Journal of Current Researches on Social Sciences
(JoCReSS)
www.stracademy.org/jocress
ISSN: 2547-9644

Year: 2016
Volume: 6
Issue: 1

Crossref doi: 10.26579/jocress-6.1.13

Modeling Volatility in Emerging Markets: Comparison between Symmetric Garch Model and Ms-Garch Model

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Keywords
GARCH Model, Markov Switching Model, volatility clustering.

Abstract
In this paper, in order to estimate time-varying volatility, I used the GARCH models (GARCH, E-GARCH, A-GARCH, GJS-GARCH etc.) and Markov Switching (MS) model. The main purpose of this study was to make a comparison between these models. For this purpose, I worked on the BİST100 index data that ranged between 2005 and 2015. In order to monitor the errors in estimation, I created two sample periods for every two years. The results proved my hypothesis that the MS model is better at catching volatility clustering. For this reason it is more useful for emerging markets. However, I also found that all the models produced the same results except recession periods.

Konjonkntürel Etkilerin Oynaklık Üzerindeki Etkisinin Modellenmesi: Otoegresif Modeller ile Markov Modelinin Karşılaştırılması

Anahtar Kelimeler
GARCH Model, Markov Switching Model, volatility clustering.

Özet
Bu çalışmada, zaman içerisinde değişen varyansı tahmin etmek için GARCH modelleri (GARCH, E-GARCH, A-GARCH, GJS-GARCH gibi) ve MS (Markov Switching) modelini kullandım. Çalışmanın temel amacı modeller arasında bir karşılaştırma yapmaktır. Bu amaçla BIST100'e ait 2005 – 2015 arası endeks verileri üzerinde çalıştım. Tahmin hatalarını izlemek için, veriler her iki yılda bir örneklem ve tahmin dönemi olarak düzenlenmiştir. Elde edilen sonuçlar, ekonomik rejim değişikliğine duyarlı MS modellerinin daha güçlü tahmin yapmayı sağladığı şeklindeki hipotezin gelişmekte olan piyasalar için geçerli olduğunu göstermiştir. Ayrıca resesyon dönemleri hariç tüm modellerin aynı sonuçlar ürettiğini buldum.

1. Introduction

In this study, I worked on volatility models known as GARCH (The Generalized Autoregressive Conditional Heteroscedasticity) Models which are created by Engle (1982) and Bollerslev (1986). I made a comparison between the Symmetric GARCH Model and Markov Switching GARCH (MS-GARCH) Model. I made my

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comparison at the BORSAİSTANBUL which has the characteristics of a developing country.

Nowadays, the crises in the financial markets have changed structurally. The more frequent and less impacting crises have replaced the more devastating and rare crises. This development has radically changed the processes for pricing financial assets. In the previous periods, the crises were considered to be extreme situations and the stock prices were considered to be dependent on purely random processes. All the models about stock price process had used geometric Brownian motion. But the jumps caused by the crisis were modeled as discrete random process such as the Poisson process.

First, the recently held hypothesis that volatility is constant in stock pricing is to be abandoned. It has been found that the stock price process is autoregressive and it should be modeled by the GARCH process. For this reason, many kind of GARCH models were created. But because of the financial and economic crisis which occurred often, modeling stock price process required the use of the stochastic processes. These processes have different regimes. Consequently, structural break parameters were added to the models. After determining the structural breaks that occurred before and after different regimes, switching models were developed. The most important of these switching models are the Markov Switching GARCH (MS-GARCH) models. They explain the stock price process as two regimes.

The empirical studies about MS-GACH model found that following a regime change there is a different period. This period doesn't have the same features as the other two periods. After discovering this, researchers looked for models that have three or four regimes. But they reached parameters that could not be counted and this made models with three or four regimes untenable. Latest research has unearthed a new parameter which explains the first stage of bullish market. This is called bounce-back effect and has become a part of the GARCH model.

In this study, I started by making a comparison between the symmetric GARCH model and MS-GARCH model. I used the BIST100 index. The main aim of this study was to determine the most appropriate model for Turkey Stock market. My second intention was to determine whether or not there is a bounce – back effect in the Turkish Stock Market.

2. Theoretical Background

The commonly accepted stochastic process which is used to follow the stock price process is the Geometric Brownian Motion. We can use $X(t) = \mu t + \sigma B(t)$ to describe stock price process. If $S(t)$is stock price at t time, we can write stock price as,

$$S(t) = S_0 e^{X(t)} = S_0 e^{[\mu t + \sigma B(t)]}$$

According to this equation, the determinants of stock price are the last monitored price, the mean and volatility. This process is random because of the volatility parameter. Finally, the two components of future price are just the mean parameter, known as trend, and the volatility parameter, known as the deviation from the mean.

