THE EFFECTS OF VIX INDEX VALUES ON RETURNS OF BIST-100 INDEX

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Master Thesis
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AFYON KOCATEPE UNIVERSITY
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MASTER THESIS

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OATH TEXT

I state that the work titled “The Effects Of VIX Index Values On Returns Of BIST-100 Index”, which I submitted as a master thesis, was written by me without any help that would be contrary to scientific moral values and traditions, and that I benefited from them by referring to them and I confirm this with my honor.

17/06/2020

Ali Ahmad AHMADY

DECISION OF THESIS JURY AND APPROVAL OF INSTITUTE DIRECTORATE

JURY MEMBERS

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ÖZET

VİX ENDEKS DEĞERLERİNİN BİST-100 ENDEKSİNİN GETİRİ ÜZERİNDEKİ ETKİLERİ: BİST ÖRNEĞİ

Ali Ahmad AHMADY

AFYON KOCATEPE ÜNİVERSİTESİ
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Bu çalışmanın amacı, VİX endeks değerlerinin BİST 100 endeksinin getirileri üzerindeki etkisini incelemektir. Çalışmada 3 Ocak 2001-31 Ocak 2020 dönemine ait literatüre uygun günlük veriler kullanılmıştır. Her iki endeks için günlük olarak hesaplanan veriler çeşitli kaynaklardan elde edilmiştir. BİST endeksine ilişkin veriler Borsa İstanbul'dan alınırken; VİX endeksinin verilerine Yahoo, Finance ve Bloomberg Terminal veritabanlarından erişilir. ARDL / Sınır Testi yaklaşımı, VİX endeksinin BİST-100 endeksi üzerindeki etkisini araştırmak için metodolojisi olarak kullanılır. Literatürde yaygın olarak kullanılan artırılmış Dickey-Fuller (ADF) ve Phillips Perron (PP) birim kök testleri, serinin birim kök içerip içermediğini belirlemek için yapıldı. ARDL modelinin hata terimlerinin otokorelasyonlu olup olmadığını belirlemek için Breusch-Godfrey LM Testi uygulanır. Değişkenler arası nedensellik ilişkilerinin analizinde, farklı kararlılık düzeylerine sahip serilerin analizine imkan veren Toda-Yamamoto Granger nedensellik testi uygulanmıştır. Sonuçlara göre, VİX endeksi ile BİST-100 endeksi arasında güçlü bir ters ilişki var.

Anahtar Kelimeler: VİX Endeksi, BİST Endeksi, ARDL, ADF/PP Testi, LM Testi.

ABSTRACT

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The aim of this study is to investigate the effects of VIX index values on returns of BIST 100 index. In the study, daily data were used in accordance to the literature for the period between January 3, 2001 and January 31, 2020. Data for both indices calculated on a daily basis were obtained from various sources. While the data for the BIST index were taken from Borsa Istanbul; the data of the VIX index are accessed from Yahoo, Finance and Bloomberg Terminal databases. ARDL/Bound Test approach is used as its methodology to investigate the impact of the VIX index on the BIST-100 index. Augmented Dickey-Fuller (ADF) and Phillips Perron (PP) unit root tests, which are widely used in the literature, were performed to determine whether the series contain unit root. Breusch-Godfrey LM Test is applied to determine whether the error terms of the ARDL model are autocorrelated or not. In the analysis of causality relationships between variables, Toda-Yamamoto Granger causality test, which allows analysis of series with different levels of stability, is applied. According to the results, there is a strong inverse relationship between VIX index and BIST-100 index.

Keywords: VIX Index, BIST Index, ARDL, ADF/PP Test, LM Test.

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LIST OF SYMBOLS AND ABBREVIATIONS

%: Percentage
ADF: Augmented Dickey-Fuller
AIC: Akaika Information Criterion
ARDL: Autoregressive Distribution Lag
BIST: Borsa Istanbul
CBOE: Chicago Board of Option Exchange
DJIA: Dow Jones Industrial Average
ECM: Error Correction Model
ET: Eastern Time
HV: Historical Variables
ISE: Istanbul Stock Exchange
ISO: International Standard Organization
IV: Implied Variables
NASDAQ: North American Stock Exchange
NBER: National Bureau of Economic Research
NBFC: Non-Banking Financial Companies
OCT: Over the Counter
OEX: Options with American-Style Exercise
PP: Phillips- Perron
S&P 500: Standard & Poor 500
VIX: Volatility Index
VXO: Volatility Index/Variable Standard Oscillator

INTRODUCTION

Along with the increasing technological developments, financial liberalization has led to the ease of international capital flows, accelerated the circulation of information, thereby enabling the integration of financial markets in different countries. This situation causes other markets to be affected by the positive or negative developments occurring in any market. Financial liberalization can offer new investment opportunities for investors. However, a crisis or price fluctuation in the financial markets may affect other markets or countries in a short time. This high level of links between markets both encourages and enforces financial practitioners and decision-making mechanisms to investigate these relationships.

In an environment of increasing uncertainty, market traders attach great importance to asset price volatility as an important source of information that affects decisions such as capital allocation, financial protection and portfolio diversification (Emna and Myriam, 2017: 52). On the other hand, the volatility that occurs in one of the integrated financial markets with the increasing globalization phenomenon is followed by many investors as it affects other financial markets simultaneously and can be determinant in investment decisions (İskenderoğlu & Akdağ, 2018: 490). In this context, the VIX (Volatility Index) index is considered as one of the important volatility indicators monitored by the markets.

Calculated by the Chicago Board of Option Exchange (CBOE), the VIX index is an implied volatility index based on the S&P 500 index, derived from the volatility of the 22-day trading options and derived without reference to the restrictive option pricing model (Becker, Clements and McClelland, 2009: 1034). The VIX index, which started to be calculated since 1993, is initially calculated on the basis of the S&P 100 index, and since September 2003, its calculation is on the basis of the S&P 500 index (Korkmaz and Çevik, 2009: 89; Fernandes, Medeiros and Scharth, 2013: 2; Ozair, 2014 : 83). In fact, 28 indices are calculated in six different categories for the measurement of volatility expected by CBOE (CBOE, 2018). However, the VIX index, calculated by taking into account the S&P 500, is an indicator for the prediction of future expected movements of the securities markets (Kaya and Çoşkun, 2015: 176). The VIX index is also called the implied volatility index (Konstantinidi, Skiadopoulos and Tzagkaraki, 2008; Korkmaz & Çevik, 2009; Lee & Ryu, 2013). The VIX index is the most widely used modeless implied volatility (Model-Free Implied Volatility) indicator (Lee and Ryu, 2013: 3; Emna and Myriam, 2017: 53). The aforementioned index is a forecast in the market as opposed to model-based volatility, which are formed by leveling past volatility based on estimates, and has the potential to reflect information that a model-based estimate cannot make (Becker, Clements and McClelland, 2009: 1033). Therefore, VIX is a volatility index obtained directly from the market rather than volatility estimates from models such as ARCH / GARCH.

Although the VIX index is an improved version of the calculation technique included in the Nobel prize-winning works in 1973 by Black and Scholes, the calculations related to the index later became available with the contributions of Merton (1973) (Shaikh and Padhi, 2014: 45; Kula and Baykut , 2017: 28). The increase in the index means that the volatility expectation in the market will increase and the decrease in the index will decrease the volatility expectation in the market. There is a negative relationship between VIX index and stock market index. In general, the VIX index exceeding 30% indicates that investors' perceptions of risk have increased and future expectations have deteriorated, while the index remains below 20%, which indicates that investors' perception of risk has decreased (Kaya, Güngör and Özçomak, 2014: 2).

Again, the VIX index can direct the investment behavior of investors and investor behavior can shape the markets. It can be thought that VIX index may cause changes in market returns in different countries due to the fact that international investments have reached significant amounts (İskenderoğlu & Akdağ, 2018: 489). The VIX index is an important indicator on stock returns on a global scale and provides investor guidance for the future of stock markets (Erdoğdu and Baykut, 2016: 58). Indeed, the VIX index is closely monitored by the central banks of various countries, such as the TCMB (İskenderoğlu & Akdağ, 2018: 490). VIX index reflects the fear in the markets, is important in terms of financial vulnerability and is seen as the pioneer of the crises (Kaya, 2015: 5). At the same time, the index can be used in many asset pricing models as it is generally used as a measure of market risk (Konstantinidi, Skiadopoulos and Tzagkaraki, 2008: 2401).

As can be understood from the explanations above, VIX index can influence stock markets by directing investor behavior. Continuing its activities since 1986, the Istanbul Stock Exchange (ISE) and changing in 2012 with the name of Borsa Istanbul (BIST), general economic and political conditions due to occasional changes and cyclical fluctuations lived though, it has always been an important driving force of Turkey's economy. Sustainable in developing countries such as Turkey and it is essential that the financial markets are working effectively to ensure a healthy economic development. One of the most effective branches of the financial markets is the stock exchanges. In this study, the effects of VIX index values on returns of BIST-100 index are examined. The study uses ARDL bound test to reveal cointegration relationships between variables.

After the introduction part, which constitutes an overview of the study, the literature reviews of VIX as well as BIST-100 indices are included in the first chapter. Then, in the second and third chapter, definitions and types of risk and volatility indices are explained in details. In the fourth chapter, the methodology (ARDL model), the data used in the study and preliminary statistics of these data are explained. The fifth chapter includes, presentation of the empirical findings related to the study and analysis of results.

FIRST CHAPTER

LITERATURE REVIEW

In this part of the thesis study, a comprehensive summary of the previous studies regarding VIX index and BIST-100 index is given. Since VIX index is a broad subject, there exist different papers and scholarly articles each explaining a specific relation and effect of it to stock market, which are reviewed briefly here one by one.

1. LITERATURE REVIEW OF VIX INDEX

Bahadur and Kothari (2016) studied the VIX and its predicting strength by considering a provision of Indian stock market. Authors conducted a study on CNX Nifty 50 index by using data of the daily closing values which consisted of 1656 observations between March 2009 and December 2015. They used AR, ARSD and PODV models in their research methodology. As a result what they could obtain from the study is that in the short term, India VIX has a predictable strength for future stock market volatility. Compared to downward movements of stock market, it has the ability to better predict the upward movements. In addition, for future low price changes, the precision of the predictions stated by India VIX is said to be higher than for higher stock price movements. According to the study the Indian stock markets volatility can be predicted only up to 60 days since the prevalent value of India VIX is influenced by volatility of the past period up to one month and has the ability to predict for next one month's volatility.

Ahoneimi (2008) investigated the VIX indicator’s forecasting and modeling. The author used eighteen years of daily observation as data set, starting from the beginning of 1990 till the end of 2007, excluding public holidays which resulted in a sample of 4537 observation. ARIMA (1,1,1), ARIMAX, AFIRMA and GARCH (1,1) models were used in this study among which AFIRMA model failed to provide an acceptable prediction of accuracy over 50 percent. In order to change in the VIX correctly, more than 58 percent of trading days were projected over an unpredictable period of five years. Results obtained from this investigation show that, more support will be offered to the model choices in simulation of out-of-sample trades with S&P 500 options.

Shaikh and Padhi (2013-2015) examined how equity index returns and implied VIX are related. From the period November 1, 2007 to April 30, 2013, the authors presented an asymmetric and seasonal nature of India VIX. Specifically, many different sub-periods such as individual years, complete sample, and low-volatility trading periods have been included in this study. In its methodology, simple OLS method has been used for its regression model to find out how simultaneous stock index and volatility index are related to each other. As a result, compared to positive returns shocks, changes in India VIX look bigger in the negative return shocks, and for Japan and China volatility index same results have been reported. It has also been said that VIX in spite of being observed at its high level on the market opening, stayed low on the days forward. Finally the results of ending the options show the facts that India VIX is more natural on the day it expires.

Majmudar and Banerjee (2004) investigated forecasting of the VIX. In this paper by using VIX data obtained from Chicago Board Options Exchange (CBOE), the authors aimed to forecast volatility. A total of 3490 data points have been collected for the period January 3, 1990 to October 31, 2003, which divided into two parts as in-sample data consisting of 75 percent of the total sample and out-sample data consisting of 25 percent of the remaining sample.

Among different models such as GARCH, EGARCH, APARCH, GJR and IGARCH used as methodology, the authors preferred EGARCH as best suitable model for this study due to its forecast accuracy. Based on findings it was detected that, in order to make more profit and make accurate predictions of future volatility, a forecaster should trade volatility as any other commodity by considering different options.

Lin and Lee (2010) studied the process of propagation for the S&P 500 index and the VIX. In order to analyze the time-varying correlated jump as well as the discontinuous jump for the changes in the VIX and the S&P 500 returns, by using CBP-GARCH model of Chan (2003), the authors collected daily data starting from January 15, 2001 to December 31, 2009. As part of its methodology, besides CBP-GARCH model, ARMA and BGARCH models have also been used.

Results obtained from the study show that between the changes in the VIX and the S&P 500 returns, evidence of important jump-diffusion process and casual relationships exist. Furthermore, there is no time variation in the relationship between the changes in the VIX and the S&P 500 returns. The study also suggested that while applying the VIX to involve in hedging activities and arbitrage, the investors and institutions must observe the informational impact on option market as well as spot market for sake of arranging the efficient investment strategies.

Zhang and Zhu (2006) investigated the futures of VIX. In order to develop a directly nifty model for pricing the VIX futures, VIX data from January 2, 1990 to March 1, 2005 of historical time series have been utilized in the study. First of all by using the SPX option market data provided from the year 1995 to 1999, Shu and Zhang (2004) estimated the market price of volatility risk. Subsequently on March 1, 2005, VIX futures are priced with various maturities and finally the model prices are compared with market prices.

The results drawn from the study show that all four futures contracts from the whole period have been overpriced by 16 percent for March futures and 44 percent for November futures as estimated by the model with the parameters. It has been found in the model that for the future price, long term mean level of variance is important. In favor of declining the difference between the market price and model price for March futures from 16 percent to 12 percent as well as for the November futures from 44 percent to 2 percent, the authors used the parameters related to the recent one year period. It has also been recommended by the study that in order to guess the volatility structural parameters in the future pricing model of VIX, the most current VIX data should be utilized.

Chow and Jiang (2018) analyzed the theory of whether return volatility is measured by VIX or not. Authors by considering assets of S&P 500 index from January 2005 to May 2014 examined, estimated VIX errors and their correlation with ex-ante returns moments. According to the findings, it has been said that as much as they enlarge the VIX, the downward biases would increase and up to 559 index basis points could be the errors. Generalized VIX (GVIX) which has been extended from Kapadia, Bakshi and Madan (2003), is used as a new method for its methodology to measure ex-ante volatility. Due to no existence of casual assumption on the process of return generating of the basic asset and variance's direct formulation, GVIX said to be generic and for true ex-ante volatility, operates as a proxy. The results of study show that there is a negative relationship between skewness (third return-moment) and estimation errors as well as true volatility as statistically understated by VIX. Finally, for expanding volatility based financial products and ex-ante return volatility estimation, formulation of The VIX needs to be applied carefully.

Bagchi (2012) researched on portfolio returns of India VIX through cross sectional analysis. Market capitalization, market to book value of equity and stock beta are the three significant parameters which have direct and cross-sectional relationship with India VIX in this study. The website of National Stock Exchange of India (NSE) provided daily based data on closing values of constituent companies of India VIX as well as Nifty 50 starting from November 1, 2007 to November 30, 2009. The order of selecting data was to have individual beta from Nifty Index, whereas market to book equity and market capitalization have been taken from individual companies and NSA India for calculation. Multiple regressions based on the three significant factors which are: Markets to book value of equity, stock beta and market capitalization have been used by the author as part of the study's methodology. According to the results taken from the research, there is a positive and important correlation between portfolio returns and India VIX which is in comparison to 30-day duration said to be larger for 45-day holding duration return. Finally, in order to help an investor to learn the mechanism of price discovery better, India VIX is said to be a preferable risk factor.

Jung (2015) analyzed VIX futures' portfolio insurance strategy. In this study by using Constant Proportion (CPPI) and Option Based Portfolio Insurance (OBPI) for VIX futures three portfolio insurance (PI) strategies are created. From Feb. 2007 to Jan. 2015 through historical return simulation of a full sample and eight subsamples, the strategies' effectiveness has been tested. For S&P 500, as a diversification and pure investment tool, the efficiency of each strategy has been evaluated. The results of study show that portfolio strategies (PI) in the subsample simulation completely protect its floor. With trendy and powerful bull markets of VIX futures, CPPI and Protective Put were almost caught up. The portfolio insurance's daily mean returns are said to be greater compared to benchmark's, in the full sample simulation. Furthermore, for S&P 500 index, the PI strategy claimed to be a proper diversification tool as well.

Soydemir, Verma and Wagner (2016) studied the asymmetric effect of the logical and illogical elements of the VIX to the returns of S&P 500 index. From the period November 1995 to November 2015, data are collected on monthly interval basis and in order to track the S&P 500 index options the authors again utilized VIX index, which is presented by Chicago Board Options Exchange (CBOE). As S&P 500 is known to be value-weighted index for its reflection on the returns of big capitalization stocks, it has been used to specify the total functioning of the market. Datastream International is the source through which constantly combined returns for VIX as well as S&P 500 indices are computed.

For its methodology part authors used two different VAR models containing thirteen and three variables respectively. Since Brown and Cliff (2004, 2005) and Lee et al. (2002) argued that investors' expectation as well as returns may act as a system, VAR model is said to be a suitable econometric approach to be used in this study. Furthermore, to gain assurance of bands around the point estimates, by using VAR characteristic, researchers are able to do Monte Carlo methods as well as policy simulations. (Doan, 1988; Genberg et al., 1987; Hamilton, 1994.)

Results obtained from 13-variable VAR model show that fears of investors depend somewhat on risk factors, and this is well-taken by three factor, the Fama and French, and the four-factor Carhart models. Particularly, positively related to momentum and negatively related to the premium between stocks growth and value, it is said that fears of investors are negatively relevant to risk premium of market. Logical and illogical fear can have important negative impacts on market returns.

Cont and Kokholm (2009) researched a stable model for volatility derivatives and index options' pricing. Collected from the period September 22, 2003 to February 27, 2009, closing daily levels of VIX and S&P 500 index shows that along with spikes in volatility there are at the same time big drops in the S&P 500 that is related to the famous "leverage effect".

