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A Study on the Prediction of KOSDAQ Index by Comparing Time Series Analysis Models

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Abstract

The purpose of this study is to suggest a KOSDAQ index prediction model by estimating and comparing the transfer function model and the multiplicative seasonal ARIMA model, which arethe time-series models. Major findings are summarized as follows.The result of data transformation showed stationarityafter the ADF test.Analysis of sample cross-correlation function (SCCF) in estimating the transfer function model showed that linear dependency relationship exists. As the result of analyzing the goodness of fit of the transfer function model using the impact response weights and the noise time series model, the white noise process was observed in the residual time series, and between the residual time series and the producer price index (PPI).In the multiplicative seasonal ARIMA model estimation, only 5 of the 9 candidate models followed the white noise process. As the result of selecting the model by comparing the values of AIC statistics and SBC statistics among five models and analyzing the goodness of fit, the residual time series follow the white noise process.The comparison of AIC statistics and SBC statistics of fitted models of the two models showed that the goodness of model fit of the multiplicative seasonal ARIMA prediction model was better with AIC=345.5553 and SBC=351.3057.Therefore, the KOSDAQ index prediction value and the predicted interval with 95%` confidence level of the multiplicative seasonal ARIMA prediction modelwere presented by inverting the square root transformed value to the original value, and as the result, the KOSDAQ index was expected to rise sharply in April and May 2020 compared to 2019.

Keywords; *Transfer function model,Multiplicative seasonal ARIMA model, ADF test, Sample correlation function, Impact response weight.*

I.INTRODUCTION

The downward trend in the global economy, which began after the second half of last year, is accelerating in 2020, and is expected to continue next year. Variables that will affect economic flows in the future include the US-China trade dispute, the Korea-Japan conflict, and the low interest rate monetary policy of central banks major countries. The US-China trade disputes, which began in 2018, have raised expectations for progress in negotiations in 2019, but seem difficult to resolve in the short term because core issues such as intellectual property rights have not been settled yet. As the domestic economy is unlikely to pick up quickly, downward pressure will continue. In addition, the conflict between Korea and Japan, which was triggered by Japan's tightening of export regulations, continues, and, if the tension is prolonged, will have a negative impact on the domestic economy. Meanwhile, the cycle variation value of the coincident composite index, which shows the domestic economic phases, has fallen below the standard since December 2018, and as of 2019, the possibility of an apparent economic improvement is low. Recently, there are signs of abnormalities in the financial markets, such as the short- and long-term interest rate reversal in the US and negative interest rates in Europe and Japan. Indeed, the central banks of major countries have already turned to quantitative easing, and this will continue next year.

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These changes in domestic and foreign conditions may act as favorable factors for securing downside rigidity in terms of stock price, but it seems to be somewhat insufficient to increase the stock price in a trend. The volatility of the stock market is expected to continue as uncertainties in the domestic market, accelerated global economic slowdown, and the possibility of downside risks become high. In particular, volatility of KOSDAQ market is expected to increase as the market activation policy such as pension fund investment and venture fund launch does not significantly affect the stock market. Recently, the KOSDAQ index has plummeted due to the biostock shock. The KOSPI index has plunged as the KOSDAQ index plummeted due to the recent shock of bio stocks. If the stock market continues to fall, the domestic economy will inevitably contract in the real market, including sluggish employment and investment. Stock price data have the characteristics of time series data with volatility, so there are many time series models for predicting stock index. Existing studies of time series models using economic and financial time series data with volatility are as follows.
Kanas presented the S&P500 index prediction model as an ANN model [1], and Tay and Cao proposed a method for introducing financial time series data into the SVM model [2]. Jeantheau published a study using the ARCH model to predict stock prices [3]. Amilonl and Liu et al. predicted stock price using the GARCH model based on Skewed-GED Distribution in the Chinese stock market [4-5], and Veloce compared the forecast values of the ARIMA model and the VAR model [6]. Roh proposed an integrated model with an artificial neural network to estimate volatility of the KOSPI 200 stock index [7], and Lee and Chun attempted to predict the KOSPI index using the DL-GARCH model integrating the GARCH model and deep learning [8]. And Li et al. predicted the stock market using SVR with stock-related social data [9].Predicting the stock price is very complicated and difficult because the stock index forecast is changed by numerous variables that are directly or indirectly intertwined with each other. However, it is important to study the prediction model using various economic indices in order to know the flow of large markets.In this study, we used 12-year data (2008-2019) of the KOSDAQ index and the producer price index provided by the Bank of Korea's Economic Statistics System, and estimated a model using the transfer function model and the multiplicative seasonal ARIMA model. The transfer function model introduces the input time series into the ARIMA model and attempts to improve the predicted value by analyzing the dynamic relationship between the input and the output time series [10]. The multiplicative seasonal ARIMA model is a comprehensive ARIMA model that can accommodate seasonal components in an ARIMA model that can be adapted to nonstationary time series data.
This study is composed as follows. Chapter 2 examines the research model and theoretical background of the main statistics. Chapter 3 empirically compares and analyzes the time series models, and presents predictions. And in Chapter 4 conclusions and suggestions based on the analysis results are presented.

