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Prediction of the Corona 19's Domestic Internet and Mobile Shopping Transaction Amount*

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Abstract

Purpose: In this work, we examine several time series models to predict internet and mobile transaction amount in South Korea, whereas Jeong (2020) has obtained the optimal forecasts for online shopping transaction amount by using time series models. Additionally, optimal forecasts based on the model considered can be calculated and applied to the Corona 19 situation. **Research design, data, and methodology:** The data are extracted from the online shopping trend survey of the National Statistical Office, and homogeneous and comparable in size based on 46 realizations sampled from January 2007 to October 2020. To achieve the goal of this work, both multiplicative ARIMA model and Holt-Winters Multiplicative seasonality method are taken into account. In addition, goodness-of-fit measures are used as crucial tools of the appropriate construction of forecasting model. **Results:** All of the optimal forecasts for the next 12 months for two online shopping transactions maintain a pattern in which the slope increases linearly and steadily with a fixed seasonal change that has been subjected to seasonal fluctuations. **Conclusions:** It can be confirmed that the mobile shopping transactions is much larger than the internet shopping transactions for the increase in trend and seasonality in the future.

Keywords: Additive Seasonality Method, Optimal Forecasts, Shopping Transaction Amount

JEL Classification Code : C22, C53, D39, M21

1. Introduction

The spread of Corona has shocked the retail market by blocking traditional face-to-face consumption, and has made online conversion an indispensable choice for both customers and businesses. Changes in the e-commerce market, including the convergence of new items, customer bases, and on-off-line sales channels, are expected to continue after the end of Corona 19. With Corona 19, new trends are emerging in the e-commerce market. As the prevention of Corona 19 infection became the top priority, demand for personal hygiene products such as masks and cleaning agents exploded. Consumption of IT products and office supplies related to telecommuting and online lectures has increased, and consumption of related products

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has increased as they have taken skin care, cooking, and fitness directly at home instead of using service facilities. It is also a new trend that daily necessities such as food and household goods, which were mainly consumed offline, have moved to the e-commerce market. Corona 19 High-risk elderly consumers are shopping online, and Silver Surfer, which is good at IT devices and Internet use, has emerged as an important e-commerce customer base. With Corona 19, more and more elderly consumers are facing new services such as food delivery and online video service (OTT). As the traditional shopping method of visiting stores and purchasing products disappears, major technologies of the Fourth Industrial Revolution such as artificial intelligence, Internet of things, and augmented reality are melting into e-commerce (Kim, 2020).

The number of online shopping transactions reached its highest level since the statistics were written in August 2020 as the re-proliferation of the new coronavirus infection (Corona 19) and the longest rainy season ever overlapped. According to the National Statistical Office's August 2020 online shopping trend, the amount of Internet shopping transactions through PCs and mobile in August 2020 was 14.38 trillion won, up 27.5% from a year ago. As a result, online shopping product transaction amount accounted for 28.6% of total retail sales in August, up 7.7 percentage points from a year ago (20.9%), which is also the highest ever.

Because of Corona 19, social distance continues and offline shopping and eating out are restricted, so that the use of online shopping, which is a non-face-to-face consumption type, has increased significantly. As consumption shrank in February 2020, when Corona 19 first occurred, overall retail sales declined, but online shopping transaction amount remained at the existing level. As a result, the proportion of online shopping transactions among retail sales, which was 22% before Corona 19, increased to 28.3% after Corona 19.

In 2020, total online shopping transaction amount increased 16.6% and 15.2%, respectively, in 1Q 2019 and 2Q 2019. By product category, the growth rate of the transaction amount in the first quarter of this year, which was the early stage of Corona 19, was 76.7% for food service, the highest among all product groups. In addition, it was found that 'automobile and automobile products', 'food', and 'life goods' increased in order. On the other hand, as travel and cultural life were limited due to the influence of Corona 19, the transaction amount of 'travel and transportation service' and 'culture and leisure service' decreased significantly. Regarding the increase in food services, the amount of payment and the number of settlers in major delivery apps showed a sharp increase in March 2020 when the occurrence of domestic Corona 19 spread (Oh, 2020).

