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Analyzing volatility of rice price in Indonesia using ARCH/GARCH model

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Abstract

This research aims to to analyze and to study the implication of the volatility of deflated retail price of rice in out of Java which are represented by three markets in Indonesia, namely Medan, Makassar, and Banjarmasin. The period of observation is from January 1984 to August 2011. The better model in this study is Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The result of the study shows that the change of rice price in all three markets was caused mainly by seasons and yearly routine cycles. In addition, at the reformation era and at economic crisis, the rice prices were more volatile.

Abstrak

Penelitian ini bertujuan untuk menganalisis volatilitas dan mempelajari implikasi dari harga eceran beras yang terdeflasi di pasar luar Jawa yang diwakili oleh tiga harga pasar beras di Indonesia yaitu Medan, Makassar dan Banjarmasin. Periode pengamatan adalah dari Januari 1984 sampai dengan Agustus 2011. Model yang dipilih adalah Generalized Autoregressive Conditional Heteroscedasticity (GARCH). Perubahan harga beras di tiga pasar itu disebabkan oleh perubahan iklim dan siklus rutin tahunan. Di samping itu, volatilitas harga beras yang lebih tinggi di tiga pasar disebabkan oleh terjadinya era reformasi dan krisis ekonomi.

Introduction

Rice is very important to Indonesian economy both for main staple food and as a source of incomes. Swastika (2010: 7) stated that most of rice, maize and soybean in Indonesia are produced by small scale farmers so called peasant. The number of peasant in Indonesia increased from 10.8 million in 1993 to 13.7 million in 2003 and 15.6 million in 2008. Hence a price decrease of rice and other crop commodities will directly cause suffering for about 15.6 million farmers.

In Indonesia, out of 12 million hectares of paddy rice, 51 percent (6 million hectares) paddy rice is harvested at peak during wet season in February-May, 31 percent (4 million hectares) in June-September and 16 percent (2 million hectares) in October-February (Sawit, 2010: 59). Moreover, Swastika et al. (2010:2) investigated that the peak harvesting season in Java is during wet season, while in South and West Kalimantan is during dry season.

On the peak harvest time, the price of rice decreases due to over-supply and at the slack harvest time, the price of rice increases because of lack of supply. These facts show that the volatilities of rice price were caused by the fluctuation of rice production in line with the harvest season. To stabilize the rice price in Indonesia, government assigned state enterprise (BULOG) to regulate rice price since 1967.

Before September 1998 (Pre-reformation era), BULOG defended a floor price and a ceiling price for rice to control price volatility. With this instrument, BULOG was very successful in stabilizing rice price in Indonesia. However, since September 1998 (Reformation era), under structural adjustment agreements with International Monetary Fund (IMF), BULOG import monopoly was abolished and private companies were allowed to import rice. However, BULOG still accounted for around 75 percent of total rice import (Dartanto, 2010).

To control rice price volatilities since September in 1998, BULOG set Government Purchase Prices and tariff import for rice. BULOG also control rice market through distributing cheap rice for the poors. However, BULOG was less successful in controlling rice prices since then,

Indonesia is one of the rice importing country in the world. In 1998 when the country experienced economic crisis, the country imported about 2.9 million metric tons of rice which is equal to 5.88 percent of domestic production. Meanwhile, in 2010 Indonesia imported 687.58 thousand metric tons of rice which equal to 1.03 percent of domestic production (BPS in various issues). Consequently, an increase in the world price of rice will directly raise the domestic price and create hardship to most households in Indonesia.

Since the presence of the imperfect rice market in Indonesia, BULOG regulated rice price domestically through Government Purchase Price Mechanism by setting floor price for dry paddy and imposing import tariff on rice coming to Indonesian market. With the trade barriers, the volatilities of rice price in international market were not able to transmit to domestic market perfectly.

Swastika (2010:2) stated that there was high correlation coefficient between and among rice market Indonesia, indicating the presence of high market integration in rice mainly due to two factors, namely good market chains and government market intervention through BULOG for price stabilization.

Since rice plays an important role to domestic economy, Indonesian people are concerned with food and retail rice price volatilities. The stabilization of food prices included rice is needed by societies since the fluctuation of food price contributes to risk and uncertainties in food securities. In addition, due to the price of rice is always the major public issue, the rice price volatility should be taken into account through policy decision both for production and consumption sides.

