Jurnal Muara Ilmu Ekonomi dan Bisnis
Vol. 7, No. 1, April 2023 : hlm 140-149
ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

THE ANALYSIS OF HIGHEST PAYING DIVIDEND COMPANIES STOCK RETURNS VOLATILITY IN INDONESIA

Ariesta Tika K. P. S. Putri[1*], Hilary Flora A. T. Lasar[2], Regi Muzio Ponziani[3]

[1]Sekolah Tinggi Ilmu Ekonomi Trisakti, Jakarta, Indonesia*
Email: ariesta@stietrisakti.ac.id
[2]Sekolah Tinggi Ilmu Ekonomi Trisakti, Jakarta, Indonesia
Email: ariesta@stietrisakti.ac.id
[3]Sekolah Tinggi Ilmu Ekonomi Trisakti, Jakarta, Indonesia
Email: ariesta@stietrisakti.ac.id

*Penulis Korespondensi

Masuk : 02-03-2023, revisi: 12-04-2023, diterima untuk diterbitkan : 13-04-2023

ABSTRAK

Penelitian ini bertujuan untuk memodelkan volatilitas return indeks saham perusahaan dividen tertinggi di Indonesia (DIV 20) sebelum dan sesudah pandemi COVID 19. Model keluarga ARCH (Autoregressive Conditional Heteroscedasticity) digunakan dalam hal ini. Periode penelitian diperpanjang dari 18 Mei 2018 hingga 18 Februari 2022. Batas waktu dimulainya pandemi adalah 1 April 2020. Data pengembalian adalah pengembalian mingguan. Hasilnya menunjukkan bahwa sebelum pandemi, GJR-GARCH(1,1) dapat memetakan dan melacak volatilitas dengan sangat baik karena mencetak AIC dan SIC pra-pandemi terendah. Oleh karena itu, penelitian ini menguatkan bukti adanya reaksi asimetris dari partisipasi pasar terhadap kemunculan dan penyebaran berita baik dan buruk di pasar. Setelah pandemi, efek ARCH menjadi kurang jelas. Angka signifikansi menurun meskipun efek ARCH masih signifikan pada 0,15. Performa model ARCH(1) secara signifikan lebih tinggi daripada model lain pasca-pandemi. Hasil tersebut menjadi bukti bahwa pascapandemi ketidakpastian yang dihadapi pelaku pasar sangat tinggi. Hal ini mengakibatkan meningkatnya volatilitas. Model keluarga ARCH menjadi kurang signifikan karena pengembaliannya lebih acak. Analisis lebih lanjut, bagaimanapun, menunjukkan bahwa pengembalian belum mengikuti model random walk meskipun keacakan meningkat. Oleh karena itu, ARCH(1) masih sesuai untuk memodelkan volatilitas setelah Pandemi.

Kata Kunci: Model ARCH, Volatilitas, Pengembalian Index

ABSTRACT

This research aims at modeling the volatility of Indonesian highest paying dividend companies stock index (DIV 20) returns before and after pandemic COVID 19. The ARCH (Autoregressive Conditional Heteroscedasticity) family models were employed in this regard. The research period extended from 18 May 2018 to 18 February 2022. The cutoff for the commencement of pandemic was 1st April 2020. The return data were weekly returns. The results suggested that before pandemic, GJR-GARCH(1,1) could map and trace the volatility very well since it scored the lowest AIC and SIC pre-pandemic. Therefore, this research corroborated the evidence that there existed asymmetric reaction from the market participation toward the emergence and spread of good and bad news in the market. After pandemic, the ARCH effect became less obvious. The significance number was decreasing although the ARCH effect was still significant at 0.15. ARCH(1) model performance was significantly higher than the other models post-pandemic. The result presented evidence that after pandemic the uncertainty facing the market participants was very high. This resulted in the increase of the volatility. The ARCH family model was becoming less significant because the returns were more random. Further analysis, however, showed that the returns did not yet follow the random walk model despite the increasing randomness. Therefore, ARCH(1) was still appropriate to model the volatility after Pandemic.