By using L´evy processes on the underlying asset to price European options, building blocks guide to customizable analytic pricing formulas for efficient numerical methods as well as variance exchange options. In small as well as large volatility moves, to permit various conditional correlations, this model has the ability to easily separate spot and volatility correlations from vanilla skews. The model during strike and payment time has the ability to match the prices on both, VIX options and European options on S&P 500. By meeting the prices of the VIX option as well as coordinating the options' prices on the underlying subsequently, the gradation of the model is said to be accomplished.

Ishida, McAleer and Oya (2011) by using high frequency S&P 500 and VIX, investigated leverage parameter estimation of continuous random oscillation models. The authors suggested using high frequency implicit volatility data at high frequency in constructing momentum conditions based on actions taken, specifically, for stochastic volatility (SV) models of continuous time asset pricing processes, reciprocal moment conditions of the GMM / SMM estimator. Considering stochastic volatility (SV) model of the Hashton square root, to give exact estimates of the leverage parameter under this model, authors suggested the realized leverage as a leverage parameter estimator (r), provided by simulation experiments. By using unconnected daily trading session data through the simulation experiments, authors illustrated the significance of making appropriate adjustments to the instantaneous conditions as assured that the measures taken have been calculated. Except for the Heston SV characteristic, analytical phrases for instantaneous conditions are usually not available; instead using Simulated Methods of Moment (SMM) approach is possible.

Shu & Zhang (2010-2012) studied the relationship between cause and effect in the future market of the VIX. The information productivity and performance of price discovery in the rapidly developing volatility futures market: the Chicago Board of Option Exchange (CBOE) futures market of VIX has been tested in this study. To detect the leading delay dynamics among VIX futures prices and VIX, the authors used co-integration experiment of Engle–Granger along with Error Correction Mechanism (ECM).

Two main findings have been obtained from the experimental results. First says that the closest as well as the second closest VIX futures prices lead the VIX spot index during the full sample duration proving price discovery function to be part of specifications of VIX future markets. For distant future prices of VIX, causality effect couldn't be observed, hence for predicting the futures prices of VIX for next period, ancient VIX futures considered to be practical. Second, given the sampling period and estimation method, the one-way causality of VIX to VIX futures is fickle. Nonlinear Granger recognized by Baek and Brock determines causality between VIX futures prices and VIX to be bi-directional, indicating a simultaneous reaction of both future and spot prices to obtained information. On average, there are no important differences between zero and estimated parameters as shown in step by step researches, hence to verify that VIX future markets are full of information.

Koopman, Jungbacker and Hol (2004) by using measures of realised, historical and implicit volatility studied how to foresee the daily variation of the S&P 100 index. From October 17, 2001 through November 14, 2003, the authors analytically examined the implementation of one step forward anticipation of different models for the stock index of S&P 100. Generalized Autoregressive Conditional Heterogeneity (GARCH) and Stochastic Volatility (SV) models which might be providing volatility estimation and foreseeing are used to model the daily returns. UC-RV and log ARFIMA-RV models give the most precise forecasts. In the volatility equation combined as an explanatory variable, Stochastic Volatility (SV) model is said to be the best among the classes of epochal volatility models. In comparison to daily returns' based models, the results taken from the study show that much more precise volatility forecasts are generated by realized volatility models. The most exact predictions appear to be provided by models of long memory.

Saha, Malkiel and Rinaudo (2019) had an investigation on the manipulation of the VIX index as well as to see if on the expirations days of VIX futures and options were synthetically inflated or deflated VIX levels. The authors analysed two factors in their paper. First, for over the past twenty years, the level of daily VIX closing has been evaluated. From 1998 to 2007, using the 10 year duration data, the authors present a model that incorporates VIX into a set of regressions considered as "in the sample". Afterward the same set of data for the time duration starting from the year 2008 to April 2018 have been used to anticipate the VIX index which is considered as "out of the sample". The results obtained from the study show that by market principles the daily level of the VIX index's movements can be illustrated, not with manipulating. Furthermore, agreement prices of VIX futures as well as VIX's closing values are said to be persistent forces of normal market instead of being artificial as examined in the expiration days of VIX futures.

Basta and Molnar (2018) studied VIX index's long term dynamics along with VXX as its tradable counterpart. The authors used time series for both VIX as well as VXX from the time period starting from 30.01.2009 to 29.07.2016 which was achieved from different internet sources like Finance2 and Yahoo. The auto regression model which can be taken as an extension of the traditional vector and incorporate particular terms of scale were used in this study. Among the characteristics of this model are; on long timescales, the outstanding treatment, illustrating the seen attributes of VIX as well as VXX and finally proving the fact that however on long timescales VXX is leaded by VIX but in order to improve the forecasting of VXX it can't be exploited. The results found from the study show that simultaneously on timescales of days, there are correlation between changes of VIX and VXX but when it comes to timescales of months, VIX manages VXX. Furthermore it also has been found out that as we can't use the information taken from VIX index in order to enhance predictions of VXX, however VXX is leaded by VIX index, no obvious trading opportunity can be seen.

Psychoyios, Dotsis and Markellos (2010) for futures and options of VIX volatility, analysed a model of jump propagation. The authors considered a total number of 3957 observations starting from January 2, 1990 to September 13, 2005 by utilizing the VIX's daily closing values. According to the results it is said that compared to the jump propagation processes as well as the square root propagation, return propagation process of a logarithmic mean is much more suitable. Furthermore, as the logarithmic return process is promoted with a jump component, there will be an increase in the performance. Related to the experimental results, for pricing European options and futures on spot VIX, valuation model of closed form has been presented by the authors.

Mollick (2014) investigated on the VIX and the industrial average stocks variation of Dow Jones. The paper's main aim is that in order to allow the total uncertainty measured by VIX, examining the consequences of individual stock variation which forms the Dow Jones Industrial Average (DJIA). As the mixing variable (VIX) total market uncertainty has been reconsidered by the author in order to review stock belonging of each individual to DJIA in 2011. In 2011 the GARCH-M models estimate DJIA's individual equity returns based on its delays and the ARCH-M term on the average equity bond equation to the variance equation. On a daily basis starting from January 3, 1990 to December 30, 2011 for most stocks, 5738 observations is said to be the longest time interval used in this paper. In order to solve variance equation's concurrency problems, one delay for the term VIX2 has been used by author. During the period for the three recessions specified by the NBER, an artificial variable has been added by the author in order to create an interaction between business cycles and fluctuations.

According to the findings, by adding artificial variable for stagnation and the VIX to the GARCH-M models' variance equation, there has been a mixed effect in the artificial stagnation as well as there have always been increases in the variance by the

VIX coefficient. In general, VIX is predicted as a mixing variable. Being 1.039 in the market variance, the VIX effect is said to always be positive and for this index and almost equally for the 24 stocks, the GARCH effects are said to be completely eliminated as supported by blend of hypothesis distribution.

Chang, Angel, Martin, McAleer and Amaral (2011) under the Basel agreement's risk, studied the risk value forecasting of futures VIX. Daily closing prices (settlement prices) for the futures CBOE VIX 30-day maturity volatility index are the data used to estimate and predict starting from the period March 26, 2006 to January 10, 2011 taken from stream database of Thomson Reuters. Many univariate models each with distributions of different error such as, GARCH, EGARCH, GJR and Riskmetrics were used by authors as its methodology to predict VaR from VIX futures as well as for risk management under Basel II Agreement. Mean, median, infimum, supremum as well as the 10th through 90th percentiles point values of the univariate models' forecasts are also used by authors as combined single models of mature strategies. According to the experimental results, rather than being conservative the optimal strategy is said to be aggressive while managing risk is weighed for VIX futures. Especially, this includes a strategy to communicate point forecasting of VaR models intended to the national regulatory authority. In order to stay within the number of violations' limits which are allowed under the Basel II Agreement, this strategy is willing to decrease the DCC's average.

Frijns, Tourani-Rad and Webb (2013) studied the VIX relation with its futures on the daily basis. Starting from January 2, 2008 through December 31, 2012, VIX and its futures' daily dynamics have been analyzed by the authors. Some causality evidences have been seen from the VIX and its futures (VXF) while using model of Vector Autoregression (VAR) on daily data. Nonetheless, for causality of bi-directional Granger, authors found firm evidence by estimating VAR and taking data of high frequency, between VIX and its futures (VXF). All over, ranging from the VIX futures to the VIX itself, this impact looks to be more powerful than any other way. The influence of the VIX futures is more confirmed by analysis of variance disintegration as well as impulse reply. Finally, it has been observed that while there is a decreasing in the reverse causality, over the sample duration there is causality increasing from the VIX futures to the VIX. This outcome indicates that in volatility pricing, the importance of VIX futures have remarkably been high. The study confirms the idea that there are days of high VIX values as well as negative returns' days which are mostly dominated by VIX futures. Therefore, instead of trading in the index options of S&P 500, investors should use VIX futures on those days in order to protect their position.

Chang, Hsieh and McAleer (2016) investigated the relationship between the VIX and ETF stock index. The main goal of this article is to use Vector Autoregressive (VAR) models and see if ETF returns are affected in any way by VIX returns as well as if ETF returns are affected by various mobile average processes of daily returns of VIX. Contingent heteroscedasticity exists in the ETF returns as shown by the ARCH-LM test. Therefore, to incorporate contingent heteroscedasticity in the VAR assessment of ETF returns, the oblique model of BEKK is assessed. From Europe and USA in the experimental analysis, various stock indexes have been applied on the ETF returns' daily data. Yahoo Finance is the source for the ETF variables' closing daily prices, whereas data for the VIX are derived from official website of CBOE. According to the experimental results of the study, compared to the ETF returns of European market, potential important impact on the ETF returns of single market of VIX does exist. On the other hand when it comes to short run, potential important effect on ETF returns of European market exist in the daily returns of VIX. Eventually compared to the returns of S&P500, there is less effect of VIX on the returns of ETF.

Duan and Yeh (2010) studied risk premiums and leap volatility implicit by VIX. Starting from 2, 1, 1990 through 31, 8, 2007 for over 17 years, their set of data includes the index values of VIX of the CBOE, daily frequency rates of free of risk and index values of S&P 500. One month (or 22 trading days) forward index of S&P 500 volatility implied in the option prices index of market's expectation is measured by the VIX. The characteristics of the model include all pricing models of the random oscillation option with the mean return of constant variance elasticity and those that permit the price leap to be subject to random fluctuations. Under neutral risk measurement through a modern methodical relationship, linking the underlying volatility to the VIX makes the approach possible. Since the estimation option prices have not directly been used, the computational load correlated with option valuation for random variable or pricing models of jump option can be avoided. The results taken from the paper are: (a) The combination of the jump risk factor is very significant; (b) volatility risks as well as the jump have been priced; (c) random instability trend of square root is a famous weak model specification regardless of whether or not to allow price jumps. It has also been observed in the study that statistical conclusion is trustworthy; on the other hand there is no materially impact of approximation that exists in the structure of VIX index.

Hol and Koopman (2000) investigated on predicting stock index returns' variability with random and implicit volatility models. To facilitate the statistical tests' usages for involute model, an SV model with implicit fluctuations as an external variable in the variance equation has been created by authors whom they call this stochastic volatility model as SVX. Then with the so-called stable alignment term, the SVX model is expanded to an oscillation model, which is named as the SVX + model. Through likelihood methods of quasi maximum, the SVX + model could be estimated, but by using significant sampling method of Monte Carlo, the primary stress would be on the precise maximum methods of likelihood. On the index of Standard & Poor's 100, both in the sample as well as out of the sample, the models' efficiency for daily returns have been assessed. Starting from the period January 2, 1986 through December 31, 1999, the stock index of Standard & Poor's 100 is the chosen data set taken from the DataStream in which daily observations of about 3532 samples were used. Since the recent research suggests that much better predictions is given by implicit volatility, this method has been chosen otherwise, GARCH models which had initially mixed findings have been used in the related studies.

According to the findings, the latter encompasses increased information in the shape of random shocks combined into SVX models, however compared to the historical returns, the implicit fluctuations in the sample are better. For the predicting perspective starting from 1 to 10 days, the out of the sample fluctuation forecasts are estimated contrary to the squared of daily returns and the intra daily returns. Daily squared returns produce mixed results, whereas the most precise out of the sample volatility predictions are made by SVX+ model when squared of intra daily returns are used as a realized volatility's measurement. On the other hand, since the volatility predictions of the model that uses only implicit fluctuations are upwardly biased, its performance is said to be the worst.

Boscaljon, Filbeck and Zhao (2011) by using the VIX as style spin studied marketing timing. To examine the differences between performance of growth based strategies and value based strategies comparative to shifts in comprehended volatility as measured by the shifts in the VIX percentage, starting from the period 17, April, 1990 through 31, December, 2008, daily data are used which are obtained from; small cap, mid cap and big cap growth of Barra as well as small cap, mid cap and big cap value indexes. In the regression analysis to serve as a dependent variable, for all three batches size, the discrepancy between growth and value portfolios have been calculated. For long-term trading strategies, the results of the portfolio depend on shifting from value to growth stocks based on the VIX index's shifts still seem to be of economically important.

On the contrary, as for the first time proposed by Copeland and Copeland (1999), based on short-term strategies, trading strategies seem not to be important anymore. By using the percentage of one-day shift in the VIX's average moving of 75-day, for longer durations of 30 days or more, as a sign to change the style from value to growth portfolios produced positive returns. Nonetheless, in the VIX index there are no stable trading strategies pursued to decrease. Accordingly, during the time interval of market uncertainty increase witnessed by an ascending VIX, for getting high quality it seems the strategy of style spin timing might yet be an efficient strategy. The outcomes obtained from the paper indicates that during the time of the VIX index's increase by shifting to value stocks in equity portfolios, investors might be benefited.

Kokholm and Stisen (2015) along with mutation models and random fluctuation studied the VIX and SPX options' joint pricing. During the periods of 22, October, 2008 and 16, May, 2012, the data are gathered from the CBOE's main website by using SPX index and VIX index's call options in order to calibrate the models to both options of put and call as well as in a distracted market to examine their performance.

As part of its methodology to market citation on VIX options along with VIX futures and SPX, the authors mutually calibrated; the Heston model with mutation in yields, the Hoston model variance and concurrent leaps in returns (SVJJ) and the Hoston model itself. It has been found that the complete flexibility of mutations in the yields as well as fluctuations added to a random fluctuation model is crucial. Mutation in yields improves the fit of SPX options, whereas mutation in fluctuations is significant to match the upward slant better that indicate the unstable fluctuations seen in the VIX options. In addition, the findings show that with average relative pricing errors (ARPEs) which are estimated about 15 to 21 percent for the dates, along with the Feller terms the (SVJJ) model that are jointly imposed and calibrated to the VIX options and SPX failed to deliberately fit both markets. While for one of the sample dates there has been a remarkable increase on the VIX futures' pricing errors, the errors are reduced to about 8 to 12 percent on the VIX options and SPX which is said to be a suitable improvement in the Feller condition. In the conclusion it is said that in order to mutually fit option markets, more resilience is needed as for the trading goals, fit may not always be acceptable.

Kumar (2012) investigated on the attributes of volatility index of India. Starting from the period 1, November, 2007 to 31, May, 2010 in the study author used daily closing data obtained from Nifty index and Indian volatility index (Ivix). In its methodology unlike previous studies in which the core method was always conditional mean function, in order to test the relevance between the volatility index's movement and stock market author used quantile regression method.

Shown by quantile regressions, there is a moderately negative relationship between returns of stock market and Indian volatility index. It's also mentionable that Nifty returns as well as Ivix returns each has independent movement, while there is a sharp upward movement in the market. Therefore, there is an unimportant relationship just for the worst or steepest reduction as the market movement is downward. To think of the worst reduction, derivatives of oscillations that are in the Ivix might be beneficial as insurance tool's portfolio. Accordingly, as a separate asset class the Ivix's derivatives that offer the benefits of diversification would be useful to investors. Based on the results, Ivix is said to be future realized fluctuation's impartial estimator as the fluctuation predictions taken from Ivix possesses significant information about market fluctuation. To finalize the study's results, the volatility of Indian market will be remarkably impacted by an overnight shifts in the United States market volatility whereas, the shift for opposite Finally, this study shows that overnight volatility changes in the US market significantly affect the volatility of the Indian market, while the results are not the same for the opposite direction. On the other hand, neither the volatility of Indian market is affected by Asia's giant market's volatility (Japan), nor Japanese stock market volatility is affected by volatility of Indian market.

Jubinski and Lipton (2013) investigated on the reaction of commodities like: oil, VIX, gold and silver to the financial market's volatility. Gold, silver and crude oil of West Texas Intermediate (WTI) are the three futures series' daily constantly compounded returns used as dependent variables in the study. Starting from the period 2, January 1990 to 31, December 2010, for each series a total number of 5290 observations have been taken as daily NYMEX prices which are obtained from FactSet along with daily data of the VIX which has been obtained from CBOE website.

According to the findings, implicit volatility has affected all the three futures commodities returns. Confirming the opinion of precious metals, which have been viewed as safe shelters by investors in order to buy them while the equity market has a rising fluctuation, the relationship between implicit volatility and gold and silver are positive. Denoting a reaction to reduced demand forecasts, there is a negative relationship between oil and implicit volatility. To incorporate index of a dollar into proxy for different macroeconomic conditions, the findings said to be strong enough. Reciprocally, there seen to be no impact of contemporary volatility on the future series of any commodity's returns. To use goods as an equity hedge, there said to be no obligation for investors to "catch-up" since they are able to forecast the shifts in the financial markets effectively. In the financial markets, commodities relevance to volatility has gained new significance since their role has been broadened as diversification tools' portfolio.

Duan and Yeh (2011) studied dynamics fluctuation and price implicit by term structure of the VIX. Starting from the period of 2, January 1992 through 31, March 2009, CBOE's term structure data of the VIX, free risk rates and the index values of S&P 500 are the used data set of the study. To apply the model of random oscillation along or without jumps on the both, term structure of the VIX and the index value of S&P 500, the authors have developed MLE method of filter-based particle. MLE model besides being able to permit for price jumps includes all pricing models of the random oscillation option with the mean return with stable variance elasticity. According to the findings it is said that: a) the trend of volatility under neutral risk measurement means a moderate return; b) the intensity of jump said to be time-varying; c) oscillation risks and the jumps have been priced; d) VIXs' errors measurement said to be material; e) along with price jumps or without it, the oscillation process of square-root is mis-specified.

