Forecasting of Jakarta Islamic Index (JII) returns using Holt-Winters family models

Regi Muzio Ponziani

Sekolah Tinggi Ilmu Ekonomi Trisakti (*Trisakti School of* Management), Jakarta, Indonesia
Corresponding author: regi@stietrisakti.ac.id

Article history
Received, 25 October 2021
Revised 22, November 2021
Revised 1, December 2021
Accepted, 15 December 2021

Abstract

Purpose: This research aims to forecast JII returns by employing various Holt-Winters models. The models used in this research are Holt-Winters seasonality, Holt-Winters damped method, and Holt-Winters with maximum likelihood approach. Holt-Winters model is capable of recognizing and modeling trends and seasonality. Therefore, it is suitable for forecasting purposes.

Methodology: Three models are employed in this research. The first one is Holt-Winters seasonality, also known as triple exponential smoothing. This model analyzes the level, trend, and seasonality components in the return series. The second model is the Holt-Winters damped method that uses smoothing parameters to lower the overstatement effect that usually occurs within Holt-Winters seasonality. The third model is Holt-Winters with Maximum Likelihood. Holt-Winters seasonality estimates parameters by choosing the least-squares. At the same time, Holt-Winters with Maximum Likelihood uses maximum likelihood to fit in the series with certain distributions and generate forecasts by determining distributions with the most likelihood.

Findings: The result showed that Holt-Winters seasonality forecasts better than the other methods. The model could recognize the seasonal pattern and trend of the JII returns. It has the lowest Root Mean Squared Error (RMSE) as the parameter for forecast accuracy. Holt-Winters damped method has accuracy right below Holt-Winters seasonality. It can also map the pattern and trend of the returns. Holt-Winters with Maximum likelihood predicts less accurately. However, it can recognize the random walk inclination of the return, although it failed to generate the seasonal pattern and trend of the JII returns.

Originality: This research attempted to apply Holt-Winters models to predict JII returns. Most research concerning the Islamic stock index focuses on volatility and forecast based on the level of volatility. Therefore, this research can fill in the gaps in the literature in which forecast of Islamic stock index can be conducted by modeling the seasonality and trend using Holt-Winters models.

Practical implications: Investors always try to find the best generating investment return. Investors concerned with the shariah rules will always find lawful investment tools such as Islamic stocks or the Islamic stock index. Returns of the Islamic stock index can be forecast by using the Holt-Winters model. Therefore, investors might know the pattern of returns generated by investing in Islamic stocks.

Keywords: Forecast, Holt-Winters, Stock return, Seasonality

Cite this article:
Ponziani, R. M. (2021). Forecasting of Jakarta Islamic Index (JII) Using Holt-Winters Family Models. *Asian Journal of Islamic Management*, 3 (2), 111-122. https://doi.org/10.1108/AJIM.vol3.iss2.art4.

Center for Islamic Economics Studies and Development, Faculty of Business and Economics, Universitas Islam Indonesia
DOI: 10.1108/AJIM.vol3.iss2.art4

Introduction

Stock market is an important part of financing source for companies seeking liquidity. By meeting the needs of liquidity, the stock market will provide the capital necessary for the operation of the companies. Companies can continue providing goods and services and even expand operations and grow. Therefore, the literature has observed linkages between stock markets and economic development (Hismendi *et al.*, 2021). The more developed and deeper a stock market is, the more developed the economy in which the stock market resides. However, stock markets involve shariah compliant stocks and conventional stocks. Sharia-concerned companies will avoid interest from a financing arrangement and resort to the capital market to seek Islamic stocks (Hamimi & Ginting, 2019). Activities in the stock market are part of the Islamic code of conduct (*muamalah*); hence, they must satisfy shariah law in terms of the elimination of unlawful elements, namely *riba*, *ghrarar*, *maysir*, and anything forbidden (*haram*) (Abduh & Hussin, 2018). Stock market bridges investors who own surplus funds with companies that need liquidity.

Parties that have surplus funds include retail and institutional investors. Companies seek to finance their activities by issuing shares (Sutrisno, 2019). Those who have excess liquidity will look at the capital market as a means of investment. Investment in the capital market will yield dividends and capital gain that add to the principal investment. To harvest investment return, investors will try to predict whether the chosen equity investment will generate returns shortly (Handayani *et al.,* 2018). Indonesia Financial Service Authority (OJK) and National Shariah Board (Dewan Syariah Nasional) scrutinize certain stocks that meet the requirement to be categorized into shariah stocks. These stocks will then be grouped to comprise Jakarta Islamic Index (JII). The scrutiny is conducted regularly to update the list of eligible stocks. These stocks are favored by investors who prefer lawful and shariah-compliant investments (Masrizal *et al.,* 2019).

