TURKISH CREDIT DEFAULT SWAP
AND
RELATIONSHIP WITH FINANCIAL INDICATORS

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İSTANBUL BİLGİ ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
BANKACILIK FİNANS YÜKSEK LİSANS PROGRAMI

ÖĞR.GÖR. ALİ BATU KARAALİ

2011

Turkish Credit Default Swaps and Relationship with Financial Indicators

Türkiye Kredi Temerrüt Takasları ve Finansal Göstergelerle İlişkisi

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Toplam Sayfa Sayısı	: 52

Anahtar Kelimeler (Türkçe)	Anahtar Kelimeler (İng.)
1) Kredi Temerrüt Takası	1) Credit Default Swap
2) Birim Kök	2) Unit Root
3) Granger Nedensellik Testi	3) Granger Causality Test
4) Regresyon Analizi	4) Regression Analysis
5) Vektör Otoregresyon Modeli	5) Vector Autoregression Model

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Abstract

The credit default swap (CDS) is the building stone of hedging strategies for credit exposures, and basis of more advanced credit derivative products. The CDS market has appeared to become a major asset class in the capital markets. One largely confined to banks, to market participants have expanded to include insurance companies, hedge funds, mutual funds, pension funds, and other investors looking for yield enhancement or credit risk transference. The literature review presents the recent work on interactions of credit default swap and other variables.

The scope of this study is to find out if there is a relationship separately between CDS spreads and financial indicators as Eurobond, Dow Jones Index, Istanbul Stock Exchange Index (ISE–100), Foreign exchange currency (Fx) rates. In our empirical work, we collect CDS, Eurobond and Dow Jones data from Bloomberg data provider, ISE–100 closing price data from ISE web site and Fx –TRY currency rates from web site of Central Bank of the Republic of Turkey for dates from March 3rd, 2002 to January 22nd, 2010. E-views 5 program is used for One Variable and Multivariable Regression, Correlation, Granger Causality Tests and Vector Autoregression Tests . Dow Jones rates, and the way of the interaction runs from Eurobond and Dow Jones to CDS. Results enable to interpret the relationship between CDS–ISE 100 and CDS–currency rates. Causality runs for both variables from CDS.

To life,

Acknowledgements

First of all, I would like to express my gratitude to my dissertation advisor Ali Batu Karaali (Assistant General Manager-Treasurer of HSBC Bank). I appreciate his intellectual comments, knowledge and assistance which helped me a lot in preparing my thesis. With his instructions I have started to be interested in derivative markets and especially credit default swaps.

I am also thankful to Ferhat Kasap for his help while preparing my thesis.

I would also like to thank my colleagues from Turkland Bank and HSBC Bank for their understanding in this period. Special thanks to Assistant General Manager (Treasurer of Turkland Bank) Münevver Eröz for her comments, thanks to Sevgi Üstün and Didem Çalışkan for their support.

Very special thanks go to PhD Candidate in Economics Coşkun Tarkoçin from HSBC, who became more of a mentor and a friend than a partner, and who taught almost everything I have learned in my work life and encouraged me to start a graduate program.

Finally and most importantly, I would like to thank my family who has never stopped supporting and encouraging me through my entire life. Without their love and belief I would do nothing.

Table of Contents

1. INTRODUCTION 1

1.1 CREDIT DEFAULT SWAPS: THE BASICS 1

1.2 HISTORY OF CREDIT DEFAULT SWAPS 4

1.3 MARKET DATA 6

2. EMPIRICAL ANALYSIS 11

2.1 LITERATURE REVIEW 11

2.2 DATA AND DESCRIPTIVE STATISTICS 12

2.3 UNIT ROOT TESTS 19

2.4 REGRESSION ANALYSIS 27

2.5 GRANGER CAUSALITY TESTS 38

2.6 VECTOR AUTOREGRESSION (VAR) MODEL 43

3. CONCLUSION 47

References 49

Autobibliography 52

List of Tables

Table		Page
1	Credit Product Composition Percent	8
2	Buyers of Protection Percent	9
3	Sellers of Protection Percent	9
4	Descriptive Statistics of Data	13
5	Descriptive Statistics of Turkey CDS_5Y by Years	13
6	Descriptive Statistics of Turkey Eurobond by Years	14
7	Descriptive Statistics of ISE 100 By Years	16
8	Descriptive Statistics of Dow Jones by Years	17
9	Descriptive Statistics of Fx Basket by Years	18
10	Correlations among Variables	19
11	ADF Unit Root Test on Turkey_CDS5Y	21
12	ADF Unit Root Test on Eurobond	21
13	ADF Fuller Unit Root Test on ISE_100	22
14	ADF Unit Root Test on Dow Jones	22
15	ADF Unit Root Test on Fx Basket	23
16	ADF Unit Root Test on Turkey_CDS5Y	23
17	ADF Unit Root Test on Eurobond	23
18	ADF Unit Root Test on ISE_100	24
19	ADF Unit Root Test on Dow Jones	24
20	ADF Unit Root Test on Fx Basket	24
21	Descriptive Statistics of Growth Ratios of Variables	25
22	Correlations among Growth Ratios of Variables	25
23	Regression Output Table Turkey CDS 5Y-ISE100	31
24	Regression Output Table Turkey CDS 5Y-Dow Jones	32
25	Regression Output Table Turkey CDS 5Y-Fx Basket	34
26	Regression Output Table Turkey CDS 5Y-Eurobond	35
27	Multivariate Regression Output Table	36
28	Wald Test	38
29	Determining Compatible Number of Lags	40
30	Pairwise Granger Causality Tests	41
31	VAR Estimates	45

List of Figures

Figure **Page**

1 Growth of Credit Default Swaps..7

2 Total Derivatives and Credit Default Swaps......................................8

3 CDS5Y Spreads in Basis Points...14

4 Eurobond Yields in Percentage..15

5 ISE 100 Closing Prices...16

6 Dow Jones..17

7 Fx Basket Rates..18

8 Graphs For Non-Stationary and Stationary Time Series..................25

9 CDS-ISE 100 Scatter...32

10 CDS-Dow Jones Scatter..33

11 CDS-Fx Basket Scatter...34

12 CDS-Eurobond Scatter...36

13 CDS Against All Scatter...37

14 Way of Interactions...43

Abbreviations

ADF	Augmented Dickey-Fuller Test
AIC	Akaike Information Criterion
AIG	American International Group Insurance Company
BBA	British Bankers Association
BISTRO	Broad Index Secured Trust Offering
CBRT	Central Bank of the Republic of Turkey
CDS	Credit Default Swap
DW	Durbin-Watson
DCDS	First Difference of CDS data
DDow Jones	First Difference of Dow Jones data
DEurobond	First Difference of Eurobond data
DFx basket	First Difference of Foreing Exchange Currency data
DISE	First Difference of Istanbul Stock Exchange data
ESS	Explained Sum of Squares
FAS	Financial Accounting Standarts
FPE	Final Prediction Error
Fx	Foreign Exchange
HQ	Hannan-Quinn Information Criterion
ISDA	International Swaps and Derivatives Association
ISE	Istanbul stock Exchange
iBoxx	Bond Market Indices
iTraxx	A group of international credit derivative indexes that are monitored by the International Index Company (IIC)
OLS	Ordinary Least Squares
OTC	Over the Counter
RSS	Residual Sum of squares
SC	Schwarz Information Criterion
SD	Standard Deviation
SE	Sum of Errors
Trac-x	Transport Capacity Exchange
TSS	Total Sum of Squares
VAR	Vector Autoregression

1. INTRODUCTION

Credit Default Swap (CDS) has been one of the most fascinating developments of last two decades in financial markets, particularly in credit markets. CDS market is used to differentiate credit risk from other risks. In addition, it provides an efficient way to trade credit risk. The big volume of CDS trading, flourishing of CDS related products and its phenomenal role in current credit crisis indicate the importance of this relatively new financial product.

The purpose of this study is to explore the interactions and causality relationship between CDS and other financial indicators. This paper is organized as follows: In section 1, a summary of CDS market is given. In section 2, general information about previous research and an analysis on related data is provided. Finally, in last section our results have been summarized.

1.1 CREDIT DEFAULT SWAPS: THE BASICS

Credit derivatives are exciting innovations in financial markets. They give the potential to companies to trade and manage credit risk. The most popular credit derivative is a credit default swap (CDS) (Hull & White, 2000).

A CDS is a contract that provides insurance against the risk of default by a particular company or even a particular debt. The contract will determine the reference entity or the reference liability. The reference entity means the issuer of the debt instrument. It could be a corporation, a sovereign government bond, or a bank loan (Fabozzi, 2004).

Credit event means a default by the company. The buyer of the CDS accepts to make periodic payments to the seller and these payments end if there is a default by the reference entity or a default by the counterparty (Hull, 2001).

Whenever a credit event exists, usually it requires a final accrual payment by the buyer. The total par value of the reference entity that can be sold is known as the swap's notional principal. The buyer of CDS has the right to sell a particular entity, issued by the company, for its par value when a credit event occurs (Hull, 2004).

The swap then could be settled by either a physical delivery or a cash delivery. If the contract of the swap requires physical delivery, the swap buyer delivers the reference entity to the seller in exchange for their par value. When the contract requires cash delivery, the calculation agent asks the dealers to determine the current market price, P, of the reference entity after some specified number of days of the credit event. The cash delivery is then a settled (100-P) percent of the notional principal (Hull & White, 2000).

In a credit default swap, the protection buyer makes a payment (a fee), called swap premium, to the protection seller. In the end there exists the right to receive a payment depends on the default of the reference entity. The payments made by the protection buyer are called the premium leg; the contingent payment that might have to be made by the protection seller is called the protection leg (Fabozzi, 2001).

These contracts are logically default options, not swaps. The difference from a regular option is that the cost of the option, which is called the premium, is paid in a deferred payment instead of in an advance payment. When the premium is paid in advance, these contracts might be called default put options. Default swaps and default options are not the same instruments, however, because a default swap requires deferred payments only until a triggering default event exists (Jorion, 2003).

This financial derivative has been driven by the demand from banks and insurance companies to protect their underlying entities against credit defaults. Hedge funds and investment banks' also need their private trading desks for more liquid instruments to speculate on credit risk. Trading in CDS contracts can have a wide impact on market because of its fantastic growth. Because of the rapid growth of market, a number of policy concerns about market stability and risk of adverse selection have been raised by the regulatory supervision of the CDS market. This would affect both the tendency of investors to trade in the market and therefore the liquidity of CDS contracts (Tang & Yan, 2007).

There are different kinds of credit default swaps: Binary credit default swaps, basket credit default swaps, contingent credit default swaps, and dynamic credit default swaps. In a binary credit default swap, the payment when the default exists, is a specific dollar amount. In a basket credit default swap, there is a specified group of reference entities and payment is done when one of these reference entities defaults. In a contingent credit default swap, the payment requires a credit event together with an additional trigger. This trigger might be a credit event related to another reference entity or a specified movement in some market variable. In a dynamic credit default swap, the notional amount determining the payoff is linked to the mark-to-market value of a portfolio of swaps (Hull & White, 2000).

