Special Issue on Applied Economics and Finance

BORSA ISTANBUL TOURISM INDEX VOLATILITY: MARKOV REGIME SWITCHING ARCH MODEL[1]

Borsa İstanbul Turizm Endeksi Volatilitesi: Markov Rejim Değişim ARCH Model

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Abstract: This paper examines the volatility of Borsa Istanbul Tourism Index by means of the two stage Markov-Switching Autoregressive Conditional Heteroskedasticity Model. The estimation of stock price volatility has a critical importance for investors to make the right investment decision. Especially in such places as Borsa İstanbul where high volatility is experienced the right estimation of volatility is vital. It is suggested in the literature that consideration of regime switching in estimation of volatility is necessary for consistent estimation. This study examines three periods from 05/02/2003 to 09/14/2018; before the 2008 financial crisis, during the crisis and after the crisis. According to these results by the Markov-Switching Autoregressive Conditional Heteroskedasticity Model the tourism index volatility could not return to pre-crisis levels. It was determined that the volatility of the Tourism Index is permanent in three periods and the volatility much higher after the crisis due to the global crisis.

Keywords: Borsa Istanbul, Tourism,, Volatility Models, Markov Model, Switching ARCH Model

Öz: Bu çalışmanın amacı iki aşamalı Markov Rejim Değişim Otoregresif Koşullu Değişen Varyans model ile Borsa İstanbul Turizm Endeksi volatilitesini incelemektir. Yatırımcıların doğru yatırım kararı verebilmesinde hisse senedi fiyat oynaklığının tahmini kritik öneme sahiptir. Özellikle de yüksek oynaklığın yaşandığı Borsa İstanbul gibi piyasalarda oynaklığın doğru tahmini hayatidir. Literatürde oynaktaki rejim değişikliğinin oynaklık tahmininde dikkate alınmasının tutarlı tahmin için gerekli olduğu öne sürülmektedir. Çalışma 02/05/2003 ve 14/09/2018 dönemleri arasında 2008 finansal krizi öncesi, 2008 krizi ve 2008 finansal krizi sonrası olmak üzere üç dönemde yapılmıştır. Markov Rejim Değişim Otoregresif Koşullu Değişen Varyans modeli ile elde edilen sonuçlara göre Turizm endeksi volatilitesi kriz öncesi döneme geri dönememiştir. Küresel krizin etkisiyle turizm endeksinin üç dönemde de volatilitesi devamlıdır ve kriz sonrası dönemde volatilite kriz öncesi döneme göre yüksektir.

Anahtar Sözcükler: Borsa İstanbul, Turizm, Volatilite Modelleri, Markov Model, Rejim Değişim ARCH Model

1. Introduction

The tourism sector is the service industry that generates the highest positive net foreign exchange inflow. The importance of foreign exchange inflow is still increasing in crisis and post-crisis periods. Figure 1 shows the share of narrow in the foreign trade deficit of tourism revenues by years. In the pre-crisis period, tourism revenues narrow the foreign trade deficit between 40 percent and 80 percent. This rate is around 40 percent in the post-crisis period. Is this decline due to the decrease in investor interest in the tourism industry? What is the impact of volatility on the tourism industry for the investor?

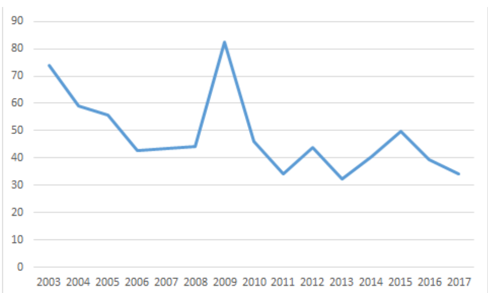

Figure 1. The Share Of Narrow in The Foreign Trade Deficit Of Tourism Revenues (%)
Source: Association of Turkish Travel Agencies

