Can bagging improve the forecasting performance of tourism demand models?

Haiyan Song*

School of Hotel and Tourism Management

The Hong Kong Polytechnic University

Hong Kong SAR

Stephen F. Witt

School of Hospitality and Tourism Management

University of Surrey

The United Kingdom

Tianran Qiu

School of Hotel and Tourism Management

The Hong Kong Polytechnic University

Hong Kong SAR

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Abstract

This study examines the forecasting performance of the general-to-specific (GETS) models developed for Hong Kong through the bootstrap aggregating method (known as bagging). Although the literature in other research areas shows that bagging can improve the forecasting performance of GETS models, the empirical analysis in this study does not confirm this conclusion. This study is the first attempt to apply bagging to tourism forecasting, but additional effort is needed to examine the effectiveness of bagging in tourism forecasting by extending the models to cover more destination-source markets related to destinations other than Hong Kong.

Keywords: bagging, general-to-specific modeling, tourism demand, Hong Kong

1. Introduction

Tourism demand modeling and forecasting plays a crucial role in the process of decision making among tourism stakeholders in both the public and private sector. As policy makers and private practitioners base their decisions largely on tourism demand forecasts, efforts to improve the accuracy of tourism demand forecasts are ongoing.

In the field of tourism demand forecasting, the general-to-specific (GETS) modeling procedure has proved an effective tool due to its ease of specification and robustness in model estimation (Song, Witt, and Gang, 2013). In contrast to its counterpart, the specific-to-general approach, the GETS procedure starts with a general model that contains all possible influencing factors, and reduces the model to its final form by eliminating insignificant factors recursively using t-statistics (Narayan, 2004; Katircioglu 2009; Wang, 2009; Song and Lin, 2010). However, as it suffers from an unstable decision rule (the rule for eliminating insignificant factors using t-statistics) in the model reduction process, the final forecasts may not be "optimal."

One possible way to overcome this “unstable decision rule” problem is the bootstrap aggregating (bagging) method proposed by Breiman (1996) and Bühlmann and Yu (2002). Inoue and Kilian (2008) and Rapach and Strauss (2010, 2012) demonstrated its effectiveness using estimations of U.S. inflation and U.S. national and regional employment growth, respectively. In this paper, we try to apply the bagging procedure to GETS forecasting based on Hong Kong tourism data to investigate whether GETS-bagging can overcome the “unstable decision rule” problem in demand forecasting for the Hong Kong tourism industry.

The rest of the paper is structured as follows. Section 2 briefly introduces the literature related to Hong Kong tourism demand forecasting, GETS, and the GETS-bagging procedure. Section 3 discusses the GETS-bagging method and the dataset used in the study, Section 4 shows the results of the forecasting exercise, and Section 5 concludes.

2. Literature Review

Hong Kong is one of the world’s most popular tourist destinations. According to the Hong Kong Tourism Board (HKTB, 2016), Hong Kong received 59.3 million visitors in 2015, putting it among the most popular tourist destinations in the world. Tourism has been and remains the second largest source of foreign currency in Hong Kong, and the income generated has contributed around 6% of Hong Kong’s GDP over the last decade. Many businesses such as retailing, catering, accommodation, and entertainment are directly and indirectly influenced by the growth of tourism in Hong Kong.

Over the past two decades, growing research attention has been drawn to the modeling and forecasting of Hong Kong’s tourism demand. A few studies have focused on modeling the trends and business cycles of tourism demand in Hong Kong based on time-series forecasting techniques (Wong (1997). Among others, Hiemstra and Wong (2002) and Song and Wong (2003) identified the key factors affecting Hong Kong’s tourism demand and analyzed the demand elasticity based on econometric models. Song et al. (2010) and Song et al. (2011) investigated the forecasting performance of alternative time-series and econometric forecasting techniques, while Song, Wong, and Chon (2003) predicted the future growth of Hong Kong’s tourism demand from key source markets. Song, Witt, and Zhang (2008) and Song et al. (2012a) developed a system to generate reliable forecasts of Hong Kong’s tourism demand.