Credit default swaps can be used by financial investors in different ways such as hedging and speculating. Example of the former one is that; investing in a risky bond is equal to investing in a risk-free bond and selling a credit default swap together. The risky bond price is a and promises to pay $a+2x$ in maturity. The risk-free price is $a+x$. Buying the risky bond is then equal to buying the risk-free bond at $a+x$ and selling a credit default swap worth x at the same time. The first cost is the same in two conditions, a. If the company defaults, the final payment will be the same. The protection buyer reduces exposure to the reference entity but accepts new credit exposure to the seller. To be effective, there has to be a low correlation between the default risk of the underlying credit and of the counterparty (Jorion, 2003). Example of the latter way of using CDS is that; investors can go both long and short positions in a particular credit without holding the underlying entity. This makes a credit default swap more accessible and easier to trade than its underlying reference entity. There are tradable CDS indexes (iBoxx, Trac-x, LevX, LCDX) which allow financial investors quick and easy ways to buy and sell credit risk (Byström, 2005). In June 21, 2004, the two main CDS indexes, iBoxx and Trac-x, were merged to form the CDX in North America, emerging markets and the iTraxx in Europe and Asia. Markit became the administrator for the CDX and calculation agent for iTraxx and acquired both families of indices in November 2007, and owns the iTraxx, CDX, LevX, and LCDX indices for derivatives, and the iBoxx indices for cash bonds (Markit, 2008).

1.2 HISTORY OF CREDIT DEFAULT SWAPS

During the recent credit crisis, Credit Default Swaps has received great attention because of toxic assets' huge demand on financial markets. In 1997, a credit derivative team at JP Morgan's (New York City, USA) launched CDSs with newspaper articles. At that time, they named this new derivative type as BISTRO (not CDS) which stands for Broad Index Secured Trust Offering. This product was a later stage in the development of CDS trading and the credit derivative market (Levy, 2009).

David Mengel (2007) describes evolution of CDS market from 1980 until today in four stages in his overview of credit derivative market.

The first stage of the credit derivative trading can be characterized as a defensive step. It mainly includes attempts taken by major banks to eliminate some of the credit exposure on their balance sheets. According to regulation (FAS 133)[1], reporting standards for derivative instruments are

[1] Financial Accounting Standarts

considered as a hedge of the exposure to the fair value of a liability, a firm commitment or a cash flow. This regulation enables a firm to reduce its credit exposure from its balance sheet. This stage took place in the late 1980s and early 1990s. During this period, banks had sold their loans to the other banks or private investors in return for periodic payments by using product similar to CDSs. When default happened, similar to the CDS contract, the loans or bonds that have credit exposure were being delivered to the investor, who would take the losses instead of the bank.

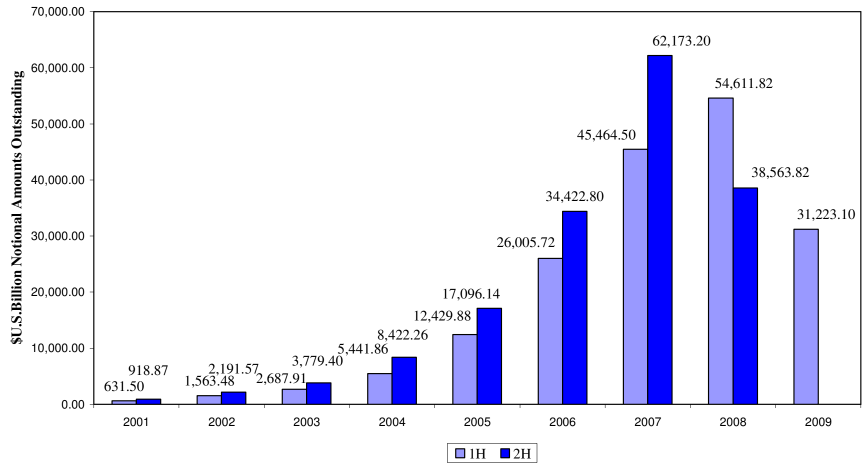
The second stage took place between 1991 and the late 1990s. The main change during this stage is the development of financial engineering technology for pricing the transfer of credit risk. The BISTRO was a financial tool designed to remove loans from banks' balance sheets and in turn free up cash. This product has worked by establishing a new company by the bank. The new company has bought the debt of the banks' balance sheets, and then issued bonds that were sold to different investors. Any investor who bought these bonds was betting against the default of the original borrowers, to whom the bank established in the first place.

The third stage is the mature CDS market which exist today and the standardization of its trade and contractual terms. During this stage, single name CDS contracts were developed and started being traded over-the-counter (OTC). Moreover, some new regulations were developed to organize and guide trade and define capital requirements. The International Swaps and Derivatives Association (ISDA) introduced the standardized contractual agreement, which offers the standard CDS agreement accepted by most of the traders today. Counterparty risk management begins with ISDA or other related transaction documentation. This is followed by measurement of both current exposure and potential losses if default were to occur in the future and finally collateral net exposures are made (Chaplin, 2005).

The fourth stage is the expansion of the types of players engaged in trading in the CDS market. Originally CDS trading was centered around banks' activities, this stage saw the entry of hedge funds as major players into CDS market. Hedge funds started to take the position of sellers or buyers, based on seeking exposure or hedging the credit risk. The entry of the hedge funds into the CDS market also introduces new trading motivations. Hedge funds are now using CDSs to trade misprices in credit risk, to remove unwanted credit risk from their portfolio and to trade CDS bond basis spreads. This fast dynamic hedge fund activity in the CDS market has contributed to increased trade volume and increased liquidity which has resulted in better price discovery (Mengle, 2007).

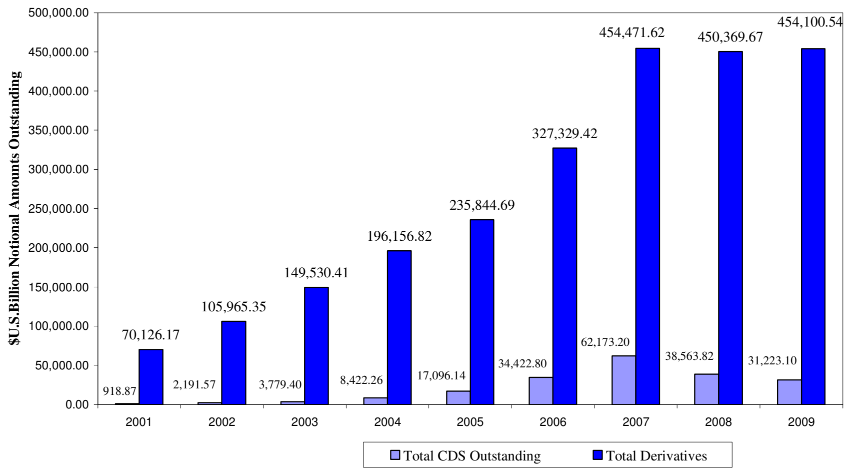
1.3 MARKET DATA

Since the credit derivates are mostly traded OTC, it is hard to generate an exact estimate of its gross market size. However, it is clear that the CDS market has the largest share in the credit derivative market, and the total credit derivative market has experienced a dramatic growth over the past decade. According to ISDA market survey, estimated gross market has reached to 62 trillion dollars in 2007 and it came down to 31 trillion dollars at the end of the second quarter of 2009. Figure 1 provides estimates for single name CDSs from 2001 to 2009, and Figure 2 provides estimates of the credit derivatives market in general (includes; interest rate swaps, currency swaps, credit default swaps and equity swaps) compared to CDS. As it can be seen in Figure 2, the credit derivative market had almost doubled from 2006 to 2007. The CDS market grew more than 25 trillion dollars during the same period. In 2003, the total CDS global notional amount was 3.7 trillion dollars, indicating a market growth of approximately 1,000 percent by 2007.



Source: ISDA Market Surveys,2001-1H2009

Figure 1. Growth of Credit Default Swaps



Source: ISDA Market Surveys,2001-1H2009

Figure 2. Total Derivatives and Credit Default Swaps

Average notional amounts for individual deals vary by region and sector. In North America, average notional amounts for investment grade CDSs are between 10 and 20 million dollars. Concerning CDSs with reference entities below investment grade, the numbers are about half of the size. In Europe, average notional amounts for investment grade CDSs are around 10 million euro. The 5-year maturity is traditionally the most liquid contract, but liquidity increases for longer maturities up to 10 year ones (Mengle, 2007).

Table 1 presents a market breakdown with respect to product type between 2000 and 2008. As it can be seen, the market share of single name CDS had increased from 2000 until 2004. During this period it has increased from 30 percent to above 50 percent, and then it started to decrease back to 33 percent. After their emergence, CDS indices has quickly become rival to single name CDSs. Their market share has changed from 9 percent in 2004 to 30 percent in 2006. Single CDSs and CDS indices comprise over 60 percent of the credit derivative market share together. CDS derivative, such as options, still do not comprise a large share of the market (1-5 percent between 2000-2008).

Table 1 Credit Product Composition Percent

Credit Product Composition Percent

Credit Product	2000	2002	2004	2006	2008*
CDS	38	45	51	33	30
Basket Products	6	6	4	2	1
Full Index Trades			9	30	29
Tranched Index Trades			2	8	10
Synthetic CDOs-Fully Funded			6	4	16
Synthetic CDOs-Partially Funded			10	12	
Funded CDS	10	8	6	3	3
Credit Spread Options	5	5	2	1	3
Equity Linked Credit Products			1	0	
Swaptions			1	1	
Other	41	36	8	6	8

*Forecast

Source: Brititish Bankers Association(2006), Mengle (2007), Bank of America (2008)

The market breakdown for sellers and buyers is shown in Table 2 and 3. The data indicates couple interesting patterns. First, while banks are still the main players in the market both as the seller and buyer, their market share had decreased at the expense of hedge fund activity. In 2000, the banks' share among CDS buyers was 81 percent, and 63 percent among CDS sellers, respectively. On the other hand, Hedge Funds had 3 and 5 percent in corresponding sides in that year. In 2006, banks' activity as buyer dropped to 59 percent, and to 44 as the seller, respectively. In contrast, in this year hedge funds had increased their market shares dramatically both as seller and buyer to 28 percent as buyer and to 32 percent as seller.

Table 2 Buyers of Protection Percent

Credit Product	2000	2002	2004	2006
Banks	81	73	67	59
Banks-Trading Activities				39
Banks-Loan Portfolio				20
Insurers	7	6	7	6
Hedge Funds	3	12	16	28
Pension & Mutual Funds	2	3	6	4
Corporates	6	4	3	2
Other	1	2	1	1

Source: Brititish Bankers Association(2006), Mengle (2007)

Table 3 Sellers of Protection Percent

Credit Product	2000	2002	2004	2006
Banks	63	55	54	44
Banks-Trading Activities				35
Banks-Loan Portfolio				9
Insurers	23	33	20	17
Hedge Funds	5	5	15	32
Pension & Mutual Funds	5	5	8	7
Corporates	3	2	2	1
Other	1	0	1	1

Source: Brititish Bankers Association(2006), Mengle (2007)

Another interesting point is the net exposure of each sector to credit risk. While hedge funds are fairly balanced between their long and short position in credit risk, banks are net buyers of protection, and insurance companies are net sellers of protection. Moreover, when we look at the different applications of CDS activity within the banks' sector, their activity is fairly balanced in exposure to credit risk, similarly for hedge funds. The source of net protection buying CDSs in banks results from their loan portfolio activity. This naturally requires more hedging of credit risk rather than exposure to it. Insurance companies, on the other hand, are net sellers of credit protection, traditionally having a share of between 20 to 30 percent as the seller, compared to a share of 6 to 7 percent as the buyer. Indeed, this fact is consistent with their function as insurance providers. In this way they gain exposure to risk. Also, it sheds light on the recent credit crisis and the collapse of the mega insurance company AIG. AIG has suffered from CDS activity and eventually brought the company bankruptcy.

2. EMPIRICAL ANALYSIS

2.1 LITERATURE REVIEW

The market for Credit Default Swaps (CDSs) has been growing very quickly in the last twenty years and during the credit crisis, the role of the CDS market has been drawing greater attention. Focusing on the market for CDS contracts, there exist many studies about the relationship among CDS prices and financial indicators.