1. LITERATURE REVIEW OF BIST-100 INDEX

Dogan and Topal (2014) analyzed the dividend payments' effect on performance of company based on a case taken from Istanbul Stock Exchange (BIST). Outside of financial sector between the time period of 2008 to 2011, authors used 172 companies' data. The study divided firms into two different groups: the ones that make regular payments of dividends and the other ones that don't regularly pay dividends. To find out whether there exist a distinction between financial performances based on market and accounting of both of these groups or not, the study conducted tests. Multiple regressions such as descriptive statistics and T test methods have been used by empirical analyses.

According to the results of analysis it has been observed that performances of companies have been affected by the dividend payments. In addition, there found to be a significant positive statistical relationship between performance index Tobin's q based on market and the dividends per share rate (DPS) in groups, whereas between accounting performance indexes ROA and ROE as well as dividends per share rate (DPS), there is a statistically insignificant relationship. Developed by John Lintner (GL) and Myron Gordon, these findings provide quality support for the relation of dividend.

Eyuboglu and Eyuboglu (2015) examined Borsa Istanbul Stock Exchange (BIST) effect of the month January in the 23 sector and sub sector indices. To achieve this aim, the authors calculated each index return and then in order to test whether there is a difference between the returns of the month, the artificial variables are created and inserted into the regression equations. January effect's empirical evidence hasn't been provided by the results of the study at the market level (BIST-100). Amongst twenty three indices, only in two of them importantly abnormal monthly returns have been seen at the sector and sub sector level. These two indices in which January effects have been found are leasing factoring and sports indices.

Accordingly, since there are no chances of gaining abnormal returns in these mentioned twenty one indices, fund managers and investors are suggested to retain their positions in the stocks. In the months of January and March, remarkably higher returns have been observed in the sports index while, in the month of May it has importantly been negative. In January and March the mean returns of sport index are 0.0032, 0.0027 and for May its -0.0040. On the other hand for the index of leasing factoring, the returns in the months of January, April and June said to be higher compared to the other months of the year. The mean returns for these three months are respectively 0.0029, 0.0033 and 0.0031. These finding are said to be very substantial for regulatory authorities, managers as well as investors.

Akar and Baskaya (2011) by using spectral analysis method, investigated on the detection of Turkish stock market's long term cyclical behavior. Along with Istanbul Stock Exchange 100 Index (ISE-100), the indices of four other sectors which are subsequently: Financial Index, Technology Index, Industrial Index and Services Index have been used as source of weekly time series data in the study. For ISE-100, February 1986 is the beginning of sample period whereas, for Financial Index and Industrial Index its January 1991, for the Technology Index its July 2000, and for the Services Index its January 1997; and all of them continue up till March 2010. It's also mentionable that Central Bank of the Republic of Turkey's Electronic Data Delivery System is the main source from which all these observations have been taken.

According to the results of this study, the time period of 160 weeks and 52 weeks are detected for Istanbul Stock Exchange 100 and following up 2 years and 1.5 years cycles for the remaining sectors. For those Turkish stock investors who want to invest for long terms, this study's information and results can be useful.

Muzir, Bulut and Şengül (2010) by considering a case from Istanbul Stock Exchange investigated on the Asset Pricing Models' performance estimation and their ability to capture the economic crises' effects. Among 100 companies that exist in Istanbul Stock Exchange ISE 100 Index, since the necessary data for all the listed companies in the ISE 100 Index aren't accessible, authors were able to select a sample of only 45 companies with complete data that 20 of which are also listed in the ISE 100 Index. Starting from the time period of January 1996 to December 2004 relating the companies' stocks in the sample (108 observations for each stock), monthly actual rates of return data based on TL were taken from the Istanbul Stock Exchange's official website whereas, the Central Bank of Turkey's official website is the source for the collection of the data on the predetermined macroeconomic indicator for the same time interval.

According to the factor analysis of the results, five factors can explain 68.3 percent of the return variation. On the other hand, a low coefficient of determination has been generated by APT model which is 28.3 percent and when compared to 5.4 percent of inferior explanation power of CAMP, APT model proves to be more competent. In addition, to capture the effects of any economic crisis on return variations, APT model has been observed to be more robust.

Canbaş and Arioğlu (2008) by taking evidence from Turkey tested Fama and Frenchs' three Factor Models. By employing firms' data from different sectors, regions and countries, the authors tested the explanatory power of the Model which included data of the firms existed in Istanbul Stock Exchange (ISE) as well. By utilizing data set including for a longer time period firms from the financial sector, the main purpose of this paper is to find out whether the variation in common stock returns of firms that exist in ISE could be captured by 3 Factor Model or not.

Starting from July 1993 to June 2004 time period, firms that are quoted to ISE are included as sample. Compared to the t-statistics of the slopes of the other factors for all the cases, the t-statistics of the slopes of the market factor has been seen to be higher and more significant as a result of the regressions run. Therefore, in explaining the common stock returns' variation, the most important factor could be emphasized to be the market factor. Except in one case where the BM portfolio's average monthly excess return was taken as the independent variable in the regression, for all the cases the t-statistics of the slopes of the HML factor were important. Accordingly, in explaining the common stock returns' variation the second important factor could be emphasized to be HML too. Thinking of the results, in the Model there may be still some missing factors in spite of the possibility to emphasize that over the time period of July 1993 to June of 2004, most of the variation in common stock returns could be explained by 3 Factor Model. To be better said, common stock returns' variation couldn't be entirely captured by the Model.

Deran, Iskenderoglu and Erduru (2014) studied financial ratios as well as regional differences by considering city indices of Istanbul Stock Exchange (ISE) companies' comparative approach. City indexes whose scopes are attempted to set above, financial ratios and financial performances comparison is highly substantial for investors' decisions. The most companies that are registered in Istanbul Stock Exchange (ISE) in 2011 are in Istanbul, Kocaeli, Bursa and Izmir which the financial performances comparison of the firms that are included in their city indexes is aimed in this study. In order to compare the companies in different regions, a total of 16 ratios that show financial structure, profitability, liquidity and stock market performance of the firms in 2011 annually analysis have been calculated. Public Disclosure Platform is the source from which the companies' data are calculated by income statements and balance sheets. To reveal any important difference in the operations of companies in different regions, Mann-Whitney U Test as well as Independent Sample t test has been employed.

According to the results obtained from analysis, in regard with cash ratio and acid test ratio only between enterprises that operate in Izmir and Istanbul there was a statistically important difference and among these two cities, ratio averages of Istanbul enterprises are higher compared to the enterprises operating in Izmir. On the other hand, it has been observed from the results of the analysis of financial structure ratios that between the city indexes, there exists no statistically important difference. To say it in a better way, enterprises that are included in the city indexes shown to have similar equity capital and long-term debt paying ability. It also has been found that there statistically exists an important difference between Istanbul-Bursa, Bursa-Kocaeli and Izmir-Bursa when we consider city indexes in terms of net profit margin and return on assets. However, in terms of price earnings ratio between the city indexes, no statistically important difference has been observed, but in regard to profit per share and between the included enterprises in the city index of Istanbul-Bursa in terms of MV/BV, an important difference exists between the city indexes of Istanbul-Bursa and Bursa-Istanbul. Finally in this study it has been found from differences that financial management differs among regions.

Tas and Dursunoglu (2005) by using hypothesis studied random walk test for Istanbul Stock Exchange (ISE). Behaviors of stock prices of the ISE 30 index have been examined in this study. Starting from the time period of 1, January 1995 to 1, January 2004, the data includes 30 stocks that have been contained in ISE 30 index, as well as these 30 indexes' daily returns of stock priceon have been examined. The concentration of this study is on a question concerning the ISE 30 index's weak form efficiency and for answering it two tests have been conducted which are: Dickey- Fuller Unit Root Test and the Run Test. A model that explains the market inefficiencies is used for the market efficiency.

Due to mostly low market capitalization of shares and low level of trade volume, the ISE is accepted to be inefficient. By using both Augmented Dickey- Fuller Unit

Root Test and Run Tests, since stock price index changes at all frequencies, the randomness of the stock returns' hypothesis have been rejected. There is a possibility of interpretation of the rejection of null hypothesis that gives the idea of market not being weak form efficient. The interpretation of random walk null hypothesis can be done by the stock market prices' mean reverting tendency. It is said that abnormal profits can be earned by those traders that make their living by analyzing stocks' historical returns and taking the advantage of this study's information to project their future returns. As a conclusion shown by the results, both Dickey- Fuller Unit Root Tests and Run Tests' results are same and rejected random walk in the ISE.

Bayyurt and Sagbansua (2007) by using a multi-criteria Data Envelopment Analysis (DEA) model among top 1000 manufacturing firms trading in ISE studied the efficiency determination of 11 concrete companies in Turkey. In order to evaluate companies' efficiency in Turkey, Data Envelopment Analysis (DEA) is said to be an efficient and powerful mechanism that can be beneficial in strategic planning. In this study by using output maximization model, the least efficient firm has been found and the compared with the composite firm. The information on how much a company's performance can be improved by using the same resources can be provided by the output maximization model.

DEA results say more about utilization of resources however they tell nothing about company's needs of resource. In order to make an inefficient company to become efficient about its set of reference of efficient units, many opportunities could be offered by DEA and the ability of other companies in achieving same outputs with fewer resources can be the motivation for this change. It has been suggested that in later studies non-financial variables that also affect the business performance should be included. A good example can be average defective ratio or sales returns to measure the quality of production, maturity, top managers' experience, employees' salaries, contribution to social associations to represent firms' social goals, qualified workers for growth, absenteeism, number of accidents for quality of work life or number of disagreements between employee and employer.

Kasımoğlua , Göreb and Altınc (2016) analyzed the competitiveness of Istanbul Financial Center. By considering the financial markets and instruments in micro perspective and banking system, this study's main aim is to see the comparison between Istanbul Financial Centre with selected twelve centers. Kuala Lumpur, Shanghai, New

York, Moscow, Hong Kong, Frankfurt, London, Dubai, Toronto, Paris, Singapore and Tokyo are the selected financial centers that by using ranking analysis are compared with Istanbul Financial Center. In order to characterize Istanbul's position in financial markets and banking, The World Bank Islamic Banking Database, The World Bank Global Financial Development Database (GFDD) and the World Bank World Development Indicators Database have been utilized. For financial markets 13 indicators and for banking sector 9 indicators have been taken into account, which in the ranking analysis are considered as the values average between the years 1992 and 2012.

Returns of Equity (ROE), Domestic Credits, Deposit Money Bank's Assets, International Banking, Islamic Banking, Cost Efficiency, Total Assets, Liquid Liabilities and Bank Nonperforming Loans to Gross Loans (%) are the indicators calculated as GDP's percentage for banking sector analysis by not considering number of contracts indicators. Whereas, IPO value, currency contracts, commodity contracts, stock contracts, mutual funds, index contracts, interest rate contracts, ETF turnover, stock market capitalization, stock market value traded, OTC foreign exchange, international debt securities and domestic debt securities are used in the financial market part.

As a result to attract new financial resources, compared with countries like Eastern Europe and Russia, Turkey has more chances as in terms of geographical proximity, some advantages are offered by Istanbul province. The strengths of capital markets and well-developed banking sector should be brought together by Istanbul Regional Financial Center. Besides the contribution to domestic rebalancing between the capital markets and banking sector, next stage of financial support of Turkey and Istanbul will be supported by a capital market that is deep and efficient. Additionally, by giving consideration to global financial centers as the derivatives trading's largest venue, there should be priority to the development of derivatives' action plan.

Attracting new businesses, new financial instruments, new international funds, creating new opportunities, encouraging efficiency and stimulating job in order to increase financial sector's contribution to GDP should be Turkey's objective. Finally it is said that by implementing right strategies as well as by paying attention to financial system's characteristics in global and regional centers, Istanbul will firstly grow and develop as a financial center that is national and then as a regional and finally as an international financial center.

KILIÇ (2005) by considering Istanbul Stock Exchange and by using Markov Chains Methodology tested the Weak Form Efficient Market Hypothesis. The main purpose of this study is to test if Istanbul Stock Exchange's daily returns are followed by a martingale (random walk) process or not taking to account the Markov Chains Methodology. According to the study's results, all the available historical information been fully reflected by stock prices considering Weak Form Efficient Market Hypothesis at any given time. In predicting stock return of future, there is no value of volume and historical data on prices under a random walk, or to say it in a better way, the uselessness of technical analysis and statistical analysis is confirmed. Only depending on historical stock prices for buying and selling stocks in a try of outperforming above market return is said not to be skill but an attempt of testing the chance. Additional researches such as five minute intraday returns can be done toward the high frequency returns in order to observe whether there is a chance of intraday buying and selling strategy outperformance or not.

SECOND CHAPTER

RISK

Since risk plays an important role in VIX index, in this part of thesis study, risk and all types of it will be explained in details.

1. DEFINITION OF RISK

The word "Risk" in many scientific fields is a significant concept, hence no concord has been made on how to define and interpret it (Aven, 2011). Definitions given to it are based on many different things some of which are: objectives, uncertainty, probabilities, and expected values. According to some authors, by considering the available knowledge, risk is epistemic and subjective while to some others because of the probabilistic features of certain parameters, it is stochastic and yet to some others risk is given ontological status autonomous from the person identifying it. In an authoritative manner, the situation has not been resolved simply.

From one point of view, the development of the field and efficient risk management is certainly hindered by this situation, then again, the possibility of rather good reasons exist for such a situation. Necessarily, different models, procedures and methods of risk are required for specific areas, for instance, engineering and medicine. But, while fundamentally facing the same challenge which is finding a concept that explains system activity and leads to different outcomes than expected, planned or intended, or different from its goals, the question arise is that whether these areas need to have such infinite views of the concept of uncertainty and risk.

Since with different human perception and situations the meaning of risk varies, the word risk has to clearly be defined. In a chronological order, an overview of key definitions of risk is given.

- ❖ Risk in the sense of the potential accident's severity and the feasibility of the event is the influence's expression and probability of an accident (MIL-STD-882D, 2000).
- ❖ Risk is the probability's combination and scope of the results (Risk Management Vocabulary ISO 2002).
- ❖ Risk is an unknown result of an activity or event relevant to human value's somewhat (IRGC, 2005).

- ❖ Risk is the equivalent of an expected damage (Campbell, 2005).
- ❖ The word ‘Risk’ due to hazard is like a damage, disease or injury to the employees’ health (Law on Safety and Health at Work, 2005).
- ❖ The word ‘Risk’ with respect to something of humans’ value is severity and uncertainty of the events and results of an activity (Aven & Renn, 2009).
- ❖ Risk is the uncertainty’s influence on objectives (Risk Management, ISO, 2009).

The most important remark of the risk is that without previous research into the context, hazard, objectives, vulnerability, interested parties and resilience it can’t be addressed directly as it is a derived category. While conducting risk assessment, analysis and management, to be aware of potential contradictory interpretations of concepts is important, in spite of the fairly philosophical level of discussion on different definitions. Surprisingly, while dealing with risk, one of the possible strategies might be to change the paradigm and consider safety problems from a different perspective in order to distance from risk as a concept.

The International Standardization Organization (ISO)’s Definition of Risk:

Risk is involved in all activities of certain organizations. Risks are managed in organizations by identifying, analyzing and subsequently assessing whether to apply treatment options in order to make their criteria of risk satisfied. In order to ensure about no need of further treatment, they consult and communicate with involved parties, observe and analyze risk and apply measures during this process. (Risk Management ISO, 2009). By giving the following five remarks, ISO tries to clarify some of these questions.

- ❖ From the expected – positive or negative, an effect is a deflection.
- ❖ There are different aspects of objectives like: environmental goals, financial, health and safety that can be applied at various levels like: project, product and process, organization-wide and strategic.
- ❖ Risk, by referring to potential events and results or a combination of them, is often characterized.
- ❖ Risk is mostly explicated as an event’s combination of consequences (considering shifts in situations) and the likelihood of occurrence’s association.

- Uncertainty is the condition or even part of lack of information related to, likelihood, results, comprehending or knowledge of an event.

Aven (Aven, 2011) criticized, affirming the relevance of risk to uncertainty, but doubting on it to really be as a consequence of uncertainty or rather of a hazard or a cause or the hazard's disposal. Are there no risks if there is no objectives defined and simultaneously risk is related to objectives? Undoubtedly many interpretations may arise by this definition. Adams (Adams, 2014) finds out that the definition is not precise enough as the remarks are numerous. In the second remark, against the background of uncertainty, risk is described as consequences of accomplishing objectives and organizational setting. Same definition explains risk management as optimization process which makes the objectives' achievements more likely. Many other authors criticize the unclear definition of risk to neither being mathematically based nor has said enough about data, probability and models.

1. TYPES OF RISK

Risk, in financial management can be said as project's material loss that might cause inefficiency in project's tenure, productivity and legal issues. In finance, the classification of different types of risk is made in two main groups.

2.1. SYSTEMATIC RISK

Systematic risk in an organization is due to external factor's influence. From an organization's perspective, these factors are normally uncontrollable. Since enormous number of organizations are affected by it that function under same domain or similar stream, it is a macro in nature which can't be planned.

There are three main types of systematic risk explained below.

2.1.1 Interest Rate Risk

Interest-rate risk appears because of the interest rates' time to time variability. As the fixed rate of interest are carried by debt securities, they are particularly affected by it.

There are two types of interest-rate risk explained below.

- ❖ Price Risk: Arises due to the commodity's possibility of fall or decline, investment and shares' prices in the future.
- ❖ Reinvestment Rate Risk: It is due to the fact that same rate of return taken from the dividend or interest from an investment can't be reinvested as the earlier one.

2.1.2 Market Risk

Market risk's six different types are explained below.

- ❖ Absolute Risk: Is a contentless kind of risk. To give an example, the percentage chance of a tossed coin is fifty-fifty to get ahead or vice versa.
- ❖ Relative Risk: At various business functions' level, it is the risk's assessment or evaluation. To simplify it by an example, from a foreign exchange fluctuation point of view, if the export sales are an organization's maximum sales, a relative risk may be higher.
- ❖ Directional Risks: Risks in which a disclosure to the particular market assets causes to rise of loss are called directional risks. A good example for such

risks can be the experienced loss of some shares held by an investor when there is a fall in those shares market price.