In the last category, the authors developed a web-based system called the Hong Kong Tourism Demand Forecasting System (HKTDFS) which uses the GETS procedure. The factors considered in the HKTDFS include the income level of tourists from the source markets, the prices of tourism products/services in Hong Kong (measured by Hong Kong’s CPI relative to that of the source markets adjusted by the exchange rate between the Hong Kong dollar and the source market currencies), the prices of substitute destinations (also adjusted by the relevant exchange rates), the marketing expenditure of such destinations, etc. (Song, Witt, and Li, 2009). The system starts with an autoregressive distributed lag model (ADLM) incorporating all possible factors that may affect the demand for Hong Kong tourism together with their lagged values (four-period lagged values for each variable as the system uses quarterly data) and dummy variables (including seasonal dummies and one-off event dummies). This model is then estimated using the OLS method. The insignificant variable with the largest p-value is eliminated, and the OLS estimation process repeated until all variables left in the model are both statistically and economically significant (that is, the coefficients of the variables have the correct signs according to economic theory). Song et al. (2012b) showed that the ADLM used in the HKTDFS produces relatively accurate forecasts. However, they also mentioned that the model can generate relatively large forecasting errors for volatile markets such as mainland China and Taiwan (with a mean absolute percentage error greater than 10%). Furthermore, using t-statistics as a decision rule to eliminate variables can be problematic as the explanatory variables are correlated (Breiman, 1996). This “unstable decision rule” also prevents the forecasting system from being fully automated. The investigation in this paper can therefore be considered an extension of the HKTDFS, as it explores an alternative way to reduce the forecasting error and automate the forecasting process.

The term “bagging” was introduced by Breiman (1996) to stand for “**b**ootstrap **agg**regat**ing**.” It is an ensemble method combining multiple predictors. To improve the accuracy of the model, it trains multiple models on different samples (data splits) and averages their predictions. A large number (e.g. B) of bootstrap samples are first drawn, B predictions are then generated by applying the model to these samples, and the bagging predictor is finally calculated by averaging these predictions. This is based on the concept that the "averaging of misclassification errors on different data splits gives a better estimate of the predictive ability of a learning method" (Zhao and Cen, 2013). Experiments show that the bagging predictor works well for unstable learning algorithms, and a reduction of 21% to 46% can be made in mean squared errors (MSE) when bagging is applied to the regression tree (Breiman, 1996).

3. The Model and Data

The GETS procedure was used in the web-based HKTDFS by Song, Witt, and Zhang (2008). As a potential extension of that study, the same procedure is adopted in this investigation. The model starts with a general ADLM in the form of

$$q_{i,t+h}^{h} = \alpha_i + \sum_{j=1}^{k} \beta_{i,j} X_{i,j,t} + \varepsilon_{i,t+h}^{h}, \tag{1}$$

where $q_{i,t+h}^{h}$ is the demand for Hong Kong tourism (measured by total tourist arrivals) among residents in country i at time $t+h$; t is the time index with a maximum of T; h is the forecast horizon; $X_{i,j,t}$ are the vectors of k explanatory variables, including the lagged values of the independent and dummy variables; $\varepsilon_{i,t+h}^{h}$ is the error term; and α and βs are the parameters to be estimated.

Due to the data requirements for the bagging procedure, monthly data is used in this investigation instead of the quarterly data used in the HKTDFS. For the same reason, only relative price, substitute price, and GDP per capita (together with their lagged values) are considered as independent variables in this study. These variables are proven to be the most important factors determining tourism demand (Witt and Witt 1995; Li, Song, and Witt, 2005). Thus, the GETS procedure in this investigation is more of a "lag selector" than a "variable selector" in the HKTDFS. The model then becomes

$$q_{i,t+h}^{h} = \alpha_i + \sum_{j=0}^{12} \beta_{i,j} RP_{i,t-j} + \sum_{m=0}^{12} \gamma_{i,m} SP_{i,t-m} + \sum_{n=0}^{12} \varphi_{i,n} GDP_{i,t-n} + \sum_{k=2}^{12} d_{i,k} DS_k + \sum_{p=1}^{x} d_{i,p} DE_p + \varepsilon_{i,t+h}^{h}, \tag{2}$$

where $RP_{i,t}$ is the relative price; $SP_{i,t}$ is the substitute price; $GDP_{i,t}$ is the GDP per capita in a particular source market; $DS_k s$ is the seasonal dummy (the first dummy for January being omitted to avoid collinearity); $DE_p s$ is a x one-off event dummy; and $\alpha, \beta, \gamma, \varphi,$ and d are the parameters to be estimated.