Houweling and Vorst (2002) and Hull (2003) both argue that when the USD swap rate is used as risk-free rates, the price discrepancies between bond spread and CDS rates are quite small both in the short run and the long run. Longstaff (2003) who finds that both CDS and stock markets lead the bond market, but no clear lead-lag relationship was identified between CDS markets and stock markets. However, Chan-Lau and Kim (2004) find no equilibrium price relationship between sovereign CDS and sovereign bond markets, although prices converge in the long term. Haibin (2004) finds the price discrepancy between CDS rates and yield spreads very substantial in the short run. Blanco (2004) analysis dynamic relationship between investment-grade bonds and credit default swaps, and conclude that CDS rates is the upper bound and yield spread is the lower bound of the credit risk premium. Neftci, Santos and Lu (2004) find the information that helps to predict defaults and the succeeding financial crises with the difference between the CDS rate and the bond risk premium. Bystrom (2005) compares CDS spreads and stock prices using the European iTraxx CDS indices and finds that stock prices slightly lead the CDS market. He also finds a positive correlation between CDS prices and stock volatilities; CDS spreads tend to increase with increasing CDS stock price volatilities. Alexandar and Kaeck (2008) find that lead-lag relationship between stocks and CDS is a regime dependent one. They show how the CDS market is extremely sensitive to stock volatilities during period of CDS market turbulence, whereas under ordinary market circumstances CDS spreads are sensitive to stock returns than they are to stock volatilities.

In the context of the above literature, this study addresses the relation among credit risk as expressed CDS spreads and other financial indicators such as Fx basket, Dow Jones Index, Eurobond rates and stock exchange returns.

2.2 DATA AND DESCRIPTIVE STATISTICS

Raw data of this study covers the time period of 8 years between March 3rd 2002 and January 22nd 2010, 1896 daily data and holidays were excluded. The complete data set is used for extracting the general pattern and behavior of Turkish CDS throughout various financial indicators and also for descriptive statistics. CDS, Eurobond and Dow Jones Index are provided from Bloomberg. Stock Price Index is provided from Istanbul Stock Exchange 100 closing price. Fx (TRY against Euro and Dollar) rates are provided from Central Bank of the Republic of Turkey (CBRT)'s web site and calculated Fx basket with fifty percent of both rates. From the beginning of 2005, CBRT removed 6 zeros form currency and made the equation of 1 New Turkish Lira to 1,000,000 Old Turkish Liras. Therefore, data before 2005 were divided to 1,000,000 to have the appropriate data set.

The mean CDS5Y spread for the data set is 393.93 basis points with standard deviation of 285.07. The difference between minimum and maximum values of variables is quite high and that cannot be undervalued. The mean of Eurobond yields is 8.53 with 1.92 standard deviation. Maximum value of 1896 observations is 14.55, which shows there have been some picks during sample years. The mean of ISE 100 prices is 30,158.78 with standard deviation of 13,912.95. Maximum value is 58,522.07 which is four times bigger than its standard deviation. The mean of Dow Jones is 10,492.47 and mean of Fx basket is 1.60, standard deviation of former is 1,611.84 and latter is 0.14 (see Table 4).

Table 4 Descriptive Statistics of Data Set

Proper Name	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
CDS5Y	1896	393.93	285.07	1,416.88	116.55
Eurobond	1896	8.53	1.92	14.55	6.16
ISE100	1896	30,158.78	13,912.95	58,522.07	8,730.91
Dow Jones	1896	10,492.47	1,611.84	14,164.53	6,547.05
Fx Basket	1896	1.60	0.14	2.03	1.21

The data set become increasingly robust over time with the number of 193 observations per year in 2002, 239 in 2003, 2004 and 2006, 245 in 2005, 244 in 2007, 241 in 2008, 242 in 2009 and 14 observations per year in 2010 (see Table 5 and Figure 3). Default swap spreads vary over time with spreads historically high levels in 2002 and reverting back to an average of 170.62 basis points in 2007.

Table 5 Descriptive Statistics of Turkey CDS_5Y by years

Year	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
2002	193	917.15	262.18	1,285.00	518.33
2003	239	759.71	241.54	1,416.88	317.83
2004	239	393.84	100.36	687.50	232.17
2005	245	247.10	53.09	374.13	152.81
2006	239	187.10	45.49	332.71	116.55
2007	244	170.62	20.99	258.28	135.93
2008	241	316.01	115.28	824.61	170.01
2009	242	284.02	101.34	523.25	164.95
2010	14	171.84	4.61	179.17	166.01

Figure 3 CDS5Y spreads in basis points

Table 6 reports the statistics for the common factors which include Eurobond yields in percentage. As shown in the table, the spot yields are decreasing with a positive mean. Historically high levels were shown in 2002 with 14.55 in percentage and decreasing level until 6.53 by the year 2010. During 2008 there is a more volatile view because of the effects of the global crisis (See Figure 4).

Table 6 Descriptive Statistics of Turkey Eurobond by years

Year	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
2002	193	12.48	1.07	14.55	10.63
2003	239	10.83	1.18	14.11	8.42
2004	239	8.62	0.75	10.67	7.77
2005	245	7.94	0.35	8.76	7.15
2006	239	7.42	0.39	8.68	6.82
2007	244	7.02	0.14	7.31	6.77
2008	241	7.64	0.89	11.87	6.79
2009	242	7.23	0.85	9.58	6.16
2010	14	6.41	0.04	6.53	6.35

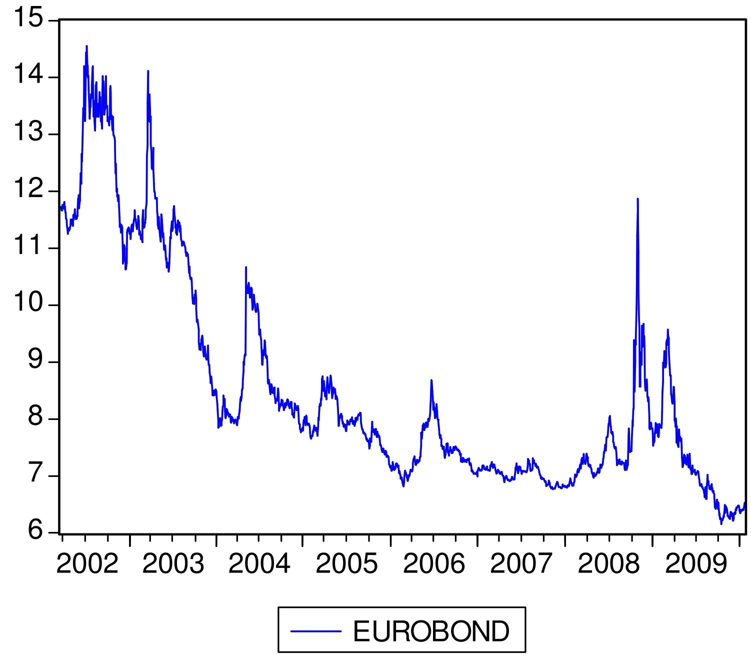


Figure 4 Eurobond yields in percentage

The mean ISE prices for the data set are 10,643.33 in 2002 and increasing to 37,460.50 in 2009 with standard deviation of 9,767.48. The mean is 54,337.07 for the first fourteen days of 2010. When we look at the minimum prices of the years after 2004, we could see that they have higher than the years before 2004. We can rush to the conclusion of different trends of these years (see Table 7). As we could see in the graph of ISE (Figure 5), it has an increasing trend until 2008. It again refers to global crisis and makes a downtrend. During the recovery period it rises sharply and returned to its level before crisis. As we mentioned before, the minimum price level is not as low as beginning years.

Table 8 reports the statistics for Dow Jones prices. As shown in table, means are increasing until the end of 2007 with the standard deviation of 525.48 and starts decreasing very sharply. Historically the highest price is in 2007

Table 7 Descriptive Statistics of ISE 100 by years

Year	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
2002	193	10,643.33	1,380.81	14,209.59	8,730.91
2003	239	12,253.39	2,365.07	18,532.85	9,072.99
2004	239	19,929.55	2,155.70	25,038.48	16,092.69
2005	245	29,396.37	4,290.62	39,858.19	23,053.86
2006	239	39,740.24	3,762.96	48,050.06	31,614.20
2007	244	48,253.72	5,470.61	58,522.07	36,812.67
2008	241	37,902.48	7,416.42	54,527.59	21,027.98
2009	242	37,460.50	9,767.48	52,961.75	22,694.59
2010	14	54,377.07	727.69	55,457.05	52,490.47

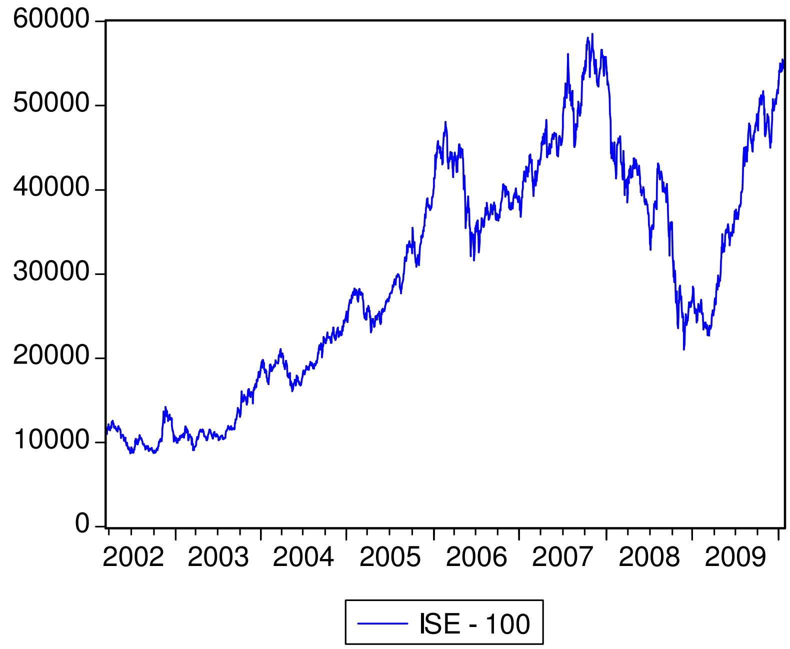


Figure 5 ISE 100 closing prices

with 14,164.53 and the lowest price is in 2009 with 6,547.05. The 2002 index has an increasing trend until 2008, like other indicators we are studying. The Dow Jones trend and falling down could be seen in Figure 6.

Table 8 Descriptive Statistics of Dow Jones by years

Year	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
2002	193	8,983.30	828.58	10,479.84	7,286.27
2003	239	9,016.76	695.96	10,453.92	7,524.06
2004	239	10,310.31	244.36	10,854.54	9,749.99
2005	245	10,548.94	199.30	10,940.55	10,012.36
2006	239	11,412.31	495.71	12,510.57	10,667.39
2007	244	13,173.98	525.48	14,164.53	12,050.41
2008	241	11,293.76	1,521.26	13,058.20	7,552.29
2009	242	8,860.95	1,011.45	10,548.51	6,547.05
2010	14	10,581.31	142.27	10,725.43	10,172.98

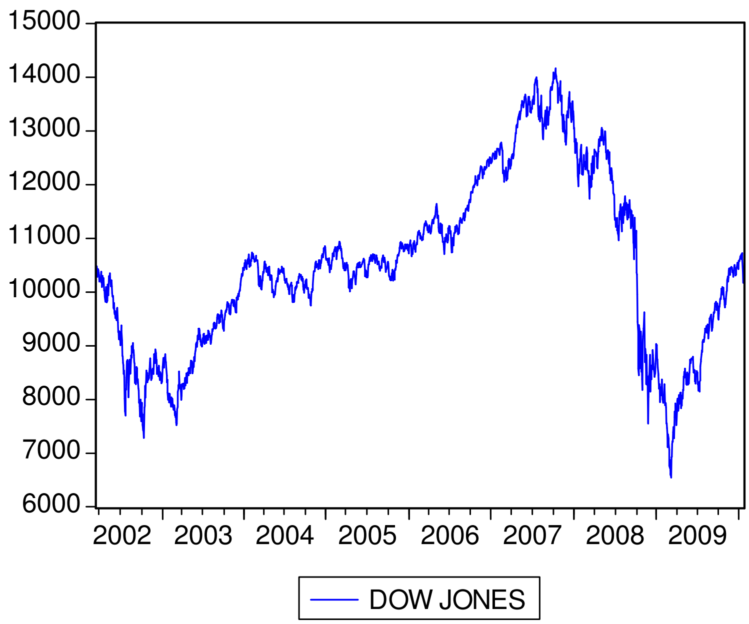


Figure 6 Dow Jones

The statistics for Fx basket as shown in Table 9, means of rates are between 1.52041 and 1.84926. Historically high levels in 2009 with 2.02975 in and decreasing level until 1.815 by the year 2010. Fx basket rates are quite volatile during the sample years and it shows that the lowest rates are not under 1.4 level after 2003 (See Figure 7).

