540	-5.593631	-5.584176	-5.574846	-5.575324	-5.576988
3.000000	-5.593203	-5.583293	-5.574730	-5.575873	-5.576806	-5.557471
4.000000	-5.586294	-5.577145	-5.575127	-5.576104	-5.573706	-5.559361
5.000000	-5.578274	-5.570232	-5.563819	-5.566859	-5.558645	-5.554000

Note: \* It indicates the optimal ARMA(p/q) model according to the Schwarz Information Criterion.

Table 3 shows the calculations to determine the appropriate order of ARMA structure according to the Schwarz Information Criteria. According to this criterion, the model with the lowest coefficient is determined as the appropriate model. In this case, the optimal model was determined as ARMA(0,0). In other words, there is no AR and MA structure in the model.

When investigating the relationship between the variables, the study aimed to obtain more specific findings with two different models. The first of these models included the full sample period (2010:01-10/2022:12-11). The second model was estimated by excluding the period from the sample (2010:01-10/2021:12-05), which includes the rapid upward trend in which the bist100 index value exceeds the 2000s. In the next step, ARCH effects in these models and the optimal MS-GARCH method were determined.

**Table 4: ARCH-LM Test Results of Fixed MS**

	Full Sample	Subsample
Lags	F-Stat. (Prob.)	F-Stat. (Prob.)
ARCH 1-1 test	7.0383 (0.0082)	14.645 (0.0001)
ARCH 1-5 test	2.5021 (0.0434)	3.2406 (0.0068)
ARCH 1-10 test	1.2335 (0.2658)	1.7552 (0.0657)

Engle (1982) stated that before ARCH/GARCH analysis, whether the series contains an ARCH effect should be investigated. The ARCH-LM test developed by Engle (1982) provides information on whether there is heteroscedasticity in the model. In case of the presence of the ARCH effect in the series, it is more appropriate to perform analysis with models such as ARCH/GARCH. According to this test, the probability value calculated for different lags is less than 0.05, indicating the presence of the ARCH effect in the model. The ARCH-LM Test findings through the Fixed MS method are shown in Table 4. According to the values in Table 4, the fixed MS model includes the ARCH effect. These findings indicate that it would be more proper to establish a model via the MS-GARCH method.

**Table 5: Determining the Optimal MS-GARCH Model**

Model	Full Sample			Subsample		
	SC	HQ	AIC	SC	HQ	AIC
Switching variance with shared GARCH	-6.0444	-6.0853	-6.1112	-6.1432*	-6.1868*	-6.2145*
Switching GARCH	-6.0396	-6.0808	-6.1099	-6.1273	-6.1796	-6.2129

Note: \* It indicates the optimal model according to different information criteria.

As the diagnostic tests indicated, the optimum model was determined through different MS-GARCH specifications. The results of different information criteria regarding the optimality of the MS-based models are shown in Table 5. Four models with two regimes were estimated. All information criteria indicate that the optimal model is switching variance with the shared GARCH of the subsample (2010:01-10/2021:12-05). Therefore, models were estimated for both subsample and full sample (2010:01-10/2022:12-11) with the same specification. These MS-GARCH (1,1) models are presented in Table 6.

**Table 6: MS-GARCH (1,1) Model Estimations**

	Full Sample	Subsample
	2010:01-10/2022:12-11	2010:01-10/2021:12-05
<b>Regime (0)</b>		
constant	0.00473* (0.002)	0.00195* (0.011)
rcds	-0.0908 (0.054)	-0.2286* (0.000)
$\sigma$	0.00396 [0.00110]	0.00393 [0.00090]
<b>Regime (1)</b>		
constant	0.00026 (0.691)	-0.0034 (0.247)
rcds	-0.3298* (0.000)	-0.5775* (0.000)
$\sigma$	0.00427 [0.00088]	0.00001 [0.00281]
$\alpha_1$	0.11195 [0.03456]	0.06547 [0.03156]
$\beta_1$	0.72846 [0.08155]	0.78281 [0.07157]
p{0 0}	0.87678 [0.07061]	0.87798 [0.07258]
p{1 1}	0.95382 [0.04401]	0.27799 [0.19580]
<b>Diagnostic Tests</b>		
LR Test	72.379 (0.000)	47.670 (0.000)
SIC	-6.0443	-6.1432
Log-likelihood	2072.54	1942.70
ARCH LM Test	0.42312 (0.5156)	0.02759 (0.868)
Portmanteau Test	27.297 (0.3412)	22.061 (0.575)

Note: \* indicates significance at the 5% level and [...] shows standard errors.