II. RESEARCH MODEL

A.Transfer Function Model

The transfer function model is a time series model composed of the past values of the output time series and the present and past values of the white noise plus the present and past values of the input time series [11]. In this study, the model using the output time series as the KOSDAQ index ($Z_t = \mathrm{KOSDAQ}$) and the input time series ($X_t = \mathrm{PPI}$) as the producer price index is as follows:

$$\begin{aligned} Z_t &= \mu + \nu(B)X_t + n_t \\ &= \mu + \frac{\omega_s(B)}{\delta_r(B)}B^b X_t + \frac{\theta(B)}{\phi(B)} + \varepsilon_t \end{aligned} \tag{l}$$

Where,
$\nu(B) = \sum_{j=-\infty}^{\infty} \nu_j B^j$: transfer function,
$n_t = \frac{\theta(B)}{\phi(B)}\varepsilon_t$: noise process,
$\omega_s(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s$,
$\delta_r(B) = 1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r$,
$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$,
$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$,
b : delay parameter,
$\varepsilon_t \sim \mathrm{i.i.d.}(0, \sigma_t^2)$, and X_t and $\varepsilon_t$are mutually independent.

In the analysis of the transfer function model, the sample cross correlation function (SCCF) is

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$$\widehat{\rho_{zx}}(k) = \frac{\widehat{\gamma_{zx}}(k)}{\sqrt{\widehat{\gamma_{zz}}(0)\sqrt{\widehat{\gamma_{xx}}(0)}}} \quad (2)$$

where,

$\widehat{\gamma_{zx}}(k) = \frac{1}{n}\sum_{t=k+1}^{n}(Z_t - \bar{Z})(X_{t-k} - \bar{X}), k \geq 0,$

and $\widehat{\gamma_{zx}}(k) = \frac{1}{n}\sum_{t=1}^{n+k}(Z_t - \bar{Z})(X_{t-k} - \bar{X}), k < 0.$

If the normal time series Z_t and X_t do not correlate with each other and X_t is a white noise process, $Var[\widehat{\rho_{zx}}(k) \simeq \frac{1}{(n-k)}]$. If large sample, $Var[\widehat{\rho_{zx}}(k)] \simeq \frac{1}{n}$ holds [12].

2.2 Multiplicative Seasonal ARIMA Model

In case of nonstationary time series, where both trend and seasonal factors exist at the same time, the d-order non-seasonal time differencing is used to remove the trends, and then if there are seasonal components, the D-order seasonal time differencing is used to convert it into normal time series. In other words, when the seasonal cycle is S, Z_t(KOSDAQ index) follows the multiplicative seasonal ARIMA(p,d,q)(P,D.Q)probability process when the d-order non-seasonal and D-order seasonal time differenced time series $W_t = (1-B)^d(1-B^s)^D Z_t$ follows the stationary probability process.

