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Asymmetry in Return and Volatility Spillovers Between Stock and Bond Markets in Turkey

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ABSTRACT

This study analyzes the asymmetric volatility spillovers in the stock and bond (S&B) markets in Borsa Istanbul during 2003-2019. Financial crises have increased the importance of the transition between the S&B markets. Apart from the full period, the 2008 financial crisis period is examined separately to see the effects of the spillovers during the crisis period. First, asymmetric volatility tests with the sign bias test were performed. Then, to find out whether S&B market volatility wwas asymmetric, we investigated with the GJR-GARCH model. Finally, asymmetric volatility was examined between the two markets test with the VARMA-AGARCH model. According to the asymmetric volatility test results, negative volatility asymmetry existed in the bond market for the full period. Asymmetric volatility was positive in both market during the crisis time. Return spillovers from the stock market to bond market for the full period. It was the opposite direction during the crisis period. Volatility spillover was bidirectional between the stock market and the bond market. However, during the global crisis period, volatility spillover was bidirectional from the stock market to the bond market

Keywords: Asymmetric Volatility Spillovers, Borsa Istanbul, VARMA-AGARCH.

JEL Classification Codes: G11, G12, C32

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INTRODUCTION

Stocks and bonds (S&B) are the most crucial products of the financial markets. Therefore, the S&B markets have a critical impact on investment decisions because of the size of funds collected. The bond market investor is better suited to the risk-averse investor profile, and the stock market investor takes risks. Because bonds - even if there are relative differences between their types - carry lower risk than stocks. This results in different risk-return balances for S&B investors. Bond investors have lower risk and thus return expectations, whereas stock investors have higher expectations.

Volatility is also a crucial factor in investment decisions. When stock prices expose to distinct changes, such as the financial crisis and technological change, volatility increases. Equilibrium prices taken from asset pricing models affect volatility changes. Therefore, investors closely follow volatility. Spillovers modeling and estimation in financial markets are also critical for researchers. Volatility spillovers among markets are also effective in asset pricing and investment decisions. Spillovers affect the creation of information contagion and integration among S&B markets (Zhang et al., 2013: 214).

Fundamental macroeconomic indicators, such as GDP, unemployment rate, exchange rate, money supply and VIX, use stock market analysis (Chen et al., 1986; Fama and French, 1989; Fama, 1990; Schwert, 1990; Lee, 1992; Bekaert and Hoerova, 2014). Dean et al. (2010: 272) argue that the volatility spillovers among the S&B markets have not occurred suddenly or completely. Macroeconomic news on the stock market, which causes unanticipated prices to drop in bond prices, will be that high-interest rates will slow down economic growth, and stock cash flows will decrease. This will cause share prices to fall. In such a case, the spillovers are from the bond markets to the stock market. The lower correlation between S&B connection is important for strong diversification. S&B correlation, while having a positive relationship with inflation risk, investors make extra efforts to diversify their investment risk (Li, 2002: 27). In this study, we will

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examine only stocks and bonds in terms of the internal dynamics of financial markets, not from a macroeconomic perspective. Our focus is on the interaction between S&B markets.

We investigate the return and volatility spillovers in the S&B markets of Borsa Istanbul. We attempt to reveal the behavior of S&B investors, who have different attitudes towards risk, especially in Borsa Istanbul. Therefore, this study is one of the leading articles investigating asymmetric volatility spillovers between Turkish S&B markets.

Investors behave differently during extreme volatility periods compared to more stable situations. Therefore, the 2008 Global Financial Crisis has been analyzed separately in this study. How do these two types of investors behave in a crisis period? Has the crisis a critical position in the behavior of investors and market spillovers? We are also investigating the answers to these questions. The search for answers to these questions is the motivation.

Other parts of the present study are as follows. The theoretical framework is established in Section 2. Section 3 reviews the studies that examine Borsa Istanbul volatility and symmetric, asymmetric and volatility spillovers models. The present study has performed analysis for two different periods: the full and the global crisis periods. The method is explained in section 5. First, volatility asymmetry is a test for the asymmetry diagnostic proposed by Engle and Ng (1993). Then, the effects of positive and negative news on volatility will be investigated by Glosten Jagannathan Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) model. Finally, asymmetric return and volatility spillovers between S&B markets returns will be analyzed by Vector Autoregressive Moving Average-Asymmetric Generalized Autoregressive Conditional Heteroskedasticity (VARMA-AGARCH) model. It provides the conclusion in Section 6. In the conclusion part, we will compare the crisis period findings and the whole period findings. Thus, this study will show whether the behavior of the investors in the S&B markets has changed in times of crisis.

THEORY

Investors do not have inadequate information about the return and risk factors between stocks and bonds. The incomplete research on the connection among interest rates, bond prices and the failure to faith that bonds are less risky as regards stocks are the source of this inadequate information (Jung et al., 2007: 411).

Bond investors and stock investors are different in terms of risk-taking behavior. Cash flows expected from bond investments contain less uncertainty than stocks. In addition, since stocks represent equity, they include both the possibility of profit and loss, whereas bonds represent a debit with certain long-term conditions and agree upon in advance. Thus, based on the structural differences between the two investments, investor expectations and behavior of both investments may change.

Investors are reviewing their investment decisions more frequently to take measures against both S&B risks in times of high uncertainty in the stock markets. The volatility of the stock market has a critical position in understanding the negative correlation periods between the stock and the bond (Connoly et al., 2005: 189). The stock market excess return extremely harmonizes with the bond market excess return (Shiller and Beltratti, 1992: 44). Variables used to estimate excess bond returns can also estimate excess stocks returns (Campbell and Ammer, 1993: 32). The reason for the change in the correlation sign between S&B markets is causality. Correlation does not mean causality. However, most investors feel that the causality from the bond prices to the stock prices is positive (a decline in stock prices also reduces stock discount rates) and from the stock prices to the bond prices is negative (Ilmanen, 2003: 55). Although it is nontrivial to specify the dimension to which these economic factors affect, correlation into the negative field can benefit measurement fundamental dynamics (Baele et al., 2010). Many papers present a significantly negative link between bond yields and equity prices (Gök and Çankal, 2020: 301)

The perspective of the asset exchange approach is that stocks and bonds are in competition. The emergence of information shapes the perception of investors for classifying assets. The news that bonds are more preferred than stocks encourage investors to purchase bonds and sell stocks; however, news that stocks are the most preferred means of exchange of stocks. This effect is symmetrical. In addition, it mostly relates bond price changes to general economic conditions, while stock price changes are mainly because of corrections related to company valuation. This behavior is the original evaluation of news (Dean et al. 2010: 273). According to Campbell and Vuoteenaho (2004), expected cash flows and discount rates shocks (news) should be tested separately. The news about positive cash flow raises stock value but decreases when discount rates increase. However, the sudden increase in the discount rate shows that expected returns will be superior. Koutmos (1999) states that prices capture bad news faster than good news, and this means asymmetric price correction.

