Volatility Forecasts Jakarta Composite Index (JCI) and Index Stock Volatility Sector with Estimated Time Series

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This study aims to explore the comparative ability of forecasting models and the time series volatility of capital markets in Indonesia using JCI daily index data and sectoral indices from January 2010 to December 2014. The use of ARCH-family ARCH model (1.1) and GARCH (1.1) used to capture symmetrical effects, while TGARCH (1.1), EGARCH (1.1), APGARCH (1.1) on asymmetric effects. The results show that JCI return has an asymmetrical effect and the closest forecasting model is EGARCH (1.1). Returns for AGRI, MINING, BASICIND, INFRA, FIN, TRADE indices also have asymmetrical effects but are modeled with TGARCH (1.1). Meanwhile, the MISCIND, CONSUMER, PROPERTY indexes have a symmetrical effect and are modeled with GARCH (1.1). These models can explain forecasting closest to the real as well as provide guidance investors in the Indonesia capital market as one of the emerging markets.

Keywords: *Estimation of Volatility Time Series; ARCH family; Symmetry Effect; Asymmetric Effect; JCI and Nine Sectoral Indexes*

JEL Classification: G11, G12, G17

Introduction

Technical analysts understand and analyze stock movements to maximize returns and minimize risk. In the economic field, this simple concept has a long history. Engle (2004) explains that since research has linked risk with variance in portfolio values. In avoiding risk, by trying to optimize portfolio and investor behavior (Markowitz, 1952; Tobin, 1958). Then, research emerged that produced the CAPM (Capital Asset Pricing Model) theory. CAPM shows the natural relationship between expected return and variance (Lintner, 1965; Mossin, 1966; Sharpe, 1964; Treynor, 1965). Furthermore, a model has been developed to evaluate option prices (Black & Scholes, 1972; Mer-

ton, 1973). Researchers realize that volatility changes over time. They find different answers for different periods.

Estimates of volatility are important financial issues in decision making and assessment of financial market status. This explains that the return on the price of financial securities is more or less predictable on a daily or monthly basis. The volatility of returns is predicted along with phenomena and conclusions that are important for financial economics and risk management. Panggabean (2018) explains that current data is correlated not only with data from the recent past (say 2-3 days), but also from distance past (say, 6 months ago). Long memory, therefore, implies an ability of a time series to 'memorize' its distant past. A time series with long-memo-

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ry, therefore, provides evidence against the efficient market hypothesis. In the stock market, this also implies that past data contains some useful information for making future decisions including using technical analysis for trading purposes.

Abnormalities, autocorrelations, and heteroscedasticity are some of the problems that are usually present in this type of time series data. The resulting variant cannot be explained with a linear or OLS model. To deal with autocorrelation and heteroscedasticity problems, a dynamic estimation theory of volatility is needed and this is a role filled by the ARCH family model. In 1982, R. F. Engle introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model to predict volatility. Then by Bollerslev in 1986, it was refined to Generalized Autoregressive Conditional Heteroscedasticity (GARCH).

In many cases, conditional variance in the ARCH and GARCH models has symmetrical behavior and thus may not fully capture nonnormality issues. This behavior is known as asymmetric shock. Francq and Zakoian (2010) state the use of leverage to explain the fact that volatility tends to have an overreaction to price decreases compared to the same price increase (Black, 1976; Christie, 1982).

The asymmetric effect was tested by Nelson (1991) by proposing an Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model followed by Zakoian in 1994 by modeling the Threshold Autoregressive Conditional Heteroscedasticity (TARCH) and Asymmetric Power Generalized Autoregressive Conditional Heteroscedasticity (APGARCH) developed by Ding et al. (1993).

Models to predict volatility using ARCH and GARCH and their families have been used as research in various emerging markets including Indonesia. Henry (1998) observing the GARCH, EGARCH, GJR, GQARCH models on Hang Seng index, Anton (2006) on LQ 45 shares with EGARCH, Akbar (2008) examined GARCH and IGARCH models on nine sectoral indexes and LQ 45, Kamaludin (2008) on 15 stock exchanges in Asia with TARCH, Hamadu and Ibiwoye (2010) with ARCH, GARCH,

EGARCH models, TARCH on Nigerian Stock Exchange (NSE), Elsheikh A. and Zakaria S. (2011) examined GARCH, GARCH-M, EGARCH, TGARCH, APGARCH in the Sudan Stock Exchange (KSE) stock index, Nastiti and Suharsono (2012) studied five different sector issuers and entered the LQ 45, Alam et al. (2013) used the ARCH-GARCH, EGARCH, PARCH, TARCH models in the composite stock index and sectoral index in Bangladesh, Swarna (2013) who examined the ARCH model in the composite stock index and sectoral index in India, Tripathy and Garg (2013) with ARCH, GARCH, GARCH-M, EGARCH, TGARCH on stocks in developing countries (China, India, Brazil, Mexico, Russia , South Africa), Li et al. (2013) compared GARCH, GARCH-t, EGARCH, EGARCH-t, GJR-GARCH, GJR-GARCH-t models on the Shanghai stock index, Eliyawati et al. (2014) GARCH model in LQ 45 shares, Syarif (2014) on JII shares. All of these studies prove that stock returns show random road volatility at any time, but researchers note that no research performs results on JCI and nine sectoral indices that reflect stocks in Indonesia.

The standard ARCH model assumes that there is no shift in volatility, but especially in developing countries market, there may be sudden changes in volatility because these countries experience more economic, political and social events than market developments. It is important to take account of the shift in estimating volatility persistence especially for developing countries market described by Çağlı et al. (2011).