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Z_t = \delta + \theta(B)\Theta(B^s)\varepsilon_t \quad (3)$$

Where,

$\varepsilon_t \sim (0, \sigma_\varepsilon^2),$

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p,$

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q,$

$\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_p B^{p_s},$

$\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta_q B^{q_s}.$

2.3 Model Selection Criteria

The choice of models is not just based on a statistical criterion, but to build a model that can be realistically explained. Thus, new criteria are needed for deciding which model to choose among many. There are several criteria for selecting the most suitable model for time series among several models. The selection criteria statistics of the model used in this study are Akaike's Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) statistics [13] [14].

$$AIC = -2\ln(L) + 2m \quad (4)$$
$$SBC = -2\ln(L) + m\ln(n)$$

Where,m is the number of parameters in the model and n is the number of time series data.

The method is to select the model with minimum AIC and SBC values as the value L of the likelihood function calculated from the maximum likelihood estimator of the parameter increases, that is, the smaller the value $-2\ln(L)$, the higher the model fit.

2.4 Augmented Dickey-Fuller Test (ADF test)

The Augmented Dickey-Fuller test (ADF test), which performs the unit root test based on that the time series Z_t(KOSDAQ index) follows the AR(p) probability process, is as follows [15].

$$Z_t = c_t + \phi Z_{t-1} + \sum_{i=1}^{p-1}\phi_i \nabla Z_{t-i} + \varepsilon_t \quad (5)$$

Where,$\nabla = 1 - B$. (Equation 5) can be expressed as follows using the differential time series.

$$\nabla Z_t = c_t + \phi_0 Z_{t-1} + \sum_{i=1}^{p-1}\phi_i \nabla Z_{t-i} + \varepsilon_t \quad (6)$$

where, if $\phi_0 = \phi - 1$, the test for hypothesis $H_0: \phi = 1$ is the same as the test for $H_0: \phi = 0$.

III. RESULTS

Time series models used in this study are the transfer function model and the multiplicative seasonal ARIMA model. Using these two models, we estimated the model and diagnosed the goodness of fit. Based on the results, we presented a KOSDAQ index prediction model.

A. Data Conversion and Stationary Time Series Test

The time series of the KOSDAQ index data showed a stochastic trend as shown in [Figure 1]. Thus, the first-order time difference was used to eliminate the trend, and the logarithmic and square root transformations were taken to stabilize the variance since the variance was not constant, As the result, the variation in the time series plot for the square root transformation was relatively more stable. Moreover, it was converted to stationary time series when the seasonal time differencing was also performed as autocorrelation was shown at time lag 12 in the sample autocorrelation function (SACF) and at time lags 1 and 12 in the sample partial

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autocorrelation function (SPACF) after the first differencing ($\nabla\sqrt{\text{KOSDAQ}}$).

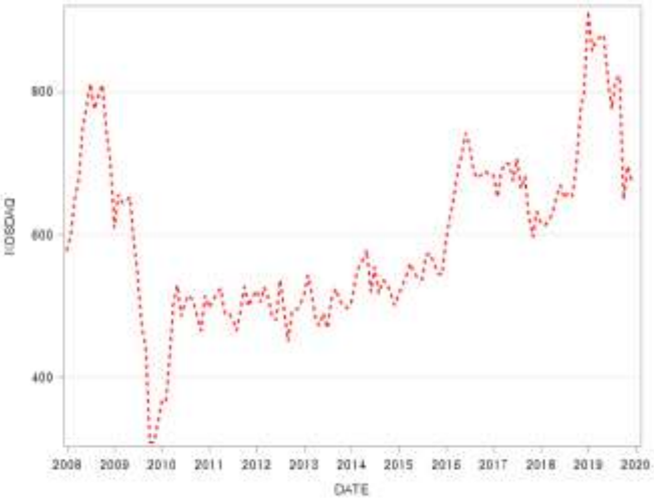

Fig 1. Trend of KOSDAQ Index

Autocorrelations was found at time lag 6 in the first and seasonal differences of the KOSDAQ index, namely the sample partial autocorrelation function (SPACF) and the sample inverse autocorrelation function (SIACF) of $\nabla_{12}\nabla\sqrt{\text{KOSDAQ}}$, and at time lag 1 in the first and the seasonal differences of the producer price index, namely the sample partial autocorrelation function (SPACF) and sample inverse autocorrelation function (SIACF) of $\nabla_{12}\nabla\sqrt{\text{PPI}}$. Therefore, the Augmented Dickey-Fuller (ADF) test of $\nabla_{12}\nabla\sqrt{\text{KOSDAQ}}$ and $\nabla_{12}\nabla\sqrt{\text{PPI}}$and the seasonal unit root test of $\nabla_{12}\nabla\sqrt{\text{KOSDAQ}}$ showed that the p-value of the Tau statistic was smaller than the significance level $\alpha = 0.05$, and it was determined to be a stationary time series that no longer requires time differencing. The test results are shown in (Table 1).