According to King and Wadhwani (1990), financial contagion is an error that may occur in one market and may affect other markets. Volatility transmission is more likely if the news is bad. Bad news can come from all sides and there may be an asymmetry in the signs of shocks (Bae et al., 2003). Fleming et al. (1998: 136) assume that in the change's behavior in the hedging demand, traders consider the correlation between different markets. This enables portfolio diversification to reduce the risk of speculative profits between markets. In addition, strong volatility occurs between markets because of the change in expectations in different markets. This is important in terms of risk and return-based asset allocation and risk management strategies that change.

Dean et al. (2010) conclude that the bond and stock spillovers effects are strong in Australia and spillovers effect reduces stock returns with bond market bad news. The good news in the stock market is spillovers to the reduce bond return. The volatility of the bond market does not affect stock market variables. Zhang et al. (2013) have revealed that mutual volatility spillovers emerge between the stock and the bond markets in Brazil, South Africa and France, one-way spillovers from the bond to the equity in the US, the U.K., and Germany.

LITERATURE

The literature section comprises two parts. The first part examines the studies regarding volatility in Borsa Istanbul. The second part contains symmetric volatility models, asymmetric volatility models, and volatility spillovers models.

Volatility in Borsa Istanbul (BIST)

Yavan and Aybar (1998) investigated volatility analysis in Borsa Istanbul using Generalized Autoregressive Conditional Heteroskedasticity in Mean (1,1) (GARCH-M (1,1)), Exponential Generalized Autoregressive Conditional Heteroskedasticity in Mean (1,1) (EGARCH-M (1,1)) and Threshold Generalized Autoregressive Conditional Heteroskedasticity in Mean (1,1) (TGARCHM (1,1)) models with daily returns between 1986-1996. To our knowledge, there is no evidence that negative news about negative asymmetry causes more volatility than positive news. The effect of the news is symmetrical. However, another study conducted in the same year, using the GARCH and EGARCH models with the monthly data between 1989-1996 for the volatility analysis in Borsa Istanbul provides evidence that negative news leads to more volatility than positive news (Okay, 1998). In addition, Akar (2005) investigates the asymmetric effect of volatility with daily data for the Istanbul 100 Index between 1990-2004 and observes that negative deviations cause more volatility than positive deviations in the study use the TAR-GARCH model. Payaslıoğlu (2001) estimates volatility in Borsa Istanbul 100 Index with daily data between 1990 and 2000 using GARCH-M, EGARCH-M and TGARCH-M models, and asymmetry cannot emerge. Doğanay (2003) concluded that using conditional methods to model the variability of Government debt securities index (GDS) returns and predict variances for the next day in a volatility study conducted with GARCH and EWMA model in Borsa Istanbul GDS Indexes.

Mazıbaş (2004) uses GARCH, EGARCH, GJR-GARCH, A-GARCH and C-GARCH methods for volatility modeling in Borsa Istanbul's main Indexes (Compound, Finance, Service and Industrial). In this study, which uses daily, weekly, and monthly data between 1997-2004, there is an asymmetric effect. With weekly and monthly data, the models provide more satisfactory results and the models are insufficient in daily data.

Özçiçek (2005) investigates the volatile connection between the exchange rate (USD/TL exchange rate) and stock indexes (BIST100, Financial, Industrial and Services). The asymmetric effect is stronger when stock indexes decrease or the exchange rate increases (negative news). Soytaş and Oran (2011) examine the effect of volatility spillovers between the Borsa Istanbul 100 Index and the Borsa Istanbul Electricity Index and oil prices. Using the Granger causality test developed by Cheung and Ng, they find the causality connection between the variance of world oil market returns and the electricity index, but this is not valid for Borsa Istanbul. Tokat (2013) uses the BEKK (Baba, Engle, Kraft and Kroner)-MGARCH model between gold, foreign exchange (USD/TL exchange rate) and Borsa Istanbul 100 Index. The shocks in the foreign exchange market impact the gold market and Borsa Istanbul exhibits a volatility structure independent of other variables.

Yıldız (2016) applies TGARCH, GARCH-M, EGARCH, PARCH and CGARCH methods for the symmetric and asymmetric volatility analysis of the Borsa Istanbul sub-indexes, Services, Financial and Industrial indexes. According to the results of the EGARCH and TGARCH model, negative news in all three indexes has more impact on volatility than positive news. The most successful model for BIST Industrial and BIST Financial indexes is the TGARCH model, and for the BIST Service index, it is the CGARCH model.

Demirgil et al. (2015) applied Vector Autoregressive Moving Average (VARMA), the E-GARCH and BEKK models on the mean for asymmetric volatility estimation between oil prices and the industrial production index. Their findings Show that the changes in oil prices affect industrial production asymmetrically. Cihangir and Uğurlu (2017) conducted asymmetric volatility research in the Borsa Istanbul gold market using Asymmetric Power ARCH (APARCH), Threshold ARCH (TARCH) and EGARCH models. The best explanation for gold return volatility is the APARCH model, and the effect of good news is more effective on volatility than the effect of bad news. Baykut and Kula (2018) investigate the volatility structure in the Borsa Istanbul 50 Index by symmetrically ARCH and GARCH, asymmetrically PARCH, EGARCH and TGARCH models. They select the most appropriate model for Borsa Istanbul 50 index as the GARCH (2.1) model and the heaviest model. Tüzemen and Köseoğlu (2018) examine the effect of asymmetric volatility between the VAR-EGARCH model and the oil markets and Borsa Istanbul sector indexes. The asymmetric volatility diffusion effect exists in all sectors except the mining sector. Gunay (2019) tests whether the volatility of Borsa Istanbul is affected by credit default swaps, asset swaps and zero-volatility spreads with the Markov Regime Switching VAR model. Kaya and Soybilen (2019) investigate the asymmetrical effects of production, interest rate and exchange rate on stock prices in Borsa İstanbul. The exchange rate and the industrial production index have asymmetric effects on Turkish stock prices both in the long run and the short run, but the interest rate has only long-run asymmetric effects.

Ekinci and Gençyürek (2021) examine return and volatility spillover between Borsa Istanbul Sector Indices using the time-varying VAR (TVP-VAR) model. The industry and finance sectors are in the leading position to shock and volatility spillover. Technology, Tourism, Transportation, Food and Retail-Trade sectors are lagging. Gürbüz and Şahbaz (2022) apply wavelet analysis for the volatility spillover effect between derivative markets and spot markets in Borsa İstanbul. Spot markets are influenced by the previous volatilities of derivatives markets, as well as their own previous volatilities.