Dartanto (2010: 340) found that during 1993 to 1996, the domestic rice price was less volatile compared to the world price, which was indicated by the low ratios of the standard deviation between domestic and world rice price (0,19). It is perceived that the effects of BULOG's market intervention were relatively effective. During 2001-2003, the fluctuation of domestic rice price was 1.5 times larger than that of world rice price. During 2004-2007, the fluctuation of the domestic rice price was 2.5 times larger than that of the world rice price. During 2008-2010, an increase in production, reduction in import tariff, and restricted in import policy were able to insulate the domestic price from the domestic fluctuation with respect to the world rice price.

To improve effectiveness of rice-price stabilization policies, it requires accurate information about the behavior of the price of rice. The research is aimed to analyze and compare retail rice price volatilities in three markets in Indonesia namely Medan, Makassar, and Banjarmasin. Specifically, the aims of the research are (a) to seek appropriate prediction of retail price of rice phenomenon in three markets/cities in Indonesia, (b) to analyze the difference characteristic volatilities among markets/cities in Indonesia and (c) to analyze the pattern of price volatilities changes related to the changes of economic system since reformation era, and (d) to analyze the implication of rice price volatilities to national economy.

Methods

Concept and definition

This research studies the volatility of rice price in Indonesian market. Volatility means unstable, tends to vary and difficult to predict. The key elements are variability and uncertainty. At least, there are three reasons why modeling and forecasting price volatilities are important. Firstly, the results of the price volatilities studies are useful for decision making related to risk. Secondly, the precise results of the forecasting may be characterized by "time-varying", so the accuracy of forecasting can be obtained by modeling its variance. Thirdly, related to the second argument, it is required to formulate the appropriate forecasting model and more accurate technical forecasting.

Volatility at some point of time can be divided into two components. The first component is that its behavioral can be predictable and the second is unpredictable. Theoretically the weight of each component can be studied. Practically, the capability of publics and government in managing the problem concerning risk tends to concentrate at variance which can be predicted. As the results, the prediction becomes less accurate, especially if its fluctuation pattern changes from what they have been experienced. Even though the volatility is one of the most important concepts in the return of financial markets, it is also relevant to price of commodities markets volatilities (Sumaryanto, 2009: 137-138).

Research coverage

Retailed rice price volatility analysis in this research is focused on three markets which represent markets out of Java in Indonesia. The coverage of information needed is not only the tendency or changes, but also covering the price volatilities. Comprehensives and availabilities of information about price volatilities are useful to formulate effective decision making on managing risk and uncertainties of retail rice price.

Data

This research used BULOG time series data of monthly retail rice price of medium quality white rice in Indonesian Rupiah (IDR) per Kg. for three markets in Indonesia during January 1984 to August 2011. On the other hand, Consumer Price Index for January 1984 to August 2011 is obtained from Central Board of Statistics (BPS).

It is hypothesized that the volatilities of retail rice price at three markets in Indonesia vary. It is also hypothesized that since the reformation era, the retail rice price is more volatilein all three markets.

Analysis method

According to Sumaryanto (2009: 138) previously, forecasting methods for time series data mostly used are Autoregressive (AR), Moving Average (MA), or combination of AR and MA (ARMA or ARIMA). With these methods, it will be obtained precise prediction results when the variance of the errors is constant; it is called homoscedastisity. However, the problem arises when these methods are applied to commodities market as of capital market and money market on which their price fluctuation tends to be clustered. Volatility clustering describes the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign) to follow small changes. In other words, the current level of volatility tends to be positively correlated with its level during the immediately preceding periods called heteroscedasticity. For this reason, it needs a new approach to encounter the problems of heteroscedasticity arising from volatility clustering.

Autoregressive conditional heteroscedasticity (ARCH) models are now commonly used to describe and forecast changes in volatility of financial time series (Bauweks et al. (2006: 79).

Historically, economists viewed heteroscedasticity as largely a cross-sectional. It turns out, however, that heteroscedasticity is pervasive in the time series context of financial asset return, in which volatility clustering is contiguous of high or low volatility features prominently (Diebold, 2004: 171).

The heteroscedastic model developed for such purpose of present particular importance due to the extended concern in the both academic and applied literatures for volatility measuring. Volatility represents the conditional standard deviation of the underlying asset returns. It has many applications in the financial domain, among which there is the calculation of the value at risk of a financial positioning risk management and asset allocation under the mean-variance framework (Matei, 2009: 42-43).