- ❖ Non-Directional Risk: Such kind of risk comes when trader does not consistently follow the trading’s method. A good example is, to mitigate the risk; the dealer would purchase and sell the shares simultaneously.
- ❖ Basis Risk: The imperfectly matched risks that causes the possibility of loss arising is the definition for basis risk. For instance, the risks existing in two non-identical but related markets’ offset positions.
- ❖ Volatility Risk: It is a shift in the securities price because of a shift in the risk-factor’s volatility. To clarify it by an example, it’s applicable to the derivative instruments’ portfolios in which a major influence of prices is the volatility of its underlying.

2.1.3. Purchasing Power or Inflationary Risk

The reason for purchasing power risk to also be called as inflationary risk is the fact that purchasing power is adversely affected by it. During an inflationary period, investment in securities isn’t desirable.

There are two main types of power or inflationary risk as below.

- ❖ Demand Inflation Risk: It raises when prices increase or simply the result of demand excess over supply. It happens as supply can’t expand anymore and fails to cope with the demand. Therefore, when factors of production aren’t utilized in maximum level, then demand inflation occurs.
- ❖ Cost Inflation Risk: It is caused when the goods and services’ prices have a sustained increase. In other words, it is affected by higher cost of production. The final price of finish goods consumed by people is inflated by a high production cost.

2.2. UNSYSTEMATIC RISK

Unsystematic risk arises when within an organization; the internal factors dominance is influenced. From an organization’s perspective such factors are normally controllable. Since it only affects a particular organization, it is micro in nature. To mitigate the risk, organizations can take necessary actions therefore, it can be planned.

There are three main different types of unsystematic risk as explained below.

2.2.1 Business or Liquidity Risk

The reason behind business risk to also be called as liquidity risk is that it emerges from securities' sales and purchase influenced by changes in technology, business cycle and so on.

There are two types of business or liquidity risk as below.

- ❖ Asset Liquidity Risk: It arises when an inability to pledge assets or sell at their expected value when needed cause to losses. A good example can be assets sold cheaper than their real value.
- ❖ Funding Liquidity Risk: It arises when in order to make an on time payment, there is no accessibility to the enough funds to do so. To say an example, as explained in the agreement's service level by customer and organization, the commitments aren't fulfilled.

2.2.2 Financial or Credit Risk

Financial risk that can also be called as credit risk comes to existence when the organization makes a capital structure change. In order to source funds for the projects, there are three main methods included by capital structure as follows:

- ❖ Owned Funds: Share Capital is a good example for it.
- ❖ Borrowed Funds: Loan Funds is the example we can give for it.
- ❖ Retained Funds: Reserve and Surplus can be used as an example here.

There are four main types of financial or credit risk explained below.

- ❖ Exchange Rate Risk which or Exposure Rate Risk: When a potential change is observed in one country's exchange rate of currency in relation of currency of another country and vice versa, such form of financial risk appears. To clarify it with an example, it is faced by businesses or investors when either they have borrowings or loans in a foreign currency, or operations and assets across national borders.
- ❖ Recovery rate Risk: To a credit risk analysis, it is often a neglected aspect. The recovery rate is normally required for evaluation. A good example for recovery rate can be the given funds as a loan by banks or Non-Banking Financial Companies (NBFC) to the customers.

- ❖ Sovereign Risk: Governments are mostly associated with it when they don’t have the ability of meeting reneging on loans they guarantee, loan obligations and so forth.
- ❖ Settlement Risk: It arises when in an agreement of business or trade, a security or its value in cash isn’t delivered by counterparty.

2.2.3 Operational Risk

They are risks of business process failing that occur because of the errors made by human. Operational risks are not the same in each and every industry. The reason behind their occurrence is the breakdown in the policies, internal procedures, systems and people.

There are four main types of operational risks explained below.

- ❖ Model Risk: To value financial securities, various models are used in which model risk is associated. It is because of the possibility if loss resulting from the financial- model’s weaknesses which are used to manage and asses a risk.
- ❖ People Risk: It happens while people deviate from the behavior that they are expected to have by not following the rules and procedures of their organizations.
- ❖ Legal Risk: Is when parties for entering an agreement among themselves, are not lawfully competent. Besides that, it can be associated to regulatory risk in which a transaction may be revised with retrospective effect in the future when it conflicts with a government particular legislation or policy.
- ❖ Political Risk: It arises because of shifts in the government policies. The shifts might be followed by undesirable effects on investors which in third-world countries, is particularly prevalent.

THIRD CHAPTER

VOLATILITY

1. DEFINITION OF VOLATILITY

Volatility is said to be a statistical measure of the return's dispersion for a given market index or security. Mostly, the security becomes riskier when volatility is higher. Volatility, as either variance or standard deviation between same market index or security's returns is often measured. Sometimes volatility in either direction is associated with big swings in the securities markets. For instance, a market is called "volatile" when over a sustained time period; there is more than one percent of rise or fall in the stock market. When pricing options contracts, an asset's volatility is said to be a key factor.

Volatility is the uncertainty or risk's amount relevant to the changes in the value of a security's size. When a security's value can potentially be spread out over a bigger values' range, it is called a higher volatility which means that over a short period of time, there can be a dramatically change in the security's price in either direction. On the other hand, when there is no dramatically fluctuation in the value of security or it tends to be steadier, it is called a lower volatility.

By quantifying daily returns (daily based move of a percentage) of the asset, the variation of an asset can be measured. Based on historical prices, historical volatility represents the variability's degree in the returns of an asset. This number is expressed as a percentage and is without a unit. In general, while the return's dispersion around the mean of an asset is captured by variance, volatility is that variance's measurement in a specific time period. Therefore, volatility can be reported in daily, weekly, monthly or annualize basis. Thus we can assume volatility as the annualized standard deviation which is shown as: Volatility = $\sqrt{}$ (variance annualized).

1.1. IMPLIED VOLATILITY VS. HISTORICAL VOLATILITY

Since from a given market index or stock, the variance or deviation of returns is unambiguously formally the definition of volatility, there is an existence of key distinction among two different sorts of volatility measures, called as implied volatility and historical volatility measures.

1.1.1 Implied Volatility (IV)

Implied volatility, the second name of which is projected volatility, for options traders is said to be amongst the most important metrics. Option traders through implied volatility would be able to make a market's determination of how volatile it will be going forward. A way of how to calculate probability will also be given to them by this concept. It is significant to know that implied volatility is not suggested to be considered as a science. Implied volatility, dissimilar to historical volatility is derived from an option's price and for the future, it represents volatility expectations. Due to it being implied, past performance cannot be used as an indicator of future performance by traders. Alternatively, the potential of the option in the market have to be estimated by them.

1.1.2 Historical Volatility (HV)

Historical Volatility, which is also known as statistical volatility, measures the underlying securities' fluctuations by gauging changes in price over predetermined time periods. Since it is not forward-looking, compared to implied volatility, it is less prevalent metric. There will be more than a normal rise in the securities' price by a rise in the historical volatility. Relatively, an expectation that something will or has changed occurs. On the other hand, a drop in historical volatility means that an uncertainty has been removed, therefore, things return to the way they used to be.

This measurement might be on intraday changes basis, but often on the basis of the change from one closing price to the next, movements are measured. There is a possibility of measuring historical volatility in increase ranging almost from 10 to 180 trading days with dependent to the options trade's intended duration.

1.2. SYSTEMATIC VS. SPECIFIC VOLATILITY

Between systematic and specific volatility, another key difference exists irrespective of the used method in its volatility estimation. With respect to the factors of systematic risk and taken by the stock exposure, there is the possibility of decomposition of total volatility for any given stock into systematic volatility as well as specific volatility, which by influencing a particular firm is driven by uncertainty.

A remarkable attention has been paid to idiosyncratic volatility by the recent financial literature. According to Malkiel and Xu (2002) and Campbell et al. (2001), there has been over time increase on idiosyncratic volatility, whereas Brandt et al.

(2009) document that by 2007 this trend by falling below pre-1990s level completely reversed itself and declare that 1990s' idiosyncratic volatility increase to be an "episodic phenomenon" rather than a time trend.

Bekaert et al. (2008) suggests that neither for the USA nor for any other developed country a trend exist. There is another fact to be considered about idiosyncratic volatility. Goyal and Santa-Clara (2003) include that for excess returns of future, idiosyncratic volatility has forecasting power, whereas Wei and Zhang (2005) and Bali et al. (2005) discover that to the sample chosen, there is no robust of positive relationship.

There is an expectation of high correlation between average specific and systematic volatility risk indicators, while introducing two different risk measures' underlying, since both of them regarding fundamental of economics, give a reflection of the total uncertainty that investors experience at a specific point of time.

2. VOLATILITY INDICES

Since for market participants, information regarding volatility changes is very important, in order to make measures of volatility accessible for investors in shape of volatility devices which are made by the feature of tracking an asset market's aggregate volatility, a number of initiatives are launched. The calculation of this kind of indices are based on option prices as well as on implicit as for actual volatility measures it is opposed. From now on, we can find volatility indices on major stock indices as the Dow Jons Industrial Average, S&P 500, DAX, EUROSTOXX 50 and currently from November 2010 on the Nikkei 225. The most known volatility index is the VIX that is made from the equity index options' prices on S&P 500.

2.1. VIX

CBOE Volatility Index (VIX), which was initially designed for market expectation measurement of volatility implied of 30-day duration at-the-money option prices of S&P 100 index, had been introduced by Chicago Board Options Exchange (CBOE) Global Markets in 1993. In short period of time, U.S. stock market started using the VIX Index as its premier benchmark volatility. On CNBC business news shows, Barron's and other leading financial publications, Wall Street Journal, CNN/Money and Bloomberg TV, the VIX Index featured regularly and is often known as the "Fear Gauge".

The Black-Scholes Model was the basis of implied volatility. The VIX Index, in order to consider a new way of expected volatility measurement, to be continuously and widely used by volatility traders, financial theorists and risk managers, has been updated in 2003 by CBOE together with Goldman Sachs. Basis of new VIX Index is on the U.S. equities' core index "S&P 500 Index", and by aggregating S&P 500 Index's put and calls weighted prices over a great variety of strike prices, it estimates expected volatility. The VIX Index is transformed from being concept of an abstract into a practical standard for volatility of hedging and trading by a script supply to replicate exposure of volatility with a SPX options' portfolio. The VIX is model free: the only necessary assumption is the arbitrage opportunities' absence rather than Black-Scholes holds' assumption.

In 2014, the VIX Index is enhanced by CBOE through including series of S&P 500 Weeklys. Weekly options which are nowadays accessible on hundreds of ETFs, ETNs, indexes and equities and have become a very actively-traded and popular tool of risk management, for the first time introduced in 2005 by CBOE. Nowadays, on average close to 350,000 contracts traded daily along with one-third of all SPX traded options are counted by SPX weeklys.

The VIX Index is allowed by the inclusion of SPX Weeklys to be calculated with option series of S&P 500 Index which for expected volatility, exactly match the target timeframe of 30-day that intended to be represented by VIX Index. It is ensured that between 23 and 37 day to expiration of SPX options usage, an interpolation of two points along with volatility term structure of the S&P 500 Index will always be reflected by the VIX Index.

In April 2016, the dissemination of the VIX Index began outside of U.S. trading hours by CBEO. Starting from 3 a.m. to 9:15 a.m. Eastern Time (ET) during extended trading hours, and starting from 9:30 a.m. to 4:15 p.m. ET during regular trading hours, the VIX Index is now available. A smoothing algorithm for values of the VIX Index as part of its expansion is implemented by CBOE, which during both regular and extended market hours is disseminated.

Table 1. *Currently Available Volatility Indices with Their Underlying Indices*

Index	Ticker	Underlying	Index Provider
AMEX Volatility Index	QQV	QQQ	AMEX
CBOE Volatility Index®	VIX	SPX	CBOE
CBOE DJIA Volatility Index	VXD	DJX	CBOE
CBOE NASDAQ-100 Volatility Index	VXN	NDX	CBOE
CBOE Russell 2000 Volatility Index	RVX	RUT	CBOE
CBOE S&P 100 Volatility Index	VXO	OEX	CBOE
CBOE S&P 500 3-Month Volatility Index	VXV	SPX	CBOE
CBOE VIX Premium Strategy Index	VPD	VIX	CBOE
CBOE Capped VIX Premium Strategy Index	VPN	VIX	CBOE
CBOE Crude Oil Volatility Index	OVX	USO	CBOE
CBOE Gold Volatility Index	GVZ	GLD	CBOE
CBOE EuroCurrency Volatility Index	EVZ	FXE	CBOE
AEX Volatility	VAEX	AEX	Euronext

Source: The Cross-Sectional Volatility Index by Felix Goltz, el. (2011).

Table 1. *(Continuation) Currently Available Volatility Indices with Their Underlying Indices*

BEL 20 Volatility	VBEL	BEL 20	Euronext
CAC 40 Volatility	VCAC	CAC 40	Euronext
FTSE 100 Volatility	VFTSE	FTSE 100	Euronext
DAX Volatility	VDAX-NEW	DAX	Deutsche Borse AG
SMI Volatility	VSMI	SMI	SIX Swiss Exchange AG
EURO STOXX 50 Volatility	VSTOXX	EURO STOXX 50	STOXX Limited
NIKKEI Volatility Index	VNKY	NIKKEI 225	Nikkei Inc.
India NSE VIX	INVIXN	NIFTY 50	India NSE
KOSPI 200 Volatility Index	VKOSPI	KOSPI 200	Korea Exchange
Mexico Volatility Index	VIMEX	IPC	MexDer

Volatility indices with similar methodology as the ones provided by CBOE are developed by other exchanges (as shown in the above table). To give an example, on major equity indices like the CAC40, AEX and BEL20, volatility indices have been developed by Euronext. By respective exchanges, on SMI and DAX indices volatility indices are developed too.

The computation of volatility indices are directly done by the options exchange. The VSTOXX which is indicator of volatility index based on option prices of Dow Jones EURO STOXX 50, rather than by an options exchange is the index provider and is computed by STOXX, said to be the notable exception. Options with a short time expiry period are typically used by volatility indices. Therefore, market expectations over, for example, the next month is indicated by them. It is mentionable that for different time horizons, there are some indices as well. For example, eight sub-indices are calculated for 1, 2, 3, 6, 9, 12, 18 and 24 months to expiry in the VSTOXX.

2.1.1 Volatility as an Asset Class

Asset managers and investors are led to more precisely observe the downside risk and volatility of their equity holdings due to recent appearance of much stricter regulatory constraints as well as market turbulence. Regarding the volatility as a tradeable asset class rather than a mere statistical indicator that measures uncertainty of stock return, increased the interest of investors.

2.1.2. VIX Future & Options

On 24 March, 2004, the first VIX futures' exchange-traded contract is introduced by CBOE on CBOE Futures Exchange (CFE) which is all-electronic and new. On February 2006, "VIX options" that in the history of CBOE, is said to be the most successful new product launched by CBOE. Following that in 2015, a growth to approximately 800,000 daily contracts in trading activity that is combined in both VIX options and futures, has been observed.

Among the characteristics of VIX futures and options are that in an efficient single package, they are intended to deliver pure volatility disclosure. To all investors, from the smallest retail trader or the largest hedge funds and institutional money managers, a transparent, continuous and liquid market for the products of VIX is given by CFE/CBOE.

2.1.3. Beyond the VIX Index

Apart from the VIX Index, Short-Term Volatility Index of CBOE (VIX9DSM), reflecting S&P 500 Index's 9-day expected volatility, 3-Month Volatility Index (VIX3MSM) of CBOE S&P 500, 6-Month Volatility Index (VIX6MSM) and 1-Year Volatility Index (VIX1YSM) of CBOE and S&P 500 are the other several broad market volatility indexes calculated by CBOE. CBOE DJIA Volatility Index (VXDSM), CBOE Russell 2000 Volatility Index (RVXSM) and Nasdaq-100 Volatility Index (VXNSM) are calculated by CBOE too.

2.1.4. The VIX Index and other Volatility Indices

The existence of historical prices of more than 25 years is one of the most important characteristics of the VIX Index. A useful perspective is provided by this extensive data to an investor on how prices of options are in response to a variety of market conditions. From 1986 to the present price history, based on OEX options for the original CBOE Volatility Index (VXO) is available. For an investor's ability to see the comparison between the new VIX Index and VXO, that gives information regarding volatility "smile" or "skew", a similar historical record from 1990 for the VIX Index, has been created by CBOE.

3. TRADING VOLATILITY

3.1. MOTIVES FOR TRADING VOLATILITY

Diversification of equity risk through a long implied volatility exposure is among the main motivations for volatility's trading. It is notable that there is a strong negative correlation between equity returns and volatility of equity returns, as they tend to move in an opposite directions. Additionally, in stock market downturns, high volatility and negativity in correlation are particularly pronounced that when stock market faces losses and other diversification forms are not very effective and it is needed the most, then a protection is offered by it.

For negative correlation of equity volatility to the equity market, "Leverage effect" can be a possible explanation. (Black (1976), Christie (1982), Schwert (1989)): an increase (decrease) in prices of equities decrease (increase) leverage of the company, by this means a decrease (increase) in equity holders' risk decreases (increases) equity volatility. "Volatility feedback effect" given by (French et al. (1987), Bekaert et Wu (2000), Wu (2001), Kim et al. (2004)) is another alternative explanation which assumes incorporation of volatility in stock prices, the future required return on equity will be increased by a positive volatility shock and on the other hand, there will be a simultaneous fall expectation in the stock prices.

The existence of rational economic details that explain the reverse relationship between volatility and return on equity is a reassuring indication of the expected diversification benefits' robustness, which is within the equity universe, stands in distinction with the known portfolio diversification's lack of robustness. Here diversification is known that, when it is most urgently required because of the convergence of all correlations at a time of high market turmoil, it fails precisely.

Surely, there should be an expectation that long volatility exposure's benefits of risk diversification might come at a cost. Whether to be short volatility, a positive risk premium and conversely, to be long volatility a negative risk premium over time has been found by recent academic research. Since hedge market-wide risk is helped by a long position in volatility, a premium may be intently paid by options' buyers caused by the negative correlation that exists between market index volatility and market index returns (Bakshi and Kapadia (2003)). According to the finding in a recent paper of Carr and Wu (2010), a strongly negative beta is generated from negative correlation between return variance and stock index returns, but only a fraction of the negative variance risk premium is explained by this negative beta. Recent literatures identify other risk factors such as momentum, size and book-to-market which can't demonstrate risk premiums' strongly negative variance too and according to them, an independent variance risk factor is the source through which most of the market variance risk premium is created.

