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Stock Indices Forecasting: A Comparison of Holt-Winters Seasonality and Dynamic Harmonic Regression

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Abstract

This research aims to investigate the performance of various time-series forecasting approaches in predicting stock indices in Indonesia. This research compared the performance of additive Holt-Winters seasonality, multiplicative Holt-Winters seasonality, and Dynamic Harmonic regression. The stock indices being forecast are SRI-KEHATI, LQ45, and IHSG. Forecasting SRI-KEHATI index is the novelty in this research. SRI-KEHATI index contains all the companies that comply with the requirements regarding sustainability and concerns for the environmental impact of the companies operations. Decompositions of SRI-KEHATI, LQ45, and IHSG reveal that the trend and seasonality components are all existent within all indices. The results showed that Holt-Winters models are superior to Dynamic Harmonic Regression. Multiplicative Holt-Winters seasonality forecast best for SRI-KEHATI and LQ45. Additive Holt-Winters excelled at predicting IHSG. Although Dynamic Harmonic Regression had less accuracy, its performance was still very outstanding since its mean average percentage errors never exceeded 8%. The result signifies the excellence of the Holt-Winters model for predicting stock indices and also shows that Dynamic Harmonic Regression also scores high in accuracy. Both models validate the time variance notion of the stock market proposed by Boudreaux (1995). The practical benefit for Investors is that this research enables investors to forecast the stock indices in the future and make adjustments in their trading strategy thereof.

Keywords: Additive; Dynamic Harmonic Regression; Holt-Winters Seasonality; Multiplicative
JEL Classification: A2, G4, I2*

1. INTRODUCTION

The stock market has been very pivotal for economic growth (Anderi, 2020). A well-functioning capital market will drive productivity in the economy and thus spur economic growth. The influence of the stock market on the economy is both short-term and long-term (Kapaya, 2020). In the short-run, the stock market enables the increase in the production of goods and services that will circulate in the economy and embody the incomes of the population and, in the long run, the development of a country will ultimately depend on how well entrepreneurs and companies can obtain funds to expand or begin the operations.

Stock market not only provides funds that come from the surplus unit within a country but it also enables foreign investment to flow in to the productive sector that needs liquidity (Hoque & Yakob, 2017). Together with the banking system, stock market forms the bulk of capital from the surplus unit ready to be distributed to the productive endeavors within an economy. From the perspective of the capital provider, the stock market also is instrumental in providing a vehicle for investment (Pahlevi & Oktaviani, 2018). Stock market provides matching of investors' requirements of investment instruments providing reasonable yield to those in need of liquidity to resume operating activities that have the probability of generating income. Investors will in turn reap the reward of stock return as a result of price appreciation in addition to dividend distribution. Hence, the investors should be educated or informed enough to find out that return comes along with the risk that the investment will yield a negative return (Tanjung, Komariah, & Yusuf, 2020). Stock market risk has been a focus of attention by investors. Risk is often denoted by the volatility of the price movement (Escobari & Jafarinejad, 2019). The more volatile the stock's price movement the greater the opportunity to earn a capital gain. On the other hand, volatility also brings the downside risk in which investment by the investor declines in value (Herliawan, Kim, Saputra, & Ferdinand, 2020). Therefore, volatility is associated with the uncertainty that must be borne by the investors i.e. one factor that comprises the investment risk (Handayani, Farlian, & Ardian, 2019). Volatility is denoted by the speed of change in price. A highly volatile stock means that the stock's price undergoes rapid change in a short time. On the other hand, the less volatile a stock is, the later the movement of the price. In order to mitigate the risk of investment in stock, investors resort to forecasting the stock movement (Mallikarjuna & Rao, 2019). If the price of stock is predictable, then the investors can plan better the investment decisions regarding purchasing or selling the stocks. The determinants of the stock price volatility can consist of many factors, including micro- and macroeconomic factors (Kengatharan & Ford, 2019; Nasarudin, Suhendra, & Anggraini, 2019). These factors will interact and provide a dynamic that result in the shift of the share price (Nugroho & Robiyanto, 2021). Since the investment return or loss depends on which direction the price moves, investors will attempt to predict the final results of the share price movement. Therefore, forecasting occupies pivotal position in the investors' decision on investment. Ultimately, many forecasting methods were developed for many purposes and one of them is to aid investors in investing in the stock market. One popular method for forecasting is Holt-Winters seasonality (HWS). This method has been proven capable of capturing the trend and seasonal components of the data and generating a model for forecasting with reliable accuracy (Pertiwi, 2020; Muna & Kuntoro, 2021). Holt-Winters seasonality will be compared with Dynamic Harmonic Regression (DHR) in terms of performance in the forecasting. No research has been conducted to investigate the performance of dynamic harmonic regression in forecasting concerning stock market activities. DHR is more popular for prediction in science, such as for predicting power systems (Zavala & Messina, 2014) Therefore, this research will be the first to investigate such matter and compare its performance with a more well-known technique of Holt-Winters seasonality. Both methods will be employed to forecast stock indices. SRI-KEHATI, LQ45, and IHSG are the forecasting objects in this research. Again, research involving SRI-KEHATI index is still very rare. SRI-KEHATI is comprised of stocks from companies that have an environmental and sustainability focus. The results will reveal the performance of both methods and how the three stock indices can be forecasted. The results of the research will benefit many parties involved in capital market activities and regulations. Investors will benefit from selecting the best method for predicting stock index. One particular method of interest is How good the performance of Dynamic Harmonic Regression is compared to Holt-Winters models. Financial Service Authority (knows as OJK/*Otoritas Jasa* Keuangan) can also benefit from this research. By employing the chosen method in this research, OJK can predict how the capital market progresses each day. Financial Service Authority can anticipate whenever any negative development on the capital market is looming. This research will show which method is better at predicting and how much the gap is among models. In terms of theoretical usefulness, this research will validate whether a stock market movement is predictable or not. One very well-known theory in the stock market is The Monthly Effect proposed by Boudreaux (1995). According to Boudreaux (1995), movements in the stock market is not time-invariant. Therefore, the notion that movements are random and unpredictable is not entirely correct. Although share price reflect the new information flowing into the market participants, we can still track the movement of share price according to certain characteristics. Hence, Boudreaux (1995) asserted that time indeed exerted its influence on the movement of share price. Boudreaux (1995) later proved that there is pattern unique to the monthly movement of share price. At certain months in a year, there is an inclination for the share price to go up or down. This research will determine whether the time variance nature of stock market is indeed existent or not. If stock indices are time-invariant, then the forecasting techniques proposed in this research will perform badly. This will corroborate the notion that movements in stock markets are random and unpredictable. However, if the movements are time-variant, then stock indices do not move in random and can be predicted well by using forecasting techniques analyzed in this research. The implication for this research is that investors can time their investment and trading strategy according to the month when the trading and investing activities are taking place. Therefore, this research will also validate whether the stock indices indeed have time-variant or time-invariant properties.

The forecasting technique has long been employed concerning stock market. Some researchers forecast the volatility and some others forecast the share price. This research will fill in the literature gap by forecasting stock indices using Dynamic Harmonic Regression and Holt-Winters approach. Sharif & Hasan (2019) used Holt-Winters model to forecast stck price of Dhaka Stock Exchange for the period of 2016. The Holt-Winters model included the level and trend as well as the smoothing constant. They found that Holt-Winters model was very accurate for short-term prediction instead of long-term forecasting. The fourth-day prediction lied very close to the actual data. In addition, the seven and fifteen days forecasting were more accurate than thirty days forecasting. The resulting alpha and beta constants were 0.5 and 0.1. Sunarya (2019) analyzed NASDAQ composite index data from March 1971 until April 2019 in order to investigate and forecast the index volatility. He combined Autoregressive Integrated Moving Average (ARIMA) with Generalized Autoregressive Conditional Heteroscedasticity (GARCH) inn order to arrive at the model capable of forecasting the stock index. He found that a combination of ARIMA (8,0,6)-GARCH(1,1) to be the best model for forecasting. The combination of ARIMA and GARCH could better capture the trend, seasonality, and volatility of the stock index. Later, the model was used to generate forecasts for one year ahead. The resulting forecast showed only a litle fluctuation and volatility. Nikolaieva, Petrova, & Lutsenko compared the fundamental techniques of forecasting with that of time-series econometrics. Discounted Cash Flow (DCF) represented the fundamental method while ARIMA represented the econometrics method. They found that ARIMA was better used as the complement of DCF method. Using DCF method, we could figure out the financial conditions of the company, and whether it is safe and far from bankruptcy. The ARIMA models tested were ARIMA (1,1,0), ARIMA(4,1,3) with drift, ARIMA (1,2,1), and

