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VOLATILITY SHOCK PERSISTENCE IN INVESTMENT DECISION MAKING: A COMPARISON BETWEEN THE CONSUMER GOODS AND PROPERTY-REAL ESTATE SECTORS OF THE INDONESIAN CAPITAL MARKET

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ABSTRACT

Research about volatility shock persistence is very important, since it could reflect the risks that can be used to estimate the fluctuations of stock returns in the future. This paper investigates a comparison of the volatility shock persistence sectoral indexes between the consumer goods (CONS) and property-real estate (PROP) sectors, using a single index model analyzed using GARCH (Generalized Autoregressive Conditional Heteroscedasticity) and I-GARCH (Integrated-Generalized Autoregressive Conditional Heteroscedasticity). By using index return data from January 2010-December 2015, the research shows that CONS and PROP tend to produce the same results. The CONS and PROP indexes' responses to volatility shocks tended to be quite fast. Hence, the single index model of the CONS and the PROP indexes can quickly return to its normal stability. It means that, in the presence of certain information which could affect the volatility of the return from these sectors, the market will respond and adapt immediately. This might be attributed to the fact that CONS is a sector that involves fast moving products. Furthermore, the PROP sector has an indirect effect by increasing the real sectoral economic activity and economic growth in Indonesia, which has a large population. Thus, it is recommended that investors who are risk averse and risk neutral should invest in these sectors, because the volatility of both indexes can be monitored based on the existing information.

Keywords: volatility shock persistence, investment decisions, consumption sector, property-real estate sector

JEL Classification: C58, D53, G11

INTRODUCTION

Investors in the capital market, especially the stock market, face uncertainties or risks in investing. The index fluctuates wildly, on a daily, weekly, quarterly and annual basis, because of good and bad news about the conditions of the market, economy, politics, security, and the internal condition of the companies. However, turbulence or a shock can provide returns for investors, if they use the appropriate strategies for decision-making associated with their preferences and the investment period.

Rajput, Chopra, and Rajput (2012) stated that it is very important to consider the stock price volatility when making investment decisions, because the volatility reflects the risks or uncertainties that can be used to estimate the fluctuations in the stocks' returns in the future. One of the ways to investigate volatility is to analyze the volatility shock persistence. Shares with volatility persistence indicate that returns today have a big influence on the prediction of variance (volatility) for returns in the future. Thus, investors can use volatility persistence as a method to estimate stock returns when making investment decisions.

Research about volatility to explain stock returns has been conducted. Carr and Wu (2009) found there is a correlation between variance premiums and individual stock returns. Bollerslev, Marrone, Xu, and Zhou (2014) also discovered evidence that the aggregate market risk could be explained by the risk premium. Other researchers have also looked at factors that could explain the volatility. Wang (1993) found that volatility could be increased by asymmetric information associated with a firm. Jain and Strobl (2015) investigated how asymmetric information from volatility can explain excess returns.

This research utilized a time series analysis approach, in the form of the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model. This model was also used in the study by Hui-Boon Tan and Chee-Wooi Hooy (2006). The GARCH model was used because it enables the calculation of time-varying volatility. In the study, it was found that volatility clustering in a GARCH model meant it could also be a model that is very flexible and can work well. Besides using a GARCH model, this study also developed a model by adding an I-GARCH (Generalized Autoregressive Conditional-Integrated Heteroscedasticity) model, as used by Jain and Strobl (2017). In this study, the I-GARCH model was used to analyze the volatility persistence associated with excess returns.

The study focused on both the consumer goods sector and the property-real estate sector, because the consumption sector (food and beverage sub-sector, cigarette sub-sector, pharmaceutical sub-sector, sub-sector for cosmetics and household goods, and the sub-sector for household appliances) is an industrial sector generally considered as stable for investments. The cause of this stability is that the consumer goods sector is considered a sector which is immune to declines, as it involves basic human needs. In addition, the consumption sector is a sector that has a more stable risk, and it is important to consider in a portfolio of stocks due to its nature as a stock "defense".