Table 9 Descriptive Statistics of Fx Basket by years

Year	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
2002	193	1.52041	0.15327	1.68757	1.20967
2003	239	1.58825	0.09445	1.80219	1.43902
2004	239	1.59563	0.07754	1.70818	1.44056
2005	245	1.50492	0.03629	1.62300	1.45535
2006	239	1.61798	0.12169	1.90900	1.42370
2007	244	1.53972	0.06745	1.67565	1.42085
2008	241	1.59342	0.12748	1.93300	1.41890
2009	242	1.84926	0.04767	2.02975	1.77130
2010	14	1.78064	0.01546	1.81500	1.76105

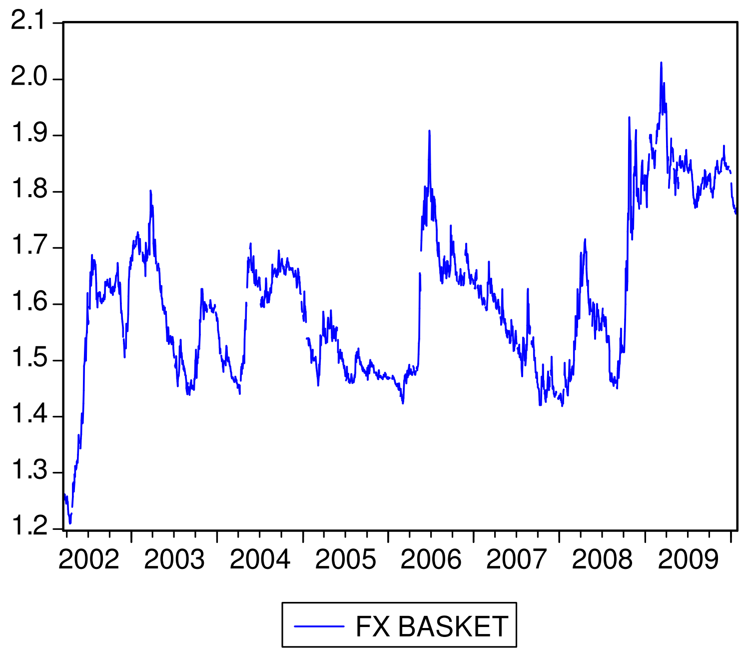


Figure 7 Fx Basket Rates

The correlation coefficients from Table 10 clearly indicate that CDS5Y–Eurobond prices and CDS5Y–ISE prices are highly correlated and CDS5Y–DJ are correlated for this data period. This shows that we are going to find serious relationship results with our analysis.

Table 10 Correlations among Variables

	CDS5Y	Eurobond	ISE100	Dow Jones	Fx Basket
CDS5Y	1.0000				
Eurobond	0.9635	1.0000			
ISE100	-0.8091	-0.8621	1.0000		
Dow Jones	-0.6619	-0.6165	0.7228	1.0000	
Fx Basket	0.0542	-0.0825	0.0408	-0.4388	1.0000

2.3 UNIT ROOT TESTS

Analysis for one of the financial instruments of a country may include not only the country specific variables, but also foreign instruments, especially based on US. Considering the previous reality in this study both domestic and foreign variables are chosen. One of them is the Dow Jones Industrial Average, which is extensively used in financial markets' analyses. The other variable used in this study is the Turkey Benchmark Eurobond rates. The reason of the Eurobond selection is, it is not a local issue, therefore it attracts foreign investors' interests. Fx spreads and ISE–100 price index are used to see whether foreign exchange and equity markets have any interactions from CDS or not.

The methodology behind this study's estimation is based on a stationary time series. A series is said to be (weakly or covariance) stationary if the mean and auto covariance of the series do not depend on time. Therefore, it is important to check whether a series is stationary or not. The formal method to test the stationarity is the unit root test. The simplest and most widely used tests for unit roots were developed by Fuller (1976) and Dickey and Fuller (1979). These tests are generally referred to as Dickey-Fuller, or DF, tests. Apart from Dickey-Fuller, the classic papers in this area are Philips (1987), Philips and Perron (1988). Banerjee, Dolado, Galbraith and Hendry (1993) provide a readable introduction to some of the basic results (Davidson & Mackinnon, 1993).

Consider a simple model:

$$y_t = a + b.y_{t-1} + \varepsilon_t \qquad (2.3.1)$$

Where *a* is an optional exogenous regressor which may consist of constant, or a constant and trend, *b* is a parameter to be estimated, and the ε_t are assumed to be white noise. If, |b| ≥ 1, y is a non-stationary series and the variance of *y* increases with time and approaches infinity. If |b| < 1, *y* is a (trend) stationary series. Thus, the hypothesis of (trend) stationarity can be evaluated by testing whether the absolute value of *b* is strictly less than one.

Subtracting y_{t-1} from both sides of the model (2.3.1), we have:

$$y_t - y_{t-1} = a + b.y_{t-1} - y_{t-1} + \varepsilon_t = a + (b-1).y_{t-1} + \varepsilon_t \qquad (2.3.2)$$

(2.3.2) can alternatively be written as below:

$$\Delta y_t = a + \delta y_{t-1} + \varepsilon_t \qquad (2.3.3)$$

In (2.3.3) $\delta = (b-1)$ and is a product of Δ. Practically (2.3.3) can be used instead of (2.3.1) and will be zero under the null hypothesis. If δ is zero *b* will be 1 and series will have a unit root. On the other hand, when δ is zero, model will be:

$$\Delta y_t = a + \varepsilon_t \qquad (2.3.4)$$

So that apart from ε_t the first difference of y_t is a constant which means this is a stationary series. If a time series become stationary in the n th difference, it is called n th level stationary and showed as L(n) so this model is a first level stationary series and showed as L(1) (Patterson, 2000).

The result of unit root tests of our series is as below (Table 11-15). The unit root tests the null hypothesis $\mathrm{H}_0 : b = 1$ against the one-sided alternative $\mathrm{H}_1 : b < 1$.

Tables below provide information about the form of the test (the type of test, the exogenous variables, and lag length used), and contain the test

Table 11 Augmented Dickey-Fuller Unit Root Test on TURKEY_CDS5Y

Null Hypothesis: TURKEY_CDS5Y has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.8244	0.3689
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Table 12 Augmented Dickey-Fuller Unit Root Test on EUROBOND

Null Hypothesis: EUROBOND has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.8680	0.3477
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

output, associated critical values, and in this case, the p-value: The Augmented Dickey-Fuller (ADF) statistic values and the associated one-sided p-values. Additionally, output reports the critical values at the 1 percent, 5 percent and 10 percent levels. For each table the statistic values are greater than the critical values so that the null hypothesis has not been rejected at conventional test sizes (Hayashi, 2000). The ADF unit root test results for the first difference of variables used in this study as below tables. Output tables (Table 16-20) show that first difference of Turkey's 5 year CDS, Turkey Eurobond, ISE 100, Dow Jones and FX Basket variables have no unit root. Therefore the null hypothesis that states that these variables have a unit root has been rejected.

Table 13 Augmented Dickey-Fuller Unit Root Test on ISE_100

Null Hypothesis: ISE_100 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.7705	0.8265
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Table 14 Augmented Dickey-Fuller Unit Root Test on DOW_JONES

Null Hypothesis: DOW_JONES has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.4550	0.5564
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

After the results of Augmented Dickey-Fuller Test, logarithm and 1st difference levels of variables are taken and used for the rest of the analysis. Therefore, growth rate of the variables will be used for all analysis studied on rest of thesis. Equation of growth ratio calculation is as below:

$$Dy = \log(y_t) - \log(y_{t-1}) \qquad (2.3.5)$$

Table 15 Augmented Dickey-Fuller Unit Root Test on FX_BASKET

Null Hypothesis: FX_BASKET has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.1510	0.6974
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Table 16 Augmented Dickey-Fuller Unit Root Test on TURKEY_CDS5Y

Null Hypothesis: D(TURKEY_CDS5Y) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-20.4756	0.0000
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Table 17 Augmented Dickey-Fuller Unit Root Test on EUROBOND

Null Hypothesis: D(EUROBOND) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-39.6155	0.0000
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Table 18 Augmented Dickey-Fuller Unit Root Test on ISE_100

Null Hypothesis: D(ISE_100) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-43.0013	0.0000
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Table 19 Augmented Dickey-Fuller Unit Root Test on DOW_JONES

Null Hypothesis: D(DOW_JONES) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-34.4588	0.0000
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Table 20 Augmented Dickey-Fuller Unit Root Test on FX_BASKET

Null Hypothesis: D(FX_BASKET) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-43.3269	0.0000
Test critical values:	1% level	-3.4336	
	5% level	-2.8629	
	10% level	-2.5675	

*MacKinnon (1996) one-sided p-values.

Descriptive statistics and correlation results of growths ratios are given below:

Table 21 Descriptive Statistics of Growth Ratios of Variables

Proper Name	Number of Observations	Mean	Standard Deviation	Maximum	Minimum
DCDS5Y	1895	-0.0006	0.0362	0.2646	-0.2709
DEurobond	1895	-0.0003	0.0129	0.1558	-0.1124
DISE100	1895	0.0008	0.0217	0.0894	-0.1007
DDow Jones	1895	0.0000	0.0133	0.1051	-0.0820
DFx Basket	1895	0.0002	0.0091	0.0553	-0.0904

Table 22 Correlations among Growth Ratios of Variables

	DCDS5Y	DEurobond	DISE100	DDow Jones	DFx Basket
DCDS5Y	1.0000				
DEurobond	0.6233	1.0000			
DISE100	-0.4928	-0.4088	1.0000		
DDow Jones	-0.3024	-0.2229	0.1032	1.0000	
DFx Basket	0.1108	0.1061	-0.0553	-0.0012	1.0000

Original time series' charts and their stationary series' charts are given in Figure 8.