ARIMA(1,0,0) with non-zero mean. All ARIMA methods yield forecasts with different trends. Atmaja, Widowati, & Warsito (2021) used Vector Autoregressive Integrated Moving Average with Exogenous Variable (VARIMAX) to forecast stock prices comprising the LQ45 index. The data spanned from 1 January 2019 to 30 September 2019 of three selected companies. The data were daily data. Apparently, the exogenous variable used in the research were variables with nominal data. They found that VARIMAX (0,1,2) was the best model for forecasting. The data were found to be nonstationary so that first-order integration was necessary to make them stationary. Meher, Hawaldar, Spulbar, & Birau (2021) conducted a research on forecasting stock market prices of some Indian pharmaceutical companies. They used daily price data extending from 1 Janury 2017 to 31 December 2019 with 782 time-series observations. Some ARIMA models performed better for selected stocks. ARIMA(24,1,47), AR(9), AR(13), AR(194), and ARIMA (29,1,115) were among the models that had the lowest Akaike Information Criterion (AIC) and Schwarz Criterion (SC), hence the best model for forecasting. The use of daily data resulted in ARIMA that extended back a long period as far as 115 lags. This shows how related are the share prices when the unit analysis becomes more detailed. ARIMA model is capable of predicting fluctuating prices that extend for a long period of time. R and R squared became the parameter to measure the performance of the forecasting method in this research.

2. HYPOTHESES DEVELOPMENT

This research will compare the forecasting performance between Holt-Winters seasonality and Dynamic Harmonic Regression. Two models of Holt-Winters seasonality will be used, namely additive and multiplicative models. Holt-Winters have been confirmed superior for prediction and forecasting (Aryati, Purnamasari, & Nasution, 2020; Dewi & Listiowarni, 2020). The superiority of Holt-Winters is linked to its capability to capture level, trend, and seasonality. The other method used is Dynamic Harmonic Regression. This method is well-known for capturing the seasonal pattern and trends that exist in the model due to the use of sines and cosines functions. However, existing research mostly apply Dynamic Harmonic Regression in the natural science context (Zavala & Messina, 2014; Ayhan, 2020). This research will be the first to apply the Dynamic Harmonic Regression model for predicting stock index. Therefore, we will find out the forecast accuracy of Dynamic Harmonic Regression compared to the more popular Holt-Winters seasonality model. The forecasting models will be applied on stock indices. Three stock indices are used, namely SRI-KEHATI, LQ45, and IHSG. LQ 45 is comprised of the 45 most liquid stocks and has been the subject of much research. However, it is very rare to find research focusing on forecasting the movement of LQ 45 index as well as IHSG index (the composite index of all stocks listed in the Indonesian stock exchange). SRI-KEHATI is an index that consists of stocks of companies that are operating environmentally friendly and adopt responsible investment. The companies are considered to be *green* and sustainable. Again, very few research researching SRI-KEHATI index, and none has involved forecasting. Therefore, this research does not state any hypothesis because the purpose of the research is to find which method performs better in forecasting stock indices. Forecast accuracy will be measured using mean absolute error (MAE) and mean absolute percentage error (MAPE).

3. METHOD, DATA, AND ANALYSIS

The data used in this research spanned from January 2010 to October 2021. All were monthly data. The data comprised the SRI-KEHATI, LQ45, and IHSG indices. The data were split into 2 categories, training and test data. Training data extended from January 2010 until December 2020. These data were used to generate models. The models generated were later employed to yield forecasts for January to October 2021. The forecast data were then compared to the test data, the actual data from January until October 2021. This would reveal the forecast accuracy of each method. Three methods were employed for forecasting, Additive Holt-Winters seasonality, multiplicative seasonality, and Dynamic Harmonic regression. Additive and multiplicative Holt-Winters seasonality include equations for level, trend, and seasonality. The following is the additive Holt-Winters model.

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

The first equation shows the general equation of additive Holt-Winters seasonality. It states that the forecast of a variable $\hat{y}$ consists of the level term (ℓ_t), trend term b_t, and seasonal term s_t. After that, each term is derived from its own equation. The level term ℓ_t is seasonally adjusted, $y_t - s_{t-m}$, and it also depends on the previous level and trend term $\ell_{t-1} + b_{t-1}$. The trending term b_t is derived from the difference in level term $\ell_t - \ell_{t-1}$, and it is also affected by the previous trend b_{t-1}. Lastly, seasonality is affected by the result of deducting the previous level and trend term from the actual observation, $y_t - \ell_{t-1} - b_{t-1}$, and is also affected by the previous seasonal term, s_{t-m}. The parameters α, β, and γ are to be estimated. The multiplicative model of Holt-Winters seasonality is as follows.

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

We can see from the above equations that the main difference between additive and multiplicative Holt-Winters seasonality lies in the calculation of level and seasonal terms. In multiplicative seasonality, the division operation is used in the computation. Just like additive seasonality, the parameters α, β, and γ are to be estimated. The third method used in this research is Dynamic Harmonic Regression. It is basically a regression function that matches the dummy variable with the dependent variable, in this case, stock indices. However, there are additional Fourier terms to capture the seasonality. The general equation for Dynamic Harmonic Regression is:

$$Y_t = a + bt + \sum_{k=1}^{K} [\alpha_k s_k(t) + \beta_k c_k(t)] + \xi$$

The terms s_k and c_k are Fourier terms. They are sines, and cosines functions mean to capture seasonality. In turn, the equation for Fourier terms are:

$$s_k = \text{Sin}\,(2\pi kt/m)$$
$$c_k = \text{Cos}\,(2\pi kt/m)$$

The term b in the general equation and m in the Fourier terms are just labeled. They are the dummy terms indicating the time function. Since we use monthly data, there will be 11 dummy variables. The critical point in Dynamic Harmonic Regression is the determination of the number of K.

4. RESULTS

The following displays the result of plotting the movement of the three stock indices over time.