ARCH model is intended to forecast the conditional variance. In this context, conditional variance is the variance that may change as the time goes by. In this model the dependent variable is a function of independent variable or past values of dependent variable. Alberg at al. (2008: 1202-1203) stated that one of the weaknesses of the ARCH model is that it often requires many parameters and a high order q to capture the volatility process. To remedy this lacuna Bollerslev (1986) proposes the GARCH model, which is based on an infinite ARCH specification that enables to reduce the number of estimated parameters by imposing nonlinear restrictions which are called Generalized Autoregressive Conditional Heteroscedasticity (GARCH).

In this research, when homoscedasticity errors assumption is not fulfilled, it will be used univariat ARCH/GARCH model. Then, the discussion will be focused on this model.

ARCH model

ARCH models are employed commonly in modeling financial time series that exhibit time-varying volatility clustering, i.e. periods of swings followed by periods of relative calm. An ARCH process can be defined in a variety of contexts. Bera et al. (1993: 309) stated that an ARCH can be defined in terms of the distribution of the errors of a dynamic linear regression model of which the dependent variable y_t is assumed to be generated by

$$y_t = x_t^i \xi + \varepsilon_t, \quad t = 1, \ldots, T \qquad (1)$$

where x_t is a k x 1 vector of exogenous variables which may include lagged values of the dependent variable, and ξ is a k x 1 vector of regression parameters. The ARCH model characterizes the distribution of the stochastic error ε_t conditional on the realized values of the set of variables $\Psi_{t-1} = \{y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2}, \ldots\}$. Bera et al. showed the assumption of original ARCH model by Engle (1982) as follows:

$$\varepsilon_t \mid \Psi_{t-1} \sim N(0, h_t) \text{ where}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2, \qquad (2)$$

The conditional variance ht with $\alpha_0 \geq 0$ and $\alpha_i \geq 0$, i =1, …, q, to ensure that the conditional variance is positive. Note that since $\varepsilon_{t-i} = y_{t-i} - x_{t-i}^i \xi$, i = 1, …, q, h_t is clearly a function of the elements of Ψ_{t-1}.

The simplest ARCH model is ARCH (1) which can be written as:

$$\varepsilon_t \mid \Psi_{t-1} \sim N(0, h_t)$$

$$ht = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \qquad (3)$$

Generalized autoregressive conditional heteroscedasticity (GARCH) model

Bera et al. (1993: 312) adopted the Engle ARCH model which was developed by Bollerslev (1986) that conditional variance ht depends not only on lagged squared errors but also on lagged variance errors. Bollerslev extended the conditional variance called Generalized ARCH (GARCH). GARCH model provides a parsimonious parameterization for the conditional variance. The general form of GARCH model is:

$$h_{t} = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \ldots + \beta_p h_{t-p}, \quad (4)$$

where the inequality restrictions
$\alpha_0 \geq 0$; $\alpha_i \geq 0$ for $i = 1, \ldots, q$ *and* $\beta_i \geq 0$ for $i = 1, \ldots, p$

The simplest and most robust GARCH model is ordered p=1 and q=1 that can be written as GARCH (1,1). The GARCH (1,1) model can be generalized to a GARCH (p,q) model that is a model with additional lag terms, namely:

$$e_t \left| Y_{t-1} : \; N\left(0, h_t\right)\right.$$

The sum of α_1 + β_1 gives the degree of persistence of volatility in the series. The closer the sum to 1, the greater is the tendency of volatility to persist for longer time. If the sum exceeds 1, it is indicative series with a tendency to meander away from mean value. The GARCH estimates have been used to identify periods of high volatility and volatility clustering (Sekhar 2005: 17).

The value of α_1 and β_1 will influence the volatilities of variables in time series. The value of α_1 reflects as a reaction coefficient and β_1 is a persistence coefficient. When α_1 is less than β_1, the effect of the persistence coefficient will outweigh the effect of reaction coefficient. It means that the effect of price volatilities will last for a longer time before going back to a normal condition. If α_1 is greater than β_1, the volatilities are restrained. It means that for every volatility case, there is a strong reaction to revise the volatility the normal condition where the volatility will not be lasted for a long time.