Investors also heed the volatility of the stocks they are interested in. Highly volatile stocks are considered risky because their returns could vary from time to time in a considerable gap (Nugroho & Robiyanto, 2021). Risk-averse investors will try to avoid this type of stock. However, some investors have a particular preference for volatile stocks since the fluctuation provides an opportunity for profit-taking action. Nowadays, the stock market has become global. Investors can at any time move their funds and invest in other stock markets. It renders the stock market more integrated. A capital flight will deplete liquidity in one place and increase liquidity. A gloomy look and not-so-good forecast of a stock market's prospect will provide a stimulus for investors to shift their investment elsewhere and do the prediction and forecasting whether they can obtain returns for that investment (Wulandari, 2021). It has showcased the importance of predicting and forecasting stock market prices and indexes.

Research involving the Indonesian Islamic stock index has been revolving around macroeconomic determinants (Majid, 2018; Masrizal *et al.,* 2019; Mubarok *et al.,* 2020; Nugroho & Robiyanto, 2021), volatility modeling, and forecasting (Burhanuddin, 2020; Hasbullah *et al.,* 2020; Mubarok & Bisma, 2020; Rusmita *et al.,* 2020; Bisma & Mubarok, 2021), and the performance of Islamic stocks and index (Muhari, 2020). This research will fill in the gaps in the literature by investigating how Indonesian Islamic stock index (JII). This research will conduct forecasting by employing various Holt-Winters models. It will provide insights for investors and related parties about the efficacy of the Holt-Winters model in forecasting stock index as the importance of forecasting for investors and analysts cannot be overstated.

Literature Review

Sharif and Hasan (2016) used the double exponential smoothing Holt-Winters model to forecast the data by constructing a model that consists of two estimated parameters α and β. The parameter α denotes the level parameter while β is the trend parameter. The research focuses on financial companies' shares prices in Dhaka stock exchange. The research period covered the whole year of 2016, hence daily data for one year. It found that the smoothing parameters are α, equals 0.5, and β, equals 0.1. It shows how today's price is significantly affected by prior day price. It is the essential feature of time-series data in which there will be high correlation among timely ordered data. The trend depicts a positive trend in which the share price has a positive inclination in the period covered in the study. The forecast results, when graphed, can resemble the actual results pretty closely. However, one thing that is missing is the data's seasonal feature. The curve seems to lag one period in terms of seasonal behavior.

The parameter γ usually denotes the fact that the Holt-Winters model did not include seasonal elements. Mallikarjuna and Rao (2019) researched the performance of various forecasting methods over several stock market indices. The forecasting methods covered the time-series econometrics model, such as Autoregressive Integrated Moving Average (ARIMA) and Self-Exciting Threshold Autoregressive (SETAR), as well as the artificial intelligence method such as Artificial Neural Networks (ANN), Singular Spectrum Analysis (SSA), and Hybrid Model (HM). HM combines ARIMA and ANN, combining traditional time-series econometrics and artificial intelligence capability. The ARIMA models employed by Mallikarjuna and Rao (2019) extend from 1,0,0 ARIMA to 4,0,4 ARIMA. All the ARIMA models are stationary, so no cointegrated components are necessary. The autoregressive components in ARIMA showed how the stock indices could be forecasted by the historical data of the stock indices themselves (hence the term "auto"), while the moving average components (MA) showed the role of errors at various lags to predict the current value of stock indices. The most value of MA in Mallikarjuna and Rao (2019) is 4, meaning up to 4 lags of errors have a significant contribution to forecast the value of today's stock indices. SETAR model consists of two different models. All the models are autoregressive.

The first step in SETAR is determining the threshold τ. The first model is estimated with a constant coefficient and estimated parameters of autoregressive components if the lag value is less than τ. The second model is also estimated with a constant coefficient and estimated parameters of autoregressive components if the lag value is more than τ. ANN model can be said as one of the most recent techniques in forecasting that utilize the computing power of modern equipment. ANN resembles the mechanism of neurons in the cells. Next, ANN will form many layers of neurons and assign weight to each neuron. This neuron will carry the weight as the contribution to forecasting target variables. Since the computing power is vast, the ANN can employ hundreds of thousands of neurons. Therefore ANN is also termed as using hyperparameters.

SSA model is a forecasting model that uses matrix algebra. It transforms data from time-series orders to matrix order and computes the singular value decomposition (SVD) to arrive at essential features and variables for forecasting. From SVD, it proceeds to a group of the data into several elementary matrices and performs the diagonal leveraging to derive the Hankel matrix forms that will later be converted into time-series data due to forecasting. The process itself will be automated by artificial intelligence software such as python, or R. Mallikarjuna & Rao (2019) found that no single forecasting method is universally superior compared to others. However, they found that the time series econometrics model (ARIMA and SETAR) performed well in 18 stock indices out of 24. It shows that time-series econometrics models can outperform artificial intelligence methods. Based on this finding, this research will identify one of the time series models, namely the Holt-Winters models.