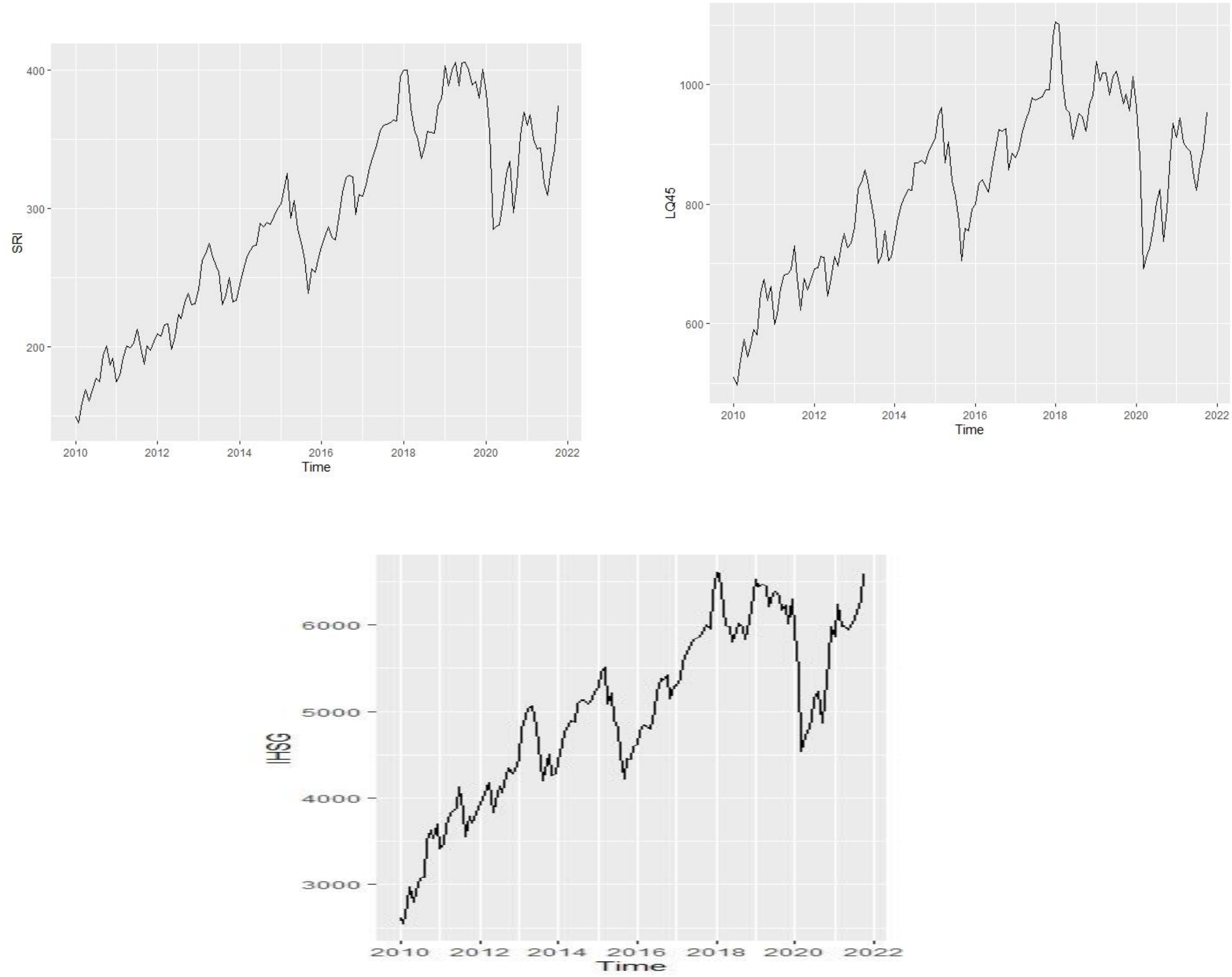


Figure 1. Movement of SRI-KEHATI, LQ45, and IHSG from 2010 until 2021

The above figure shows how SRI-KEHATI, LQ45, and IHSG indices fluctuate over time, beginning from 2010 until October 2021. All three indices show almost similar figures. Overall, the direction is the same. What differentiates the figure is the contrast in spikes and through undergone by each index. In general, the overall trend is always increasing. SSRI-KEHATI index began slightly below 150 in 2010, while LQ45 and IHSG began at around 550 and 2500 respectively. In a short time, the index show volatility. Since then, the indices have kept increasing. In 2013, all the indices showed a spike. There were sharp increases for a while, followed by sharp decreases. The difference lies in the intensity. The increases seemed drastic for LQ45 and IHSG, while for SRI-KEHATI it seemed just moderate. Beginning in the early 2014 until 2015, the indices again experienced sharp increase. The trend is very positive, although for SRI-KEHATI there is little volatility in the midst of 2014. The volatility is more apparent compared to LQ45 and IHSG. After 2015, the indices underwent a decrease until near 2016. After that, the increase continued the upward trend. The upward trend persisted until 2018, when it reached the highest peak for all three indices. From 2018 to the end of 2019, the indices were volatile. They fluctuated very much.

However, no sharp decrease was apparent. 2020 marked the beginning of the pandemic. Early 2020 saw a huge decrease in all three indices. This was the result of a decline in the economic activity due to restricted mobility all over the globe. Almost all businesses experienced hardships due to falling customer demands. Only a handful of businesses that can weather the pandemic, especially businesses dealing with online sales, and utilize digital marketing readily (Chasanah, Jahroh, & Dewi, 2021). Since then, the indices have slowly recovered and seem to have reached the highest level it once reached in 2018. Below is presented the decomposition of SRI-KEHATI index

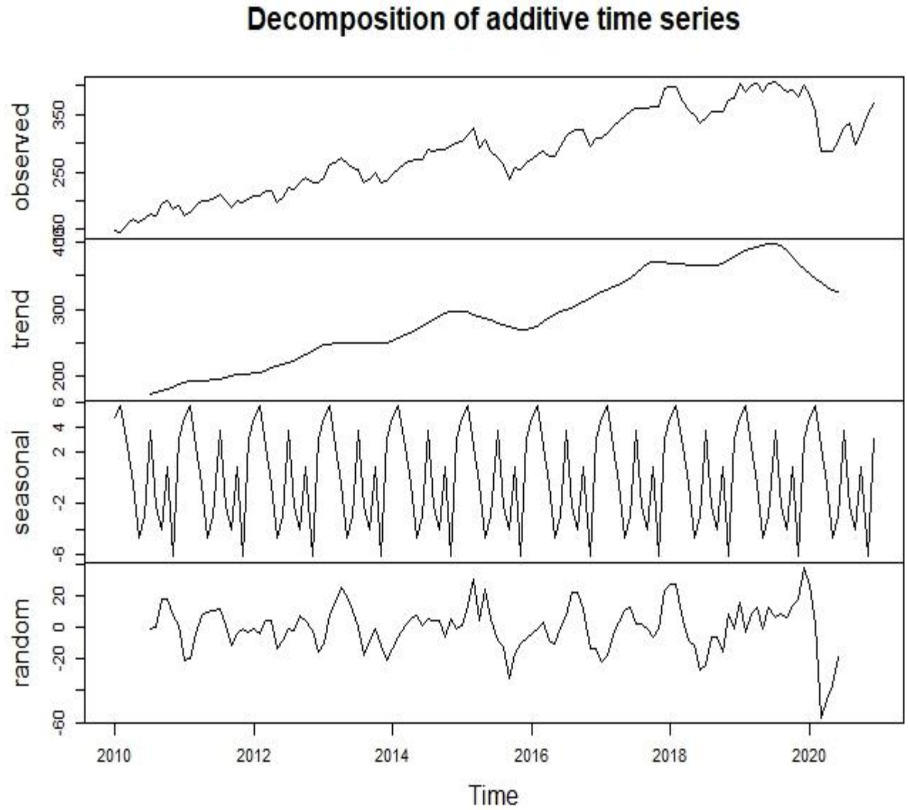


Figure 2. Decomposition of SRI-KEHATI Index

The above figure shows the decomposition of SRI-KEHATI index. The topmost subfigure shows the actual movement of SRI-KEHATI. This is the same figure as the one in figure 1. The second subfigure shows the trend of SRI-KEHATI. The trend is indeed increasing with minor volatility here and there. From 2019 onwards, there is actually an inclination for decreasing trend. This shows that the recovery from the pandemic must be conducted cautiously to ensure a smooth recovery of the economy. The third subfigure is the seasonal component. There is marked seasonality in the movement of the SRI-KEHATI. There are times when the index experiences an increase and there are times when it decreases. The models employed for forecasting in this research will attempt to model all the level, trend, and seasonal components of all the indices. Below is presented the decomposition of LQ 45 index.