Symmetric Volatility Models, Asymmetric Volatility Models, And Volatility Spillovers Models

Engle's (1982) ARCH and Bollerslev's (1986) GARCH are the models for conditional volatility modeling of S&B returns. The conditional mean and the conditional variance can be calculated synchronously in the ARCH model. The GARCH model includes the lagged values of conditional variance in the conditional variance equation. Conditional variance is in the mean equation of ARCH Mean (ARCH-M) and GARCH Mean (GARCH-M) models developed by Engle et al. (1987). Thus, the conditional variance affects the mean and the risk premium that changes according to the time considered. The effect of positive and negative news is supposed to be identical in these models. Therefore, these models are symmetric models.

Nelson (1991) developed the exponential GARCH (EGARCH) model, which assumes that the positive and negative shock (asymmetry) that may do in the series have a different effect on the estimation of volatility. EGARCH supports Black's (1976) leverage effect (negative news in volatility estimation is more effective than positive news). The logarithmic of conditional variance in the EGARCH model provides information about asymmetric information, and the use of standardized error terms gives information about the magnitude of the shock. The threshold ARCH (TARCH or GJR) model asymmetrically predicts the effect of negative and positive news using a dummy variable (Glosten et al. 1993). Ding et al. (1993) developed an asymmetric power ARCH (PARCH) model that contains the parameter that shows the most asymmetric effect directly on the data. Another model that measures the asymmetric effect is the TGARCH model developed by Zakoian (1994).

The symmetric and asymmetric models described above are univariate. Multivariate models have an important role in modeling co-movement. Simultaneous dependencies increase the importance of multivariate modeling. Bollerslev et al.'s (1988) Vector GARCH (VEC-GARCH) model, Bollerslev's (1990) constant conditional correlation model (CCC-GARCH), Engle and Kroner's (1995) BEKK model, Engle's (2002) dynamic conditional correlation (DCC-GARCH) model, Ling and McAller's (2003) vector ARMA GARCH (VARMA-GARCH) model and McAlleer et al. 's (2009) ARMA AGARCH (VARMA-AGARCH) model are some of the multivariate models. In this study, first, asymmetric volatility in S&B markets will be tested with a univariate GJR-GARCH (1,1) model. Then, the asymmetric return and volatility spillovers between the two markets will be analyzed by the multivariate VARMA-AGARCH (1,1) model.

Chan et al. (2005) investigate the patent growth rate in the USA from Canada, France, Germany and Japan by Constant Conditional Correlation (CCC), VARMA-GARCH and VARMA-AGARCH methods to measure technological capacity. The conditional variances of the patent growth rate of the four countries are interconnected. This result shows global factors affect the technological capacity of the USA. Chang et al. (2010) use CCC, Vector ARMA-GARCH and Vector ARMA-Asymmetric GARCH (VARMA-AGARCH) methods for the volatility spillovers, asymmetry and hedging estimation in oil markets. Volatility spillovers and asymmetric effects emerge from West Texas (WTI) and Brent markets to Dubai and Tapis (Asia-Pacific) markets. Chang et al. (2011) apply CCC, Dynamic Conditional Correlation (DCC), and VARMA-GARCH methods for volatility spillovers on spot and futures, rubber markets in Bangkok, Singapore, Tokyo and Osaka in Asian markets. There is the effect of volatility spillovers between spot and futures markets. Chang et al. (2013) investigate the volatility spillovers between the WTI and Brent oil markets and the FTSE100, NYSE, Dow Jones and S & P500 stock markets. They use CCC, VARMA-GARCH and VARMA-AGARCH methods. They present a mini-proof for the volatility spillovers among oil and stock markets according to asymmetric methods. In addition, the VARMA-AGARCH method is superior to other methods in showing the asymmetric reaction of negative and positive shocks on conditional variance.

Dean et al. (2010) use asymmetric BEKK and asymmetric DCC models to examine the asymmetric return and volatility spillovers between Australian S&B markets. The spillovers between the S&B markets is strongly asymmetrical. In return volatility, bad news in bond markets affects lower stock returns, while good news in stock markets leads to lower bond returns. However, bond market volatility is effect stock market news. Hung (2020) conducted research for the conditional correlations and spillovers of volatilities across Hungary, Poland, the Czech Republic, Romania and Croatia with CCC, DCC and BEKK model. The volatility spillover among these markets is significant.

Jin (2015) examines the spillovers of asymmetric returns and volatilities among the interbank and barter treasury bills markets in China using the VARMA-AGARCH method, one of the multivariate GARCH models. The spillovers of return emerge from two conditions: the shock sign (good or bad news) and the source of the shock (market type). In volatility asymmetry, the negative shocks in the treasury bills clearing market have a higher effect than the positive ones. There are volatility spillovers from the treasury bills clearing market to the interbank market. Hakim and McAlleer (2010) investigate spread and volatility spillovers in New Zealand, Singapore, the US, Australia and Japan with VARMA-GARCH in bonds, equity and foreign exchange markets. All markets affect all other markets in terms of magnitude spillovers. While it reaches the same findings in volatility spillovers, the US is a market that strongly influences other markets, even if the volatility is not dominant. In addition, volatility spillovers from the exchange rate markets to the S&B markets and from the S&B markets to the exchange rate market. They observe the asymmetric effect in eight of the 20 cases they have examined. Allen et al. (2013) examine the effect of volatility spillovers from the Chinese stock market to the Australia, Hong Kong, Singapore and Japan and US markets using GARCH, VARMA-GARCH and VARMA-AGARCH methods. The VARMA-AGARCH model has different consequences than the other two models in the volatility calculation, and they have similar results to the VARMA-GARCH. Volatility spillovers effect from the Chinese stock market to other markets.

Tule et al. (2017) examine the effect of asymmetric volatility propagation of oil shocks in the Nigerian bond market using the VARMA-AGARCH method. There is a volatility transfer between Nigeria's bond market and Brent and WTI oil markets. In particular, the decline in oil prices after 2014 increased the costs of oil producer Nigeria in energy production and led the government to borrow more on the bond market. This increased the volatility propagation effect. Tule et al. (2018) also investigate the volatility between the Nigerian Nair-dollar exchange rate and the Nigerian Stock Exchange stock market index by the VARMA-AGARCH model. This study concludes that capital inflows and the existence of the Nigerian Stock Exchange affect the Nigerian Naira-Dollar exchange rate. Given the unidirectional and breaking points from the Nigerian Stock Exchange to the Naira-Dollar exchange rate in the long term, there is a mutual volatility spillovers effect in the long term. Moreover, the fall in oil prices in 2014 and beyond had a significant effect on the Naira-Dollar exchange rate. Zeng et al. (2021) investigate the effects of volatility spillover in European Union carbon financial markets using the BEKK-GARCH model. They find an asymmetric volatility spillover between the European Union allowance (EUA) and certified emissions reduction (CER) markets. The return and volatility spillover are also examined in the cryptocurrency markets. Koutmos (2018) examines the return and volatility spillover among 18 main cryptocurrencies using variance decomposition and vector autoregression methods. Between 2015 and 2018, Bitcoin is identified as the most dominant cryptocurrency among all cryptocurrencies in terms of return and volatility spillover. The return and volatility spillover increase over time. Katsiampa et al. (2019) examine the volatility spillover between Bitcoin, Ether and Litecoin between 2015 and 2018 using the BEKK-MGARCH model. Past shocks and volatility of cryptocurrencies affect its current conditional variance. There is a bidirectional volatility spillover among all cryptocurrencies. Kumar and Anandarao (2019) investigated the volatility spillover among Bitcoin, Ethereum, Ripple and Litecoin between 2015-2018 using DCC-IGARCH and wavelet models. The volatility of cryptocurrencies can be explained by their fluctuations. The correlation structure between cryptocurrencies is weak during market collapses, especially in Bitcoin prices.

