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The variance-covariance method using IOWGA operator for tourism forecast combination

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Abstract
Three combination methods commonly used in tourism forecasting are the simple average method, the variance-covariance method and the discounted MSFE method. These methods assign the different weights that can not change at each time point to each individual forecasting model. In this study, we introduce the IOWGA operator combination method which can overcome the defect of previous three combination methods into tourism forecasting. Moreover, we further investigate the performance of the four combination methods through the theoretical evaluation and the forecasting evaluation. The results of the theoretical evaluation show that the IOWGA operator combination method obtains extremely well performance and outperforms the other forecast combination methods. Furthermore, the IOWGA operator combination method can be of well forecast performance and performs almost the same to the variance-covariance combination method for the forecasting evaluation. The IOWGA operator combination method mainly reflects the maximization of improving forecasting accuracy and the variance-covariance combination method mainly reflects the decrease of the forecast error. For future research, it may be worthwhile introducing and examining other new combination methods that may improve forecasting accuracy or employing other techniques to control the time for updating the weights in combined forecasts.

Keywords: Tourism forecasts; Forecast combination; IOWGA operator; Theoretical evaluation; Forecasting evaluation.

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1. Introduction

As the accuracy of tourism demand forecasting has important financial implications for tourism businesses in terms of investment in tourism facilities and human resources, the tourism forecast combination has attracted some authors. Wong et al. (2007) first examined the efficiency of combining tourism forecasts based on three different combination methods which are the simple average method, the variance-covariance method and the discounted MSFE method. The results show that forecast combination does not necessarily outperform the best individual forecast, but can considerably reduce the risk of forecasting failure. Then Song et al. (2009) extended the study by carrying out statistical comparisons between the combined forecast and the individual model forecasts. The empirical results show that combined forecasts are more accurate than the average individual-model forecasts for all the combination methods at the statistically significant. This provides a strong recommendation for the application of forecast combination in tourism. Shen, Li, and Song (2008) also investigated the performance of the combination methods and the variance–covariance combination method turns out to be the best among the three combination methods which have been used in tourism forecasting. This study provides relatively robust evidence for the efficiency of combination forecasts.

There are three combination methods used in the previous studies on the tourism forecast combination. These methods assign the different weights to each individual forecasting model. The weight of the individual forecasting model can not change at each time point. However, the forecast performance of the individual model may be different at each time point (That is the forecast accuracy of the individual model would be higher at some time point and be lower at another time point). Chen and Sheng (2005) introduced the induced ordered weighted geometric averaging (IOWGA) operator into the variance-covariance combination method for overcoming the defect of previous combination methods and a new forecast combination method named IOWGA operator combination method is proposed. The IOWGA operator combination method considers forecast accuracy to be the induced factor of the forecast for each individual forecasting model. This method can make the large weight assigned to the individual forecast with high forecast accuracy at each time point for each combination model.

This study aims to introduce the IOWGA operator combination method into tourism forecasting and further investigate the performance of the previous three combination methods and the IOWGA operator combination method based upon the tourism demand data. First, the tourism data set includes various countries/regions which are at different stages of economic development and recent good demand models are employed in the study. Next the tests for the performance of the combination methods are divided into the theoretical evaluation for the representative data period 2000Q1 to 2002Q4 during which the forecasts are first used to calculate the optimal weights and the forecasting evaluation for the data period 2004Q2 to 2011Q4. For the forecasting evaluation, we extend the unstable forecasting period for 15 quarters which were strongly affected by the financial and economic crisis. The empirical results of the forecasting evaluation can be the evidence that which combination method is more suitable for tourism forecasting under the unstable process. The rest of the paper is organized as follows: Section 2 gives a brief introduction to the research background. The next section presents the forecast combination methods. Section 4 describes the data and the single models used in the study. Then the empirical results are discussed in Section 5, and the last section concludes.

