Ex-ante Tourism Forecasting Assessment

Anyu Liu

Senior Lecturer

School of Hospitality and Tourism Management

University of Surrey, Guildford, Surrey, GU2 7XH, UK

Tel.: +44 (0)1483 688757

Email: anyu.liu@surrey.ac.uk

Vera Shanshan Lin*

Associate professor

School of Management

Zhejiang University, Hangzhou, China

Tel.: +86 571 8820 6872

Email: shanshanlin@zju.edu.cn

Gang Li

Professor

School of Hospitality and Tourism Management

University of Surrey, Guildford, Surrey, GU2 7XH, UK

Tel.: +44 (0)1483 686356

Email: g.li@surrey.ac.uk

Haiyan Song

Professor

School of Hotel and Tourism Management

The Hong Kong Polytechnic University, Hong Kong SAR, China

Tel.: +852 3400 2286

Email: haiyan.song@polyu.edu.hk

* *Corresponding author*.

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ABSTRACT

Although numerous studies have focused on forecasting international tourism demand, minimal light has been shed on the factors influencing the accuracy of real-world *ex-ante* forecasting. This study evaluates the forecasting errors across various prediction horizons by analyzing the annually published forecasts of the Pacific Asia Tourism Association (PATA) from 2013 to 2017, comprising 765 origin-destination pairs covering 31 destinations in the region. The regression analysis shows that the variation in tourism demand and gross domestic product (GDP), covariation between tourism demand and GDP, order of lagged variables, origin, destination, and forecasting method all have significant effects on the forecasting accuracy over different horizons. This suggests that tourism forecasting should account for these factors in the future.

Keywords: *International Tourism Demand, Forecasting Errors, Data Characteristics, Forecasting Horizons, Ex-ante Forecasts*

1. Introduction

The latest statistics released by the World Travel and Tourism Council (WTTC) show that when considering the direct, indirect, and induced effects on the economy (World Travel & Tourism Council (WTTC) 2020), the travel and tourism industry contributed 10.3% to total global gross domestic product (GDP) and accounted for 10.4% of global employment in 2019. Given the importance of the tourism industry to the global economy, tourism policymakers, development experts, and industry practitioners have paid increasing attention over the past few decades to the management of the tourism sector's contributions throughout the world, and particularly in developing countries.

The perishability of tourism goods and services means there is a need for accurate and comprehensible tourism-demand forecasts (Archer 1987). Forecasts are crucial for government agencies and business stakeholders to develop effective policies and appropriate marketing strategies for promoting a destination's tourism and economic development. Most tourism-related investments, such as infrastructure and hotels, are long-term investments. Stakeholders increasingly make decisions based on long-term tourism demand forecasts, although, for daily operations, tourism and hospitality businesses use short-term demand forecasts to allocate resources for revenue management.

The importance of accurate tourism-demand forecasts has led to numerous efforts to improve the accuracy of forecasting methods. Several groups of researchers have reviewed the methodological developments and forecasting applications of tourism-demand modeling and forecasting practices over the past five decades, such as Witt and Witt (1995), Li, Song and Witt (2005), Song and Li (2008), Wu, Song and Shen (2017), and Song, Qiu and Park (2019).

Scholars generally agree that no single forecasting method can consistently outperform all other methods (Song and Li 2008, Athanasopoulos *et al*. 2011, Gunter and Önder 2016) and that most tourism-demand forecasting studies have focused on *ex-post* forecasts. *Ex-post* forecasts use the actual values of explanatory variables over the forecasting period to predict the dependent variables and to evaluate their accuracy when econometric models are applied. *Ex-post* forecasts are useful when assessing the performance of a particular econometric forecasting method because the error from predicting explanatory variables is not mixed with the forecast error of the dependent variable. *Ex-ante* forecasts, in contrast, use the predicted values of explanatory variables. *Ex-ante* forecasts are generated in a real-world context where no prior information on any influencing variable over the forecasting period is incorporated into the forecast generation. Hence, *ex-ante* forecasts have more direct implications for real-world forecasting. However, the performance of *ex-ante* tourism forecasting has been largely overlooked. In addition, tourism forecasting assessments previously focused on comparing different forecasting techniques and less on the factors that influence the accuracy of tourism forecasts (Peng, Song and Crouch 2014).

To bridge the above research gap, this study presents the first attempt to explore the determinants of *ex-ante* forecasting accuracy over different forecasting horizons using the 2013–2017 five-year forecasts published annually by the Pacific Asia Travel Association (PATA). The identified determinants (factors) will aid in developing and improving the accuracy of future forecasting models. Furthermore, the findings of this study will assist tourism practitioners in evaluating the reliability of forecasts and thus in making effective decisions. Most importantly, the identification of these factors will guide real-world forecasting and reduce the risk of real-world decision failures caused by poor demand forecasts.

The remainder of this paper is structured as follows. Section 2 briefly reviews the forecasting methods applied in the tourism field. Section 3 introduces the method and data used in this study. Section 4 presents the findings and discussion. Section 5 concludes with a summary of the implications and addresses the study's limitations.

2. Literature Review

Tourism forecasting studies have primarily used quantitative forecasting methods, such as non-causal time-series models, causal econometric models, and artificial intelligence (AI)-based models.

2.1 Time Series Models

The most widely used non-causal time-series models include Naïve I, Naïve II, exponential smoothing (ES) models, and autoregressive moving average (ARMA) family models (Wu, Song and Shen 2017). These are often considered benchmarks for evaluation and comparison purposes. Benefitting from this flexibility in practice, more advanced techniques have been applied to develop further time-series models to improve forecasting accuracy. Athanasopoulos and de Silva (2012) extended the ES method to a multivariate setting and found that multivariate models are superior to their univariate counterparts. Chen, Li, Wu, and Shen (2019) developed a multi-series structural time series model to forecast seasonal tourism demand in Hong Kong. They found that their method achieved higher accuracy than the ARIMA and ES methods. Apergis, Mervar, and Payne (2017) applied a Fourier transformation to quarterly ARIMA models, generating an improved ARIMA model that outperformed other time series methods.

