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Prediction of Sales on Some Large-Scale Retailing Types in South Korea*

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Abstract

Purpose – This paper aims to examine several time series models to predict sales of department stores and discount store markets in South Korea, while other previous trial has performed sales of convenience stores and supermarkets. In addition, optimal predicted values on the underlying model can be got and be applied to distribution industry.

Research design, data, and methodology - Two retailing types, under investigation, are homogeneous and comparable in size based on 86 realizations sampled from January 2010 to February in 2017. To accomplish the purpose of this research, both ARIMA model and exponential smoothing methods are, simultaneously, utilized. Furthermore, model-fit measures may be exploited as important tools of the optimal model-building.

Results - By applying Holt-Winters' additive seasonality method to sales of two large-scale retailing types, persisting increasing trend and fluctuation around the constant level with seasonal pattern, respectively, will be predicted from May in 2017 to February in 2018.

Conclusions - Considering 2017-2018 forecasts for sales of two large-scale retailing types, it is important to predict future sales magnitude and to produce the useful information for reforming financial conditions and related policies, so that the impacts of any marketing or management scheme can be compared against the do-nothing scenario.

Keywords: Large-Scale Retailing Type, ARIMA Model, Exponential Smoothing Method, Optimal Forecasts.

JEL Classifications: C22, C53, D39, M21.

1. Introduction

In general, we often define large retail trade as "a type in which either single type of goods or various goods is made available to a large number of customers in a big shop under a single roof or may be made available at the convenience of customers". Industry data reported that major South Korean discount retailers found their sales come close 1.8 percent in 2016 to exceed 40 trillion won, by virtue of an increase in new outlet. In recent time, large retailing industry in Korea has suffered slowly-moving sales growth because of slower-run discount store markets from operating. Jeong (2016) investigated the optimal forecasting for sales of small-scale retailing types such as convenience stores and supermarkets in South Korea. He found that the predicted values of sales at convenience stores can have the pattern of the precipitous and lasting increase, although forecasts for sales at supermarkets can be expected to be lagging over 2017 by utilizing a seasonal ARIMA-Intervention model. Kim et al. (2014) tried to find which factors can affect sales on department stores in South Korea, and measured the influence both position and non-position factors. In particular, they showed that 'area of sales property', 'parking space' and 'number of luxury goods' are positively correlated with profit of department store. Youn (2004) set a clear vision on distribution markets by considering the fact that most jobs in South Korea are focused on the marketing field and analyzed the distribution industry from the internal viewpoints of distribution companies. In this research, we analyze several univariate time series models such as ARIMA model, exponential smoothing method, so that we can forecast the upcoming values of two large-scale retailing types in South Korea.

A short outline for time series models under consideration will, in section 2, be shown, together with model-fit statistics and in section 3, the results of several time series analyses and forecasts for sales of two large-scale retailing types will be presented. Finally, summary and concluding remarks will

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be stated.

2. Time Series Analysis

In order to forecast the future value of sales at department stores as well as discount store markets in South Korea, the following time series models can be considered:

2.1. ARIMA(Autoregressive Integrated Moving Average) Model

(Anderson, 1971; Bianchi et al, 1998; Bowerman et al, 2005; Box et al, 1994; Brown, 1959; Fuller, 1976; Hamiltan, 1994; Jeong, 2010; Jeong, 2016; Pankraz, 1983)

An autoregressive integrated moving average (ARIMA) model forecasts a value(s) in a dependent time series as a linear combination of its own past values, past shocks, and past and current values of other series, and can be expressed as follows:

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

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

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

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

$$\Phi_p(B) = (1-\Phi_1 B - \Phi_2 B^2 - \cdots - \Phi_p B^p),$$

and $\epsilon'_t s$ are white noises.

Here, (p, d, q) and $(P, D, Q)_s$ are non-seasonal order and seasonal order, respectively (Anderson, 1971; Choi, 1992; Fuller, 1976; Hamilton, 1994; Pankratz, 1983; Pankratz, 1991; Tsay & Tiao, 1984).

2.2. Exponential smoothing method

(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).

This method is one of most widely used models to make a smoothed time series. While in single moving averages the past realizations are weighted equally, exponential smoothing allots exponentially decreasing weights as the realizations is older. That is to say, recent realizations are assigned relatively more weight in predicting than more remote realizations.

2.2.1. Simple exponential smoothing method

This method is used for forecasting a time series when there is no trend or seasonal pattern, but the mean (or level) of the time series is slowly changing over time. This is utilized for short-range prediction, usually just one-time period into the future. The forecast for the next period is

$$\hat{y}_{t+1} = \hat{y}_t + \alpha(\hat{y}_t - \hat{y}_t)$$

where αis a smoothing constant between 0 and 1.