2. Background of the study

Tourism demand forecasting gradually becomes an important component in tourism research, since various effective methods have been introduced into the tourism demand forecasting. Witt and Witt (1995) reviewed the early tourism demand forecasting literature. Li, Song, and Witt (2005) provided a review of eighty-four post-1990 empirical studies of international tourism demand modeling and forecasting using econometric approaches. Song and Li (2008) reviewed the published studies on tourism demand modeling and forecasting since 2000. The methods used in analyzing and forecasting tourism demand not only include the pure time series forecasting models and econometric models, but also emerge a number of new techniques. This study identifies some new research directions including using forecast combination to improve the forecasting accuracy. Moreover, Song, Witt, and Li (2003) employed the general-to-specific modeling approach to generate the ex ante forecasts of the demand for Thai tourism. Song and Witt (2006) forecasted the tourism demand for Macau using the VAR modeling method. Li, Song and Witt (2006) used the TVP and constant parameter linear AIDS method to forecast tourist expenditure by UK residents in many Western European countries. Song, Witt and Jensen (2003) found that the TVP model generates the most accurate one-year-ahead forecasts by comparing the performance of ADLM, ECM, VAR and TVP models with those generated from two time series models in forecasting the tourism demand for Denmark. Song and Lin (2010) and Song et al. (2011) used the UECM model to quantify the impacts of the financial and economic crisis on inbound and outbound tourism in Asian countries and identified the factors that influence the demand for hotel rooms in Hong Kong for assessing the impacts of the ongoing financial and economic crisis, respectively. Vanegas Sr (2013) used co-integration and error correction models (ECM) to systematically analyze the factors affecting the international tourism demand for El Salvador. Atsalakis, Chnarogiannaki, and Zopounidis (2014) used the Adaptive Neuro-Fuzzy Inference System (ANFIS) in making the forecasts. Gunter and Önder （2015）compare the predictive accuracy of various uni- and multivariate models in forecasting international city tourism demand.

Since Bates and Granger (1969) proposed the concept of combining forecasts, many studies about the forecast combination techniques are constantly emerging. Winkler and Makridakis (1983) investigated the simple average combination method and five procedures for estimating weights. Two procedures are more accurate overall than individual forecasts and than the simple average combination method. Granger and Ramanathan (1984) showed that the optimal weights can be determined by a regression model in the variance-covariance and then this regression-based combination method attracted much interest among researchers. Clemen (1989) reviewed many published studies about the forecast combination methods and showed that forecast combination can generally improve the forecasting accuracy through the considerable literature. Chan et al. (1999) demonstrated that OLS combination performs worse than principal comment regression combination in improving forecasting accuracy. All the previous combination methods assign the different weights to each individual forecasting model and the weight of the individual forecasting model can not change at each time point. Chen and Sheng (2005) introduced the induced ordered weighted geometric averaging (IOWGA) operator into the variance-covariance combination method and a new forecast combination method named IOWGA operator combination method is proposed. The IOWGA operator combination method can make the large weight assigned to the individual forecast with high forecast accuracy at each time point for each combination model. Feldkircher (2012) evaluated the forecast performance of model-averaged forecasts based on the predictive likelihood carrying out a prior sensitivity analysis regarding Zellner's *g* prior. Wang et al. (2014) combined exponential prediction, hyperbola prediction and grey prediction to propose a new method to improve the forecast accuracy of gas emission in coal mines. Pauwels and Vasnev (2014) proposed the use of forecast combination to improve predictive accuracy in forecasting the U.S. business cycle index, as published by the Business Cycle Dating Committee of the NBER. Wang, Deng, and Guo (2014) developed a new BCM (Bayesian combination method) to improve the performance of the traditional BCM, and a numerical application demonstrates that the new BCM considerably outperforms the traditional BCM both in terms of accuracy and stability.

3. Forecasting combination

In this study, four forecast combination methods are used to test the performance of the different forecasting models. These are the simple average method, the variance-covariance method (Var-Cov), the discounted MSFE method and the IOWGA operator method. The first three forecast combination methods have been widely employed in the tourism demand forecasting (Wong et al. 2007; Song et al. 2009; Shen, Li, and Song 2008). These three methods assign the different weights which can not change at each time point to each individual forecasting model. The fourth one is a new forecast combination method which has not been employed in tourism demand forecasting (Chen and Sheng 2005). This method considers forecast accuracy to be the induced factor of the forecast for each individual forecasting model, following the weighting thought that the large weight will be assigned to the individual forecast with high forecast accuracy at each time point for each combination model. The essence of the IOWGA operator method is the variance-covariance method using IOWGA operator for the forecast combination. The new forecast combination method is presented as follows.