Compared to the second half of 2019, the number of products decreased in the first half of this year due to fashion, travel and transportation services, and cultural and leisure services. On the other hand, as the time spent in the house increased due to restrictions on going out and telecommuting, the product group such as 'home appliances', 'foods', 'life goods', and 'furniture'. In 2020, mobile shopping of online shopping transactions increased 16.6% and 21.0%, respectively, in in 1Q 2019 and 2Q 2019. Mobile shopping transactions during online shopping amounted to 9,326.5 billion won, up 27.8% from a year ago, the highest ever. In addition, the proportion of mobile shopping compared to all online shopping increased from 65% to 67.8% in February 2020 after Corona 19. As mobile shopping usage increases, live commerce, a new mobile-based commerce platform, has emerged and has become a popular alternative to Corona 19 (Oh, 2020).

Jeong (2020) obtained the optimal forecasts for online shopping transactions by using univariate time series models in South Korea. He found that online shopping transactions are expected to increase steadily by mid-2021, and it can be predicted that the related domestic e-commerce, domestic distribution volume, and domestic logistics volume are activated.

In order to investigate the changes in the online shopping market, Sun et al. (2017) conducted a prediction study on the production index of internet shopping, home shopping, and general retail, and identified the causal relationship between each retail distribution channel by analyzing ARIMA model and Granger-Causality test. As a result, while general retail showed a slight uptrend, internet shopping continued to grow rapidly and causality test showed that both home shopping and general retailing did not affect internet shopping in short-term time lag, but after time lag 3.

Cho et al. (2020) examined the change of total stock area of domestic logistics warehouses and studied the determinants of supply based on the current status of supply and loss of domestic logistics warehouses since 1971. In order to analyze the influence of online shopping transaction amount, the multiple regression model selected as the main independent variables such as the manufacturing gross domestic product, stock price index, interest rate (three years of corporate bonds), economic activity population, import amount, sales facility and online shopping transaction amount for 17 years was analyzed. As a result, online shopping transaction the amount had the greatest effect on the time difference in the 10th quarter, and all variables had a significant effect on the model of more than 10,000m^2 of logistics real estate area compared to other models.

Xin and Kim (2017) analyzed the determinants affecting the purchase intention of online shopping malls for Chinese consumers and differentiated them from the existing studies by introducing the innovativeness of users and the frequency of Internet use for the empirical analysis of the determinants of the service quality of online shopping malls. As a result of the empirical analysis, traits such as reliability and convenience were turned out be a crucial clincher of consumer's purchasing intention, and the quality of products was an important determinant in the group with high frequency of internet use.

Jeun et al. (2020) aimed to find out how the obstacles, which consumers feel when purchasing products in the Internet shopping mall environment, influence the propensity to consume and intention to repurchase, and to investigate how mental risk plays a moderating part between product purchase inhibition factors and consumption propensity. They conducted to find out the factors that hinder the purchase of products, consumer propensity, repurchase intention, and psychological risk in the Internet shopping mall environment, and to improve the process of satisfaction with the purchase and the broader understanding of consumers.

Jeong and Wang (2016) performed two kinds of cluster analysis step by step based on the developmental characteristics of e-commerce, such as Internet Merchant Index, Internet Shopping Index, and e-commerce development index, and classified the major 50 major cities in China into four similar clusters. And, using multidimensional scale, they positioned each city for the attributes in two-dimensional plane. Fifty key cities were apparently categorized into four homogeneous groups, and Shenzhen was turned out to be predominant over the rest of cites in terms of each attributes, along with Gwangju and Hangzhou.

In this research, both multiplicative ARIMA model, and Holt-Winters Multiplicative seasonality method are exploited to forecast the upcoming values of the Corona 19's domestic both internet and mobile shopping transaction amount in South Korea.

A brief description for the underlying univariate time series models and goodness-of-fit measures will, in section 2, be shown, together with data source and in section 3, findings of statistical analyses and forecasted values for both internet and mobile shopping transaction amount will be presented. Finally, concluding remarks and limitations of this work will be stated.

2. Data collection, data description and statistical methods

2.1. Data collection

The data are extracted from the online shopping trend survey of the National Statistical Office and homogeneous and comparable in size based on 46 realizations sampled from January 2007 to October 2020.

The purpose of data collection is to establish the government's policy and corporate management plan by analyzing the online shopping trend and to provide necessary data to research institutes and various associations.

About 1,100 businesses are selected as research units for the whole country, and determined to operate an online shopping mall on the Internet. Overseas direct sales are conducted by domestic businesses selling products overseas on the Internet, and made using data that were customs clearance through e-commerce among customs clearance data of the Korea Customs Service.