This equation is based on the assumption that stock prices are not related each other. That is why, it is accepted that historical prices cannot be used to predict the future price. But, in the 1970s, researchers tried to explain stock prices with a process which includes the autoregressive (AR) component and a moving average (MA) component. Because this type of time series includes both AR (for p) and MA (for q) the process is known as ARMA (p,q) and is shown as follows,

$$Y_t = \delta + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

δ is the constant term (mean of Y_t) and ε_t is the error term. They have mean of zero and constant variance. But the weakest aspect of this model is that the mean and the volatility of the model are constant. Empirical studies have proven that the constant volatility assumption about stock price data is invalid (Bollerslev and et all, 1992:6). Using high frequency data, changes in volatility increase and volatility clustering comes up. In this situation, the difference between long term volatility and short term conditional volatility increases. The GARCH (Generalized Autoregressive Conditional Heteroscedasticity) volatility models developed by Engle (1982) and Bollerslev (1986) were designed especially to catch volatility clustering in return data. The GARCH model is a time series model and it produces conditional variance based on time.

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2)$$

The basic GARCH Model is symmetric GARCH. This model assumes that the volatility response against negative shocks is the same as that of positive shocks. According to the model, the conditional variance is as follows:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2)$$

GARCH's conditional volatility is expressed as the square root of annualized conditional variance. The conditional variance at different time periods doesn't have identical and independent distribution (Zeng and Beck, 2015:52). Below the parameters of the symmetric GARCH model are interpreted in terms of response to the market shocks and mean reversion.

- α (GARCH error term) measures the response of volatility to market shocks. If this parameter is relatively high (e.g. it is greater than 0.1) volatility is very responsive to market shocks.
- β (persistence parameter) measures the persistence of conditional volatility without the market shock effect. If this parameter is relatively high (e.g. it is greater than 0.9) volatility following a crisis will take longer to die out.
- $(\alpha + \beta)$ (mean reversion parameter) is the rate of volatility's convergence. If this parameter is relatively high (e.g. it is greater than 0.99) the volatility term structure is relatively more horizontal.
- ω (constant parameter) with mean reversion parameter expresses the average of long term volatility. If $\omega/(1 - \alpha + \beta)$ is relatively high, long term volatility is also relatively high.

In order to reach a more realistic model, a different type of GARCH model has been proposed. Some examples are asymmetric GARCH (A-GARCH), GJR-GARCH, and exponential GARCH (Pagan and Schwert, 1990: 268). But most of these GARCH models are based on the assumption that the time series distribution function is unchanged (Weide, 2002:3). Alexander (2008) tried to find a solution developing some processes which have a normal mixture distribution (Alexander, 2008:163-164). For example, she created the asymmetric normal mixture GARCH model with two regimes.

$$\sigma_{1t}^2 = \omega_1 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{1,t-1}^2$$
$$\sigma_{2t}^2 = \omega_2 + \alpha_2 \varepsilon_{t-1}^2 + \beta_2 \sigma_{2,t-1}^2$$

The error term distribution in this equation is expressed as $\varepsilon_t | I_{t-1} \sim NM(\pi, \sigma_{1t}^2, \sigma_{2t}^2)$. So the error term has a conditional distribution that consists of a mixture of two normal distributions.

Because her model has two regimes the normal mixture GARCH model is the most realistic one among GARCH models. Including two regimes, the bull market and the bear market, for example, is more valuable to model stock price. But the main problem of this model relates to the probability of volatility's transition between each regime.

The Markov Switching GARCH Model allows transition between different price regimes according to the Markov process. The uniqueness of this model is found in having the mixture distribution consist of different features and its four main components. Its four components are conditional mean, conditional variance, different price regimes and conditional distribution (Marcucci, 2005:6). Conditional mean can be displayed as follows.

$$r_t = \mu_t^i + \varepsilon_t$$

Subscript (i = 1,2) shows different price regimes, ε_t is error term. The error term has zero mean and unit variance. The conditional variance of GARCH (1,1) can be displayed as follows.

$$\sigma_t^{2(i)} = \omega_1^{(i)} + \alpha_1^{(i)} \varepsilon_{t-1}^2 + \beta_1^{(i)} \sigma_{t-1}^{2(i)}$$