Another trend in time-series forecasting is the use of augmenting explanatory variables that can discern the dynamics of tourism demand. ARMAX, for instance, is an extension of the traditional ARMA models that incorporates exogenous variables (X) as predictors. Pan and Yang (2017) adopted ARMAX to analyze search engine queries, website traffic, and weekly weather information to predict a destination's weekly hotel-occupancy rates. Their findings suggested that ARMAX was superior to its ARMA counterpart. Park, Lee, and Song (2017) extended the SARIMA model by augmenting it with a Google trends index. Their model showed better out-of-sample forecasting of Japanese inbound tourist arrivals to South Korea than in-sample forecasting based on the mean squared error (MSE) and the mean absolute error. An important implication of their study was that multivariate models with appropriately selected exogenous variables are likely to outperform standard time-series models such as SARIMA or Holt-Winters. Thus, these studies' findings suggest that the forecasting accuracy of time series augmented with explanatory variables is often superior to that of univariate time-series models (Jiao and Chen 2019).

2.2 Econometric Models

Econometric models enable the causal relationship between tourism demand and its determinants to be examined and they are generally found to have good forecasting performance. Thus, they have been widely used in tourism demand-forecasting research and practice over the past five decades. Among various econometric models, the auto-regressive distributed lag model (ADLM) and the error correction model (ECM) are important for analyzing and forecasting tourism demand. Song, Qiu, and Park (Song, Qiu and Park 2019) reviewed 111 studies and found nearly half used the ADLM (26) and ECM (24) models. They also found both models were accurate, with 16 out of 26 ADLM models having the best forecasting performance and 17 out of 24 ECM models outperforming competing models.

In addition to the ADLM and ECM, the vector autoregressive (VAR) model and the vector error-correction model represent another form of model extension (Song and Witt 2006, Wong, Song and Chon 2006, Gunter and Önder 2016). They introduce temporal dynamics into static single equation models. Attempts have been made to improve the forecasting accuracy of traditional VAR models. For example, Assaf, Li, Song, and Tsionas (2019) developed a Bayesian global vector autoregression model that outperformed traditional VAR models.

More advanced forecasting models have been developed over the past two decades. They include the time-varying parameter model by Song and Wong (2003) and Page, Song and Wu (2012), the linear almost ideal demand system (LAIDS) model by Li, Song and Witt (2004) and De Mello and Fortuna (2005), the spatial panel models by Yang and Zhang (2019) and Long, Liu and Song (2019), forecasting combination by Li, Song and Witt (2006) and Li et al. (2019), judgmental forecasting by Lin, Goodwin and Song (2014) and Song, Gao and Lin (2013), and mixed frequency data models by Hirashima, Jones, Bonham and Fuleky (2017) and Wen *et al*. (2020). The newly developed methods have shown their superiority in forecasting practice.

2.3 Artificial Intelligence Models

In the past two decades, AI models have received increasing attention from tourism scholars for their ability to capture nonlinear relationships and patterns among time series and exogenous variables in tourism-demand forecasting (Law and Au 1999, Law 2000). Five main types of AI-based models are recorded in the literature: artificial neural networks (ANNs), the rough sets approach, support vector machines, fuzzy time series, and grey theory (Jiao and Chen 2019). Variations of ANN models are the most widely applied AI methods in forecasting tourism demand (Palmer, Montano and Sesé 2006, Chen, Lai and Yeh 2012). Support vector regression (SVR) models are also frequently used. Chen and Wang (2007) found that the forecasting performance of SVR models is better than that of the ANN and ARIMA models. Hong, Dong, Chen, and Wei (2011) integrated genetic algorithms into an SVR model, which yielded a model with better forecasting accuracy. Fuzzy time series models have also been used and show good performance in short-term forecasting (Yu and Schwartz 2006, Wang and Hsu 2008).

Each AI model has its own merits and drawbacks. It is logical to combine AI models to form a new model with fewer limitations. Pai, Hung, and Lin (2014) developed a novel forecasting system by combing SVR and fuzzy methods and showed that their system was more accurate in generating inbound tourism forecasts.

2.4 Tourism Forecasting Comparison

Over the past few decades, scholars have endeavored to develop tourism forecasting methods and have compared their performance with that of previous methods. For example, the forecasting performance of noncausal time-series models has been compared with that of causal econometric models, but neither has been shown to be universally superior. Li, Song, and Witt (2005) found that dynamic econometric models generally produce more accurate forecasts than other forecasting models. Based on a meta-analysis of the forecasting accuracy of various models, Kim and Schwartz (2013) found that econometric models outperform noncausal time-series models overall. Using a similar meta-regression model, Peng, Song, and Crouch (2014) examined the possible determinants of forecasting errors, concluding that dynamic econometric models tended to exhibit the lowest level of forecast errors if other factors (such as tourism origin, destination, time period, sample size and demand measure) were controlled.

AI-based methods are much less popular than time series and econometric models, and their forecasting performance is often compared with that of time series models. Claveria and Torra (2014) used data from Catalonia as an example to show that the ARIMA model was superior to the ANN model in tourism forecasting. Akın (2015) compared the seasonal ARIMA, SVR, and ANN models and revealed that SVR was the most accurate. Volchek, Liu, Song, and Buhalis (2019) showed that the ANN model was more accurate than a mixed-frequency model in the short term for forecasting the number of visitors to museums in London.

The inconclusive findings derived from the above comparisons imply that forecasting accuracy is determined by many factors: the method used for estimating a model, the selection of model specification, and the diversified characteristics of the data (e.g., the length of the sample time series, the length of the forecasting horizon and the data frequency). Goodwin and Wright (1993) found that comparative forecasting performance depends on various factors, such as the nature of the time series (e.g., trend, seasonality, noise, instability, and forecasting horizon) and situational characteristics. Peng *et al.* (2014) collected forecasting errors calculated from *ex-post* forecasts based on reports from published studies and used meta-regression to explore the influencing factors of forecasting errors. One concern related to that study is that the data used for calculating forecasting errors were derived from different data sources using different estimation and forecasting methods. Thus, measurement errors could not be excluded. In addition, the forecasting errors in Peng *et al.* (2014) were *ex-post* errors generated based on the actual values of the explanatory variables in the model. *Ex-ante* forecasts, which are often used in a practical setting, are computed based on the explanatory variables' predicted values. Thus, the evaluation of *ex-ante* forecasting performance could bring more direct and useful practical implications. Despite its importance, however, *ex-ante* tourism forecasting has been largely overlooked. Song, Li, Witt, and Athanasopoulos (2011) and Athanasopoulos et al. (2011) are exceptions as they evaluated both *ex-post* and *ex-ante* forecasting performance. However, they did not explore the factors influencing forecast errors. Thus, in this study, we aim to bridge this gap in the literature.

