EMPIRICAL STUDY OF VOLATILITY PROCESS ON ERROR CORRECTION MODEL ESTIMATION

Syamsul Hidayat Pasaribu

Yayasan AliFA

ABSTRACT

Ada dua tujuan yang ingin dicapai dalam penelitian ini. Pertama, adalah untuk menyelidiki apakah dalam estimasi model koreksi kesalahan atau error correction model (ECM) terdapat proses volatilitas. Jika ternyata ada, maka model estimasi koreksi kesalahan seharusnya diestimasi dengan menggunakan model volatilitas. Hasil empirik estimasi ECM ternyata mengindikasikan adanya proses volatilitas yang ditunjukkan oleh signifikannya pengujian Autoregressive Conditional Heteroscedasticity (ARCH).

Tujuan kedua adalah untuk menentukan model yang paling baik antara estimasi ECM dan estimasi ECM yang diikuti dengan proses volatilitas. Setelah dilakukan estimasi terhadap kedua model tersebut ternyata dapat disimpulkan bahwa estimasi model ECM dengan proses Generalized ARCH (EC-GARCH) lebih baik dibandingkan dengan estimasi model ECM. Sebagai contoh kasus digunkan model estimasi indeks harga saham gabungan di bursa efek Jakarta (BEJ).

Keywords: error correction model, volatility process, GARCH, EC-GARCH.

INTRODUCTION

One the expression in Jakarta stock composite index (JSCI) trend and it volatility is that the possibility of the significant effect of LQ45 index movements. Recent studies on volatility models, especially in the stock market volatility models used univariate expression (Bollerslev and Kroner, 1992; Bollerlev, et al, 1994). Univariate model does not explain the economic variable relations as economic theory expression. Thus, we should create model that explains the relations among the economic variables. One of the most popular dynamic models is error correction model (ECM). This model widely used in dynamic modeling because its properties explained the short-run effects as well as long-run effects.

The main purpose of the paper is to search for the volatility process on ECM. If there are volatility processes in ECM empirical estimation, we should estimate it with volatility process model. For this purpose, most of empirical studies used Generalized Autoregressive Conditional Heteroscedasticity (GARCH) specification (Engle, 1982; Bollerslev, Engle, Nelson, 1994; Engle, 2000; Engle and Patton, 2001). Thus, we may estimate the ECM by applying GARCH model. Finally, we compare the empirical estimation of ECM model and ECM with GARCH model and choose the superior model by several criteria model selection such as Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC).

The main reason to use GARCH process lies in the fact that a conditional stochastic process generates the index data with a changing variance. Therefore, it is naturally expected that GARCH is the right tool to approach to the problem since it takes the changing variances into consideration. Section

II of this study describes the data and the time series properties (such as, unit root test, co-integration test and error correction model) employed to assess the LQ45 Index and JSX Composite Index (JSX-CI) relationship and its empirical results. Section III provides GARCH processes on error correction model and the empirical results. Section IV gives the concluding remarks.

SEVERAL ISSUES OF TIME SERIES PROPERTIES

Model and Data

We built the economic relationship bet-ween LQ45 index and JSX-CI in econometric model. Let LQ45 index as independent variables and JSX-CI as dependent variable. LQ45 index consists of 45 shares, which are high in liquidity, and is selected through a set of criteria (see www.jsx.co.id for detail information). LQ45 Index was first introduced on February 24th, 1997. July 13th, 1994 is used as the basis for the index calculation, valued at 100. The premiere selection used market data from the date of July 1993 to June 1994 and resulted in 45 issuers which covered 72% of the total market capitalization and 72,5% of the regular market's total transaction value. That is why the index has major role of stock trading and composite index movements in JSX and treats as independent variables in this research.