Hedging demand, speculative and arbitrage are among other motives for volatility.

- ❖ By funds that are often implicitly short volatility such as "mutual funds and hedge funds", volatility exposure hedging. Particularly, since rebalancing costs as well as portfolio tracking error increase along with an increase in the equity market's volatility, benchmarked equity fund managers are short volatility (Hill (2004)).
- ❖ Volatility changes is the basis for directional speculative, implementation of which is when volatility is expected to fall, going short volatility exposure and when volatility is expected to rise, going long volatility exposure (Dash (2005) or Jacob (2009)).
- ❖ In order to benefit from the mean-reversion to more normal levels in a number of main spreads like historical volatility versus implied volatility, one month implicit volatility versus quarterly volatility, and so on, non-directional speculative arbitrage bets.

Undoubtedly, the instruments' availability that can be used for making volatility indices investable quantities, is the dependence to market participants' ability for trade's implementation on volatility.

3.2. INSTRUMENTS FOR TRADING VOLATILITY

Due to volatility being option prices' key determinant, to get volatility exposure, one possible way is to trade in options but not a clear bet only on volatility. Non-trivial exposure to changes in the underlying asset's value is not the only reason for the sensitivity of option prices to volatility. Popularity of derivatives instruments on volatility is increasing. There is a possibility of investor's more precise view implementation as well as pure play on volatility, with these instruments. Particularly, through options on the volatility indices and exchange-traded futures, investors can invest in volatility products. It is mentionable that other products such as OTC variance swaps as well as exchange traded notes are available too.

Table 2. *Products Currently Available On Volatility Indices.*

Index	Ticker	Institution (Owner)	Futures Ticker	Options on Futures
CBOE Volatility Index®	VIX	CBOE	VX (VIX Futures), VM (Mini-VIX Futures)	Available
CBOE DJIA Volatility Index	VXD	CBOE	DV	-
CBOE NASDAQ-100 Volatility Index	VXN	CBOE	VN	Available
CBOE Russell 2000 Volatility Index	RVX	CBOE	VR	Available
DAX Volatility	VDAX-NEW	Deutsche Borse AG	FVDX (delisted)	-
SMI Volatility	VSMI	SIX Swiss Exchange AG	FVSM (delisted)	-
EURO STOXX 50 Volatility	VSTOXX	STOXX Limited	FVSX (delisted), FVS (mini-futures)	-

Source: The Cross-Sectional Volatility Index by Felix Goltz, el. (2011).

Options on volatility, exchange-traded notes on volatility, variance swaps as well as forward variance swaps and futures on volatility indices are the overall number of alternative investment vehicles through which trading in volatility can be done.

3.3. FUTURES ON VOLATILITY INDICES

Volatility of the S&P 500, Russell 2000, Dow Jones Industrial Average and NASDAQ 100 are the four major CBOE volatility indices on which futures are available. For European market, there is also availability of futures on volatility indices. But futures on the volatility indices for the SMI, STOXX and DAX, due to 1000 Euros per index point of contract size, are recently on 1 July, 2009, delisted from the exchanges. Mini-futures (FVS) on the volatility index (VSTOXX) for the EURO STOXX 50 are continually offered by Dow Jones STOXX. Mini-futures on VSTOXX with 100 Euros per index point contract value, have been available since 2 June, 2009.

In volatility related products, Liquidity is among the biggest problems. Open interest as well as low trading volume are among the features of most of these volatility's futures. VIX futures, with several thousand daily volume contracts and an open interest of around 50,000 contracts is said to be the most liquid product. Mini-VIX futures on the other hand, with a low daily volume and very low open interest (100) in comparison to VIX futures is the next most liquid product.

3.4. OPTIONS ON VOLATILITY INDICES

Options on VIX, VXN as well as RXN which for asymmetric exposure can be used to these markets' volatility exposure, are also offered by CBOE. Compared to other volatility indices' option products, the largest volume and open interest is owned by the CBOE volatility index option.

Table 3. *Dollar Volume Traded For Volatility Index Options*

Option Type	2009	2008	2007	2006
RVX (Russell 2000 Volatility Index Options)	$108,980	$6,693,381	$6,274,162	-
VIX (CBOE Volatility Index)	$5,224,807,164	$5,199,374,615	$3,343,053,366	$714,252,679
VXN (NASDAQ 100 Volatility Index Options)	$2,750	$589,685	$952,775	-

Source: The Cross-Sectional Volatility Index by Felix Goltz, el. (2011).

3.5. EXCHANGE-TRADED NOTES (ETNS)

By using ETNs, investors can also get exposure to VIX. Two different kinds of ETNs that hold VIX future contracts are issued by Barclays Bank PLC. The short and medium term volatility of S&P 500 provided exposure by iPath S&P 500 VIX Short-Term Futures and iPath S&P 500 VIX Mid-Term Futures.

3.6. VARIANCE SWAPS AND FORWARD-START VARIANCE SWAPS

The usage of variance swaps and forward start variance swaps which are products of OCT, is to either implied or realized volatility's pure exposure too. These swaps usually have similar maturities to option expiry dates so that in option traders' hedging applications, they can be used. A forward-start variance swap with a feature of starting at a later date, is similar to a variance swap. Opposite to VIX futures, long term exposure to volatility term structures can be provided by variance swaps.

4. CROSS-SECTIONAL VOLATILITY INDEX AS A NEW VOLATILITY INDEX

Robust and informative volatility are critically important to a large number of market participants, since they are used as a basis for investable volatility products as well as the central role that they play as uncertainty measures of market. It has been observed that there are number of shortcomings that causes the existing volatility indices to suffer. From one side, due to the requirement for a liquid option market's presence, volatility indices for an extensive set of markets are not available; to simplify it with an example, for various sectors of developed markets, small cap stocks, growth/value stocks, or even at the broad market level in most emerging markets, volatility indices are not available. At the same time, option market problems that with underlying equity markets have little to do, where and when they exist implied volatility estimates are plagued by them.

4.1 ESTIMATION METHODOLOGY

For volatility index construction, firstly, information on the entire constituent universe should be gathered. Particularly, for filtering stocks purposes information on past returns data and for the current volatility index value construction needs to be gathered.

In order to exclude certain stocks from index computation, filters to all available stocks need to be applied. To remove those stocks that would not add useful information to the indices, two specific filters are designed which remove illiquid stocks and outliers. One filter is aimed to remove stocks that in terms of the returns observations are outliers.

Outliers stocks are stocks that within the reference period have extreme return movements. Greater robustness of the derived risk measure will be achieved with the removal of outliers in terms of current data or historical data. Another filter is aimed to remove illiquid stocks. Illiquid stocks' identifications are; as over a given day indicated by zero returns, other common liquidity measures' abnormal values consisting trading volume as well as high first-order autocorrelation, having stale prices.

Average return across all stocks as well as current return on each stock for the current time period will be computed when filtered universe of stocks are constructed. Through that, deviations for each individual stock of expected return is calculated.

The following transformation of cross-sectional variance which is said to be unbiased estimator of specific volatility within the universe is computed for the cross-sectional volatility index.

$$\text{CVIXt} = \frac{\sqrt{\sum_{i=1}^{n}(rit - rt)2}}{Nt - 1}$$

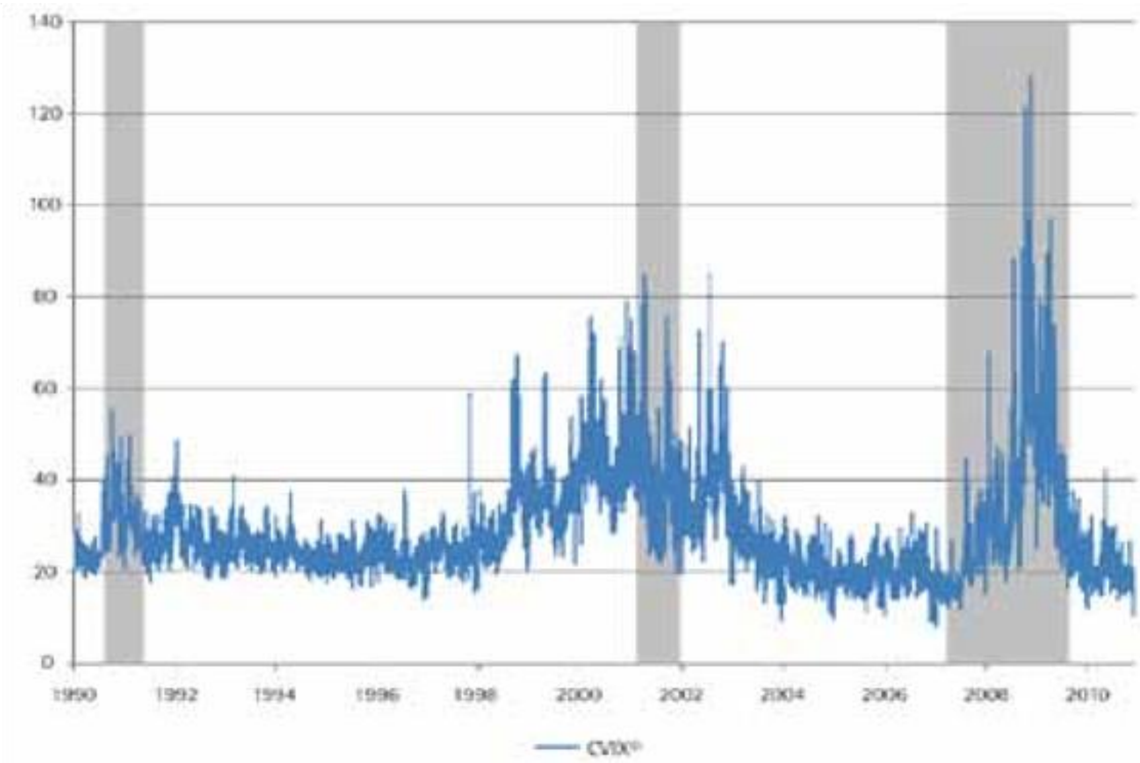
Where *rt* is the return on the equally-weighted portfolio at date t. (The Cross-Sectional Volatility Index by Felix Goltz, el. (2011)).

4.2. CROSS-SECTIONAL VOLATILITY INDEX AS A PROXY FOR ECONOMIC UNCERTAINTY

Average specific volatility can be called as a reflected proxy of investors' aggregate uncertainty regarding economic fundamentals at a given point of time. To analyze this properly, we should refer to the very nature of idiosyncratic risk. In a model of asset pricing, the risk that belongs proper to an individual firm is represented by it after accounting the risk sources that are common to all firms. It is shown that a very good measure of this idiosyncratic risk is provided by the cross-sectional variance of returns, even if to the usual common risk factors like the Fama-French factors or the market return, the risk exposures are ignored.

Cross-sectional volatility index's time series against NBER recessions for the 1990 to 2010 period has been plotted in order to know the correlation between cross sectional volatility and economic conditions. As we can see in the figure 1, which shows the recession periods of NBER, indicates that most of the time there is a coincidence between the peaks in the remaining in the high-mean high-variance regime's probability and the contraction periods. Accordingly, with being high and quite variable of the dispersion returns when economic growth subsides, the cross-sectional volatility index measures seems to be counter-cyclical.

Figure 1. *The Cross-Sectional Volatility Index and Recession Periods' Time Evolution.*



Source: Cross-sectional volatility index's daily time series. NBER recessions are shown in the shaded areas. The sample period is January 1990 to November 2010. (The Cross-Sectional Volatility Index by Felix Goltz, el. (2011)).

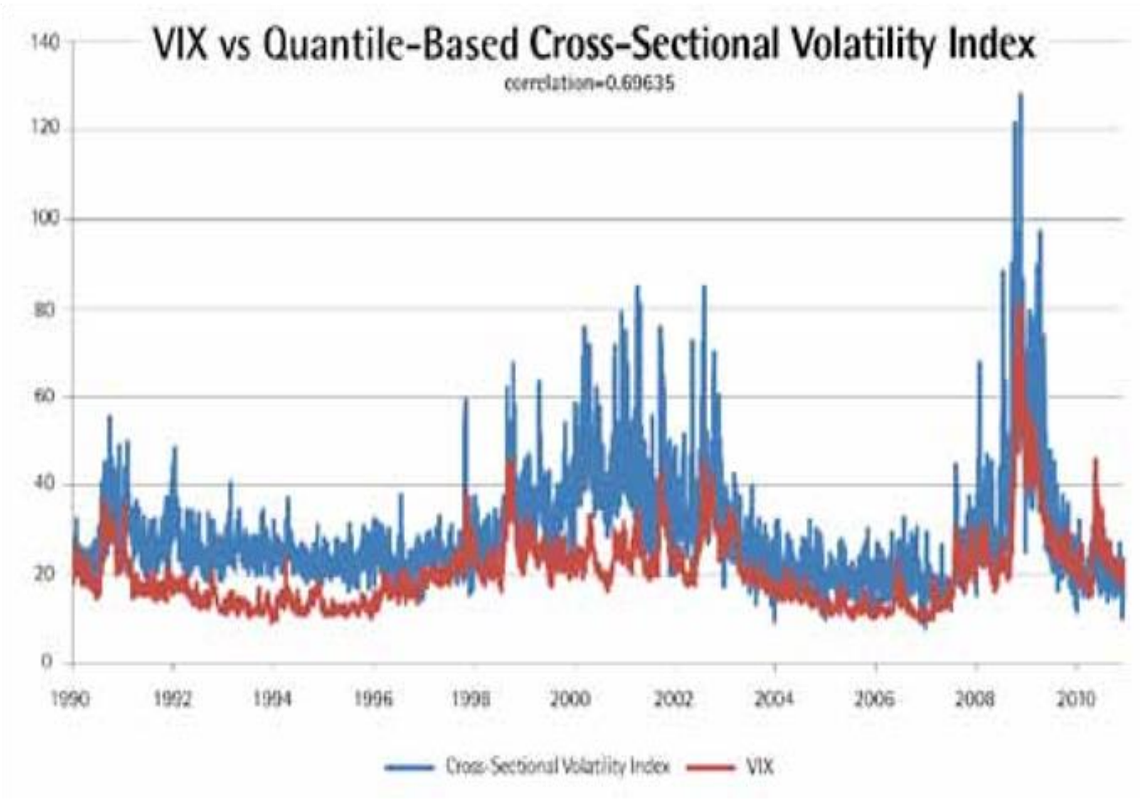
4.3. COMPARISON BETWEEN CROSS-SECTIONAL VOLATILITY INDEX AND VIX INDEX

As said before, since average and systematic specific volatility indicators are the investors' faced aggregate uncertainty's reflection regarding economic fundamentals at a given point of time, they both should be highly correlated. This intuition is confirmed and high correlation is found between VIX index, based on option prices a systematic risk's imperfect measure, and the cross sectional volatility index, an unbiased and a model-free proxy for specific risk.

Shown in figure 2 is the quantile-based cross-sectional volatility index's time series, ranging from January 1990 to November 2010 sample period, based on S&P 500's daily stock return data in comparison with the VIX index.

A high correlation (0.70) that confirms the option-implied volatilities' close relativeness to its average idiosyncratic volatility counterpart is found on the sample period. It is also found that with a conditional correlation that tends to be higher in down markets, there is a robust to changes of high correlation in market condition. To give an example, when one standard deviation below the mean are the daily market returns, it is estimated that the VIX and the cross-sectional' correlation is (0.73), which compared to unconditional estimate of (0.70), is slightly higher.

Figure 2. *The Cross-Sectional Volatility Index and the VIX Index's Time Evolution*



Source: The quantile-based cross-sectional volatility index's time series, ranging from January 1990 to November 2010 sample period, based on S&P 500's daily stock return data in comparison with the VIX index. (The Cross-Sectional Volatility Index by Felix Goltz, el. (2011)).

FOURTH CHAPTER

AUTOREGRESSIVE DISTRIBUTED LAG (ARDL) MODEL

1. COINTEGRATION TEST

Through cointegration, modeling time series can be done for keeping their long-run information intact. For evaluating the long-run relationship's existence between set of variables within a dynamic specification framework by providing estimation procedure and tests, the first to formalize the idea of cointegration were Granger (1981) and, Engle and Granger(1987). The examination of how time series which, might drift extensively away from equilibrium and might individually be non-stationary could be paired in a way that is ensured that they will not drift too far apart by working of equilibrium forces, is done by cointegration test. Therefore, individually non-stationary but integrated to an order, I(d)'s certain stationary linear combination of variables is what cointegration involves.

Among underlying economic time series that converges over time, the econometric concept that mimics the existence of a long-run equilibrium is said to be cointegration. Accordingly, a stronger economic basis and statistical for connection model of empirical error, which brings short and long-run information in modeling variables together, is established by cointegration. If a meaningful long run relationships is empirically exhibited by a model, establishing a test for cointegration is a needed step. If cointegration establishment among underlying variables is failed, continuing to work with variables in differences instead becomes imperative which causes the missing of long run information. Autoregressive Distributed Lag (ARDL) cointegration technique or bound cointegration testing technique is among several cointegration tests, other than Engle and Granger (1987) procedure.

The series subject to analysis in the study (XKURY and VIX) were determined as stationary at different levels. This does not enable the use of Engle-Granger and Johansen cointegration tests. At this point, the limit test approach developed by Pesaran et al. in 2001 is suitable to use. According to this approach; Regardless of which level the series are stationary, it is tried to determine whether there is a cointegration between the datasets examined.

2. AUTOREGRESSIVE DISTRIBUTED LAG (ARDL) APPROACH TO COINTEGRATION TESTING OR BOUND COINTEGRATION TESTING APPROACH

Cointegration procedure of Johansen and Juselius (1990) is not applicable, when one cointegrating vector exists. Therefore, regardless of whether the underlying variables are I(0), I(1) or both, exploring Autoregressive Distributed Lag (ARDL) approach for a long-run relationship to cointegration or bound procedure which is proposed by Pesaran and Shin (1995) and Pesaran et al (1996b), becomes imperative. In such a case, realistic and efficient estimates will be given by the application of ARDL approach to cointegration.