To carry out the GETS procedure, this general model is then estimated using OLS. The estimates for all of the coefficients are then sorted by their t-statistics in ascending order. The variable associated with the first coefficient (the coefficient with the smallest t-statistics or largest p-value) is eliminated from the model if it is statistically insignificant. Here, the elimination of insignificant variables is done in a recursive manner instead of as a one-off act, as suggested by Song, Witt, and Li (2009). The above procedure is repeated until all variables left in the model are significant (or all variables are dropped). The treatment of seasonal dummies is worth mentioning: as seasonality always has a considerable influence on tourism demand, all seasonal dummies are excluded from the variable elimination procedure. The GETS forecasts are calculated as

$$\hat{q}_{i,t+h}^{h,GETS} = \hat{\alpha}_i + \sum_{j=0}^{12} \hat{\beta}_{i,j} I_{i,j} RP_{i,t-j} + \sum_{m=0}^{12} \hat{\gamma}_{i,m} I_{i,m} SP_{i,t-m} + \sum_{n=0}^{12} \hat{\varphi}_{i,n} I_{i,n} GDP_{i,t-n} + \sum_{k=2}^{12} \hat{d}_{i,k} DS_k + \sum_{p=1}^{x} \hat{d}_{i,p} I_{i,p} DE_p, \qquad (3)$$

where $I_{i,j}$, $I_{i,m}$, $I_{i,n}$, and $I_{i,p}$ are relevant dummies that take the value of one if the associated coefficient is significant, and zero otherwise, and $\hat{\alpha}_i$, $\hat{\beta}_{i,j}$, $\hat{\gamma}_{i,m}$, $\hat{\varphi}_{i,n}$, $\hat{d}_{i,k}$, and $\hat{d}_{i,p}$ are the OLS estimators of the model.

In the bagging procedure, a large number (B=100 in this investigation) of bootstrap samples are generated from the original dataset. As the dataset contains time-series data, the moving-block bootstrap is used to maintain the structure of the data. For each draw, a block of 12 observations (as monthly data is used) is picked from the dataset (with replacement). After $\lceil T/_{12} \rceil$ draws, a sample of $(\lceil T/_{12} \rceil \times 12)$ observations is generated, and the first T observations from this sample are used as one bootstrap sample. For each bootstrap sample (indexed by b), a series of GETS forecasts can be calculated using equation (3). The GETS-bagging forecasts can then be calculated as the average of these GETS forecasts,

$$\hat{q}_{i,t+h}^{h,GB} = \frac{1}{B}\sum_{b=1}^{B} \hat{q}_{i,t+h,b}^{h,GB}, \tag{4}$$

where $\hat{q}_{i,t+h,b}^{h,GB}$ is the GETS forecast for bootstrap sample b and $\hat{q}_{i,t+h}^{h,GB}$ is the GETS-bagging forecast for the total number of arrivals of residents from country i at time $t + h$.

The data used for this investigation include the total arrivals in Hong Kong $(q_{i,t})$ from three source markets, namely mainland China, the U.S., and the U.K., where mainland China represents a short-haul market and the U.S. and U.K. represent long-haul markets. Australia was considered a long-haul sample from Oceania but was later excluded due to data availability. These data are obtained from statistical reports of the Hong Kong Tourism Board (HKTB).

The relative price is the price of Hong Kong tourism relative to that of the source markets $(RP_{i,t})$, it is defined as

$$RP_{i,t} = \frac{CPI_{HK,t}/EX_{HK,t}}{CPI_{i,t}/EX_{i,t}}, \tag{5}$$

where $CPI_{i,t}$ is the consumer price index for Hong Kong (or the origin country i), and $EX_{i,t}$ is the exchange rate between the Hong Kong dollar (or currency of origin country i) and the U.S. dollar.

The substitute price is the price of tourism in substitute destinations relative to Hong Kong $(SP_{i,t})$, and is defined as

$$SP_{i,t} = \sum_{j=1}^{6} \frac{CPI_{j,t}}{EX_{j,t}} w_{i,j,t}, \tag{6}$$

where $j = 1, 2, 3, 4, 5,$ and 6, representing the 6 substitute destinations of mainland China, Taiwan, Singapore, Thailand, Korea, and Japan (Song and Wong, 2003), and $w_{i,j,t}$ is the share of international tourist arrivals at region j, calculated as

$$w_{i,j,t} = \frac{q_{i,j,t}}{\sum_{j=1}^{6} q_{i,j,t}}. \quad (7)$$

Notice that when mainland China is the origin country under examination, it is excluded from the calculation of the substitute price.