The single model of long-run relationship between LQ45 and JSX can be express as following equation,

$$ci_t = \mu + \beta lq_t + u_t. \qquad (1)$$

Daily data for the period of February 1st, 1996 – December 28th, 2001 (exclude holidays) employed is as follows: JSX-CI and LQ45 index. Both variables are in natural logarithms, so $ci = ln\ (JSX\text{-}CI)$ and $lq = ln(LQ45)$, respectively. The original data source of the variables is the JSX, however obtained from the database of the Accounting Research Center of Faculty of Economics

Gadjah Mada University. The sample size is taken to be 1451 and all calculations in this research use Eview Version 3.

Unit Root Test

We start the analysis by establishing the time series properties of individual variables. The aim here is simply to show that the variables are integrated of the same order. The sampling distribution of OLS estimator is not well behaved if the disturbance is non-stationary. If a unit root present, it is essential to first difference the variables, thereby eliminating the unit root and achieving stationarity before attempting to estimate the model.

For this purpose, we use augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979, 1981). The ADF test in year 1979 used test statistics based on ordinary least squares (OLS) estimation while the 1981 article used test statistics on the base of maximum likelihood (ML) estimation. Note that the augmented Dickey-Fuller tests are performed with trend and intercept in level data, but without trend and intercept in first difference data.

Table 1. Augmented Dickey-Fuller Test for a Unit Root

Variables	t – ADF (1979)	t-ADF (1981)
Ci	-2.425 (1)	-2.817 (1)
lq	-2.882 (1)	-3.684 (1)
Δci	-24.571* (1)	-39.381* (1)
Δlq	-24.805 * (1)	-40.213* (1)

Note: Optimal lag length in parentheses based onSchwarz Information Criterion (SIC). * significant at 1%.

The ADF test results are reported in Table 1. It clearly shows that all variables in this study are non-stationary (have unit roots) in level. They would be stationary in first difference. Thus, all variables in this research are called as integrated of order one or I(1).

Co-integration and Error Correction Model

One way to identify the co-integrating relationship between *ci* and *lq* is by identified the time series paths a long of observations. This identification is shown in Figure 1. It is not mistake to say that *ci's* path movements similar to *lq's* path movements. This figure tells us that maybe there is long run relationship (co-integration) between those variables.
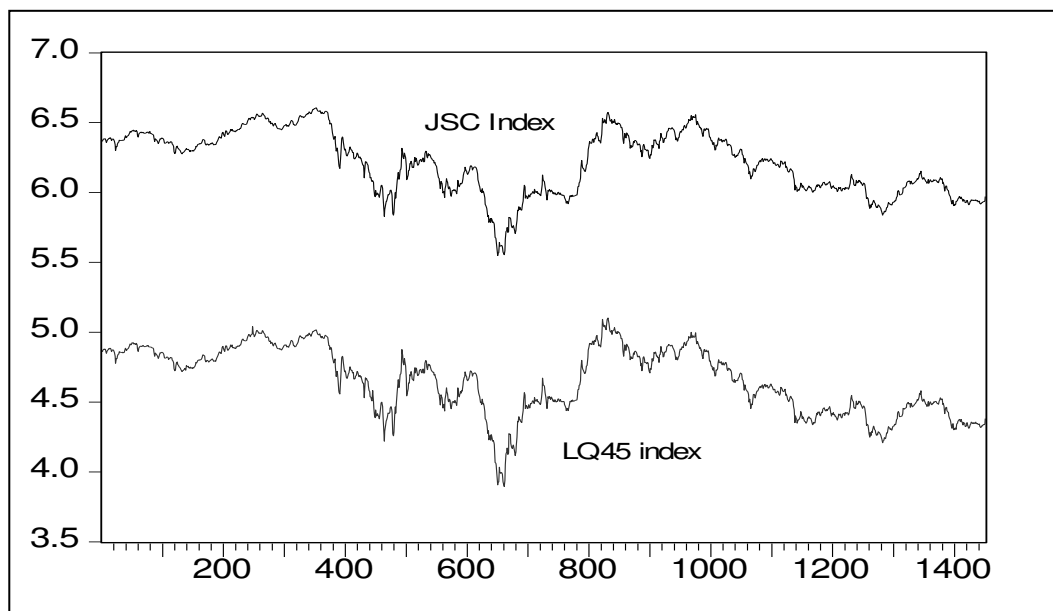