2.2.2. Holt's linear method

Holt (1957) extended the previous exponential smoothing to linear trends exponential smoothing, for the purpose of predicting realizations with trends. The forecast for this method is found that using two smoothing constants, α, β (with constants between 0 and 1), and the following equations:

Level: $L_t = \alpha y_t + (1-\alpha)(L_{t-1} + Q_{t-1}),$

Slope: $Q_t = \beta(L_t - L_{t-1}) + (1-\beta)Q_{t-1},$

Forecasts: $\hat{y}_{t+j,t} = L_t + jQ_t,$

where L_t and Q_t are estimates of the level and the slope of the series at time t, respectively.

2.2.3. Damped linear trend method

This method is a modification of Holt's linear method to allow the "damping" of trends. The equations for this method are

Level : $L_t = \alpha(\frac{y_t}{s_{t-m}}) + (1-\alpha)(L_{t-1} + Q_{t-1}),$

Slope: $Q_t = \beta(L_t - L_{t-1}) + (1-\beta)\phi Q_{t-1},$

Forecasts : $\hat{y}_{t+j,t} = L_t + \sum_{i=1}^{j} \phi_i jQ_t$

The next two Holt-Winters methods are based on three smoothing equation - level, slope and seasonality, depending on whether seasonality is modeled in a multiplicative or an additive way.

2.2.4. Multiplicative seasonality method

We can use this model in case that realizations increase, so does the seasonal pattern.

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: $\hat{y}_{t+j,t} = (L_t + jQ_t) S_{t-j+|(j-1)\mathrm{mod}j|+1}$.

2.2.5. Additive seasonality method

We can use this model in case that the magnitude of the type of seasonality is fixed as the series fluctuates.

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: $\hat{y}_{t+j,t} = (L_t + jQ_t) S_{t-j+|(j-1)\mathrm{mod}j|+1}$

For the purpose of satisfying optimal properties of the underlying model, the following statistics can be exploited:

2.3. Model-fit measures to select the optimal model

(Chatfield, 1988; Chatfield, 1993; Chatfield, 1995; Chatfield, 1996; Chatfield, 1997; Chatfield, 2002; Hurcich & Tsai, 1990).

- Stationary R-squared. This measure is better than ordinary R-squared when a trend or seasonality in time series can be detected. If it is a negative value, then we can conclude that the baseline model is dominant to the model under consideration.
- R-squared. A statistic of the proportion of the whole variation in the time series accounted for by the model. This measure can be valid when the time series satisfy stationarity. A negative value of this measure means that the baseline model is dominant to the model under consideration, while a positive value does that the underlying model is more appropriate than the baseline one.
- Root Mean Square Error (RMSE). A measure of how much a response variable shifts from its model-forecasted level.
- Mean Absolute Percentage Error (MAPE). This measure is not dependent on the units detected and be taken advantage of comparing the time series with different ones.
- Mean absolute error (MAE). A measure how much the time series fluctuate its model-predicted level.
- Maximum Absolute Percentage Error MaxAPE). The biggest predicted error, depicted as a percentage. This measure is useful to estimate a worst situation for predicted values.
- Maximum Absolute Error (MaxAE). This measure is useful to estimate the worst-case scenario for predicted values.
- Normalized Bayesian Information Criterion (BIC). This statistic is a score focused on the MSE and covers a disadvantage for the number of coefficients in the model under consideration and the length of the time series.

3. Summary and Research Results

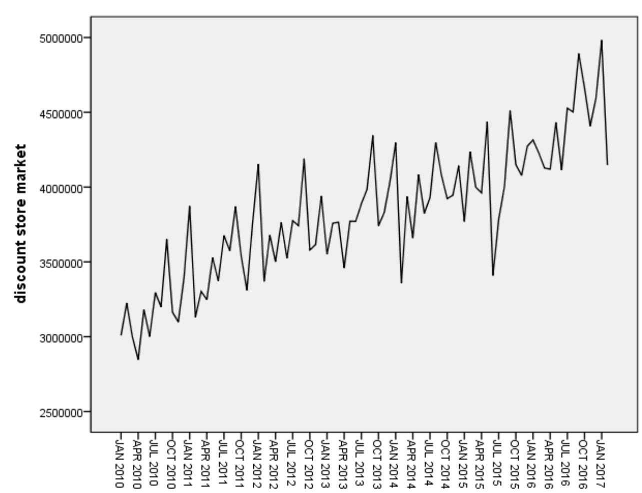
3.1. Summary

First, several time series models, in this work, are applied to obtain optimal forecasts by using TSAPPLY and MODELFIT procedures in IBM SPSS 23.0.