Part 2 of the literature review summarizes the following. Different Multivariate GARCH models, which are symmetric and asymmetric, propose to show volatility. These include Bollerslev et al. (1988) VECH model, Bollerslev's (1990) CCORR model, Engle and Kroner's (1995) BEKK model, Engle's (2002) DCC model and Ling and McAleer's (2003) VARMA-GARCH model and Hoti et al. (2002) and McAleer, Hoti and Chan's (2009) VARMA-Asymmetric GARCH (VARMA-AGARCH) model stands out. The VARMA-AGARCH model captures the asymmetry of the volatility response to the news.

Summarizing the literature section, VARMA-AGARCH model uses for stock markets, bond markets, foreign exchange markets, oil markets, and futures markets to volatility spillovers between markets. The two-variable models of Hoti et al. (2002) and McAleer et al. (2009) are important in terms of complexity and predictability.

Asymmetric return and volatility spillover have been examined in many studies. VARMA AGARCH is better than other methods for analyze the asymmetric effect. TGARCH and EGARCH models are generally used in studies related to Turkey. Demirgil et al. (2015) also focus on macroeconomic data. In this study, we aim to fill the research gap in the literature by investigating the asymmetric spillovers effect between S&B markets in Turkey. Therefore, this model is more appropriate for this study. It also provides powerful results that negative return shocks affect volatility more than positive shocks. VARMA-Asymmetric GARCH (VARMA-AGARCH) model is proper for analyzing the volatility spillovers.

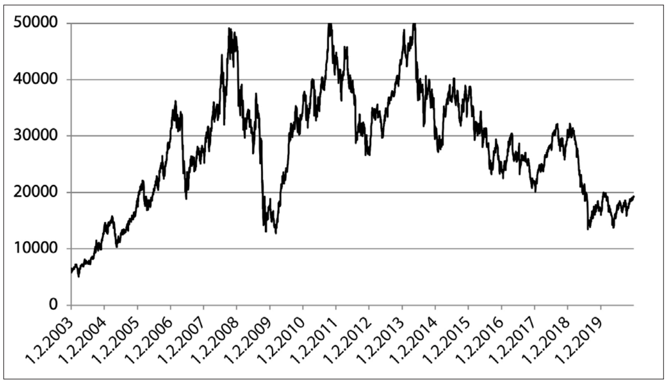
DATA[1]

Borsa Istanbul Stock Exchange Index (BIST100) and Active Bond Index returns (BR) are between 01.02.2003 and 12.31.2019, including 4220 daily observations. Data are dollar-based to adjust seasonal effects. Besides the full period, this study covers the crisis period between 2008 and 2010. Active Bond Index is an index created by the Finnet database. We calculate this index based on the bond where the highest supply and demand meet the highest trading volume. We accept the bond return with the highest trading volume as the indicator of the bond market. We calculate BIST 100 Index and bond market return series with the formula $\log\left(\frac{index_t}{index_{t-1}}\right)$.

Graph 1 reflects the BIST100 index. The first period is the bullish market from the beginning of 2003 to the end of 2005. The second period is a fluctuating market from 2006 to the end of 2012; the third period dominates by the bear market from the beginning of 2013 until the end of 2019. The downward trend in the bond index is shown in Graph. 2, which remained relatively stagnant from 2005 to the 2008 Financial Crisis, followed by a steady course of lower levels in the 2008 Financial Crisis. Graph. 2 also shows that the bond index decreased continuously without slowing down from the beginning of the data set from 2003 to mid-2006. The index increased from mid-2006 until the emergence of the global crisis and implementation of the crisis measures from the global and national economic context., Because of the measures taken in 2009, the index declined rapidly. Despite the decrease in the tendency, the decrease continued in the following periods.

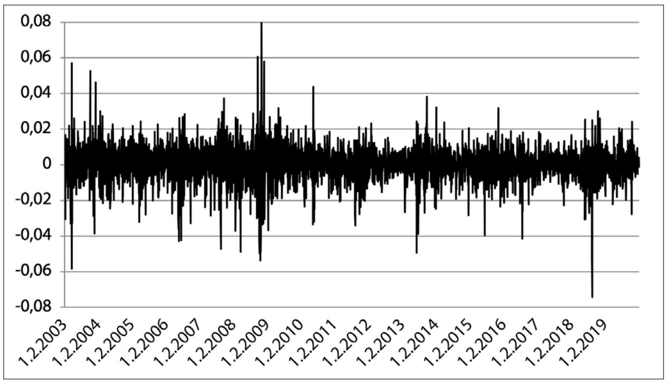
Graph. 3 shows the return on Borsa Ist anbul in the next few years in the 2001 Crisis, the volatility cluster in the 2008 Financial Crisis, and the years 2013-2014 when Gezi Park events took placeIt is possible to conclude that the volatility cluster is quite frequent, in the return of BIST 100. It has been found that high returns and low returns take place. Graph. 4 shows a volatility cluster in bond returns during the review period. Bond yield volatility increased again after mid-2018. It shows that bond spillovers release in a larger range than a normal distribution. Periods of high returns should not be followed by low returns for normal distribution. Returns should have moved in a narrower range. When S&B returns are compared, the volatility cluster of stock returns is higher and spillovers occur on a larger scale as expected.

[1] The data collected from the database. According to the current legislation, there is no need for an Ethics Committee Approval Document for the research conducted in the database.