The CPIs of mainland China, Korea, Japan, the U.K., and the U.S. are obtained from the OECD database; the CPI of Hong Kong is obtained from the Census and Statistics Department of the Hong Kong SAR Government; the CPI of Taiwan is obtained from National Statistics, Republic of China (Taiwan); the CPI of Singapore is obtained from Statistics Singapore; and the CPI of Thailand is obtained from the Bank of Thailand. The exchange rate data for all countries/regions above are obtained from OANDA fxTrade™.

The model includes three one-off event dummies. The first represents the effect of the 9/11 attack, which takes the value of one from September, 2001 to December, 2001 and zero otherwise. The second represents the effect of the Beijing Olympics in 2008, which takes the value of one from July, 2008 to December, 2008 and zero otherwise. The third represents the effect of the subprime mortgage crisis starting from 2008, which takes the value of one from January, 2008 to December, 2010 and zero otherwise.

4. The Forecasting Results

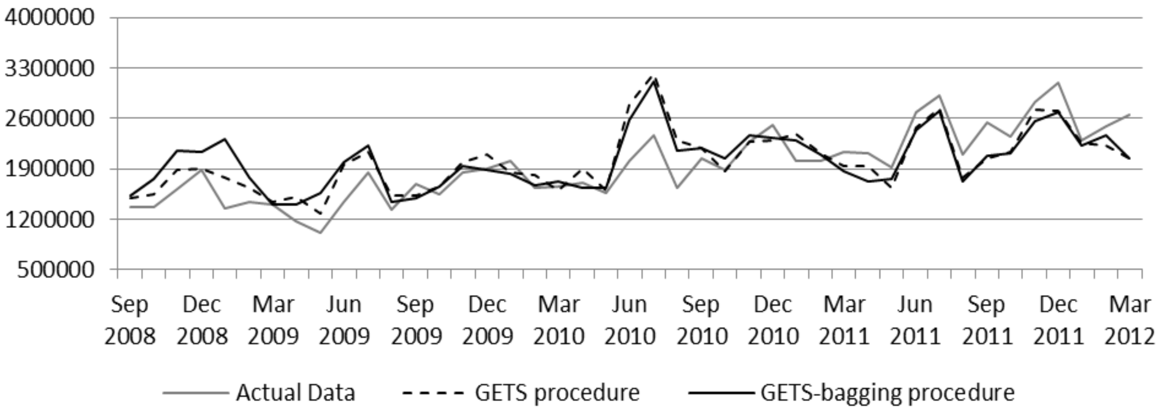
The GETS-bagging forecasts are generated using equations (3) and (4) and the data described in Section 3. To compare the forecast accuracy of the GETS-bagging procedure with that of the pure GETS procedure, a series of GETS forecasts are also generated using equation (3) and the original dataset.

Figure 1 shows the results for the 1-period-ahead ($h = 1$) total arrival forecasts of all three countries. The results for $h = 2$ to 12 are available up request.