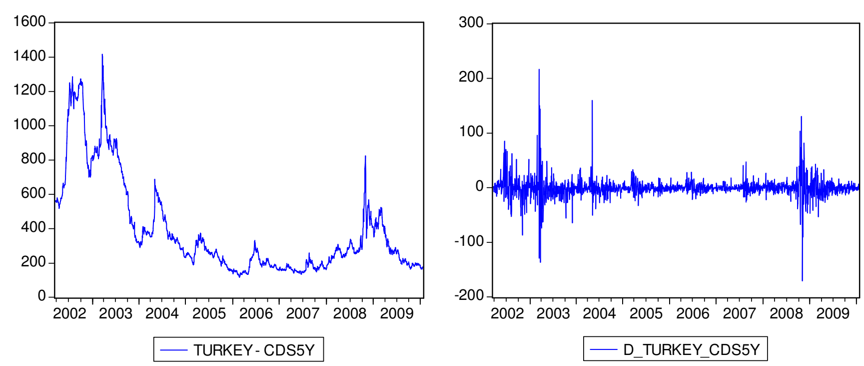


Figure 8 Graphs for non-stationary and stationary time series

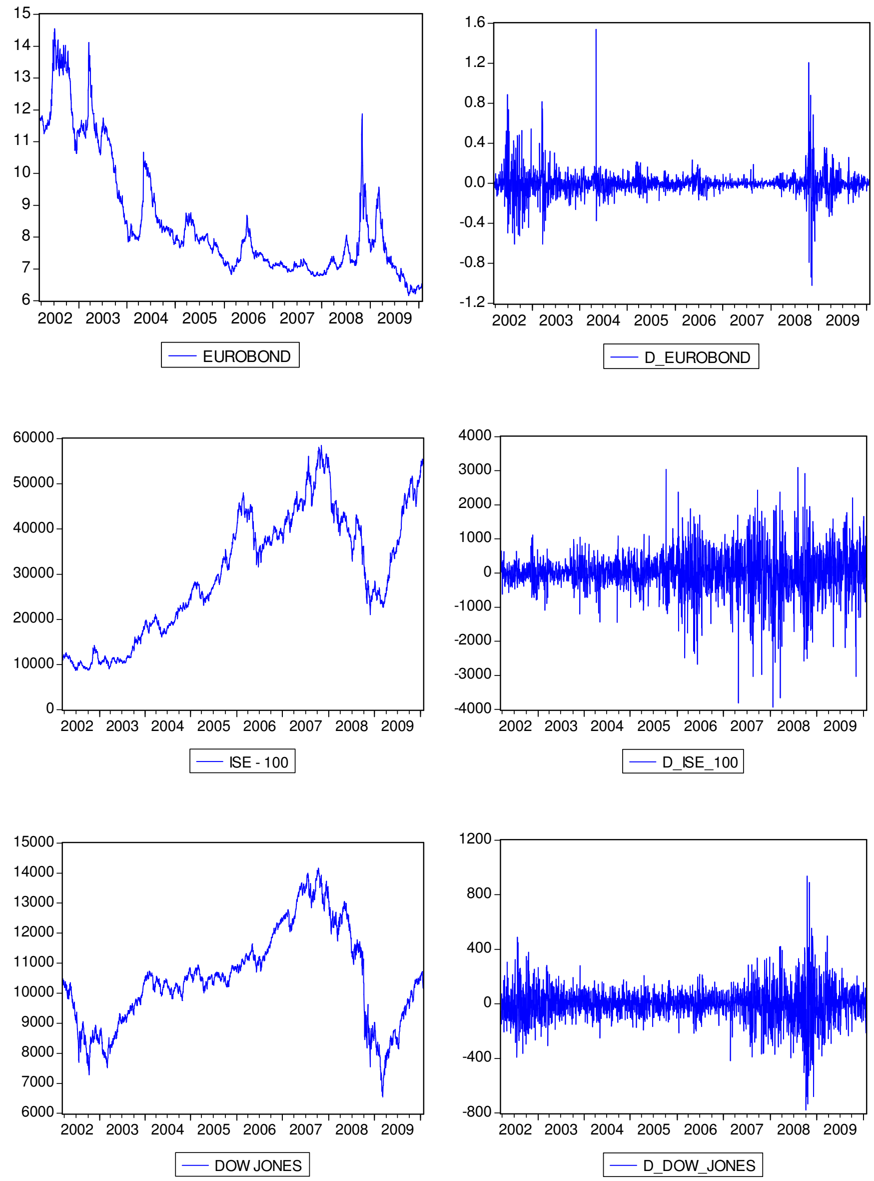


Figure 8 Graphs for non-stationary and stationary time series (continuing)

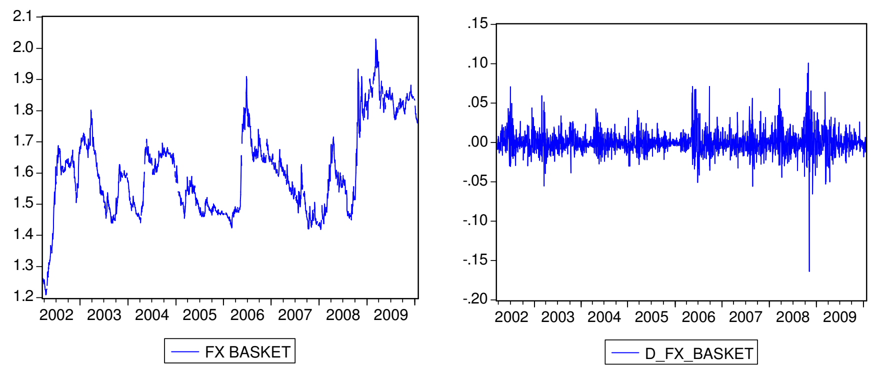


Figure 8 Graphs for non-stationary and stationary time series (continuing)

2.4 REGRESSION ANALYSIS

In order to understand the relationship between CDS spreads and financial indicators that were introduced in previous section, two variable and multivariable regressions will be used.

A scattergram is a visual representation of the relationship among variables. It uses a two dimensional graph where the values of dependent, or *y* variable, are on the vertical axis, and those of the independent, or *x* variable, are on the horizontal axis. The basic property indicated by a scatter gram is whether there is a positive or negative relationship between variables.

In a two variable regression below, equation estimated for several variable pairs that include Turkey 5Y CDS.

$$y = c_1 + c_2.x + \varepsilon \qquad (2.4.1)$$

In two variable models it is assumed that there is a linear relationship between series. There may be a more sophisticated relationship between financial variables but the purpose of this analysis is understanding the basic relationship and whether the relationship is positive or negative. In order to estimate parameters the Ordinary Least Squares (OLS) process is used. OLS process in simple terms minimize sum of square errors (Maravall & Gomez, 2004).

Regression analysis results from Eviews, includes some additional statistical parameters. These parameters are R^2, adjsuted-R^2, standard error of the regression (S.E. of regression), sum-of-squared residuals, log likelihood, Durbin-Watson statistic, mean and standard deviation (S.D.) of the dependent variable, Akaike Information Criterion (AIC), Schwarz Criterion (SC), F-Statistic (Maravall & Gomez, 2004).

An important property of R-squared (R^2) is that it is a nondecreasing function of the number of explanatory variables or regressors present in the model; as the number of regressors increases, R^2 almost invariably increases and never decreases. Stated differently, an additional *x* variable will not decrease R^2. In the two-variable regression, the variability of the dependent variable or total sum of squares (TSS) can be separate into explained sum of squares (ESS) and residual sum of squares (RSS). R^2 could be measured in following equation:

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum \varepsilon_i^2}{\sum y^2_i} \qquad (2.4.2)$$

To further analyze the importance of added variable to a regression, there is a measure known as the adjusted coefficient of determination, or adjusted-R^2. The importance of adjust-R^2 is, R^2, must go up if a variable with any explanatory power is added to the regression. Consequently, a relatively high R^2 may reflect the impact of a large data set of independent variables rather that how well the set explains the dependent variable. Adjusted-R^2 could be indicated in the following expression:

$$adjusted - R^2 = 1 - (1 - R^2) x \frac{n-1}{n-k-1} \qquad (2.4.3)$$

Where the k is the number of independent variables and n is the number of observations, whenever there is more than one independent variable, adjusted-R^2 is less than or equal to R^2 (Maravall & Gomez, 2004).

The standard error of the regression is a summary measure based on the estimated variance of the residuals. The standard error of the regression is computed as:

$$s = \sqrt{\frac{\varepsilon'\varepsilon}{(T-k)}} \tag{2.4.4}$$

The sum-of-squared residuals can be used in a variety of statistical calculations, and is presented separately:

$$\varepsilon'\varepsilon = \sum_{t=1}^{T} (y_i - x_i'.b)^2 \tag{2.4.5}$$

Eviews reports the value of the log likelihood function (assuming normally distributed errors) evaluated at the estimated values of the coefficients. Likelihood ratio tests may be conducted by looking at the difference between the log likelihood values of the restricted and unrestricted versions of an equation. Results from Eviews do not ignore constant terms. The log likelihood is computed as:

$$l = -\frac{T}{2}[1 + \log(2\pi) + \log(\varepsilon'\varepsilon / T)] \tag{2.4.6}$$

The Durbin-Watson (DW) statistic measures the serial correlation in the residuals. The statistic is computed as:

$$DW = \sum_{t=2}^{T} (\varepsilon_t - \varepsilon_{t-1})^2 / \sum_{t=1}^{T} \varepsilon_t^{\,2} \tag{2.4.7}$$

As a rule of thumb, if the DW is less than 2, there is evidence of positive serial correlation. The DW statistic in our output is very close to one, indicating the presence of serial correlation in the residuals (Maravall & Gomez, 2004).

The mean and standard deviation of y are computed using the standard formula:

$$\bar{y} = \sum_{t=1}^{T} y_t \;/T \quad ; \quad s_y = \sqrt{\sum_{t=1}^{T} (y_t - \bar{y})^2 /(T-1)} \qquad (2.4.8)$$

The Akaike Information Criterion (AIC) is often used in model selection for non-nested alternatives smaller values of the AIC are preferred. For example, the length of a lag distribution can be chosen by choosing the specification with the lowest value of the AIC. AIC is computed as:

$$AIC = -2l/T + 2k/T \qquad (2.4.9)$$

The Schwarz Criterion (SC) is an alternative to the AIC that imposes a larger penalty for additional coefficients:

$$SC = -2l/T + (k \log T)/T \qquad (2.4.10)$$

The F-statistic reported in the regression output is from a test of the hypothesis that all of the slope coefficients (excluding the constant, or intercept) in a regression are zero. For ordinary least squares models, the F-statistic is computed as:

$$F = \frac{R^2/(k-1)}{(1-R^2)/(T-k)} \qquad (2.4.11)$$

Under the null hypothesis with normally distributed errors, this statistic has an F-distribution with $k-1$ numerator degrees of freedom and $T-k$ denominator degrees of freedom. The p-value given just below the F-statistic, denoted probability (F-statistic), is the marginal significance level of the F-test. If the p-value is less than the significance level you are testing, say 0.05, you reject the null hypothesis that all slope coefficients are equal to zero. For the example above, the p-value is essentially zero, so the null hypothesis could be rejected that all of the regression coefficients are zero. F-test is a joint test so that even if all the t-statistics are insignificant, the F-statistic can be highly significant.

Wald test used to test the joint significance of coefficients. In this study related to the relationship, Wald test examined whether all coefficients are jointly equal to zero. If slope coefficient in regression analysis is not equal to zero, this means there could be a positive or negative relationship between variables.

Table 23 Regression Output Table Turkey CDS 5Y-ISE100

Dependent Variable: DTURKEY_CDS5Y
Method: Least Squares
Sample (adjusted): 3/22/2002 1/22/2010
Included observations: 1895 after adjustments
DTURKEY_CDS5Y=C(1)+C(2)*DISE_100

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.0001	0.0007	0.1200	0.9045
C(2)	-0.8212	0.0333	-24.6418	0.0000

R-squared	0.2429	Mean dependent var	-0.0006
Adjusted R-squared	0.2425	S.D. dependent var	0.0362
S.E. of regression	0.0315	Akaike info criterion	-4.0742
Sum squared resid	1.8829	Schwarz criterion	-4.0683
Log likelihood	3,862.2830	Durbin-Watson stat	1.9777

The regression estimation results show that there is a negative relationship between Turkey CDS 5Y and ISE 100 variables. According to t-statistics and probability values above, calculated coefficient is statistically significant. This result inline with our priori expectation there should be a negative relationship between these variables. If Istanbul Stock Exchange Index is higher, Turkish Credit Default Swap spread should be lower.