This method assigns the weights to each individual forecast according to forecast accuracy of the individual model at each time point, which can overcome the defect of previous combination methods. Let x_t ($t = 1, 2, 3, \dots, T$) be the actual values of a time series. Let x_{it} ($i = 1, 2, 3, \dots, n$) be the one-step ahead forecasts generated by the ith individual forecasting model. Set

$$\lambda_{it}=\begin{cases}1-\left|(x_t-x_{it})/x_t\right| & \left|(x_t-x_{it})/x_t\right|<1\\ 0 & \left|(x_t-x_{it})/x_t\right|<1\end{cases}\quad i=1,2,\cdots,\ \mathrm{n},\ t=1,2,\cdots,\ \mathrm{T}$$

where λ_{it} denotes the forecast accuracy of the ith individual forecasting model at time t, $0 \leqslant \lambda_{it} \leqslant 1$. We consider the forecast accuracy (λ_{it}) as the induced value of the forecast (x_{it}), the forecasting accuracies and the forecasts can form n two-dimensional arrays $<\lambda_{1t}, x_{1t}>$, $<\lambda_{2t}, x_{2t}>$, … , $<\lambda_{nt}, x_{nt}>$. Let $w=(w_1, w_2, \ldots, w_n)^T$ be the column vector of weights for the OWGA of the different forecasting models involved in the combination model. Then we sort the forecasting accuracies ($\lambda_{1t}, \lambda_{2t}, \ldots, \lambda_{nt}$) of the different forecasting models at time t from high to low and set λ–index(it) be the subscript of the forecast accuracy at ith sequencing. The combination forecast by using IOWGA operator method at time t can be generated from the forecasting accuracies ($\lambda_{1t}, \lambda_{2t}, \ldots, \lambda_{nt}$) of the different individual forecasting models according to the formula (1).

$$\mathrm{IOWGA}\left(<\lambda_{1t}, x_{1t}>, <\lambda_{2t}, x_{2t}>, \ldots, <\lambda_{nt}, x_{nt}>\right)=\prod_{i=1}^{n} x_{\lambda-index(it)}{}^{w_i},\quad t=1,2,\cdots,\ T \tag{1}$$

The formula (1) shows the weighting feature of the Variance-Covariance method Using IOWGA Operator. The weights of the new combination forecasting method are closely relevant to the forecast accuracy of the individual forecasting model at every time point, not to the kind of the individual forecasting model.

Let $e_{a\text{-index}(it)}=\ln x_t-\ln x_{\lambda\text{-index}(it)}$, the minimum sum of square logarithm errors (min F) for the new combination forecasting method for T time points is given by

$$\begin{aligned}\min F&=\min\sum_{t=1}^{T}\left(\ln x_t-\ln\prod_{i=1}^{n}x_{\lambda-index(it)}^{w_i}\right)^2\\&=\min\sum_{t=1}^{T}\left(\sum_{i=1}^{n}w_i\left(\ln x_t-\ln x_{\lambda-index(it)}\right)\right)^2\\&=\min\sum_{i=1}^{n}\sum_{j=1}^{n}w_iw_j\left(\sum_{t=1}^{T}e_{a-index(it)}e_{a-index(jt)}\right)\end{aligned}\tag{2}$$

So the new combination forecasting model based upon the variance-covariance method using IOWGA operator is shown as follows:

$$\min F(W)=\sum_{i=1}^{n}\sum_{j=1}^{n}w_iw_j\left(\sum_{t=1}^{T}e_{a-index(it)}e_{a-index(jt)}\right)$$

$$\text{s.t}\begin{cases}\sum_{i=1}^{n}w_i=1,\\ w_i\geq 0,\quad i=1,2,\cdots,\ n\end{cases}\tag{3}$$

The weights of each single forecasting model can be calculated according to formula (4) if the w* satisfies non-negativity:

$$w^*=R^TE^{-1}/R^TE^{-1}R \tag{4}$$

where $\sum_{i=1}^{n} w_i = 1$, E is the covariance matrix of the single forecasting model, and R is a (n×1) dimensional vector whose each element is equal to 1. The estimation of E can be expressed as $E_{ij} = \sum_{t=1}^{T} e_{a-index(it)} e_{a-index(jt)}$. If we impose the constraint that the element of w* satisfy non-negativity, the estimation can be solved by quadratic programming (QP). This study uses the QP approach in estimating the 'optimal' weights w* as it has been applied successfully by numerous authors (Wong et al. 2007; Song et al. 2009; Chan et al. 2010). Then the 'optimal' weights w* can be used to generate the combination forecasts according to formula (5).

$$\text{IOWGA}(<\lambda_{1t}^{*}, x_{1t}>, <\lambda_{2t}^{*}, x_{2t}>, \ldots, <\lambda_{nt}^{*}, x_{nt}>) = \prod_{i=1}^{n} x_{\lambda-index(it)}^{\ w_i^{*}}, \quad t = T+1, \ T+2, \cdots \tag{5}$$

Where k-step ahead combination forecast is generated based upon $\lambda_{i,T+k}^{*} = \frac{1}{k} \sum_{t=N-k+1}^{T} \lambda_{it}$.