According to this equation, conditional variance not only depends on the observed variance but also price regime. This situation required to integrate all regimes. When we do this the sample grows exponentially. This is the path – dependence problem. Many researchers tried to eliminate this problem. For example, Cai (1994), Hamilton and Susmel (1994), Gray(1996), Dueker(1997), Lin(1998) and Klaassen(2002) . Finnaly, Klaassen (2002) came up with the best model. He showed the conditional variance as follow:

$$\sigma_t^{2(i)} = \omega_1^{(i)} + \alpha_1^{(i)} \varepsilon_{t-1}^2 + \beta_1^{(i)} E_{t-1} \left\{ \sigma_{t-1}^{2(i)} \middle| s_t \right\}$$

Expectation operator in this equation produces as follows:

$$E_{t-1} \left\{ \sigma_{t-1}^{2(i)} \middle| s_t \right\} = p_{ii,t-1} \left[\left(\mu_{t-1}^i \right)^2 + \sigma_{t-1}^{2(i)} \right] + p_{ji,t-1} \left[\left(\mu_{t-1}^j \right)^2 + \sigma_{t-1}^{2(j)} \right] - \left[p_{ii,t-1} \mu_{t-1}^i + p_{ji,t-1} \mu_{t-1}^j \right]^2$$

Klaassen (2002)'s model has two advantages. First, this model is more eligible to catch volatility's permanency when there is a shock in market. Second, his model allows estimating a great number of volatility.

3. The Study

In this study, I used the daily prices of BİST100 index between 2005 and 2015. The data divided into two years. The results obtained by using the symmetric GARCH, the MS-GARCH and historical volatility were compared to take the superiority of each other (Benninga, 2008: 513). The descriptive statistics of returns is summarized in follow chart.

Table 1: Descriptive Statistics

	2005-2007	**2007-2009**	**2009-2011**	**2011-2013**	**2013-2015**
Mean	0,00124	-0,0006	0,001177	0,000618	-7,2E-05
Standard error	0,000741	0,001093	0,000671	0,000614	0,000737
Median	0,001602	-0,00146	0,00205	0,001173	0,00015
Standard Deviation	0,016616	0,02434	0,015001	0,013764	0,016371
Sample variance	0,000276	0,000592	0,000225	0,000189	0,000268
Kurtosis	1,81648	2,412481	1,993715	2,901937	5,400991
Skewness	-0,57226	0,144921	-0,28479	-0,63855	-0,63683
Range	0,137736	0,211409	0,134884	0,123164	0,173017
Maximum	-0,08671	-0,09014	-0,06593	-0,0734	-0,11064
Minimum	0,051027	0,121272	0,068952	0,049763	0,062379
Sum	0,623589	-0,29645	0,588431	0,310366	-0,03562
Count	503	496	500	502	493
Con. Level (95,0%)	0,001456	0,002147	0,001318	0,001207	0,001449

The descriptive statistics are no different as of year. Returns have negative mean only two periods (2007-2009 and 2013-2015). In the 2013-2015, the Kurtosis is higher than other periods. This results show that the returns of this period are more homogeneous and have leptokurtic distribution.

The volatilities of each period were obtained by three methods. First, the symmetric GARCH model was used. Primarily for this, GARCH parameters were prepared and estimated the next year volatilities by using the generated model. Similarly, after obtained the parameters of two different regimes were estimated volatilities. Finally, using MS-GARCH Model by created Klaassen (2002) was obtained volatilities. MATLAB software was used to model two GARCH models. For this aim, MATLAB codes about GARCH Models by Marcucci (2005). The parameters of GARCH and MS-GARCH models and MS-GARCH model transition probabilities show follow table.

Table 2: The Parameters

Panel 1: MS-GARCH Model Parameters							
		Omega	**Alpha**	**Beta**	**Ω/(1−α)**	**the trans. prob.matrix**	
2005-2007	Regime 1	0,00329	0,5715	0,3444	0,0076	0,390	0,0002582
	Regime 2	1,39E-04	0,1741	0,3444	0,0002	0,610	1,00E+00
2007-2009	Regime 1	4,09E-04	0,0021	0,8279	0,0004	-1,00E-06	0,0545490
	Regime 2	2,95E-05	9,63E-02	0,8279	3,2E-05	0,999	9,45E-01
2009-2011	Regime 1	0,00021	0,7334	0,2550	0,0008	0,129	0,3437104
	Regime 2	9,21E-05	0,0198	0,2550	9,4E-05	0,871	6,56E-01
2011-2013	Regime 1	0,00255	0,7648	0,2462	0,0109	0,612	0,0007042
	Regime 2	1,12E-04	0,0516	0,2462	0,0001	0,388	9,99E-01
2013-2015	Regime 1	0,00122	0,8347	0,1983	0,0074	0,358	0,0528421
	Regime 2	1,33E-04	0,0293	0,1983	0,0001	0,642	9,47E-01