Distribution assumption

Franq (2004: 605) proved that unbiased estimation method for ARCH/GARCH model is Maximum Likelihood (ML). Sumaryanto (2009:141) stated that there are three assumptions that can be used to its estimation: (i) normal distribution (Gaussian), (ii) Student's t-distribution, and (iii) Generalized Error Distribution (GED) with or without estimating coefficient parameters.

The Procedures of volatility measurement for ARCH/GARCH methods

Like analysis with ARMA model, data that will be analyzed with ARCH/GARCH model requires the long time span of observations. Sumaryanto (2009: 141-145) outlined five procedures to analyze price volatility with ARCH/GARCH model:

1. Data preparation

Data preparation will cover: (i) data collection and completeness of data so that there are no missing data, (ii) smoothing stochastic behaviour through elimination of deterministic factors such as trend, seasonality and cycles. For price data, trend is eliminated by deflation. In some cases seasonality and cycles can be also eliminated by transformation of data to logarithm.

In this research, Consumer Price Index (CPI) is used to be a deflator using year of 1996 as a based-year. Smoothing is also used to overcome the seasonality factor by introducing dummy variables "month" to the model. Since there are twelve months in a year, there are eleven dummy variables introduced. Dummy variable base is the month of "December" since previous analysis concluded that the smallest coefficient variation for CPI is at that month of December.

2. Unit root test

Time series models usually contain unit root that could be spurious. To avoid spurious regression, variables studied should be stationary which does not contain unit root. Statisticians working with time series models suggested a simple solution to the spurious regression problems by introducing the first difference on variable concerned. Hence, the first step which is required to be done before developing ARMA or ARCH/GARCH model is unit root test.

There are various methods to test the existence of unit root. In this research, it will be applied Augmented Dickey-Fuller (ADF) and Phillips-Peron to test the existence of unit root. Under the null hypothesis, if the computed absolute value of t-statistic exceeds the Mac. Kinnon DF absolute critical t-values, then one cannot reject the hypothesis that the time series data has been stationary.

3. ARMA model estimation

When the data has been stationary, ARMA parameters can be estimated. The procedures follow Box-Jenkin methods (1976).

Theoretically, there are few forms of ARMA model such as ARMA (p,q), ARMA (p,d,q), ARMAX which is ARMA with exogenous variables (included dummy variables), ARMA with SAR (Seasonal Autoregressive) which represents seasonal auto regressive phenomenon, ARMA with SMA (Seasonal Moving Average) that represents moving average phenomenon of which its character is seasonal, or ARMAX with SAR and SMA.

4. Testing the existence of ARCH

After the most appropriate ARMA model is found, the next step is to identify the existence of ARCH by investigating ARMA residues. This can be done by Lagrange Multiplier or ARCH-LM test. If null hypothesis (Ho) is failed to reject, it means that ARMA error is homoscedastic. So the existence of ARCH is not significant. On the contrary, if Ho is rejected, it means that the ARMA error is heteroscedastic and so that existence of ARCH is significant. It implies that the more appropriate model is not ARMA but ARCH/ GARCH model.

5. The estimation process of ARCH/GARCH

The estimation process of ARCH/GARCH cannot be done automatically. It needs some trials and errors to get an appropriate ARCH/GARCH model with different distribution (normal, Student, GED, Student with fixed df, GED with fixed parameters). So that, it can be obtained significant coefficient parameters which fulfill requirements (agree with sign and magnitudes as required by an ARCH/GARCH model). It also has to satisfy DW-test and its Prob. F-test. After appropriate ARCH/GARCH model is obtained, it needs more diagnostic toward ARCH/GARCH residues with ARCH –LM test to make sure whether the variances of residues have been constant. If all of those requirements are satisfied, and the results of accuracy of forecasting of the model are also satisfied, it is concluded that ARCH/GARCH models have been appropriates. The method of estimation on this case is Maximum Likelihood (ML). In this research, computation uses the program of Eviews 6.0.

Results and Discussions

Stationary tests

The results of Root Unit Test (Table 1) shows that all retail rice prices in three markets in Indonesia have been stationary after one time differentiated (Dlog rice price at time *t* minus log rice price at time t_{-1}). Please see the results of ADF and Adj. T-statistic Phillips Peron test column which exceeds the Mac Kinnon. The stationary of retail rice prices data will be used to estimate ARMA or ARCH/GARCH model.