The scatter gram indicates that there is a negative relationship between ISE 100 and Turkey CDS 5Y growth variables. One interpretation of the graph could be that as investors start to buy Turkish stocks, therefore this means Turkey CDS spread in another term default probability should be lower.

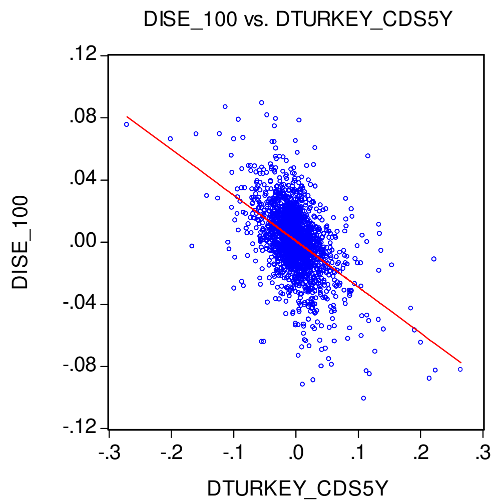


Figure 9 CDS-ISE 100 Scatter

Table 24 Regression Output Table Turkey CDS 5Y-Dow Jones

Dependent Variable: DTURKEY_CDS5Y
Method: Least Squares
Sample (adjusted): 3/22/2002 1/22/2010
Included observations: 1895 after adjustments
DTURKEY_CDS5Y=C(1)+C(2)*DDOW_JONES

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.0006	0.0008	-0.7806	0.4352
C(2)	-0.8233	0.0597	-13.8008	0.0000

R-squared	0.0914	Mean dependent var	-0.0006
Adjusted R-squared	0.0909	S.D. dependent var	0.0362
S.E. of regression	0.0345	Akaike info criterion	-3.8918
Sum squared resid	2.2595	Schwarz criterion	-3.8860
Log likelihood	3,689.5090	Durbin-Watson stat	1.8321

The regression estimation results show that there is a negative relationship between Turkey CDS 5Y and Dow Jones Index. According to t-statistics and probability values above, calculated coefficient is statistically significant. The adjusted R^2 value of 0.0914 means approximately 9 percent of the variation in Turkey CDS 5Y is explained by variation in Dow Jones Index. Since adjusted R^2 at most can be 1, the regression line of these two parameters, which is shown in Figure 10, does not fit our data extremely well; as could be seen from that figure the actual data points are not very tightly clustered around the estimated regression line. But coefficient that is significantly different from zero gives a signal about the relationship which is the main purpose of this study.

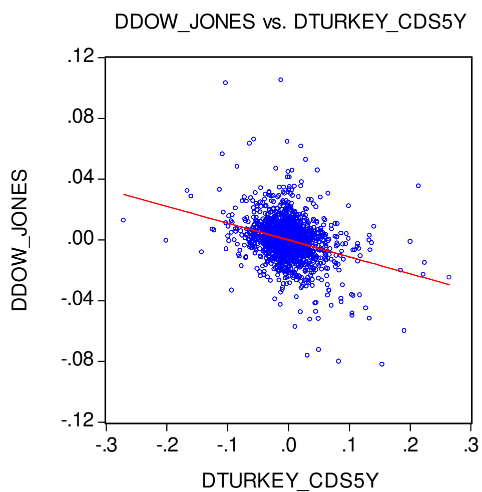


Figure 10 CDS-Dow Jones Scatter

The regression estimation results show that there is a positive relationship between Turkey CDS 5Y and FX basket variables. According to t-statistics and probability values above, calculated coefficient is statistically significant. The adjusted R^2 value of 0.0117 means that only 1 percent of the variation in Turkey CDS 5Y is explained by variation in Fx Basket. This might seem a rather low value, but typically one obtains low R^2 values, possible because of the diversity of the units in data.

Table 25 Regression Output Table Turkey CDS 5Y-Fx Basket

Dependent Variable: DTURKEY_CDS5Y
Method: Least Squares
Sample (adjusted): 3/22/2002 1/22/2010
Included observations: 1895 after adjustments
DTURKEY_CDS5Y=C(1)+C(2)*DFX_BASKET

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.0007	0.0008	-0.8279	0.4078
C(2)	0.4402	0.0908	4.8484	0.0000

R-squared	0.0123	Mean dependent var	-0.0006
Adjusted R-squared	0.0117	S.D. dependent var	0.0362
S.E. of regression	0.0360	Akaike info criterion	-3.8083
Sum squared resid	2.4564	Schwarz criterion	-3.8024
Log likelihood	3,610.3680	Durbin-Watson stat	1.8127

This shows, heteroscedasticity should be studied on.

In Figure 11 there is a slightly increasing regression line which is inline with regression positive coefficient result.

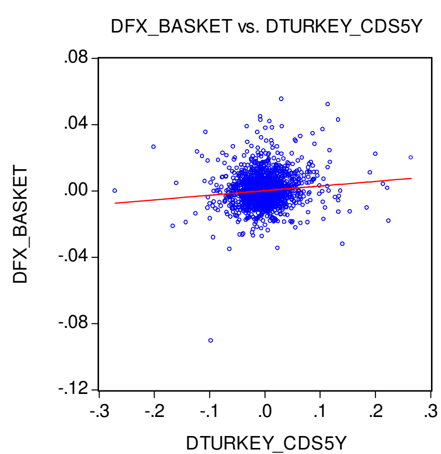


Figure 11 CDS-Fx Basket Scatter

Table 26 Regression Output Table Turkey CDS 5Y-Eurobond

Dependent Variable: DTURKEY_CDS5Y
Method: Least Squares
Sample (adjusted): 3/22/2002 1/22/2010
Included observations: 1895 after adjustments
DTURKEY_CDS5Y=C(1)+C(2)*DEUROBOND

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.0001	0.0007	-0.0987	0.9214
C(2)	1.7573	0.0507	34.6837	0.0000

R-squared	0.3886	Mean dependent var	-0.0006
Adjusted R-squared	0.3882	S.D. dependent var	0.0362
S.E. of regression	0.0283	Akaike info criterion	-4.2879
Sum squared resid	1.5206	Schwarz criterion	-4.2820
Log likelihood	4,064.7830	Durbin-Watson stat	2.1367

The regression estimation results show that there is a positive relationship between Turkey CDS 5Y and Eurobond. According to t-statistics and probability values above, calculated coefficient is statistically significant. The adjusted R^2 value of 0.3882 means approximately 39 percent of the variation in Turkey CDS 5Y is explained by variation in Eurobond. This result inline with priori expectation that says there should be positive relationship between these variables. If Eurobond yield is higher, Turkish Credit Default Swap spread should be higher also.

Figure 12 indicates that there is a positive relationship between Eurobond and Turkey CDS 5Y growth variables. Another interpretation of the graph could be that as investors start to buy Turkish Eurobonds, Eurobond's price will increase and yield will decrease, therefore Turkey CDS spread should be lower. Investors will have more incentive to buy Turkish Eurobond with lower default probability which directly related to lower CDS spreads.

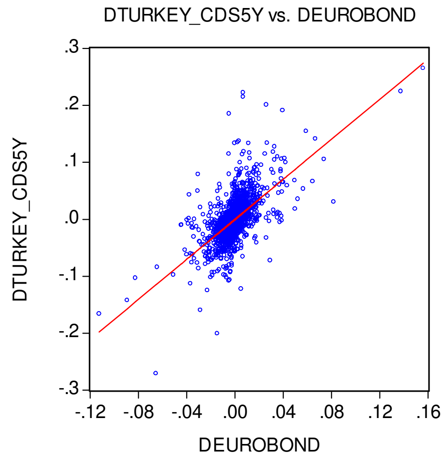


Figure 12 CDS-Eurobond Scatter

Table 27 Multivariate Regression Output Table

Dependent Variable: DTURKEY_CDS5Y
Method: Least Squares
Sample (adjusted): 3/22/2002 1/22/2010
Included observations: 1895 after adjustments
DTURKEY_CDS5Y=C(1)+C(2)*DEUROBOND+C(3)*DFX_BASKET
+C(4)*DISE_100+C(5)*DDOW_JONES

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.0002	0.0006	0.2612	0.7939
C(2)	1.3115	0.0522	25.1050	0.0000
C(3)	0.1812	0.0660	2.7459	0.0061
C(4)	-0.4709	0.0301	-15.6301	0.0000
C(5)	-0.4614	0.0461	-10.0086	0.0000

R-squared	0.4855	Mean dependent var	-0.0006
Adjusted R-squared	0.4845	S.D. dependent var	0.0362
S.E. of regression	0.0260	Akaike info criterion	-4.4574
Sum squared resid	1.2794	Schwarz criterion	-4.4428
Log likelihood	4228.4180	Durbin-Watson stat	2.2809

The regression estimation results show that multivariate regression has the biggest adjusted R-squared and Log likelihood measures. This shows additional parameters increased variables power to explain CDS spreads.

Above equation tells us that holding other variables constant, increasing the Eurobond growth rate by 1 point, CDS spread growth by increase 1.31 point. Also, holding other variables constant, increasing the DISE_100 and Ddow_Jones variables will decrease the CDS 5Y spread growth rate. Multivariate analysis results are inline with single variable regression results in terms of coefficients. Based on output table it is clear that Eurobond and Fx Basket have positive relationship with Turkey CDS 5Y. But ISE 100 and Dow_Jones variables have negative relationship. According to t-statistics and probability values in Table 27, calculated coefficients are statistically significant.

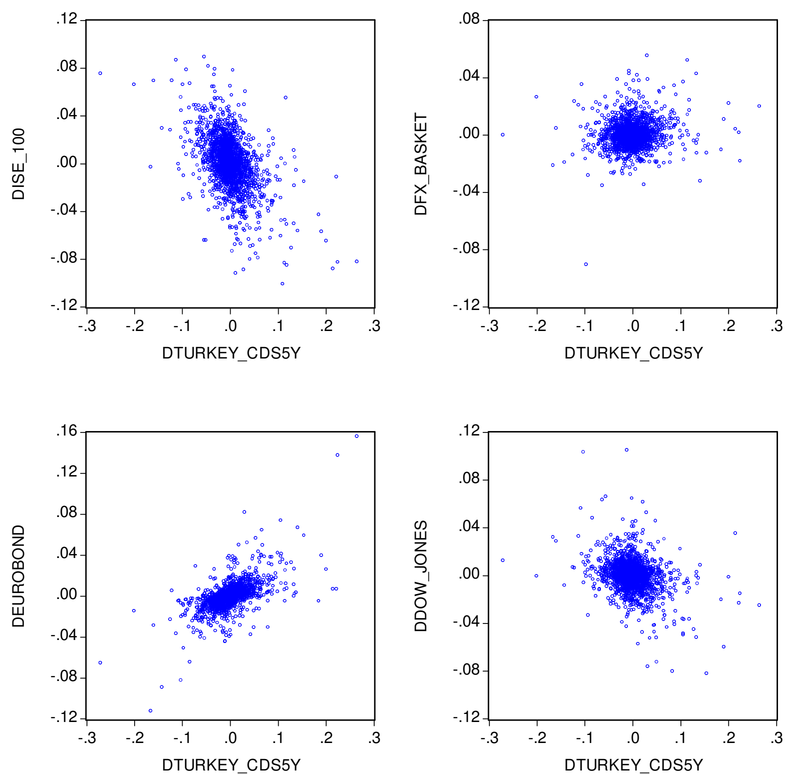


Figure 13 CDS against All Scatter

Table 28 Wald Test

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	446.3994	(4, 1891)	0.0000
Chi-square	1,785.5980	4.0000	0.0000

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	1.3113	0.0522
C(2)	0.1816	0.0659
C(3)	-0.4707	0.0301
C(4)	-0.4615	0.0461

Restrictions are linear in coefficients.