Angabini and Wasiuzzaman (2011) determined that in the Malaysian stock market the symmetrical GARCH model has outperformed two asymmetric GARCH models (EGARCH and GRJ) despite the asymmetrical and leverage effects associated with the 2007/2008 global financial crisis. This shows that in emerging markets there is a tendency for symmetrical effects (modeled by GARCH) to emerge and asymmetric effects (modeled by GARCH family).

From the background of the technical analysis described above, it can be seen that time

Figure 1. JCI for 2010 - 2014
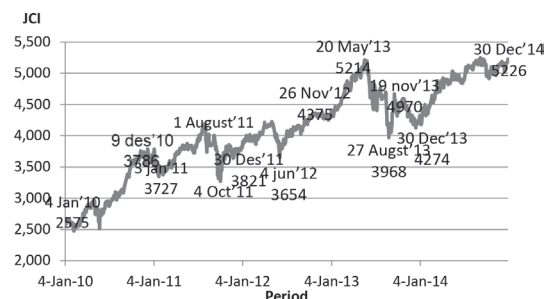
series data, especially financial data such as stock price index, are often volatile. Volatility is shown from data experiencing heteroscedasticity and if using an OLS estimation it will be able to give an incorrect sense of precision. The focus of this research is only to use the model because it is sufficient to represent symmetric and asymmetric shocks to predict stock indices on the Indonesian stock exchange.

Stock market activity is a challenge for the Indonesian government, which is very vulnerable to global financial turmoil. The development of shares in Indonesia, which was reflected by JCI, informed the short-term fluctuation of shares in the domestic stock exchange in May 2010 due to a change in the Minister of Finance.

Dependence on foreign capital in the financial markets and selling prices that are influenced by global factors will also affect the volatility of the capital market. As shown in JCI from September 2011 to the beginning of October 2011, the stock price index declined at 3269.4. This condition was triggered by the debt crisis in several Eurozone member countries. Events weakening rupiah and concerns tapering off also hit the stock market performance since May 20, 2013 until August 2013 with the selling was done by a foreign investor that had a drop of 1247.134 points, or 23.91%.

This study is beneficial for issuers and investors in the Indonesia Stock Exchange. With the dynamic nature of predicting stock market volatility, it will help investors and the government formulate the strategies needed.

The purpose of this study is whether the prediction of JCI volatility and sectoral indices can be modeled by the GARCH approach in the form of symmetrical or asymmetrical

effects and which GARCH process is suitable for modeling the volatility of stock indexes in Indonesia.

To highlight this research, this paper was prepared by presenting studies related to the JCI stock index and its 9 sectors as well as ARCH, GARCH, and their families. Next, explain the data analysis methodology that will be used. The next section presents the results obtained and selects the best model among the ARCH/GARCH families studied. Finally, summarize the conclusions and propose further studies in this field.

Literature Review

Benchmark

Benchmarks on the Indonesia Stock Exchange (IDX) are known as indexes. Kartika (2008) explains that the index functions as an indicator of market trends, meaning that the index movement describes the market conditions at the time whether the market is active or sluggish. The movement of the index becomes an important indicator for investors to determine whether they will sell, hold, or buy a stock or several shares.

The Indonesia Stock Exchange in 2016 has 17 types of the stock price index, including the Jakarta Composite Index (JCI) and nine Sectoral Indexes.

Time Series

Time series is a set of data in a certain period. Anton (2006) explains that the time series data does not provide definitive answers about what will happen in the future, but the analysis

is quite meaningful in the forecasting process and helps reduce forecasting errors.

Financial econometrics exists because there are many cases, especially in the financial and economic fields in general which deal with time series, namely the sequence of observations at different times. Engle et al. (2007) explained that since the work of Haavelmo (1944), time-series economics was considered as the realization of the stochastic process. That is, every economy, time series are considered observations of random variables. This stochastic process is a sequence of variables characterized by a combined probability distribution for each set at different time points.

The concept of risk and return means that the higher the risk that is expected to occur, the investment decision requires an estimation of the higher return known as the best-expected return even though there is no guarantee that it is correct.

Volatility

Volatility is the standard deviation of a stock return in a certain period. This changes from time to time as presented by analysts. The volatility of stock returns explains the risk of stock returns. Price volatility at t-time is estimated at time t-1 so that it is usually measured using standard deviation stated by Engle (2001).

Historical volatility, which is widely used, is estimated by historical data and is equivalent to a standard deviation of stock returns over a while. But if you get a short term in the observation you will get a noise result and if you take a series of long periods, you will get a smooth result that has not responded to recent information. Historical volatility does not respond to the situation so ARCH models are examined to fill this gap. ARCH Volatility provides a weight between new data and data provided by the information that has occurred long ago. A special feature of the ARCH model is that it can calculate these weights based on historical data. There are many extensions of the ARCH model that illustrate non-linearity, asymmetry and long memory properties of volatility described by Neokosmidis (2009).

Autoregressive Conditional Heteroscedasticity (ARCH)

The Autoregressive Conditional Heteroscedasticity (ARCH) model was first introduced by Engle (1982) to model residual volatility that often occurs in financial data. This model will be able to modify both cases of heteroscedasticity and correlation.

In the ARCH model, the variance of the error is allowed to change (heteroscedasticity). Unlike the OLS (Ordinary Least Square) model, the condition of the variance is a constant error (homoskedasticity).

Volatility clustering is often found in financial time series data. Volatility clustering is a condition characterized by a tendency to high volatility at a time and is followed by high volatility at a later time and vice versa.

Variance now depends on the variance of the past so that heteroscedasticity can be modeled and variance is allowed to change over time stated by Engle (1982).

Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

The GARCH model was developed by Bollerslev in 1986. The basic, residual quadratic GARCH model includes the conditional variance equation because the signs of residuals or shock do not affect conditional volatility.

Conditional variance of σ at time t does not only depend on squared error terms in the previous period (such as ARCH), but also on the conditional variance (error variance) in the previous period described by Gujarati (2004).

It can be seen that current volatility is a function of yesterday's volatility and yesterday's squared error. This specification is often meant in financial issues, where the variance of this period is predicted by traders to form a weighted average of long-term (constant), forecasting variance from the last period (GARCH), and information about volatility in the previous period (ARCH). If the sudden return is large either up or down, the trader will increase the variance estimate for the next period.

Asymmetric Shock

Francq and Zakoian (2010) explain that classic GARCH modeling has weaknesses. Indeed, the construction of the conditional variance only depends on the modulus of the last variable, namely the positive and negative results of the past have the same effect on current volatility. This contradicts many empirical studies in the stock series which show a negative correlation between current results and past results. If the conditional distribution is symmetrical in the last variable, the correlation is zero. However, conditional asymmetry is an increase in volatility because the decline in prices is generally stronger than the same price increase. In financial volatility, bad news (negative shock) tend to have a greater impact on the volatility than the good news (positive shock). In other words, volatility tends to be higher in the market when it falls than in the market when it rises (Miron and Tudor, 2010).

Asymmetric effects are also often referred to as leverage effects. Figlewski and Wang (2000) explain that the most common explanation for asymmetry is linking the volatility of a stock with the level of leverage in underlying the company's capital structure. The research of Black and Scholes (1972) discusses the impact of leverage on stock price behavior (Galai and Masulis, 1976; Geske, 1979; Merton, 1973). The reason comes from the classic principle of Modigliani and Miller (1958) that the fundamentals of company assets are the whole of the company, while company securities (such as stocks, bonds, etc.) are only different ways of solving ownership of these assets. From that perspective, Black and Scholes (1972) observed that the volatility of stock returns must come entirely from fluctuations in the total value of the company. In a company that has equity and debt in the capital structure, the claims of debtholders on firm value are limited to the nominal value of bonds, so that almost all variations in the total value of the company will be transmitted to equity, except when the company approaches bankruptcy.

Figlewski and Wang (2000) continue to suppose that there is an increase in the overall value of the company. Because capital is smaller than the company's total value, a proportional return on shares will be greater than the entire company. Therefore stocks that leverage must be more volatile than the whole of the company, with differences being a function of the relative amount of debt and equity in the company's capital structure. Stock volatility varies due to the volatility relationship occurring systematically and asymmetrically with returns, that is, when negative stock returns cause equity values to fall while debt is in a fixed state, company leverage is increased to increase stock volatility in the future. The opposite effect must occur when positive stock returns. Empirical evidence supporting this theoretical argument is presented by Christie (1982), who found a positive correlation between the level of leverage on the company's balance sheet and the volatility of its shares. The GARCH and family models stochastic volatility adopts the "leverage" parameter which is treated as a coefficient that will be estimated from the data return.

The asymmetrical effects that occur on stock returns make the GARCH model be considered inadequate for the volatility model. Therefore, testing is also carried out using EGARCH, TGARCH, and APGARCH models which allow it to be more suitable to capture asymmetric shocks in the volatility of stock returns.

Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)

Asymmetric fluctuations in the effects of volatility were investigated by Nelson in 1991 by developing EGARCH or Exponential GARCH models.

When the shock has an exponential asymmetric impact on volatility as explained by Anton (2006), the EGARCH model captures the asymmetric response of time-varying variance to shock and at the same time to ensure that variance is always positive also confirmed by Elsheikh A. and Zakaria S. (2011). In macroeconomic and financial market analysis, negative shock usually implies bad news that leads to a more definite future. As a result, shareholders will need a higher expected return to com-

pensate for the bearing increase in risk in their investment.

Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH)

TGARCH as EGARCH also accommodates the presence of asymmetric fluctuations. This TGARCH was introduced by Zakoian (1994).

Asymmetric Power Generalized Autoregressive Conditional Heteroscedasticity (APGARCH)

APGARCH is a well-known GARCH family model and was developed by Ding et al. (1993). Standard deviations are somewhat modeled as variance modeling in some GARCH family models. This model is also able to estimate the power parameter δ instead of imposing on the model described by Elsheikh A. and Zakaria S. (2011).

The APGARCH model where $\delta = 2$, in the equation generally becomes a classic GARCH model that allows for leverage effects and when $\delta = 1$ conditional standard deviation will be estimated. Besides, it will be able to increase the flexibility of the Asymmetric Power GARCH model by considering δ as another coefficient that must also be estimated as explained by Miron and Tudor (2010).

In general, this volatility research is carried out on data that fluctuates in value over time. The current research besides referring to existing literature, it also takes references from similar previous studies, including:

Research by Cao and Tsay (1992) on NYSE and AMEX shares in the period January 1928 until December 1989 using the ARMA, GARCH, EGARCH, TAR models. The result is TAR better than GARCH and EGARCH for large stock returns. While the best EGARCH in the longest volatility for small stock returns.

Anton's research (2006) on the LQ45 index for the period 2003 to 2004 with the GARCH and EGARCH method. The result is significant GARCH (1,1), whereas EGARCH (1,1) is not fulfilled because there is no leverage effect.

Hamadu and Ibiwoye's research (2010) on

the daily returns of insurance stocks of the Nigeria Stock Exchange (NSE), the period of December 15, 2000, until September 9, 2008, with ARCH, GARCH, EGARCH, TARCH models. The result is EGARCH is more suitable for evaluating the volatility of insurance stocks in Nigeria.