The virtual business place set up to trade goods or services using computers, information and communication facilities is referred to as an Internet shopping mall, and Internet shopping malls that mainly deal with PCs and mobiles are defined as online shopping malls (Statistics Research Institute, 2018). The online mall is subject to transactions such as households, businesses, and governments. Mobile apps are applications that can be installed and used in smart devices such as mart phones and smart pads, and are called apps (APP), mobile apps, applications, and applications. The mobile shopping transaction amount means the amount of transactions made by consumers who access the shopping mall through mobile apps or web optimized for mobile devices.

2.2. Data description

Table 1 and Table 2 represent internet and mobile shopping transactions in South Korea for a total of 46 realizations from January 2007 to October in 2020, respectively.

We can find out the repeated patterns that the internet shopping transaction amount in Figure 1 are smaller in February and larger in November than other months, while the mobile shopping transaction amount in Figure 2 have smaller in February and larger values in December. That is, these repeated periodic patterns imply that seasonal variations exist, as shown in Figures 1-2.

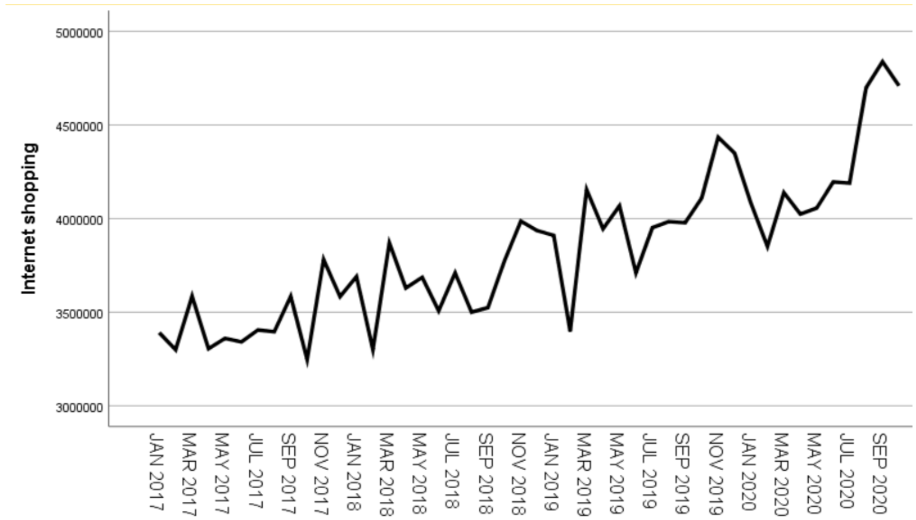

Figure 1: Time-plot of internet shopping transaction amount

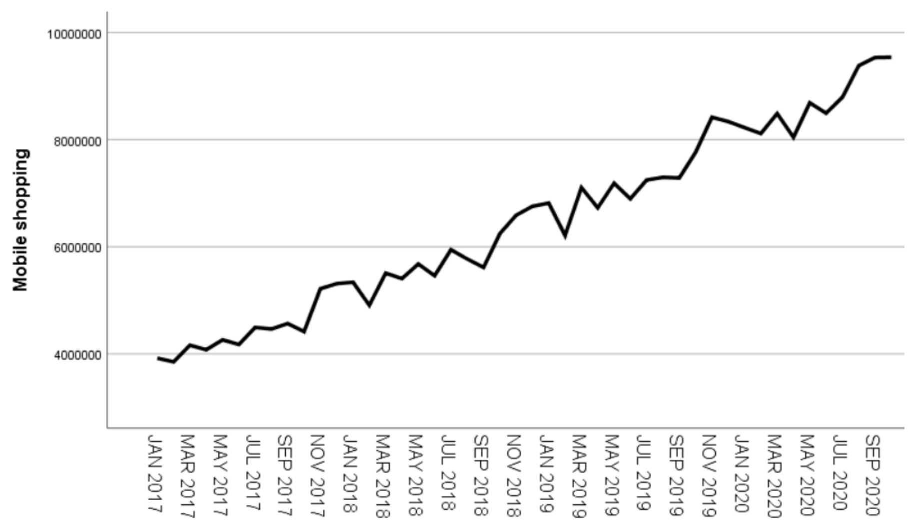

Figure 2: Time-plot of mobile shopping transaction amount

At the same time, both shopping transactions remain on a steady rise overall and, in particular, we can see that the increase in the amount that mobile shopping transactions occupies among online shopping transactions is steeper than the amount of internet shopping transactions by comparing Figure 1 with Figure 2.