Unlike the consumption sector, the property and real estate sectors (the property and real estate sub-sector and the construction sub-sector) are vulnerable to macroeconomic conditions such as interest rate fluctuations, inflation, and exchange rates. However, in the Indonesian capital market, investments in these sectors offer much greater profits, without large capital investments, compared to direct investments. Anto (2015) states that investment in property and real estate in Indonesia promises an absolute return, because the increasing number of people in Indonesia is not accompanied by any expansion in the available land. This drives the prices of property, especially homes, upwards from time to time. Furthermore, the investment opportunities in property and real estate in Indonesia are very extensive.

This research also tried to examine whether there are any differences in volatility persistence between the CONS and PROP sectors that will impact on policy differences in investment decisions. These decisions may be influenced by the investors' preferences (risk averse, risk neutral or risk taker).

LITERATURE REVIEW

Volatility is a very important thing to take into account, so that the estimated stock price becomes more appropriate and reasonable. One way is to analyze the volatility persistence (volatility shock persistence). Research into persistent volatility began with the research conducted by Engle (1982), Poterba and Summers (1986), and Engle and Bollerslev (1986), using the GARCH model to measure persistent volatility.

Further research into volatility was also undertaken in Malaysia by Hui-Boon Tan and Chee-Wooi Hooy (2006), which also used a time series analysis approach, in the form of GARCH. Their results showed that the volatility of shock persistence on the return index of the technology sector was greater than the volatility shock persistence on the overall return of the KLSE (Kuala Lumpur Stock Exchange). Islam and Mahkota (2013) also studied the volatility persistence of the KLCI (Kuala Lumpur Composite Index), JKSE (Jakarta Stock Exchange Composite Index) and the STI (Straits Times Index) using GARCH. Their study showed that the daily return can be explained by the GARCH model and the JKSE was the most volatile stock market of the three.

However, the research above did not examine the effect of persistence volatility with excess returns. This is very important since volatility persistence could affect the stock returns at different information asymmetry levels (Jain & Strobl, 2017). Therefore, this study includes the I-GARCH model to analyze the volatility persistence associated with excess returns.

Research about volatility persistence with I-GARCH has been undertaken by Patton and Sheppard (2015) on the S&P 500 index and the individual index of 105. Their research distinguished the volatility of positive and negative returns. The results show that future volatility is strongly influenced by negative return volatility, compared to positive return volatility. The same study was also conducted by Jain and Strobl (2017) on the NYSE (New York Stock Exchange) firms from 1989-2014, and found that volatility persistence can significantly explain the excess returns. They used the I-GARCH model to analyze persistent volatility associated with excess returns. Thus, this research develops the GARCH model by adding the I-GARCH model as used by Jain and Strobl (2017) to analyze the effect of volatility persistence on excess returns.

METHOD, DATA, AND ANALYSIS

The data used in this study were the sector indexes, namely the daily consumption sector (CONS), the daily property and real estate sector (PROP), and the daily market index (JKSE) for the period of the study from January 2010 to December 2015. The daily data were obtained from JSX Statistics, accessed from www.idx.co.id.

Because the CONS and PROP sectors had different levels of risk, they became the objects of the research. Therefore, this research tried to compare whether the volatility of the PROP sector index and the volatility of the CONS sector index were associated with volatility shock persistence. By comparing the volatility persistence analysis of these sectors, the study examined to what extent investment decision making would be different, based on the risk-taking profile of the investors. The technical analysis of the data, with the sequence of the research, explained the steps for measuring the volatility persistence (see Figure 1). It started with collecting data from the CONS, PROP, and JKSE daily indexes from January 2010 to December 2015. After the data from the three indexes were obtained, the calculation of the natural logarithm of the return was conducted in accordance with the theory of the geometric rate of return, as show in the following formula (Cooper, 1996):

$$R_i = \ln\left[\frac{P_t}{P_{t-1}}\right] \quad (1)$$

In which, P_t is a closing price index on day t, and P_{t-1} is a closing price index on day t-1. Furthermore, after the return index was obtained, stationary testing of the data was conducted to determine whether the return had a tendency to a constant mean and variance. Stationary testing of the data was conducted using the unit root test, based on the Augmented Dickey-Fuller test approach.