***Keywords:** ARCH models, Volatility, Index Returns*

1. INTRODUCTION

Stock market is very instrumental in providing funds for companies seeking financing. Shares issued by companies will provide for the funds needed. The shares in turn act as an instrument of investment. Investors who invest in shares will expect returns generated by the movement of the

https://doi.org/10.24912/jmieb.v7i1.23150

shares and the dividends of the shares. Investors are inclined to choose shares based on their risk preference. Shares that have high volatility will have a very fluctuating share prices. Whenever there is a sharp increase in the price, there lies a high probability that at the next period the price will drop significantly. Hence, volatility is denoted by the distribution of the historical past data of the prices or variances. Frequent and abrupt change in the deviation of variance means a very volatile share (Aggarwal, et al. 1999). This not only provides an opportunity for profit but also signifies high risk that must be borne by the investors when the share price declines. Therefore, volatility in price encompasses volatility in share price that must be taken into consideration by investors (Wulandari 2021).

Micro- and macroeconomic factors have been known to influence volatility of shares. Nazir, et al. (2010) have established that dividend has the power to affect volatility in a negative manner. Higher dividend render the share price stable. Hence, investors also derived stable returns. Lee, et al. (2019) focused on corporate governance variable in its relation to the stock volatility. By employing firm size as the moderating variable, they found that corporate governance was inclined toward stabilizing the stock volatility. The fluctuations of stock price would be lessened by introducing corporate governance factor. Further, they also found that the smaller the foreign ownership exposure on a firm, the stronger the stabilizing effect of corporate governance. Xie, et al. (2019) found that residual state ownership had negative effect on stock volatility. They stated that the bigger the influence of government in corporate decision making, the larger the effect of volatility mitigation. This evidence corroborate the contention that government ownership is an incredible signal that can reduce investor uncertainty. Kurniasari and Reyes (2020) found that interest rate influenced volatility negatively, while profitability and exchange rate had negative influence on volatility. Niewinska (2020) examined factors that were posited to affect returns volatility of banking stocks. She found that internal as well as external factors influenced returns volatility. The internal factors were comprised of the ratio of long-term investments to assets, solvency, and price-to-book ratio.

The external factors were employment rate, market returns, and implied volatilities of other stock indices such as S&P500 and EUROSTOXX50. This result was particularly unique because a macroeconomic factors as remote as unemployment rate could still affect stock returns volatility. Nugroho and Robiyanto (2021) proved the existence of inter-sectoral volatility spillovers. Gold return volatility was proven to positively affect stock index and exchange rate volatility influence stock index negatively. This portends that shocks in one instrument of investment like gold can be contagious to other investment instrument (stock in this case). Exchange rate was proxied as monetary and macroeconomic factors that could exert influence on stock volatility.

Subsequent to identifying the factors that contribute to the returns volatility this research proceeds to the identification of the research object. The focus of this research will be the returns volatility of the companies that belong to the category of highest dividend paying companies. In Indonesia stock exchange, a special index is formed in 2018 that is comprised of companies of most dividend payout. There has been no research that investigate this special index return before. Therefore, this research will contribute to the literature by investigating highest paying dividend index in Indonesia stock exchange. This research also heeds to the current phenomena involving the pandemic effect. Later, research period will be divided into 2, namely pre-pandemic and post-pandemic period. The volatility models that best explain the volatility of the stock index will be identified and compared. Therefore, we will know what the effect of the pandemic toward the returns volatility of the highest paying dividend stock index. No prior research has ever investigated this issue. Prior research will be explored in the subsequent

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

section. This research will fill in the gaps in the literature by investigating the volatility of shares issued by the highest paying dividend companies.

To the researchers' knowledge, no prior research has ever investigated this phenomenon. Investors most likely will target shares from companies that are generous in dividend payment. Therefore, they will be exposed to the market risk of share price movement. In this regard, this research will contribute by investigating the volatility of such shares and, hence, will aid investors in recognizing the volatility pattern of such shares.

Literature Review

Amit and Bammi (2016) employed a variety of GARCH models to investigate volatility models of Bombay Stock Exchange. The models employed were ARCH and also those that belong to GARCH families that employ 1 component of residual and 1 component of previous period variance. They found that the GARCH models identified the presence of leverage effect in Bombay stock market. This is particularly true because Amit and Bammi (2016) used data period before and after economic recession 2008-2009 in USA. Therefore, leverage effect was particularly strong during the bad economic condition. Kingsley and Peter (2019) specifically picked insurance stocks listed on the Nigerian Stock Exchange. They endeavoured to find the best models to map the volatility of the insurance stocks. Using daily data extended from March 2011 to December 2015, they found that the best model for volatility modeling was ARCH(3) and GARCH(1,1). This result is particularly interesting because ARCH(3) suggests that residuals form three prior periods can still exert influence on the current period variance. This showed a long-range influence in temporal period. Kingsley and Peter (2019) proceeded further to analyze the value at risk (VaR) and found the VaR value to be less than 10%, at maximum. This showed how imposing risk can be very obvious for investors during recession.