2.3. Statistical methods and model fit measures

In order to obtain the optimal forecasted values of both internet and mobile shopping transaction amount in South Korea, the popular univariate time series models, autoregressive integrated moving average(ARIMA) model and exponential smoothing method, are considered (Anderson, 1971; Bianchi et al., 1998; Bowerman et al., 2005; Box et al., 1994; Brown, 1959; Fuller, 1995; Hamilton, 1994; Jeong, 2010; Jeong, 2016; Pankraz, 1983; Tsay & Tiao, 1984).

Considering the univariate time series analysis for the underlying time series data, we can find that seasonal variation exists in both time series as seen in 2.2, so we can select the multiplicative ARIMA model and the two kinds of Holt-Winters seasonality techniques as below:

Multiplicative ARIMA Model:

$$y_t = \frac{\Theta_Q(B^s)\theta_q(B)}{\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D}\epsilon_t,$$

where $\Theta_Q(B^s) = \left(1 - \Theta_s B^s - \Theta_{2s}B^{2s} - \cdots - \Theta_{Qs}B^{Qs}\right)$

$\Phi_P(B^s) = (1 - \Phi_s B^s - \Phi_{2s}B^{2s} - \cdots - \Phi_{Ps}B^{Ps}),$

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

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

and $\epsilon_t's$ are white noise. Here, (p,d,q) and $(P, D, Q)_s$ are non-seasonal order and seasonal order, respectively.

Exponential smoothing method:

The following exponential smoothing methods used in the presence of seasonality can be considered (Anderson, 1994; Archibald, 1990; Archibald & Koehler, 2003; Bartolomei & Sweet, 1989; Brown, 1963; Broze & Mélard, 1990; Gardner, 1985; Gardner, 2006; Jeong, 2009; Roberts, 1982; Rosas & Guerrero, 1994; Trigg & Leach, 1967; Winters, 1960).

- **Holt-Winters Multiplicative seasonality method:**
  Level: $L_t = \alpha y_t + (1-\alpha)(L_{t-1} + \phi Q_{t-1}),$
  Slope: $Q_t = \beta(L_t - L_{t-1}) + (1-\beta)Q_{t-1},$
  Seasonality: $S_t = \delta(\frac{y_t}{L_{t-1} + b_{t-1}}) + (1-\delta)S_{t-j},$
  Forecasts: $\hat{y}_{t+j,t} = (L_t + jQ_t)S_{t-j+|(j-1)mod j|+1}.$
- **Holt-Winters Additive seasonality method:**
  Level: $L_t = \alpha(y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + Q_{t-1}),$
  Slope: $Q_t = \beta(L_t - L_{t-1}) + (1-\beta)Q_{t-1},$
  Seasonality: $S_t = \delta(y_t - L_{t-1} - b_{t-1}) + (1-\delta)S_{t-j}$
  Forecasts: $\hat{y}_{t+j,t} = (L_t + jQ_t)S_{t-j+|(j-1)mod j|+1.}$

In order to search for the optimal forecasted values based on the underlying models, the statistical measures are as follows:

- R-squared: $1 - \frac{\sum_{t-1}^{n}(y_t - \hat{y_t})^2}{\sum_{t-1}^{n}(y_t - \bar{y})^2},$
- Stationary R-squared: $1 - \frac{\sum_{t-1}^{n}(z_t - \hat{z_t})^2}{\sum_{t-1}^{n}(\Delta z_t - \overline{\Delta z})^2},$ where Δz_t is differenced data after variable transformation of y_t.

We note that the more the two statistics above have a large value, the better the fit.

- Root Mean Square Error: $\text{RMSE} = \sqrt{\sum_{t=1}^{n}\frac{e_t^2}{n}},$
- Mean Absolute Percentage Error: $\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right|,$
- Mean absolute error: $\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|e_t|,$
- Maximum Absolute Percentage Error: $\text{MaxAPE} = 100\max\left(\left|\frac{e_t}{y_t}\right|\right),$
- Maximum Absolute Error: $\text{MaxAE} = \max(|e_t|)$, Here $e_t's$ are residuals, i.e., $e_t = y_t - \hat{y}_t$, t=1,…,n.