Volatility modeling has many applications from derivative products to option pricing, hedge fund portfolios to risk premiums (Badhani, 2008; Charfeddine and Ajmi, 2013). Engle's (1982) Auto-Regressive Conditional Heteroskedasticity (ARCH) model is used methods to describe the volatility of stock returns, heteroskedasticity and volatility clustering. Measurement of return volatility requires the determination of price given components expressed by return shocks (error

[1] Bu çalışma Melih Kutlu ve Aykut Karakaya özet bildirisi olarak, "*ICOAEF'18, IV. International Conference on Applied Economics and Finance & EXTENDED WITH SOCIAL SCIENCES, November 28 – 29 – 30, 2018 / Kuşadası – Turkey*" Kongresinde sanal oturumda sunulmuştur ve kongre procedia özet kitapçığında basılmıştır.

term) (Andersen et. al, 2010). Engle (1982) has shown the simultaneous modeling of the conditional mean and variance of a time series with the ARCH model. Shocks, which are the determinants of financial asset returns, are non-autocorrelated but dependent. This dependency is explained by the quadratic function of the past values of the shocks.

Many lag lengths related to error terms are significant in ARCH model. Therefore, too many parameters must be calculated. Bollerslev's (1986) Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) is developed to solve this problem. The difference between ARCH model and GARCH model is that the GARCH model includes lags in conditional variance in conditional variance equation. Therefore, the number of parameters calculated decreases.

ARCH and GARCH models are widely used in financial time series analysis. But these models disregard regime switching. Hamilton (1989) presents regime switching based on the markov chain. The study is conducted on the business cycles afterwards the model used in the analysis of financial time series.

According to Hamilton and Susmel (1994) ARCH and GARCH predict high volatility and persistence level. With this, they reduce the predictive power. In addition, parameter estimation of a model that ignores regime switching creates problems in terms of reliability. Badhani (2008), Canarella and Pollard (2007), Charfeddine ve Ajmi (2013), Chen and Lin (2000), Li and Lin (2003), Marcucci (2005) present Switching ARCH (SWARCH) models to do a better job in forecasting than the GARCH models. Gür and Ertuğrul (2012) investigate exchange rate volatility for Turkish economy between July 2, 2001 and May 31, 2010, using ARCH, GARCH and SWARCH model. They observed that the SWARCH model is the better model than other models to predict.

When it is looked at the work related to Borsa Istanbul Tourism Index, Algan, et al. (2017) have also considered the impact on financial markets of terrorist acts in Turkey and they used non-parametric quantile causality test. There is no causal relationship between terrorist acts and financial markets in terms of average return. Acts of terrorism in Turkey, tourism, food, they reached the conclusion that increasing the yield volatility caused uncertainty in sectors such as basic materials.

Gökmen and Çömlekçi (2018) aim to identify co-integration among countries with tourism indices among the 25 countries with the highest income in the tourism revenues ranking. They used Johansen cointegration test and Vector Error Correction (VEC) tests. As a result of the analysis, it was found that BIST Tourism Index and Spain's BCNRBC Index, Taiwan's THOI Index and Greece's FTATTRA Index were cointegration in the long term.

Hamarat and Tufan (2008) investigated whether the Turkish Tourism Sector Index was effective in the context of Effective Markets. Logistic regression was used as a method. In the Tourism Sector Index, the days of the week were observed anomaly, while the month effect was not observed. The study provided evidence that the Turkish Tourism Sector Index was not effective in the weak type. Tan (2017) tested the effect of month of Ramadan by regression analysis in Borsa İstanbul sectoral indices. Found that the effect of the month of Ramadan for the Borsa Istanbul Tourism Index was present. There are also company-based studies on the tourism index. In the literature, there is no study on the regime switching for the Borsa Istanbul Tourism Index.