Figure 1. Trend of Composite Index and LQ45 Index on JSX, February, 1ˢᵗ, 1996-December, 28ᵗʰ, 2001 (in natural logarithm)

Given a group of non-stationary series or random walks stochastic processes (note both the variables I(1)), we may be interested in determining whether the series are co-integrated, and if they are, an identifying the long-run equilibrium relationship. Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series might be stationary. If such a stationary, or I(0), linear combination exists, the non-stationary, time series are said to be co-integrated. The stationary linear combination is called the co-integrating equation and may be interpreted as a long-run equilibrium relation-ship between the variables.

If there is a linear combination of the variables such as equation (1), or we can write that equation as,

$$u_t = ci_t - \mu - \beta lq_t \qquad (2)$$

where, μ is constant term, and find that u_t is I(0) or stationary, then we say that the variables *ci* and *lq* are co-integrated. We can say it as before, they are on the same wavelength. In the language of co-integrating theory, a regression such as equation (1) is known as a co-integrating regression and the parameter μ and β are known as the co-integrating parameters.

There are number methods for testing for co-integration that have been proposed (see Engle and Granger (1987), Gonzalo (1994)). Two simple methods are (1) the ADF test on u_t estimated from co-integrating regression and (2) the co-integrating regression Durbin Watson (CRDW) test (Sargan and Bhargava, 1983). The co-integrating regression results is,

$$ci_t = 1.956641 + 0.914550 \, lq_t \qquad (3)$$
$$(0.056824)* \quad (0.12139)*$$

R^2-adjusted = 0.956; CRDW = 0.013; ADF (1976) = -1.936; ADF (1981) = -1.621 and values in parentheses are robust standard error of Newey-West (1987) Heteroskedasticity and Auto-correlation Consistent (HAC) Covariance with truncation lags=7. The asterisks indicate the coefficients estimated significant at 1% critical level. The results of equation (3) show that CRDW statistics and ADF (1981) indicate no co-integrating regression while the ADF (1976) indicates there is co-integrating equation at least 5% critical level. This results show us that the residual of equation (3) is stationary or I(0).

Having established that composite index is co-integrated with LQ45 index, we moved onto examining the associated error correction mechanism that describes the short-run dynamics. The general model of error correction model could be specified as following equation (see Thomas, 1997).

$$\Delta ci_t = \gamma_1 \, EC_{t-1} + \sum_{i=1}^{p} \lambda_i \, \Delta ci_{t-i} +$$

$$\sum_{j=0}^{q} \eta_j \, \Delta lq_{t-j} + \varepsilon_t \qquad (4)$$

where Δ as usual denotes first difference and EC represents the residuals from co-integrating equation (3). The coefficients η_j imply the impacts of LQ45 index to Composite Index in the short run. We will use general specification approach to set the best estimation of equation

(4). The estimation of ECM yielded the following results:

$$\Delta ci_t = -0.008744 \, EC_{t-1} - 0.210188 \, \Delta ci_{t-1} +$$
$$(0.002862)* \qquad (0.082685)**$$

$$0.784243 \, \Delta lq_t + 0.191034 \, \Delta lq_{t-1} \qquad (5)$$
$$(0.011863)* \qquad (0.069545)*$$

R^2-adjusted = 0.958; SEE = 0.004; LM[degree of freedom = 1] = 0.676[0.411]; RESET = 2.878 [0.0898]; ARCH(degree of freedom = 1, 5, and 20) = 197.919[0.000], 221.254[0.000], and 220.559[0.000], AIC = -8.135, SIC = -8.120. LM is a serial correlation test, RESET is a functional form test, and ARCH is ARCH test, AIC is Akaike Information Criterion, and SIC is Schwarz Information Criterion. Numbers in parentheses denote standard errors of Newey-West consistent HAC with truncation lags=7, while those in brackets denote p-values. The two asterisks indicate that the coefficient is significant at 5% critical level.