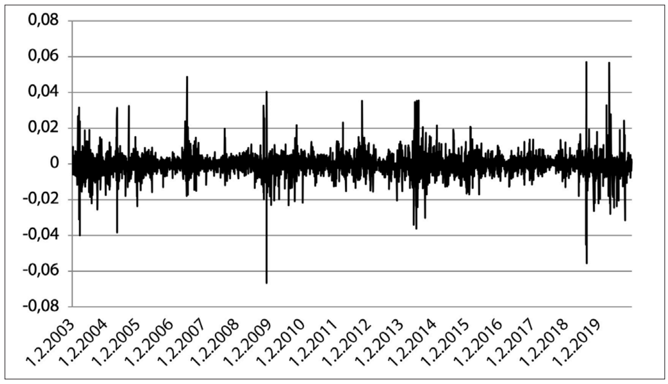


Graphic 1. BIST100 Index (Daily)

Graphic 2. Bond Index (Daily)



Graphic 3. BIST100 Return (Daily)



Graphic 4. Bond Index Return (Daily)

METHODOLOGY

First, we perform unit root tests of return series to keep away from spurious regression. In the investigation of stationary, the extended series Dickey-Fuller (ADF (1979)), Philip Perron (PP (1988)) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS (1992)) unit root tests are used. After the stationary test, the existence of serial correlation and ARCH effect return series are analyzed. For this purpose, Ljung and Box's (1978) Q test and ARCH-LM (1982) test are applied. In the third stage, the asymmetric structure of the volatility in the returns is investigated by the asymmetry diagnostic tests by Engle and Ng (1993). The diagnostic indicators presented for the determination of asymmetry volatility are calculated by the following regression equations:

$\varepsilon_{i,t-1}$ is the error term of the data in t-1. $S_{i,t-1}$ is a dummy variable that takes the value of if it is $\varepsilon_{i,t-1}$ < 0, 1, if not 0. $S^{+}_{i,t-1}$ is a dummy variables that takes the value of if it is $\varepsilon_{i,t-1}$> 0, 1, if not 0. In the first three asymmetry tests given above, the test value t and the statistical significance of the parameter b are reported. Joint asymmetry test on equation number four, the value and statistical significance of the F test for the test that b_1 b_2 and b_3 are all zero are reported (Patterson, 2000: 729).

The Sign Bias Test examines the positive and negative innovation (shocks) effect on volatility. The Negative Bias Test investigates the cause of big and small negative innovation, and the Positive Bias Test is for big and small positive innovation, the Joint symmetry Test inventigates both the magnitude and the volatility of the signal.

Sign Bias $$\varepsilon^2_{i,t} = \alpha + bS^{-}_{i,t-1} + u_{i,t} \quad (1)$$

Negative Size Bias $$\varepsilon^2_{i,t} = \alpha + bS^{-}_{i,t-1}\varepsilon_{i,t-1} + u_{i,t} \quad (2)$$

Positive Size Bias $$\varepsilon^2_{i,t} = \alpha + bS^{+}_{i,t-1}\varepsilon_{i,t-1} + u_{i,t} \quad (3)$$

Joint $$\varepsilon^2_{i,t} = \alpha + b_1S^{-}_{i,t-1} + b_2S^{-}_{i,t-1}\varepsilon_{i,t-1} + b_3S^{+}_{i,t-1}\varepsilon_{i,t-1} + u_{i,t} \quad (4)$$

In the fourth stage, the GJR-GARCH model has been preferred for the asymmetric volatility of the S&B market returns series, whose volatility is asymmetrical. The volatility equation GJR-GARCH (1993) model is given below:

$$y_t = \omega_0 + \omega_1 y_{t-1} + \varepsilon_t \quad (5)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \left[(\varepsilon_{t-1}^2)(I_{t-1})\right] \quad (6)$$

$$I_t = \begin{Bmatrix} 0, \epsilon_t \geq 0 \\ 1, \epsilon_t < 0 \end{Bmatrix} \quad (7)$$

Equation 5 is the mean equation. In equation 6, I_t as an indicator that separates positive and negative shocks (good and bad news) of equal magnitude. Since conditional variance h_t is positive, it is expected that and $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\alpha_1 + \beta < 1$. In addition, α_1 represents the persistence of short-term positive shocks (good news) and $\alpha_1 + \gamma$ means the persistence of short-term negative shocks (bad news). The duration of the shock is computed as the number of operation days with the half-life formula $\left(\frac{ln(0.5)}{\ln(\alpha_1+\beta)}\right)$.

In the last stage, asymmetric return and volatility spillovers between S&B markets returns are analyzed by VARMA-AGARCH analysis. The VARMA-AGARCH analysis method is preferred because it can capture the effects of spillovers and volatility spillovers between stock market returns and the bond market return series. First, we form conditional mean return equations for S&B markets returns. It presents conditional return equations, which are shown below.

$$r_{S,t} = \mu_S + \emptyset_S r_{S,t-1} + \theta_S^+ r_{B,t-1}^+ + \theta_S^- r_{B,t-1}^- + \varepsilon_{S,t} \quad (8)$$

$$r_{B,t} = \mu_B + \emptyset_B r_{B,t-1} + \theta_B^+ r_{S,t-1}^+ + \theta_B^- r_{S,t-1}^- + \varepsilon_{B,t} \quad (9)$$

$$\varepsilon_t \left| F_{t-1} = \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{B,t} \end{bmatrix} = D_t \eta_t \right. \quad (10)$$

Inequations8and9, $i=S, B$ for $r_{i,t-1}^+ = \max(0, r_{i,t-1})$, $r_{i,t-1}^- = \min(0, r_{i,t-1})$ and $r_{S,t}$ ve $r_{B,t}$ give the stock market and the bond market return at time t, respectively. ε_t is the error term. Furthermore, in equation 10, η_t is independent and identically distributed, $F_{(t-1)}$ is the available historical information vector at the time t-1. $D_t = diag(h_S^{0,5} h_B^{0,5})$ and h_S and hB show the conditional variances of stock market return and bond market return at time t, respectively.

The return at time t-1 in a market gives the information set of that market's return at time t. The lagged returns of another market may also affect the conditional return of one market. The coefficients determine the asymmetry of the return spillovers θ^+ and θ^- in the return sequence of positive and negative lags in the return equations. If θ^+ or θ^- parameter coefficients are statistically significant, it is judged that there is a return spillovers and if $\theta^+ \neq \theta^-$ the spillovers effect is asymmetric. In terms of the magnitude of the coefficients, θ^+ and θ^- it can be argued that investors in one market use potential information from another market. Their lagged returns are included in the equations.