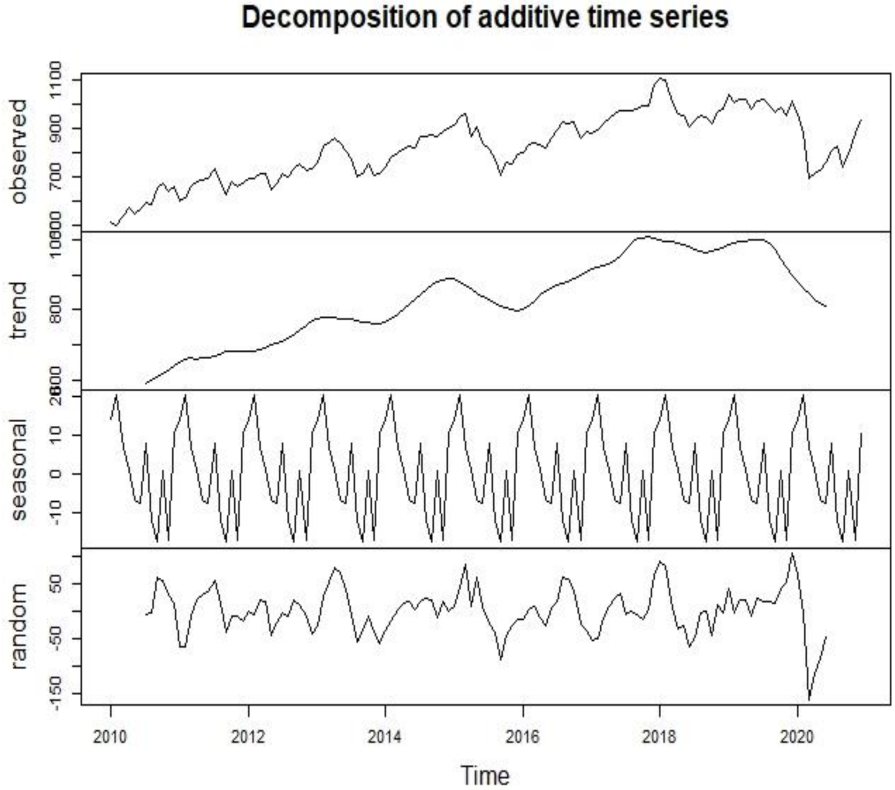


Figure 3. Decomposition of LQ45 Index

The above figure shows the decomposition of LQ45 index. As mentioned in the previous figure, the top most subfigure shows the actual movement of LQ45. As before, this is the same figure as the one in figure 1. The second subfigure shows the trend of LQ45. The trend was always increasing until 2018. From 2018 to 2019, it fluctuated a little bit. From 2019 onwards, there is again a tendency for decreasing trend. Again, this shows that the recovery from the pandemic must be conducted carefully so that there is a smooth recovery of the economy. The third subfigure is the seasonal component. There is marked seasonality in the movement of the LQ45. There are times when the index experiences an increase, and there are times when it decreases. Below is presented the decomposition of IHSG index.

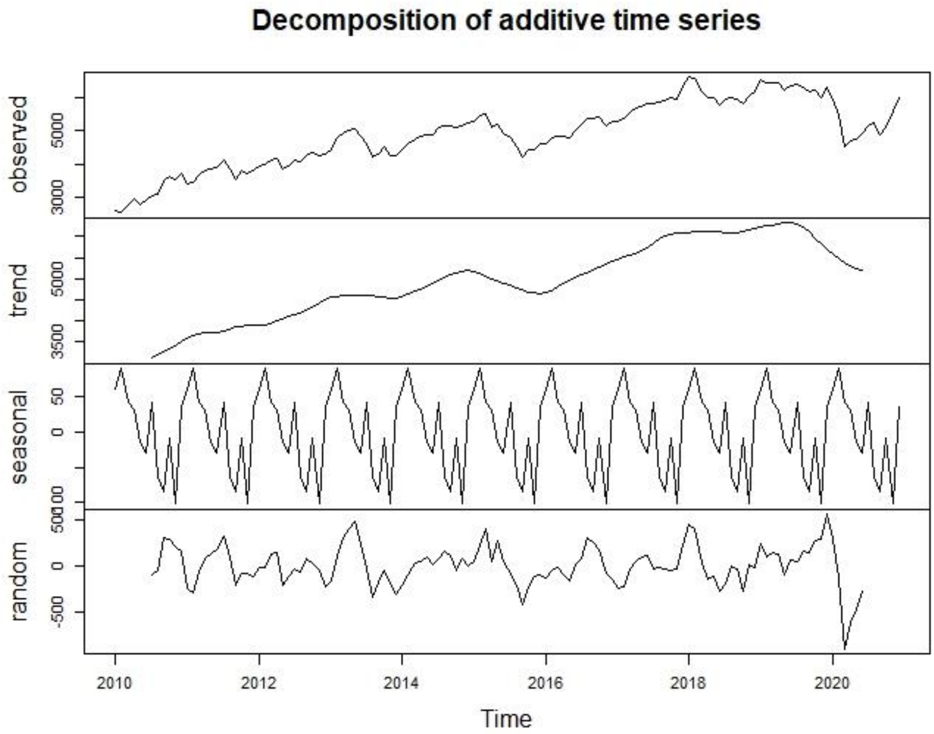


Figure 4. Decomposition of IHSG Index

The above figure shows the decomposition of IHSG index. Just like before, the top most subfigure shows the actual movement of IHSG. Again, this is the same figure as the one in figure 1. The second subfigure shows the trend of IHSG. The trend was always increasing until 2018. From 2018 to 2019, it tended to be flat. From 2019 onwards, there is again a tendency for decreasing trend. This shows the effect of the pandemic. Subsequently, there is a stark seasonality in the movement of the IHSG. There are moments when the index experiences an increase and vice versa. The table below shows the analysis of Additive Holt-Winters seasonality on all the indices.

Table 1. Additive Holt-Winters Seasonality Estimation

Holt-Winters Parameters	**Alpha**	**Beta**	**Gamma**
SRI-KEHATI	0.999	0.0001	0.0001
	Initial States: l = 153.1047 b = 1.6494 s = 3.1017; -6.0291; 0.674; -3.303; -1.2531; 3.3258; -1.9115; -5.5738; -0.3131; 2.5892; 5.5202; 3.1727 AIC = 1365.411; AICc = 1370.78		
Holt-Winters Parameters	**Alpha**	**Beta**	**Gamma**
LQ45	0.9999	0.0118	0.0001
	Initial States: l = 563.1412 b = 7.894 s = 8.7132; -16.4406; -0.3203; -17.3635; -11.5588; 7.092; -6.8469; -6.2627; 4.291; 7.2163; 18.9376; 12.5426		

	AIC = 1642.082; AICc = 1647.451		
Holt-Winters Parameters	**Alpha**	**Beta**	**Gamma**
IHSG	0.9999	0.0126	0.0001
	Initial States: l =2944.0426 b = 59.6173 s = 36.3238; -101.0168; -8.364; -85.794; -63.175; 42.1652; -30.1417; -15.259; 31.5182; 42.1706; 90.0808; 61.4919 AIC = 2076.182; AICc = 2081.550		

The above table shows the result of estimation using additive Holt-Winters seasonality. As can be seen, all indices have identical levels and seasonal components. These denote that the timing of the increase and decrease of the indices are exactly the same. When there is a variable that triggers the movement of the stock price, all indices will fluctuate similarly. The seasonal component shows the timing of increase and decrease seasonally are exactly the same for all indices. What differs the three indices is the trend component. IHSG has the highest trend component. This shows that the slope of the figure is the most positive of all. SRI-KEHATI has the lowest trend. Therefore, compared to other indices, SRI-KEHATI is the flattest. Below are the forecast results based on additive Holt-Winters