4. Data and models

4.1. Data

The demand for China's inbound tourism from ten major origin countries/regions are concerned for this study and these ten major origin countries/origins include Hong Kong, Japan, Singapore, Taiwan, Canada, Australia, USA, South Korea, UK and Philippines. The demand variable is measured by tourist arrivals in China from these ten major source markets. There are three main explanatory factors which influence the demand for China's inbound tourism. One is the income variable which is measured by the real gross domestic product (GDP) index (Y2005=100). The others are the own price and the substitute price which are all based upon the exchange rate (EX) index (Y2005=100) and the consumer price index (CPI) (Y2005=100). The substitute destinations for China consist of Japan, Hong Kong, Singapore, South Korea and Taiwan. Moreover, the impacts of the seasonal and one-off event can be captured by seasonal and one-off event dummies including in the forecasting models.

The sample data ranges from 1991Q1 to 2011Q4. The data period 2000Q1 to 2002Q4 is used for the theoretical evaluation for the forecast combination methods and the data period 2004Q2 to 2011Q4 for the forecasting evaluation for these. The major data are collected from the Yearbook of China Tourism Statistic published by the Nation Tourism Administration of China, International Financial Statistics and the Source OECD database published by Organization for Economic Cooperation and Development, the official websites of National Statistics Bureaus of China and International Financial Statistics published by the international Monetary Fund.

4.2. Modeling methods

There are one time series model and three econometric models employed in this study, which were widely and successfully used in recent studies of tourism demand (Wong et al. 2007; Song et al. 2009; Song, Gartner, and Tasci 2012). The first econometric model is the VAR, which is a systemic estimating method and takes all variables as endogenous variables in addition to the constant, time trend and dummies. The Aikake Information Criterion (AIC) can be used for determining the optimal lag length of explanatory variables. The second econometric model is the ADLM, which is known as the general-to-specific approach. This method carries out a stepwise reduction process from the initial estimation of the general ADLM. The third econometric model is the UECM developed by Pesaran, Shin, and Smith (2001), which considers the process the tourists making travel decisions with the variables of current and lagged values. This approach establishes the causal relationships between tourism demand and many macroeconomic variables. Last, the SARIMA model is used as the time series model. It is short multiplicative seasonal autoregressive moving average model based on the foundation of ARMA model with integrating d order trend difference and D order seasonal difference operation in cycle S steps.

5. Empirical results and discussion

There are ten countries/regions with the sample data period (1991Q1 to 2011Q4) that are used to test the performance of the different forecast combination methods in this study. As four single forecasting models are employed in this study, there are 11 different combination models for each forecast combination method for each country/region. The individual forecasting models are first estimated based upon the actual data from 1991Q1 to 2000Q4. Then one-step-ahead forecasts are calculated for the four forecasting models. The combination forecasts can be obtained by assigning the weights to each individual one-step-ahead forecast for the 11 combination models according to QP with m=8 from 2004Q2. The forecasts used to calculate the optimal weights are from 2001Q1 to 2002Q4 and from 2004Q2 to 2011Q3 which avoid the influence of SARS. The tests for the performance of the combination methods are divided into the theoretical evaluation for the representative data period 2000Q1 to 2002Q4 and the forecasting evaluation for the data period 2004Q2 to 2011Q4. Due to the impacts of financial and economic crisis from 2008Q2, we split our analysis about the forecasting evaluation into two different forecasting periods: 2004Q2 to 2008Q1 and 2004Q2 to 2011Q4 (Wu, Zhang, and Lu 2011). The forecasting period 2004Q2 to 2008Q1 indicates the stable forecasting situation which avoids the influence of the financial and economic crisis, and the forecasting period 2004Q2 to 2011Q4 indicates the unstable forecasting situation which were affected by the financial and economic crisis in a lasting situation.

Table 1. MAPE for single and combined forecasts of tourist arrivals in China from 10 major source markets – simple average method, representative data period 2000Q1-2002Q4.