Table 1. ADF Unit Root Test and Seasonal Unit Root Test

Augmented Dickey-Fuller Unit Root Tests			
TYPE	Lag	Tau	Pr< Tau
Zero Mean	6	-4.06	<.0001
Single Mean	6	-4.05	0.0017
Trend	6	-4.06	0.0093
Zero Mean	1	-5.80	<.0001
Single Mean	1	-5.79	<.0001
Trend	1	-5.78	<.0001
Seasonal Augmented Dickey-Fuller Unit Root Tests			
Zero Mean	6	-19.70	<.0001
Single Mean	6	-19.57	<.0001

In addition, it was confirmed by the graphical method in the transfer function model that the time series data of the KOSDAQ index were the stationary time series as shown in (Figure 2), and in the multiplicative seasonal ARIMA model as shown in the red line of (Figure 2).

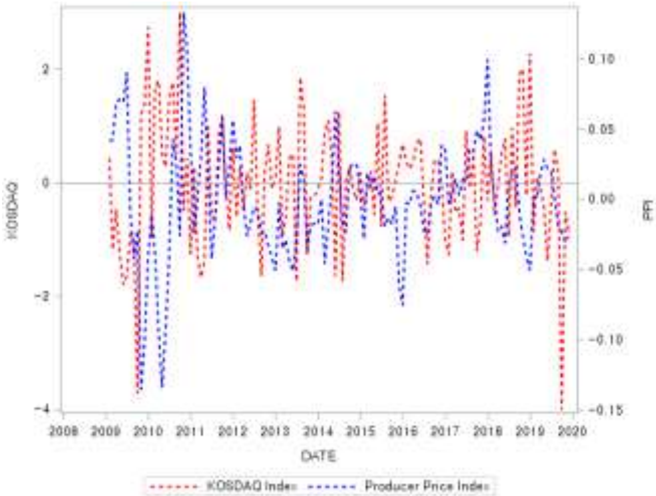

Fig .2. Stationary Time Series of KOSDAQ Index Predictive Model Estimation

In order to determine whether the constant term is included in the model prior to model estimation, T-test for the mean 0 of $\nabla_{12}\nabla\sqrt{\text{KOSDAQ}}$ and $\nabla_{12}\nabla\sqrt{\text{PPI}}$ were performed and the results showed that the p-values of the t-statistics were 0.8146 and 0.7633 respectively, which were greater than the significance level $\alpha = 0.05$. Thus the constant terms were not included in the estimated transfer function prediction model and the estimated multiplicative seasonal ARIMA prediction model.

The results of estimating the transfer function prediction model are as follows.

In the results of autocorrelation analysis of the stationary input time series $\nabla_{12}\nabla\sqrt{\text{PPI}}$ by data transformation, the non-seasonal model was modeled as MA(2) by the sample autocorrelation function (SACF), and as AR(1)by the sample partial autocorrelation function (SPACF) and the sample inverse autocorrelation function (SIACF). For the seasonal model, $\text{MA}(1)_{12}$by the sample autocorrelation function (SACF), and $\text{AR}(1)_{12}$ by

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the sample partial autocorrelation function (SPACF) and the sample inverse autocorrelation function (SIACF). And $\mathrm{ARIMA}(1,1,1)(1,1,1)_{12}$ model was selected considering above. The estimation of the pre-whitening parameter of $\nabla_{12}\nabla\sqrt{\mathrm{KOSDAQ}}$ by the selected model is shown in (Equation 7).

$$\frac{(1-0.47733\ \mathrm{B})(1-0.06367\ \mathrm{B}^{12})}{(1+0.29307\ \mathrm{B})(1-0.86561\ \mathrm{B}^{12})} \qquad (7)$$