Emenike and Enock (2020) analyzed stock return volatility in Uganda stock market. Using daily data from September 2011 to December 2017 they found that exponential GARCH was able to identify the existence of asymmetric reaction to bad news and good news. Usually investors reacted more to bad news (Sari, et al. 2017). However, Emenike and Enock (2020) found that the opposite was true. Good news significantly increased the volatility of the stock market suggesting that investors reacted more to good news than to bad news. Nugroho, et al. (2020) investigated the modeling of Milan-based capital market and the leading market index in Europe namely Stoxx 600. They compared the performance of GARCH(1,1) and QGARCH(1,1) under three assumptions. The first assumption is that the distribution is of normal (Gaussian) error distribution. The second assumption is that of Student-t General Error Distribution (GED). The last assumption is that the error is distributed by means of Skewed General Error Distribution (SGED). They found that, in general, QGARCH(1,1) outperformed GARCH(1,1) in modeling the volatility. Specifically, QGARCH(1,1) with Skewed General Error Distribution (SGED) performed best for the modeling. Yong, et al. (2021) examined market index in Malaysia and Singapore. The market index returns were divided into before and after pandemic data. They found that, overall, EGARCH(1,1) in particular was able to capture the leverage effect present in both markets. However, GARCH(1,1) and GARCH-M(1,1) also had a relatively well established performance.

In addition, it was found that returns were negatively correlated with volatility. Specifically for GARCH-M(1,1), the risk premium effect can be traced so that it was reflected in the model. Although unfortunately, the coefficient for the risk premium was not able to exceed the threshold for significance. The literature review section shows us that ARCH and GARCH model are

https://doi.org/10.24912/jmieb.v7i1.23150

indeed perfectly suitable for modeling volatilities. Therefore, this research proceeds with ARCH and GARCH model, along with GJR-GARCH for asymmetric effect. The next section explores the technical definitions of ARCH, GARCH and GJR-GARCH.

2. RESEARCH METHODS

This research employed return data of share index that consists of high paying dividend enterprises. This is a newly constructed index in Indonesian stock exchange. There are 20 entities that make up this index that is why the index is called IDXHIDIV20. The time span extended from the first time the index was constructed in Indonesian stock exchange, 18 May 2018, to 18 February 2022. From the index available during the time period, return was calculated. The equation for index return proxy is (Andika, et al. 2019):

$$\textbf{Return} = \frac{\ln (I_t - I_{t-1})}{I_{t-1}}$$

I_t denotes the index at time t. Hence, the equation shows that the return is the quotient in natural logarithmic form between two indices number. This research purports to compare the volatility models of high-paying dividend enterprises share index between pre-covid and post-covid period and analyze the results. The threshold for pre and post period is 2 April 2020. That was when government first issued decree on social distancing, recognizing covid 19 as a pandemic. The period before 2 April 2020 is admitted as pre-covid period while after 2 April 2020 is analyzed as post-covid period. The research will examine whether the volatility model is best explained by the ARCH family models namely ARCH(1) and ARCH(2) or the GARCH family models that include GARCH(1,1) and GJR-GARCH(1,1). Therefore, firstly, the research must examine whether ARCH effect is present on the data. The regression equation for investigating the ARCH effect is:

$$e_t^2 = \gamma_0 + \gamma_1 e_{t-1}^2 + v_t$$

We can see from the ARCH testing equation the prior period autoregressive component can influence the the residual of the return data of current period. The residual is obtained from what is known as a mean equation. A mean equation is basically derived from forming a regression equation in which the dependent variable is only a constant. This means attributing the value of 1 to all observations of independent variable. From the mean equation the residual is taken to determine the presence of ARCH effect. Subsequent to ARCH effect testing, the research will proceed by calculating the AIC and SIC for each model and pick the lowest values. The model with lowest value is deemed to be the best performing model. There will be 4 equations employed to capture the fluctuations or volatility of the stock return. Two models come from the ARCH models namely, ARCH (1) and ARCH (2) and two models come from GARCH family models namely GARCH (1,1) and GJR GARCH (1,1). The equation for ARCH model is as follows (Rodriguez 2017):