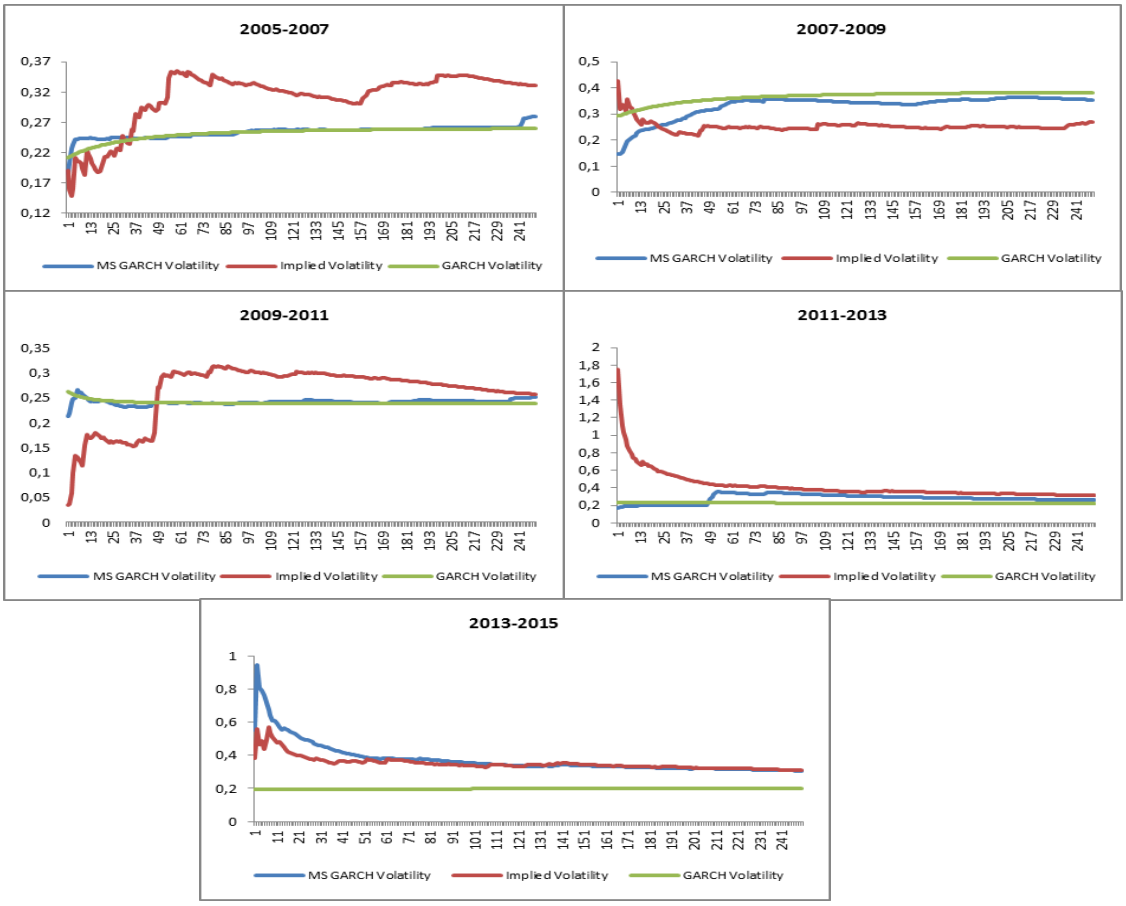
Panel 2: Symmetric GARCH Model Parameters							
		Omega	**Alpha**	**Beta**	**Ω/(1−α)**	**α + β**	**L.L.**
2005-2007		0,000027 (2,398)	0,15397 (3,1845)	0,750493 (9,907)	3,191E-05	0,904463	1369,474
2007-2009		2,56E-05 (2,430)	0,101045 (4,516)	0,856719 (25,493)	2,847E-05	0,957764	1171,485
2009-2011		3,69E-05 (2,467)	0,107764 (3,592)	0,726502 (8,731)	4,135E-05	0,834266	1401,509
2011-2013		7,73E-06 (2,682)	0,109465 (5,305)	0,851815 (33,167)	8,680E-06	0,96128	1475,605
2013-2015		3,17E-06 (8,509)	-0,03347 (-4,475)	1,012053 (179,043)	3,067E-06	0,978584	1386,04

The alpha parameters of Regime 1 in MS-GARCH model is generally bigger than 0.1 (except 2007-2009). At the same time, being $\Omega/(1-\alpha)$ is higher in this regime than other regime show that this regime is the high volatility regime. If we reviews this results with together alpha, we can reach that the response to extreme events in this regime is higher than other. Because there is a single regime in the symmetric GARCH model, the results oϕ $\Omega/(1-\alpha)$ show that the response to extreme events is weak in all price process.