Mubarok and Bisma (2020) attempted to determine which stocks within JII have the lowest and highest volatility. They contended that volatility is vital for forecasting and stock movement predictability. Tracking the movement of the stock for 20 years, they employed the GARCH model to analyze the pattern of volatility. The current value of stock volatility is determined by the prior period volatility and the lagged error value. They also found that stock with code TLKM has the lowest level of risk, while UNTR has the highest risk. Hence, TLKM is appropriate for risk-averse inventors, while UNTR is suitable for risk-taking investors. Rusmita *et al.* (2020) investigated capital market volatility employing MGARCH analysis. MGARCH belongs to the family of GARCH model that uses a constant covariance matrix to reduce parameters so that estimation becomes less complicated. Just like GARCH model in general, MGARCH posits that variance will be affected by lagged variance and lag residuals. In the research, they compared the stock markets of Indonesia and Malaysia. They found that, for the case of Malaysia, the Islamic stock index is more volatile than the conventional one.

The parameters of lagged residuals are more significant than the counterpart of Indonesia's. It gives more opportunity for investors to reap gains from the movement of stock price. While for Indonesia, the Islamic stock index has less volatility. They relate this finding to the low-risk investment in Islamic stocks. Investors will keep the shares in their inventory, which causes the price movement to be less active. They also found a specific correlation between conventional and Islamic stock indexes, although internationally, Indonesia and Malaysia have a very low correlation in the stock index. They also pointed out that it might not benefit investors wanting to diversify portfolios among Indonesia and Malaysia stocks. Burhanuddin (2020) employed various GARCH models to investigate some international Islamic stock indexes, such as FTSE All-World Shariah Index (FTSE: SWORLDS), Dow Jones Islamic Market World Index (DJIM), MSCI World Islamic Index (MSCI: MIWO), and S&P Global BMI Shariah Index (S&P: SPSHGLUP). The GARCH model is classified into symmetric and asymmetric models. Asymmetric GARCH model means negative shock will have a higher impact on the volatility of the series, while symmetric GARCH treats positive and negative shocks equally.

Burhanuddin (2020) found that asymmetric GARCH models are more superior to the symmetric ones to map and forecast the volatility patterns of Islamic stock indices. The asymmetric models in question are EGARCH, TGARCH, and PGARCH. However, the resulting root means squared errors (RMSE) and mean absolute errors (MAE) are low among asymmetric models. Therefore, he concluded that no one ultimate asymmetric model could overcome the other models. Therefore the use of multiple models is recommended. Hasbullah, Rusyaman, & Kartiwa (2020) aimed to examine how Islamic stocks are correlated with the composite market index. Causality is determined using Granger Causality and Vector Autoregressive (VAR), while volatility is analyzed using the GARCH model. They found a bi-direction of causality between Islamic stocks and composite market index. Further, they also found that the spillover from composite market index to Islamic stocks can be modeled using GARCH (1,1). It means the volatility of the conventional stock market can be used to predict the volatility of the Islamic stock index. This fact is corroborated by the Granger causality existed. They expected the result to add value to the investment decision by investors in the stock market.

Bisma and Mubarok (2021) researched the volatility of certain Islamic Stocks. They focused on six stocks that belong to JII. They investigated the movement of these stocks from January 2009 to December 2020. They found that all the stocks in the research have volatility that significantly belongs to GARCH model. Therefore there is a time-varying conditional variance of the volatility. Further, they stressed that investors that prefer low risk could invest in stock with code ASII, and risk-taking investors should choose stock with code UNTR. Finally, they recommend using the GARCH model to investigate the volatility of JII. It hints that there are inter-period correlations among volatilities of different periods. We have to use the prior period volatility and residuals to forecast volatilities. We can only forecast the share price using the maximum likelihood method after forecasting the volatility.

Mallikarjuna and Rao (2019) show that time-series econometrics models are powerful for forecasting. It provides an underpinning for this study to use other time-series models, Holt-Winters models, to forecast returns of the Jakarta Islamic Index. Forecasting of Islamic stock index returns is still very rare in literature. Most research prefers to forecast volatility using the existing framework of GARCH models. We can determine whether JII return has seasonality and trend by employing Holt-Winters.

Research Methods

This research investigated the best forecasting technique among Holt-Winters Model. There were three models tested in this research: Holt-Winters seasonality, Holt-Winters damped method, and

Holt-Winters with Maximum Likelihood. All three models would be applied to the JII data. JII data contained JII index from January 2010 until August 2021. The JII data were divided into two categories. The first category was training data. These data extended from January 2010 to December 2020. Training data served the function of the model generator. The three Holt-Winters models would be applied against training data in order to produce the appropriate model forecasting. After finding the model, all Holt-Winters models would then be used to generate forecasts for January 2021 until August 2021. These forecast numbers were then compared to the actual data of January 2021 to August 2021 to determine the best forecasting model. The first model being applied to training data was Holt-Winters seasonality. This model includes three parameter estimates: level, trend, and seasonality parameters. This model can identify correlations among periods, including the seasonal pattern and trend. The equations for Holt-Winters seasonality are as follow:

$$\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m(k+1)}$$
$$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$$
$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)\, b_{t-1}$$
$$s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$$