Autoregressive Distributed Lag (ARDL) approach to cointegration, unlike Johansen and Juselius (1990)'s cointegration procedure, helps in cointegrating vector(s) identification. It means that, underlying variables each stands as an equation of single long run relationship. The ARDL model of the cointegrating vector will be reparametrized into Error Correction Model (ECM), by identification of one cointegrating vector (i.e the underlying equation). Short-run dynamics (i.e. traditional ARDL) as well as long run relationship of a single model's variables are given by the reparametrized result. Since on one hand the ARDL is an equation of dynamic single model and on the other hand it is the same form with the ECM, the re-parameterization is possible. The inclusion of regressor's unrestricted lag in a regression function is what ARDL simply mean. Given the endogenous variable, in order to know whether model's underlying variables are cointegrated or not, this cointegration testing procedure helps. However, ARDL approach to cointegration isn't applicable when multiple cointegrating vectors are there. Therefore, the alternative becomes Johansen and Juselius (1990) approach.

The reason for using the ARDL / Bound Test approach to explore the effect of the VIX index on the BIST-100 index is that the variables used in the analysis are not stationary at the same level and that none of the variables are quasi-stationary.

In the first phase of the ARDL/Bound Test approach, an unrestricted error correction model is established. In order to test the presence of cointegration relationship between variables, after determining the delay length m the bound test based on the *F* test statistics is applied. Here, the null hypothesis $(H_0 : \beta_1 = \beta_2 = \beta_3 = 0)$

indicates that there is no cointegration between variables. The calculated F test statistic value is compared with Pesaran, Shin and Smith (2001)'s table of lower and upper critical values. If the calculated F test statistic value is less than the subcritical value, the null hypothesis is accepted, which indicates that there is no cointegration. If the F test statistic value is greater than the upper critical value, the null hypothesis cannot be accepted, which means that there is cointegration. If the calculated F test value falls between the upper and lower critical values; in this case, it is not possible to reach an exact information on whether there is cointegration or not.

If cointegration is determined between the series examined as a result of analyzes, for the prediction of long-term coefficients start as the next step. After calculating the coefficients that reveal the long-term relationship, by observing the diagnostic tests of the model, suitability of the model is checked. As a final step, CUSUM test is applied and the existence of long term relationship is tried to be shown graphically.

The specification of ARDL ($p, q1, q2......qk$) model is given as follows;

$$\Phi(L,p)yt = \sum_{i=1}^{k} \beta i \text{ (L, qi) x}it + \delta wt + ut \tag{1.1}$$

Where,

$\Phi(L,p) = 1- \Phi_1 L - \Phi_2 L^2 -....-\Phi_p L^p$

$\beta(L,q) = 1- \beta_1 L - \beta_2 L^2 -....-\beta_q L^q$, $\quad$ *for* $i=1,2,3.......k$, $\mathbf{u}_t \sim iid(0;\delta^2)$.

L is a Lag operator such that $L^0 yt=Xt$, $L^1 yt=yt-1$, and wt is a sx1 deterministic variables' vector such as the seasonal dummies, exogenous variables, intercept term or time trends with the fixed lags. $P=0,1,2...,m$, $q=0,1,2....,m$, $i=1,2....,k$: namely a total of $(m+1)^{k+1}$ different ARDL models. 'm', the maximum lag order, is selected by the user. Sample period, $t = m+1, m+2...., n$.

OR

The ADRL (p,q) model specification:

$$\boldsymbol{\Phi}(L)yt = \boldsymbol{\varphi} + \boldsymbol{\theta}(L)xt + ut \qquad (1.2)$$

With

$$\boldsymbol{\Phi}(L) = 1 - \boldsymbol{\Phi}1L - \ldots - \boldsymbol{\Phi}pL^p,$$

$$\boldsymbol{\theta}(L) = \boldsymbol{\beta}0 - \boldsymbol{\beta}1L - \ldots - \boldsymbol{\beta}qL^q.$$

Hence, the general ARDL *(p,q1,q2......qk)*model;

$$\Phi(L)yt = \boldsymbol{\varphi} + \boldsymbol{\theta}1(L)x1t + \boldsymbol{\theta}2(L)x2t + \boldsymbol{\theta}k(L)xkt + \mu t. \qquad (1.3)$$

It is suitable to define the lag polynomial *Φ(L,p)* and the vector polynomial *β(L,q),* by using the lag operator L applied to each component of a vector, $L^k y = yt\text{-}k$. The ARDL models can by ordinary least squares can consistently be estimated, as far as the error term ut can be assumed to be a white noise process, or in a wider sense, stationary as well as independent of *xt, xt-1, … and yt, yt-1, …* **.**

2.1. AUTOREGRESSIVE DISTRIBUTED LAG MODEL (ARDL) APPROACH'S APPLICATION REQUIREMENTS TO COINTEGRATION TESTING

- ARDL technique is applicable, irrespective of whether the underlying variables are I(0) or I(1) or both. By help of this, associated with standard cointegration analysis' pretesting problems in which the variables classification into I(0) and I(1) is required, can be avoided. This indicates that the pre-testing of the variables consisted in the model for unit roots, is not required for the bound cointegration testing procedure and when a long-term relationship exists between the underlying variables, it is robust.
- Representation of the ARDL error correction becomes rather more efficient, if the idea of a single long run relationship existence as well as small or finite sample data size is established by the F-statistics (Wald test).
- The ARDL approach is said not to be applicable when multiple long-run relations are established by the F-statistics (Wald test). Thus, Johansen and Juselius (1990) approach can be applied alternatively. In other words, a multivariate procedure should be employed, if a feedback effect (multiple long run relationships) between variables is shown by the different single equation/expression of the individual variable's underlying as dependent variable.

- ❖ ARDL approach is applicable rather than applying Johansen and Juselius, if the idea that there is a single long-run relationship is established by the Maximal eigenvalue or the F-statistics.

2.2. ADVANTAGES OF THE ARDL APPROACH

- ❖ Since in ARDL technique, endogeneity is less problematic due to it's free of residual correlation (i.e. assuming all variables to be endogenous), each of the underlying variables stands as a single equation.
- ❖ ARDL procedure can differentiate between explanatory and dependent variables, as there is single long run relationship. In other words, between the exogenous variables and dependent variables, the existence of only a single reduced form equation relationship is assumed by the ARDL approach (Pesaran, Smith, and Shin, 2001).
- ❖ The cointegrating vectors' identification, in which multiple cointegrating vectors are there, is where this approach's major advantage lies in.
- ❖ Through a simple linear transformation, in which without losing long run information, short run adjustments with long run equilibrium integrates, we can derive the Error Correction Model (ECM) from ARDL model. For capturing the generating process of data in general to specific modeling frameworks, an important number of lags is taken by the associated ECM model.

2.3. STEPS OF THE ARDL COINTEGRATION APPROACH

2.3.1 Determination of the Variables Long Run Relationship Existence

At the first step, for a long run relationship establishment among the variables, by calculating the F-statistic bound (cointegration's bound test), the long-run relation existence between under investigation variables, is tested. On each of the endogenous variables, unlike others which assumed to be exogenous variables, the bound F-statistic is carried out.

Practically, long-run relationship hypothesis testing among the underlying variables, is where relationship testing among the ARDL model's forcing variable(s) leading us. By doing so, the underlying variable's current values will be excluded from the ARDL approach to cointegration. By using an ARDL (p,q) regression with an I(d) regressors, this approach is illustrated.

$$yt = \Phi 1yt\text{-}1 + \ldots + \Phi pyt\text{-}p + \theta 0xt + \theta 1xt\text{-}1 \ldots + q1xt\text{-}p + u1t \qquad (1.4)$$

Or

$$xt = \Phi 2xt\text{-}1 + \ldots + \Phi pxt\text{-}p + \theta 0yt + \theta 1yt\text{-}1 \ldots + q1yt\text{-}p + u2t \qquad (1.5)$$

$t = 1, 2 \ldots. T \qquad \mu t \sim iid\ (0, \delta 2).$

Constant and linear time trend deterministic regressors are not included for the sake of convenience. Where unknown parameters are: Φ, $\theta 0$ and $\theta 1$ as well as I(d) process is xt(or yt) generated by;

$xt= xt\text{-}1+\mathcal{E}t;$ *or* $yt= yt\text{-}1+\mathcal{E}t;$

No long-run relationship would be there, if Φ =1. Practically, this is shown as follow: Model approach of the ARDL (p, q1,q 2......qk) to Cointegration testing;

$$\Delta Xt = 0i + \sum_{i=1}^{k} \alpha i\, \Delta X_{t\text{-}1} + \sum_{i=1}^{k} \alpha i \Delta Y_{t\text{-}i} + \delta_1 X_{t-1} + \delta_2 Y_{t-1} + v_{1t} \qquad (1.6)$$

$$\Delta Xt = \delta 0i + \sum_{i=1}^{k} \alpha i\, \Delta Y_{t\text{-}1} + \sum_{i=1}^{k} \alpha i \Delta X_{t\text{-}i} + \delta_1 Y_{t-1} + \delta_2 X_{t-1} + v_{1t} \qquad (1.7)$$

For all lags, ut and Ɛt are uncorrelated in a way that with respect to ut, xt (or yt) is strictly exogenous. Thus, Ɛt is said to be a general linear stationary process. The model is dynamically stable since, (Cointegration/stability Condition) /Φ/ <1. This assumption implies the existence of a stable long run relationship between yt(xt) and xt (yt), since it is resembling to an AR(1) process's stationarity condition.

The maximum lag order of ARDL model which is chosen by the user is 'k'. On the joint null hypothesis, where the lagged variables' coefficients ($\delta 1 Xt-1\ \delta 1 Yt-1$ *or* $\delta 1 Yt-1\ \delta 1 Xt-1$) are zero, the F-statistic is carried out. The long-run relationship is corresponded by (δ1 – δ2), whereas the short-run dynamics of the model is represented by ($\alpha 1 - \alpha 2$). It is needed to test the hypothesis which is saying that the lag level variables' coefficients are zero. The long-run relationship's non-existence null is defined by;

Ho: $\delta 1 = \delta 2 = 0$ (Null, i.e. no existence of the long run relationship)

H1: $\delta 1 \neq \delta 2 \neq 0$ (Alternative, i.e. existence of the long run relationship)

In each of the models, this is tested according to the number of variables.

It can also be shown as follows:

$$FX\,(X1 \mid Y1 \ldots\ldots Yk) \tag{1.8}$$

$$Fy\,(Y1 \mid X1 \ldots\ldots Xk) \tag{1.9}$$

In both equations, the testing of the hypothesis is done by means of the F-statistic. Regardless of whether system's variables are I (0) or I (1), this F-statistics' distribution is non-standard. In Pesaran and Pesaran (1996a), and Pesaran et al. (2001), F-statistics' critical values for various number of variables (K), as well as whether a trend and/or an intercept is contained in ARDL model is available. Two sets of critical values are given by them. All the variables being I (0) is assumed by one set (i.e. existence of no cointegration among the underlying variables is the meaning given by lower critical bound assumption) on the other hand, the assumption of another set is that ARDL model's all variables are I (1) (i.e. existence of cointegration among the underlying variables is the meaning given by upper critical bound assumption).

A band that covers all the possible variables' classifications into I (0) and I (1), exists for each application. Though as said by Narayan (2005), since the Pesaran et al. (2001)'s basis of existing critical values are on large sample sizes, it is not applicable for small sample sizes. Thus, for small sample sizes, a critical values set ranging from 30 to 80 observation is provided by Narayan (2005). Respectively, 2.496 - 3.346, 2.962 – 3.910, and 4.068 – 5.250 at 90%, 95%, and 99%, are the critical values. Without considering whether underlying variables are I (0) or I (1) or fractionally integrated, we can make a conclusive decision, if for joint significance of the level variables, the relevant computed F-statistic in each of the equations, δ1, and δ2 falls outside this band. This means, the H0 is rejected when the computed F-statistic is greater than critical value of upper bound (the variables are cointegrated). On the other hand, H0 can't be rejected if the F-statistic is below the critical value of lower bound (no cointegration exists among the variables).

ARDL approach is not applicable when in both equations, long run/multiple long run relationships exist, thus, as an alternative, Johansen and Juselius (1990) approach can be used. The inference's result will be inconclusive and depends on underlying variables being I (0) or I (1), in the case that there be a fall of computed statistic within (between the lower and upper bound) the critical value band. At such a stage of the analysis, unit root tests on the variables should be carried out by investigator (Pesaran and Pesaran, 1996a). It is mentionable that, since the computed F-statistics of the bound test are based on the assumption that the variables are I (0), I (1) or mutually cointegrated, it is rendered invalid if the variables are I (2) (Chigusiwa et al., 2011).

2.3.2 Appropriate Lag Length Selection for the ARDL Model/ Selected ARDL Model's Long Run Estimation

The ARDL approach to cointegration is applicable if between the underlying variables, a long run relationship exists, whereas in other equation, no long run relations hypothesis between the variables can't be rejected. Since we need to have Gaussian error terms (i.e. standard normal error terms which don't undergo with autocorrelation, heteroscedasticity, non-normality etc.), it is very significant to find the suitable lag length in the ARDL model for each of the underlying variables. Resolution of the optimum lag length (k) is necessary for selecting the long run underlying equation appropriate model which can be done through use of proper model order selection criteria like; Schwarz Bayesian Criterion (SBC), Hannan-Quinn Criterion (HQC) or Akaike Information Criterion (AIC).

The AIC, SBC and LP values for the model are given as;

$$\text{AICp} = \text{-n/2(1+log2}\pi\text{)-n/2log}\delta^2\text{-P}$$

$$\text{SBCp} = \log(\delta^2) + (\text{logn/n})\ \text{P}$$

$$\text{HQC} = \log\delta + (\text{2loglogn/n})\ \text{P}$$

$$\text{LRp, p} = \text{n} (\log[\Sigma\text{p}]-\log[\hat{}\Sigma\text{p}])$$

Where: δ^2 is the estimator of Maximaum Likelihood (ML) for the regression disturbances' variance. ˆΣp is the sum of squared residuals estimation and, n is the estimated parameters number, p=0, 1, 2……P, in which P is the selected model's optimum order. The ARDL model is suggested to be estimated in terms of variables in their levels form. There should be an alternation in the variables' lags, compared and re-estimated model. Selection criteria of the model- that model performs relatively better, that has the smallest SBC, AIC estimates or small standard errors as well as high R2. The long run coefficients are among the best performed estimates. With the aim of avoiding spurious regression, if a long run relationship between the underlying variables is satisfied, then it is appropriate to commence.

The estimation of long-run coefficients for yt (or xt) to a unit change in xt (or yt) are done by;

$$\hat{\theta}i = \frac{\hat{\beta}_i\,(1,\ \hat{q}_i)}{\hat{\phi}\,(1,\ \hat{p})} = \frac{\hat{\beta}_{i0} + \hat{\beta}_{i1} + \ldots + \hat{\beta}_{iq}}{1 - \hat{\phi}_1 - \hat{\phi}_2 - \ldots\ \hat{\phi}_p} \qquad i=1,\ 2\ldots$$

Where ˆp and ˆqi , i =1, 2,. . .k are the selected(estimated values of p and q, i =1, 2. . ,k Likewise, the estimation of long-run coefficients related to the exogenous/deterministic variables with fixed lags are done by;

$$\hat{\psi} = \frac{\hat{\delta}\,(\hat{p},\ \hat{q}1,\ \hat{q}2\ldots\ \hat{q}k)}{1 - \hat{\phi}1 - \hat{\phi}2 - \ldots \hat{\phi}p}$$

Where ˆδ (ˆp, ˆq1, ˆq2… ˆ qk) indicates the OLS estimate of δ for the selected ARDL model. Practically, this can also be shown as follows:

Long run equation of the selected ARDL (k) model;

$$Yt = 0 + \sum_{i=1}^{k} \alpha 1\, X_{1t} + \sum_{i=1}^{k} \alpha 2\, X_{2t} + \sum_{i=1}^{k} \alpha 3\, X_{3t} + \sum_{i=1}^{k} \alpha n\, X_{nt} + v_{1t} \qquad (1.10)$$

Where k is the number of optimum lag order. Xs (X1t, X2t, X3t ….. Xnt) are the long run forcing variables or the explanatory.

The estimation of the associated Error Correction Model (ECM) is provided by the best performed model.

2.3.3. ARDL Model's re-parameterization into Error Correction Model (ECM)

As mentioned before, spurious results may be derived from the regression of non-stationary variables in a model. Differencing the data in order to get variable's stationarity is one method of resolving this. In such a case, from the regression model, parameters' estimations might be correct and problem of the spurious equation resolved. Nevertheless, only the short-run relationship between the variables is given by the regression equation. No information regarding parameters' long run behavior in the model is given by it. A problem is constituted by it since long-run relationships between the variables under consideration is what researchers are mainly interested in and for the purpose of resolving this, the cointegration and the ECM concept becomes imperative. Both, long-run as well as short-run information is now incorporated with the ECM's specification.