This study is designed to examine the factors influencing *ex-ante* forecasting errors using a large set of visitor arrival forecasts in a real forecasting exercise published by Pacific Asia Travel Association (PATA) across different years. The research team was commissioned by PATA in 2013 to produce annual visitor forecasts for the following five years. The research team has full access to all real-world forecasts. To the best of our knowledge, this is the first empirical study to address the aforementioned challenges of tourism forecasting directly. Crucially, the *ex-ante* arrivals forecasts over different years and across different origin-destination pairs were generated using the same econometric forecasting methods and consistent data sources and measurement. Therefore, the forecasts are highly comparable, and the findings are more robust and generalizable than those of many previous studies.

3. Method and Data

3.1 Method

The choice of an error measure can affect the ranking of forecasting methods (J. Armstrong 2001a). The two most frequently used error measures to measure tourism-forecasting accuracy are the MAPE and the root mean square error (RMSE) adopted in this study. These measures can be used to examine the size of forecast errors in both relative (percentage) and absolute (volume) terms. It is important to use more than one measure of errors, as no single measure has been shown to provide an unambiguous indication of forecast accuracy (J. Armstrong 2001b, Mathews and Diamantopoulos 1986).

There is a consensus in the general forecasting literature regarding the influencing factors of forecasting accuracy, which mainly include the forecasting horizon, data availability, level of aggregation, type of product, and historical stability of data series (Schnaars 1984). However, opinions diverge about how some of these factors affect forecasting accuracy. Most scholars agreed that the longer the forecasting horizon, the less accurate the forecast, but this finding is situationally based on the selection of forecasting methods. The findings on how data availability affects forecasting accuracy are inconsistent, but generally longer data series are more likely to result in more accurate forecasts (Schnaars 1984). Most studies argued that one of the key determinants of forecasting accuracy is the stability of the data series over time. Forecasts obtained from unstable series are highly likely to be inaccurate.

Based on the literature, this study investigates the factors influencing forecasting accuracy in the context of tourism from 1 step ahead to 21 steps ahead, using Equation (1), as follows:

$$lnY = c + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \quad (1)$$

where Y is the dependent variable to measure forecasting errors (two error measures are used: MAPE and RMSE); ln is the natural logarithm; β_1 to β_3 are the estimated coefficient vectors; X_1 to X_3 are the vectors of the influencing factors; c represents the constant term; and ε is the vector of error terms. Equation (1) is estimated by applying the median (or least absolute deviations) regression with robust standardized deviations, the estimated coefficients of which minimize the sum of the absolute value of the residuals. Compared with the ordinary least square (OLS) method, the median regression is more robust against heteroscedasticity, and the residuals do not have to follow the normal distribution.

The magnitude and fluctuation of visitor arrivals have significant effects on forecasting errors; thus, the geometric means of the coefficient of variation (*CV*) of the historical visitor arrivals in the short term (*VC_Arr_s*) and long term (*VC_Arr_l*) of the five years are included in X_1. *CV* is calculated based on the last eight data points (i.e., eight quarters) of the historical data to measure the series' short-term variations. The full-sample arrivals are used to measure the long-term variations. The income level of the source markets has been shown to be the most influential determinant of tourism demand (Song and Li 2008, Wu, Song and Shen 2017). This suggests that the variation in income series may also result in the fluctuation of the arrivals series. Thus, the geometric means of the CV of source markets' GDP (*VC_GDP_s* & *VC_GDP_l*) and its covariance with tourism demand in the short term (*VC_Arr_GDP_s*) and long term (*VC_Arr_GDP_l*) are included as explanatory variables. The calculation of short-term and long-term covariances is similar to the calculation of the variation in the visitor-arrivals series, which means that the last eight data points and the full-sample series of the arrivals are used to compute the variables *VC_Arr_GDP_s* and *VC_Arr_GDP_l*, respectively. To capture the effect of the demand volume on forecasting accuracy, we use the average of the last data point of the arrivals series (*Last_Arr*) collected during the PATA project in 2013–2017. Data characteristics are also considered as the determinants of forecasting accuracy (Goodwin and Wright 1993). Thus, X_2 is composed of two variables: the average length of historical data (*Length_h*) and the average maximized order of the lagged variables (*Num_lag*). These two variables examine the influence of the sample size on forecasting accuracy.

Similar to Peng *et al.* (2014), dummy variables are included in vector X_3, such as the location of the destination (*D_Americas & D_Asia*), the location of the source markets (*S_Americas*, *S_Europe*, *S_Asia*, and *S_Pacific*), the travel distance (*Inter_Dummy*) between the destination and the origin market and the types of forecasting methods (*ADL-ECM*). The following ADL-ECM model is adopted in this study:

$$\begin{aligned}\Delta \ln V_{i,j,t} = \lambda_0 + \sum_{q=1}^{m_1} \psi_{i,j,q} \Delta \ln V_{i,j,t-q} + \sum_{r=1}^{m_2} \psi_{Y_{i,r}} \Delta \ln GDP_{i,t-r} \\ + \sum_{w=1}^{m_3} \psi_{P_{i,j,w}} \Delta \ln RP_{i,j,t-w} + \lambda_1 \ln V_{i,j,t-1} + \lambda_2 \ln GDP_{i,t-1} \\ + \lambda_3 \ln RP_{i,j,t-1} \\ + \sum_{d=1}^{D} \theta_d Dummies + u_{i,j,t} \end{aligned} \quad (2)$$

where $V_{i,j}$ is the visitor arrivals from source market *i* to destination *j*, GDP_i stands for the gross domestic product of the source market to represent the income level, and $RP_{i,j}$ is the relative price between the source market *i* and destination *j* adjusted by the exchange rate. Dummy variables are also included to reflect the impact of one-off events on demand, such as the September 11 terrorist attacks in 2001 and SARS in 2003. ln and Δ are natural logarithm and difference calculator, respectively. The Akaike Information Criterion is used to select the lag orders. The ADL-ECM model can capture the short-run effect and also the long-run relationships among variables. In particular, income and price elasticities can be calculated accordingly, and have important practical implications for destination management organizations. Although the ADL-ECM model requires strict cointegration relationship among variables, it is selected as the primary forecasting method to generate tourism demand forecasts in the PATA regional forecasting project because its forecasts have informative, practical implications. According to Song, Qiu, and Park (2019), the ADL-ECM model is also the most frequently used and best performing model in the tourism demand forecasting literature in the last five decades. More technical details of the ADL-ECM model can be found in the studies of Song and Lin (2010), Song, Gao, and Lin (2013), and Lin, Liu, and Song (2015).