The results of ARMA estimation

After the retail rice prices have been stationary, through Box-Jenkins procedures (1976), the ARMA will be called ARIMA, since the data has been differentiated for one period of time. Table 2 shows the results of ARMA process. The best ARIMA model is obtained by including seasonal factors into its AR and or MA process. In this study, Dummy variables (D1, D2, …, D12) represent the months of January to December respectively. DR represents for reformation era (January 1998 up to now = 1, otherwise = 0. DRAD represents Dummy variable for social unrest in relation with reformation era, October 1997-September 1998 = 1, otherwise= 0.

The existence of ARCH

Table 3 shows the results of ARCH from ARMA by LM-test. To test its consistency, the existence of ARCH was tested for three different time lags. In general, if at time lag (1) Ho is rejected, there is tendency that Ho is also rejected for lag (2) and lag (3). On the other hand, if Ho cannot be rejected at lag (1), then Ho also cannot be rejected at lag (2) and lag (3).

Table 1: The Results of Unit Root Test for Monthly Retail Rice Price in Three Markets/Cities in Indonesia, Period of January 1984 – August 2011

Markets/Cities	**Variable**	**ADF Test**		**Philips – Peron Test**	
		t-Statistic	**Prob***	**Adjt.t-Statistic**	**Prob***
Medan	Log(Ᵽ rice)	-3.288335	0.0700	-2.745343	0.2191
	D(Log(P-rice))	-12.52750	0.0000	-15.93236	0.0000
Makassar	Log(Ᵽ rice)	-2.554843	0.3016	-2.491135	0.3324
	D(Log(P-rice))	-18.77961	0.0000	-19.02152	0.0000
Banjarmasin	Log(Ᵽ rice)	-3.254415	0.0759	-2.941283	0.1509
	D(Log(P-rice))	-15.06809	0.0000	-14.85409	0.0000

*) Mackinnon (1996) one-sided p-values.
Critical value of ADF statistics and Phillips -Peron statistics: at Level 1 percent – 3.986026; and at level 5 percent – 3.423459 and at level 10 percent – 3.134688

Table 2: ARMA Model for Monthly Retail Rice Price in Three Markets in Indonesia, Periods of January 1984 - August 2011.

Monthly Retail P-rice (Deflated by CPI)	ARMA Model*)
Medan • d(log(p-rice))	D(Log(P-rice)) = 0.003288 + 0.032524 DRAD - 0.027156D3 + 0.146298 (AR 1) - 0.605274 SAR (11)+ 0.723417 SMA (11) Back cast : 1984M03 1985M01
Makassar • d(log(p-rice))	D(Log(P-rice)) = 0.001240 + 0.023945DRAD - 0.018348D5+0.028552D11+0.757053 AR(1) + 0.854255 SAR(11)- 0.824442 MA(1)–0.918518 SMA(11) Back cast : 1984M02 1985M01
Banjarmasin • d(log(p-rice))	D(Log(P-rice)) = 0.002682 + 0.051622 DRAD + 0.027162 D2 – 0.018299 D9 – 0.038629 D10 + 0.120081 AR (1) – 0.147856 AR (2) + 0.723973 SAR (12) – 0.943834 SMA (12) Back cast : 1984M02 1985M01

*) D is a time series data which has been differentiated for one period of time. All coefficients are significantly different from zero.

Table 3: The Results of Lagrange Multiplier ARCH Test for ARMA Model Error for Retail Rice Prices in Three Markets in Indonesia, January 1984- August 2011.

Markets/Cities	Lag	F_Statistic & TR^2 ($Obs*R^2$)		Prob.F (df,n)	Prob X^2
Medan	Lag (1)	F-Stat	6.045653	Prob.F (1,316)	0.014476
		TR^2	5.969705	Prob.Chi_Square (1)	0.014554
	Lag (2)	F-Stat	14.64974	Prob.F (2,314)	0.000001
		TR^2	27.05490	Prob.Chi_Square (2)	0.000001
	Lag (3)	F-Stat	9.880800	Prob.F (3,312)	0.000003
		TR^2	27.41755	Prob.Chi_Square (3)	0.000005
Makassar	Lag (1)	F-Stat	13.62988	Prob.F (1,316)	0.000262
		TR^2	13.14899	Prob.Chi_Square (1)	0.000288
	Lag (2)	F-Stat	6.935046	Prob.F (2,314)	0.001129
		TR^2	13.41025	Prob.Chi_Square (2)	0.001225
	Lag (3)	F-Stat	4.730330	Prob.F (3,312)	0.003045
		TR^2	13.74763	Prob.Chi_Square (3)	0.003270
Banjarmasin	Lag (1)	F-Stat	0.833069	Prob.F (1,314)	0.362087
		TR^2	0.836157	Prob.Chi_Square (1)	0.360498
	Lag (2)	F-Stat	4.753232	Prob.F (2,312)	0.009258
		TR^2	9.314077	Prob.Chi_Square (2)	0.009495
	Lag (3)	F-Stat	5.523363	Prob.F (3,310)	0.001047
		TR^2	15.93228	Prob.Chi_Square (3)	0.001171