The first equation shows that the forecast for a certain value depends on the level parameter and trend and seasonality parameter. The level parameter is seasonally adjusted, as can be seen from the term $y_t - s_{t-m}$. The term bt denotes the trend of the series. The trend depends on the value of the level term ℓ_t. Since ℓ_{t-1} will be deducted from ℓt, we can investigate the trend by looking at the movement of the JII data from time to time. The seasonal equation, $s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$, shows the pattern of the series from the same month for different years. Therefore, if the JII index tends to experience a rise, for example, every January due to the January effect, then the model will be able to pick up the pattern. The coefficients α, β, and γ are to be estimated. Each coefficient relates to the level, trend, and seasonality. The second model is Holt-Winters damped method. This model also includes the level, trend, and seasonality components. The difference with Holt-Winters seasonality lies in the forecast equation used by parameter to smoothen the forecast results. The forecast equation is as follows:

$$y_{t+h|t}=[\ell_t+(\phi+\phi_2+\cdots+\phi_h)b_t]s_{t+h-m(k+1)}$$
$$\ell_t=\alpha(y_t/s_{t-m})+(1-\alpha)(\ell_{t-1}+\phi b_{t-1})$$
$$b_t=\beta*(\ell_t-\ell_{t-1})+(1-\beta)\phi b_{t-1}$$
$$s_t=\gamma y_t(\ell_{t-1}+\phi b_{t-1})+(1-\gamma)s_{t-m}$$

We expect the forecast results to be more smoothed than Holt-Winters seasonality due to damping parameters ϕ. This research used the standard value of ϕ that is the default value in R software equal to 0.98.

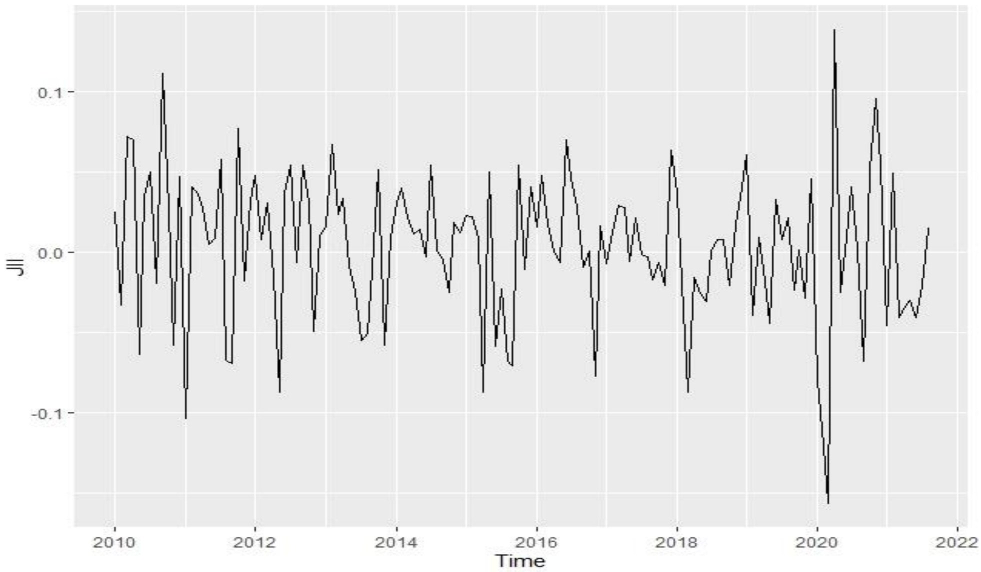
The third model is Holt-Winters with Maximum Likelihood. The previous two models of Holt-Winters are based on the least squared method. In comparison, this third method employs maximum likelihood to find the data distribution. The statistical program will try to fit the series or data into many different distributions and determine which distribution has the highest probability to be the distribution of the data. Therefore, the distribution is not based on Gaussian distribution as the normal distribution usually does. The software used in this research is R Studio.

Forecast accuracy will be determined using Mean Absolute Error (MAE), Mean Squared Error, and Root Mean Squared Error (RMSE). Basically, all three measure the divergence of forecasts from the actual results (the difference between ŷ and y). For MSE and RMSE, the difference will then be squared and sum together for all forecast periods divided by the number of forecast periods. Lastly, the root number will be taken from this average in RMSE. These three measures are very common as a standard check of forecast accuracy (Tripathy, 2017). In mathematical terms:

$$\text{MAE} = 1/n\ (\hat{y} - y)$$
$$\text{MSE} = 1/n(\textstyle\sum_{t=1}^{N}(\hat{y} - y)^2)$$
$$\text{RMSE} = \sqrt{1/n(\textstyle\sum_{t=1}^{N}(\hat{y} - y)^2)}$$

Results and Discussion

Figure 1. displays the time-series movement of the JII index from January 2010 to August 2021.