VARMA-AGARCH transfers the conditional variances of both markets and captures the effects of time-varying conditional correlations. The VARMA - AGARCH model conditional variances are below:

$$h_{S,t} = \omega_S + \alpha_{S,1}\varepsilon_{S,t-1}^2 + \alpha_{S,2}\varepsilon_{B,t-1}^2 + \beta_{S,1}h_{S,t-1} + \beta_{S,2}h_{B,t-1} + \gamma_S\left(\varepsilon_{S,t-1}^2 \times \left(\varepsilon_{S,t-1}^2 < 0\right)\right) \quad (11)$$

$$h_{B,t} = \omega_B + \alpha_{B,1}\varepsilon_{B,t-1}^2 + \alpha_{B,2}\varepsilon_{S,t-1}^2 + \beta_{B,1}h_{B,t-1} + \beta_{B,2}h_{S,t-1} + \gamma_B\left(\varepsilon_{B,t-1}^2 \times \left(\varepsilon_{B,t-1}^2 < 0\right)\right) \quad (12)$$

In equations 11 and 12, $\alpha_{S,1}$ and $\alpha_{B,1}$ represent the connection between the volatility of a market and its positive lag, in short, the ARCH effect. $\beta_{S,1}$ and $\beta_{B,1}$ measure the GARCH effect. $\alpha_{S,2}$, $\alpha_{B,2}$, $\beta_{S,2}$ and $\beta_{B,1}$ show the volatility spillovers between the stock market and bond market. γ_s and γ_B represent the asymmetry volatility between the volatility of a market and its own negative lag.

EMPIRICAL RESULTS

Table 1 shows descriptive indicators for return and volatility asymmetry of Borsa Istanbul Return (S) and Bond Return (B).

Mean, median and standard deviation findings show the risk-return comparison of the two markets. In full period, the unconditional mean, standard deviation and median show the stock market has much more returns and volatility than the bond market. The mean return in the stock market is higher than the bond market; its standard deviation is higher. Thus, it determines that the risk is high in the market with high returns. It also suggests that the stock market performed better during the periods when the S&B markets return is positive and negative, respectively. The bond market performed better during the periods when the stock market return was negative and the bond market returns was positive. The bond market performed better during the periods when the S&B markets returns are negative.

Table 2 shows the model descriptive statistics of the S&B markets returns report. The mean returns of BIST 100 (S) are positive, while the bond (B) return is negative.

Table 1. Unconditional and Conditional Returns Descriptive Statistics

	Mean (%)		Standard Dev. (%)		Median (%)		Correlations
	S	B	S	B	S	B	
Full Period	0.013	-0.001	0.955	0.620	0.012	-0.029	-0.052
S>0, B>0	0.673	0.349	0.619	0.451	0.541	0.220	0.163
S>0, B<0	0.691	-0.414	0.646	0.482	0.530	-0.268	-0.263
S<0, B>0	-0.713	0.414	0.726	0.502	-0.510	0.257	-0.277
S<0, B<0	-0.628	-0.391	0.776	0.442	-0.498	-0.270	0.145

Table 2. Variables Statistics

	S	B
Descriptive Statistics		
Median	0.000116	-0.000291
Mean	0.000134	-0.000001
Standard Dev.	0.009555	0.006203
Min.	-0.074311	-0.066605
Max.	0.082776	0.056977
Observations	4220	4220
Distribution Statistics		
Skewness	-0.356482	0.182917
Kurtosis	9.177929	17.94541
Jarque-Bera	6800.375**	39298.36**
Unit Root Tests		
ADF	-60.045**	-60.192**
PP	-608.025**	-60.737**
KPSS	0.739	0.118
ARCH Effect Tests		
Q (5)	27.287**	30.277**
Q (10)	45.735**	45.058**
Q^2 (5)	409.49**	593.48**
Q^2 (10)	689.02**	709.46**
ARCH Test	175.217**	284.707**
Asymmetry Tests		
Sign Bias	3.872**	0.158
Negative Size Bias	-12.585**	-10.961**
Positive Size Bias	0.551**	11.972**
Joint	50.115**	119.401**

**, * indicate significance values of 1% and 5%, respectively.

A similar finding is the subject of the median. The unit root tests of ADF (1979), PP (1988) and KPSS (1992), which frequently use in stock analysis and bond market returns series, test for the stationary show that S&B market return series are stationary. Engle's (1982) ARCH-LM test to research the ARCH effect is used to test the S&B markets returns series and to show that the ARCH effect is present in the series. In addition, Ljung-Box's (1978) Q test observes that there is a series correlation in both return and return square series. Thus, conditional heteroscedasticity is the model in volatility estimations because of the stationary and ARCH effect of S&B markets returns. Jarque and Bera's (1980) test results observe that the return series are not normal distribution and series have leptokurtic (fat tail). Thus, volatility estimations are made according to GED distribution.

Engle and Ng's (1993) asymmetry diagnostic tests results are presented in Table 2. For Engle and Ng test, we test standardized errors estimated with least squares. If the reaction of volatility to shocks is asymmetrical, the "Sign Asymmetry" indicators will be statistically significant. In addition, the magnitude of the shock will also affect volatility. Because of these tests, the existence of asymmetric volatility in the conditional volatilities of stock market returns and bond market returns emerges. We find the stock market return to be sensitive to signs, negative values, positive values, and joint tests. We find the bond market spillovers to be sensitive to negative value, positive value, and joint tests. Therefore, the null hypothesis that the volatility is not asymmetric based on the negative value, positive value, and joint test results reject in both markets. These findings show that we should investigate the relationship between return and volatility between S&B markets with an ARCH-type asymmetric model.

Full Period Analysis

Asymmetric return and volatility estimations of daily S&B markets returns, which have 4220 observations covering 01.02.2003 and 12.31.2019, are estimated by GJR-GARCH and then we look for asymmetric return and volatility spillovers by VARMA-AGARCH.

Asymmetric Return and Volatility Estimation

In this section, volatility clustering, the fat tail, skewness, asymmetry, ARCH effect and non-normal distribution characteristics of the stock market (S) and the bond market (B) will be taken into consideration by GJR-GARCH model preferred to capture volatility clustering. Table 3 presents the GJR-GARCH (1,1) estimation results using the Generalized Error Distribution (GED) to capture the thick tail, skewness, and non-normally distribution characteristics of daily returns. ARCH and Ljung-Box Q tests of GJR-GARCH estimation results of the S&B market returns series show no ARCH effect.

In the S&B markets, conditional mean equation, a lagged return (ω_1) was positive and statistically significant, as shown in Table 3. This consequence shows a correlation between the previous day return and the current return in both markets. When looking at the conditional variance equation, the ARCH (α_1) and GARCH (β) parameter coefficients are positive and statistically significant. This implies that there is a volatility cluster in both markets. In addition, the sum of ARCH and GARCH coefficients is less than 1. The leverage effect is statistically significant in the S, whereas it is not significant in the B. The stock market leverage effect coefficient has a negative sign. The negative leverage effect on the S shows that good news has a stronger impact than bad news. There is no evidence that the news in the B is more powerful than good news or bad news. The persistence of the shock in the S is much higher than in the B. The mean shock persistence is approximately 69 and 55 trading days in the S&B Markets, respectively.