There are two interesting results from estimation equation (5). First, the coefficient of EC is significant at least 1% critical level. This result implies that there is long run relation between *ci* and *lq*. Thus, the co-integrating equation in (3) is correctly specification. The second is the very significant of ARCH test with 1 (one day) lag included or 5 (a week) and 20 (a month) lags included. It implies that the equation of (5) following the ARCH processes. This results had proven that empirical estimation of ECM contain the volatility processes. The first purpose of this research had been confirmed.

THE VOLATILITY PROCESS

The basic version of least squares model assumes that the expected value of all error terms, if were squared, is the same at any given point of estimation. This assumption is called homoscedaticity or constant variance. This is the focus on volatility models called ARCH (Auto-regressive Conditional Heteroskedasti-

city) models. ARCH models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modeled as a function of past values of the dependent and independent (exogenous) variables (Engle, 2001).

ARCH models were introduced by Engle (1982) and generalized as GARCH (Generalized ARCH) by Bollerslev (1986). These models are widely used in various branches of econometrics, especially in financial time series analysis. Bollerslev, Chou, and Kroner (1992) and Bollerslev, Engle, and Nelson (1994) provided the recent surveys of theory and empirical of ARCH models.

A popular member of volatility models is the GARCH(p,q) model. Following the results of equation (5), the GARCH(p,q) model of the equation (4) becomes,

$$\Delta ci_t = \gamma_1\, EC_{t-1} + \lambda_1\, \Delta ci_{t-1} + \eta_1 \Delta lq_t +$$

$$\eta_2\, \Delta lq_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \psi_{t-1} \sim (N, \sigma^2_t). \qquad (6)$$

$$\sigma^2_t = \omega + \sum_{i=1}^{p} \varphi_i \varepsilon^2_{t-i} + \sum_{j=1}^{q} \phi_j \sigma^2_{t-j} \qquad (7)$$

Each φ_i, $\phi_j > 0$ and sum of $\varphi_i + \phi_j \leq 1$ for i, j $\geq$ 1 should be satisfied for the model not to be explosive and to guarantee positive variances. If φ_i and/or ϕ_j have negative values, they will not have economic meaning. However, with the inclusion of one period lag value of volume in the equation this condition may fail, despite it will be tested empirically. Those models can be estimated via maximum likelihood once a distributions of the innovations, ε_t, has been specified.

A commonly employed assumption is that the innovations are normal distribution (Gaussian). Bollerslev and Wooldridge (1992) had proven that maximum likelihood estimated

the GARCH model assuming Gausian errors were consistent even if the true distribution of innovations is not Gaussian. The usual standard errors of estimators were both consistent when the assumption of Gaussianity of the errors was violated. Bollerslev and Wooldridge had provided a method for obtaining consistent estimated of those.

Table 2 provides the empirical estimation of some GARCH(p,q) classes. First, we used GARCH specification for GARCH(3,0), GARCH(2,0), GARCH(2,1) and GARCH(1,1). We may chose the suitable model based on tree selection criteria, namely, Loglikelihood Ratio (LR), Akaike Information Criterion, and Schwarz Information Criterion. Based on those criteria, we choosed the GARCH(3,0) specification as the suitable model.

Evaluating the empirical model of GARCH(3,0), we use residual tests based on Correlogram–Q-statistics of the standardized residuals. We use lags to include equal to 20, and show that Q-statistics equal to 14.155 [p-value=0.823] and it is not significant. Thus, we can make a conclusion that the mean equation is correctly specified.

We do the test of residual based on correlogram squared residuals for remaining ARCH in the variance equation and to check the specification of the variance equation. If the variance equation is correctly specified, all Q-statistics should not be significant. The test statistics for include 20 lags, is 1.0614 [p-value =1.000]. Again, it is not significant.

ARCH-LM test carries out Lagrange multiplier tests to test whether the standardized residuals exhibit additional ARCH. If the test statistics is not significant, the variance equation is correctly specified. The ARCH-LM test for one lag also has no significant value, LM(1)=0.5791 [p-value=0.4466]. It implies that there is no ARCH left in the standardized residuals.

