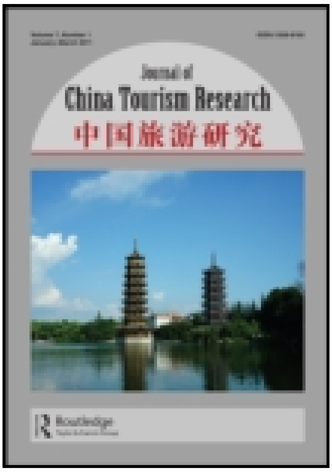

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Modeling and Forecasting Inbound Tourism Demand for Long-Haul Markets of Beijing

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Modeling and Forecasting Inbound Tourism Demand for Long-Haul Markets of Beijing

北京入境旅游需求建模与预测分析: 以长线市场为例

EDDY K. TUKAMUSHABA
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This paper aims to identify the most influencing factors of Beijing's inbound tourism demand using the autoregressive distributed lag model (ADLM) and then generates forecasts of international tourist arrivals from the United States, the United Kingdom, and Canada for the period of 2010Q3–2015Q4. The general-to-specific modeling approach was adopted to achieve final models while the exponential smoothing method was used to produce forecasts for independent variables. Results show that factors such as "word of mouth" effect, income level of the origin source markets, the costs of tourism in Beijing, and the cost of tourism in the competing destinations are crucial determinants of the tourism flows from three long-haul international markets. A group of error measures, such as the mean absolute percentage error (MAPE), root mean square percentage error (RMSPE), mean absolute error (MAE), root mean square error (RMSE), and Theil's U statistic, were used to evaluate the forecasting accuracy. The results suggest that all three models have good forecasting abilities with the MAPEs ranging from 5.73% to 14.89%. Implications are discussed and recommendations as well as future research directions are provided.

KEYWORDS. Inbound tourism demand, long-haul, ADLM, forecasting

本文基于北京 3 个主要长线市场（美国，英国和加拿大）的季度数据，采用自回归分布滞后模型（ADLM），旨在探求影响北京入境旅游需求的主要因素，并给出 2010Q3–2015Q4 期间三个客源国的访京游客人数的预测。本文根据从一般到具体的计量经济建模方法得到最终模型，并利用指数平滑法得到自变量的预测值。实证结果表明，"口碑效应"，客源国的收入水平，北京的旅游成本，和替代目的地的旅游成本是决定北京的三个长线市场的旅游需求的重要影响因素。文中使用平均绝对百分比误差（MAPE），均方根百分比误差（RMSPE）,平均绝对误差（MAE），均方根误差（RMSE）和泰尔U指数等作为评价预测精度的指标。研究结果表明，三个模型具备很好的预测能力—计算得到的 MAPE 在 5.73% 和 14.89% 之间。文中通过对北京三个长线市场的旅游需求弹性的分析和未来入境人数的预测，为北京旅游产业政策制定提供了政策建议和依据，同时也指出了未来的研究方向。

关键词: 入境旅游需求, 长线市场, ADLM, 预测

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Introduction

Tourism demand forecasting has gained popularity amongst different scholars in recent years (Song, Wong, & Chon, 2003; Song & Witt, 2003; Song & Li, 2008; Song & Hyndman, 2011). This can be attributed to the economic importance of tourism to countries that are able to attract tourists. Tourism demand forecasting therefore is vital for policy and decision making in countries that seek to develop a tourism industry. Since 2010, China has moved up to third position in the world's top ten tourism destinations in terms of international tourist arrivals (World Tourism Organization [UNWTO], 2011; 2012). This ranking corroborates the earlier predictions in UNWTO (2001) that China would overtake the United States to become the world's top tourist destination by 2020. Growth in tourist arrivals has been attributed to international events, the 2008 Olympics and the 2010 Shanghai World Expo, which have helped to enhance the country's profile and boost international tourism receipts. International tourism receipts reached US$ 48.5 billion in 2011, making China the fourth highest international tourism revenue earner globally (UNWTO, 2012).