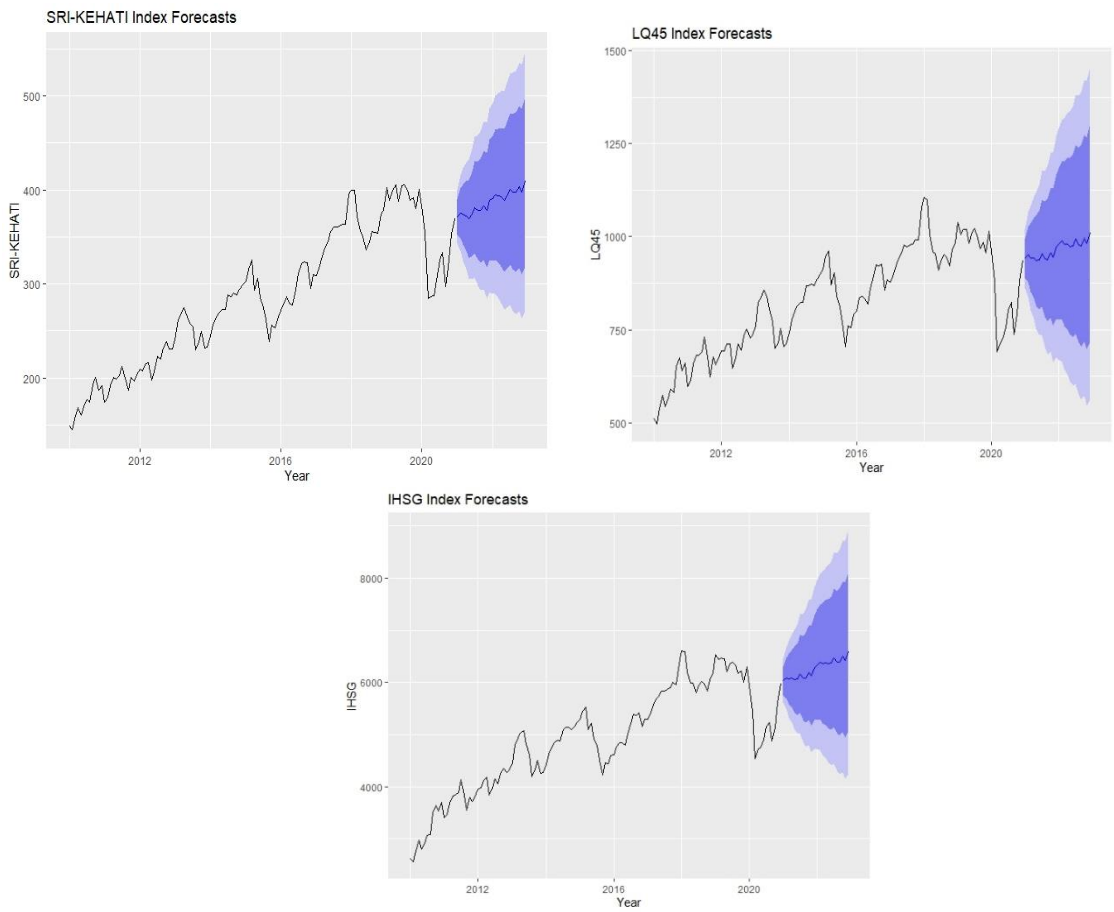


Figure 5. Forecasts of SRI-KEHATI, LQ45, and IHSG using additive Holt-Winter seasonality

The above figure shows us the forecast result using additive Holt-Winters seasonality. Overall, additive Holt-Winters predict that there will be little volatility between January 2021 and October 2021. This shows that the recovery from the pandemic will be gradual and slow. Therefore, there will not be any sharp increase or decrease. Any marked seasonal elements that existed before the pandemic in 2020 will completely be eliminated. Volatility will still exist during the period. The increasing trend will be obvious for SRI-KEHATI and IHSG indices. While for LQ45, since its liquidity will be decreased, the trend will not be so apparent. As will be seen in a later section of the article, the forecast accuracy of additive Holt-Winters is very high. Next, we will perform a multiplicative Holt-Winters seasonality estimation of the parameters.

Table 2. Multiplicative Holt-Winters Seasonality Estimation

Holt-Winters Parameters (M)	**Alpha**	**Beta**	**Gamma**
SRI-KEHATI	0.7227	0.0136	0.2771
	Initial States: l = 156.2261 b = 1.8207 s = 0.9789; 0.9646; 1.0161; 1.0345; 1.0521; 1.041; 0.9899; 1.0018; 1.0023; 0.9527; 1.0247; 0.9414 AIC = 1390.280; AICc = 1395.649		
Holt-Winters Parameters	**Alpha**	**Beta**	**Gamma**
LQ45	0.9585	0.0886	0.0027
	Initial States: l = 563.9634 b = 7.0837 s = 1.0026; 0.9638; 0.9639; 0.9633; 0.988; 1.0192; 1.012; 1.0156; 1.0201; 1.0119; 1.0271; 1.0126 AIC = 1662.698; AICc = 1668.066		
Holt-Winters Parameters	**Alpha**	**Beta**	**Gamma**
IHSG	0.8622	0.0454	0.1375
	Initial States: l =2962.2842 b = 58.4708 s = 1.0175; 0.9995; 1.0015; 0.9559; 0.9966; 1.0163; 0.9925; 1.0229; 1.0115; 0.9803; 0.9899; 1.0156 AIC = 2100.953; AICc = 2106.321		

The above table shows the result of estimation using multiplicative Holt-Winters seasonality. As can be seen, all indices have different levels, trend, and seasonal components. These denote that the timing of the increase and decrease of the indices are not the same. The model is able to identify each unique equation for each index. We can expect that multiplicative Holt-Winters will be more accurate than the additive Holt-Winters model. When there is a variable that triggers the movement of the stock price, all indices will fluctuate differently. The seasonal component shows the timing of increase and decrease seasonally are not the same for all indices. SRI-KEHATI is the index with the most seasonal component. The coefficient of the seasonal component is 0.2771. The second index after SRI-KEHATI with the most seasonality is IHSG. In terms of trend components, LQ45 has the most upward trend with a coefficient of 0.0886. The lowest trend component is owned by SRI-KEHATI with a coefficient of 0.0136. Again- SRI-KEHATI is the index with the flattest movement over time. Below are the forecast results based on multiplicative Holt-Winters

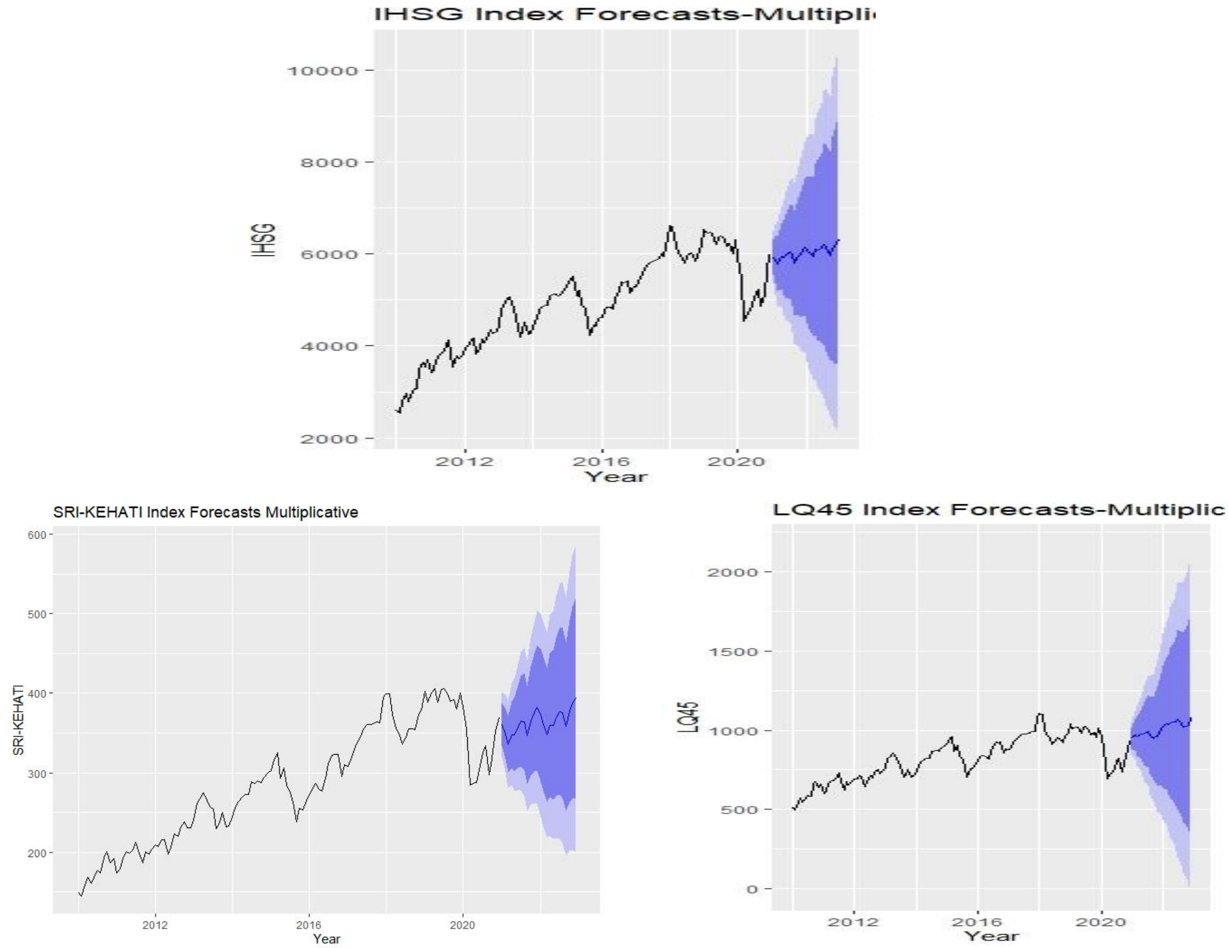


Figure 6. Forecasts of SRI-KEHATI, LQ45, and IHSG using multiplicative Holt-Winter seasonality