The settings of the dummy variables are as follows. If the country of origin is in the Americas, its value is set to one and is zero otherwise. The settings of Europe, Asia, and the Pacific are similar, with Africa used as the reference group. A similar rule is applied to the setting of destination dummies. As the PATA visitor forecasts focus on the inbound arrivals to the Asia and Pacific region, there are only two vectors in the destination dummies: the Americas and Asia. The Pacific region is used as the reference group. The dummy variable is set to unity if the country of origin and country of destination are located on different continents and is zero otherwise. The number of times that the ADL-ECM is applied in the five rounds of forecasting exercise is taken to represent the effect of the methodology on forecasting accuracy.

3.2 Data

The forecasts used in this study are obtained from the annual reports of PATA Visitor Forecasts (2013, 2014, 2015, 2016, 2017). We use 5-year-ahead quarterly forecasts of visitor arrivals for more than 30 destinations (over 1,000 destination-origin pairs) in the Asia Pacific region. The actual visitor arrivals data across five years from 2013 to 2017 (i.e., actual values of 21 quarterly visitor arrivals) are available to enable calculation of 1-quarter-ahead to 21-quarters-ahead forecasting errors (i.e., MAPE and RMSE) for 765 origin-destination pairs covering 31 destinations.

The descriptive statistics of the forecast errors are presented in Table 1. An examination of the degree of accuracy across the two criteria (MAPE and RMSE) shows that the overall accuracy tends to decline as the forecasting horizon extends. The error ranges and standard deviations in Table 1 show that MAPE is more sensitive than RMSE. The GDP index (2010 = 100) used in the PATA reports to generate the forecasts is also used to calculate the covariance in X_1. All vectors in X_1 and X_2 take the natural logarithm, except the maximized order of lagged variables, the magnitude of which would be quite similar after logarithmic transformation.

[Insert Table 1 about here]

4. Findings and Discussion

Forty-two regression models are run, with 2 dependent variables (MAPE and RMSE) and 21 forecasting horizons. Due to space constraints, selected results are presented in Figure 1 and Tables 2 and 3. The Pseudo R^2, proposed by Koenker and Machado (1999), is used to evaluate the models' goodness-of-fit. Table 2 shows that the highest Pseudo R^2 of the MAPE models is exhibited by the 1-step-ahead model (0.24), and the value then decreases over horizons to reach 0.04 in the 21-steps-ahead model. The same pattern can be observed in the RMSE models. The 3-step-ahead model fits the data best, as shown by its Pseudo R^2 of 0.76, and also decreases as the forecasting horizon extends. In the 21-steps-ahead RMSE model, the explanatory variables can explain approximately 52% of the variation in the data. The Pseudo R^2 of the models decreases as the forecasting horizon extends, suggesting that forecasting longer-term visitor arrivals is associated with higher uncertainty. The relatively low Pseudo R^2 values are not a concern here, as our focus in this study is to identify the key determinants of forecasting errors, which means that the statistical significance of individual independent variables' coefficients is more important. Consistent with the findings of Peng *et al*. (2014), the Pseudo R^2 values also indicate that the relative errors are more difficult to explain than absolute errors, which may be attributable to information loss during transformation of the absolute errors to relative indexes by dividing by an absolute term.

[Insert Figure 1, Tables 2 and 3 about here]

Across various forecasting horizons, 11 out of 17 variables show more significant effects in MAPE models than in RMSE models (See Figure 1). In particular, the absolute values of visitor arrivals in the most recent period have a positive and significant effect on RMSEs for all 21 horizons, indicating that the absolute forecasting errors are highly related to the number of visitor arrivals. When the MAPEs are calculated, the indexes are divided by absolute terms. Thus, the influence of the number of visitor arrivals on MAPEs and RMSEs varies. Due to the aforementioned information loss, the absolute magnitude of the effect in the MAPE models is smaller than that in the RMSE models. As the forecasting horizon extends, the elasticities of the visitor arrivals of the last period in the MAPE models range from -0.09 for the 1-step-ahead forecasts to -0.05 for the 21-steps-ahead forecasts. The coefficients in the RMSE models are much larger, ranging from 0.87 to 0.99.

The variation in the number of visitor arrivals has a significant influence on forecasting accuracy. There is a positive relationship between the short-term variation in visitor arrivals and the forecasting error in the 1-step-ahead to 21-steps-ahead horizons, except for the 12-, 15-, 19-, 20-, and 21-steps-ahead forecasts in the MAPE models. When using the RMSE to measure forecast errors, the variation in visitor arrivals in the short-term mainly influences the short-term forecasting accuracy, particularly that of the 2- to 4-step-ahead horizons.

The long-term variation in visitor arrivals plays a more important role than the short-term variation. The significant relationship between the CV of visitor arrivals in the long term and forecasting accuracy can be seen across all the 21-steps-ahead horizons of the MAPE models, aside from the first three horizons. In the RMSE models, significant relationships can be identified in 16 out of 21 estimations, which is more than with short-term variation. Thus, the greater the fluctuation in visitor arrivals in the long run, the larger the forecasting errors, and the more difficult it is to produce accurate forecasts.

The variation in the GDP of a source market is a significant determinant of MAPE in the first seven horizons and the 3- and 4-steps-ahead RMSE models. Similar patterns are found in the short-term interactions between the variations in visitor arrivals and GDP in the MAPE and RMSE models. Given the significant role of the short-term variation in visitor arrivals, it could be argued that the variation in GDP seems to moderate the effect of the variation in visitor arrivals on forecasting accuracy. In other words, given the same level of fluctuations of visitor arrivals in the short term, the stronger the fluctuation of GDP, the larger the forecasting error would be (see Figure 2). The correlation is particularly true for the short-term forecasts: the moderating effect of GDP on the relationship between the variation in visitor arrivals in the short-term strengthens and forecasting errors become stronger as the variation in visitor arrivals increases. However, the effect of short-term GDP variation and its moderating effect on the errors declines significantly from the 7-steps-ahead horizon onward. There are only 2 significant GDP variations and corresponding interactions in the remaining 14 MAPE models and 2 significant GDP variations in the RMSE models. The interaction terms are not found to be significant in the last 14 RMSE models.