Balcılar and Demirer (2015), using Markov Switching (TVTP-MS) model in BIST, investigated how investors are affected by global risk factors. The volatility in global and domestic market is influential on the changing transmission probability. Especially in the US market, indexes are more effective on regime changes. Hassan et al. (2016) examined relation between return and volatility in different types of exchange-traded funds (ETFs) traded in the Borsa Istanbul, using Toda-Yamamoto, Granger type causality; bootstrap based Hatemi-J. In their study they found that the negative return shocks are more impactful than positive ones on volatility. Kamışlı et al. (2016), examined volatility spillovers between industrial services and financial sectors of Borsa Istanbul during 2008 Financial Crisis and Greece Debt Crisis, using afner and Herwartz causality test. The findings of the study show that there is a volatility spillover from the service sector to the industrial sector before the global crisis. There is no spillover effect after the global crisis. The crisis is changing the volatility spillover. Kırıkkale et al. (2018) aimed to examine the impact of exchange rate, gold price, and BIST100 on housing stock prices in Turkey, using Dynamic Ordinary Least Squares (DOLS), Full Modified Ordinary Least Squares (FMOLS), Autoregressive Distributed Lag (ARDL) and Markov Switching tests. According the Markov Switching findings, BIST has a positive and statistically significant impact on stock price of real estate industry in the Turkish stock market. The gold price coefficient is found significant for low volatility and non-significant for high volatility. Yayvak et al. (2015) examined time variation in betas of nonfinancial firms traded in the BIST, using threshold Capital Asset Pricing Model. Significant time is the variation in market risk of industry portfolios with respect to monthly rate of changes in the currency basket.

The aim of this study is to present the volatility structure including the regime switching in the tourism industry. Borsa İstanbul Tourism Index is taken as data representing the tourism industry. The literature review shows that a regime change model test for the tourism index has not been conducted. For this purpose, it is aimed to present the role of crisis in the existence and persistence of regime switching in tourism index.

2. Data Set and Econometric Method

In the study, Borsa İstanbul Tourism Index weekly data are divided into three periods, pre- crisis (May 2, 2003 – June 29, 2007), crisis (July 6, 2007 - May 29, 2009) and post-crisis (June 5, 2009 – September 14, 2018) periods. Periods are prepared according to the Central Bank of Turkey's reports . The data are both realized by the dollar rate and converted into the logarithmic difference series by the following formula:

$$y_t = 100(lnP_t - lnP_{t-1})$$

When the descriptive statistics in Table 1 are analyzed, it is seen that the average returns of Tourism index are positive in the pre-crisis period and negative in the post-crisis period. According to the Jargue Bera normality test, normality assumption could not be obtained. This shows that there may be volatility in the series.

Table 1. Descriptive Statistics of Borsa İstanbul Tourism Index Logarithmic Difference Series

	Pre-Crisis Period (216 Obs.)	*Crisis Period (100 Obs.)*	*Post-Crisis Period (485 Obs.)*
Mean	0.828853	-1.020212	-0.243297
Median	1.061772	-0.669648	-0.002789
Maximum	15.58313	28.23281	20.49160
Minimum	-18.39658	-33.55108	-21.87390
Standart Deviation	5.870289	8.505356	4.994125
Skewness	-0.431028	-0.393591	-0.613416
Kurtosis	3.636295	6.065073	5.779311
Jargue Bera	10.37994*	41.72637*	186.5166*
***, **, and * refer to the Jargue Bera at significance levels of 10%, 5%, and 1%, respectively			

First, we test structural break unit root test. In order not to experience spurious regression, data test with Lumsdaine-Papell (1997) unit root test for two structural breaks. Zivot Andrews (1992) test has the single break. This break increase in the Lumsdaine Papel unit root test and forms Model AA, Model CA, and Model CC shown folllowing. DU1 and DU2 show structural changes, DT1 and DT2 show changes in the trend. If the t statistic of alpha coefficient is greater than the critical value, the unit root base hypothesis is rejected and the series is stationary.