$$\sigma_t^2 = \lambda + \sum_{i=1}^{q} \alpha_i e_{t-i}^2$$

The above equation shows that a volatility of stock return in a given time period is dependent upon the squared residuals of prior period. For ARCH (1) then there will be only one parameter for the prior period residuals. However, ARCH (2) model will estimate two parameters in the equation namely e_{t-1} and e_{t-2}. We can surmise that the conditional variance in a given time period is affected by prior period residuals and residuals from two previous periods. The second model in this research is GARCH (1,1). In this model, conditional variance is posited to be influenced by prior period variance and residual (Hansen and Lunde 2005). GARCH (1,1) model is as follows:

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

$$\boldsymbol{\sigma_t^2 = \lambda + \alpha\, e_{t-1}^2 + \beta\, \sigma_{t-1}^2}$$

The third model is GJR-GARCH(1,1) model. In this model, there is asymmetric treatment between good news and bad news. It is hypothesized that market participants will react to both good news and bad news. However, the reaction to bad news incite more response from market participations more when there is good news. The GJR-GARCH Model is as follows (Ramasamy and Munisamy 2012):

$$\boldsymbol{\sigma_t^2 = \lambda + (\alpha + \gamma I_{t-1})\, e_{t-1}^2 + \beta\, \sigma_{t-1}^2}$$

where: I_{t-1} equals to 0 when e_{t-1} is positive and it equals to 1 when e_{t-1} is negative. This reflects the more reaction by market participants given that there is bad news.

3. RESULTS AND DISCUSSIONS

Before dwelling onto data analysis, firstly we display the figure for stock index return of high paying dividend companies for pre-covid and post-covid periods in graph 1.

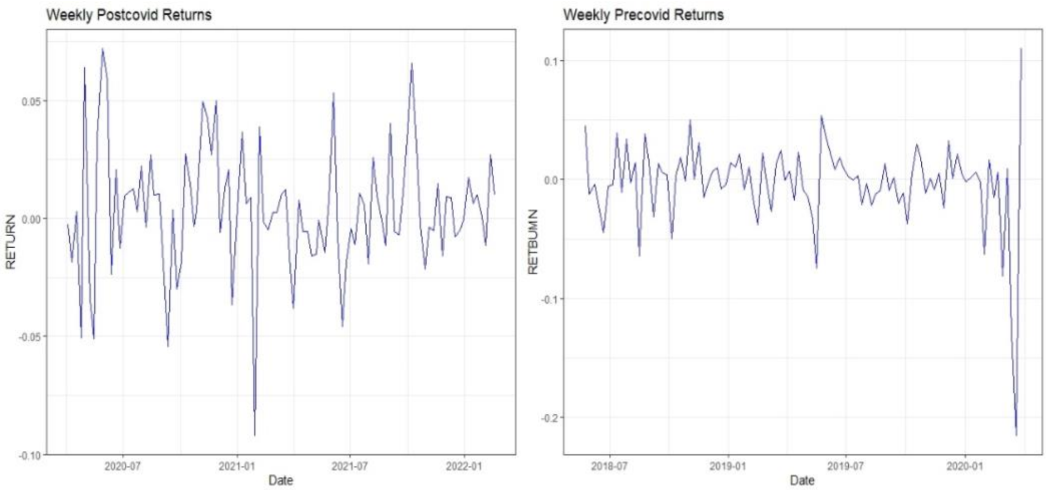

Figure 1. Plots of Stock Index Returns of Highest Paying Dividends Companies

Figure 1 shows the historical movement of stock returns for high paying dividend companies before and after COVID pandemic. Weekly precovid returns are pretty volatile. However, the range of the returns never exceeded 0.1 and -0.1 except when it was approaching the pandemic in which case it exceeded 0.1 and even more than -0.2. Around April and May 2021, the return volatility exceeded 0.05 and -0.05. Besides the time stamps mentioned, the returns never exceeded 0.5 or -0.5. Therefore, the returns were pretty volatile but it did not fluctuate very much. Every peak is followed by through. After covid period, the returns were much more volatile. Sharp increases were followed by sharp decreases. This feature signified increasing variance in the data. Around February 2022, there was a sharp decrease in the returns. Many occurrences in which the returns exceeded 0.05. However, this high return was short-lived because decreases always followed. This could be caused by the sudden disruptions to the companies' operations. Normal operation suddenly was being impeded by restrictions imposed by government to keep the pandemic from spreading. This presented a big challenge to the companies. Market participants saw companies as being impeded by the pandemic. This in turn resulted in the volatility of the share prices in general. Volatility in share price positively affected share index. Approaching the end of the research period, the returns did not fluctuate so much. This could indicate that the economy and stock market have got used to the pandemic situation