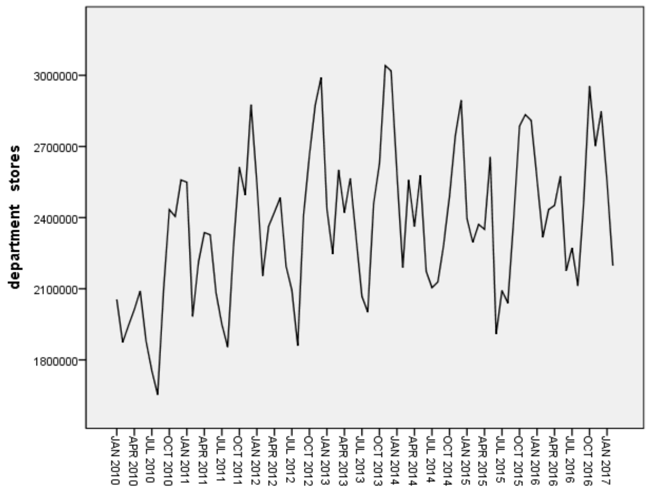
<Table 1> shows that the main descriptive statistics of sales at both discount store markets and department stores in South Korea for 86 realizations from January in 2010 to February in 2017, including mean, standard deviation, minimum and maximum.

<Table 1> Summary statistics

Statistic Variable(Sales)	N	Minimum	Maximum	Mean	Std. Deviation
Discount Stores Markets	86	2,847,287	4,982,538	3,827,226.4	455,347.7
Department Stores	86	1,653,658	3,040,996	2,369,966.5	312,886.9



<Figure 1> Time-plot of sales at discount store markets



<Figure 2> Time-plot of salesat department stores

From both <Figure 1> and <Figure 2>, we may find out that there exists seasonal variation with displaying periodic behavior within the underlying series. While the level seems to fluctuate around the sample mean in <Figure 2>, the slope in <Figure 1>increases steady and persistently. That is, the series of <Figure 1>appears to need to be differencing to accomplish stationarity in building ARIMA models.

3.2. Findings of Sales at Discount Store Markets

Considering the pattern of the trend and the type of seasonality from <Figure 1>, Holt's linear, damped linear and Holt-Winters' additive seasonality method can be considered, we can compare optimal dominance among them in terms of model-fit measures in <Table 2>. Similarly, we may take into account ARIMA models, ARIMA(0,0,1)(0,0,1)$_{12}$ and ARIMA(3,1,0)(0,0,1)$_{12}$, by applying an iterative procedure based on three stages – identification, estimation, and diagnostic checking, so that we can find the optimal ARIMA model.

<Table 2> Optimality selection for sales at discount store markets in terms of exponential smoothing methods

Model Goodness-of fit measures	Winter's additive seasonality	Holt's linear	Damped linear
Stationary R-squared	**.808**	.830	.508
R-squared	**.846**	.692	.697
RMSE	**180,996.80**	254,219.21	253,518.63
MAPE	**3.37**	5.09	5.04
MAE	**127,949.14**	194,521.74	192,808.83
MAXAPE	**15.36**	21.94	22.35
MAXAE	**523,625.96**	748,094.16	762,120.28
Normalized BIC	**24.37**	24.99	25.04

<Table 3> Optimality selection for sales at discount store markets in terms of ARIMA models

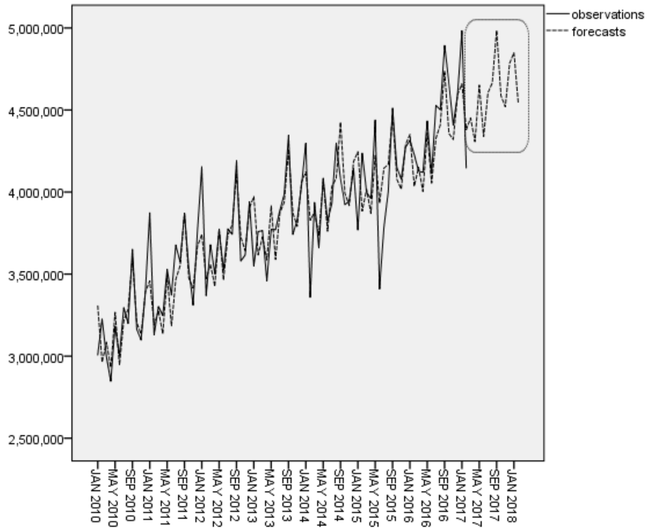
Model Goodness-of fit measures	ARIMA(0,1,1)(0,0,1)$_{12}$	ARIMA(3,1,0)(0,0,1)$_{12}$
Stationary R-squared	**.548**	.507
R-squared	**.712**	.686
RMSE	**243,993.97**	256,414.11
MAPE	**4.83**	5.09
MAE	**184,263.59**	194,660.06
MAXAPE	**20.92**	21.95
MAXAE	**713,303.33**	748,364.15
Normalized BIC	**24.97**	25.12
P-value of Box-Ljung Statistic	**.660**	.659