Table 2. Re-estimated Equation (5) allows GARCH Process

Variables	GARCH(2,0)	GARCH(3,0)	GARCH(2,1)	GARCH(1,1)
EC_{t-1}	-0.005460 (0.001635)* ((0.002581))**	-0.004328 (0.001808)** ((0.002498))***	-0.004534 (0.001801)** ((0.002592))***	-0.004082 (0.001911)** ((0.002277))***
Δlq_t	0.794228 (0.002425)* ((0.007976))*	0.794396 (0.002070)* ((0.009043))*	0.797712 (0.002542)* ((0.008493))*	0.799931 (0.002610)* ((0.009550))*
Δlq_{t-1}	0.065273 (0.016279)* ((0.101578))	0.0041169 (0.020741) ((0.036258))	0.027536 (0.022098) ((0.072184))	0.001621 (0.023413) ((0.083212))
Δci_{t-1}	-0.041177 (0.022524)*** ((0.109059))	0.031844 (0.024762) ((0.047153))	-0.003872 (0.027689) ((0.087006))	0.026313 (0.028722) ((0.103899))
ω	7.91E-06 (1.05E-07)* ((3.01E-06))*	7.02E-06 (1.21E-07)* ((2.86E-06))**	4.54E-06 (3.77E-07)* ((2.18E-06))**	2.89E-06 (2.84E-07)* ((1.26E-06))**
ε^2_{t-1}	0.181054 (0.029201)* ((0.139491))	0.194491 (0.028264)* ((0.140099))	0.178255 (0.027180)* ((0.154387))	0.309271 0.031848 ((0.202144))
ε^2_{t-2}	0.591893 (0.032708)* ((0.351613))***	0.100134 (0.032441)* ((0.099216))	0.338985 (0.035939)* ((0.319336))	- - -
ε^2_{t-3}	- - -	0.515035 (0.037882)* ((0.251700))**	- - -	- - -
σ^2_{t-1}	- - -	- - -	0.351979 (0.044844)* ((0.112003))*	0.594282 ((0.033913))* ((0.069884))*
Log likelihood	6122.333	**6153.40**	6136.766	6117.695
AIC	-8.440763	**-8.48226**	-8.459305	-8.434361
SIC	-8.415262	**-8.45312**	-8.430161	-8.408860

In the conditional mean equation, the error correction variable (EC_{t-1}) and Δlq_t have significant impacts to composite index at least 5% and 1% critical level while Δlq_{t-1}, and Δci_{t-1} have no significant values. The coefficient of EC is now corrected to be –0.004 rather that –0.009 in ECM model. The other coefficients also have been corrected to become 0.794, 0.004, and 0.032 for variables Δlq_t, Δlq_{t-1}, and Δci_{t-1}, respectively instead the values of those coefficients in ECM model.

In variance equation, the ARCH terms also have significant values at least 1% critical level. The results indicate that the volatility of ECM is not persistent, with the sum of ARCH(1) to ARCH(3) being 0.81. These results imply that the variance of model is not quite persistence.