https://doi.org/10.24912/jmieb.v7i1.23150

and could begin to operate accordingly. After examining the volatility plot, Equation (1) and (2) signify the ARCH test to see whether the ARCH effect is present in the data:

$$\mathbf{e_t^2 = 0.0007124 + 0.5190003^{***}\, e_{t-1}^2}$$
$$\mathbf{(0.0004693) \quad (0.092596)} \qquad \mathbf{(1)}$$

$$\mathbf{e_t^2 = 0.0005974^{***} + 0.1645045^{*}\, e_{t-1}^2}$$
$$\mathbf{(0.0001495) \quad (0.1006711)} \qquad \mathbf{(2)}$$

*****significant at 0.01**
****significant at 0.05**
***significant at 0.1**

Equation (1) presents the ARCH test for index return before pandemic. The residual at current period is regressed against prior period regression. The residual is derived from the mean equation, namely regression the stock return against some constant. Equation (1) confirms the presence of the ARCH effect. The prior period residual is significantly affecting current period residual. The significance level is well below 1%. Therefore, we can continue with ARCH and GARCH modeling. Equation (2) presents the ARCH test for post-pandemic returns. The constant now becomes significant at 1%. This is a major change from the pre-pandemic data. Before, the constant is not significant. Subsequently, the independent variabel, prior period residual, becomes less significant in affecting the current period residual. However, the significance is still below 0.1. In fact, the significance level now becomes 6%, slightly below 5% significance. Pandemic renders the residual is less affected by prior period residual. That means the volatility is becoming more and more unpredictable. We cannot solely rely on the historical data to predict the upcoming data because past data become less influential to the upcoming data. The uncertainty is higher after pandemic than before. Therefore, market participants should not merely rely on the historical data to predict index. Table 1 will present the ARCH-GARCH modeling on the pre-pandemic index returns data.

Table 1. Volatility Modeling of Pre-COVID Stock Index Returns

Pre-COVID	**ARCH(1)**	**ARCH(2)**	**GARCH(1,1)**	**GJR-GARCH(1,1)**
λ	0.0007143	0.0005015 ***	0.0001445	0.0001434**
α_1	0.3284280**	0.3158179**	0.3433193***	0.15580
α_2	-	0.2568305**	-	-
β_1	-	-	0.1421967***	0.60580***
γ_1	-	-	-	0.98810***
Return	-0.00346393	-0.0020909	-0.0018845	-0.00436331
AIC	-4.089823	-4.185502	-4.196171	-4.302268
SIC	-4.091737	-4.188860	-4.199530	-4.307448

Table 1 shows the results of estimating the volatility by employing ARCH and GARCH models. Based on ARCH(1) model, the constant is not statistically significant. Yet, the coefficient of α1 is significant. This shows that prior period residual is statistically significant toward the index variance. This confirms that ARCH can be used to capture the estimators of the volatility of index returns for highest paying dividend companies. ARCH(2) model has all significant parameters. The constant has a value of 0.0005015 and the significance number is even lower than 0.01. The α1 and α2 estimators are significant at 0.05. This means current variance is being affected by prior period residuals and residuals from t-2. The AIC for ARCH(2) model is lower than ARCH(1). ARCH(2) model is more suitable for modeling the volatility of the index return.

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

The third model is GARCH(1,1). In this model, the parameters of $\alpha_{1,}$ and $\beta_1$are significant. The λ parameter, nevertheless, has significance number of more than 0.1. The coefficients for prior period residuals and prior period variance are significant at 0.01. The AIC is even lower for GARCH(1,1) compared with ARCH(1) and ARCH(2). The last model is GJR-GARCH. This model deals with asymmetrical treatment of good news and bad news. The parameter of $\gamma 1$ is significant at 0.01. This corroborates the idea that the market participants react more to the bad news. The $\beta 1$ coefficient is also significant. Prior period residual contains information that can affect current period variance of the returns. However, the coefficient of α_1 is not statistically significant. Meaning the estimated conditional variance is not influence by prior period residuals. Table 1 also shows the estimated return produced by each model using maximum likelihood method. All models estimate that the index return of the highest paying dividend companies are negative. GJR-GARCH(1,1) estimate that the average return of the index is -0.4%, the lowest of all model. GARCH (1,1) estimates the average return index to be around -0.1%, the highest of all. ARCH (1) and ARCH(2) estimates the return to be -0.3% and -0.2% respectively. Overall, approaching the pandemic, stock market was not in a bullish state because the returns tended to be negative which point to the condition in which there was a decrease in share price in general. Table 2 will exhibit the estimation results of the parameters using post-pandemic returns data.