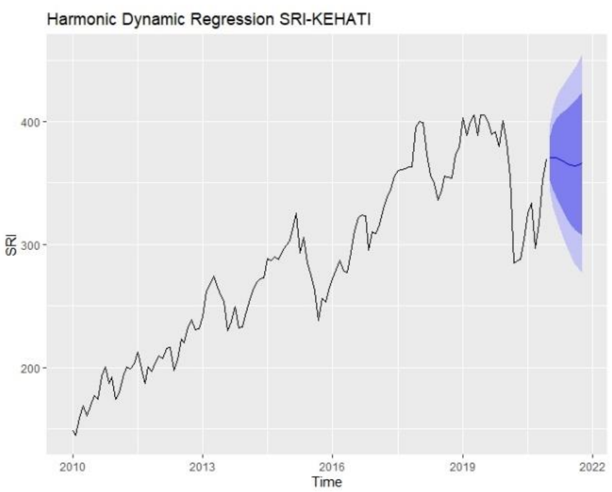
The above figure shows us the forecast result using multiplicative Holt-Winters seasonality. Overall, multiplicative Holt-Winters predict that there will be little volatility between January 2021 and October 2021. This reinforces the notion derived from additive Holt-Winters seasonality that the recovery from pandemic will be gradual and slowly. Therefore, there will not be any sharp increase or decrease. Any marked seasonal elements that existed before the pandemic in 2020 will completely be eliminated. Volatility will still exist during the period. SRI-KEHATI is predicted to be the stock index with most volatility. It contains more peaks and through than IHSG and LQ45. The increase and decrease in the movement of SRI-KEHATI are more obvious than two other indices. Following SRI-KEHATI, IHSG is the next most volatile index although in general it is not very turbulent in movement. We can see peaks and through throughout the forecast period for IHSG. This is in contrast to LQ45, in which it is the least volatile index. Multiplicative Holt-Winters seasonality will later be found out as the most accurate forecasting method. Next, we will perform the selection of Dynamic Harmonic Regression model.

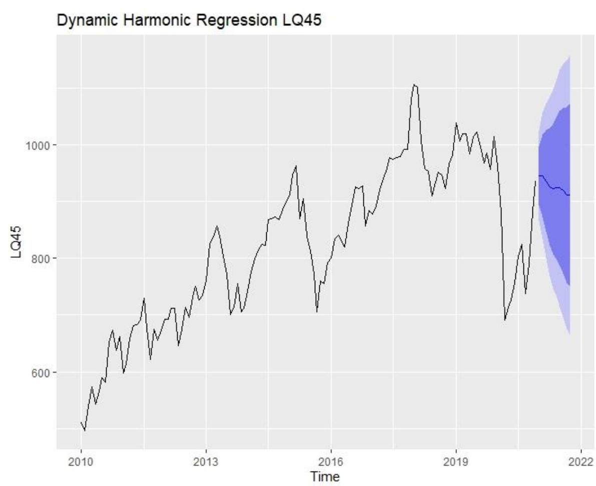
The first step in Dynamic Harmonic Regression model is the determination of *sine* and *cosine* components. Dynamic Harmonic Regression contains the sigma element of Sin (2πkt/m) and Cos (2πkt/m). Therefore, we have to determine the number of k that renders Dynamic Harmonic Regression optimal. The parameter of k number determination is corrected Akaike Information Criterion (AICc). The lower the number of AICc, the better the model. The table below shows the computation of AICc up to k equals 6.

Table 3. Determination of k based on AICc

k	SRI-KEHATI	LQ45	IHSG
1	AIC=1074.11 AICc=1074.3	AIC=1339.78 AICc=1340.69	AIC=1769.91 AICc=1770.82
2	AIC=1074.23 AICc=1074.71	AIC=1344.85 AICc=1345.33	AIC=1774.51 AICc=1774.99
3	AIC=1077.12 AICc=1078.03	AIC=1348.24 AICc=1349.15	AIC=1778.01 AICc=1778.92
4	AIC=1076.59 AICc=1078.08	AIC=1348.06 AICc=1349.55	AIC=1775.57 AICc=1777.4
5	AIC=1077.66 AICc=1079.88	AIC=1347.80 AICc=1350.02	AIC=1774.25 AICc=1776.89
6	AIC=1077.99 AICc=1080.64	AIC=1347.66 AICc=1350.3	AIC=1773.85 AICc=1776.97

The table above shows the value of AICc for each k. The parameter used is AICc. The AIC number is also included as comparison. The analysis shows that for all indices the amount of k is 1. By including one component of sine and cosine function, the Dynamic Harmonic Regression model formed will be very optimal for prediction. The AICc for SRI-KEHATI at k = 1 is 1074.3. This number is pretty close to k = 2, in which it differs only in decimal. After that, no value of k is close enough to k=1. For LQ45 and ISHG, k=1 also gives the lowest AICc. No other number is close after that to the AICc given by k =1. Therefore, all indices will be forecast using the same model of Dynamic Harmonic Regression that includes only one term of sine and cosine functions. The figure below shows the forecasting results using Dynamic Harmonic Regression.





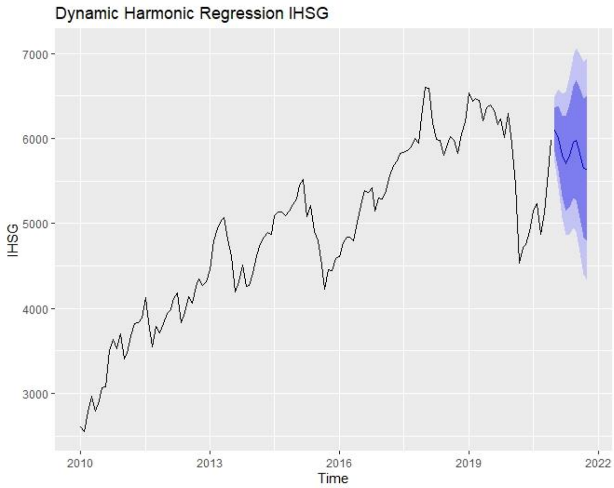


Figure 7. Forecasts of SRI-KEHATI, LQ45, and IHSG using Dynamic Harmonic Regression

The above figure shows the forecast results according to Dynamic Harmonic Regression. For SRI-KEHATI, the results tend to be flatter than Holt-Winters seasonality. Volatility is less obvious. The trend is a little bit downward trend. So Dynamic Harmonic Regression can still pick up the trend and seasonality of the historical data and project them into the future. For, KQ45, the downward trend is more obvious than that of SRI-KEHATI. Beginning from January 2021 to October 2021, it is predicted that the index will decrease. The LQ45 is presumed to be more volatile than SRI-KEHATI. Therefore, we can see fluctuations in a downward fashion. For, IHSG, the downward trend is the steepest. However, the volatility is also very stark. The index will go up and down in a decreasing trend. Beginning in January it will go down, around two months later it will start increasing before decreasing again. Dynamic Harmonic Regression really picks up the trend and seasonality of the historical data and project them into the forecasts. The fluctuation in IHSG provides opportunity for the profit-taking actions by the investors. Next is the table that shows forecast accuracy for Sri-KEHATI.