The Likelihood Ratio (LR) Test gives an idea of whether the models are linear or not. If the probability value of the LR Test statistic is less than 0.05, it means that the model is not linear. In this case, nonlinear models such as the MS model give better results than linear models, as shown here. Furthermore, the ARCH-LM Test and Portmanteau Test indicate that there is no ARCH effect or autocorrelation problem in models.

Table 6 exhibits the findings of the MS-GARCH (1,1) models. These two models show similar tendencies in terms of diagnostic test findings and the signs and significance of the coefficients. However, there are critical differences from period to period and from regime to regime. Regime 0 represents low volatility; Regime 1 represents high volatility. We can define Regime 0 as the expansion period and Regime 1 as the recession period. In addition, since the dependent variable is the stock market, we can call these regimes the bull and bear markets, respectively. In both models, the constant terms in the expansion period are positive and significant, while the constant terms in the recession period are statistically insignificant. CDS negatively affects the Turkish stock market in both models and both regimes. As the CDS increases, the return of the Turkish stock market decreases. However, the size of this effect is much higher during recession periods. Moreover, there is a vital finding that drastically differentiates the two sample periods. While the full sample Regime 0 coefficient of  $rcds$  is -0.0908, the subsample Regime 0 coefficient is -0.2286. The full sample Regime 1 coefficient of  $rcds$  is -0.3298, while the subsample Regime 1 coefficient is -0.5775. In short, CDS affects the Turkish stock market approximately twice as much in the subsample period as in the full sample period. Moreover, this effect exists in both bull and bear markets.

**Table 7: Transition Probabilities**

	Full Sample		Subsample	
	Regime 0, t	Regime 1, t	Regime 0, t	Regime 1, t
Regime 0, t+1	0.87679	0.04617	0.87798	0.72201
Regime 1, t+1	0.12321	0.95382	0.12202	0.27799

The transition probabilities of the MS-GARCH models are presented in Table 7. The transition probability from Regime 0 to Regime 0 is high in both models. This indicates that Regime 0 is persistent. Regime 1 is also persistent in the full sample period.

The findings of the analysis are in line with the studies by Fei et al. (2017), Ceylan et al. (2018), and Anton and Nucu (2020) in terms of model non-linearity and regime-switching. In addition, as in the studies by Fei et al. (2017), Topaloğlu and Ege (2020), and Saritaş et al. (2021), a negative relationship is confirmed between the two variables.

## **6. Conclusion**

This study examines the effects of CDS on the Turkish stock market. More specifically, it questions whether the sensitivity of the Turkish stock market to CDS has changed over time. The main findings of the study are as follows. First, it is seen that the return series of the variables have high volatility, especially in crisis periods. Second, the relationship between the two variables is nonlinear and includes the ARCH effect. Therefore, the models are set via the MS-GARCH method. Third, the subsample period excluding 2022 observations is more optimal than the full sample period. Nevertheless, the findings of both sample periods are included to make a comparison. Fourth, the effect of CDS on the Turkish stock market is greater in the high-volatility regime than in the low-volatility regime. Fifth, CDS has a negative impact on the Turkish stock market in both low and high volatility periods. Sixth and most importantly, CDS affects the Turkish stock market approximately twice as much in the subsample period as in the full sample period in both regimes.

The findings of this study highlight important signals and policy implications for the Turkish economy. First of all, in this study, as in many other studies, the potential impact of CDS on the Turkish stock market is emphasised once again. Increases in CDS reduce Turkish stock market returns during bull and bear market periods. This is proof that financial markets in Turkey are

vulnerable to CDS. Policymakers should take measures to reduce CDS to ensure financial stability. However, the relationship between the two markets has changed as a result of factors such as high profitable balance sheets, the seeking for returns arising from inflation, and the low-interest policy in 2022. It seems as if the Turkish stock market is less vulnerable to CDS during this period. However, this should not mislead policymakers. Because other driving forces of the stock market came into play in this period. Policies against the wind not only increase the profitability in the Turkish stock market at incredible levels but also have the characteristic of a potential bomb. It should be noted that financial markets are characterised by boom-and-bust cycles. Therefore, it is thought that more moderate and risk-oriented policies are needed to ensure stability in financial markets.