By observing the results of the ARCH-LM test, it can be concluded that variance of retail rice prices for all three markets contains ARCH effect, except lag (1) for Banjarmasin since all TR^2s have probabilities of less than 0.05. So that, the forecasting models assume that the variances are heteroscedasticity which suggest that the appropriate forecasting models are ARCH/GARCH. The ARIMA models are only appropriate for homoscedastic variances.

Volatility of rice price for three major markets in Indonesia

The results of ARCH/GARCH estimation

After investigating the distribution of log-likelihood, it is known that GED with the fixed score of parameters is Medan. On the other hand, Makassar and Banjarmasin are without fixed-parameters. Furthermore, based on the ARCH-LM test (Table 4), the null hypothesis (Ho) is accepted (which means that all variance equations are constant) together with the accuracy level of forecasting, AIC and SBC criterion, the sign and magnitude of coefficient parameters, it is concluded that all three markets namely Medan, Makassar and Banjarmasin have GARCH (1,1) model.

Medan market

Mean Equation

$$\begin{aligned} D(\log(P\text{-rice})) = {} & 0.004509 - 0.026112D3 \\ & (2.015628)\ (-4.396970) \\ & + 0.039350\ DRAD \\ & (4.812699) \\ & + 0.141961\ AR(1) \\ & (2.315043) \\ & - 0.582186SAR(11) \\ & (-9.879341) \\ & + 0.698361\ SMA(11) \\ & (10.48892) \end{aligned} \qquad (1.1)$$

Log like hood = 674.7311 (distribution of GED with fixed parameter at 2.7)
DW = 1.966960, AIC = -4.173863, SBC = -4.067635

Table 4: The Results of ARCH- LM Test of Retail Rice Price for ARCH/ GARCH Model for Three Markets/Cities in Indonesia, January 1984-August 2011

Lag		F-Statistic TR^2 and Prob. F (df n) for each lag Prob. X^2			
Medan	1	F-Statistics	0.183949	Prob.F(1,316)	0.668294
		TR^2	0.185005	Prob.Chi-Square (1)	0.667107
	2	F-Statistics	0.499510	Prob.F(2,314)	0.607310
		TR^2	1.005365	Prob.Chi-Square (2)	0.604906
	3	F-Statistics	0.740120	Prob.F(3,312)	0.528797
		TR^2	2.232935	Prob.Chi-Square (3)	0.525490
Makassar	1	F-Statistics	0.192695	Prob.F(1,316)	0.660983
		TR^2	0.193797	Prob.Chi-Square (1)	0.659775
	2	F-Statistics	0.376406	Prob.F(2,314)	0.686633
		TR^2	0.758187	Prob.Chi-Square (2)	0.684482
	3	F-Statistics	0.310170	Prob.F(3,312)	0.818035
		TR^2	0.939637	Prob.Chi-Square (3)	0.815854
Banjarmasin	1	F-Statistics	1.414429	Prob.F(1,314)	0.235221
		TR^2	1.417055	Prob.Chi-Square (1)	0.233889
	2	F-Statistics	1.119727	Prob.F(2,312)	0.327677
		TR^2	0.244874	Prob.Chi-Square (2)	0.325486
	3	F-Statistics	0.888960	Prob.F(3,310)	0.447111
		TR^2	2.678249	Prob.Chi-Square (3)	0.443936

Equation (1.1) shows that the peak harvest time in wet season for Medan market is on March which is reflected on negative sign of Dummy 3 (D3) on which the price of rice decreased significantly. The positive sign and significance of DRAD show the rice price increase as the impact of monetary crisis period of October 1997-September 1998.