The next stage, the single index model, was used to estimate the return index. In general, a single index model illustrates that when the market price moves it will be followed by a rise in stock prices, and vice versa. It shows the relationship between the returns of the securities to market changes, such as stock market indexes (Elton et al., 2014). This approach is called a single index model, using the stock market index as a proxy. The single index model is used in this study because risk is calculated based on only two factors, which consist of the market risk and the individual risk. This is different to Markowitz's model, that measures risk with a correlation matrix between the variance and covariance, which has more complexity than the single index model. Furthermore, the single index model is able to compare all the securities on a benchmark, and to compare the securities with others. The regression equation for the single index model in the study is as follows (Elton et al., 2014):

$$R_i(t) = \alpha_i + \beta_i R_M(t) + e_i(t) \quad (2)$$

In which, R_i is an excess return from a sectoral index, α_i is an expected excess return, β_i is stock's return due to the movement of the market, R_M is an excess market return, and e_i is a sectoral specific surprise or residual.

After the CONS and PROP indexes were estimated using single index modeling, auto-correlation tests were needed. An autocorrelation test is used to test the correlations among errors from period t-1 and period t. The consequences of autocorrelation problems in a model are that the estimator stands consistent, but not efficient, and the result of the hypothesis testing is inaccurate.

Autocorrelation in this study used the correlogram Q-stat (this study used 36 lags). If all of the p-values of the 36 lags were statistically significant at α = 0.05, it could be stated that there were autocorrelation problems in the models. Therefore, the modeling continued using ARIMA (Autoregressive Integrated Moving Average). It was conducted by inserting elements of the Autoregressive (AR) order and Moving Average (MA) order into the model until there were no autocorrelation problems in the model. ARIMA modeling is done by looking at the p-values of the 36 lags that came out from 95% of the confidence intervals (spikes). It indicated that there were correlations between the lags. Those which had spikes were inserted into the ARIMA equation to be estimated.