In contrast, only 3 out of 21 models identify significant variations in GDP in the long-term in the MAPE models and in two cases in the RMSE models. Eight (ten) significant moderating effects are found in the relationship between the variations in visitor arrivals and forecasting errors in the long-term in MAPE (RMSE) models. However, such significant relations are mostly found in the 16- to 21-steps-ahead forecasts. Four cases are found in the MAPE models and five in the RMSE models. In contrast to these short-term findings, variations in arrivals and GDP in the long term moderate the errors in the long-term forecasting period. This confirms that the variations in the dependent and independent variables are key determinants of forecasting accuracy.

[Insert Figure 2 about here]

The variable significantly influenced only one fifth to one fourth of the errors in the 21 horizons, but that does not mean that the length of a historical series is not an important influencing factor of forecasting accuracy. In fact, the length of a historical time series has a negative effect on the forecasting errors in 3 and 5 of the 21 MAPE and RMSE models, respectively. The earliest starting date for the PATA projects can be traced back to 1995; thus, a sufficient sample size was available to build the forecasting models and generate the forecasts. However, the extension of the historical data does not further improve forecasting accuracy, despite it doing so when there are far fewer observations.

Errors decrease for most forecasting horizons in the MAPE (19 out of 21) and RMSE (15 out of 21) models when higher lag-orders of the variables are introduced into the forecasting models. More historical information is required to estimate models and generate forecasts as more lagged variables are included in a model. This finding suggests that the inclusion of more lagged terms can improve accuracy. One key feature of the ADL-ECM is its ability to capture the dynamic behaviors in tourism demand (such as habit persistence) by including the lagged variables (Song and Witt, 2000). Thus, this finding provides clear justification for the theoretical foundation of the widely applied ADL-ECM model in tourism forecasting practice.

The destination regions and the source market have limited effects on forecasting accuracy. The MAPE models show that compared with the benchmark of African source markets, an average of only 4 out of the 21 horizons give significant differences in forecast errors for the Americas, Europe, Asia, and the Pacific. In models where significant effects of the source market region are found, American source markets are forecasted more accurately in the short run, whereas Asian markets are associated with larger forecasting errors in the long run compared to African markets. The rapid and sustained growth of emerging markets such as China and India add great uncertainty to forecasting. Some unexpected regional events such as the 2015 MERS pandemic in South Korea and the 2015 earthquake in Nepal resulted in large decreases in the forecasting accuracy for these destinations. This results in larger errors in forecasting compared to more mature markets. This finding is strongly supported by the results of the RMSE models, particularly in long-run forecasts. Seven out of 10 horizons have significantly larger errors in Asian markets than in African markets when forecasts are more than 12 steps ahead. A higher number of significant effects are found in the RMSE models, as MAPE is a relative error measure and some information is likely to be lost when it is divided by the actual value.

The influence of destination region on forecasting accuracy is also limited. There are only two (two) horizons in the Americas and nine (five) horizons in Asia that have significantly different forecasting errors regarding the Pacific destinations in the MAPE (RMSE) model. In general, this shows that the forecasting errors between American and Pacific destinations are similar. The limited significant horizons indicate that American destinations such as the USA and Canada can achieve higher forecasting accuracy because these markets are more mature. Compared with Pacific destinations, Asian markets are more difficult to forecast because of the higher frequency of unexpected factors such as political tension and natural disasters in some destinations and source markets.

Inter- and intra-continental travel is used as a dummy variable to represent travel distance. The estimation results show that travel distance may not play an important role in determining forecasting accuracy. A significant effect is found in only 5 and 4 out of 21 horizons of the MAPE and RMSE models, respectively. Following the increased use of ADL-ECM over the five years, no evidence is found that the forecasts become more accurate, as half of the coefficients of the MAPE and RMSE models in the 21 horizons are significant. This supports Witt and Witt (1995): there is no single model that is always superior. It also shows the necessity of using combined forecasts to obtain more accurate forecasting results (Song *et al*. 2009).

5. Conclusions and Implications

This study investigates the influencing factors of *ex-ante* forecasting accuracy based on PATA's real-world visitor forecasting project. The forecasts of 765 origin-destination pairs covering 31 destinations in the Asia Pacific region are used as the main source of data to compute forecasting accuracy and further examine its determinants.

The main findings are summarized as follows. First, as the forecasting horizon extends, the uncertainty increases, which means that forecasting becomes increasingly difficult in the more distant future. Second, the fluctuation of visitor arrivals tends to decrease forecasting accuracy, and the fluctuation of GDP further strengthens this negative effect. Third, the inclusion of a higher lag-order of the variables in a forecasting model is likely to result in more accurate forecasts, suggesting that the lagged effect of both the tourism demand variable and its determinants should not be ignored in future forecasting practice. Fourth, forecasting visitor arrivals in Asian markets tends to be more difficult than in other regions. The difficulty is possibly attributable to the rapid growth and dynamism of the emerging Asian markets being affected by multiple factors, such as political instabilities and market-specific features, which add to the difficulty of generating accurate forecasts. Last, the methods used to estimate and forecast tourism demand may not lead to accurate forecasting.

The findings of this study are consistent with those of Peng, Song, and Crouch (2014), who concluded that forecasting method selection, sample size, and destination-origin pairs significantly affected forecasting accuracy. Such findings have been observed in the forecasting practice of other industries, such as the manufacturing industry (Tokle and Krumwiede, 2006). Extensive efforts have been made over the past few decades to improve forecasting accuracy in tourism research, but few studies have investigated the determinants of accuracy. Thus, an important contribution of this study is its use of *ex-ante* forecasts produced in a real-world forecasting setting to examine the influencing factors of forecasting errors across various horizons. The most important original quality of this study is its attempt to explore the relationship between forecasting accuracy and variations in its explanatory variables, which innovatively extends the literature on tourism demand and informs the forecasting practice in the tourism industry.

Econometric models such as ADL-ECM can capture regular fluctuations in tourism demand in line with economic cycles. However, when a severe external shock (e.g., an economic or social crisis, or a natural disaster) takes place in either an origin market or a destination, the pre-established long-run relationship between tourism demand and its determinants will not be applicable in the short term. No quantitative model is capable of capturing such unexpected shocks in a timely manner, resulting in a loss of accuracy in the short term. As argued by Witt and Witt (1995), no single model can outperform others in every case. Forecasting accuracy varies across different models when facing an unexpected shock; the forecasting performance of certain econometric models tend to be more robust to high volatility in some tourism data.