The low probability values indicate that the null hypothesis that C(1)=0, C(2)=0, C(3)=0, C(4)=0 is strongly rejected. Therefore, there is a relationship between Turkey CDS 5Y and financial indicators analyzed.

2.5 GRANGER CAUSALITY TESTS

To simplify the analysis assume there are two time series of interest, which are denoted y_t and x_t. The central idea is that y_t is not Granger caused by x_t if the optimal predictor of y_t does not use information from x_t. In applications of this idea the predictor is usually restricted to be an optimal linear predictor and optimality is defined as minimizing the mean squared error of the h-step predictor of y_t. To be specific suppose y_t and x_t have a vector autoregressive (VAR) representation in which y_t depends upon lags of itself and lags of x_t and symmetrically x_t depends upon lags of itself and lags of y_t (Patterson, 2000). If y_t is weakly exogenous for α and, in addition, x_t does not Granger cause y_t, then y_t is said to be strongly exogenous for α. Granger causality or non causality is concerned with whether lagged values of y_t do or do not improve on the explanation of y_t obtainable from only lagged values of x_t itself (Granger, 1969). A simple test is to regress y_t on lagged values of itself and lagged values of x_t (2.5.1). If the latter are jointly insignificant, x_t is said not to Granger cause y_t. If one or more lagged x_t values are significant then x_t are said to Granger cause y_t (2.5.2). The test, however, is often very sensitive to the number of lags included in the specification. Changing lag length can result in changed conclusions. If strong exogeneity holds, β may be estimated from the conditional distribution alone and used to make forecasts of x_t conditional on forecasts of y_t, the latter in turn being derived from the past history of y_t alone (Johnston & Dinardo, 1997).

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + \beta_1 x_{t-1} + ... + \beta_p x_{t-p} + \varepsilon_{1t} \qquad (2.5.1)$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + ... + \alpha_p x_{t-p} + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} + \varepsilon_{2t} \qquad (2.5.2)$$

Before Grange Causality analysis, the number of lagged terms to be introduced in the causality tests is an important practical question (Hamilton, 1994). The result of proper number of lags is as follow.

FPE and AIC give lag 3 as compatible number of lags. On the other hand, HQ gives lag 2 and SC gives lag 1. Since AIC was chosen in stationary tests before, lag length criteria will also be chosen for analysis. For this model lag length will be 3. The results are as follows: the null hypothesis in each case is that the variable under consideration does not “Granger cause” the other variable.

Table 29 Determining Compatible Number of Lags

VAR Lag Order Selection Criteria
Endogenous variables: DTURKEY_CDS5Y DDOW_JONES DEUROBOND DFX_BASKET DISE_100
Exogenous variables: C
Sample: 3/21/2002 1/22/2010
Included observations: 1883

Lag	LogL	FPE	AIC	SC	HQ
0	26121.91	6.17E-19	-27.73968	-27.72497	-27.73426
1	26971.06	2.57E-19	-28.61503	-28.52676*	-28.58252
2	27052.01	2.42E-19	-28.67446	-28.51263	-28.61486*
3	27091.75	2.39E-19*	-28.69012*	-28.45472	-28.60342
4	27108.55	2.41E-19	-28.68141	-28.37246	-28.56762
5	27125.64	2.43E-19	-28.67301	-28.29049	-28.53213
6	27150.00	2.43E-19	-28.67233	-28.21625	-28.50435
7	27177.41	2.42E-19	-28.67489	-28.14525	-28.47982
8	27204.27	2.42E-19	-28.67686	-28.07366	-28.45471
9	27227.18	2.42E-19	-28.67464	-27.99788	-28.42539
10	27255.85	2.41E-19	-28.67855	-27.92822	-28.40220
11	27279.63	2.42E-19	-28.67724	-27.85336	-28.37381
12	27309.92	2.40E-19	-28.68287	-27.78542	-28.35234

* indicates lag order selected by the criterion
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 30 Pairwise Granger Causality Tests

Sample: 3/21/2002 1/22/2010
Lags: 3

Null Hypothesis:	Obs	F-Statistic	Probability	
DDOW_JONES does not Granger Cause DTURKEY_CDS5Y	1892	37.9425	0.0000	
DTURKEY_CDS5Y does not Granger Cause DDOW_JONES		0.4855	0.6924	*
DEUROBOND does not Granger Cause DTURKEY_CDS5Y	1892	6.7170	0.0002	*
DTURKEY_CDS5Y does not Granger Cause DEUROBOND		27.6658	0.0000	
DFX_BASKET does not Granger Cause DTURKEY_CDS5Y	1892	6.6795	0.0002	*
DTURKEY_CDS5Y does not Granger Cause DFX_BASKET		349.9370	0.0000	
DISE_100 does not Granger Cause DTURKEY_CDS5Y	1892	0.9671	0.4073	*
DTURKEY_CDS5Y does not Granger Cause DISE_100		48.1654	0.0000	
DEUROBOND does not Granger Cause DDOW_JONES	1892	0.3676	0.7764	*
DDOW_JONES does not Granger Cause DEUROBOND		38.4952	0.0000	
DFX_BASKET does not Granger Cause DDOW_JONES	1892	1.5277	0.2054	*
DDOW_JONES does not Granger Cause DFX_BASKET		109.6460	0.0000	
DISE_100 does not Granger Cause DDOW_JONES	1892	0.6844	0.5615	*
DDOW_JONES does not Granger Cause DISE_100		112.0220	0.0000	
DFX_BASKET does not Granger Cause DEUROBOND	1892	7.6029	0.0000	
DEUROBOND does not Granger Cause DFX_BASKET		187.1940	0.0000	
DISE_100 does not Granger Cause DEUROBOND	1892	2.0009	0.1119	*
DEUROBOND does not Granger Cause DISE_100		21.5551	0.0000	
DISE_100 does not Granger Cause DFX_BASKET	1892	352.3070	0.0000	
DFX_BASKET does not Granger Cause DISE_100		0.2211	0.8818	*

The hypothesis that "DCDS 5Y does not Granger Cause DDow Jones" cannot be rejected with 0.6924 probability, but the hypothesis that "DDow Jones does not Granger Cause DCDS 5Y" can be rejected with almost zero probability. Therefore, it appears that Granger causality runs one-way from DDow Jones to DCDS 5Y and not the other way, since the F value (0.4855) is statistically insignificant.

The Granger Causality test results between DEurobond - DCDS 5Y and DFx Basket - DCDS 5Y show with almost zero probability, some different analysis should have done for making comment on their relationship.

Results for DISE 100 and DCDS 5Y suggest that the direction of causality is from DCDS 5Y to DISE 100 and null hypothesis that "DISE 100 does not Granger Cause DCDS 5Y" cannot be rejected with 0.4073 probability, the hypothesis that “DCDS 5Y does not Granger Cause DISE 100” can be rejected with almost zero probability.

The hypothesis that “DEurobond does not Granger Cause DDow Jones” cannot be rejected with 0.7764 probability, but the hypothesis that “DDow Jones does not Granger Cause DEurobond” can be rejected with almost zero probability. It shows that Granger causality runs from DDow Jones to DEurobond and not the other way.

Results for DFx Basket and DDow Jones indicate that the direction of causality is from DDow Jones to DFx Basket and null hypothesis that “DFx Basket does not Granger Cause DDow Jones” cannot be rejected with 0.2054 probability, the hypothesis that “DDow Jones does not Granger Cause DFx Basket” can be rejected with almost zero probability.

The hypothesis that “DISE 100 does not Granger Cause DDow Jones” cannot be rejected with 0.5615 probability, but the hypothesis that “DDow Jones does not Granger Cause DISE 100” can be rejected with almost zero probability. It shows that Granger causality runs from DDow Jones to DISE 100 and not the other way.

The Granger Causality test results between DEurobond - DFx Basket show with almost zero probability, some different analysis should have done for making comment on their relationship. But this is not purpose of this study.

Results for DISE 100 and DEurobond suggest that the direction of causality is from DEurobond to DISE 100 and null hypothesis that “DISE 100 does not Granger Cause DEurobond” cannot be rejected with 0.1119 probability, the hypothesis that “DEurobond does not Granger Cause DISE 100” can be rejected with almost zero probability.

The hypothesis that “DISE 100 does not Granger Cause DFx Basket” can be rejected with almost zero probability, but the hypothesis that “DFx Basket does not Granger Cause DISE 100” cannot be rejected with 0.8818 probability. It shows that Granger causality runs from DISE 100 to DFx Basket and not the other way.

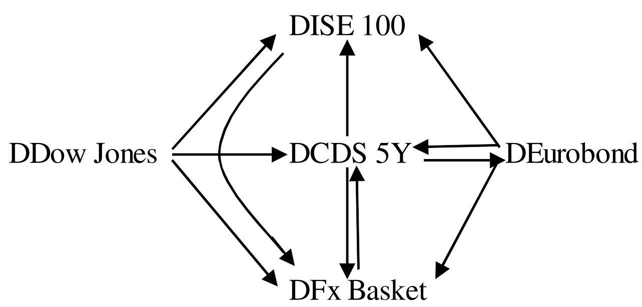


Figure 14 Way of Interactions

Regarding Granger causality test results, way of interactions can be seen in Figure 14 above. Dow Jones and variables as Eurobond and CDS (that mostly traded in international markets) have significant effects on domestic variables as basket currency spreads and stock exchange spreads. And also Dow Jones and Eurobond have some effects on CDS, which is the main purpose of this study.

2.6 VECTOR AUTOREGRESSION (VAR) MODEL

The vector autoregression (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system.

The mathematical representation of a VAR is:

$$y_t = \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + \beta x_t + \varepsilon_t \tag{2.6.1}$$

where y_t is a k vector of endogenous variables, x_t is a d vector of exogenous variables, $\alpha_1,...,\alpha_p$ and β are matrices of coefficients to be estimated, and ε_t is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

VAR estimation results with 3 lags can be seen in Table 31. Table shows impacts of lagged variables on the others.

As we can see in the first column, statistically significant T-statistics of DEurobond(-1) with 4.1251, DDow_Jones(-1) with -9.8481 and DFX_Basket(-2) with 3.6893 allow us to talk about the existence of impacts on DCDS5Y. R-squared of these variables shows that only 0.1011 of changes in DCDS5Y could be explained by these lagged values of indicators. But in our multi variable regression model (Table 27) variables represent same time period (not lagged values), R-squared was 0.4855, comparatively high. Therefore, VAR model and regression model have different implications. In order to explain relationship among variables both models have contribution. VAR model is more useful to make strategic forecasts by using lagged variables.