The Turkish stock market needs to be analysed more comprehensively in terms of its unprecedented experiences as of 2022. Future studies may analyse the dynamics of the highly profitable period in Turkish stock markets from the end of 2021 in more detail. It is recommended that high-frequency econometric analysis takes into account, in addition to CDS, company and bank balance sheets, inflation rate, and policy interest.

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## References

- Altınok, H., & Akça, A. (2021). BRICS+ T ülkelerinde sanayi üretim endeksi ve kredi temerrüt takası arasındaki ilişki: Konya bootstrap nedensellik yaklaşımı. *Maliye Dergisi*, (180), 252-269.
- Ang, A., & Timmermann, A. (2011). Regime changes and financial markets. *Netspar Discussion Paper. DP 06/2011-068*, 1-32.
- Anton, S. G., & Afloarei Nucu, A. E. (2020). Sovereign credit default swap and stock markets in Central and Eastern European countries: Are feedback effects at work?. *Entropy*, 22(3), 338. Doi: <https://doi.org/10.3390/e22030338>
- Asandului, M., Lupu, D., Mursa, G., & Musetescu, R. (2015). Dynamic relations between CDS and stock markets in Eastern European countries. *Economic Computation and Economic Cybernetics Studies and Research*, Issue 4/2015.



- Augustin, P., Subrahmanyam, M. G., Tang, D. Y., & Wang, S. Q. (2016). Credit default swaps. *Annual Review of Financial Economics*, 8, 175-196.
- Ballester, L., Escrivá, A. M., & González-Urteaga, A. (2021). The Nexus between sovereign CDS and stock market volatility: new evidence. *Mathematics*, 9(11), 1201. Doi: <https://doi.org/10.3390/math9111201>
- Bauwens, L., Preminger, A., & Rombouts, J. V. (2010). Theory and inference for a Markov switching GARCH model. *The Econometrics Journal*, 13(2), 218-244. Doi: <https://doi.org/10.1111/j.1368-423X.2009.00307.x>
- Bildirici, M., & Ersin, Ö. (2014). Modeling Markov switching ARMA-GARCH neural networks models and an application to forecasting stock returns. *The Scientific World Journal*, 2014. Doi: <https://doi.org/10.1155/2014/497941>
- Bildirici, M., Sonüstün, B., & Gökmenoğlu, S. M. (2019, November). CDS-Stock market chaotic relationship-Turkish stock market case. In *AIP Conference Proceedings* (Vol. 2178, No. 1, p. 030068). Doi: <https://doi.org/10.1063/1.5135466>
- Bolaman Avcı, Ö. (2020). Interaction between CDS premiums and stock markets: Case of Turkey. *Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 13(1), 1-8. Doi: <https://doi.org/10.25287/ohuibf.526638>
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327. Doi: [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)
- Celik, S., & Koc, Y. D. (2016). Relationship between sovereign credit default swap and stock markets: the case of Turkey. *The MacrotHEME Review*, 5(4), 36-40.
- Central Bank of the Republic of Turkey, the Electronic Data Delivery System, (Date accessed: 12/20/2022).
- Ceylan, F., Tuzun, O., & Ekinci, R. (2018). The effect of credit default swaps (CDS) on BIST100 in Turkey: MS-VAR approach. *Ecoforum journal*, 7(1).
- Chau, F., Han, C., & Shi, S. (2018). Dynamics and determinants of credit risk discovery: Evidence from CDS and stock markets. *International Review of Financial Analysis*, 55, 156-169. Doi: <https://doi.org/10.1016/j.irfa.2017.11.004>
- Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: Journal of the Econometric Society*, 1057-1072. Doi: <https://doi.org/10.2307/1912517>
- Diebold, F. X. (1986). Modeling the persistence of conditional variances: A comment. *Econometric Reviews*, 5(1), 51-56. Doi: <https://doi.org/10.1080/07474938608800096>
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007. Doi: <https://doi.org/10.2307/1912773>
- Esen, S., Zeren, F., & Şimdi, H. (2015). CDS and stock market: panel evidence under cross-section dependency. *South-Eastern Europe Journal of Economics*, 13(1).