Table 2. Volatility Modeling of Post-COVID Stock Index Returns

Pre-COVID	**ARCH(1)**	**ARCH(2)**	**GARCH(1,1)**	**GJR-GARCH(1,1)**
λ	0.0005528***	0.00052856 ***	0.00042581	0.0004182
α_1	0.2269308	0.19726005	0.2101716	0.2041299
α_2	-	0.05829145	-	-
β_1	-	-	0.1943557	0.2074479
γ_1	-	-	-	-0.0733387
Return	0.0019102	0.0022123	0.00207390	0.0021655
AIC	-4.396581	-4.378843	-4.378991	-4.359267
SIC	-4.398347	-4.382090	-4.382090	-4.364049

Table 2 shows the volatility modeling after pandemic strikes worldwide. According to all models, the return in the post-pandemic era is positive. The weekly return ranges from 0.0019102 (the lowest according to ARCH(1)) to 0.0022123 (the highest according to ARCH(2)). The only strongly significant parameter in ARCH(1) model is the constant (significant at 0.01). However, the parameter $\alpha 1$ is only significant at 0.15 (p-value of 0.139). Hence, it is weakly significant. ARCH(1) model has the lowest value of AIC (AIC of -4.396581). ARCH(2) model again has significant constant value. The constant of 0.00052856 is significant at 0.01. The coefficients of $\alpha 1$ and $\alpha 2$ are both insignificant. The ARCH effect becomes blurred as we move away from ARCH(1) models. This can be seen in GARCH(1,1) and GJR-GARCH(1,1). No significant parameters are present in both model. GJR-GARCH(1,1) has the highest AIC. Therefore, GJR-GARCH is very unsuitable for modeling volatility of post-pandemic return. GARCH(1,1) has the second lowest AIC. However, no significant parameters render it useless to model the volatility. Therefore, ARCH(1) model is the best among the models examined for modeling the volatility. However, the significance parameter should be relaxed to include 0.15 significance. We also conduct additional analysis to investigate whether the return data follow a random walk model. The result of Augmented Dickey Fuller test of stationarity with an intercept and no trend is as follows:

$$\mathbf{\Delta RET_t = 0.003318 - 0.93186^{***}\ RET_{t-1}}$$
$$\mathbf{(0.002745)\ \ (0.101826) \qquad (3)}$$

https://doi.org/10.24912/jmieb.v7i1.23150

The coefficient of RET_{t-1} (prior period return) is highly significant. We can reject the hypothesis that the data is nonstationary and follow a random walk model. Therefore, it is appropriate to model the volatility using ARCH(1) model because the data do not have the random walk characteristics. Figure 2 will show the conditional variance best on the best model for pre-and post-COVID returns.