The linear dependency was confirmed by estimating the sample cross-correlation function (SCCF) between $\nabla_{12}\nabla\sqrt{\mathrm{KOSDAQ}}$ and $\nabla_{12}\nabla\sqrt{\mathrm{PPI}}$ using Equation (7). The tentative transfer function model selected by estimating the impact response weights and applying $\mathrm{b}=0,\mathrm{r}=0,1,2$in sequence was given as (Equation 8).

$$\nabla_{12}\nabla\sqrt{\mathrm{KOSDAQ}} = \frac{(-7.8619+6.21869\ \mathrm{B})}{(1-0.8635\ \mathrm{B})}\nabla_{12}\nabla\sqrt{\mathrm{PPI}}+\varepsilon_t \qquad (8)$$

The graph of the estimated impact response weights is shown in (Figure 3).

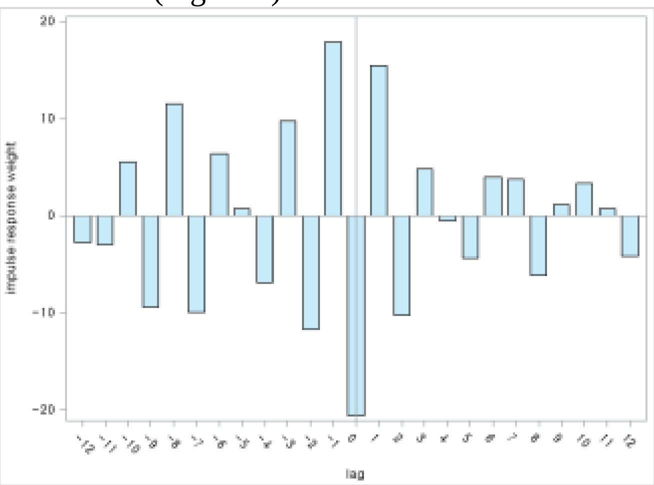

Fig 3. Bar Graph of Impact Response Weight

The autocorrelation analysis results of the tentative transfer function model showed that the non-seasonal model was modeled as MA(1) by sample autocorrelation function (SACF), and AR(3) by sample partial autocorrelation function (SPACF) and sample inverse autocorrelation function (SIACF). For the seasonal model, $\mathrm{MA}(1)_{12}$by the sample autocorrelation function (SACF), and $\mathrm{AR}(3)_{12}$by the sample partial autocorrelation function (SPACF) and the sample inverse autocorrelation function (SIACF).Therefore, the noise time series model was estimated by applying this model.The estimated transfer function prediction model of KOSDAQ index using the transfer function model and the noise time series model is shown in (Equation 9).

$$\nabla_{12}\nabla\sqrt{\mathrm{RKOSDAQ}} = \frac{(-4.84-0.60\mathrm{B})}{(1+0.74\mathrm{B})}\nabla_{12}\nabla\sqrt{\mathrm{RPPI}} + \frac{(1+0.04\mathrm{B})(1-0.44\mathrm{B}^{12})}{(1+0.77\mathrm{B}+0.56\ \mathrm{B}^2+0.34\mathrm{B}^3)(1+0.37} \qquad (9)$$

Estimation of the multiplicative seasonal ARIMA prediction model is as follows.

The autocorrelation analysis of the stationary time series $\nabla_{12}\nabla\sqrt{\mathrm{KOSDAQ}}$ showed that the seasonal sample autocorrelation function (SACF), sample partial autocorrelation function (SPACF) and sample inverse autocorrelation function (SIACF) were truncated at time lag 12, And non-seasonal models were found to have nonzero values at time lags 1, 2 and the like. This means that the model $\mathrm{ARIMA}(\mathrm{p},1,\mathrm{q})(\mathrm{P},1,\mathrm{Q})_{12}$ without a constant term is a suitable model. Therefore, if we observe the principle of parameter saving and scope it as $0 \le \mathrm{p},\mathrm{q},\mathrm{P},\mathrm{Q} \le 1$, the nine candidate models are as follows.