Associated with the ARDL *(ˆp, ˆq1, ˆq2…, ˆ qk)* model, by rewriting equation (1.4) in terms lagged levels and the first differences of yt...x1t... , x2t. . . xkt and wt, the unrestricted Error Correction Model (ECM) can be obtained. First note that; $yt = \Delta yt + yt\text{-}1$

$$y_{t-1} = y_t - \sum_{i=1}^{s-1} \Delta y_{i-j} \qquad s = 1, 2 \dots p$$

Similarly:

$$w_t = \Delta w_t + w_{t-1}$$

$$x_t = \Delta x_t + x_{t-1}$$

$$x1t\text{-}s = yit\text{-}1 - \sum_{i=1}^{s-1} \Delta x_{it-j} \qquad s = 1, 2 \dots qi$$

By substituting these relations with (4.1) we get;

$$\Delta y_t = -\,\phi\,(1,\ \hat{}p)\ ECt_{-I} + \sum_{i=1}^{k} \beta_{i0}\,\Delta x_{it} + \delta\Delta w_t \sum_{j=1}^{p-1} \phi_j \Delta_{t-j} \sum_{i=1}^{k} . \sum_{j=1}^{kq-1} \beta_{ij}\,\Delta x_{i,1-j} + \mu t \qquad (1.11)$$

The error correction term is ECt defined by;

$$EC_t = \varepsilon_t = y_t - \sum_{i=1}^{k} \theta_i\,.\,x_{it} - \psi' w_t$$

As the error term from the cointegration model (1.6 and 1.7) that through equation normalizing on Xt (1.6) and Yt (1.7) respectively, their coefficients are derived, the term ECt as the adjustment parameter's speed or feedback effect is obtained. The extent to which disequilibrium is being corrected, that is, in previous period how much disequilibrium is being adjusted in yt is shown by ECt. A divergence is denoted by a positive coefficient, whereas convergence is denoted by a negative coefficient. ECt=1 estimation indicates 100% adjustment taking place within the period or in other words, there is a full and instantaneous adjustment. On the other hand, ECT= 0.5 estimation means in each period/year, 50% adjustment takes place. If the estimate of ECt= 0, it indicates the existence of no adjustment and there is no sense of claiming a long-run relationship. Remember that the quantitative importance of the error correction term is measured by;

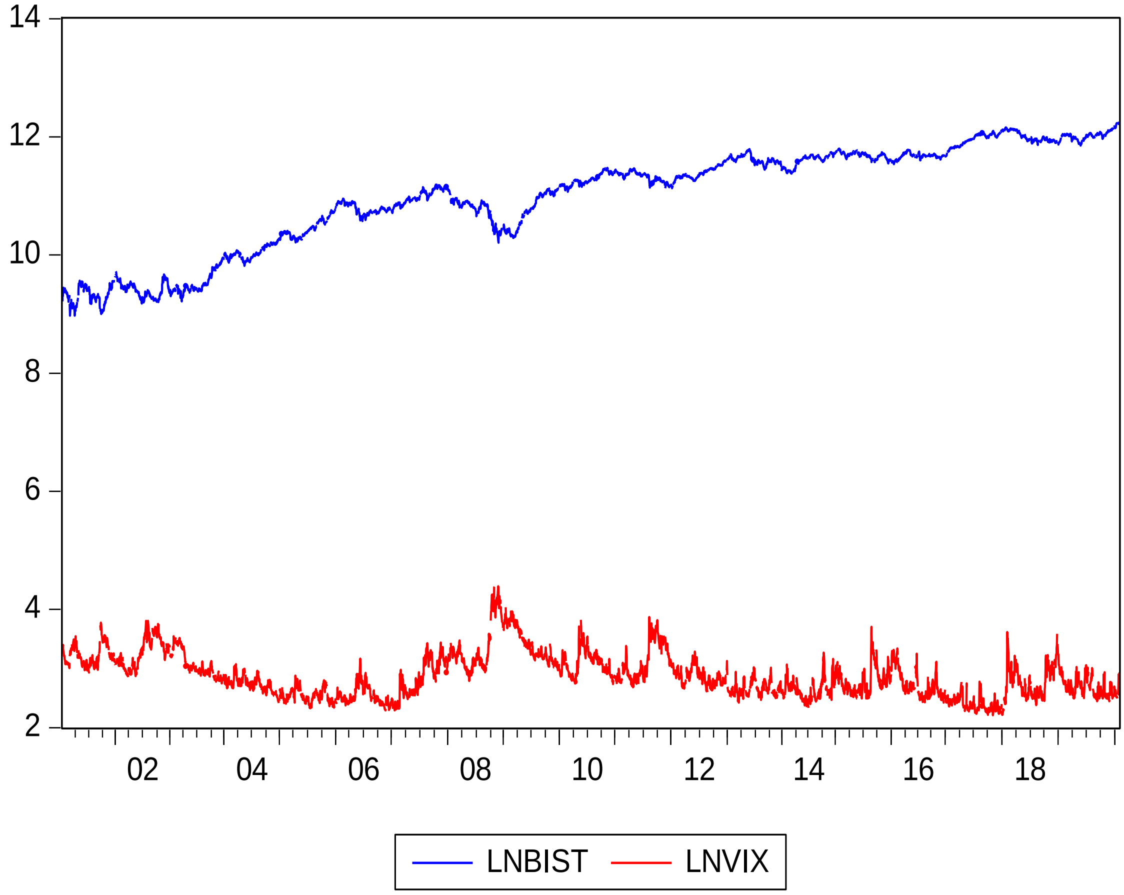
$$\Phi\ (1, \hat{}p) = 1- \hat{}\phi1 - \hat{}\phi2 - . . . \hat{}\phi p$$

The rest of the coefficients which are ˆϕj and βij, are related to the convergence to equilibrium of the model's short run dynamics. Derived from the estimated cointegration model of equation 1.6 and 1.7, ECt is the residuals. Through OLS method, we can estimate the ARDL models as well as its associated ECM.

3. DATA SET

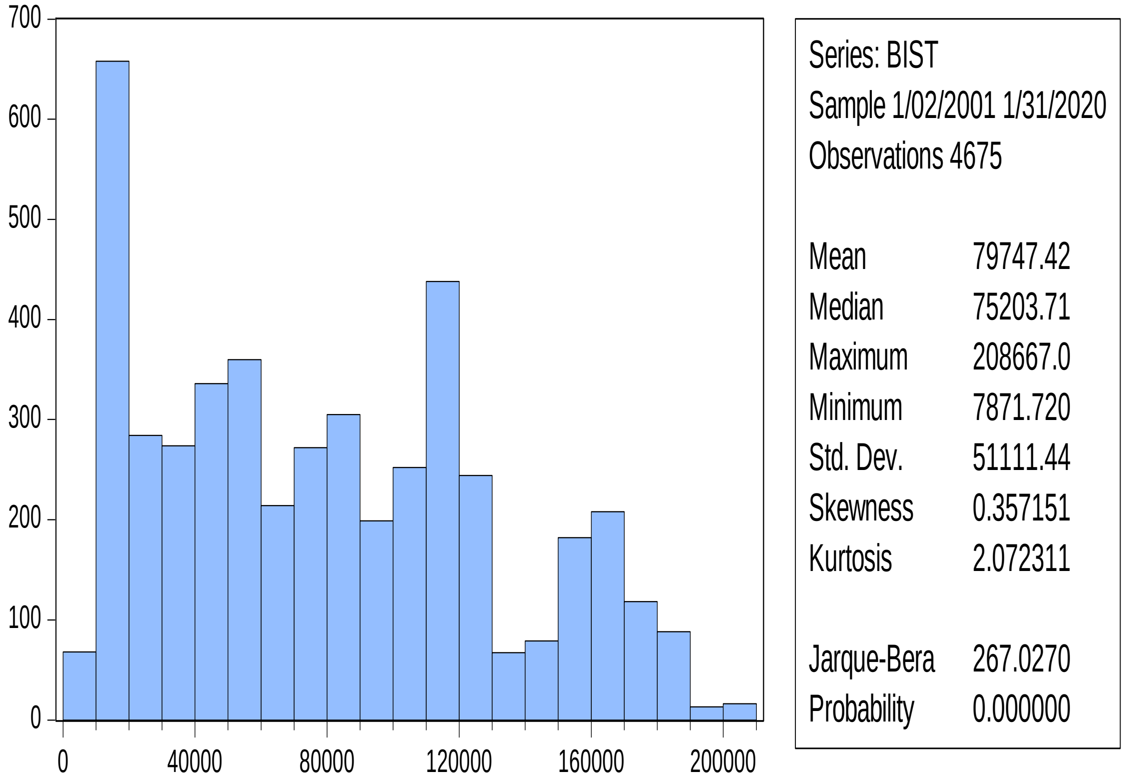
This study investigates the effect of VIX index on BIST-100 index. For this purpose, analyzes were carried out on daily data between January 3, 2001 and January 31, 2020. Data for both indices calculated on a daily basis were obtained from various sources. While the data for the XKURY index were obtained from Borsa Istanbul; the data of the VIX index are accessed from yahoo, finance and Bloomberg Terminal databases. Before starting the analysis, day harmonization was made between both indices. According to this; VIX index value on the day when Borsa Istanbul is not calculated; on the day when the VIX index value is not calculated, Borsa İstanbul value is not included in the calculations.

Figure 3. The Daily Values of BIST-100 and VIX Indices with Logarithms between 2001-2020



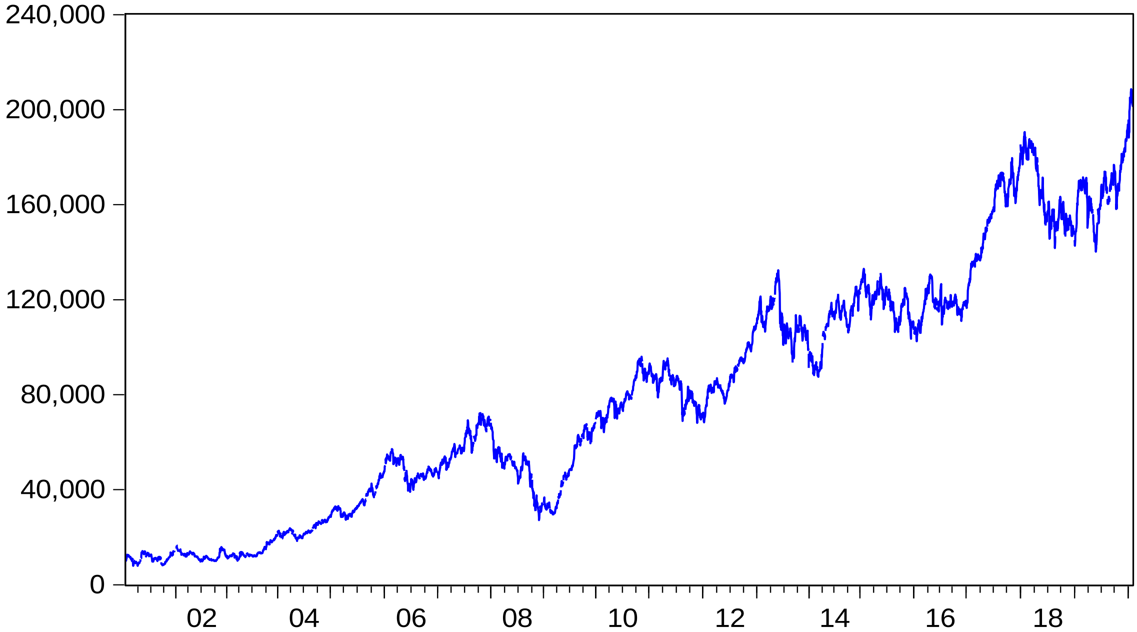
In Figure 3, there is a graphical representation of the daily returns of the VIX index and BIST-100 index, which are the subject of analysis, for the analysed period (03.01.2001-31.01.2020). When examined in both indices whose natural logarithm is taken; In the period of 2008-2009, when the global financial crisis was effective, the VIX index, which is the volatility index, increased, whereas the BIST-100 index showed great decreases as a result of the increase in volatility. This emerging situation is also expected in terms of finance theory. As the volatility in the market increases, the risk increases and investors' trust decreases. As a final result, significant decreases are observed in index returns. In the study, descriptive statistics of the series were obtained after drawing the return graph and performing the unit root test. These statistics, which are important in terms of revealing the characteristic of the BIST index; it consists of mean, standard deviation, skewness and kurtosis coefficients and Jarque-Bera test.

Figure 4. *Descriptive Statistics of BIST-100 Return Index*



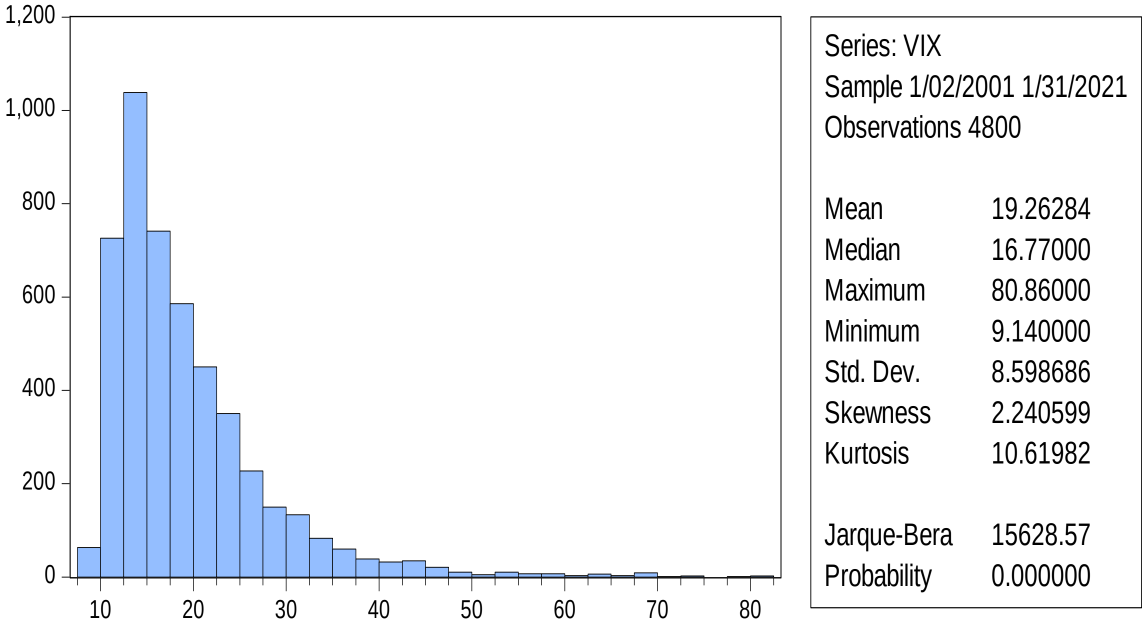
Looking at Figure 4, positive returns of the index for the relevant period (2001-2020) were determined. The maximum return to index in this period is 208667.0; minimum return - calculated as 7871.720. Skewness of the series with a standard deviation of 51111.44 is 0.357151. Since the coefficient of skew is positive, it is seen that the series is crooked to the right and the right tail is long. Considering another descriptive statistical value, kurtosis coefficient, since it is 2.0723, it is revealed that the series follow a horizontal course and is normal as it is less than 3. Finally, when looking at the results of the Jarque-Bera test conducted to determine whether the returns of the BIST index show normal distribution, it was determined that the series did not show a normal distribution. Since the obtained test statistic value (2.0723) is higher than 0.992 table value of 5.99, the series is not normally distributed.

__Figure 5.__ Graph of BIST-100 Return Index (2001-2020)



As shown in Figure 6, for the sample period of (2001-2020), a number of 4800 observation is taken. The maximum return to index is, 80.86000 whereas the minimum return to index is 9.140000. With a standard deviation of 8.598686, the skewness of the series is, 2.240599. According to the descriptive value of kurtosis coefficient, which is 10.61982, we can say that since it is more than 3, then it is not normal.

__Figure 6.__ Descriptive Statistic of VIX Index



When it comes to Jarque-Bera test, to see whether rate of VIX index show a normal distribution, again since the obtained test statistic value is (15628.57), we can say that the series don't show a normal distribution.

4. UNIT ROOT TESTS

However, the pre-testing of the variables in the model for the unit root is not required by the ARDL approach to cointegration, but we use it to see that our t-statistics variables are either I (0) or I(1) and not I (2) or beyond that which makes it invalid. Therefore, it is important to implement unit root test to ensure that none of the variables is integrated of order 2 or beyond. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are employed by the study to determine the order of integration of the variables.

Null Hypothesis: BIST has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=31)

Table 4. *Augmented Dickey-Fuller at level*

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			0.185853	0.9718
Test critical values:	1% level		-3.431566	
	5% level		-2.861963	
	10% level		-2.567038	

Table 5. *Phillips- Perron at level (1)*

			Adj. t-Stat	Prob.*
Phillips-Perron test statistic			0.216394	0.9737
Test critical values:	1% level		-3.431566	
	5% level		-2.861963	
	10% level		-2.567038	

Table 6. *Augmented Dickey-Fuller at first difference*

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-68.41522	0.0001
Test critical values:	1% level		-3.431567	
	5% level		-2.861963	
	10% level		-2.567038	

Table 7. *Phillips- Perron at level (2)*

			Adj. t-Stat	Prob.*
Phillips-Perron test statistic			-68.42200	0.0001
Test critical values:	1% level		-3.431567	
	5% level		-2.861963	
	10% level		-2.567038	

4.1 RESULTS OF UNIT ROOT TEST

Results taken from Augmented Dickey-Fuller show that critical value is less than 5%, which means that our test is stationary. As with the Augmented Dickey-Fuller tests, the Phillips- Perron tests do not reject the null hypothesis and accordingly at any reasonable significance level our decision is *I* (1).

5. ANALYSIS AND FINDINGS

Figure 3 shows time series plots of logarithm of two variables in the specified range. Before analysing the long-term relations of the BIST-100 index with the VIX index, it was tried to determine whether the series move together or opposite by looking at the correlation relationship between these logarithms variables. The aim is for the series to move in opposite directions which means, it has a negative correlation. The reason behind this is, the opposite relationship between volatility index and return index. As stated in the studies of Sharpe (1964) and Merton (1973), an increase in volatility in the market leads to a decrease in stock returns. Therefore, BIST-100 index is expected to decrease as a result of increasing VIX index, which is the volatility index used in the study. Correlation matrix created for this purpose is given in Table 8:

Table 8. *Inter-index Correlation Table*

Indices	*LNBIST*	*LNVIX*
LNBIST	1.00	-0,43
LNVIX	-0.43	1.00

The results in Table 8 show the strong negative relationship between BIST-100 and VIX index. This result is in parallel with the literature and expectations. In the second stage of the study, stationarity analyses of the series were made. For this purpose, ADF and PP unit root tests, which are widely used in the literature, were performed to determine whether the series contain unit root. Unit root test results are given in Table 9.

Table 9. *Results of ADF and PP Unit Root Test for BIST and VIX Indices*

Variables	ADF			PP		
	Level	First Difference	Decision	Level	First Difference	Decision
BIST Index	-3.43 (0.97)	-68.41 (0.00)	$I(1)$	-3.43 (0.97)	-68.42 (0.00)	$I(1)$
VIX Index	-3.43 (0.00)	-	$I(0)$	-3.43 (0.00)	-	$I(0)$

Therefore, the two indices examined are not stable at the same level. This result does not allow the use of Engle-Granger and Johansen cointegration tests. The reason for this is that both models, which are called classical cointegration tests, allow the series to be analysed with a difference from the same rank for the cointegration test. Thus, the result of the BIST variable *I (1),* VIX variable *I (0)* obtained in the study was determined by Pesaran and Shin in 1997 has made it mandatory to use the ARDL (Autoregressive Distributed Lag) model developed by Pesaran et al. in 2001. This model (ARDL) is a method used without the need to know whether the series used in the analysis contain unit roots. In the ARDL model, also known as Bound Test, one of the series is I (0) and the other is I (1), which allows analysis and reveals whether there is a cointegration relationship between the series examined.