Research Methods

This research can be grouped based on the objectives, benefits, and time of the object of research. This research is based on the purpose is descriptive research. If based on the benefits of research, then this is applied research. Whereas if according to the research time, this research is a time series research.

The research conducted is research with forecasting testing which is research in explaining the phenomenon of stock volatility. This test is to empirically analyze the econometric model that is suitable for predicting volatility in the JCI and the stock price index in nine sectors.

a. Jakarta Composite Index (JCI)

This JCI is used to measure the combined performance of all shares listed on the IDX.

b. Sectoral Stock Price Index (SSPI)

The Sectoral Stock Price Index on the IDX is a sub-index of the JCI. All issuers listed on the IDX are classified into nine sectors.

In this study, the population used by researchers is the Stock Price Index on the Indonesia Stock Exchange (IDX). Samples were selected by purposive sampling method. This sample is the JCI and nine Sectoral Indexes which consist of: agriculture, mining sector, basic and chemical industry sectors, various industrial sectors, consumer goods sector, property and real estate sector, infrastructure sector, financial sector, and trade and services sector for 5 years.

The data used in this study are secondary in the form of daily (daily) 5 working days from 2010 to 2014. These daily data are high-frequency data where researchers and practitioners want to find interesting events and want to exploit high-frequency data to get a more precise estimate on ordinary horizon forecasting.

Whereas to collect research data, researchers used the documentation method.

Data Analysis Technique

Descriptive Statistics

Descriptive statistics are presented to provide information on the characteristics of research variables, including the mean, maximum value, minimum value, and standard deviation. In descriptive statistics, normality testing is also carried out using the Jarque-Bera Test.

Calculating Stock Returns

All closing prices of the stock index must be changed in the form of returns before doing the ARCH family modeling. Continuously compounded return series models are calculated using closing price index data:

$$R_t = \frac{ln(P_t)}{ln(P_{t-1})} = ln(P_t) - ln(P_{t-1}) \qquad (1)$$

where R_t is the return on period t, P_t is a daily closing stock price index at a certain time t, P_{t-1} is a closing stock price index for the previous period and ln is a natural logarithm.

Stationary Testing

Stationary data is shown to tend to move closer to the mean or fluctuate around the mean which makes the data do not contain trend elements. This stationary condition will eventually explain the behavior of data based on the residual element (error term).

To test the data stationarity using the unit root test. If the data contains a unit root, then the data is not stationary and that needs a differentiation until the data becomes stationary. To test the existence of unit root, the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) test standards were employed in this study. The procedure for determining stationary data or not by comparing the statistical value of ADF and PP with the critical value of the MacKinnon statistical distribution.

Testing of Autocorrelation

Widarjono (2013) explains that in the OLS method assumption, autocorrelation is the correlation between one disturbance variable and another disturbance variable. This violates the assumption that the covariance of the υi and υj is equal to zero. Winarno (2009) also explains that autocorrelation is the relationship between one observation residual and another observation residual. Autocorrelation arises more easily on time series data because based on their nature, current data is influenced by data from previous periods.

The consequences of autocorrelation are: the standard calculation of OLS method errors cannot be trusted, and also the estimation interval and hypothesis testing based on t and F distributions cannot be trusted to evaluate regression results.

Testing the existence of this autocorrelation can use the residual test by looking at the correlogram of Q-Stat on the model. If a significant p-value is found, which is smaller than 5% of 30 lags, the modeling still contains autocorrelation. The model containing this autocorrelation is continued to ARIMA modeling where AR (autoregressive) or MA (moving average) elements will be included in the model until there is no autocorrelation effect in the model.

Heteroscedasticity Testing

The use of the previous ARCH and GARCH models needs to be examined first to detect any element of heteroscedasticity. There are two tests to test the ARCH effect, namely ARCH LM Test and Correlogram Squares of Residual.

Test the correlogram, if there are no ARCH elements in squared residuals, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) should be zero in all lags or statistically insignificant. Conversely, if ACF and PACF are not equal to zero, the model contains ARCH elements. The ARCH LM test where chi-squares (χ) counts is greater than the critical value of chi-squares (χ^2) at a certain degree of confidence (α), then the model contains an ARCH element.

ARCH

Variance now depends on the variance of the past so that heteroscedasticity can be modeled and variance is allowed to change over time explained by R. F. Engle (1982). In general, the ARCH (p) model can be expressed in the form of equations:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + ... + \alpha_p \varepsilon_{t-p}^2 \tag{2}$$

where $\alpha_0 > 0$, $\alpha_{1,...,} \alpha_p > 0$ and α_1 are slopes. σ^2 is an error variance while ε^2 is an error term. Error variance depends on the lag term of the term squared error, which means that the news about the previous period is measured as a lag of squared error (ε_{t-p}^2).

GARCH

In general, GARCH (p, q) models can be expressed in terms of equations:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2 \\ + \beta_1 \sigma_{t-1}^2 + ... + \beta_q \sigma_{t-q}^2 \tag{3}$$

where α_0 is constant, $\alpha_p > 0$, $\beta_q > 0$, $\alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2$ is the form of ARCH term, and $\beta_1 \varepsilon_{t-1}^2 + ... + \beta_p \varepsilon_{t-q}^2$ is the GARCH term form.