Table 2. Model Identification of $\mathbf{ARIMA(p,1,q)(P,1,Q)_{12}}$

ARIMA $(\mathrm{p},1,\mathrm{q})(\mathrm{P},1,\mathrm{Q})_{12}$	p-value >0.05	AIC	SBC
$(1,1,0)(1,1,0)_{12}$	pass	356.3071	362.0575
$(0,1,1)(0,1,1)_{12}$	pass	345.6812	351.4316
$(1,1,0)(0,1,1)_{12}$	pass	345.5553	351.3057
$(1,1,1)(0,1,1)_{12}$	pass	347.0377	355.6633
$(1,1,1)(1,1,0)_{12}$	fail		
$(1,1,)(1,1,1)_{12}$	fail		
$(1,1,1)(1,1,1)_{12}$	fail		
$(0,1,1)(1,1,0)_{12}$	pass	356.3737	362.1240
$(1,1,0)(1,1,1)_{12}$	fail		

From Table 2, the Portmanteau test result of the residual time series shows that the models with $\mathrm{p}-\mathrm{value} > 0.05$ at all time lags are 5 models (Table 2 second column "pass" value), of which the model $\mathrm{ARIMA}(1,1,0)(0,1,1)_{12}$ is selected with the smallest values of AIC, SBC, and $\widehat{\sigma_\varepsilon^2}$. As the result of estimation by the model $\mathrm{ARIMA}(1,1,0)(0,1,1)_{12}$, all the parameters were significant as $\mathrm{p}-\mathrm{value} <$

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$0.05 = \alpha$ in the significance test Therefore, the estimated multiplicative seasonal ARIMA prediction model of KOSDAQ index is shown in (Equation 10).

$$(1 - 0.10019\ \mathrm{B})(1 - \mathrm{B}^{12})\nabla_{12}\nabla\sqrt{\mathrm{KOSDAQ}} = (1 - \mathrm{B})(1 - 0.68938\ \mathrm{B}^{12}) \quad (10)$$

3.3Goodness of Fit Test

After fitting the models of (Equation 9) and (Equation 10), p-values of t-statistics were 0.1852 and 0.8822, respectively, greater than the significance level for the mean 0 of the residual time series, indicating that the means appeared to be statistically 0. The autocorrelation analysis of (Equation 9) and (Equation 10) showed that the p-value histograms for the Portmanteau test follow the white noise process by being below the 0.05 boundary of the vertical axis at all time lags. As the result of the Portmanteau test for the existence of cross-correlation between the residual time series and the producer price index in (Equation 9), the p-values of the χ^2-statistics were greater than the significance level $\alpha = 0.05$ at all time lags, and thus, white noise process was also observed between the residual time series and the producer price index as shown in (Table 3).

Table 3. Portmanteau Test Statistics between the Residual Time Series and the Producer Price Index

To Lag	Chi-Square	DF	Pr>ChiSq
5	4.57	3	0.2058
11	10.88	9	0.2843
17	13.99	15	0.5266
23	18.06	21	0.6451

In addition, as the result of the Portmanteau test for autocorrelation analysis of the residual time series in (Equation 10), the p-values of the χ^2-statistics were greater than the significance level $\alpha = 0.05$ at all time lags, and thus, it was shown that the residual time series also followed white noise process as shown in (Table 4).

Table 4. Portmanteau Test Statistics of the Residual Time Series

To Lag	Chi-Square	DF	Pr>ChiSq
6	7.52	4	0.1109
12	9.60	10	0.4762
18	16.28	16	0.4339
24	18.85	22	0.6548

Prediction Model Selection

Both the transfer function prediction model (Equation 9) and the multiplicative seasonal ARIMA prediction model (Equation 10) were judged to be suitable models. (Table 5) shows the comparison between two models using AIC and SBC statistics, which are model selection criteria.

Table 5. Prediction Model Comparison

Classification	AIC	SBC
Transfer Function Prediction Model	429.8647	454.7243
Multiplicative Seasonal ARIMA Prediction Model	345.5553	351.3057

In the comparison of (Table 5), the values of AIC and SBC of multiplicative seasonal ARIMA prediction model are smaller than those of transfer function prediction model. Since this means that the multiplicative seasonal ARIMA prediction model is better fitted, the multiplicative seasonal ARIMA prediction model was chosen as the KOSDAQ index prediction model.