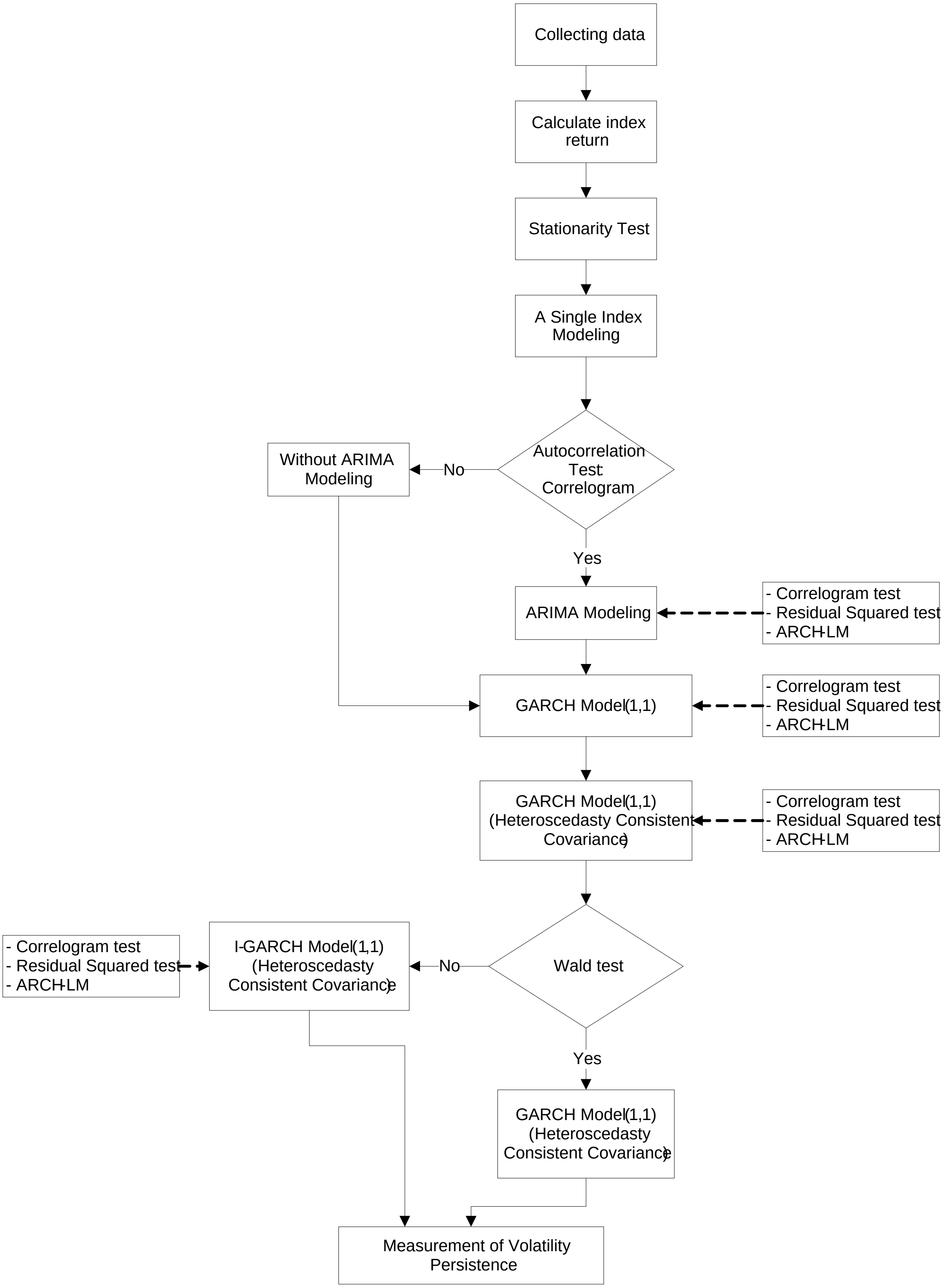

Figure 1. Flowchart for the sequence of volatility persistence measurement
(*Source*: Jain and Strobl (2015) that the sequence of the analysis is presented in the form of a flowchart).

If the autocorrelation function had spikes, the model used an estimation of MA, and if the partial autocorrelation function had spikes, the model used an estimation of AR. Furthermore, if both the autocorrelation function and partial autocorrelation function had spikes, the model used an estimation of ARIMA.

The formula below is a single index model including the ARIMA order.

$$R_{it} = \alpha + \beta_1 R_m + \sum_{p=1}^{n} Y_p Y_{t-p} \quad (3)$$

Where, $\sum_{p=1}^{n} Y_p Y_{t-p}$ is a variable of AR to cure the autocorrelation. The ARIMA modeling was conducted until there were no longer any autocorrelation problems in the model, then an ARCH (Autoregressive Conditional Heteroscedasticity) effect test was conducted. The ARCH effect test in this study was conducted using two methods, namely the correlogram squared of residuals and the ARCH-LM test. Both of them are used to test whether residuals in the model have a homogeneous variance. From the first method, if all of the 36 lags in the correlogram Q-stat are significant, the variance in the model's equations for the ARCH/GARCH specifications was correct.

Then a second test, the ARCH-LM test was conducted. This ARCH-LM test is the test of the Lagrange Multiplier (LM) to test the ARCH effect on the residuals. If there were ARCH effects in the residuals, the modeling could be continued using ARCH/GARCH. The GARCH model was used to obtain an optimal estimation of the variance level, as the variance at time t (σ_i^2), depending on past information, reflected in the squared residuals and the variance in the previous period (t-1).

The most common GARCH model is GARCH (1,1) or GARCH (p, q). Estimating the conditional variance GARCH (1,1) was conducted using the following equation (Engle, 1982):

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (4)$$

$$\alpha_0 > 0, \alpha_1, \ldots, \alpha_i;\ \beta_1, \ldots, \beta_j$$

where, α is a coefficient of ARCH and β is a coefficient of GARCH. This study used GARCH (1.1) because it is able to calculate the time-varying volatility. Furthermore, the GARCH (1,1) used in this study was the GARCH (1,1) with a covariance consistent heteroscedasticity option. This option is used if the model is not normally distributed, the parameters remain consistent and asymptotically is valid.