Generally, the performance of the ADL-ECM model is fairly satisfactory. However, if an unexpected crisis or shock occurs, such as the COVID-19 pandemic, the forecasting model adopted before the crisis may fail to predict tourism demand during and shortly after the crisis. Alternatively, newly emerged forecasting models that can use mixed-frequency data to better reflect data volatility could be more appropriate than traditional econometric models. Interval forecasts and forecasting combination techniques (Li et al., 2019) are also recommended for practitioners to reduce forecasting failures and improve forecasting accuracy. In addition, integration of judgmental forecasting methods with econometric models (Lin, Goodwin, and Song, 2014) that combine the opinions and expertise of experts under alternative scenarios with the quantitative forecasting techniques could also be useful to improve forecasting accuracy when the tourism system is subject to significant external shocks, such as COVID-19.

Scholars can use the findings in this study to improve forecasting accuracy, which will enable tourism practitioners to make better investment decisions. Government and industry stakeholders should also be more cautious when using the forecasting results generated from historical data with higher levels of variability or when using long-term forecasts. The accuracy of the forecasting will be lower than that generated from stationary data or short-term forecasts. They should also be more cautious when using predictions of visitor arrivals from or to the Asian markets. It is also important to note that the persistent application of one forecasting method may not improve forecasting accuracy.

One limitation of this study is that only two methods were included in the PATA visitor forecasting project, ADL-ECM and exponential smoothing with state space models, with ADL-ECM predominantly used for producing the original forecasts. The findings would be more comprehensive if more forecasting methods, particularly combined forecasting models, were included in real-world forecasting exercises. Moreover, the error measures were calculated from 1-step- to 21-steps-ahead forecasts, which implies a time span of only five consecutive years. The factors influencing the forecasting accuracy over the longer term could be investigated if longer error series are available.

Although both the relative error (MAPE) and the absolute error (RMSE) were used in this study, the findings of these two measures are not always consistent. This difference can be explained by the fact that these error measures are mathematically calculated. Thus, they differ in their sensitivity to marginal changes. These error measures are also not applicable to all conditions. In particular, they may suffer from a skewed distribution when the forecasts are close to zero (Armstrong and Collopy 1992, Hyndman and Koehler 2006). Therefore, more error measures should be introduced in future research to provide a more comprehensive analysis and further strengthen the findings.

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Table 1. Descriptive Statistics of Forecasting Errors

	MAPE				RMSE			
Forecasting Horizons	Minimum	Maximum	Mean	Std. Deviation	Minimum	Maximum	Mean	Std. Deviation
1	0.013	2.779	0.139	0.162	9.151	857071	10076.2	46997.14
2	0.015	1.140	0.151	0.118	7.410	1238623	14467.2	70022.65
3	0.021	1.412	0.161	0.130	10.382	902453	14953.9	61668.08
4	0.017	2.255	0.181	0.153	9.474	1275227	16880.3	78481.87
5	0.025	3.786	0.208	0.214	7.567	1813867	18941.2	92589.39
6	0.016	3.161	0.221	0.211	6.015	1905185	22120.9	106220.43
7	0.009	3.355	0.235	0.206	8.291	2401922	22005.4	111678.69
8	0.016	4.794	0.260	0.302	8.605	2339709	23825.6	116770.47
9	0.017	2.651	0.271	0.269	5.673	2823941	25926.3	130506.48
10	0.014	4.587	0.288	0.308	6.674	2906007	27696.6	138675.37
11	0.004	4.947	0.311	0.369	9.535	4066720	29347.9	174901.21
12	0.022	7.294	0.330	0.428	3.622	4452778	33539.0	197010.59
13	0.005	5.405	0.345	0.465	3.419	5092787	34023.9	213091.79
14	0.001	5.501	0.358	0.443	3.890	5406538	35219.4	224151.54
15	0.005	6.075	0.378	0.474	3.323	5383603	33594.7	215201.32
16	0.009	9.696	0.396	0.593	3.955	6067054	38046.2	248615.54
17	0.000	7.596	0.403	0.570	4.847	6457312	36959.1	258390.28
18	0.000	14.616	0.421	0.789	0.477	7713609	36214.1	296965.29
19	0.002	9.553	0.429	0.733	0.640	7333226	37281.2	286492.88
20	0.001	8.447	0.436	0.673	1.374	8309122	40458.6	325258.63
21	0.000	24.286	0.478	1.224	0.492	8542534	40861.0	335432.47