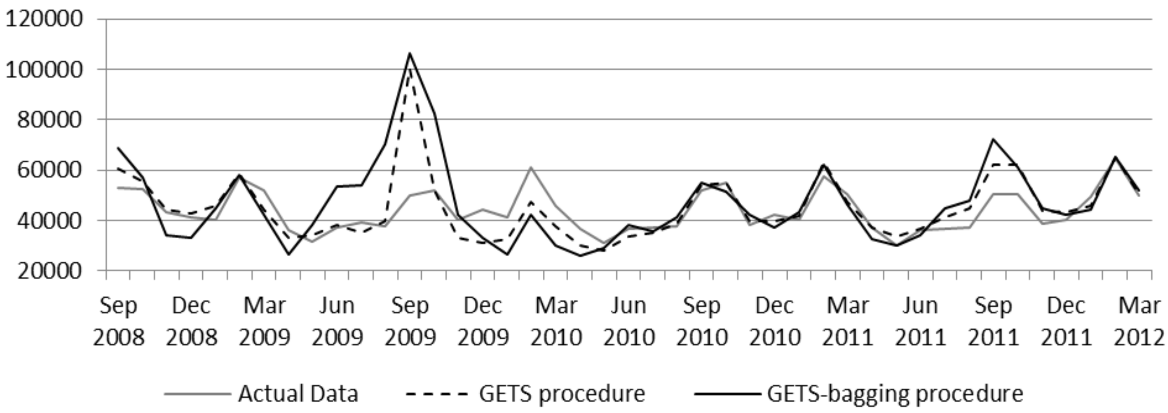
From Figure 1, we can see that the forecasts of both procedures work similarly, but that the GETS-bagging procedure responds more to variations in the explanatory variables. This "overreaction" problem downgrades the performance of the GETS-bagging procedure. Both procedures work poorly in the early stage of the forecasts, caused by significant changes in the explanatory variables after 2008 due to the subprime mortgage crisis, although it is already controlled by the dummy. This phenomenon is more significant in the case of the U.S., which suffered the most during the crisis. In the case of the U.K., a spike is forecast by both procedures around September, 2009.

Figure 1. 1-period-ahead forecasts

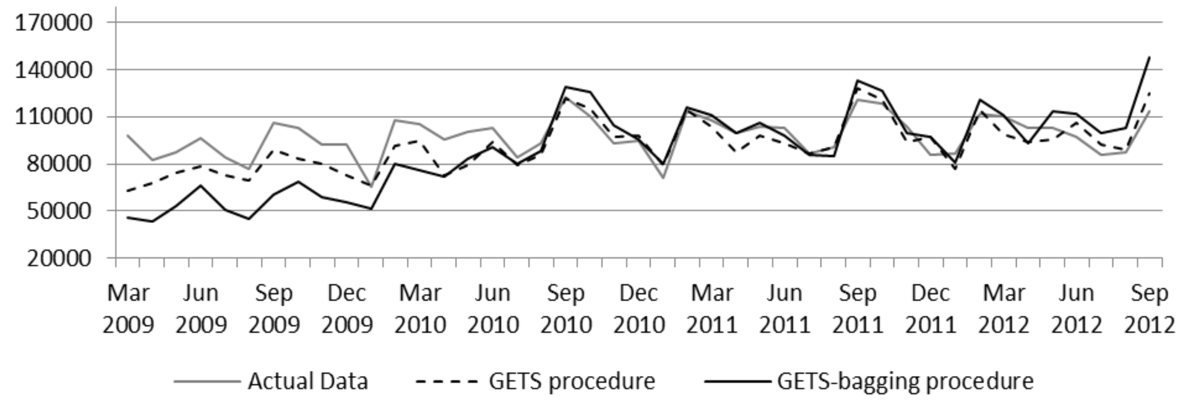
A) Mainland China



B) U.K.



C) U.S.



This is caused by a significant increase in the exchange rate of the pound sterling (GBP) against the U.S. Dollar (USD), which increased from 0.589 USD/GBP in October, 2008 to a peak of 0.704 USD/GBP in March, 2009, and recovered to 0.604 USD/GBP in August, 2009. The GETS-bagging procedure responds more to this shock and generates less accurate forecasts than does the GETS procedure. This spike in the forecasts becomes smaller as the forecast horizon increases (results are available from the authors upon request), but the improvement is smaller in the GETS-bagging procedure than in the GETS procedure. In the case of mainland China, the forecasts become less accurate when the forecast horizon increases, whereas the opposite occurs in the case of the U.K. The forecast accuracy improves as h increases from 1 to 6 but worsens afterwards for the U.S. Thus it seems that the performance of both procedures has little to do with the forecast horizon. This phenomenon is also identifiable in the forecasting accuracy in later sections. In general, the GETS-bagging procedure does not outperform the GETS procedure as expected; therefore improving the HKTDFS by switching from the GETS to the GETS-bagging procedure is not an option.

Four measures of forecasting accuracy, namely the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and mean absolute scaled error (MASE), are calculated to compare the forecasts of the two procedures.