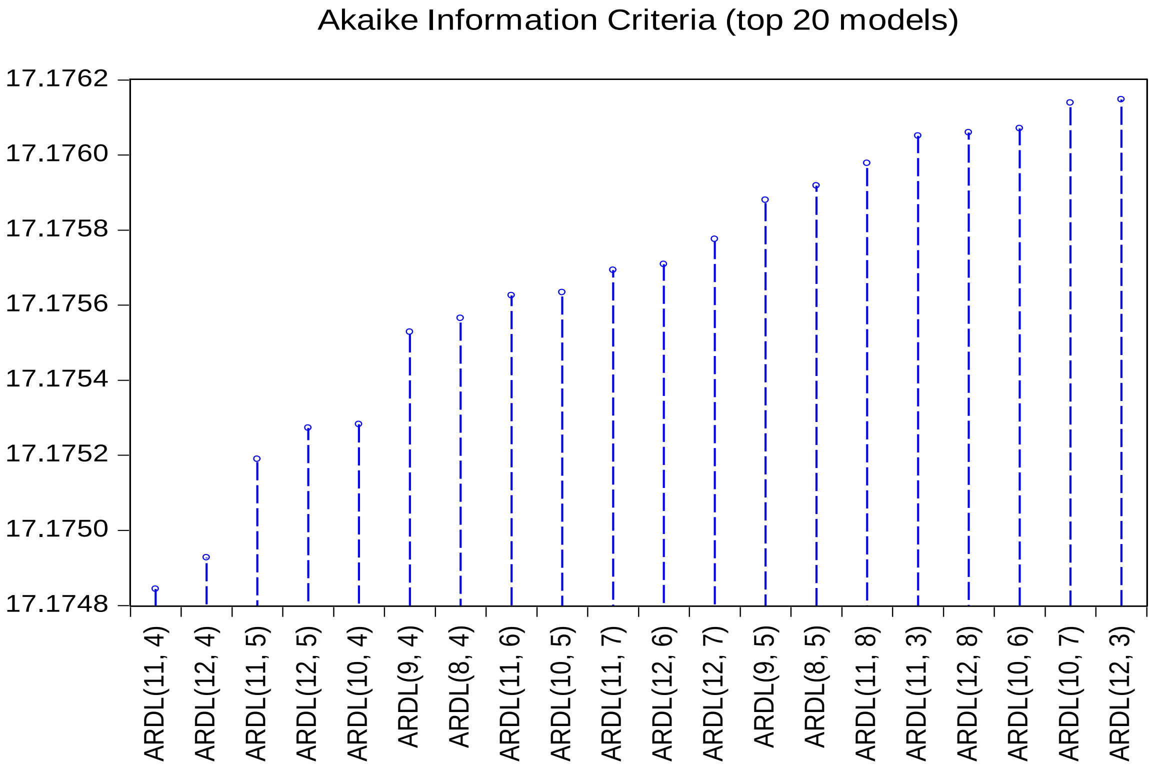
An unrestricted error correction model is established for the application of the Bound Test, which will be used to test the presence of a possible long-term relationship between the indices. For this purpose, the model selection criterion and the autoregressive distributed lag model obtained by choosing Akaike Information Criteria (AIC) are given in Table 10 below.

Table 10. *ARDL (11, 4) Model Prediction Results*

Variable	Coefficient	Std. Error	$t-$Istatistic	Probabilities
C	177.0771	71.16097	2.488403	0.0129
BIST(-1)	0.975723	0.014814	65.86390	0.0000
BIST(-2)	0.034098	0.020696	1.647529	0.0995
BIST(-3)	0.040649	0.020557	1.977323	0.0481
BIST(-4)	-0.073584	0.020424	-3.602778	0.0003
BIST(-5)	0.003621	0.020388	0.177604	0.8590
BIST(-6)	-0.018517	0.020384	-0.908386	0.3637
BIST(-7)	-0.005368	0.020388	-0.263264	0.7924
BIST(-8)	0.057925	0.020355	2.845737	0.0045
BIST(-9)	-0.046252	0.020386	-2.268839	0.0233
BIST(-10)	0.054325	0.020401	2.662903	0.0078
BIST(-11)	-0.028879	0.014437	-2.000356	0.0455
VIX	-77.41520	11.35530	-6.817537	0.0000
VIX(-1)	-100.2338	15.25024	-6.572604	0.0000
VIX(-2)	130.2003	15.30845	8.505126	0.0000
VIX(-3)	6.496359	15.43725	0.420824	0.6739
VIX(-4)	31.95835	11.68336	2.735373	0.0063

According to the results in Table 10, the autoregressive distributed lag model ARDL (11, 4), where the BIST-100 index is estimated as a dependent variable. This model states that in addition to the past values of the BIST-100 variable in twelve periods and the current values of the VIX variable, this variable is explained with the past values of the four periods. ARDL (11, 4) model was preferred because it has the smallest AIC value among other possible models. The 20 models with the lowest AIC values among all possible models are given in Figure 7.

Figure 7. *Top 20 Models with the Lowest Akaike Information Criteria*



It is important that the error terms of the obtained ARDL (11.4) model do not have an autocorrelation problem. Otherwise, since the lagged values of the dependent variable BIST-100 are included in the model as the explanatory variable, the parameter estimators obtained from the model will not be consistent. Whether the error terms of the model are autocorrelated or not, is investigated with the Breusch-Godfrey LM Test.

Table 11. *Breusch-Godfrey Serial Correlation LM Test*

F-statistic	0.852203	Prob. F(2,4545)	0.4265
Obs*R-squared	1.711264	Prob. Chi-Square(2)	0.4250

According to the test result, it was determined that there was no autocorrelation problem. Since the results obtained are higher than 5% significance level, there is no autocorrelation problem between series. After determining that the error terms of the model are not autocorrelated, Bound Test application is started. Bound Test results obtained on the basis of ARDL (11, 4) model are given below in Table 12.

Table 12. *Results of Bound Test*

k	*F* - statistic	Critical Values at 1% Significance Level		Critical Values at 2.5% Significance Level		Critical Values at 5% Significance Level		Critical Values at 10% Significance Level	
		Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
1	6.220064	6.1	6.73	5.3	5.83	4.68	5.15	4.05	4.49

Note: K (1) in the model shows the number of independent variables.

Table 12, after estimating the ARDL (11.4) model, Pesaran et al. (2001) shows the critical values at 1%, 2.5%, 5% and 10% significance levels. The *F*-statistic for the Bound Test appears to be 6.22. Since this value is between the upper and lower limit at 1% significance level, it does not allow for a definite long-term relationship. When looking at the significance levels of 2.5% and above, it is determined that the statistic is higher than the upper value. This shows that there is a long-term relationship between the series at the 2.5% significance level. When it is accepted that the level of significance in the social sciences is generally taken as 5%; according to this result, it is possible to reject the null-hypothesis “there is no long-term relationship (cointegration) between variables” at 5% significance level.

Table 13. *Cointegrating Form Table*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(BIST(-1))	-0.018018	0.014787	-1.218563	0.2231
D(BIST(-2))	0.016079	0.014764	1.089120	0.2762
D(BIST(-3))	0.056728	0.014429	3.931519	0.0001
D(BIST(-4))	-0.016856	0.014413	-1.169505	0.2423
D(BIST(-5))	-0.013235	0.014395	-0.919448	0.3579
D(BIST(-6))	-0.031752	0.014396	-2.205661	0.0275
D(BIST(-7))	-0.037119	0.014394	-2.578754	0.0099
D(BIST(-8))	0.020806	0.014388	1.446045	0.1482
D(BIST(-9))	-0.025446	0.014402	-1.766892	0.0773
D(BIST(-10))	0.028879	0.014405	2.004743	0.0450
D(VIX)	-77.415197	11.323269	-6.836824	0.0000
D(VIX(-1))	-168.655010	11.512450	-14.649793	0.0000
D(VIX(-2))	-38.454705	11.753289	-3.271825	0.0011
D(VIX(-3))	-31.958346	11.665354	-2.739595	0.0062
C	177.310446	36.724160	4.828169	0.0000
CointEq(-1)	-0.006259	0.001449	-4.320694	0.0000

Table 14. *Long-Run Co-efficient*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VIX	-1437.037015	437.337012	-3.285880	0.0010
@TREND	37.276152	2.465134	15.121350	0.0000

When long term coefficients are analyzed, it is determined that they are statistically significant at 1% significance level. According to this result, the decreases in the VIX Index reflect negatively on the BIST-100 index in the long run. However, there is a linear relationship between the trend in financial markets and BIST-100. This relationship can be expressed by the following equation.

*Cointeq = BIST - (-1437.0370*VIX + 37.2762*@TREND)*

By looking at the graph of the CUSUM test applied to the standardized recursive residues of the predicted model, we can see that CUSUM statistics remain within the limit values of 5% significance level. This illustrates that there is a long-term relationship between VIX Index and BIST-100 index. CUSUM test chart is given in Figure 6.

Figure 8. *CUSUM*

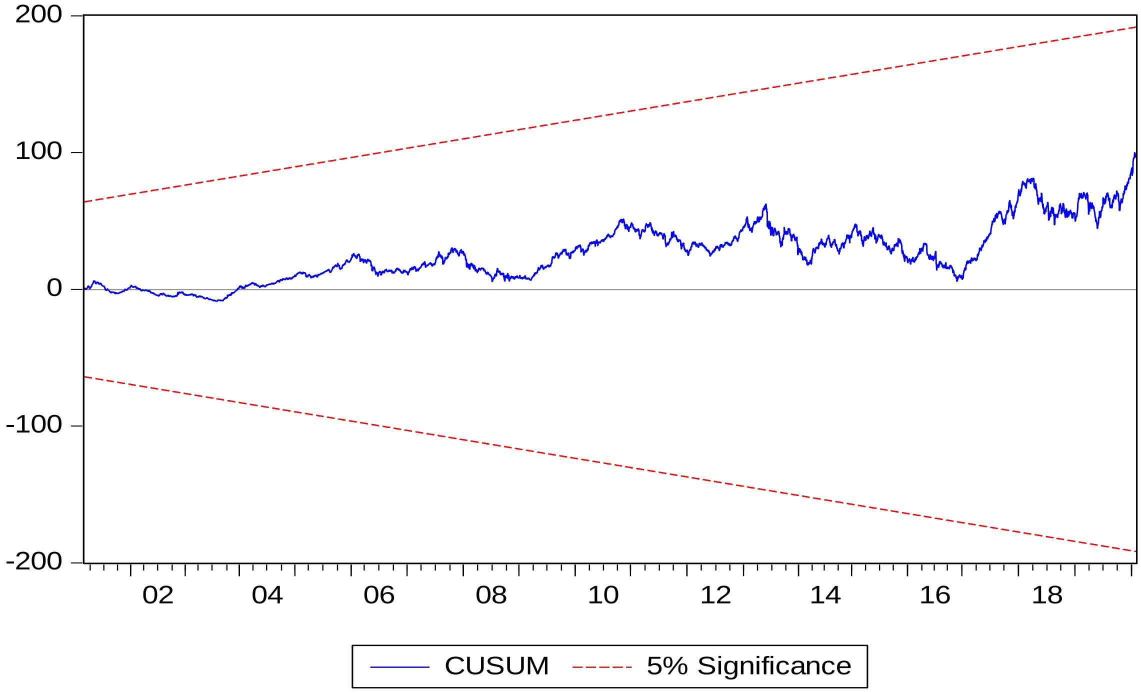
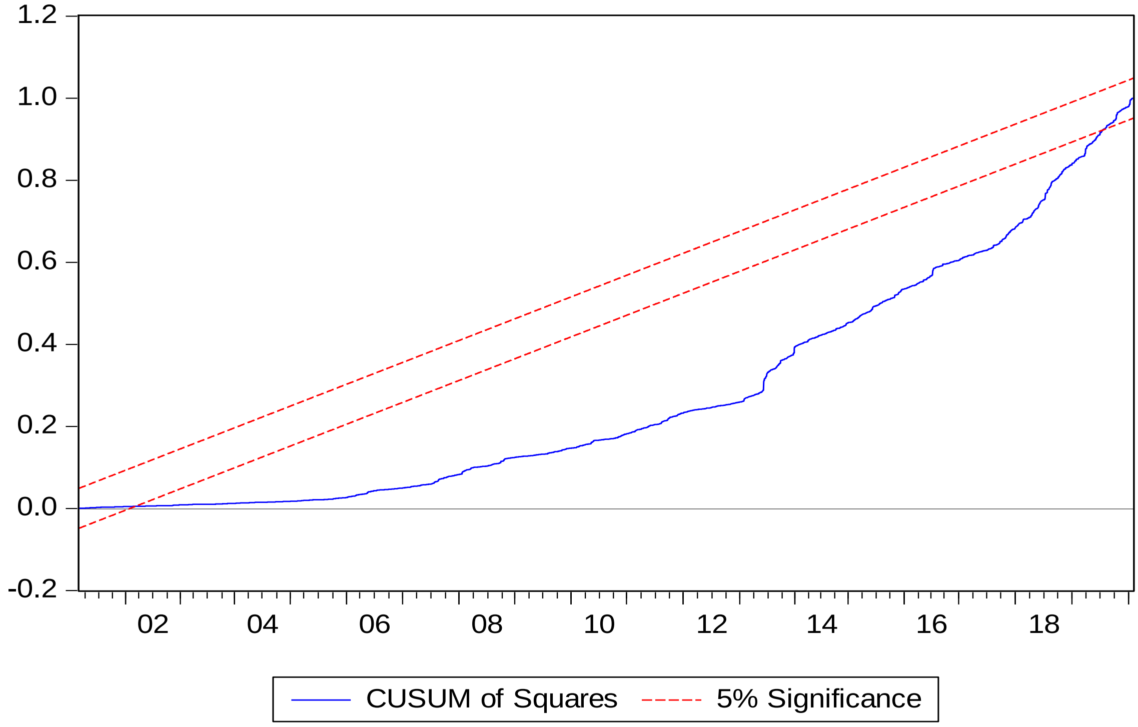


Figure 9. *CUSUM SQ*



The CUSUM SQ test result could not be provided. Apart from this, it was tested whether there was a model building error with the Ramsey test and it was observed that the F statistic value received a probability value of 0.58. This result reveals that there is no model building patient since it is higher than 5%.

5.1. CAUSALITY RELATIONSHIP

After determining the stationarity levels of variables, the presence of Granger causality relationship between BIST-100 and VIX Index variables was investigated with the causality analysis proposed by Toda and Yamamoto (1995). The reason why this method is preferred in the study is that the variables whose causality relationship is examined are stationary from the same level and cointegration between them does not require preliminary knowledge.

Table 15. *Toda-Yamamoto Granger Causality Test Results*

Null-Hypothesis (H_0)	*χ^2 test statistic*	*Decision*	*Result*
VIX Index is not the reason of BIST-100's Granger.	13.67 (0.02)	Rejected	VIX Index is the reason of BIST-100's Granger.

Explanation: Values in parentheses show their values of *p*. For the VAR model, the delay length was determined according to the Akaike Information Criterion (AIC) and the last prediction error criterion (FPE), it was obtained as *K=6* and $d_{\max} = 1$.

Table 15 shows the results of the Toda-Yamamoto Granger causality analysis test. When these results are analyzed, "VIX Index is not the Granger cause of BIST-100." Null hypothesis is rejected at 5% significance level. It means that there is a causality relationship from VIX index to BIST-100 index.

CONCLUSION

The VIX index is a significant index used as an indicator for the forecast of future expected movements of securities markets all over the world. The VIX index, which has been calculated since 1993, is a modeless index based on the S&P 500 index, calculated by the Chicago Options Exchange, and formed by the volatility of 22-day trading options. What is meant by the fact that the index is modeless; based on estimates, the levelling of the past volatility to some extent unlike model based volatility estimates, the index is a volatility estimate and has the potential in reflecting information that a model-based estimate cannot. The increase in the index means that the volatility expectation in the market will increase and the decrease in the index will decrease the volatility expectation in the market. The VIX index can direct the investment behaviour of investors and investor behaviour can shape the markets. At the same time, the index is usually a measure of market risk. Since it is used, it can be used in many asset pricing models.

The aim of this study is to investigate the effects of VIX index values on returns of BIST 100 index. In the study, daily data were used in accordance with the literature for the period between January 3, 2001 and January 31, 2020. Data for both indices calculated on a daily basis were obtained from various sources. While the data for the BIST index were taken from Borsa Istanbul; the data of the VIX index are accessed from yahoo, finance and Bloomberg Terminal databases. ARDL / Bound Test approach is used as a methodology to investigate the impact of the VIX index on the BIST-100 index and the reason for preferring this model is that the variables used in the analysis are not stationary at the same level and that none of the variables are quasi-stationary. Also, in the analysis of causality relationships between variables, Toda-Yamamoto Granger causality test, which allows analysis of series with different levels of stability, is applied.

According to the results shown in the Inter Index Correlation Table, there is a strong negative relationship between BIST-100 and VIX index. This result is in parallel with the literature and expectations. In the second stage of the study, stationarity analyses of the series were made. For this purpose, Augmented Dickey-Fuller (ADF) and Phillips Perron (PP) unit root tests, which are widely used in the literature, were performed to determine whether the series contain unit root. Breusch-Godfrey LM Test is applied to investigate whether the error terms of the ARDL model are autocorrelated or not. According to the test result, it was determined that there was no autocorrelation problem. Since the results obtained are higher than 5% significance level, there is no autocorrelation problem between series.

The *F*-statistic for the Bound Test appears to be 6.22. Since this value is between the upper and lower limit at 1% significance level, it does not allow for a definite long-term relationship. When looking at the significance levels of 2.5% and above, it is determined that the statistic is higher than the upper value. This shows that there is a long-term relationship between the series at the 2.5% significance level. When it is accepted that the level of significance in the social sciences is generally taken as 5%; according to this result, it is possible to reject the null-hypothesis “there is no long-term relationship (cointegration) between variables” at 5% significance level.

According to the results of Toda-Yamamoto Granger test analysis, VIX index is not the Granger cause of BIST-100. Null hypothesis is rejected at 5% significance which means that there is a causality relationship from VIX index to BIST-100 index.

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