We note that the more the five statistics above have a smaller value, the better the fit (Chatfield, 1988; Chatfield, 1993; Chatfield, 1995; Chatfield, 1996; Chatfield, 1997; Chatfield, 2002; Hurcich & Tsai, 1990, Ljung & Box, 1978). Time series models under consideration, in this research, are applied to come by optimal forecasts calculating TSAPPLY and MODELFIT algorithms in IBM SPSS 25.0.

3. Research Results and Summary

3.1. Results of Internet Shopping Transaction amount

Thinking over the pattern of the seasonality from Figure 1, both Holt-Winters addictive seasonality method and ARIMA(1,1,0)(1,0,0)$_{12}$ model can be chosen as the optimal candidates, and optimal predominance among them can be compared in terms of goodness-of-fit measures as given in Table 1.

At this time, ARIMA(1,1,0)(1,0,0)$_{12}$ model can be chosen by going through an iterative procedure on identification, estimation, and diagnostic checking steps (the details are omitted).

Table 1: Optimal model selection for internet shopping transaction amount

Method / Goodness-of fit statistics	Holt-Winters Additive seasonality	ARIMA(1,1,0)(1,0,0)$_{12}$
Stationary R-squared	**.63**	.47
R-squared	**.87**	.76
RMSE	**146248.46**	195925.12
MAPE	**2.85**	3.88
MAE	**109231.17**	149184.09
MAXAPE	**9.00**	10.76
MAXAE	419398.35	**418593.86**
Normalized BIC	**24.04**	24.54

As a result of Table 1, Holt-Winters' additive seasonality method may be taken into account as optimality to predict the future data, since it has the larger two R^2, and the smaller RMSE, MAPE, MAE, MaxAPE except MaxAE over ARIMA(1,1,0)(1,0,0)$_{12}$ model.

Table 2: Best forecasted values and 95% confidence intervals of internet shopping transaction amount

Time period	Forecasted values	95% Lower Confidence Limit	95% Upper Confidence Limit
Nov 2020	4,955,105	4,660,167	5,250,044
Dec 2020	4,843,671	4,513,898	5,173,444
Jan 2021	4,806,002	4,444,736	5,167,267
Feb 2021	4,500,150	4,109,924	4,890,376
March 2021	4,975,140	4,557,957	5,392,323
April 2021	4,763,888	4,321,387	5,206,390
May 2021	4,830,696	4,364,248	5,297,145
June 2021	4,726,465	4,237,239	5,215,691
July 2021	4,851,854	4,340,864	5,362,844
August 2021	4,932,584	4,400,719	5,464,449
Sept 2021	5,019,529	4,467,577	5,571,482
Oct 2021	4,998,031	4,426,696	5,569,366

By fitting Holt-Winters' additive seasonality method to internet shopping transaction amount, the forecasted values can be obtained from November in 2020 to October in 2021 from both Table 2 (see Forecasted values) and Figure 3 (see the dotted box). We can check future 12-month forecasts with maintaining upward trend and seasonal variation.