(Source: OJK, 2021)

Figure 1 Jakarta Islamic Index Returns

Figure 1. shows the data of JII from January 2010 to August 2021. We can see that visually the data are stationary. It will always revert to the mean with seemingly constant variance. The seasonality is present, indicated by the existence of peaks and throughs. The returns are very high at certain times, as spikes (peaks) in the figures. While at other times, the returns are very low, like valleys. The Holt-Winters model will take the seasonality into account when we use it to forecast the returns from January to August 2021. The trend is not visible by naked eyes. If there is a trend in the data, the coefficient of the trend must be minimal because it is not markedly noticeable. Basically, an increasing return will have a certain peak from which the return starts to decrease. When it reaches the low peak, the return will revert to the mean by increasing. It went on and on from January 2010 to the beginning of 2020. The beginning of 2020 marks the commencing of the COVID pandemic. We can see a very sharp decrease around March or April 2010. This decrease in return reached an all-time low in which this low return never happened before during the periods covered in the research. The return was around -15%. It means, in general, the stock prices that comprise JII index suffered from 15% decrease in price. A price decrease can be interpreted as temporary depletion of investors' welfare.

At the beginning of the COVID, people need liquidity to cover their daily necessities. Therefore, liquidity was drawn from the stock market to enter into the banking system or cash withdrawal (Nurchayono *et al.,* 2021). To obtain liquidity, investors will sell stocks. The simultaneous act of selling propagates and starts lowering the share price. However, due to the mean reversion property usually seen in capital market data, a vast decrease means there is a significant probability that the share price will bounce back and increase drastically. It is truly realized in the research data. Following an immense decrease in returns, JII returns increased enormously in the following periods. The return reached an all-time high, never before seen in the periods covered in this research. Since then, the return keeps fluctuating until the end period. Figure 2 displays the decomposition of JII data.

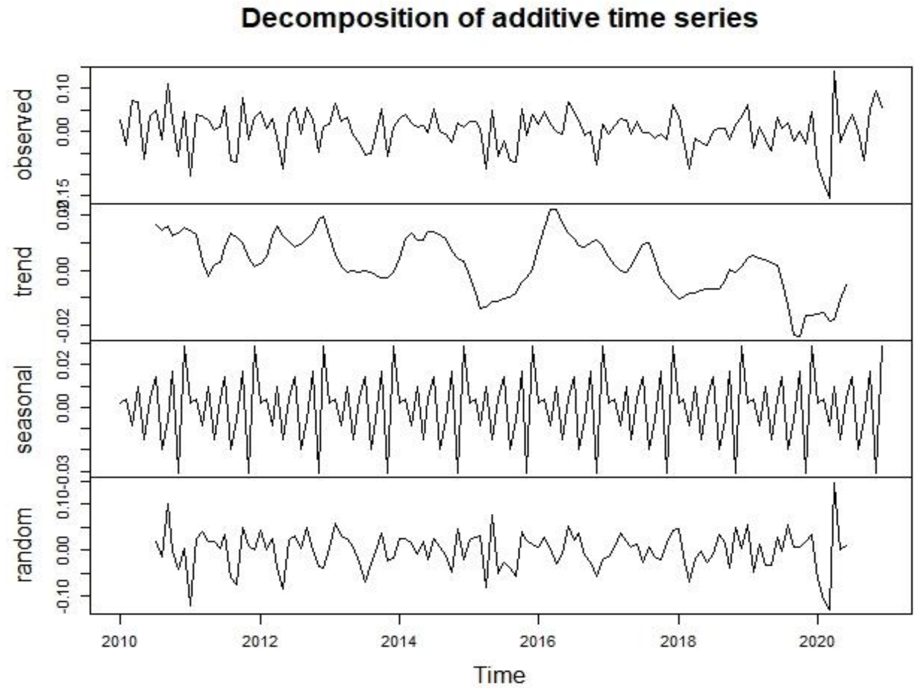


Figure 2. Decomposition of Jakarta Islamic Index Returns Data

Figure 2. shows that the JII returns data indeed contain seasonality element. There are certain times when the returns are high and when the returns are low. The Holt-Winters models have been able to capture this seasonal pattern. Therefore we can expect some parameters for the seasonal equation. The trend component indeed exists. Overall, there is a slightly decreasing trend for JII returns. However, it is not a steadily decreasing trend. Increasing trends intersperse with decreasing trends that make the trend less obvious. However, it is a downward trend. Therefore we can expect the parameter estimate for trend will exist in the trend equation. The random component is pretty significant. It comprises the unsystematic component of the return movement. The table below shows the result of parameters estimation using Holt-Winters seasonality, Holt-Winters damped method, and Holt-Winters with Maximum Likelihood.