Exponential GARCH

The EGARCH model is generally formulated with the equation:

$$ln\sigma_t^2 = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + ... + \alpha_p \left| \frac{\varepsilon_{t-p}}{\sigma_{t-p}} \right| \\ - \gamma_q \frac{\varepsilon_{t-q}}{\sigma_{t-q}} + \beta_1 ln\sigma_{t-1}^2 + ... + \beta_q ln\sigma_{t-q}^2 \tag{4}$$

The use of ln in the conditional variance equation shows that conditionals are exponential. The use of ln also guarantees that the variance is never negative. Variance equation consists of two elements as expressed by Widarjono

(2013), namely: magnitude effect ($\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right|$) which shows the magnitude of the effect of volatility in the t-p period on current variance and sign effect ($\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$) which shows the difference in the effect of positive and negative shock in period t on current variance. The γ sign is an asymmetric response parameter or parameter leverage. This sign γ is expected to be positive in the most empirical cases so that it contributes to an increase in volatility of γ which in the end negative shock will increase volatility in the future (uncertainty) while positive shock has a low effect on future uncertainties.

Threshold GARCH

This TGARCH was introduced by Zakoian (1994) with the general equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} \\ + \beta_1 \sigma_{t-1}^2 + ... + \beta_q \sigma_{t-q}^2 \tag{5}$$

where d is the dummy variable, $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and $d_{t-1} = 0$ if $e_{t-1} > 0$. In this TGARCH model, news good news in period t – 1 ($\varepsilon_{t-1} > 0$) and bad news in period t – 1 ($\varepsilon_{t-1} < 0$) has a different effect on the conditional variance. Good news has an impact on α and bad news has an impact on α+γ. If $\gamma > 0$, the leverage effect occurs. Therefore, if γ is significant and positive, the negative shock has a greater effect on σ_t^2 than positive shock so that it will contribute to increased volatility, which means yesterday's volatility contributed α+γ.

Asymmetric Power GARCH

Ding et al. (1993) propose APGARCH (p, d, q) with general equations:

$$\sigma_t^\delta = \alpha_0 + \Sigma_{i=1}^p \alpha_i (\left| \varepsilon_{t-i} \right| - \gamma_i \varepsilon_{t-i})^\delta + \Sigma_{j=1}^q \beta_i \sigma_{t-j}^\delta \tag{6}$$

where α_i and β_i are standard ARCH and GARCH, δ is positive coefficients and γ_i is the leverage effect, and $\delta > 0$, $|\gamma_i| \leq 0$ for i = 1,2,…,r, $\gamma_i = 0$ for all i<r and r≤p. When $\delta = 2$, the above

Figure 2. Data Plots for JCI and Sectoral Indexes (Index and Return)

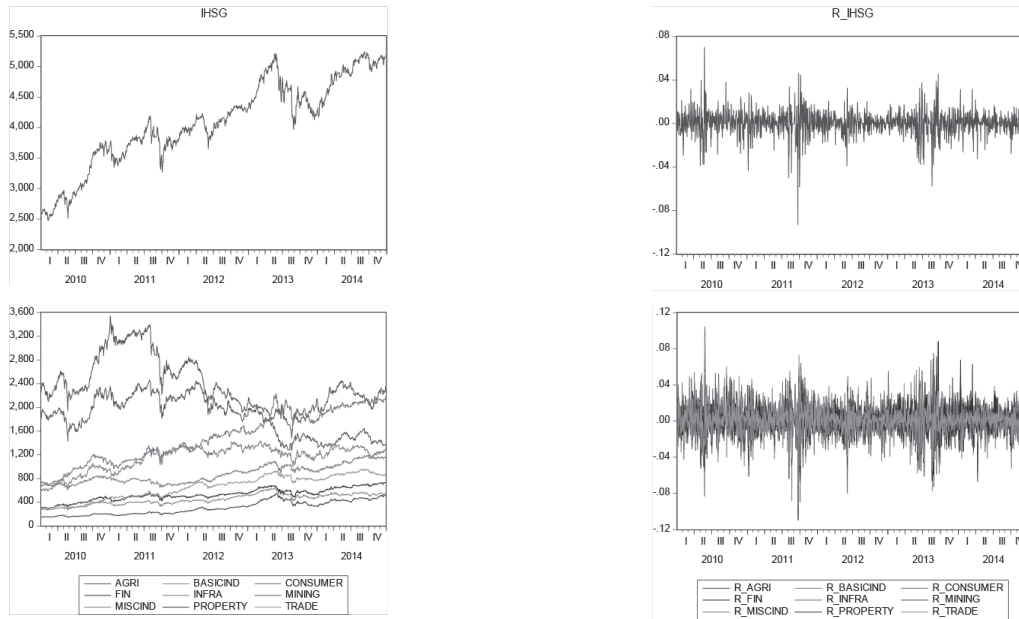Table 1. Descriptive Statistics

STAT	R_ JCI	R_ AGRI	R_ BASC	R_ CONS	R_ FIN	R_ INFR	R_ MIN	R_ MISC	R_ PROP	R_ TRADE
Mean	0.001	0.000	0.001	0.001	0.001	0.000	(0.000)	0.001	0.001	0.001
Med	0.000	-	-	0.000	0.000	-	-	-	0.000	0.000
Max	0.070	0.100	0.100	0.080	0.070	0.040	0.100	0.090	0.090	0.050
Min	(0.090)	(0.090)	(0.110)	(0.070)	(0.110)	(0.080)	(0.100)	(0.100)	(0.070)	(0.070)
S. D	0.012	0.015	0.015	0.013	0.014	0.012	0.015	0.018	0.015	0.011
Skewn	(0.670)	0.000	(0.360)	(0.040)	(0.440)	(0.390)	(0.190)	0.050	(0.380)	(0.440)
Kurtos	9.810	9.070	8.600	6.430	8.880	6.360	8.910	5.780	7.380	7.210
J.B.	2,613	1,997	1,730	640	1,919	646	1,905	420	1,071	1,004
Prob	-	-	-	-	-	-	-	-	-	-
Obsrv	1,302	1,302	1,302	1,302	1,302	1,302	1,302	1,302	1,302	1,302

Source: Various sources, processed

equation becomes a classic GARCH model that allows for leverage effects and when $\delta=1$ conditional standard deviation will be estimated. Also, it will be able to increase the flexibility of the Asymmetric Power GARCH model by considering δ as another coefficient that must also be estimated (Miron & Tudor, 2010).