Table 2. Regression Results of MAPE with Selected Forecasting Horizons

Variable	**1**	**2**	**3**	**4**	**8**	**12**	**16**	**21**
lnLast_Arr	**-0.09*****	**-0.08*****	**-0.10*****	**-0.08*****	**-0.06*****	**-0.04****	**-0.05*****	**-0.05****
	[-6.33]	[-5.39]	[-7.42]	[-5.91]	[-3.93]	[-2.31]	[-2.65]	[-2.04]
lnVC_Arr_s	**0.72*****	**1.07*****	**0.50****	**0.63*****	**0.40***	0.31	**0.58****	0.70
	[3.15]	[5.25]	[2.05]	[3.25]	[1.68]	[1.23]	[2.13]	[1.61]
lnVC_Arr_l	-0.24	**0.28***	0.16	**0.39****	**0.42****	**0.70*****	**0.70*****	**0.45***
	[-1.18]	[1.74]	[0.94]	[2.44]	[2.14]	[3.51]	[3.07]	[1.66]
lnVC_GDP_s	**0.27****	**0.30*****	**0.26****	**0.24*****	0.16	0.06	0.11	0.19
	[2.53]	[3.67]	[2.56]	[2.84]	[1.59]	[0.53]	[1.02]	[0.94]
lnVC_GDP_l	**-0.20***	0.06	**-0.15***	-0.10	0.02	0.17	0.12	0.12
	[-1.90]	[0.66]	[-1.76]	[-1.17]	[0.17]	[1.47]	[0.90]	[0.65]
lnVC_Arr_GDP_s	**0.10***	**0.20*****	0.09	**0.12****	0.06	0.02	0.06	0.13
	[1.77]	[3.84]	[1.54]	[2.41]	[1.01]	[0.38]	[0.75]	[1.16]
lnVC_Arr_GDP_l	**-0.18***	0.04	-0.01	0.00	0.08	**0.20****	**0.23****	0.16
	[-1.95]	[0.50]	[-0.17]	[0.05]	[0.91]	[2.18]	[2.10]	[1.21]
lnLength_h	**-0.41*****	**-0.27***	0.04	-0.21	**-0.43*****	-0.35	-0.32	0.04
	[-3.08]	[-1.93]	[0.23]	[-1.37]	[-2.61]	[-1.52]	[-1.31]	[0.12]
Num_lag	**-0.09*****	**-0.15*****	**-0.09*****	**-0.15*****	**-0.13*****	**-0.11****	**-0.12*****	**-0.11****
	[-2.70]	[-5.35]	[-2.93]	[-5.22]	[-4.06]	[-2.24]	[-2.63]	[-2.10]
S_Americas	**-0.35****	**-0.27***	-0.07	**-0.21***	-0.00	0.16	-0.02	0.17
	[-2.43]	[-1.94]	[-0.49]	[-1.84]	[-0.02]	[0.68]	[-0.05]	[0.58]
S_Europe	**-0.30****	**-0.21***	-0.18	**-0.18***	-0.13	0.03	-0.20	-0.10
	[-2.47]	[-1.65]	[-1.35]	[-1.70]	[-0.77]	[0.15]	[-0.69]	[-0.39]
S_Asia	-0.04	0.05	0.14	0.01	0.19	0.25	0.06	0.22
	[-0.31]	[0.34]	[1.07]	[0.11]	[1.13]	[1.16]	[0.20]	[0.78]
S_Pacific	**-0.34****	-0.17	-0.19	-0.14	-0.23	-0.08	-0.13	-0.24
	[-2.16]	[-1.05]	[-1.20]	[-1.12]	[-1.15]	[-0.32]	[-0.38]	[-0.81]
D_Americas	-0.09	-0.04	-0.03	0.04	-0.13	**-0.24****	-0.08	-0.13
	[-0.88]	[-0.46]	[-0.32]	[0.56]	[-1.53]	[-2.11]	[-0.71]	[-0.89]
D_Asia	0.11	0.07	0.09	0.10	**0.19****	0.17	**0.24****	0.15
	[1.23]	[0.96]	[1.21]	[1.56]	[2.03]	[1.59]	[2.40]	[0.94]
Inter_Dummy	0.04	-0.01	-0.06	**-0.12***	0.09	0.12	0.11	0.20
	[0.45]	[-0.06]	[-0.66]	[-1.75]	[0.87]	[1.15]	[1.22]	[1.25]
ADLM	**0.04***	**0.05*****	**0.04***	**0.07*****	**0.05****	**0.06****	**0.06****	**0.06***
	[1.86]	[2.90]	[1.66]	[3.14]	[2.44]	[1.99]	[1.99]	[1.72]
Constant	0.43	0.74	**-1.55****	-0.01	0.83	0.64	1.08	-0.53
	[0.59]	[1.07]	[-2.03]	[-0.01]	[1.06]	[0.60]	[0.91]	[-0.34]
Pseudo R^2	**0.24**	**0.22**	**0.19**	**0.22**	**0.17**	**0.11**	**0.10**	**0.04**

Note: Figures in brackets are *t* values; *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Table 3. Regression Results of RMSE with Selected Forecasting Horizons

Variable	**1**	**2**	**3**	**4**	**8**	**12**	**16**	**21**
lnLast_Arr	**0.87*** **	**0.91*** **	**0.90*** **	**0.90*** **	**0.92*** **	**0.95*** **	**0.93*** **	**0.90*** **
	[52.26]	[52.87]	[70.11]	[64.18]	[51.99]	[35.95]	[43.64]	[28.79]
lnVC_Arr_s	-0.05	**0.63** **	**0.60*** **	**0.55** **	**0.49* **	0.49	0.52	-0.42
	[-0.19]	[2.55]	[3.52]	[2.53]	[1.75]	[1.45]	[1.40]	[-0.88]
lnVC_Arr_l	0.27	0.32	**0.27* **	**0.43* **	0.36	**0.73*** **	**0.95*** **	**0.71** **
	[1.29]	[1.59]	[1.80]	[1.87]	[1.56]	[3.01]	[4.00]	[2.40]
lnVC_GDP_s	-0.09	0.11	**0.30*** **	**0.18** **	0.15	0.01	0.06	**-0.38* **
	[-0.70]	[1.03]	[3.33]	[1.97]	[1.28]	[0.03]	[0.42]	[-1.70]
lnVC_GDP_l	0.05	0.03	-0.14	0.06	0.06	**0.36** **	**0.31* **	**0.38** **
	[0.37]	[0.27]	[-1.39]	[0.48]	[0.49]	[2.31]	[1.75]	[2.10]
lnVC_Arr_GDP_s	-0.07	0.01	**0.12*** **	**0.11** **	0.07	0.06	0.07	-0.14
	[-1.22]	[1.52]	[2.76]	[2.05]	[0.96]	[0.73]	[0.74]	[-1.10]
lnVC_Arr_GDP_l	0.07	0.03	-0.01	0.06	0.09	0.21	**0.28** **	**0.29** **
	[0.71]	[0.40]	[-0.11]	[0.63]	[0.78]	[1.79]	[2.15]	[2.22]
lnLength_h	-0.12	0.15	-0.08	**-0.29** **	**-0.37** **	**-0.67*** **	**-0.64** **	-0.13
	[-0.69]	[0.78]	[-0.61]	[-1.96]	[-2.07]	[-2.88]	[-2.31]	[-0.38]
Num_lag	**-0.14*** **	**-0.15*** **	**-0.11*** **	**-0.12*** **	**-0.11*** **	-0.06	-0.06	-0.07
	[-5.13]	[-3.75]	[-3.73]	[-3.96]	[-2.66]	[-1.42]	[-1.19]	[-1.20]
S_Americas	**-0.23* **	**-0.42*** **	-0.23	-0.20	0.03	0.32	0.23	0.35
	[-1.85]	[-3.40]	[-1.00]	[-0.93]	[0.15]	[1.19]	[0.92]	[1.04]
S_Europe	**-0.22* **	**-0.30*** **	-0.28	-0.27	-0.16	0.14	0.04	-0.03
	[-1.72]	[-2.58]	[-1.19]	[-1.23]	[-1.04]	[0.53]	[0.17]	[-0.08]
S_Asia	0.14	-0.02	0.07	0.03	0.25	**0.52* **	**0.40* **	**0.58* **
	[1.07]	[-0.17]	[0.28]	[0.13]	[1.51]	[1.92]	[1.85]	[1.86]
S_Pacific	-0.22	-0.20	-0.18	-0.26	-0.11	0.21	0.09	0.04
	[-1.38]	[-1.55]	[-0.72]	[-1.16]	[-0.58]	[0.79]	[0.32]	[0.12]
D_Americas	0.09	0.04	-0.04	0.02	-0.06	-0.12	-0.10	0.25
	[0.84]	[0.38]	[-0.44]	[0.21]	[-0.57]	[-1.06]	[-0.82]	[1.40]
D_Asia	-0.09	**-0.17* **	0.02	0.04	0.07	**0.19* **	**0.18* **	0.07
	[-0.87]	[-1.97]	[0.22]	[0.50]	[0.74]	[1.86]	[1.74]	[0.41]
Inter_Dummy	-0.06	-0.11	-0.03	-0.08	-0.07	0.19	**0.19* **	0.18
	[-0.67]	[-1.33]	[-0.36]	[-0.96]	[-0.68]	[1.48]	[1.65]	[0.96]
ADLM	0.04	0.03	**0.07*** **	**0.06*** **	0.04	**0.05* **	**0.07** **	0.04
	[1.48]	[1.21]	[3.23]	[2.62]	[1.32]	[1.79]	[2.12]	[0.93]
Constant	**12.10*** **	**12.57*** **	**13.39*** **	**14.31*** **	**14.85*** **	**15.96*** **	**16.14*** **	**12.02*** **
	[15.09]	[13.38]	[22.29]	[18.28]	[16.18]	[15.43]	[12.57]	[7.17]
Pseudo R^2	**0.72**	**0.74**	**0.76**	**0.75**	**0.73**	**0.68**	**0.64**	**0.52**