- Fei, F., Fuertes, A. M., & Kalotychou, E. (2017). Dependence in credit default swap and equity markets: Dynamic copula with Markov-switching. *International Journal of Forecasting*, 33(3), 662-678. Doi: <https://doi.org/10.1016/j.ijforecast.2017.01.006>
- Forte, S., & Pena, J. I. (2009). Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS. *Journal of Banking & Finance*, 33(11), 2013-2025. Doi: <https://doi.org/10.1016/j.jbankfin.2009.04.015>
- Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*, 357-384. Doi: <https://doi.org/10.2307/1912559>
- Hammoudeh, S., & Sari, R. (2011). Financial CDS, stock market and interest rates: Which drives which?. *The North American Journal of Economics and Finance*, 22(3), 257-276. Doi: <https://doi.org/10.1016/j.najef.2011.04.001>
- Inclan, C., & Tiao, G. C. (1994). Use of cumulative sums of squares for retrospective detection of changes of variance. *Journal of the American Statistical Association*, 89(427), 913-923. Doi: <https://doi.org/10.1080/01621459.1994.10476824>
- Kandemir, T., Vurur, N. S., & Gökğöz, H. Türkiye'nin CDS primleri ile Bist100, döviz kurları ve tahvil faizleri arasındaki etkileşimin cDCC-EGARCH ve varyansta nedensellik analizleriyle incelemesi. *Karamanoğlu Mehmetbey Üniversitesi Sosyal Ve Ekonomik Araştırmalar Dergisi*, 24(42), 510-526.
- Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics*, 8(2), 225-234.
- Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: default risk or liquidity? New evidence from the credit default swap market. *The Journal of Finance*, 60(5), 221-353.
- Mateev, M. (2019). Volatility relation between credit default swap and stock market: new empirical tests. *Journal of Economics and Finance*, 43(4), 681-712. Doi: <https://doi.org/10.1007/s12197-018-9467-5>
- Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, 29(2), 449-470. Doi: <https://doi.org/10.2307/2978814>
- Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American economic review*, 48(3), 261-297.
- Ozsoy, T. (2022). Turkish Stock Market's 80% rally fuels world's top gains in 2022, Bloomberg, <https://www.bloomberg.com/news/articles/2022-11-22/inflation-hit-turks-lift-stocks-to-world-s-top-2022-performer?leadSource=uverify%20wall>, (Date accessed: 12/22/2022).
- Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335-346. Doi: <https://doi.org/10.1093/biomet/75.2.335>
- Sansó, A., Carrion, J. L., & Aragón, V. (2004). Testing for changes in the unconditional variance of financial time series. *Revista de Economía Financiera*, 2004, 4, p. 32-52.
- Saritaş, H., Kiliç, E., & Nazlıoğlu, E. H. (2021). CDS primleri ve derecelendirme (raiting) notları ile BIST 100 endeksi arasındaki ilişkinin incelenmesi: Türkiye örneği. *Maliye ve Finans Yazıları*, (116), 73-92. Doi: <https://doi.org/10.33203/mfy.854876>

- Schwert, G. W. (1989). Why does stock market volatility change over time?. *The Journal of Finance*, 44(5), 1115-1153. Doi: <https://doi.org/10.1111/j.1540-6261.1989.tb02647.x>
- Sovbetov, Y., & Saka, H. (2018). Does it take two to tango: Interaction between credit default swaps and national stock indices. *Journal of Economics and Financial Analysis*, 2(1), 129-149.
- Sun, X., Wang, J., Yao, Y., Li, J., & Li, J. (2020). Spillovers among sovereign CDS, stock and commodity markets: A correlation network perspective. *International Review of Financial Analysis*, 68, 101271. Doi: <https://doi.org/10.1016/j.irfa.2018.10.008>
- Topaloğlu, E. E., & Ege, İ. (2020). Kredi temerrüt swapları (CDS) ile Borsa İstanbul 100 endeksi arasındaki ilişki: kısa ve uzun dönemli zaman serisi analizleri. *İşletme Araştırmaları Dergisi*, 12(2), 1373-1393. Doi: <https://doi.org/10.20491/isarder.2020.918>
- Ustaoğlu, E. (2022). Analysis of Relations between CDS, Stock Market, and Exchange Rate: Evidence from Covid-19. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 7(2), 301-315. Doi: <https://doi.org/10.30784/epfad.1085420>
- Wee, D. C., Chen, F., & Dunsmuir, W. T. (2020). Likelihood inference for Markov switching GARCH (1,1) models using sequential Monte Carlo. *Econometrics and Statistics*. Doi: <https://doi.org/10.1016/j.ecosta.2020.03.004>
- [www.investing.com](http://www.investing.com), (Date accessed: 12/20/2022).