As a result, Holt-Winters' additive seasonality method and ARIMA(0,0,1)(0,0,1)$_{12}$ can be chosen, respectively, as seen from <Table 2> and <Table 3>. At last, Holt-Winters' additive seasonality method may be considered as the optimal model to forecast the forthcoming data in that it satisfies the properties that has the largest R^2, and the smallest RMSE, MAPE, MAE, MaxAPE and MAxAE.

<Table 4> Optimal forecasts and two 95% confidence limits of sales at discount store markets

Time period	Forecasts	95% Lower Confidence Limit	95% Upper Confidence Limit
MAR 2017	**4,451,399**	2,255,076	2,656,388
April 2017	**4,307,456**	2,204,712	2,610,286
May 2017	**4,650,779**	2,301,766	2,716,772
June 2017	**4,338,728**	1,900,891	2,332,154
July 2017	**4,604,838**	1,801,740	2,257,244
August 2017	**4,665,628**	1,657,716	2,146,017
Sept 2017	**4,984,796**	1,997,374	2,527,062
Oct 2017	**4,587,536**	2,254,731	2,834,040
Nov 2017	**4,520,199**	2,272,750	2,909,338
Dec 2017	**4,785,251**	2,339,478	3,040,355
Jan 2018	**4,849,130**	1,903,694	2,675,229
Feb 2018	**4,537,496**	1,532,668	2,380,655

By applying Holt-Winters' additive seasonality method to sales at discount store markets, persisting increasing trend with seasonal pattern may be predicted from May in 2017 to February in 2018 from both <Table 4> and <Figure 3>.



<Figure 3> Optimal forecasts of sales at discount store markets in South Korea

3.3. Findings of Sales at Department Stores

We can analyze and evaluate sales at department stores in South Korea, just as we do in section 3.2. Taking into account existence and pattern of seasonality from <Figure 2>, Holt-Winters' additive and Holt-Winters' multiplicative seasonality method can be allowed for. At the same time, ARIMA(1,0,0)(1,0,0)$_{12}$ and ARIMA(0,0,3)(1,0,0)$_{12}$ can be chosen as candidates of proper ARIMA models by applying a iterative procedure based on three stages, just like in section 3.2.

<Table 5> Optimality selection for sales at department stores in terms of exponential smoothing methods

Model Goodness-of fit measures	Holt-Winters' Additive	Holt-Winters' Multiplicative
Stationary R-squared	**.668**	.586
R-squared	**.898**	.885
RMSE	**100,884.83**	107,297.89
MAPE	**3.31**	3.33
MAE	**78,716.46**	79,879.88
MAXAPE	**11.05**	12.25
MAXAE	281,694.02	**266,481.50**
Normalized BIC	**23.20**	23.32

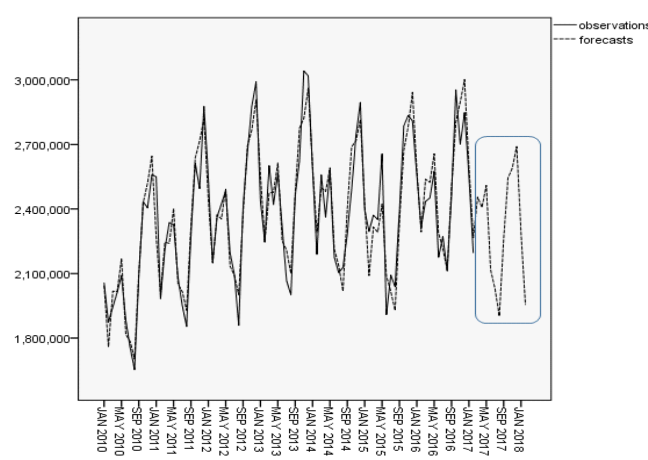
Based on eight model-fit measures, Holt-Winters' additive seasonality method can be selected as a final and optimal model to forecast the future values of sales at department stores in South Korea as seen from <Table 5> and <Table 6>.