B.Prediction

Applying the selected multiplicative seasonal ARIMA prediction model, 1-lag and multi-lag predictions of the fitted period and the prediction intervals with 95% confidence level are presented in (Figure 4). The analysis results are the values converted to the square root, so the results are inversely transformed to the original values.

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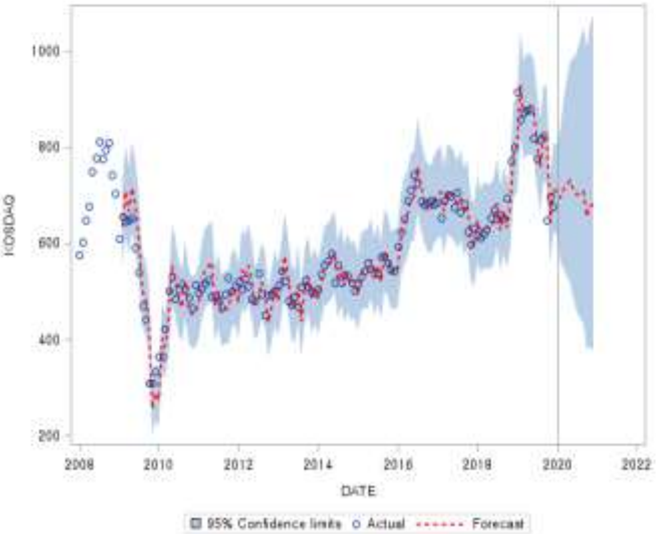

Fig. 4. Prediction by Model ARIMA$(1,1,0)(0,1,1)_{12}$without Constant Term

Predictions from January to December 2020 (12 months) converted into the original value from the KOSDAQ index values converted into the square root are shown in (Table 6).

Table 6. 12-Month Forecast by 2020

Month	January	February	March
Predicted Value	706.686	693.302	710.674
Month	April	May	June
Predicted Value	721.471	729.744	711.550
Month	July	August	Septemb er
Predicted Value	700.642	703.832	707.083
Month	October	Novemb er	Decembe r
Predicted Value	654.640	676.961	680.481

From the results in Table 6, the KOSDAQ index is expected to rise sharply in April and May compared to the previous year (2019), and is expected to remain at the same level as the previous year from June.

IV.CONCLUSIONS

This study presents the KOSDAQ index prediction model by estimating and comparing the time series models, the transfer function model and the multiplicative seasonal ARIMA model, using time series data (KOSDAQ index and producer price index) from January 2008 to December 2019. The results are as follows.

First, as the result of the T-test on the mean 0 of the data transformed into stationary time series by the data transformation, the p-value of the t-statistic was greater than the significance level $\alpha = 0.05$, so the constant term was not included in the model.

Second, the transfer function model estimated the pre-whitening parameters by performing the prewhitening process on the producer price index, which is the stationary input time series. And examination of cross-correlation of the KOSDAQ index, which is the stationary output time series, and the producer price index, which is the stationary input time series, did not violate the causality of the model. The estimated impact response weights were used to identify and estimate the transfer function model and the noise time series model. The result showed that the noise time series model followed the white noise process. Therefore, after fitting the model by integrating the transfer function model and the noise time series model, the autocorrelation analysis showed that the model is no longer cross-correlated between the residual time series and the producer price index.

Third, the multiplicative seasonal ARIMA model estimation showed that only 5 out of 9 candidate models followed the white noise process. Among the five models, the model with the AIC statistic and the SBC statistic having the smallest values was chosen. The autocorrelation analysis of the residual time series showed a fitted model following the white noise process.

Fourth, the comparison of two fitted models with AIC statistics and SBC statistics showed that the multiplicative seasonal ARIMA model is more appropriate.

Fifth, the KOSDAQ index is expected to rise in April and May 2020 compared to 2019 as the results obtained by inversely transforming the square root transformed values to the original values of the KOSDAQ index prediction value and the 95% confidence level predicted by the multiplicative ARIMA model, and is expected to remain at the same level as 2019 over time from June.

The result of this study cannot guarantee accurate predictions considering the global economic situation and the internal and external situation of companies. However, it is expected to be used as an important basis to present a direction in developing

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a prediction model in the difficulties and complex reality of stock index prediction.

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