MODEL AA $$\Delta y_t = \mu + \alpha y_{t-1} + \beta t + \theta_1 DU1_t + \phi_1 DU2_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t$$

MODEL CA $$\Delta y_t = \mu + \alpha y_{t-1} + \beta t + \theta_1 DU1_t + \phi_1 DU2_t + \gamma_1 DT1_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t$$

MODEL CC $$\Delta y_t = \mu + \alpha y_{t-1} + \beta t + \theta_1 DU1_t + \phi_1 DU2_t + \gamma_1 DT1_t + \gamma_1 DT2_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t$$

Second, the ARCH effect is investigated. Third, GARCH and SWARCH models are established and BDS test is performed. The BDS test developed by Brock et al. (1987) is the test that indicates whether the model is incorrect when applied to error terms. When the test is applied to the error terms of the linear time series, it reveals whether the nonlinear structure that the model should be included in the model.

Table 2 shows the ARCH model developed by Engle (1982), the GARCH model developed by Bollerslev (1986) and the SWARCH model developed by Hamilton and Susmel (1994). Engle's (1982) ARCH model is explained by the quadratic function of the past values of the shocks. The difference between ARCH model and GARCH model is the GARCH model includes conditional variance lags (h_{t-j}) into conditional variance equation. Therefore, the number of parameters calculated decreases.

ARCH and GARCH disregard regime switching. Hamilton and Susmel (1994) developed the SWARCH model because of the reliability problem of parameter estimates which do not allow a change in the regime. The method shows a nonlinear structure that allows for regime changes.

Table 2. ARCH, GARCH and SWARCH Models

ARCH	*GARCH*	*SWARCH*
$r_t = \phi_0 + \sum_{i=1}^{m} \phi_i r_{t-i} + u_t$ $u_t = h_t^{1/2} \varepsilon_t$ $h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2$	$r_t = \phi_0 + \sum_{i=1}^{s} \phi_i r_{t-i} + u_t$ $u_t = h_t^{1/2} \varepsilon_t$ $h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \gamma_j h_{t-j}$	$r_t = \phi_0 + \sum_{i=1}^{s} \phi_i r_{t-i} + e_t$ $e_t = u_t \sqrt{g_{s(t)}})$ $u_t = h_t^{1/2} \varepsilon_t$ $h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2$

In SWARCH model, s(t) is unobservable variables. The possibility of transition from one regime to another by means of fixed transition possibilities (P_{ij}) and the transition matrix shown below can be calculated. Each value in the matrix P as conditional probability:

$$P_{ij} = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix}$$

$$P(S_{t=j} / S_{t-1=i}) = P_{ij} \quad (i, j = 1, 2)$$

The duration of stay in the first and second regimes can be calculated as follows.

$$\frac{1}{1-P_{11}} \; ; \; \frac{1}{1-P_{22}}$$

3. Emprical Results

According to the results of Lumsdaine Papel Unit Root Test in Table 3, the data set is stationary in three periods. ARMA models are establish after being stationary and the ARCH effect is investigated up to four lag in the most suitable models according to Akaike Information Criterion (AIC) and Schwarz Information Criterion (SC). ARCH effect is observed in all periods in Table 4.

Table 3. Lumsdaine Papel Unit Root Test

	Coefficient	*Structural Break Time*	*Lag*
Pre-Crisis Period	-1.1962 (-7.4755*)	09.04.04 23.09.05	3
Crisis Period	-1.0226 (-10.1915*)	15.08.08 21.11.08	0
Post Crisis Period	-0.9882 (-21.7090*)	29.04.11 05.05.17	0
***, **, and * refer to significance levels of 10%, 5%, and 1%, respectively.			

Table 4. ARCH Effect

	Pre-Crisis Period	*Crisis Period*	*Post Crisis Period*
ARMA (p,q)	(2,1) AIC:6.379012 SC:6.448189	(0,0) AIC:7.129219 SC:7.155271	(0,0) AIC:6.056461 SC:6.065089
ARCH LM (1)	3.032973***	4.733320**	4.036590**
ARCH LM (2)	3.806100	6.163499**	5.127450***
ARCH LM (3)	6.358471***	12.76386**	7.188920***
ARCH LM (4)	8.765545***	12.63903**	7.254782

LM: TxR^2 T: no of observation R^2 : Coefficient of auxiliary regression coefficient.
***, **, and * refer to significance levels of 10%, 5%, and 1%, respectively.
Lags are shown in paranthesis