Table 3. Return and Volatility Forecasts in BIST100 and Bond Market

	S	**B**
Conditional Mean		
ω_0	0.0002**	-0.0003
ω_1	0.0919**	0.0652**
Conditional Variance		
α_0	0.0001**	0.0001**
α_1	0.1156**	0.1325**
β	0.8744**	0.8559**
γ	-0.0976**	-0.0017
Good News Effect	0.0001	0.0001
Bad News Effect	0.0975	-0.0016
Shock Persistence	0.9900	0.9874
Half-life (Day)	68.97	54.66
Skewness	-0.3657	-0.2105
Kurtosis	5.4725	8.5727
Log Likelihood	14080.51	16626.30
Q (5)	1.2583	2.7100
Q (10)	1.3050	3.7480
Q^2 (5)	1.9953	5.6241
Q^2 (10)	1.7296	9.2246
ARCH Test	1.1274	3.7673

**, * indicate significance values of 1% and 5%, respectively.

Asymmetric Return and Volatility Spillovers

Stock market (S) and bond market (B) returns volatility spillovers are estimated by VARMA-AGARCH method in Turkey. The findings are given in Table 4. The VARMA-AGARCH estimation results of the S&B market returns series do not have an ARCH effect because of ARCH Test and Ljung-Box Q Test. Looking at the conditional mean equations, there is proof of short-term predictability in S&B market returns, although different in form. The asymmetric return spillovers effect of S to B determines. The connection between the negative and positive past returns of the S and the current B return is statistically significant. Thus, a decrease in the stock market causes a 4.8% decrease in the bond market on the following trading day. An increase (decrease) in the S causes an increase (decrease) of approximately 5.8% in the bond market on the following trading day. The effect of asymmetric return spillovers on B return to S following trading day return is not statistically significant. The increase or decrease of the B on the current trading day does not affect the S return on the following trading day. Thus, we can conclude that the good and bad news on the S return affected the B return, whereas the good and bad news on the B return did not affect the S return.

The parameter coefficients of a lagged conditional volatility (GARCH terms) that give volatility sensitivity in the S&B market, conditional variance equations in Table 4 are statistically significant ($\beta_{S,1}$ and $\beta_{B,1}$). Current conditional volatility changes in bond market return and stock market return are dependent on their own lagged shocks. This underestimation of the parameter coefficients of a lagged shock (ARCH terms $\alpha_{S,1}$ and $\alpha_{B,1}$) shows that the conditional volatilities do not convert very speedily with the incentive of return uncertainties (error terms-innovations). The GARCH parameter coefficients show the relationship between current volatility and a lagged volatility greatly. This finding reveals that past volatility has a significant impact on current volatility and that volatility gradually develops over time. Therefore,

Table 4: Return and Volatility Spillovers of BIST100 and Bond Markets

S		B	
Conditional Mean			
μ_S	0.0005	μ_B	-0.0001
$\varnothing_S$	0.0782**	$\varnothing_B$	0.1139**
θ_S^+	0.0395	θ_B^+	-0.0580**
θ_S^-	0.0101	θ_B^-	-0.0481*
Conditional Variance			
ω_S	0.0001**	ω_B	0.0001**
$\alpha_{S,1}$	0.1232**	$\alpha_{B,1}$	0.1088**
$\alpha_{S,2}$	0.0084	$\alpha_{B,2}$	0.0120*
$\beta_{S,1}$	0.5989**	$\beta_{B,1}$	0.8658**
$\beta_{S,2}$	0.1172**	$\beta_{B,2}$	0.0105*
γ_S	0.0756	γ_B	-0.2381**
Skewness	-0.3446	Skewness	-0.1501
Kurtosis	5.3390	Kurtosis	7.2919
Log Likelihood	12157.75	Log Likelihood	15371.50
Q (5)	2.6136	Q (5)	2.3448
Q (10)	17.761	Q (10)	5.1742
Q^2 (5)	12.7058	Q^2 (5)	8.9367
Q^2 (10)	15.8542	Q^2 (10)	9.0361
ARCH Test	8.3159	ARCH Test	7.6208

**, * indicate significance values of 1% and 5%, respectively.

S&B market investors can implement active investment strategies that take into account volatility persistence and market trends. However, it should be kept in intellect that the applicability of these strategies will depend on the size and stability of the return periods. Negative volatility asymmetry (γ_B) exists in the bond market.

GARCH term (bond market) $\beta_{S,2}$ in Table 4 shows the long-term shock spillovers from B volatility to S volatility. On the other hand, the stock market GARCH term $\beta_{B,2}$ gives the long-term shock spillovers from S volatility to bond market volatility. The ARCH terms $\alpha_{S,2}$ and $\alpha_{B,2}$ show the short-term shock spillovers between the two markets. The sum of these ARCH and GARCH coefficients explains the magnitude of the volatility spillovers effects between the two markets.

The effect of the S ARCH term ($\alpha_{B,2}$) on B volatility is significant, as shown in Table 4. However, the effect of the B ARCH term ($\alpha_{S,2}$) on S volatility is not significant. The short-term volatility transition occurred in one direction from the S to the B. The long-term volatility transition has been bidirectional ($\beta_{S,2}$ *and* $\beta_{B,2}$).

Global Crisis Period Analysis

Asymmetric return and volatility estimations of the stock market (S) and the bond market (B) returns with a total frequency of 528, covering the period of 03.16.2008 and 04.23.2010, which are the periods of the Global Financial Crisis are tested by GJR-GARCH and then asymmetric return and volatility spillovers are investigated by VARMA-AGARCH.

Asymmetric Return and Volatility Estimation

In a global crisis, the GJR-GARCH (1,1) estimation results using the Generalized Error Distribution (GED) to capture fat tail, skewness and normal distribution characteristics of returns are given in Table 5. ARCH and Ljung-Box Q tests of GJR-GARCH estimation results of the S and B returns series show no ARCH effect.

In the S and B, lagged return (ω_1) in the conditional mean equation is positive and statistically significant. There is a correlation between the previous day's return and the current return in the S and B in the period of the global crisis. When looking at the conditional variance equation, the ARCH (α_1) and GARCH parameter (β) coefficients are positive and statistically significant. This implies that volatility clusters in both markets during the crisis. In addition, the sum of ARCH and GARCH coefficients is fewer than 1. It is observed that the leverage effect (γ) is statistically significant in the S, whereas it is not significant in the B. Leverage effect parameter coefficient in the S is positive. The leverage effect on the S shows that during the global economic crisis, bad news has a stronger impact than good news. The news that emerged during the global crisis in the B did not reveal any significant evidence that the impact of good news or bad news is stronger. The persistence of the shock in the S&B market during the crisis period is close. The mean persistence of the shock determines around 26 trading days in the stock market and the bond market during the crisis period.