Selection of the Best Model

The purpose of the comparison of models is to choose the best model. The model can minimize errors in using predetermined sample periods. This is because there is no definite forecasting model. Therefore, some models produced from the time series analysis process need to be selected for the best model by referring to the appropriate residual model calculation criteria.

The criteria used to choose the best model based on residuals are Akaike 'Information Criterion (AIC) and Bayesian Schwartz's Information Criterion (BSIC). The minimum AIC and SIC models are those that represent the correct model and can be interpreted as the best model.

Results and Discussion

Overview and Analysis of Descriptive Statistics

The overall data used is high-frequency data totaling 1302 data. The data was taken from the closing price of 5 working days obtained from ICAMEL (Indonesian Capital Market Electronic Library) from 2010 to 2014. The data processed in this study is the data return from the stock index. The following is a graph of the

Table 2. Stationary Test

Unit Root Test	ADF Statistic	PP Statistic	Prob*	Test Critical Value		
				1% Level	5% Level	10% Level
R_JCI	-21.4718	-35.3457	0.0000	-3.4352	-2.8636	-2.5679
R_AGRI	-34.0889	-34.0371	0.0000	-3.4352	-2.8636	-2.5679
R_MINING	-33.6485	-33.5708	0.0000	-3.4352	-2.8636	-2.5679
R_BASICIND	-23.3769	-37.0743	0.0000	-3.4352	-2.8636	-2.5679
R_MISCIND	-23.6429	-36.4202	0.0000	-3.4352	-2.8636	-2.5679
R_CONSUMER	-35.5696	-36.1020	0.0000	-3.4352	-2.8636	-2.5679
R_PROPERTY	-33.8458	-33.9263	0.0000	-3.4352	-2.8636	-2.5679
R_INFRA	-22.6092	-36.5392	0.0000	-3.4352	-2.8636	-2.5679
R_FIN	-21.1041	-35.5781	0.0000	-3.4352	-2.8636	-2.5679
R_TRADE	-32.4919	-32.3246	0.0000	-3.4352	-2.8636	-2.5679

Source: Various sources, processed

Table 3. ARIMA Parameter Estimates

Stock Index	Model Identification
Jakarta Composite Index (JCI)	AR (3), AR (4)
Agriculture Index (AGRI)	AR (1)
Mining Index (MIN)	AR (1), AR (3), AR (5), AR (7), AR (10)
Basic Industry and Chemicals Index (BASC)	AR(1), AR (3), AR (4), AR (15)
Miscellaneous Index (MISC)	AR (3)
Consumer Goods Industry Index (CONS)	AR (3), AR (4), AR (14)
Property, Real Estate, and Building Construction Index (PROP)	AR (1)
Infrastructure, Utilities, and Transportation Index (INFR)	AR (3), AR (4), AR (10)
Finance Index (FIN)	AR (3), AR (4)
Trade, Services, and Investments Index (TRADE)	AR (1), AR (3), AR (4), AR (11)

Source: Various sources, processed

plot of the closing stock price index and the plot return.

The data has a mean and variance that is not constant. This can be shown from the phenomenon of volatility clustering where fluctuations are relatively high and are followed by low and high return fluctuations.

All stock index return data are not normally distributed. It is known that the Jarque-Bera value is greater than the probability value. Descriptive statistical testing also explains that all stock index returns have kurtosis (high level of shedding) that exceeds the value of 3 as the normal limit. This situation indicates that stock index return data has constant volatility between times.

Data Analysis

Before the ARCH family modeling, the data that has been changed to return must be stationary testing, autocorrelation testing, and heteroscedasticity testing. Stationary testing is obtained from the absolute critical value of the t-statistic ADF and PP is greater than the abso-

lute critical value of MacKinnon at the level of 5% and the probability value is <0.05, which means that the data has no unit root and is stationary.

ARIMA modeling is then performed to obtain a model that is free from autocorrelation by looking at the Q-Stat Correlogram. Then the model is generated as shown in Table 3.

Then followed by heteroscedasticity testing. This test using two methods, namely by looking at the correlogram of residuals squared in each model and ARCH-LM. Based on the p-value results that can be analyzed, it can be concluded that all models estimated have heteroscedasticity conditions.

Residual data is now free from autocorrelation. The model will be measured by ARCH (1), GARCH (1,1), TGARCH (1,1), EGARCH (1,1), APGARCH (1,1) models. The choice of model (p, q) is (1.1) as a simplification of the model (parsimony) because the model that is said to be the best is the simplest and also in previous studies, there are no specific criteria for identifying lag (p, q) in the volatility model. Of all the models that will be measured, a