	Taiwan	HK	Japan	Korea	Philippines	Singapore	UK	Canada	USA	Australia
S	1.70	8.32	5.69	4.42	5.99	8.06	4.61	4.45	8.84	4.00
E	13.21	7.37	10.42	16.59	11.93	14.04	5.74	5.12	7.67	8.86
V	4.84	3.91	5.63	5.66	7.63	8.88	5.71	7.17	7.87	4.03
A	10.64	4.73	5.88	22.04	11.59	10.16	6.92	11.73	12.14	3.32
SEVA	3.10	5.85	5.41*	10.26	8.90	8.67	5.17	6.80	8.33	1.79*
SEV	6.29	6.22	6.21	6.41	8.14	8.89	4.90	5.49	7.39*	2.73*
SEA	3.77	6.81	5.80	13.64	9.53	9.34	5.03	6.73	8.71	1.22*
SVA	3.46	5.34	5.55*	8.15	7.89	9.03	5.45	7.59	8.95	2.11*
EVA	3.84*	5.03	5.37*	12.92	10.17	8.95	5.60*	7.77	8.26	3.57
SE	7.21	7.85	7.48	9.44	8.50	10.35	4.71	4.79	8.25	2.43*
SV	3.07	5.65	5.66	4.16*	6.70	8.47	4.98	5.68	7.85*	1.84*
SA	5.17	6.52	5.52*	12.16	8.33	9.11	5.33	7.80	9.84	3.31*
EV	8.82	5.18	6.75	8.35	9.46	9.47	5.17*	6.02	7.04*	6.10
EA	5.23*	6.05	6.14	19.31	11.76	10.15*	5.54*	8.07	8.94	3.68
VA	4.70*	3.98	5.63	11.08	9.29	9.52	6.31	9.45	9.28	2.63*

Note: S, E, V and A denote SARIMA model, ECM model, VAR model and ADLM model, respectively. ‘*’ indicates forecast combination model is at least as good as the best of the single forecasting models involved in the combination model.

Table 2. MAPE for single and combined forecasts of tourist arrivals in China from 10 major source markets – discounted MSFE method with β=0.9, representative data period 2000Q1-2002Q4.

	Taiwan	HK	Japan	Korea	Philippines	Singapore	UK	Canada	USA	Australia
S	1.70	8.32	5.69	4.42	5.99	8.06	4.61	4.45	8.84	4.00
E	13.21	7.37	10.42	16.59	11.93	14.04	5.74	5.12	7.67	8.86
V	4.84	3.91	5.63	5.66	7.63	8.88	5.71	7.17	7.87	4.03
A	10.64	4.73	5.88	22.04	11.59	10.16	6.92	11.73	12.14	3.32
SEVA	1.98	4.76	5.29*	4.39*	7.66	8.56	5.02	5.56	7.94	1.67*
SEV	2.07	4.77	5.45*	4.38*	7.28	8.32	4.82	5.15	7.25*	1.38*
SEA	1.75	6.15	5.25*	5.05	7.87	8.59	4.85	5.27	8.29	2.11*
SVA	1.90	4.32	5.54*	4.06*	7.07	8.98	5.10	5.77	8.59	2.59*
EVA	3.65*	4.30	5.17*	4.89*	9.62	8.77*	5.47*	6.37	7.79	2.22*
SE	1.80	7.79	6.62	4.81	7.12	9.14	4.53*	4.74	8.14	1.68*
SV	1.95	4.20	5.66	4.24*	6.46	8.47	4.84	5.17	7.71*	2.30*
SA	1.73	5.72	5.48*	4.53	6.84	9.04	4.89	5.37	9.75	3.27*
EV	5.53	4.11	5.36*	4.73*	8.88	8.67*	5.16*	5.75	7.05*	5.38
EA	5.02*	5.59	5.06*	18.63	11.76	9.25*	5.34*	6.14	8.18	2.34*
VA	3.17*	3.90*	5.64	4.47*	8.78	9.47	6.23	8.53	8.61	2.84*

Note: S, E, V and A denote SARIMA model, ECM model, VAR model and ADLM model, respectively. ‘*’ indicates forecast combination model is at least as good as the best of the single forecasting models involved in the combination model.

Table 3. MAPE for single and combined forecasts of tourist arrivals in China from 10 major source markets – variance-covariance method, representative data period 2000Q1-2002Q4.