As the political and cultural hub of China, Beijing fully exploits its advantages to build itself into an international convention and exhibition capital and a high-end tourist destination. In 2011, Shenzhen, Guangzhou, Shanghai, and Beijing were the top city destinations in terms of arrivals (Euromonitor International, 2012), but Beijing retains a top position as the most visited city in China due to a rich variety of places of interest, among other considerations. Whilst Beijing received about 0.19 million international tourists and merely made an income of US$ 100 million in 1978, the international tourist arrivals increased to 5.2 million (28 times more than what it was in 1978), representing an average annual growth of 10.6% over 1978–2011, and the international tourism revenue reached US$ 5.04 billion (50 times more than the 1978 figure) in 2010 (China National Tourism Administration [CNTA], 2012). The majority of international visitors (about 86.3% averagely from 2005–2011) were foreign visitors while the rest of the remaining 13.7% were compatriots from Hong Kong, Macau, and Taiwan. The United States was the biggest source market for Beijing's international inbound tourism during the period 2005–2011, accounting for about 14% of the total inbound market. Benefiting from the close proximity as well as visa-exemption entry, Japan and South Korea remained the second and third ranked source markets respectively for arrivals to Beijing, representing about 11.6% and 10.3% over the same period. Other countries, such as Germany, the United Kingdom, Russia, France, Canada, Australia, and Singapore, were among the top ten source markets over 2005–2011 (CNTA, 2012).

Alongside the booming inbound tourism that has been seen in the past decades is the vulnerability of Beijing's tourism industry to external shocks, including the serious flood in 1998, SARS epidemic in 2003, and the global economic and financial crisis in 2008. Growth in arrivals in 2003, for example, witnessed a significant slowdown of 40.4% because of the SARS epidemic. Whilst the effect of external shocks may not be underestimated, they seem to be neutralized by the international events, boosting tourism prospects time and again. One such mega event was the Beijing Olympic Games in 2008, which was widely seen as a boost to Beijing's tourism demand. Sands (2009) argued that the 2008 Beijing Olympics created an enormous improvement in infrastructure in terms of transportation, accommodation, attractions, and publicity that has since made China open its doors for tourism. Statistics released by CNTA (2012) showed that Beijing had a total of 0.39 million visitor arrivals (including 0.03

million from Hong Kong, Macau and Taiwan, and 0.36 million foreigners) in the period of the Olympic Games.

However at the same time, 2008 remained probably China's, in particular Beijing's, most challenging and painful year. The year witnessed an unprecedented world economic crisis that started in the United States and Europe and subsequently affected the rest of the world. In addition, China endured severe snowstorms in the first few months of the year followed by a devastating earthquake in Sichuan in May 2008, claiming about 90,000 lives and leaving millions homeless. Furthermore, it was the same time in April 2008 when the authorities introduced a stringent visa regime. Visitors had to prove that they had paid for accommodation, while multiple entry visas became much more difficult to obtain. As expected, this single important policy has had a lion's share of the blame for the subsequent slump in demand that occurred throughout China, although some commentators argue that this could have been due to the economic recession. Growth in the number of visitors to China during 2008 dropped by 13% (when compared to the previous year), although Beijing saw an 8.8% increase in total visitors (2.2% of whom were foreigners). Clearly, vulnerability to external shocks can be devastating and damaging to the tourism industry.

However, against this background, studies on the demand for Beijing tourism have been limited, particularly by quantitative analysis. A review of literature in tourism demand modeling and forecasting related to Greater China (including mainland China, Hong Kong, Macau, and Taiwan) by Li (2009) showed that Hong Kong attracted overwhelming attention among international studies, followed by mainland China and Taiwan; however, no English articles related to tourism demand modeling and forecasting in Beijing were identified in Li's research. The Chinese studies spread their geographic focuses among national, regional/provincial, city/town levels, and scenic spots, but only four studies put their focus on Beijing's inbound tourism. Among the four studies, three used trend extrapolation models (i.e. including the deterministic time trend as the regressor to a tourism demand series) with the same dependent variable (i.e. tourist arrivals) but in different types of data frequency (i.e. monthly, quarterly, and annual data). As found by Li (2009), trend extrapolation models dominated the Chinese studies on time-series forecasting, even with its obvious limitation that such as basic regression is unable to cope with business cycles and irregular shocks to the system and its medium- to long-term forecasts could be seriously misleading. Though the common trend identified in the general tourism demand literature is the popularity of using quarterly data, the annual frequency has dominated both Chinese and international studies in Li's study over the review period of 1992–2007. The last tourism demand study of Beijing reported by Li (2009) adopted a gravity model, which included tourist arrivals as dependent variable while income in origin country, population, travel time, travel distance, and travel cost by surface were independent variables.