Table 4. Choose the Best Model

Index	AIC-SIC	ARCH (1)	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)	APGARCH (1,1)
R_JCI	AIC	-6.17332	-6.33537	-6.34088	-6.34146	-6.34074
	SIC	-6.15341	-6.31148	-6.31300	-6.31359	-6.31287
R_AGRI	AIC	-5.68406	-5.80967	-5.81663	-5.80037	-5.80079
	SIC	-5.66816	-5.78980	-5.79279	-5.77652	-5.77694
R_MIN	AIC	-5.63187	-5.74685	-5.75600	-5.74214	-5.73902
	SIC	-5.59990	-5.71088	-5.71603	-5.70217	-5.69905
R_BASC	AIC	-5.63535	-5.76226	-5.78019	-5.77416	-5.77372
	SIC	-5.60729	-5.73019	-5.74411	-5.73807	-5.73764
R_MISC	AIC	-5.25169	-5.29323	-5.29230	-5.29166	-5.29136
	SIC	-5.23577	-5.27333	-5.26842	-5.26778	-5.26749
R_CONS	AIC	-5.92354	-6.02309	-6.02215	-6.01568	-6.01498
	SIC	-5.89950	-5.99504	-5.99009	-5.98362	-5.98293
R_PROP	AIC	-5.66402	-5.78886	-5.78844	-5.77761	-5.77613
	SIC	-5.64812	-5.76899	-5.76459	-5.75376	-5.75228
R_INFR	AIC	-6.14008	-6.19977	-6.20460	-6.20091	-6.20149
	SIC	-6.11609	-6.17179	-6.17262	-6.16893	-6.16951
R_FIN	AIC	-5.74437	-5.86198	-5.86912	-5.86258	-5.86232
	SIC	-5.72446	-5.83809	-5.84125	-5.83471	-5.83444
R_TRADE	AIC	-6.18955	-6.29867	-6.30324	-6.29484	-6.29516
	SIC	-6.16156	-6.26667	-6.26725	-6.25884	-6.25917

Source: Various sources, processed

Table 5. Forecasting Return Index

Stock Index	The Best Model	Return Forecast	Variance Forecast	Predict S.E.	Lower Limit	Index Forecast	Upper Limit	Actual Stock Index (t+1)
R_JCI	EGARCH (1,1)	0.000520	0.000052	0.007234	5154.60	5229.67	5305.90	5227.00
R_AGRI	TGARCH (1,1)	-0.000060	0.000139	0.011786	2296.10	2350.90	2407.00	2351.00
R_MIN	TGARCH (1,1)	-0.000290	0.000101	0.010056	1341.40	1368.60	1396.40	1369.00
R_BASC	TGARCH (1,1)	0.000603	0.000103	0.010127	533.09	544.00	555.13	543.67
R_MISC	GARCH (1,1)	0.000094	0.000185	0.013602	1272.10	1307.20	1343.30	1307.10
R_CONS	GARCH (1,1)	0.000371	0.000088	0.009391	2138.20	2178.73	2220.00	2177.90
R_PROP	GARCH (1,1)	0.001420	0.000124	0.011149	514.06	525.65	537.51	524.91
R_INFR	TGARCH (1,1)	0.001749	0.000074	0.008602	1142.50	1162.32	1182.50	1160.30
R_FIN	TGARCH (1,1)	0.000839	0.000090	0.009498	718.48	732.25	746.30	731.64
R_TRADE	TGARCH (1,1)	0.001629	0.000105	0.010260	862.19	880.07	898.31	878.63

Source: Various sources, processed

model that has the smallest AIC and SIC will be selected as a reference in forecasting each stock index.

Based on the appropriate residual model calculation criteria to choose the best model using AIC and SIC, we can conclude the model that matches the sample period used to predict.

After obtaining the best model, the autocorrelation and heteroscedasticity tests were conducted again so that all indexes were free from autocorrelation and heteroscedasticity. Forecast return index based on the chosen model, the forecasting is generated as follows:

Forecasting results if observed turn out to be close to the actual stock index (one day after the sample period) so that it can be concluded that the model used is good enough in forecasting each stock price index in the sample period.

Discussion

Modeling and forecasting the volatility of returns on the stock market has become a fertile field of empirical research in financial markets. This study attempts to explore the comparative capabilities of different statistical and econometric volatility forecasting models in the Indonesian market context, namely the JCI and nine Sectoral Indexes. Five models of estimation of volatility that are considered different will be used in this study.

Stock index return volatility has been mod-

eled using the ARCH family whose characteristics include a symmetrical effect model and an asymmetric effect model that captures volatility clustering and leverage effects. These models are ARCH (1,1), GARCH (1,1), TGARCH (1,1), EGARCH (1,1), APGARCH (1,1) which are the first two models to capture symmetrical effects and the next three models for catch an asymmetrical model.

To find out which model is most suitable for predicting the stock price index, the researcher must see which model has the smallest AIC and SIC, because the model represents the correct model and can be interpreted as the best model.

After obtaining the most suitable model, proceed with seeing a symmetrical or asymmetrical effect. Asymmetric effects are measured by probability values at $\gamma < 0.05$ and negative γ coefficients (for EGARCH models) or positive (for TGARCH and APGARCH models) which means the model has an asymmetrical effect. This coefficient γ will be the leverage effect on volatility. This leverage effect reflects that if there is positive information, the index return will rise more slowly, but if there is negative information, then the index return will decrease rapidly because of leverage increases.

Symmetrical effects are found in models that are α_1 and β_1 with probabilities <0.05 and $\gamma > 0.05$. This symmetrical effect reflects if there is positive information, the return will rise quickly and if there is negative information, the return will decrease rapidly. The symmetrical GARCH model in this study allows for the persistence of volatility where volatility that occurs now is still influenced and can be explained from the volatility that occurred in the past and requires a long time to return to normal conditions. Volatility shock persistence can be measured by adding coefficients of $0.95 \leq \alpha_1$ and $\beta_1 < 1$. The higher coefficient β_1 (GARCH) indicates that the shock at the variance will take a long time to return (persistence). While the higher the value of α_1 (ARCH) indicates that the reaction of volatility is very intensive towards market movements.