Table 1. Holt-Winters Seasonality Estimates

Holt-Winters Seasonality Estimates			
Parameters	Alpha	Beta	Gamma
	0.0125	0.0001	0.0434
	Initial States: l = 0.0173 b = -0.0001 s = 0.034; -0.0221; 0.0175; -0.0112; -0.0191; 0.014 -0.0012; -0.0123; 0.0027; 0.0009; 0.002; -0.0052 Sigma = 0.0477 AIC = -141.85308 AICc = -136.48466		

Table 1. shows the parameter estimates for α, β, and γ. The β coefficient indicates the trend of the JII returns. The model is capable of recognizing this trend. It denotes the strength of Holt-Winters models to recognize and pattern the trend inclination of the data (Aryati *et al.,* 2021). The

values for α and γ are quite significant, 0.0125 and 0.0434. The value of β is 0.0001, indicating the trend is very smooth and does not change abruptly. There are 12 different values for s, one for each month. So there is seasonality in the data. A particular month will influence the value for the same month next year. We can infer that Holt-Winters seasonality can capture the trend and seasonality in the data. Table 2 displays the result from Holt-Winters damped method.

Table 2. Holt-Winters damped method estimates

Holt-Winters damped method			
Parameters	Alpha	Beta	Gamma
	0.0001	0.0001	0.0107
	Initial States: l = 0.0208 b = -0.0005 s = 0.0352; -0.0316; 0.0144; -0.0075; -0.0203; 0.0156 0.006; -0.0143; 0.0034; -0.0024; 0.0026; -0.0012 Sigma = 0.047 Phi = 0.979 AIC = -144.06505 AICc = -139.01195		

Table 2. shows the parameter estimates for α, β, and γ from damped method testing. The β coefficient indicates the trend of the JII returns. The model is capable of recognizing this trend despite its small value. The values for α and β are both 0.0001. It is how the damped method works. It tries to smooth the result to avoid overfitting and overestimation and therefore attaches a small number of α. Therefore the parameters of estimation will not be substantial. Again, there are 12 different values for s, one for each month. So, according to the damped method, there is seasonality in the data as well. A particular month will influence the value for the same month next year. Therefore we can infer that Holt-Winters damped method seasonality can capture the trend and seasonality in the data although with smaller parameter estimates. The following table displays the result from Holt-Winters with Maximum Likelihood.

Table 3. Holt-Winters with Maximum Likelihood estimates

Holt-Winters with Maximum Likelihood			
Parameters	Alpha	Beta	Gamma
	0.0001	0	0
	Initial States: l = 0.0042 Sigma = 0.0468 Phi = 0.979 AIC = -159.5707 AICc = -159.3832		

Table 3. shows the result of estimation by Holt-Winters with Maximum Likelihood. This model recognizes the random walk pattern in the data. Random walk is very typical for capital market data. Therefore Holt-Winters with Maximum Likelihood does not suggest any equations for trend and seasonality. When there is no trend and seasonality, the forecast will revolve around a specific mean. Therefore every forecast will be the same. The difference in actual results is recognized as some random errors. We may expect that the forecast is just a level line constituting a specific mean. The forecast results of each model are shown in Table 3.