Figure 2 and 3 show us the actual values, fitted values, and residual values of empirical estimation of ECM and EC-GARCH(3,0) model. We may use Akaike Information Criterion and Schwarz Information Criterion for model selection. Based on these criteria, all support to choose the EC-GARCH(3,0) over ECM. Thus, the second purpose of this research had been confirmed.
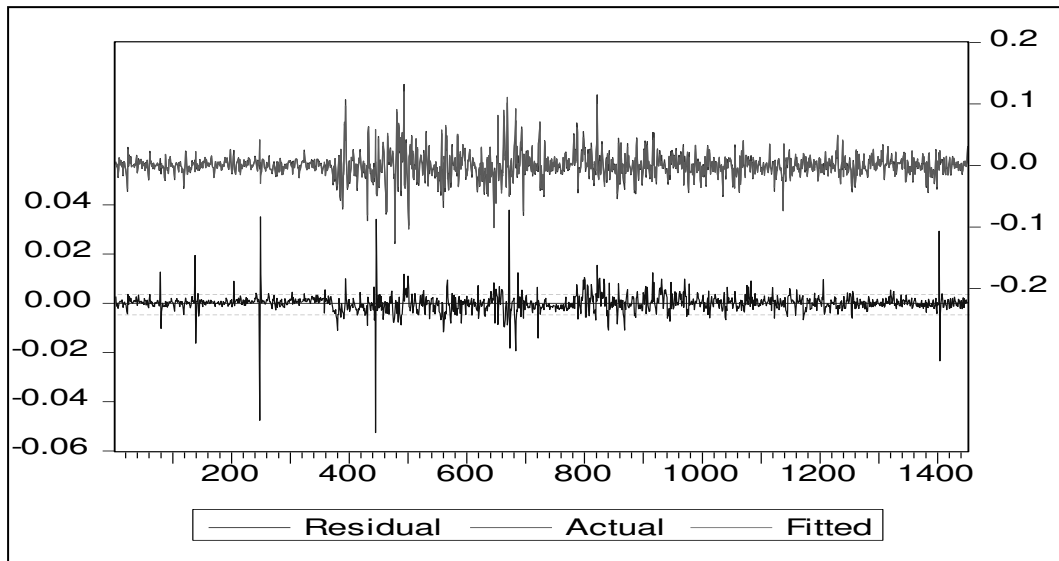

Figure 2. The Actual, Fitted, and Residual Values of Error Correction Model
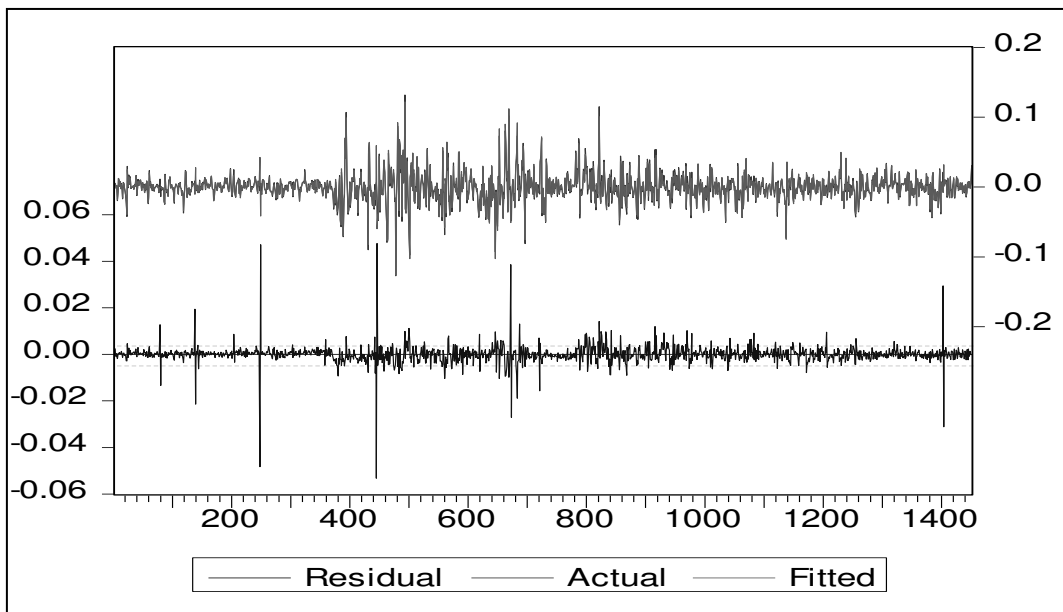

Figure 3. The Actual, Fitted, and Residual Values of EC-GARCH(3,0) Model

CONCLUSION

The purposes of this paper have been proven above. The error correction model not always produce constant variance (homoscedasticity) and the results of this research have proven that such as model produces non-constant variance (heteroscedasticity). These results imply that model is following volatility processes. Thus, we had estimated the ECM with GARCH processes (EC-GARCH model), and produced the better estimation than its ECM by several criteria model selection. Finally, both purposes of this research had been confirmed.

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