Table 4. Forecasts Accuracy of SRI-KEHATI

	SRI	**HWA Sri**	**HWM SRI**	**DHR**
Jan 2021	359.64	371.18	360.7541	370.6444
Feb 2021	367.36	375.1731	349.4274	371.0095
Mar 2021	350.01	373.8948	336.1343	370.4575
Apr 2021	342.83	372.641	348.2814	369.1364
May 2021	343.31	369.029	348.3868	367.4000
Jun 2021	318.28	374.3379	357.8487	365.7138
Jul 2021	309.3	381.2276	365.0877	364.5294
Aug 2021	329.1	378.2961	363.8599	364.1643
Sep 2021	342.4	377.8912	347.0746	364.7162
Oct 2021	373.68	383.5229	365.3615	366.0374
MAE		**32.12836**	**18.656**	**25.31841**
MAPE		**0.097163**	**0.0568468**	**0.076562**

The above table presents the forecast results for SRI-KEHATI using all methods. The column SRI denotes the actual SRI-KEHATI index. HWA and HWM are additive Holt-Winters and multiplicative Holt-Winters. DHR is the results generated by Dynamic Harmonic Regression. The forecast accuracy is measured using mean absolute error (MAE) and mean absolute percentage error (MAPE). The lower the number of MAE and MAPE, the more accurate the forecast. Overall, additive Holt-Winters seasonality results in forecast error of 32.12836. This is equivalent to 9.7163% error. This is actually a very good result. The difference between the actual numbers and the forecast results on average do not exceed 10%. Multiplicative Holt-Winters seasonality yields average error of 18.656 or equivalent to 5.68468% error. This is the best forecast accuracy among all methods. The forecast error is the lowest. We can safely say that forecasting SRI-KEHATI index using multiplicative Holt-Winters seasonality is the most appropriate method since it can pick up the volatility, seasonality, and trend and thus generate the lowest error. The last column is the results of Dynamic Harmonic Regression. The accuracy lies in between additive and multiplicative Holt-Winters seasonality. The mean error is 25.31841 and the error percentage is 7.6562%. All three methods generate error percentage lower than 10%. Hence all three methods are actually feasible for forecasting SRI-KEHATI index. Next is the table that shows forecast accuracy for LQ45.

Table 5. Forecasts Accuracy of LQ45

Date	LQ45	HWA	HWM	DHR
Jan 2021	911.98	941.8731	949.4998	945.6223
Feb 2021	944.75	951.4382	969.4762	945.1739
Mar 2021	902.79	942.8886	961.872	935.6893
Apr 2021	893.73	943.1256	943.1256	925.7514
May 2021	888.65	935.7387	935.7387	922.0399
Jun 2021	844.85	938.3221	938.3221	923.5251
Jul 2021	823.04	955.4271	955.4271	923.7676
Aug 2021	866.49	939.9439	939.9439	918.6854
Sep 2021	894.68	937.2934	937.2934	911.6646
Oct 2021	952.59	957.5144	957.5144	910.6278
MAE		**52.00152**	**31.70579**	**42.29218**
MAPE		**0.060159**	**0.033299**	**0.048596**

The above table presents the forecast results for LQ45 using all methods. The column LQ45 denotes the actual LQ45 index. Just like before, HWA and HWM are additive Holt-Winters and multiplicative Holt-Winters. DHR is the results generated by Dynamic Harmonic Regression. Additive Holt-Winters seasonality results in forecast error of 52.00152. This is equivalent to 6.0159% error. This is actually a very good result. The difference between the actual numbers and the forecast results on average do not exceed 10%. Multiplicative Holt-Winters seasonality yields average error of 31.70579 or equivalent to 3.3299% error. This is the best forecast accuracy among all methods. The forecast error is the lowest. We can indeed infer that forecasting LQ45 index using multiplicative Holt-Winters seasonality is the most appropriate method since it can pick up the volatility, seasonality, and trend and thus generate the lowest error. The last column is the results of Dynamic Harmonic Regression. The accuracy lies in between additive and multiplicative Holt-Winters seasonality. The mean error is 42.29218 and the error percentage is 4.8596%. All three methods generate error percentage even lower than 7%. This proves that all three methods are actually feasible for forecasting LQ45 index. Next is the table that shows forecast accuracy for IHSG.

Table 6. Forecasts Accuracy of LQ45

Date	IHSG	HWA	HWM	DHR
Jan 2021	5862.352	6029.652	5931.156	6105.347
Feb 2021	6241.796	6083.751	5877.429	6005.214
Mar 2021	5985.522	6061.35	5786.379	5800.427
Apr 2021	5995.616	6076.165	5933.418	5705.925
May 2021	5947.463	6054.834	5925.496	5802.612
Jun 2021	5985.489	6065.458	5959.273	5959.774
Jul 2021	6070.039	6163.241	6047.805	5983.957
Aug 2021	6150.3	6083.391	5975.39	5830.836
Sep 2021	6286.94	6086.19	5797.58	5654.149
Oct 2021	6591.35	6189.144	5958.62	5642.59
MAE		**143.2129**	**206.1929**	**311.2026**
MAPE		**0.023056**	**0.032776**	**0.049796**

The above table presents the forecast results for IHSG using all methods. The column IHSG denotes the actual IHSG index. Just like before, HWA and HWM are additive Holt-Winters and multiplicative Holt-Winters. DHR is the results generated by Dynamic Harmonic Regression. Additive Holt-Winters seasonality results in forecast error of 143.2129. This is equivalent to 2.3056% error. This is the best forecast accuracy. Additive Holt-Winters seasonality diverge only 2.3056% from the actual results. Multiplicative Holt-Winters seasonality yields average error of 206.1929 or equivalent to 3.2776% error. This is the second best forecast accuracy. It differs only around 0.972% from the best accuracy. The accuracy of Dynamic Harmonic Regression lies as the lowest following additive and multiplicative Holt-Winters seasonality. The mean error is 311.2026 and the error percentage is 4.9796%. Although it is the lowest in accuracy, it is still very good for prediction. The error is below 5%. All three methods are very feasible for forecasting IHSG index.

5. DISCUSSION

The comparison between the actual index from January to October 2021 and the forecast results of additive and multiplicative Holt-Winters seasonality showed that all three methods are capable of generating good forecast results. Holt-Winters seasonality and Dynamic Harmonic Regression can recognize the pattern of trend and seasonality in the data and use that information for generating forecasts. The forecast results display trend and seasonality in a different state for each index. The fluctuations and movement in the stock indices research are similar in general to one another. The shocks coming from macroeconomic conditions will affect companies in general, whether it is environment-conscious companies, companies with the highest market liquidity or general companies listed in the stock markets. We can infer that stock indices in Indonesia have a recognized pattern and seasonality that can be captured by the time-series econometrics model. This research also supported the theory proposed by Boudreaux (1995). Boudreaux (1995) proved that although market returns move randomly according to the information flowing into the market, the movement of the share price can still be patterned and extracted for forecasting purposes. By using monthly returns, this research confirmed their usefulness for forecasting. Seemingly random movement of share price became more systematic over a longer period. This is because the trend and seasonality are more apparent in the longer term. Holt-Winters seasonality and Dynamic Harmonic regression are able to capture the dynamics of trends and seasonality. Both methods score fairly high in terms of accuracy. More importantly, Holt-Winters seasonality can outperform Dynamic Harmonic regression in forecasting stock indices. Ultimately, it is appropriate to use time series models in forecasting Indonesian stock indices.

6. CONCLUSION, LIMITATIONS, AND SUGGESTIONS

Conclusion

The results purport to investigate the performance of various time-series forecasting approaches in predicting stock indices in Indonesia. Three stock indices were investigated, namely SRI-KEHATI, LQ45, and IHSG. SRI-KEHATI is a stock index that is composed of firms that have environmental awareness and sustainable green operations. LQ45 consists of 45 companies with high market liquidity. IHSG is the general stock index consisted of all forms listed in the Indonesian stock exchange. As the forecasting technique, Holt-Winters seasonality and Dynamic Harmonic Regression were employed. Specifically, the additive and multiplicative Holt-Winters seasonality were all utilized. The analysis revealed that for SRI-KEHATI index, all method yielded a forecast error of a maximum of 9.7163% by Additive Holt-Winters seasonality. Dynamic Harmonic regression had a forecast error of 7.6562%. Multiplicative Holt-Winters seasonality had the best accuracy with error percentage of only 5.68468%. No errors exceeded 10%. Hence, the three method are superior in predicting SRI-KEHATI index. For LQ45, multiplicative Holt-Winters was the most superior, followed by Dynamic Harmonic Regression. The additive Holt-Winters seasonality occupied third place with a forecast error percentage of 6.0159%. The multiplicative model had a forecast error of around 3.33% and a Dynamic Harmonic Regression of 4.86%. Again all three methods are very good in predicting LQ45 index. In terms of forecasting the IHSG index, additive Holt-Winters seasonality had the highest accuracy (forecast error of 2.3056%). The least accurate is the multiplicative Holt Winters seasonality (forecast error of 4.9796%). Dynamic Harmonic Regression came in second place. Again, the forecast errors were even below 5%. Therefore, Holt-Winters seasonality and Dynamic Harmonic Regression are all appropriate model for forecasting stock indices in Indonesia. This research results have practical implications for market participants and regulators alike. For investors, Holt-Winters models and Dynamic Harmonic regression perform very well in stock index prediction. Both models score very low in the inaccuracy rate. The error is well below 5%. For regulators, the forecasting method investigated can be utilized to anticipate the future condition of capital markets. Therefore, regulators can take necessary steps to prevent bad economic conditions from happening. This research also validated the monthly effect hypothesis suggested by Boudreaux (1995). Monthly returns used in this research can be utilized for forecasting purposes with very good accuracy. Therefore, market participants can time their investing and trading activities according to the monthly inclination of share movement based on forecasting results.