Note: Figures in brackets are *t* values; *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

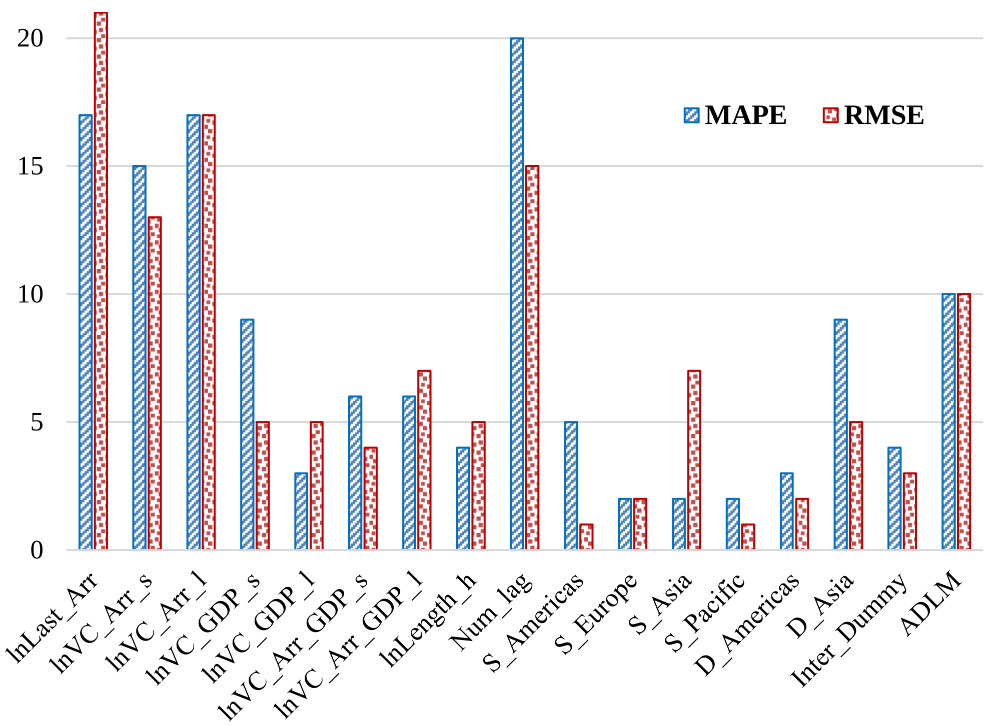

Figure 1. Frequencies of Significant Variables across 21 Horizons in MAPE and RMSE Models

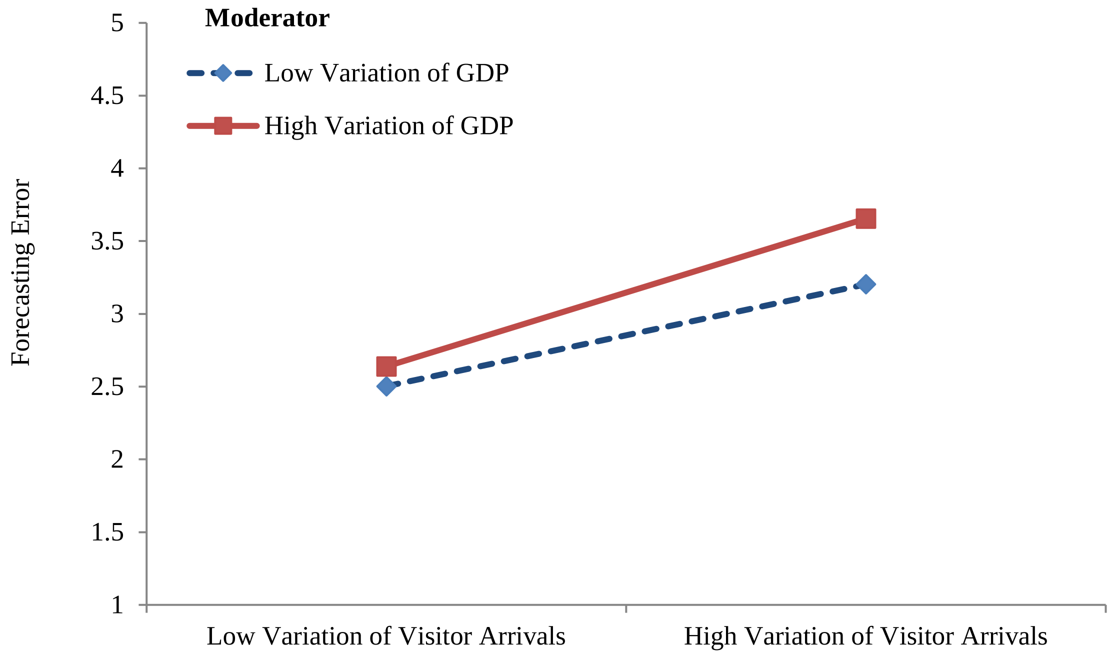

Figure 2. The Moderating Effect of the Variation in GDP on the Relationship between the Variation in Visitor Arrivals and the Forecasting Error