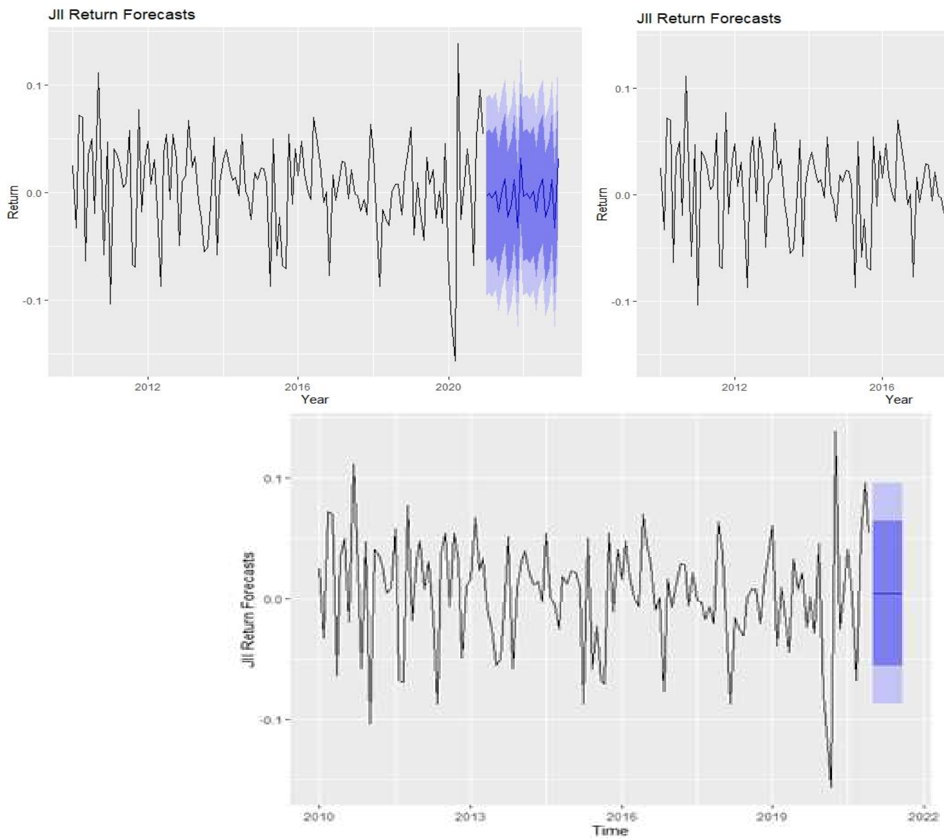


Figure 3 Holt-Winters Jakarta Islamic Index return forecasts

Figure 3 consists of three different forecast results. The top left figure shows forecast results from Holt-Winters seasonality. We can see that the results are not as marked as the actual data. The spikes and the valleys are not very drastic. However, they still exist. It represents the seasonality of the data. The top right figure shows estimation results from Holt-Winters damped method. The figure seems similar to the results of Holt-Winters seasonality, but they are different in terms of seasonality (γ value of 0.0434 for the Holt-Winters seasonality versus 0.0107 for the damped method). The difference will be noticeable when the forecast results are written in table form. The lower figure displays forecast results from Holt-Winters with Maximum Likelihood. As previously stated, the model recognized the random walk pattern and therefore decided that the best estimates be a certain mean number. Table 4 displays the forecast figures and forecast accuracy.

Table 4. Forecasts Results and Accuracy

Date	Actual Return	HW Seasonal	HW Damped	HW Max Likelihood
01/01/2021	-0.04548	-0.00751	-0.00352	0.004229
01/02/2021	0.049356	-0.00626	-0.00074	0.004229
01/03/2021	-0.0408	-0.00867	-0.00541	0.004229
01/04/2021	-0.03345	0.001284	0.001654	0.004229
01/05/2021	-0.03042	-0.02124	-0.01791	0.004229
01/06/2021	-0.04108	-0.00435	0.00314	0.004229
01/07/2021	-0.02115	0.009235	0.013018	0.004229
01/08/2021	0.01479	-0.02339	-0.02271	0.004229
MAE		0.034364	0.036367	0.036679
MSE		0.001323	0.001430	0.001495
RMSE		0.036379	0.037815	0.038671

Table 4 shows the forecast results in number. The Holt-Winter seasonality predicts that negative returns will occur 5 out of 8 months. In reality, it happens in 6 out of 8 months. However, the timing has some errors too. It mispredicts the negative returns in February and August 2021, when both months have positive returns in reality. Holt-Winter seasonality scores lowest in all three measures—the lower the number, the better the forecast accuracy. The Holt-Winters damped model correctly identified six months with negative returns. However, the timing is once again in err. It predicts that February and August will experience negative returns when in reality, they do not. It also predicts that positive return occurs in April and June, whereas both months suffer from negative returns. The Holt-Winters with Maximum Likelihood predicts uniformly. There will be only one prediction in all months, namely 0.4229% return. It is typical of the random walk model. Any deviation from the actual return will be deemed as a random error. The Holt-Winters seasonality model has the least RMSE, followed by Holt-Winters damped method. Holt-Winters with Maximum Likelihood has the most RMSE. We can conclude that Holt-Winters seasonality is the best model for predicting JII returns, followed by the Holt-Winters damped method. Holt-Winters with Maximum Likelihood has the worst accuracy, but it supports other research that states that capital market data most likely has a random walk model.

Conclusion

This research purpose is to compare forecast accuracy among Holt-Winters family models. Holt-Winters is chosen because of recognizing and modeling trends and seasonality. The models tested were Holt-Winters seasonality, Holt-Winters damped method, and Holt-Winters with Maximum Likelihood. The results show that Holt-Winters seasonality has the highest accuracy in forecasting, followed by Holt-Winters damped method. Both models are capable of modeling the trend and seasonality. The forecast results reveal the spike and the valley. Holt-Winters with Maximum Likelihood came up with the finding of the random walk model. Therefore the forecast revolved around a specific mean. The forecast results are one straight line. Another insight derived from the results is that JII returns are positive. The investors will get more returns in the long run by investing in companies' stock that adheres to Islamic values and standards. Markets value companies that comply with Islamic prescriptions. It proves that Islamic values provide companies with more sustainable and valuable market valuations. The limitations in the study involve the use of a research period that extends from normal times to pandemic periods. It has the potential to present some structural breaks in the data. Future research could investigate whether there is a significant difference in Islamic stock returns before and after the pandemic.