RMSE is a quadratic scoring rule which measures the average magnitude of the forecasting errors. It is calculated by

$$RMSE_i^h = \sqrt{\frac{\sum_{t=1}^{T}\left(\hat{q}_{i,t+h}^{h,GB} - q_{i,t+h}^{h}\right)^2}{T}}. \tag{8}$$

MAE is the average magnitude of the forecasting errors without considering their direction. It is calculated by

$$MAE_i^h = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{q}_{i,t+h}^{h,GB} - q_{i,t+h}^{h}\right|. \tag{9}$$

As errors are squared before being averaged in the RMSE, this gives a relatively high weight to large forecasting errors whereas the MAE gives equal weight to all forecasting errors. Together, the difference between RMSE and MAE can be used to diagnose the variation in the forecasting errors of both the GETS-bagging and GETS procedures.

The MAPE and MASE are measures of forecasting accuracy at the percentage level. They are calculated by

$$MAPE_i^h = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\hat{q}_{i,t+h}^{h,GB} - q_{i,t+h}^{h}}{q_{i,t+h}^{h}}\right|, \tag{10}$$

and

$$MASE_i^h = \frac{\sum_{t=1}^{T}\left|\hat{q}_{i,t+h}^{h,GB} - q_{i,t+h}^{h}\right|}{\frac{T}{T-1}\sum_{t=2}^{T}\left|q_{i,t+h}^{h} - q_{i,t+h-1}^{h}\right|}, \tag{11}$$

respectively. As these two measures are scale-free error metrics, they can be used not only to compare the GETS-bagging and GETS procedures in this investigation, but also to compare these two procedures with other procedures in future investigations.

Table 1 shows the RMSE of the two procedures for all three countries. The numbers in parentheses for the RMSE of the GETS-bagging procedure are the percentages of the RMSE of the GETS-bagging procedure relative to that of the GETS procedure. Thus, an improvement in the GETS-bagging procedure is shown if the number is below 100%. However, all these numbers are above 100%. This means that, according to the RMSE in this investigation, the GETS-bagging procedure is outperformed by the GETS procedure. The same conclusion can be drawn from the MAE, MAPE, and MASE comparisons (see Appendix).

Table 1. The RMSE of both procedures for all three countries

h	Mainland China		U.K.		U.S.	
	GETS	GETS -bagging	GETS	GETS -bagging	GETS	GETS -bagging
1	316992.29	347383.78 (109.6%)	9401.16	13944.74 (148.3%)	11836.58	21395.19 (180.8%)
2	342914.17	365484.59 (106.6%)	6026.12	15518.18 (257.5%)	11997.23	21530.27 (179.5%)
3	370967.52	382118.47 (103.0%)	6063.99	15194 (250.6%)	12187.47	20762.62 (170.4%)
4	363281.29	409763.51 (112.8%)	6166.34	14072.01 (228.2%)	13308.6	20842.35 (156.6%)
5	360874.27	429463.34 (119.0%)	5941.2	11482.92 (193.3%)	11069.28	20177.43 (182.3%)
6	408599.73	481190.18 (117.8%)	6196.81	10049.01 (162.2%)	11974.54	18972.67 (158.4%)
7	452876.15	579940.73 (128.1%)	5718.32	7830.49 (136.9%)	11974.12	21652.69 (180.8%)
8	424726.69	561524.24 (132.2%)	5706.74	7899.73 (138.4%)	12046.05	24285.48 (201.6%)
9	431886.14	530321.82 (122.8%)	7140.06	8432.27 (118.1%)	11011.98	25755.24 (233.9%)
10	398612.85	519010.39 (130.2%)	7593.48	8484.53 (111.7%)	14024.57	27406.42 (195.4%)
11	425273.43	482090.82 (113.4%)	6620.05	8537.44 (129.0%)	10757.54	33441.7 (310.9%)
12	458713.61	472027.7 (102.9%)	6951.79	8804.68 (126.7%)	11120.63	37875.14 (340.6%)

As mentioned above, the difference between the RMSE and MAE can be used to diagnose the variation in the forecasting errors. The percentage of this difference is calculated by

$$\Delta\% = \frac{RMSE - MAE}{MAE}. \tag{12}$$

Table 2 compares this difference for both procedures for all countries.