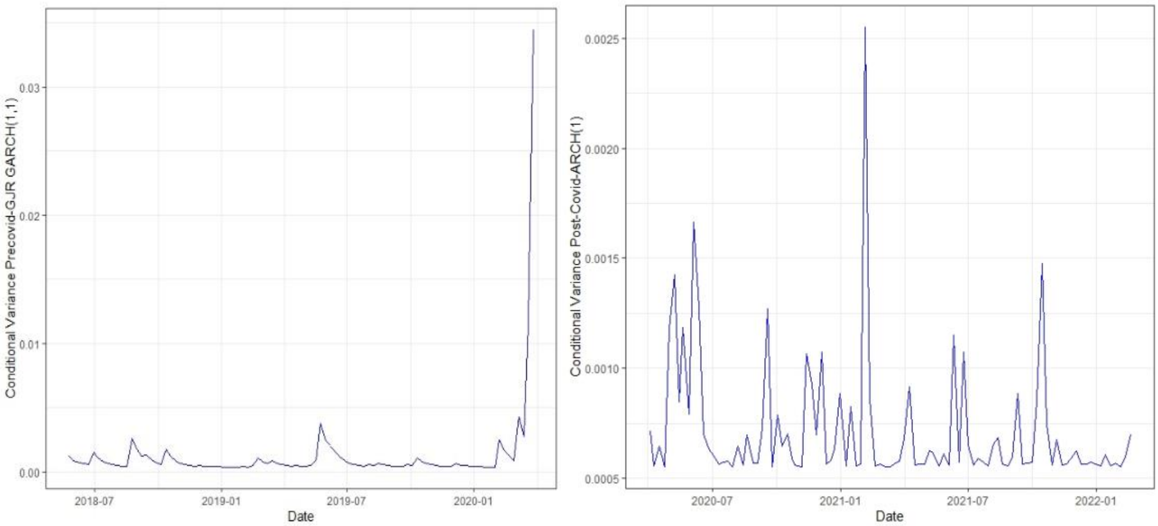

Figure 2. Plots of Conditional Variance of Stock Index Return of Highest Paying Dividends Companies

The bove figure shows the volatility of returns data before and after COVID. According to GJR-GARCH(1,1), the volatility before COVID was very mild. Not many turbulences occurred in the stock market. The most notable volatility ever occurred was just before July 2019. The volatility increased dramatically for a moment before reverting back to stability. This shows that the movement of the stock index was not rampant. Approaching the pandemic, the volatility suddenly surged dramatically. This portends the situation in which stock price and returns increased dramatically and suddenly and abruptly decreased. This could be a sign of high uncertainty facing the market participants. After COVID stroke, the returns data were more turbulent. The conditional variance increases frequently. This means that decrease or increase in stock price and returns will be followed with immediate increase or decrease of the following period returns. Right after January 2021, volatility increased very dramatically. Volatility was larger in magnitude toward the end of the research period compared to before COVID data. It can be inferred that it is so hard to see stability in stock price and returns after COVID.

4. CONCLUSION AND SUGGESTION

This research aims to determine the model with the highest performance for tracing the volatility of stock returns comprising the stock index for highest-paying dividend companies. The ARCH family models were employed. The models consist of ARCH family models, ARCH(1) and ARCH(2), and GARCH family models, GARCH(1,1) and GJR-GARCH(1,1). The return data were divided into pre-COVID and post-COVID data. Upon testing the model, GJR-GARCH(1,1) was found to have the highest performance for detecting and mapping the fluctuations of returns by scoring the lowest AIC and SIC. According to GJR-GARCH(1,1) the stock return was negative before COVID. This pointed to the fact that there is a sign of unfavorable economic condition before COVID. GJR-GARCH also proved that Indonesian market participants react more to the bad news than to the good news. Hence, asymmetric treatment to the news existed in the stock market. Post-Covid, the ARCH effect become less significant. The testing of ARCH

https://doi.org/10.24912/jmieb.v7i1.23150

 ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

effect proved the significance of ARCH effect was above 0.05 and less than 0.1. This means it becomes very hard to model and predict volatility after the pandemic hit. The economic condition becomes fuller of uncertainty. Hence, the systematic element of volatility decreases and the unsystematic element increases. Although ARCH effect lessens, it is still significant at 0.1. This means it can still model the volatility of highest paying dividend stocks. Further testing showed that ARCH(1) model was found to have the greatest performance to capture fluctuations of the index return. One caveat applies however, that the significance of the ARCH component now becomes less than ever before. The prior period residuals were significant at 0.15 for affecting the volatility. This proves even further that the volatility is moving toward the random walk model although it is not statistically random. Additional analysis showed that random effect did not happen. It is just that the movement of the index return was more random and less systematic. In this regard, ARCH(1) model is still appropriate to model the volatility. The limitation in this research lies in the use of weekly returns. Using more aggregated data means the movement is more systematic and therefore the daily random component is more and more diminished. Further research could endeavor to use daily return data to investigate the volatility of stock index return comprising the highest paying dividend companies.