Asymmetric Return and Volatility Spillovers

Table 6 presents the return and volatility spillover findings estimated by a VARMA-AGARCH method of stock (S) and the bond market (B) during the global crisis period present. VARMA-AGARCH estimation results do not have an ARCH effect results of the ARCH Test and Ljung-Box Q Test. Conditional mean equations, there is evidence of short-term forecast in S and B returns, although different in format. The effect

Table 5: Return and Volatility Estimate in BIST100 and Bond Market in Crisis Period

	S	B
Conditional Mean		
ω_0	0.0003	-0.0001
ω_1	0.0924*	0.1361**
Conditional Variance		
α_0	0.0001*	0.0001*
α_1	0.1020**	0.0560**
β	0.8712**	0.9178**
γ	0.1601**	0.0302
Good News Effect	0.0001	0.0001
Bad News Effect	0.1602	0.0393
Shock Persistence	0.9732	0.9738
Half-life (Day)	25.52	26.11
Skewness	0.0777	-1.3252
Kurtosis	4.2921	13.4513
Log Likelihood	1645.381	1948.929
Q (5)	1.2846	5.6758
Q (10)	16.293	8.2436
Q^2 (5)	1.3512	2.6912
Q^2 (10)	5.9291	4.5345
ARCH Test	1.2394	2.5133

**, * indicate significance values of 1% and 5%, respectively.

of asymmetric return spillovers from the stock market to the bond market is not statistically significant . The increase or decrease of the S on the current trading day does not affect the return of the B on the following trading day. There is a one-way asymmetric return spillovers from the B to the S. The effect of asymmetric return spillovers from the B to the S is statistically significant. The relationship between the negative past return of the B and the current S return is statistically significant . Thus, a decrease in the B guide to a decrease of approximately 18% spillovers in the S on the following trading day. Thus, on the B return affectS return whereas good and bad news on S return does not affect the S return.

Parameter coefficients of lagged conditional volatilities (GARCH terms) that give volatility sensitivity in S and B, conditional variance equations in the crisis period in Table 6 are statistically significant . The parameter coefficients of the ARCH terms are also significant . The small estimation of the parameter coefficients of a lagged shock (ARCH) shows that the conditional volatilities do not change very quickly due to the effect of return uncertainties (error innovations). The GARCH parameter coefficients, which show the relationship between current volatility and a lagged volatility, are to be larger in the B than in the S. This finding reveals that past volatility has more effect on the current volatility in the B than the S and that the volatility has gradually developed over time.

Volatility asymmetry exists in the S and B . The form of asymmetry is similar in the two markets. Volatility asymmetry is positive in the S and B.

The effect of the stock market ARCH term on B volatility is significant . The effect of bond market ARCH on S volatility is not significant During the global crisis period, the transition to short-term volatility is unidirectional from the S to the B. The effect of S volatility on B volatility is significant in the long run. The effect of B volatility on S volatility is not significant in the long run. During the global crisis, the long-term volatility spillovers from the S to the B is one-way. Thus, volatility spillovers from the S to the B occur in unidirectional in Turkey during the crisis.

CONCLUSION

In this study, we have investigated the effects of asymmetric volatility spillovers in S&B markets in Turkey. The volatility persists and persistence in the stock market is high compared to the bond market that are in line with the theory and expectation. These findings are consistent with the results of Dean et al. (2010).

The negative leverage effect on the stock market shows that good news has a stronger effect than bad news in the full period. The positive leverage effect on the stock market explains that bad news has a stronger effect than good news in a global crisis period. Good and bad news are not significant in the bond market both during the full and global crisis periods. Negative volatility asymmetry exists in the bond market during the full period. This situation reveals that the bad news and good news in the stock market have a more robust effect. Volatility asymmetry is positive in the stock market and the bond market during the global crisis period. Findings of the study are consistent with the results of the study conducted by Okay (1998), Akar (2005), Mazıbaş (2004), Özçiçek (2005) and Yıldız (2016).

Table 6: Return and Volatility Spillovers of BIST100 and Bond Markets in Crisis Period

S		B	
Conditional Mean			
μ_S	0.0001	μ_B	-0,0003
$\varnothing_S$	0.0929*	$\varnothing_B$	0.1692**
θ_S^+	0.1135	θ_B^+	-0.0098
θ_S^-	-0.1795*	θ_B^-	-0.0172
Conditional Variance			
ω_S	0.0001	ω_S	0.0001*
$\alpha_{S,1}$	0.0941**	$\alpha_{S,1}$	0.2069*
$\alpha_{S,2}$	0.0640	$\alpha_{S,2}$	0.0366**
$\beta_{S,1}$	0.8909**	$\beta_{S,1}$	0.4319**
$\beta_{S,2}$	0.0135	$\beta_{S,2}$	0.0396*
γ_S	2.4526*	γ_S	0.7381*
Skewness	0.6641	Skewness	-0.8517
Kurtosis	4.0060	Kurtosis	8.0035
Log Likelihood	1634.787	Log Likelihood	1978.869
Q (5)	0.8863	Q (5)	4.5094
Q (10)	15.236	Q (10)	9.1807
Q^2 (5)	0.6503	Q^2 (5)	0.9693
Q^2 (10)	3.2636	Q^2 (10)	2.3848
ARCH Test	0.7554	ARCH Test	0.2157

**, * indicate significance values of 1% and 5%, respectively.

The crisis has not changed bond investor behavior. However, stock investors have changed their behavior. The change in asymmetric volatility spillovers over the full period and crisis period is evidence of a behavior change. Return spillovers emerge from the stock market to the bond market in Turkey in the full period. During the crisis, return spillovers emerge from the bond market to the stock market. Volatility spillovers between the stock and the bond market are mutual in the full period. Moreover, volatility spillover from the stock market to the bond market is unidirectional. Mutual (feedback) volatility spillovers between S&B markets. These findings are consistent with the results of Zhang et al. (2013) on the US, U.K. and Germany and Hakim and McAlleer (2010) on Australia, Japan, New Zealand, Singapore and the US.

This study focuses on S&B markets in Borsa Istanbul. Different results can be obtained using different methods in different S&B markets. While assessing the results, we should take these limitations of this study into account. Investors can apply active investment strategies that consider the volatility persistence and market trends of stock market investors. However, it should keep in mind that the applicability of these strategies will depend on the size and stability of the return periods. These results offer some suggestions for investors. Within the framework of this finding, we do not recommend an active investment strategy for bond market investors. Bonds are more reliable investment instruments than stocks. However, the returns are lower. Unchanging bond investor behavior in crisis times is evidence to choose bonds for reasons, such as lower risk and reduced share profits. The stock investor is affected by many factors, such as the economic condition, interest rates, and market sentiment. Therefore, bad and good shocks are more effective in stock markets. Stocks and bonds compete for investors' funds and usually have volatility spillovers between both.

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