Limitation and suggestions

The main limitation of this research is that the returns investigated are monthly returns. The justification of monthly returns is that by using longer-term, the trend and seasonality existing in the returns will be more evident. But this brings its own drawback in that the movement of the return happens daily. Therefore, monthly returns become less detailed than daily returns. Besides, the research included only two stock indices, while there are still many indices in the Indonesia stock exchange, for example, IDX80, IDXBUMN20, or IDXHIDIV20 (index that includes high paying dividend companies). Future research could also endeavor to investigate these other indices. It is also worth mentioning that Indonesia has an Islamic stock index like JII (Jakarta Islamic Index) whose fluctuations are worth researching. In terms of forecasting methodology, recent development in computing power allows for the implementation of deep learning methods, such as Recurrent Neural Network (RNN). Future research could attempt to compare the forecasting performance of this method with time-series econometrics.

REFERENCES

Anderi, K. S. (2020). Capital Market and Economic Growth in Nigeria. *Jurnal Perspektif Pembiayaan dan Pembangunan Daerah, 8*(3), 295-310. doi:https://doi.org/10.22437/ppd.v8i3.9652

Aryati, A., Purnamasari, I., & Nasution, Y. N. (2020). Peramalan Dengan Menggunakan Metode Holt-Winters Exponential Smoothing (Studi Kasus: Jumlah Wisatawan Mancanegara Yang Berkunjung Ke Indonesia). *EKSPONENSIAL, 11*(1), 99-106.

Atmaja, D. D., Widowati, W., & Warsito, B. (2021). Forecasting Stock Prices on the LQ45 Index Using the Varimax Method. *Media Statistika, 14*(1), 98-107. doi:https://doi.org/10.14710/medstat.14.1.98-107

Ayhan, M. E. (2020). Dynamic Harmonic Regression Modeling for Monthly Mean Sea Levels at Tide Gauges wIthin the Arabian Gulf. *Journal of Geodesy, 94*(46). doi:https://doi.org/10.1007/s00190-020-01371-x

Boudreaux, D. O. (1995). The Monthly Effect in International Stock Markets: Evidence and Implications. *Journal of Financial and Strategic Decisions, 8*(1), 15-21.

Chasanah, A., Jahroh, S., & Dewi, F. (2021). Digital Marketing Changes of Micro-Small Enterprises Before and During COVID-19 Pandemy in Bogor, Indonesia. *Business Review and Case Studies, 2*(1), 1-9. doi: http://dx.doi.org/10.17358/brcs.2.1.1

Dewi, N. P., & Listiowarni, I. (2020). Implementasi Holt-Winters Exponential Smoothing Untuk Peramalan Harga Bahan Pangan di Kabupaten Pamekasan. *Digital Zone: Jurnal Teknologi Informasi dan Komunikasi, 11*(2), 219-231. doi:https://doi.org/10.31849/digitalzone.v11i2.4797

Escobari, D., & Jafarinejad, M. (2019). Investors' Uncertainty and Stock Market Risk. *Journal of Behavioral Finance, 20*(3), 304-315. doi:https://doi.org/10.1080/15427560.2018.1506787

Handayani, M., Farlian, T., & Ardian. (2019). Firm Size, Market Risk, and Stock Return: Evidence from Indonesian Blue Chip Companies. *Jurnal Dinamika Akuntansi dan Bisnis, 6*(2), 171-182. doi:https://dx.doi.org/10.24815/jdab.v6i2.13082

Herliawan, I., Kim, S. S., Saputra, K. V., & Ferdinand, F. V. (2020). Idiosyncratic Tail Risk and Stock Return in Indonesia. *Jurnal Keuangan dan Perbankan, 24*(2), 241-251. doi:https://doi.org/10.26905/jkdp.v24i2.3778

Hoque, M. E., & Yakob, N. A. (2017). Revisiting Stock Market Development and Economic Growth Nexus: The Moderating Role of Foreign Capital Inflows and Exchange Rates.

Cogent Economics & Finance, 5(1), 1-17. doi:https://doi.org/10.1080/23322039.2017.1329975

Kapaya, S. M. (2020). Stock Market Development and Economic Growth in Tanzania: an ARDL and Bound Testing Approach. *Review of Economics and Political Science, 5*(3), 187-206. doi:http://dx.doi.org/10.1108/REPS-11-2019-0150

Kengatharan, L., & Ford, J. S. (2019). Factors Determining The Share Price Volatility: Evidence from Listed Companies in Sri Lanka. *Indonesian Management and Accounting Research, 18*(2), 105-126. doi:http://dx.doi.org/10.25105/imar.v18i2.6196

Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of Forecasting Methods from Selected Stock Market Returns. *Financial Innovation, 5*(40), 1-16. doi:https://doi.org/10.1186/s40854-019-0157-x

Meher, B. K., Hawaldar, I. T., Spulbar, C., & Birau, R. (2021). Forecasting Stock Market Prices Using Mixed ARIMA Model: A Case Study of Indian Pharmaceutical Companies. *Investment Management and Financial Innovations, 18*(1), 42-55. doi:http://dx.doi.org/10.21511/imfi.18(1).2021.04

Muna, S., & Kuntoro, K. (2021). Application of the Holt-Winters Exponential Smoothing Method on the Air Pollution Standard Index in Surabaya. *Jurnal Biometrika dan Kependudukan, 10*(1), 53-60. doi: http://dx.doi.org/10.20473/jbk.v10i1.2021.53-60

Nasarudin, I. Y., Suhendra, S., & Anggraini, L. F. (2019). The Determinant of Stock Price: Evidence on Food and Beverage Companies in Indonesia. *Etikonomi: Jurnal Ekonomi, 18*(1), 143-154. doi: http//dx.doi.org/10.15408/etk.v18i1.10987

Nikolaieva, O., Petrova, A., & Lutsenko, R. (2020). Forecasting of the Stock Rate of Leading World Companies Using Econometric Methods and DCF Analysis. *International Journal of Innovative Technologies in Economy, 2*(29), 33-41. doi:10.31435/rsglobal_ijite/31052020/7067

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

Pahlevi, R. W., & Oktaviani, I. I. (2018). Determinants of Individual Investor Behaviour in Stock Investment Decisions. *Accounting and Financial Review, 1*(2), 53-61. doi:https://doi.org/10.26905/afr.v1i2.2427

Pertiwi, D. D. (2020). Applied Exponential SMoothing Holt-Winter Method for Rainfall Forecast in Mataram City. *Journal of Intellegent Computing and Health Informatics, 1*(2), 46-49. doi:https://doi.org/10.26714/jichi.v1i2.6330

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. doi:https://doi.org/10.33455/ijcmr.v1i1.83

Sunarya, I. W. (2019). Modelling and Forecasting Stock Market Volatility of NASDAQ Composite Index. *Economics and Accounting Journal, 2*(3), 181-189. doi:http://dx.doi,org/10.32493

Tanjung, G., Komariah, S., & Yusuf, S. (2020). Capital Market Literacy and Students Investment Decision. *Journal of Applied Business Administration, 4*(2), 200-205. doi:https://doi.org/10.30871/jaba.v4i2.2104

Zavala, A. J., & Messina, A. R. (2014). A Dynamic Harmonic Regression Approach to Power System Modal Identification and Prediction. *Electronic Power Components and Systems, 42*(13), 1474-1483. doi:https://doi.org/10.1080/15325008.2014.934932