The AR (1) shows that the rice price level in the Medan market was determined by the price level at lag 1, ceteris paribus. The SAR (11) shows that the pattern of the rice price level was determined by the pattern of the rice price level at 11 month ago in the opposite direction, ceteris paribus. The SMA (11) shows that the pattern of market rice price level in Medan market was determined by the seasonal moving average of rice price of 11 months in positive direction, ceteris paribus.

Variance Equation:

$$ht = 0.000148 + 0.175741\ e_{t-1}^2 + 0.695986\ h_{t-1}^2 \quad (1.2)$$
$$(2.471625)\ (4.588749)\ (9.008463)$$

Variance equation (1.2) for Medan market is GARCH (1,1). The value of the parameters of α_1 and β_1 will influence the pattern of rice price in Medan. The value of α_1 reflected as a reaction coefficient and β_1 is persistence coefficient. Since α_1 is less than β_1, it shows that the effect of volatility will last for a long period of time, since the reaction to go back to the normal is smaller than the price tendency to move forward.

North Sumatera in which Medan is located had small rice surplus. Again, Lantarsih (2011: 44) stated that North Sumatera has only 574 thousand metric tons of rice in 2009. With that small surplus of rice, it was harder to recover from price shock in the shorter time. In addition, it takes a longer time by BULOG to stabilize rice price through market operation since infrastructure transportation is relatively less developed in North Sumatera.

Makassam arket

Mean Equation:

D(Log(P-rice)) = 0.003055 - 0.20320D5
(1.480618) (-2.371388)
+0.027253 D11+ 0.031123 DRAD
(5.009972) (4.163901)
-0.855086AR(1) + 0.731112SAR(11)
(-4.347985) (8.937253)
+0.887424 MA(1) - 0.820562 SMA(11) (2.1)
(5.051249) (-11.48715)

Log like hood = 596.2643 (distribution of GED without fixed score of parameter)
DW = 2.138243, AIC= -3.669369, SBC= -3.539535

Equation (2.1) shows that the peak harvest time in Makassar in wet season was on May which is reflected on negative sign and significance of D5. The slack harvest time in Makassar was in November which is reflected by the positive sign of D11. The positive sign and significance of DRAD show that the rice price increased as the impact of economic crisis on the period of October 1997-September 1998.

The AR (1) shows that the rice price level in the Jakarta market was determined by the price level at lag 1, ceteris paribus. The SAR (11) shows that the pattern of the rice price level was determined by the pattern of the rice price level at 11 month ago, ceteris paribus. The MA (1) shows that the price level in Surabaya was determined by the average of the last month of rice price. The SMA (11) shows that the pattern of market rice price level was determined by the seasonal moving average of rice price of 11 months in positive direction, ceteris paribus.

Variance Equation:

ht = 0.000396 + 0.498063 e_{t-1}^{2} (2.2)
(6.771536) (5.675690)
+ 0.403823 h_{t-1}^{2}
(7.000609)

Variance Equation (2.2) shows that the coefficient of α_1 is greater than β_1, meaning that the reaction coefficient was greater than the persistence coefficient. It implies that every rice price volatility incidence in Makassar relatively lasted only for a shorter time period before going back to the normal level.

Price shock in Makassar will be recovered in the short period of time since its province South Sulawesi had the large surplus of rice. Lantarsih (2011: 44) reported that South Sulawesi had 1.6 million) metric tons of rice surplus in 2009. Makassar which is located in South Sulawesi has also relatively good infrastructures. So, shortly after rice price shock occurs, it can be recovered by rice supply from around South Sulawesi.

Banjarmasin market

Variable Equation

D(log(P-rice)) = 0.003455 + 0.031661 D2
(1.809919) (3.410190)
-0.015564 D9 - 0.035684 D10
(-1.975882) (-6.444972)
+ 0.052572 DRAD -0.228734 AR (1)
(2.952550) (-2.587720)
-0.234794 AR(2) +0.740653 SAR(12)
(-2.539402) (12.73463)
- 0.930509 SMA(12)
(-7429283)

Log like hood = 490.4086 (distribution of GED without fixed score of parameter)
DW = 2.225035, AIC= -3.030969, SBC= -2.912391

Equation (3.1) shows that in Banjarmasin the peak harvest time was in September and October (wet season) which was reflected on the negative signs and significance of dummy months of D9 and D10. The positive sign and significance of D2 reflected that the slack harvest time was in February. DRAD shows that the rice price increased as impact economic crisis on the period of October 1997-Septembre 1998.