Table 2. The RMSE exceeds the MAE in percentages

h	Mainland China		U.K.		U.S.	
	GETS	GETS -bagging	GETS	GETS -bagging	GETS	GETS -bagging
1	127.6%	125.6% (98.5%)	178.9%	149.2% (83.4%)	124.3%	129.6% (104.3%)
2	121.6%	119.3% (98.1%)	128.9%	144.8% (112.4%)	135.6%	133.0% (98.1%)
3	122.8%	124.1% (101.1%)	126.5%	144.7% (114.4%)	127.6%	133.7% (104.8%)
4	119.7%	124.0% (103.6%)	130.7%	149.6% (114.5%)	124.4%	126.9% (102.0%)
5	120.6%	124.3% (103.0%)	117.1%	143.8% (122.9%)	122.9%	127.9% (104.1%)
6	122.2%	118.4% (96.9%)	120.2%	137.6% (114.4%)	123.2%	127.1% (103.2%)
7	121.9%	113.4% (93.0%)	122.3%	126.1% (103.2%)	122.6%	132.4% (108.0%)
8	126.9%	118.0% (93.0%)	125.0%	128.1% (102.4%)	126.6%	128.8% (101.7%)
9	116.1%	121.6% (104.8%)	122.0%	127.6% (104.6%)	124.3%	129.8% (104.4%)
10	113.9%	117.0% (102.8%)	119.5%	124.7% (104.4%)	118.7%	129.7% (109.2%)
11	125.5%	122.2% (97.4%)	122.3%	126.1% (103.1%)	122.0%	119.6% (98.1%)
12	125.3%	120.9% (96.5%)	126.0%	125.0% (99.1%)	124.4%	113.9% (91.5%)

Among the 36 groups of comparisons, 12 show the GETS-bagging differences to be smaller than the GETS differences. That is, in these 12 groups, the GETS-bagging procedure generates less variation in forecasting errors. Interestingly, of these 12 groups, 7 are forecasts for mainland China, the most volatile source market among the three. In these cases, the GETS-bagging procedure does serve to reduce the variance in forecasting error. However, the increase in bias spoils the forecasts so that the GETS-bagging procedure is outperformed by the GETS procedure. The variance reduction becomes more obvious when the source market is volatile. It is possible that, with a highly volatile source market, the reduction in variance exceeds the effects of increased bias, and the GETS-bagging procedure may then outperform the GETS procedure.

5. Concluding Remarks

The GETS-bagging procedure did not yield the expected results in our investigation. Although it reduced the variance in forecasting error to some extent in the case of mainland China, the forecasting error itself was increased compared with the GETS procedure. Furthermore, the interpretable structure is also lost in the process of bagging. However, the failure of the GETS-bagging procedure in this investigation does not imply a general failure of the procedure in tourism demand forecasting. As mentioned in Song et al. (2012b), the HKTDFS generates considerably accurate forecasts, and Breiman (1996) indicated that "bagging can improve only if the unbagged is not optimal." This may be one of the reasons the GETS-bagging procedure was outperformed by the GETS procedure in the HKTDFS. Also, the linear regression using all variables is a fairly stable procedure, but the stability may decrease as the number of variables used in the predictor decreases.

While the GETS-bagging procedure did not improve the HKTDFS, improvements in other aspects remain possible. As the model reduction process is sensitive to the sequence of removing insignificant variables, the process can vary from researcher to researcher. The final model may thus not be the "optimal" one due to this subjective influence. Judgmental adjustments with input from experts proposed by Song et al. (2012) were able to reduce the forecasting error. However, these adjustments prevent the model from being automated. Another alternative is to reconsider the dropped variables each time an insignificant variable is dropped. In the GETS process, whenever an insignificant variable is dropped, the already dropped variables can be reintroduced into the model to seek forecasting error reduction. This extra step can, to some extent, correct the "bad" drops. More importantly, it can be automated by computer. A Bayesian estimation is also an alternative. Wong, Song, and Chon (2006) showed that imposing this prior to the VAR model can improve model performance and reduce the forecasting error. Given that the t-statistics used in the GETS procedure can be problematic due to serial correlation among the explanatory variables, using Bayesian factors instead may improve the forecasting results.