In line with the general tourism demand literature, the most commonly considered influencing factors of Greater China's tourism demand, both for inbound and outbound, are tourism income, tourism prices in the destination, and one-off events such as the Asian financial crisis in 1997, the SARS epidemic in 2003, and the global economic/financial crisis in 2008 (e.g., Song & Fei, 2007; Li, 2009; Song & Lin, 2010; Song, Lin, Zhang, & Gao, 2010). Despite the extensive discussions of tourism demand elasticities in the general tourism literature, only a few studies showed interest in the research area when taking mainland China as the region focus. As explained by Li (2009), the lack of such interest in elasticity analysis among Chinese studies was associated with the unpopularity of the econometric methodology, especially at the advanced level (e.g., cointegration and error correction model). A few studies, such as Song and Fei (2007), Song, Gartner, and Tasci (2012), and Ayeh and Lin (2011), have made attempts to identify the influencing factors of mainland China's tourism with the aid of econometric models (i.e. the autoregressive distributed lag model [ADLM]) and also conduct demand elasticity analysis.

Based on the above analysis, it is found that very little research effort has been made to model and forecast the inbound tourism of a destination at a city level, particularly with the consideration of econometric methods. In this regard, we contribute to the literature by utilizing the econometric approach to estimate forecasting models, taking into account the factors that determine the tourism demand but with a particular region focus on Beijing. According to Song, Witt, and Li (2009), econometric approaches not only produce accurate forecasts of tourism demand but also can assist policymakers in assessing the influences of different determinants in terms of both magnitude and directional change. In addition, our study generates unique quarterly forecasts as well as annual forecasts of international tourist arrivals from three international markets of the United States, Canada, and the United Kingdom to Beijing over a span of 2012–2015. We also undertake robust evaluation of forecasting performance using a group of error measures, which provide some validity for the method we used to model and forecast Beijing's inbound tourism demand.

The rest of the article is organized as follows. Section 2 discusses the theoretical underpinning of tourism demand analysis using the determinants of tourism demand. Section 3 presents the empirical findings from the demand models, while evaluation of tourist arrivals forecasts in Beijing is given in Section 4. The concluding remarks, including implications for policy, are drawn in Section 5.

The Model

Tourism Demand Determinants

In order to establish tourism demand determinants, general economic theory was used as the basis for tourism demand modeling. According to Song and Li (2008), Li (2009), and Song et al. (2009), the vital factors that determine tourism demand for most tourism products/services are the tourist income, tourism prices in the destinations, and one-off events. Accordingly, this study adopts the general mathematical notation in order to model Beijing's tourism demand by residents from Canada, the United Kingdom, and the United States based on studies of Song et al. (2003) and Song and Fei (2007), which can be written as:

$$Q_{it} = AY_{it}^{\beta_1} P_{it}^{\beta_2} P_{st}^{\beta_3} e_{it} \tag{1}$$

where $Q_{it}$is the tourism demand variable measured by tourist arrivals from country i to Beijing at time t; P_{it} is the price of tourism in Beijing at time t relative to that in the i^{th} source market, and Y_{it} is the income of tourists from the i^{th} source market at time t, P_{st} is the price of tourism in the competing destinations at time t, and e_{it} is the residual term used to account for some other economic and non-economic factors that may have been omitted for the good of the model tractability or, most commonly, due to data unavailability.

Specification of Econometric Model

According to Song et al. (2003), adoption of the power function as in Eq. (1) is based on previous research that have proposed that tourism demand can be well modeled by using it than a simple linear demand function. This gives power function models the statistical significance and quick and immediate forecasting ability (Witt & Witt, 1992). In addition, it can be easily transformed into a log linear form, which can be estimated using ordinary least squares (OLS). The estimates of the coefficients of the independent variables in the log linear model represent the respective demand elasticities.