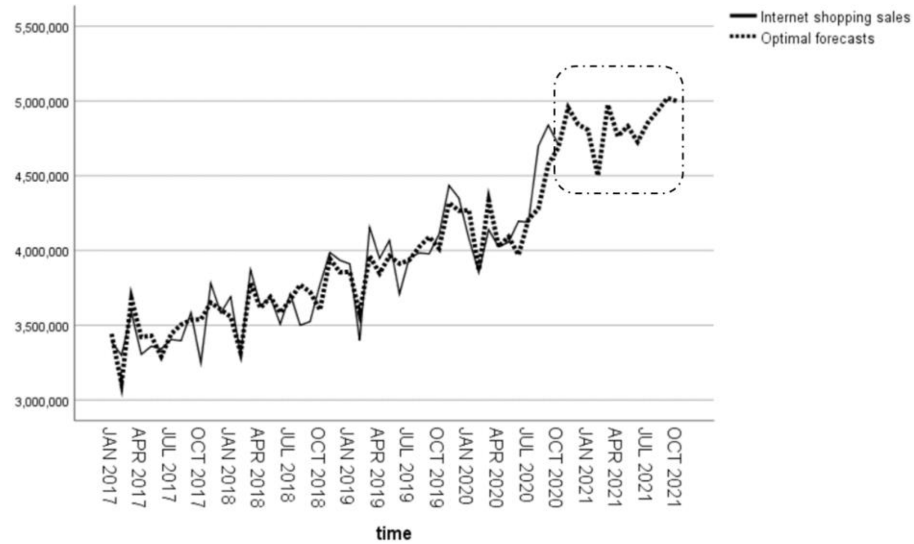

Figure 3: Optimal forecasts of internet shopping transaction amount

3.2. Results of Mobile Shopping Transaction amount

As done in section 3.1, we can choose both Holt-Winters addictive seasonality method and ARIMA(0,1,1)(1,0,0)$_{12}$ model as the optimal candidates, and thus we can consider Holt-Winters addictive seasonality method as a final model., since observing and detecting the behavior of seasonal variation from Figure 2.

Table 3: Optimal model selection for mobile shopping transaction amount

Method / Goodness-of fit statistics	Holt-Winters Additive seasonality	ARIMA(0,1,1)(1,0,0)$_{12}$
Stationary R-squared	**.64**	.58
R-squared	**.99**	.98
RMSE	**168035.90**	231992.93
MAPE	**2.00**	2.85
MAE	**126478.81**	173685.59
MAXAPE	**8.00**	8.85
MAXAE	**477953.17**	518863.95
Normalized BIC	**24.31**	24.96

Table 4: Best forecasted values and 95% confidence Intervals of mobile shopping transaction amount

Time period	Forecasted values	95% Lower Confidence Limit	95% Upper Confidence Limit
Nov 2020	9,900,692	9,561,816	10,239,569
Dec 2020	9,996,062	9,655,741	10,336,383
Jan 2021	10,053,651	9,710,715	10,396,587
Feb 2021	9,785,570	9,438,530	10,132,609
March 2021	10,366,271	10,013,352	10,719,190
April 2021	10,149,604	9,788,784	10,510,424
May 2021	10,575,673	10,204,737	10,946,609
June 2021	10,413,188	10,029,785	10,796,592
July 2021	10,812,606	10,414,303	11,210,909
August 2021	10,957,017	10,541,356	11,372,679
Sept 2021	11,014,294	10,578,835	11,449,752
Oct 2021	11,289,930	10,832,290	11,747,570

This is due to that fact that Table 3 shows that goodness-of-fit statistics corresponding to Holt-Winters addictive seasonality method are superior to those corresponding to ARIMA(0,1,1)(1,0,0)$_{12}$ model. At this time, we note that ARIMA(0,1,1)(1,0,0)$_{12}$ model can be chosen as a proper ARIMA model by going through the iterative procedure, just like in section 3.1.

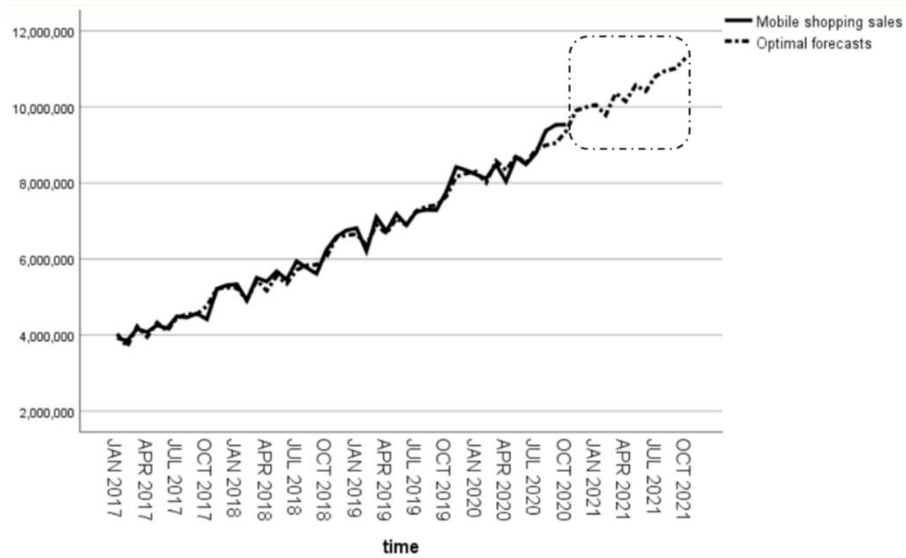

Figure 4: Optimal forecasts of mobile shopping transaction amount

Similarly, by fitting Holt-Winters' additive seasonality to mobile shopping transaction amount, the forecasted values can be obtained from November in 2020 to October in 2021 from both Table 4 (see Forecasted vales) and Figure 5 (see the dotted box). We can check the upcoming 12-month forecasts with maintaining upward trend and seasonal variation. Forecasted values from Figure 4 maintain a pattern that steadily increases while having a constant seasonal variation.