In the GARCH (1,1) model, if the total number of ARCH and GARCH coefficients are close to 1, the testing would be continued with the Wald test. If the result of the Wald test was not statistically significant, further testing would be continued using the I-GARCH (1,1) model. The model below is the model for I-GARCH (1,1) used in this study (Engle & Bollerslev, 1986):

$$\sigma^2 = \sum_{j=1}^{q} \beta_1 \sigma_{t-1}^2 + \sum_{i=1}^{p} \alpha_1 \varepsilon_{t-1}^2 \quad (5)$$

$$\sum_{j=1}^{q} \beta_1 + \sum_{i=1}^{p} \alpha_1 = 1 \quad (6)$$

The results from the I-GARCH (1,1) model would be compared with the results of the GARCH (1,1), using AIC (Akaike Information Criterion), SIC (Schwarz Information Criterion), and the log likelihood to measure the validity of the model. The smaller the values of AIC and SIC the better the parameters in the model, while the larger the log-likelihood value means the better the model could be. Conversely, if the total value of the ARCH and GARCH coefficients were below 0.95, it could be stated that it was sufficient to use the GARCH (1,1) model as the estimation model. The final step in this research was calculating the volatility shock persistence for both single index models of the CONS and PROP indexes. The calculation of volatility shock persistence in this study used the formula used by Hui-Boon Tan, Chee, and Sook (2006):

$$\left[\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i\right]^n \text{x } 100\% \qquad (7)$$

RESULT AND DISCUSSION

This study aimed to compare the volatility persistence associated with investment decision making in the CONS and PROP sectors.

Table 1. Descriptive Data

	JKSE	CONS	PROP
Mean	0.0004	0.0008	0.0008
Median	0.0011	0.0007	0.0012
Max.	0.0701	0.3806	0.1828
Min.	-0.0930	-0.3499	-0.1940
Std. Dev.	0.0116	0.0191	0.0165
Skewness	-0.5678	1.1641	-0.4130
Kurtosis	8.6252	186.45	28.286

Source: JSX Statistics (2010-2015), analyzed

The descriptive statistics (see results in Table 1) for the market index return (JKSE), the consumer return index sector (CONS), and the property & real estate return index sector (PROP), showed that even though the PROP index had higher average returns than the CONS (0.0826%), PROP had less risk than CONS. This was seen from the value of the standard deviation (std dev) for it, which was smaller than the standard deviation of CONS. But, the average return of PROP is greater than that of CONS.

Furthermore, the stationary data test was conducted in order to determine whether there was autocorrelation in the data return tested.

Table 2. Stationary Test with CL 99%

Index	ADF	CV 1%	Results
JKSE	-22.29273	-3.434627	Stationary
CONS	-26.14295	-3.434624	Stationary
PROP	-39.15063	-3.434618	Stationary

Source: JSX Statistics (2010-2015), analyzed

Based on Table 2, it was found that the JKSE, CONS, and PROP indexes had an ADF absolute value greater than the critical absolute value (5%). Hence, it could be stated that the return data of each index was already stationary. Thus, all the stocks were stationary.

After all the indexes were found to be stationary, a regression statistic for a single index model was conducted. This model used two simple regression analyses. The first regression model used the return of the JKSE index as the independent variable (X) and the return of the CONS index as the dependent variable (Y). The second regression model used the return of the JKSE index as the independent variable (X) and the return of the PROP index as the dependent variable (Y).

Table 3. Regression Statistics from Single Index Model

Y	X	Coeff.	t-Stat.	Prob.
CONS	JKSE	0.9070	25.2458	0.0000
PROP	JKSE	0.9968	37.8028	0.0000

Source: JSX Statistics (2010-2015), analyzed

Table 3 shows the return of the JKSE was statistically significant, $\alpha = 0.05$ for CONS and PROP, with coefficients that were both over 0.90. These indicated that the return movement of the JKSE had a major effect on the movements of the CONS and PROP return indexes. Because it was possible that there were correlations among the errors from period t-1 and period t, autocorrelation tests were needed. As previously explained, the correlogram Q-stat method was used to find out whether there were correlations.

Based on the correlogram Q-stat test, for both of the single index models, all of the p-values of the 36 lags were statistically significant at $\alpha = 0.05$. From the results, it could be stated that there were autocorrelation problems in the models. Therefore, the modeling continued using

ARIMA (Autoregressive Integrated Moving Average). This was conducted by inserting elements of the Autoregressive (AR) order and Moving Average (MA) order into the model until there were no autocorrelation problems in the model.