Appendix. Tables of the MAE, MAPE, and MASE of both procedures for all three countries

Table A1. MAE of both procedures for all three countries

h	Mainland China		U.K.		U.S.	
	GETS	GETS -bagging	GETS	GETS -bagging	GETS	GETS -bagging
1	248514.61	276615.46 (111.3%)	5253.77	9345.38 (177.9%)	9520.478	16505.54 (173.4%)
2	282037.25	306362.47 (108.6%)	4676.06	10714.25 (229.1%)	8845.252	16186.01 (183.0%)
3	302180.56	307888.23 (101.9%)	4795.33	10498.54 (218.9%)	9551.193	15530.67 (162.6%)
4	303385.15	330366.69 (108.9%)	4717.01	9403.36 (199.3%)	10694.32	16419.15 (153.5%)
5	299147.38	345496.76 (115.5%)	5075.21	7982.88 (157.3%)	9004.759	15774.76 (175.2%)
6	334481.12	406464.95 (121.5%)	5154.13	7302.96 (141.7%)	9720.252	14929.27 (153.6%)
7	371528.4	511454.96 (137.7%)	4676.93	6208.69 (132.8%)	9766.333	16353.55 (167.4%)
8	334608.97	475861.52 (142.2%)	4563.59	6168.62 (135.2%)	9515.025	18855.38 (198.2%)
9	372134.15	436171.47 (117.2%)	5850.82	6608.72 (113.0%)	8858.444	19840.88 (224.0%)
10	350112.39	443452.18 (126.7%)	6356.59	6805.44 (107.1%)	11813.87	21133.23 (178.9%)
11	338785.28	394423.24 (116.4%)	5412.29	6770.56 (125.1%)	8819.396	27954.85 (317.0%)
12	366183.62	390310.34 (106.6%)	5515.32	7046.35 (127.8%)	8939.031	33260.36 (372.1%)

Table A2. MAPE of both procedures for all three countries

h	Mainland China		U.K.		U.S.	
	GETS	GETS -bagging	GETS	GETS -bagging	GETS	GETS -bagging
1	13%	15% (115.2%)	12%	21% (181.4%)	10%	17% (176.1%)
2	15%	17% (110.8%)	11%	24% (228.3%)	9%	17% (185.2%)
3	16%	17% (102.8%)	11%	24% (218.2%)	10%	16% (165.1%)
4	16%	17% (106.3%)	11%	21% (197.0%)	11%	17% (155.9%)
5	14%	17% (115.9%)	12%	18% (154.3%)	9%	17% (175.8%)
6	17%	19% (114.2%)	12%	17% (138.7%)	10%	16% (156.6%)
7	18%	25% (137.3%)	11%	15% (130.3%)	10%	17% (167.1%)
8	16%	22% (136.6%)	11%	14% (131.3%)	10%	19% (195.0%)
9	18%	19% (108.3%)	13%	15% (113.7%)	9%	20% (217.2%)
10	16%	19% (115.9%)	14%	15% (107.0%)	12%	22% (175.1%)
11	15%	16% (109.0%)	12%	15% (124.1%)	9%	29% (303.6%)
12	16%	16% (96.9%)	12%	16% (127.5%)	9%	34% (363.1%)

Table A3. MASE of both procedures for all three countries

h	Mainland China		U.K.		U.S.	
	GETS	GETS -bagging	GETS	GETS -bagging	GETS	GETS -bagging
1	84%	93% (111.3%)	71%	126% (177.9%)	79%	137% (172.2%)
2	95%	103% (108.6%)	63%	144% (229.1%)	74%	134% (180.9%)
3	102%	104% (101.9%)	65%	141% (218.9%)	80%	129% (162.2%)
4	102%	111% (108.9%)	63%	127% (199.3%)	89%	133% (148.9%)
5	101%	116% (115.5%)	68%	107% (157.3%)	75%	121% (160.5%)
6	113%	137% (121.5%)	69%	98% (141.7%)	81%	114% (140.7%)
7	125%	172% (137.7%)	63%	84% (132.8%)	82%	129% (157.6%)
8	113%	160% (142.2%)	61%	83% (135.2%)	79%	149% (187%)
9	125%	147% (117.2%)	79%	89% (113%)	74%	159% (214.7%)
10	118%	149% (126.7%)	86%	92% (107.1%)	99%	165% (167.4%)
11	114%	133% (116.4%)	73%	91% (125.1%)	74%	228% (309.4%)
12	123%	131% (106.6%)	74%	95% (127.8%)	75%	278% (371.9%)

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