4. Concluding Remarks and Limitation

In this work, we forecast both internet and mobile shopping transaction amount in South Korea by choosing Holt-Winters' additive seasonality method as an optimal univariate time series technique. Since two types of online shopping transactions have seasonal variations, we consider multiplicative ARIMA model, Holt-Winters' additive and multiplicative seasonality methods simultaneously for each transaction amount, and thus choose ARIMA(1,1,0)(1,0,0)$_{12}$ model, ARIMA(0,1,1)(1,0,0)$_{12}$ model, and Holt-Winters' additive seasonality method as optimality, respectively.

First, optimal twelve forecasts of internet shopping transaction amount from November in 2020 to October in 2021 in South Korea can be 4,955,105, 4,843,671, 4,806,002, 4,500,150, 4,975,140, 4,763,888, 4,830,696, 4,726,465, 4,851,854, 4,932,584, 5,019,529 and 4,998,031, which are got by selecting Holt-Winters' additive seasonality method among seasonal exponential smoothing methods and ARIMA models.

Similarly, optimal twelve forecasts of mobile shopping transaction amount from November in 2020 to October in 2021 in South Korea can be 9,900,692, 9,996,062, 10,053,651, 9,785,570, 10,366,271, 10,149,604, 10,575,673, 10,413,188, 10,812,606, 10,957,017, 11,014,294 and 11,289,930, which are got from Holt-Winters' additive seasonality methods.

All of the optimal forecasts for the next 12 months for two online shopping transactions maintain a pattern in which the slope increases linearly and steadily with a fixed seasonal change that has been subjected to seasonal fluctuations. By comparing the estimated smoothing coefficients of two underlying Holt-Winters' additive seasonality methods considering the time series of the two online shopping transaction amount, it can be confirmed that the mobile shopping transaction amount is much larger than the internet shopping transaction amount for the increase in trend and seasonality. We note that the estimated coefficients for the trend smoothing and for the seasonal smoothing are 2.341E-5 and 2.584E-5 for internet shopping transaction amount, while .537 and .001 for mobile shopping transaction amount in terms of estimating Holt-Winters' additive seasonality methods.

Korea is the world's fifth largest e-commerce market because it has high number of high-speed Internet subscribers and mobile communication users as a powerhouse of information and communication technology. E-commerce accounts for 28.2% of the retail distribution market in Korea, the highest in the world. Consumers who have experienced the convenience of e-commerce are expected to maintain online shopping trends even after the end of Corona 19, and to make online conversion of the retail distribution market become commonplace.

It is possible to build a stable customer base by securing loyal customers through differentiated marketing such as effective royalty program and customized information for each customer, and by inducing repetitive purchase through paid membership system or exclusive application. Industry, which was the center of face-to-face service such as the food service industry and the real estate industry, can overcome physical constraints and expand customer base through online conversion by developing instant food that can be delivered to home or providing VR tour service. It is necessary to develop products and services that meet new customer needs such as convenient home life and hygiene safety improvement, diversify items, and we actively participate in research and development for introducing information technology and collaboration with technology companies (Kim, 2020).

In the first quarter of 2020, in the early days of the outbreak of Corona 19, the rate of increase in transaction amount compared to 2019 was 76.7% for food service, whose growth rate was the highest among all product groups. The transaction growth rate was followed by 'automobile and automobile products', 'food', and 'life goods'. On the other hand, as travel and cultural life are limited due to the influence of Corona 19, the transaction amount of 'travel and transportation service' and 'culture and leisure service' have decreased (Oh, 2020). Therefore, by subdividing and calculating the online shopping transaction amount by product group as future research, we can expect to get the information of the purchasing characteristics, demand forecasting and so on for reforming financial terms and relevant policies.

In this study, we analyze two different time series amounts that compost of single observations registered consecutively over time. Taking into account indispensable explanatory variables and the correlation among multiple time series, the more dynamic and complex time series models such as state space time series model and vector auto-regression model and so on may be fitted and analyzed in the future.

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