	Taiwan	HK	Japan	Korea	Philippines	Singapore	UK	Canada	USA	Australia
S	1.70	8.32	5.69	4.42	5.99	8.06	4.61	4.45	8.84	4.00
E	13.21	7.37	10.42	16.59	11.93	14.04	5.74	5.12	7.67	8.86
V	4.84	3.91	5.63	5.66	7.63	8.88	5.71	7.17	7.87	4.03
A	10.64	4.73	5.88	22.04	11.59	10.16	6.92	11.73	12.14	3.32
SEVA	1.76	3.82*	5.04*	4.27*	5.99*	8.59	4.62	4.45*	6.91*	1.13*
SEV	1.70*	3.91*	5.53*	4.27*	5.99*	8.59	4.62	4.45*	6.91*	1.24*
SEA	1.76	4.73*	5.04*	4.42*	5.99*	8.87	4.61*	4.45*	7.63*	1.13*
SVA	1.76	3.82*	5.49*	4.27*	5.99*	8.59	4.62	4.45*	7.59*	1.88*
EVA	3.14*	3.82*	5.04*	4.78*	7.63*	8.60*	5.19*	5.12*	6.91*	2.02*
SE	1.70*	7.37*	5.69*	4.42*	5.99*	8.06*	4.61*	4.45*	7.67*	1.30*
SV	1.70*	3.91*	5.63*	4.27*	5.99*	8.59	4.62	4.45*	7.59*	1.88*
SA	1.76	4.73*	5.46*	4.42*	5.99*	8.87	4.61*	4.45*	9.27	3.23*
EV	4.84*	3.91*	5.53*	5.50*	7.63*	8.60*	5.19*	5.12*	6.91*	3.94*
EA	4.94*	4.73*	5.04*	16.59*	11.59*	9.65*	5.21*	5.12*	7.63*	2.02*
VA	3.14*	3.82*	5.56*	4.78*	7.63*	8.88*	5.71*	7.17*	7.89	2.89*

Note: S, E, V and A denote SARIMA model, ECM model, VAR model and ADLM model, respectively. '*' indicates forecast combination model is at least as good as the best of the single forecasting models involved in the combination model.

Table 4. MAPE for single and combined forecasts of tourist arrivals in China from 10 major source markets – IOWGA operator method, representative data period 2000Q1-2002Q4.

	Taiwan	HK	Japan	Korea	Philippines	Singapore	UK	Canada	USA	Australia
S	1.70	8.32	5.69	4.42	5.99	8.06	4.61	4.45	8.84	4.00
E	13.21	7.37	10.42	16.59	11.93	14.04	5.74	5.12	7.67	8.86
V	4.84	3.91	5.63	5.66	7.63	8.88	5.71	7.17	7.87	4.03
A	10.64	4.73	5.88	22.04	11.59	10.16	6.92	11.73	12.14	3.32
SEVA	0.81*	3.05*	2.86*	2.97*	5.34*	5.68*	3.54*	3.80*	4.53*	0.75*
SEV	1.70*	3.91*	3.62*	2.98*	5.34*	5.68*	3.54*	3.80*	5.27*	0.91*
SEA	0.91*	4.42*	3.01*	4.42*	5.85*	5.99*	4.13*	4.11*	5.20*	1.00*
SVA	0.79*	3.05*	3.43*	2.94*	5.34*	5.78*	3.59*	4.15*	4.76*	1.08*
EVA	2.09*	3.05*	3.56*	5.25*	7.39*	7.91*	4.36*	4.35*	5.67*	1.79*
SE	1.70*	7.17*	5.12*	4.42*	5.99*	7.12*	4.34*	4.11*	6.21*	1.29*
SV	1.70*	3.91*	4.20*	2.98*	5.34*	5.78*	3.59*	4.15*	5.50*	1.53*
SA	1.28*	4.52*	3.58*	4.42*	5.85*	6.47*	4.20*	4.45*	7.18*	1.95*
EV	4.84*	3.91*	4.32*	5.66*	7.39*	8.28*	4.61*	4.35*	6.41*	3.17*
EA	2.63*	4.42*	3.99*	15.55*	10.25*	8.64*	4.98*	5.12*	6.66*	1.94*
VA	1.38*	3.05*	4.87*	4.82*	7.63*	8.49*	5.42*	7.17*	6.26*	2.01*

Note: S, E, V and A denote SARIMA model, ECM model, VAR model and ADLM model, respectively. '*' indicates forecast combination model is at least as good as the best of the single forecasting models involved in the combination model.