Table 4. ARIMA Modeling

Var. Y	Var. X	Coeff.	t-Stat.	Prob.
CONS	AR (1)	-0.4237	-16.1905	0.0000
	AR (2)	-0.1851	-6.6002	0.0000
	AR (3)	-0.0672	-2.5653	0.0104
PROP	AR (1)	-0.1204	-4.6384	0.0000

Source: JSX Statistics (2010-2015), analyzed

Based on Table 4, it was found that all of the AR variables were statistically significant, $\alpha = 0.05$. It could be stated that there were no longer any autocorrelation problems in the models. To make sure that there were no autocorrelations in the ARIMA models, a correlogram Q-stat was used. The results of this test showed that there were no autocorrelation problems in the models, as the p-values obtained by the correlogram Q-stat were statistically not significant ($\alpha = 0.05$) for all of the 36 lags.

After that, an ARCH effect test was conducted to test for a heteroscedasticity problem in every model. From the previous explanation, the ARCH effects test used in this study employed two methods, namely a correlogram squared of the residual and ARCH-LM. The results of the first test showed that the p-values in the models were not statistically significant (α= 0.05) for all of the 36 lags for both the CONS and PROP indexes. From the results, it could be stated that there were heteroscedasticity problems in both indexes' models. Moreover, the second test, the ARCH-LM test, showed that the obs-R*squared values of the 1^{st} lag to the 5^{th} lag were also statistically significant ($\alpha = 0.05$). They indicated that there were heteroscedasticity problem in the models. Hence, the next step was to proceed with ARCH/GARCH modeling. Before this model was analyzed, it needed to be tested to see whether there were autocorrelation and heteroscedasticity problems in the model. The results of the correlogram Q-stat showed that the p-values were not statistically significant (α = 0.05) for all of the 36 lags. Thus, it could be stated that there were no autocorrelation problems in the model. Furthermore, the results of the ARCH effect test showed that the p-values were not statistically significant (α= 0.05) for all of the 36 lags. From the results, it could be stated that there were no heteroscedasticity problems in the model. Similarly, the result of the ARCH-LM test showed that the R*obs-squared values of lag of the 1^{st} to the 5^{th} lag were also not significant statistically (α = 0.05). Hence, the residuals in the model were homoscedastic.

Furthermore, the GARCH (1, 1) model was then analyzed.

Table 5 shows that the total value of the ARCH and GARCH coefficients was below 0.95. It could be stated that it was sufficient to use the GARCH (1,1) model as the estimation model. The levels of volatility shock persistence in this model were calculated using formula number 7 in the methodology section.

Table 5. GARCH (1, 1) Index CONS

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000270	0.000191	1.408391	0.1590
JKSE	0.906189	0.020102	45.08054	0.0000
AR(1)	-0.034803	0.029709	-1.171454	0.2414
AR(2)	-0.015844	0.026879	-0.589434	0.5556
AR(3)	-0.024456	0.029741	-0.822301	0.4109
Variance Equation				
C	1.26E-05	1.57E-06	8.024538	0.0000
RESID(-1)^2	0.191072	0.031102	6.143457	0.0000
GARCH(-1)	0.640266	0.030713	20.84692	0.0000

Source: JSX Statistics (2010-2015), analyzed

Table 6. Proportion of shock on the CONS volatility

Variables	R_CONS
ARCH	0.191072
GARCH	0.640266
$\alpha + \beta$	0.831338

Volatility Shock Persistence	day	day	day	day	day
	5	10	15	20	25
CONS	39.71%	15.77%	6.26%	2.49%	0.99%

Source: JSX Statistics (2010-2015), analyzed

From Table 6, it can be seen that the proportion of shock on the 5th day was 39.71% and it became only 0.99% on the 25th day. Thus, it could be stated that the responses by the indexes to shocks to their volatility were quite fast. Hence, the single index model for the CONS sector quickly returned to normal.

Furthermore, the GARCH (1,1) model was then analyzed for the single index model of the PROP index. Table 7 shows the estimation of the results of the GARCH (1,1) model for the PROP index. The results of the correlogram Q-stat showed that the p-values were not statistically significant ($\alpha = 0.05$) for all of the 36 lags. Thus, it could be stated that there were no autocorrelation problems in the model. Furthermore, the results of the ARCH effect test showed that the p-values were not statistically significant ($\alpha = 0.05$) for all of the 36 lags. From the results, it could be stated that there were no heteroscedasticity problems in the model. Similarly, the result of the ARCH-LM test showed that the R*obs-squared values of the 1st to the 5th lag were also not statistically significant ($\alpha = 0.05$). Hence, the residuals in the model were homoscedastic.