References

Abduh, M., & Hussin, T. M. (2018). Factors influence intention to opt for Islamic investment schemes among market players. *Global Review of Islamic Economics and Business, 6*(2), 91-102. https://10.14421/grieb.2017.051-01

Aryati, A., Purnamasari, I., & Nasution, Y. N. (2021). Peramalan dengan menggunakan metode holt-winters exponential smoothing. *Eksponensial, 11*(1), 99-106. Retrieved from http://jurnal.fmipa.unmul.ac.id/index.php/exponensial/article/view/650

Bisma, M. F., & Mubarok, F. (2021). Jakarta Islamic index stock volatility and forecasting using realized GARCH model. *Majalah Ilmiah Bijak, 18*(1), 27-39. https://doi.org/10.31334/bijak.v18i1.1228.g715

Burhanuddin. (2020). Investigating volatility behavior: Empirical evidence from Islamic stock indices. *Journal of Islamic Monetary Economics and Finance, 6*(4), 729-746. https://doi.org/10.21098/jimf.v6i4.1256

Hamimi, S., & Ginting, Y. R. (2019). The development of Islamic capital market. *Proceeding International Seminar on Islamic Studies* (pp. 762-767). Medan: Universitas Muhammadiyah Sumatera Utara. Retrieved from http://jurnal.umsu.ac.id/index.php/insis/article/view/4248

Handayani, H., Muharam, H., Mawardi, W., & Robiyanto, R. (2018). Determinants of the stock price volatility in the Indonesian manufacturing sector. *International Research Journal of Business Studies, 11*(3), 179-193. https://doi.org/10.21632/irjbs

Hasbullah, E. S., Rusyaman, E., & Kartiwa, A. (2020). The GARCH model volatility of Sharia stocks associated causality with market index. *International Journal of Quantitative Research dan Modeling, 1*(1), 18-28. https://doi.org/10.46336/ijqrm.v1i1.3

Hismendi, H., Masbar, R., Nazamuddin, N., Majid, M. S., & Suriani, S. (2021). Sectoral stock markets and economic growth nexus: Empirical evidence from Indonesia. *Journal of Asian Finance, Economics, and Business, 8*(4), 11-19. https://doi.org/10.13106/jafeb.2021.vol8.no4.0011

Majid, M. S. (2018). Assessing volatilities of monetary policy and their effects on the Islamic and conventional stock markets in Indonesia. *Signifikan: Jurnal Ilmu Ekonomi, 7*(2), 161-172. htttp://dx.doi.org/10.15408/sjie.v7i2.7352

Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of forecasting methods from selected stock market returns. *Financial Innovation, 5*(40), 1-16. https://doi.org/10.1186/s40854-019-0157-x

Masrizal, Mustofa, M. U., & Herianingrum, S. (2019). Macroeconomic determinants of Jakarta Islamic index. *The 2nd Internationa Conference on Islamic Economics, Business, and Philanthropy (ICIEBP)*, Surabaya: KnE Social Sciences, 510-524. Retrieved from https://knepublishing.com/index.php/KnE-Social/article/view/4227

Mubarok, F., & Bisma, M. F. (2020). Modeling of Jakarta Islamic index stock volatility return pattern with GARCH model. *Al-Tijary, 6*(1), 17-30. http://dx.doi.org/10.21093/at.v6i1.2468

Mubarok, F., Arif, M. N., & Mufraini, M. A. (2020). The stability of the Indonesian sharia stock index to economic shocks. *Iqtishadia, 13*(2), 138-156. https://doi.org/10.21043/iqtishadia.v13i2.7748

Muhari, S. (2021). Kinerja Jakarta Islamic index di masa pandemi Covid 19 tahun 2020. *Al-Mizan: Jurnal Hukum dan Ekonomi Islam, 5*(1), 60-76. https://doi.org/10.33511/almizan.v5n1.60-76

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. https://doi.org/10.26905/jkdp.v25i1.4980

Nurchayono, N., Hanum, A. N., & Sukesti, F. (2021). The Covid-19 outbreak and its impact on stock market retuns: Evidence from Indonesia. *Jurnal Dinamika Akuntansi dan Bisnis, 8*(1), 47-58. Retrieved from http://jurnal.unsyiah.ac.id/JDAB/article/view/18934

Robiyanto, R., Wahyudi, S., & Pangestuti, I. R. (2017). The volatility-variability hypotheses testing and hedging effectiveness of precious metals for the Indonesian and Malaysian capital markets. *Gadjah Mada International Journal of Business, 19*(2), 167-192. https://doi.org/10.22146/gamaijb.26260

Rusmita, S. A., Rani, L. N., Swastika, P., & Zulaikha, S. (2020). Capital market volatility MGARCH analysis: Evidence from Southeast Asia. *Journal of Asian Finance, Economics, and Business, 7*(11), 117-126. https://doi.org/10.13106/jafeb.2020.vol7.no11.117

Sharif, O., & Hasan, M. Z. (2019). Forecasting the stock price by using Holt's method. *Indonesian Journal of Contemporary Management Research, 1*(1), 15-24. https://doi.org/10.33455/ijcmr.v1i1.83

Sutrisno, B. (2019). Stock performance before and after right issue in Indonesia. *Agregat: Jurnal Ekonomi dan Bisnis, 3*(2), 97-111. https://doi.org/10.22236/agregat_vol3/is2pp97-111

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. https://doi.org/10.20885/AMBR.vol1.iss1.art5