The results of the study explain that the JCI return as a reflection of the Stock Market index in Indonesia has an asymmetrical effect be- cause it gets the leverage of coefficient γ and is modeled fitted with the EGARCH (1.1) model in the sample period. This study is in line with the research of Thalassinos et al. (2015) on the Czech Republic Stock Market and Henry (1998) on the Hang Seng Index which are both using market indexes.

The results of the return on agriculture, mining, basic industry and chemicals, infrastructure, finance, and trade explain the asymmetrical effect because it gets leverage of coefficient γ but is modeled fitted with the TGARCH model (1,1) where the AIC and SIC values are smaller than EGARCH models and other models. This modeling is suitable as well as suitable modeling results used by Kamaludin (2008) to model 15 stock exchanges in Asia and also on the S & P 500 stock index by Abiyani and Permadi (2013).

The returns on miscellaneous sectors, consumer goods, and property only explain the symmetrical effect because they do not get the leverage effect and are modeled fitted with the GARCH (1,1) model. This modeling is suitable as well as the results of modeling that are suitable for use by Syarif (2014) to model the JII index.

Volatility clustering on stock index returns occurs because it is influenced by various events during the sample period so that the return index becomes volatile. Events in the range of May 2010 due to the change of finance ministers impacted the volatility of the domestic stock exchange. Then in September 2011 triggered by the European crisis made a real impact on hit capital markets around the world including Indonesia. Furthermore, events in the range of August 2013 were triggered by the issue of tapering off the Fed which resulted in a decline in the value of the rupiah so that foreign investors left the Indonesian stock exchange.

This volatility proves Indonesia's dependence on foreign countries both in foreign capital in the financial and trade markets. This will be more severe if foreign investors withdraw their funds. Dependence on foreign capital in the financial markets, especially the capital market and foreign exchange market has made Indonesia very vulnerable to global financial

turmoil. In other sectors in producing a lot of materials using imports from abroad while the selling price of its products is influenced by global factors. While the global economic crisis will make import performance higher than exports.

Every forecast, especially volatility that is beneficial to investors and issuers, must be considered a systematic process and cannot be considered as a static and permanent thing. The dynamic nature of the market requires a prediction to be reviewed, revised and discussed.

On the stock exchange, often encountered asymmetric information and described in the form of volatility by following information that occurs in the market. This volatility is often created by the noise of traders to get profit-taking. The condition of price volatility will create market risks faced by investors due to information uncertainty. To avoid risk and control risk, it is estimated that volatility will occur in the future to minimize the risks that will be received by selecting and trading transactions in the form of buying, selling or surviving. For listed companies, this volatility can measure how much issues or events occur in the market so that they can make decisions quickly in managing information disclosure given to investors.

Conclusions

The test results and discussion in the previous section can be summarized as follows:

1. JCI return characteristics as a reflection of the Exchange market index in Indonesia have an asymmetrical effect because they get a leverage of coefficient γ and are modeled fitted with EGARCH (1.1) models in the sample period, as well as AGRI, MINING, BASICIND, INFRA, FIN, TRADE with the TGARCH model (1,1). This means that if there is new positive information, then the index return will rise more slowly, but if there is new negative information, then the index return will decrease rapidly. This effect is because these indexes are affected by several events which cause returns to be volatile as in 2010 and 2011 due to the influence of the crisis in the US and Euro countries and

in 2013 the Fed's tapering off caused a withdrawal of funds foreigners out of the Indonesian capital market. While for MISCIND, CONSUMER, PROPERTY is a symmetric effect. This means that if there is positive information, the index return will rise quickly, so if there is negative information, the return index will drop rapidly. This symmetrical effect indicates that these indexes are not so affected by events in the Indonesian capital market. The difference in the volatility of each index will reflect the difference in risk from each index. Large volatility, the risk will be higher and also promises the possibility of abnormal returns.

2. The time series EGARCH volatility estimation method is a model that matches the sample period used to forecast volatility in the stock index return of the JCI which reflects the volatility of the capital market in Indonesia. Whereas AGRI, MINING, BASICIND, INFRA, FIN, TRADE sector return returns that match the sample period used with the TGARCH model (1,1). For the return index of the MISCIND, CONSUMER sector, PROPERTY can only be modeled by GARCH (1,1).

Suggestions

Some limitations that can be drawn from this study are as follows:

1. This study uses ARCH, GARCH, EGARCH, TGARCH, APGARCH models. For further research can study the characteristics and compare with other GARCH family models in finding models that match the period of the sample used for stock index forecasting so that it will further enrich the volatility estimation model using GARCH family.

2. This study uses the JCI Index and nine Sectoral Indexes. For further research, you can try to predict other stock index on the Indonesia Stock Exchange, such as the Jakarta Islamic Index (JII), Kompas100 Index, BISNIS-27 Index, PEFINDO25 Index, SRI-KEHATI Index, Infobank 15 Index, IDX30 Index, Investor33 Index, and SMinfra18 Index so that it can know the characteristics of

each index on the Indonesia Stock Exchange and compare them.

As revealed by Engle (2004) that if the data is too long, it will not be so relevant for today and if it is too short, it will be very noise. Therefore, historical volatility has no solution to this problem so that in this study, researchers considered high-frequency data for 5 years to be sufficiently representative in estimating future returns. For further research, a comparative study between high-frequency data in the form of daily data, weekly data for 1 year, 5 years, and 10 years was carried out to explain which data was more relevant for forecasting.

Investors in minimizing the risks they will receive are expected to try to estimate volatility that occurs first which is an indicator of price changes before making elections and transactions.

Issuer companies must look at the issues that occur in changes in stock prices and conduct technical analysis by estimating volatility that may occur in the future and immediately take action in managing private information disclosure given to investors so as not to be misused by noise traders for personal gain.

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