The data period selected for the theoretical evaluation is the representative of the data periods during which the forecasts are first used to calculate the optimal weights. Then the optimal weights are assigned to the individual forecasts to generate the combination forecasts. The results of the theoretical evaluation for the four forecast combination methods are shown in Table 1, 2, 3 and 4. The forecast combination model which outperforms the best single forecasting model involved in the combination model is labeled by an asterisk. In terms of the simple average method, No combination model outperforms the best individual forecasting model for Hong Kong, Philippines and Canada, and only one out of eleven combination models outperforms that for South Korea and Singapore respectively. Then the performance of the discounted MSFE method is as similar as that of the simple average method. All the combination models for Philippines and Canada perform worse than the best individual forecasting method and one out of eleven combination models outperforms that for Hong Kong. The combination models for the other countries/regions perform slightly well compared with the above combination models in terms of the simple average method and the discounted MSFE method. However, the variance-covariance method performs well for the ten countries/regions in which all the combination models are at least as good as the best individual forecasting model except Taiwan, Singapore, UK and USA. Besides five out of eleven combination models perform better than the best individual forecasting model for Singapore which is of the worst performance among Taiwan, Singapore, UK and USA. Last The IOWGA operator method performs extremely well that all the combination models are at least as good as the best individual forecasting model for the ten countries/regions. In all, there are 23, 39, 94 and 110 combination models that outperform the best individual forecasting model for simple average method, discounted MSFE method, variance-covariance method and IOWGA operator method, respectively. That means not all the combination models (110 combination models) outperform the best individual forecasting model for simple average method, discounted MSFE method and variance-covariance method except IOWGA operator method. So the IOWGA operator method obtains extremely well performance and outperforms the other three forecast combination methods from the results of the theoretical evaluation.

Table 5. Performance indicators for the four forecast combination methods for the two periods of time.

Period of time	2004Q2-2008Q1					2004Q2-2011Q4				
Combination method	BOP	WOP	MPI	WPP	BRP	BOP	WOP	MPI	WPP	BRP
Simple average	20.91	0.00	8.55	45.17	3.64	3.64	0.00	6.46	33.44	0.00
IOWGA operator(a)	28.18	4.55	7.75	20.74	29.09	49.09	0.91	24.92	9.47	50.91
IOWGA operator(b)	31.82	5.45	1.44	41.74	15.45	19.09	3.64	1.74	64.91	10.91
Var-Cov (a)	29.09	3.64	12.13	7.47	31.82	50.00	0.00	13.07	1.49	36.36
Var-Cov (b)	37.27	0.00	6.85	40.45	17.27	16.36	0.00	2.82	57.51	10.91
Discounted MSFE (a)	28.18	0.00	10.43	13.01	8.18	24.55	0.00	24.06	15.18	0.00
Discounted MSFE (b)	27.27	0.00	11.31	34.40	10.00	2.73	0.00	2.77	39.53	0.00

In practical applications, the forecast performance of the combination model is mainly concerned. Since the variance-covariance method, the discounted MSFE method and the IOWGA operator method require to first calculate the combination weights based upon the first 8 individual forecasts from 2000Q1 to 2004Q4. Two approaches are used to undertake the post-sample combination forecasts. One is the forecast combination using the FW∞ weighting method and the other is the forecast combination using the RW weighting method. For the FW∞ weighting method (a), the first 8 individual forecasts (2000Q1 to 2002Q4) are used to calculate the combination weights which are assigned to the subsequent 31 forecasts (2004Q2 to 2011Q4) for the forecasting evaluation. For the RW (rolling window) weighting method (b), the optimal weights calculated based upon the first 8 individual forecasts are assigned to the 9th forecast and then this window is continuously moved one-step ahead until the 31 combined forecasts are obtained. Furthermore, four major performance indicators (BOP, WOP, MPI, WPP) and one comparison indicator (BRP) are adopted according to the RMSE measure (Chan et al. 2010). For eliminating the effect of outliers and having the overall description about the performance, the maximum individual improvement is replaced with the average improvement for the MPI and the worst individual performance is replaced with the average reduced performance for the WPP. Then the forecasting evaluation for the four forecast combination methods will be discussed in this paper.