The results of GARCH and SWARCH models selected according to AIC and SC criteria are given in Table 5. It presents that the GARCH model calculates the high level of persistence. The findings of the crisis period persistence is meaningless. According to the results of BDS test applied to GARCH model error terms given in Table 6, the model is non-linear. Therefore the model should be installed with a non-linear model such as SWARCH. The results of regime change in Table 7 show that the low volatility regime persists in the pre-crisis period and the high volatility regime persists in the post-crisis period. The persistence of high volatility is 1.26 weeks and 33.52 weeks, respectively, before and after the crisis period. Crisis caused a change in tourism index in terms of volatility. Similar results have been obtained with the study by Kamışlı et al. (2016) and Gür and Ertuğrul (2012). As the findings of the crisis period persistence is meaningless, Table 7 does not include any finding about crisis period.

Table 5. GARCH and SWARCH Model Results

	Pre-Crisis Period	*Crisis Period*	*Post Crisis Period*
	GARCH(1,1)	*GARCH(1,1)*	*GARCH(1,1)*
α_i	0.120920	0.277391	0.065007
γ_j	0.672532	0.508608	0.867997
Persistence[a]	0.793452**	0.785999	0.933004*
AIC	6.374092	6.954030	5.920123
SC	6.452224	7.084289	5.963259
Log likelihood	-683.4020	-342.7015	-1430.630
	SWARCH(2,1)	*SWARCH(2,1)*	*SWARCH(2,2)*
Regime 1 C	1.784820*	-2.628191*	-14.87949*
Regime 2 C	-9.991953	0.043761	0.287499
Log likelihood	-683.5175	-347.0465	-1434.404
Persistence[a]	0.055555**	0.0156337	0.121443**
AIC	6.384421	7.060931	5.943932
SC	6.4781799	7.217241	6.004322

***, **, and * refer to significance levels of 10%, 5%, and 1%, respectively.
a: persistence is the sum of coefficents

Table 6. BDS Test Results

	Pre-Crisis Period		*Crisis Period*		*Post-Crisis Period*	
Dimension	*BDS Statistic*	*Prob.*	*BDS Statistic*	*Prob.*	*BDS Statistic*	*Prob.*
2	0.010054	0.0562	0.033011	0.0004	0.006233	0.1381
3	0.018544	0.0267	0.054324	0.0003	0.019147	0.0042
4	0.022314	0.0251	0.071278	0.0001	0.027471	0.0006
5	0.021133	0.0418	0.087478	0.0000	0.031699	0.0001
6	0.021705	0.0301	0.091161	0.0000	0.029705	0.0002

Table 7. Regime Switching Transition Probability Results

Term		*Regime 1*	*Regime 2*
Pre-Crisis Period SWARCH(2,1)	*Regime 1*	0.929030	0.070970
	Regime 2	0.787843	0.212157
	*Persistency**	14.09	1.26
Post-Crisis Period SWARCH(2,2)	*Regime 1*	0.185000	0.815000
	Regime 2	0.029826	0.970174
	*Persistency**	1.22	33.52
*Weekly			

4. Conclusion

In the study, the volatility of the Borsa Istanbul Tourism Index takes into regime switching in the pre-crisis and post-crisis period. Since the volatility of Tourism Index returns is non-linear, it is concluded that the appropriate estimator is SWARCH to GARCH model.

The global financial crisis in 2008 affected many sectors including the tourism sector. The crisis has an impact on both investor behavior and volatility. It is observed that the tourism index is oriented towards insisting on a low-risk regime in terms of regime persistence before the crisis. At the same time, the index shows persistence on staying in the same regime in the low-risk regime. This situation is suitable for investors who avoid risk. After the crisis, when the system is in a high risk regime, the system is determined to remain in the same regime. The post-crisis period is suitable for the investor who likes the risk. The crisis caused a change in tourism index in terms of volatility. This shows that the sector is affected by external shocks. For this reason, investor should have investments with this information.

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