Table 5: Volatilities (CSD) of Retail Rice Price in Three Market in Indonesia.

Market	Pre Era Reformation (1984 Jan-1998 August)	Post Era Reformation (1998 Sep-2011 August)	Economic Crisis (1997 Oct -1998 Sept)
Medan	0.0369	0.0462	0.0607
Makassar	0.0297	0.0309	0.0598
Banjarmasin	0.0353	0.0665	0.0698

The AR (1) shows that the rice price level in Banjarmasin market was determined by the price level at lag 1, ceteris paribus. The SAR (11) shows that the pattern of the rice price level was determined by the pattern of the rice price level at 11 month ago, ceteris paribus. The MA (1) shows that the price level in Banjarmasin was determined by the average of the last month of rice price. The SMA (12) shows that the pattern of market rice price level was determined by the seasonal moving average of rice price of 12 months in positive direction, ceteris paribus.

Variance equation

$$ht = 0.133806\, e^2_{t-1} + 0.866194\, h^2_{t-1} \quad (3.2)$$
$$(3.846781) \qquad (24.90203)$$

Variance equations (3.2) for Banjarmasin markets is GARCH (1,1) without a constant. It can be concluded that $\alpha_0 = 0$ which satisfied non-negativity assumption. Since the coefficient of α_1 is less than β_1, it shows that the reaction coefficient was greater than the persistence coefficient. It means that the rice price volatility in Banjarmasin will relatively last for the longer time before going back to the normal level.

Like Medan in North Sumatera, Banjarmasin in South Kalimantan Province had small rice surplus. Again, Lantarsih (2011: 44) stated that South Kalimantan had only about 816 thousand metric tons of rice surplus in 2009. With that small surplus of rice, it was harder to recover from price volatilities in the shorter time. Less developed infrastructure transportation in Kalimantan also contributed to the slow moving of rice from surplus areas.

Price behaviour at pre-reformation and post-reformation era

The results of the study also found that the volatilities of rice price in three markets tend to increase, especially on the last two decades, namely since the reformation era.

The CSD of retail rice price pre-reformation era for Banjarmasin was only 3.5 percent and at the post reformation era increased to 6.65 percent and reached its peak at 6.98 percent at economic crisis. For Medan, the CSD of retail rice price pre-reformation era was only 3.69 percent and at the post reformation era was 4.62 percent and reached 6.07 percent at the economic crisis (Table5). For Makassar, the CSD of retail rice price pre-reformation era was only 2.97 percent and at the post reformation era was 3.09 percent and reached 5.98 percent at economic crisis.

Conclusion

The results of the research show that the more appropriate model to make forecasting of retail rice price for all three markets/cities are GARCH model and not ARIMA model since the variance of error terms was heterocedasticity.

The very unstable prices of rice in all markets were on the period of economic crisis in October 1997-September 1998, as indicated by the highest spikes of CSD values compared to other period. The presence of economic crisis in that time impacted seriously on all retail rice price of in all three markets.

The changes in rice price in all three markets were caused mainly by the harvest time and yearly routine cycles. On the peak harvest time the prices went down caused by supply glut and in the slack harvest time the price went up caused by lack of supply.

Auto Regressive (AR), Seasonal Auto Regressive (SAR) and Seasonal Moving Averages (SMA) also contributed to rice price changes in all markets. Dummy for economic crisis (DRAD) also significantly caused rice price changes in all three markets in Indonesia.

From variance equation perspective, Medan, Makassar and Banjarmasin have GARCH (1,1) model. However, Medan and Banjarmasin have coefficient α_1 is less than coefficient β_1, which shows that the price volatilities will last for a longer time before going back to normal condition. On the other hand, Makassar as the capital city of South Sulawesi had α_1 coefficient greater than β_1 coefficient, meaning that the price volatilities will be recovered in the short period of time since this market had large rice surplus and more developed economic compared to Medan and Banjarmasin.

Related to high rice price volatilities since the reformation era which can trigger food crisis in these three markets, it is suggested to bring back the BULOG function to its previous position as the national food stabilizer mainly for rice. The reason is that BULOG was very effective in controlling rice price volatilities and rice availabilities in Indonesia before the reformation era. To make government policies to be more effectives in managing rice price volatilities in Indonesia, study for rice price behavior for Java also should be done.

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