Seven kinds of results about the forecast performance for the four forecast combination methods are generated based upon two approaches. Then the seven kinds of results are shown in Table 5. We select the values of the performance indicators of IOWGA operator (a) as the reference points for forecasting period 2004Q2 to 2008Q1. The BOP and WOP of IOWGA operator (a) are 28.18 and 4.55 respectively. The forecast performance of the four forecast combination methods are almost the same except simple average and Var-Cov (b) in terms of BOP. The WOPs of IOWGA operator (b) and Var-Cov (a) are, respectively, 5.45 and 3.64 corresponding to 6 and 4 out of the 110 forecasts. The other values of WOP are zeros that none of the series using the forecast combination method performs worst than the worst of the single forecasts. Moreover, the MPI, WPP and BRP of IOWGA operator (a) are 7.75, 20.74 and 29.09 respectively. The MPI of IOWGA operator (a) is higher than that of IOWGA operator (b) and Var-Cov (b), and gives a lower value than that of other kinds of results. In terms of WPP, Var-Cov (a) and discounted MSFE (a) give a lower value than IOWGA operator (a). Only Var-Cov (a) give a slightly higher BRP than IOWGA operator (a). Table 5 also represents the results of the forecast performance for the four forecast combination methods for the period 2004Q2 to 2011Q1. First, IOWGA operator (a) outperforms Var-Cov (a) and (b), Discounted MSFE (a) and (b), simple average, and IOWGA operator (b) in terms of MPI and BRP. Second IOWGA operator (a) performs worse than Var-Cov (a) in terms of WPP and they are of the almost same forecast performance in terms of BOP. Last the WOP of IOWGA operator (a) is only 0.91 corresponding to 1 out of 110 forecasts, and the other values of WOP are all zeros.

The forecast combination is used to maximize performance and reduce forecast error compared with the single models. First, we regard the BRP, BOP and MPI as the major indicators for maximizing performance. For the forecasting period 2004Q2 to 2008Q1, the quality of the combination forecasts from the best to the worst is Var-Cov (a), IOWG operator (a), Var-Cov (b), IOWGA operator (b), discounted MSFE (a), discounted MSFE (b) and SA. For the forecasting period 2004Q2 to 2011Q4, that is IOWG operator (a), Var-Cov (a), IOWGA operator (b), Var-Cov (b), discounted MSFE (a), discounted MSFE (b) and SA. Then we regard the WOP and WPP as the major indicators for reducing forecast error. The WOP and WPP of Var-Cov (a) give a lower value than those of other kinds of results for the two forecasting periods except the WOP for the forecasting period 2004Q2 to 2008Q1, but the WOP of Var-Cov (a) is only 3.64 for the forecasting period 2004Q2 to 2008Q1. However, we can not draw the conclusion that which forecast combination method can generate the best kind of result for the forecasting period 2004Q2 to 2008Q1, we can see that IOWGA operator (a) can be of well forecast performance for that period. Moreover, IOWGA operator (a) and Var-Cov (a) perform the best among the seven kinds of results in four out of five performance indicators for the forecasting period 2004Q2 to 2011Q4 and only the WOP of IOWGA operator (a) is up to 0.91 for that period. So IOWGA operator (a) and Var-Cov (a) perform almost the same for the two forecasting periods. From the above discussion, the IOWGA operator method can be recommended to be used in tourism forecast combination due to the forecasting evaluation. The IOWGA operator (a) mainly reflects the maximization of improving forecasting accuracy in terms of theoretical evaluation, BOP, MPI and BRP. The Var-Cov (a) mainly reflect the decrease of the forecast error in terms of WOP and WPP.

6. Conclusion

The simple average combination method, the variance-covariance combination method and the discounted MSFE combination method have been commonly used in tourism demand forecasting. These three combination methods assign the different weights to each individual forecasting model and the weight of the individual forecasting model can not change at each time point. The IOWGA operator combination method overcomes the defect of the three combination methods and can assign the large weight to the individual forecast with high forecast accuracy at each time point for each combination model. This study not only successfully introduces the IOWGA operator combination method which is the variance-covariance method improved by using the IOWGA operator into tourism forecasting, but also investigates the performance of the four combination methods through the theoretical evaluation and the forecasting evaluation. For the theoretical evaluation, the results show that the IOWGA operator method outperforms the other forecast combination methods and obtains extremely well performance. The results of the forecasting evaluation show that the IOWGA operator combination method can be of well forecast performance for the two forecasting periods. Furthermore, The IOWGA operator combination method mainly reflects the maximization of improving forecasting accuracy and the variance-covariance combination method mainly reflect the decrease of the forecast error. These empirical results show that the IOWGA operator method can be recommended to be used in tourism forecast combination due to the forecasting evaluation. For future research, improving forecasting accuracy and saving time in updating the combination weights would be concerned. It may be worthwhile introducing and examining other new combination methods that may improve forecasting accuracy or employing other techniques to control the time for updating the weights in combined forecasts. Moreover, further testing of the IOWGA combination method using the different data sets would also be valuable to allow more general conclusions to be drawn.

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