Table 7 shows that the total value for the ARCH and GARCH coefficients was below 0.95. It could be stated that it was sufficient to use the GARCH (1,1) model as the estimation model.

The GARCH (1,1) model was then analyzed.

Table 7. GARCH (1, 1) Index PROP

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000646	0.000261	2.477019	0.0132
JKSE	1.016574	0.029048	34.99578	0.0000
AR(1)	0.089144	0.047895	1.861255	0.0627
Variance Equation				
C	2.50E-05	6.30E-06	3.965063	0.0001
RESID(-1)^2	0.199265	0.062194	3.203942	0.0014
GARCH(-1)	0.630087	0.043015	14.64813	0.0000

Source: JSX Statistics (2010-2015), analyzed

Table 8. Proportion of shock on volatility

Variables	R_PROP
ARCH	0.199265
GARCH	0.630087
$\alpha + \beta$	0.829352

VSP	day	day	day	day	day
	5	10	15	20	25
PROP	39.24%	15.40%	6.04%	2.37%	0.93%

Source: JSX Statistics (2010-2015), analyzed

From Table 8, it can be seen that the proportion of shock on the 5th day was 39.24% and it became only 0.93% on the 25th day. Thus, it could be stated that the responses of the indexes to shocks to their volatility were quite fast. Hence, the single index model of the PROPS sector could quickly return to normal.

Based on the results of the study, the PROP index had a value for $\alpha+\beta$ which was smaller than the value of the CONS index. However, the difference between the two shock volatility indexes was very small and tended to be similar. The value of $\alpha+\beta$ was below 0.9. It indicated that the CONS and PROP response indexes to shocks on volatility were fast enough. Hence, the single index models for the CONS and PROP sectors could quickly return to normal.

Similarly, the proportion of shocks of the single index models of the CONS and PROP sectors were not much different on days 5, 10, 15, 20, and 25. This indicated that the volatilities that occurred in those two indexes were low, these volatilities continued, and these volatilities could possibly return to normal. Hence, it could be stated that the volatility persistence of the two indexes tended to be similar. This might be attributed to the fact that the consumption sector is a sector that involves basic human needs. Although there were increases or decreases in the macroeconomic factors, the consumption sector tended to instantly respond and adapt to market conditions.

Furthermore, the volatility or return movement of the property and real estate sector in Indonesia also tends to be responsive to macroeconomic changes. The increases or decreases of macroeconomic factors which could affect the property and real estate sectors are not likely to influence investment very much, because this sector is very much needed by people. Especially in the countries with large populations, the increasing number of people in Indonesia is not accompanied by an expansion of the land area, the availability and need for housing is creating problems (Anto, 2015). In other words, the property and real estate sector has an indirect effect by increasing the real sectoral economic activity and economic growth in Indonesia, which has a large population.

Thus, investors who are risk averse or risk neutral should invest in these sectors, because the movement of both indexes can be monitored based on the existing information. That is, the index movement occurs for fundamental (basic) reasons, not because of any irrational behavior by the markets' participants, in which speculators regulate or control the price, which makes the stock prices change.

CONCLUSION

As the conclusion, the responses of both of the CONS and PROP indexes to shocks on volatility tended to be quite fast. As a result, the single index models of the CONS and PROP sectors quickly returned to normal. Therefore, investors who are risk averse or risk neutral are recommended to invest in the CONS and PROP sectors, because the movements of both these indexes can be monitored based on the available information, and they tend to quickly adjust to changes. Macroeconomic changes which could affect both the consumer and property-real estate sectors are not likely to influence investment much, because these sectors cater to basic human needs.

LIMITATION AND SUGGESTION

This study used the GARCH (1, 1) model to measure volatility. As a result, this study was unable to distinguish between positive and negative volatilities during the study period. Hence, future studies are recommended to use the E-GARCH (Generalized Exponential Conditional Autoregressive Heteroscedasticity) model, and the T-GARCH (Generalized Threshold Conditional Autoregressive Heteroscedasticity) model, as these models can determine which volatility, either the positive or negative volatilities, is stronger in influencing the index's volatility.

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