<Table 6> Optimality selection for sales at department stores in terms of ARIMA models

Model Goodness-of fit measures	ARIMA(1,0,0)(1,0,0)$_{12}$	ARIMA(0,0,3)(1,0,0)$_{12}$
Stationary R-squared	.737	**.739**
R-squared	.737	**.739**
RMSE	**162,512.88**	163,896.74
MAPE	5.62	**5.41**
MAE	128721.85	**123,899.22**
MAXAPE	**21.45**	23.03
MAXAE	**372,200.36**	385,616.36
Normalized BIC	**24.15**	24.27
P-value of Box-Ljung Statistic	.102	**.195**

<Table 7> Optimal forecasts and two 95% confidence limits of sales at department stores

Time period	Forecasts	95% Lower Confidence Limit	95% Upper Confidence Limit
MAR 2017	**2,455,732**	2,255,076	2,656,388
April 2017	**2,407,499**	2,204,712	2,610,286
May 2017	**2,509,269**	2,301,766	2,716,772
June 2017	**2,116,523**	1,900,891	2,332,154
July 2017	**2,029,492**	1,801,740	2,257,244
August 2017	**1,901,866**	1,657,716	2,146,017
Sept 2017	**2,262,218**	1,997,374	2,527,062
Oct 2017	**2,544,386**	2,254,731	2,834,040
Nov 2017	**2,591,044**	2,272,750	2,909,338
Dec 2017	**2,689,916**	2,339,478	3,040,355
Jan 2018	**2,289,461**	1,903,694	2,675,229
Feb 2018	**1,956,662**	1,532,668	2,380,655



<Figure 4> Optimal forecasts of sales at department stores in South Korea

By fitting Holt-Winters'additive method to sales of department stores, the predicted values from May in 2017 to February in 2018 appear to fluctuate around the constant level with maintaining the seasonal pattern from <Table 7> and <Figure 4>.

4. Concluding Remarks and Limitation

In this research, we forecast both sales at discount store markets and sales at department stores in South Korea by using univariate optimal time series, Holt-Winters' additive seasonality method.

First, optimal forecasts of sales at discount store markets from March in 2017 to February in 2018 in South Korea can be 4451399, 4307456, 4650779, 4338728, 4604838, 4665628, 4984796, 4587536, 4520199, 4785251, 4849130 and 4537496, which are obtained by choosing Holt-Winters' additive seasonality method among several exponential smoothing methods and ARIMA models.

In detail, $ARIMA(0,1,1)_{12}$ and $ARIMA(0,0,3)(1,0,0)_{12}$ models are selected by performing optimal procedures of ARIMA model-construction and also three exponential smoothing methods such as Holt's linear, damped linear and Holt-Winters' additive seasonality methods.

Second, optimal forecasts of sales at department stores in South Korea can be 2455732, 2407499, 2509269, 2116523, 2029492, 1901866, 2262218, 2544386, 2591044, 2689916, 2289461 and 1956662, which are, similarly, obtained on Holt-Winters' additive seasonality methods.

Both $ARIMA(1,0,0)(1,0,0)_{12}$ and $ARIMA(0,0,3)(1,0,0)_{12}$ models are chosen by carrying out the optimal ARIMA model-construction and also two exponential smoothing methods such as and Holt-Winters' additive and Holt-Winters' multiplicative seasonality methods, at the same time.

The shape of the persisting and rather moderate rise of sales at discount stores can be forecasted over the upcoming 12 months, while sales at department stores just keep things tickling over, with both sales maintaining the seasonality pattern.

Empirically calculated estimates of sales at department stores and discount store markets and accurate predicted values of future sales are of much importance for sales planning and policy making. The sensitivity of sales to the transition of its determinants can support policy makers to assess plan B policy options in adjusting future sales at department stores and discount stores or modal shift. Accurate forecasts can provide information on future sales level in the evaluation of sales related projects and sales policies.

Taking into account 2017-2018 forecasts for sales at department stores and at discount store markets, it is of importance to be able to predict future sales magnitude and to produce the useful information for reforming financial conditions and related policies, so that the impacts of any marketing or management scheme can be compared against the do-nothing scenario.

In this paper, we treat two different time series that consist of single realizations recorded sequentially over equally spaced time intervals. Considering indispensable predictor variables and the linear interdependencies among multiple time series, dynamic regression model or vector auto-regression model, as an alternative, can be applied to the underlying time series (Pankratz, 1991; Hatemilton, 2004).

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