β parameter is low in the MS-GARCH model (except 2007-2009). This result shows that the persistence of volatility is weak. In other words, the volatility returned to normal in a short time after the 2008 crisis. In the symmetric GARCH model, β shows that the persistence is strong.

Before forecasting, continuous returns of BİST100 index of 2005-2015 are obtained for every two years. These returns are used to form model parameters and then after end of the each period the estimated volatility was obtained for next year. Finally, the results were compared with historical volatility. Thus, the results of two models were analyzed. The results are shown follows.

Graph 1: The Forward Volatilities (Historical Vol., GARCH Vol. and MS-GARCH Vol.)



As it can be seen from the chart, there isn't a marked difference among the volatilities which was obtained by tree methods. But the first outstanding difference is that the symmetric GARCH model volatilities have less variance than other model's. As mentioned in the parameters analysis, the response of this model to extreme events is low. When the difference between estimates is analyzed we can see that the symmetric GARCH volatility gets away from historical volatility more than MS-GARCH volatility.

4. Conclusions and Recommendations

Modeling volatility is most part of a financial asset price. Because, volatility is only stochastic factor affected price. Volatility in stock markets is the measure of risk and it is unique comparable factor with return. For too long a time, it is accepted that the volatility related stock price index or stock price movement is constant. But, it has been proven by empirical studies that the distribution of price process doesn't stable. Also, deviations from normal distribution show that there is second distribution function which has leptokurtic normal. As a result, the hypothesis that prices have identical and independent distribution is not mostly acceptable.

The finding of relation among prices has suggested that autoregressive time series can be use modeling price process and then the GARCH process was created. But, the truthfulness of the GARCH parameters is discussed specially for emerging

markets. In this study, the results which are obtained by using symmetric GARCH model contribute to this discussion. We can easily say that Turkey Stock Market is a respectable sample for emerging markets. That's why, we can generalize the obtained results for other emerging markets.

The historical volatilities show that the market responses extreme events and this reaction move to volatility at different level. This is named as volatility clustering. The permanent rise in volatility which can be seen at two graphics (2005-2007 and 2009-2011) clearly show this situation. After these in-sample-periods experiencing crisis, historical volatility and MS-GARCH volatility increased out-of-sample periods. But the symmetric GARCH volatility didn't react. Thus, we can say that the MS-GARCH model can catch volatility clustering after extreme events in emerging markets.

At the first six months of rising period, historical volatility reached the highest level. But at next six months this situation varied and volatility reached long-term level. MS-GARCH model couldn't catch this variation. This model which has two price regimes is inadequate to explain the rising period after extreme events like crisis. This situation which has been discussed in literature is tried to solve using the model which has more than two regimes or adding new parameter to describe first part of rising period. I suggested that it must be studied on modeling this kind of situation for our stock market.

References

Alexander C. (2008). Practical Financial Econometrics, John Wiley&Sons Ltd, England.

Benninga S. (2008). Financial Modeling, Third Edition, The MIT Press, London, England,

Bollerslev, T., Chou R.Y. & Kroner K.F. (1992). ARCH Modeling in Finance, Journal of Econometrics 52, Nort – Holland, 5 – 59, 1992.

Marcucci J, (2005). Forecasting Stock Market Volatility with Regime-Switching GARCH Models, Studies in Nonlinear Dynamics & Econometrics, De Gruyter, vol. 9(4), pages 1-55, December.

Pagan A.R. and Schwert G.W. (1990). Alternative models for conditional stock volatility Journal of econometrics, 45, 1, 267-290.

WEIDE, R.V.D., "GO-GARCH: A Multivariate Generalized Orthogonal GARCH Model", Journal of Applied Econometrics, 17: 549 – 564, Published online in Wiley Inter Science, 2002

Zeng, S. and Bec, F., (2015), "Do Stock Returns Rebound After Bear Markets? An Empirical Analysis from OECG Countries?" Journal of Empirical Finance, 30, 50-61.