REFERENCES

Aggarwal, R., Inclan, C., & Leal, R. (1999). Volatility in Emerging Stock Markets. Journal of Financial and Quantitative Analysis, 34(1), 33-55. doi:https://doi.org/10.2307/2676245

Amit & Bammi, R. (2016). Impact of News on Indian Stock Market: A Periodic Study with Asymmetric Conditional Volatility Models. Management and Labour Studies, 41(3), 169-180. doi:https://doi.org/10.1177%2F0258042X16666575

Andika, T., Fahmi, I., & Andati, T. (2019). The Macroeconomic Surprise Effects on LQ45 Stock Return Volatility. Jurnal Aplikasi Manajemen, 17(2), 235-243. doi:http://dx.doi.org/10.21776/ub.jam.2019.017.02.06

Emenike, K. O., & Enock, O. N. (2020). How Does News Affect Stock Return Volatility in a Frontier Market? Management and Labour Studies, 45(4), 433-443. doi:https://doi.org/10.1177%2F0258042X20939019

Hansen, P. R., & Lunde, A. (2005). A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH(1,1)? Journal of Applied Econometrics, 20(7), 873-889. doi:https://doi.org/10.1002/jae.800

Kingsley, A., & Peter, U. (2019). Volatility Modelling Using ARCH and GARCH Models: A Case Study of the Nigerian Stock Exchange. International Journal of Mathematics, Trends, and Technology, 65(4), 58-63. doi:http://dx.doi.org/10.14445/22315373/IJMTT-V65I4P511

Kurniasari, F., & Reyes, J. (2020). Determinants of LQ45 Index Banking Stock Price Volatility. Ultima Management: Jurnal Ilmu Manajemen, 12(2), 261-274. doi:https://doi.org/https://doi.org/10.31937/manajemen.v12i2.1771

Lee, S.-N., Hooy, C.-W., & Taib, F. M. (2019). The Effect of Corporate Governance on Firm Stock Volatility in Asia. Journal of Asia-Pacific Business, 25-47. doi:https://doi.org/10.1080/10599231.2019.1572421

Nazir, M. S., Nawaz, M. M., Anwar, W., & Ahmed, F. (2010). Determinants of Stock Price Volatility in Karachi Stock Exchange: The Mediating Role of Corporate Dividend Policy. International Research Journal of Finance and Economics (55)

Niewinska, K. (2020). Factors Affecting Stock Return Volatility in the Banking Sector in the Euro Zone. Journal of Economics and Management, 39(1), 132-148. doi:https://doi.org/10.22367/jem.2020.39.07

 https://doi.org/10.24912/jmieb.v7i1.23150

Nugroho, A. D., & Robiyanto, R. (2021). Determinant of Indonesian Stock Market's Volatility During the Covid-19 Pandemic. Jurnal Keuangan dan Perbankan, 25(1), 1-20. doi:https://doi.org/10.26905/jkdp.v25i1.4980

Nugroho, D. B., Pamungkas, B. A., & Arini, P. H. (2020). Volatility Fitting Performance of QGARCH(1,1) Model with Students-t, GED, and SGED Distributions. COMTECH: Computer, Mathematics, and Engineering Applications, 11(2), 97-104. doi:https://doi.org/10.21512/comtech.v11i2.6391

Ramasamy, R., & Munisamy, S. (2012). Predictive Accuracy of GARCH, GJR, and EGARCH Models Select Exchange Rates Application. Global Journal of Management and Business Research, 12(15)

Rodriguez, G. (2017). Selecting Between Autoregressive Conditional Heteroscedasticity Models: An Empirical Application to the Volatility of Stock Returns in Peru. Revista de Analisis Economico, 32(1), 69-94

Sari, L. K., Achsani, N. A., & Sartono, B. (2017). Pemodelan Volatilitas Return Saham: Studi Kasus Pasar Saham Asia. Jurnal Ekonomi dan Pembangunan Indonesia, 18(1), 35-52. doi:https://doi.org/10.21002/jepi.v18i1.717

Wulandari, R. (2021). Comparison of Volatility and Performance of Shares in Indonesia, Malaysia, China, and America. Asian Management and Business Review, 1(1), 46-56. doi:10.20885/AMBR.vol1.iss1.art5

Xie, F., Anderson, H. D., Chi, J., & Liao, J. (2019). Does Residual State Ownership Increase Stock Return Volatility? Evidence from China's Secondary Privatization. Journal of Banking & Finance, 100, 234-251. doi:https://doi.org/10.1016/j.jbankfin.2019.01.012

Yong, J. N., Ziaei, S. M., & Szulczyk, K. R. (2021). The Impact of COVID-19 Pandemic on Stock Market Return Volatility: Evidence from Malaysia and Singapore. Asian Economic and Financial Review, 11(3), 191-204. doi: 10.18488/journal.aefr.2021.113.191.204