Table 31 Vector Autoregression Estimates

Sample (adjusted): 3/27/2002 1/22/2010

Included observations: 1892 after adjustments

		DCDS5Y	DEUROBOND	DDOW_JONES	DISE_100	DFX_BASKET
DCDS5Y(-1)	Coefficients	0.0237	0.0741	-0.0289	-0.1063	0.0787
	Standard errors	0.0313	0.0110	0.0120	0.0179	0.0060
	t-statistics	0.7577	6.7157	-2.4157	-5.9572	13.1727
DCDS5Y(-2)	Coefficients	0.0105	0.0254	-0.0111	0.0031	0.0212
	Standard errors	0.0333	0.0117	0.0127	0.0190	0.0064
	t-statistics	0.3159	2.1656	-0.8710	0.1629	3.3370
DCDS5Y(-3)	Coefficients	-0.0140	0.0188	-0.0191	0.0005	-0.0069
	Standard errors	0.0329	0.0116	0.0126	0.0188	0.0063
	t-statistics	-0.4271	1.6223	-1.5174	0.0283	-1.1012
DEUROBOND(-1)	Coefficients	0.3379	-0.0671	0.0501	-0.0831	0.0547
	Standard errors	0.0819	0.0289	0.0313	0.0467	0.0156
	t-statistics	4.1251	-2.3200	1.6008	-1.7771	3.4938
DEUROBOND(-2)	Coefficients	0.0893	-0.0888	0.0105	-0.0726	0.0350
	Standard errors	0.0829	0.0292	0.0317	0.0473	0.0158
	t-statistics	1.0775	-3.0367	0.3320	-1.5348	2.2143
DEUROBOND(-3)	Coefficients	0.0796	-0.0222	0.0268	0.0105	-0.0300
	Standard errors	0.0823	0.0290	0.0314	0.0469	0.0157
	t-statistics	0.9672	-0.7651	0.8532	0.2237	-1.9126
DDOW_JONES(-1)	Coefficients	-0.6355	-0.1867	-0.1082	0.5352	0.0090
	Standard errors	0.0645	0.0228	0.0247	0.0368	0.0123
	t-statistics	-9.8481	-8.2022	-4.3884	14.5390	0.7282
DDOW_JONES(-2)	Coefficients	0.0994	0.0365	-0.0714	-0.1232	-0.0495
	Standard errors	0.0694	0.0245	0.0265	0.0396	0.0132
	t-statistics	1.4334	1.4921	-2.6947	-3.1150	-3.7342
DDOW_JONES(-3)	Coefficients	-0.0626	0.0902	0.0385	0.0475	0.0325
	Standard errors	0.0686	0.0242	0.0262	0.0392	0.0131
	t-statistics	-0.9114	3.7244	1.4683	1.2121	2.4792
DISE_100(-1)	Coefficients	0.0135	0.0074	-0.0274	-0.0895	-0.1498
	Standard errors	0.0455	0.0161	0.0174	0.0260	0.0087
	t-statistics	0.2958	0.4633	-1.5746	-3.4461	-17.2431
DISE_100(-2)	Coefficients	0.0266	-0.0268	-0.0084	0.0407	0.0018
	Standard errors	0.0487	0.0172	0.0186	0.0278	0.0093
	t-statistics	0.5465	-1.5631	-0.4501	1.4667	0.1946
DISE_100(-3)	Coefficients	0.0574	0.0307	-0.0267	-0.0412	0.0053
	Standard errors	0.0473	0.0167	0.0181	0.0270	0.0090
	t-statistics	1.2137	1.8366	-1.4785	-1.5244	0.5865
DFX_BASKET(-1)	Coefficients	-0.0476	0.0126	0.0051	0.1017	-0.0906
	Standard errors	0.1209	0.0427	0.0462	0.0690	0.0231
	t-statistics	-0.3937	0.2962	0.1098	1.4745	-3.9237
DFX_BASKET(-2)	Coefficients	0.4415	0.1619	-0.0221	0.0461	-0.0051
	Standard errors	0.1197	0.0422	0.0458	0.0683	0.0229
	t-statistics	3.6893	3.8346	-0.4832	0.6745	-0.2243
DFX_BASKET(-3)	Coefficients	-0.1825	-0.0884	0.0790	0.0347	0.0155
	Standard errors	0.0894	0.0315	0.0342	0.0510	0.0171
	t-statistics	-2.0426	-2.8055	2.3144	0.6812	0.9077
C	Coefficients	-0.0006	-0.0003	0.0000	0.0007	0.0004
	Standard errors	0.0008	0.0003	0.0003	0.0005	0.0002
	t-statistics	-0.6943	-1.1217	0.0768	1.6220	2.5477

Table 31 Vector Autoregression Estimates (continuing)

R-squared	0.1011	0.1107	0.0255	0.1848	0.4820
Adj. R-squared	0.0939	0.1035	0.0177	0.1783	0.4778
Sum sq. resids	2.2354	0.2783	0.3266	0.7275	0.0815
S.E. equation	0.0345	0.0122	0.0132	0.0197	0.0066
F-statistic	14.0691	15.5611	3.2753	28.3497	116.3549
Log likelihood	3692.3350	5663.4050	5511.8880	4754.2530	6824.9250
Akaike AIC	-3.8862	-5.9698	-5.8096	-5.0087	-7.1976
Schwarz SC	-3.8393	-5.9229	-5.7627	-4.9618	-7.1507
Mean dependent	-0.0006	-0.0003	0.0000	0.0008	0.0002
S.D. dependent	0.0363	0.0129	0.0133	0.0217	0.0091
Determinant resid covariance (dof adj.)		2.27E-19			
Determinant resid covariance		2.18E-19			
Log likelihood		27228.2			
Akaike information criterion		-28.69788			
Schwarz criterion		-28.4634			

In the second column, majority of lagged value T-statistics are significant and 0.1107 of changes in DEurobond could be explained by these values.

In the third column, majority of lagged value T-statistics are statistically insignificant and 0.0255 of changes in DDow_Jones could be explained by these values, which make sense. Since these are local indicators, it is not expected to be able to explain changes by these variables. Similar to previous comments with some statistically insignificant T-statistics 0.1848 of changes in DISE_100 and 0.4820 of changes in DFX_BASKET could be explained by other lagged values.

3. CONCLUSION

Credit risk is one of the most important risks in financial markets and risk management. Risk management is important for reducing credit risk and managing current position. The economic crisis of 2001 in Turkey has demonstrated that management of credit risk by using traditional ways has failed during crises because there were several shortcomings inherent to traditional methods. They were calling only on a strong guarantee, verifying credit portfolio and making provision as a precaution. Therefore, a better risk management strategy requires credit derivatives such as Credit Default Swaps (CDS) in addition to ways mentioned previously.

CDS is the most common type of financial derivatives. It is like an insurance for the buyer, it provides the privilege to sell a particular bond at its notional value when a credit event occurs. This gives the advantage of transferring credit risk from one side to another, and it removes the risk concentration. Moreover, CDS provides liquidity for illiquid assets. In emerging markets, CDS spreads are important indicatives to determine the price of bonds and T-bills. In recent years, CDS spreads has become benchmark rates for defining credit risk for a particular company or a country.

In this thesis, it is examined that whether there is a relationship between CDS and other financial variables such as Eurobond, Dow Jones, ISE–100 and Fx (TRY against Euro and Dollar) rates as 50 percent basket of EUR and USD. In the quantitative part, the dynamic relationship between Turkish CDSs and financial indicators has been analyzed by using different statistical tools. Regression analysis and correlation coefficient results have shown that a separate relationship exists between CDS and each variable. Granger Causality Test results have provides us with additional information about these relationships. It is concluded that, the CDS data of Turkey are strictly related to underlying Turkish government bonds as expected. In addition, our study has supported a negative correlation between domestic market variables (ISE–100) and foreign ones (Dow Jones). Also a low positive correlation has been found with Fx currency rate, which is actually a surprising result for us. VAR model results show one lagged Eurobond, Dow Jones and Fx basket variables are statistically significant and R-squared of these variables is less than multivariable regression results.

As a result, this study has shown that CDS spreads has a significant relationship with other financial variables such as Eurobond, Dow Jones, ISE–100 and VAR model is more useful to make strategic forecasts by using lagged variables.

References

Alexander, C. & Kaeck, A. 2008, ‘Regime dependent determinants of credit default swap spreads’, *Journal of Banking and Finance,* vol. 32., pp. 1008-1021.

Blanco, R., Brennan, S. & Marsh, I. 2004, ‘An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps’, *Banco de Espana Working paper*, no.0401, pp.11-40.

Bystrom, H. 2005, ‘Credit default swaps and equity prices: The iTraxx CDS index market’, *Lund University Department of Economics Working Paper*, pp.1-10.

Chan L. , Jorge A. & Kim, Y.S. 2004, ‘Equity prices, credit default swaps, and bond spreads in emerging markets’, *International Monetary Fund Working Paper,*no.27, pp.4-19.

Chaplin, G. 2005, *Credit Derivaties, Risk Management, Trading and Investing*, John Wiley and Sons,Ltd, West Sussex.

Davidson, R. & Mackinnon, J. 1993, *Estimation and Inference in Econometrics*, Oxford University Press, New York.

Engle, R.F. & Granger, C.W.J. 1987, ‘Co-integration and error correction: Representation, estimation and testing’, *Econometrica,* vol. 55, no.2, pp.251-276.

Ersan, İ. & Günay, S. 2009, ‘Kredi riski göstergesi olarak kredi temerrüt swapları (CDSs) ve kapatma davasının Türkiye Riski üzerine etkisine dair bir uygulama’, *Bankacılar*, no.71, pp.3-22.

Fabozzi, F.J. 2001, *Handbook of Fixed Income Securities*, 6th Edition, McGraw-Hill Publishers, New York.

Fabozzi, F.J. 2004, *Credit Derivatives Instruments Applicaions and Pricing*, John Wiley and Sons, Ltd, New Jersey.

Granger C. 1969, 'Investing Casual Relations by Econometrics Methods and Cross Spectral Methods', *Econometrica,* Econometric Society, vol.37 no.3, pp.424-438.

Haibin, Z. 2004. 'An empirical comparison of credit spreads between the bond market and the credit default swap market', *Bank for International Settlements Working Papers,* no.160, pp.2-36.

Hamilton, J.D. 1994, *Time Series Analysis*, Princeton University Press, Princeton, NJ, Chapter 20.

Hayashi, F. 2000, *Econometrics*, Princeton University Press, Princeton, NJ, Chapter 9.

Houweling, P., & Vorst, T. 2002, 'An empirical comparison of default swap pricing models', *Erasmus University Working Paper*, no. ERS-2002-23-F&A, pp.1-55.

Hull, J.C. & White, A. 2000, 'Valuing credit default swaps I: No counterparty default risk', *Journal of Derivatives,* vol.8, no.1, pp. 29-40.

Hull, J.C. & White, A. 2001, 'Valuing credit default swaps II: Modeling default correlations', *Journal of Derivatives,* vol.8, no.3 Spring, pp.5-22.

Hull, J.C. 2004, Options, *Futures and Other Derivatives*, Parentice Hall, New Jersey.

Hull, J.C., Predescu, M. & White, A. 2004, 'The relationship between credit default swap spreads, bond yields, and credit rating announcements', *Journal of Banking and Finance,* vol. 28, pp. 2789-2811.

Johnston, J. & Dinardo, J. 1997, *Econometric Methods*, McGraw-Hill 4th edition, New York.

Jorion P. 2003, *Financial Risk Manager Handbook,* 2nd Edition, John Wiley and Sons, Ltd, New Jersey.

Levy, A. 2009, *'Essays on credit default swaps'*, Ph.D. Diss., University of California.

Longstaff, F.A., Mithal, S. & Neis, E. 2003, 'The credit default swap market: Is credit protection priced correctly?', *University of California Los Angeles Working paper*.

Markit Group Limited 2008, 'Markit credit indices', *Working paper, November.*

Maravall, A. & Gomez, V. 2004, *'EViews 5 User's Guide'*, Quantitative Micro Software, LLC.

Mengle, D. 2007, 'Credit derivatives: An overview, economic review', *Federal Reserve Bank of Atlanta Working paper,* fourth quarter 2007.

Neftci, S., Santos, A.O. & Lu, Y. 2004, 'Credit Default Swaps and Financial Crisis Prediction', *City University of New York Working paper*, no.114, pp.1-14.

Patterson, K. 2000, *An Introduction to Applied Econometrics: A Time Series Approach*, Palgrave, United States of America.

Tang, D.Y. & Yan, H. 2007, *'Liquidity and credit default swap spreads'*, *University of Hong Kong Working paper*, pp.2-24.

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