When logarithmic transformation of Eq. (1) is carried out, we get:

$$\ln Q_{it} = \beta_0 + \beta_1 \ln Y_{it} + \beta_2 \ln P_{it} + \beta_3 \ln P_{st} + \varepsilon_{it} \tag{2}$$

where $\beta_0 = \ln A$, $\varepsilon_{\mathrm{it}}$ is the random error term, assumed to be normally distributed with a zero mean and constant variance ($\varepsilon_{it} \sim N(0, \sigma^2)$). β_1, β_2, and β_3 are income, own price, and cross price elasticities, respectively. In Eq. (2), we expect a positive sign of income elasticity ($\beta_1 > 0$) and a negative sign of own price elasticity ($\beta_2 < 0$). The sign of β_3 is indeterminate as it depends on whether the origin country/market takes Beijing as a competitive or complementary destination of its competitors. The sign of β_3 is therefore for empirical evidence to resolve.

However, because Eq. (2) is a static model, it relates to the current tourism demand variable and to the current values of the influencing factors and therefore does not consider the dynamic feature of tourists' decision-making process. Song et al. (2003) argued that tourism demand was a dynamic process because tourists made decisions about destination choice with time leads. This means that models used for analyzing and forecasting tourism demand should mirror this feature.

To comply with this requirement, model specification acknowledged in the literature as the ADLM was applied to capture the changing aspects of economic activities, and this specification has been adopted by a few studies (e.g., Song et al., 2003; Song & Lin, 2010; Ayeh & Lin, 2011) to forecast tourism demand. The ADLM for Eq. (2) can be re-written as:

$$\begin{aligned} \ln Q_{it} = \alpha_0 + \sum_{j=1}^{q_1} \alpha_{1j} \ln Q_{it-j} + \sum_{j=0}^{q_2} \alpha_{2j} \ln Y_{it-j} + \sum_{j=0}^{q_3} \alpha_{3j} \ln P_{it-j} + \sum_{j=0}^{q_4} \alpha_{4j} \ln P_{st-j} \\ + \delta_1 D_1 + \delta_2 D_2 + \delta_3 D_3 + Dummies + \varepsilon_{it} \end{aligned} \tag{3}$$

The lag order q_{i} ($i = 1, 2, 3, 4$) in Eq. (3) was determined by the Akaike information criterion (AIC). The general-to-specific approach was used to eliminate insignificant variables. Eq. (3) demonstrates that the current tourism demand is influenced by current values of the independent variables as well as the lagged dependent and independent variables. This specification is more acceptable than the static demand model as it takes into account the time path of tourists' decision-making process.

While estimating Eq. (3), we include three seasonal dummy variables (D_1, D_2, and D_3) to capture the influence of seasonality effects in tourist arrivals and one-off event dummy variables to capture their influences on the demand for Beijing tourism. The dummy variables assume a value of 1 in the respective years and quarters where they have an effect, and 0 otherwise (Hardy, 1993). A number of events have been taken into consideration, such as the epidemic of foot-and-mouth disease in the United Kingdom in 2001 (D2001q1fmd, which takes a value of 1 in 2001Q1 and 0 otherwise), the SARS epidemic in 2003 (D03SARS, which takes a value of 1 in 2003Q2 and 0 otherwise), the bird flu in 2003 (D03birdflu, which takes a value of 1 in 2003Q3 and 0 otherwise), the Beijing Olympic Games in 2008 (D08oly, which takes a value of 1 in 2008Q3 and 0 otherwise), the visa restriction in 2008 (D08visa, which takes a value of 1 in 2008Q2 and Q3 and 0 otherwise), and the global financial and economic crisis in 2008 (D08fin, which takes a value of 1 in 2008Q4 and 0 otherwise).

It is however important to note that there are other factors such as marketing expenditure and the change of tastes and preferences towards Beijing as a tourist destination in the source markets. These factors are difficult to measure because of insufficient data and accordingly have been left out of this study. Previous studies such as Song et al. (2003), Song and Fei (2007), Chon, Li, Lin, and Gao (2010), and Ayeh and Lin (2011), have proven that these factors do not affect the overall goodness of fit of the models.

The own price variable in this study was defined as$P_{it} = \left(CPI_{bj}/EX_{cn}\right)/(CPI_i/EX_i)$, where CPI_{bj} is the consumer price index of Beijing, and EX_{cn} is the exchange rate index of China (Yuan per US Dollar), while CPI_i and EX_i represent the consumer price index and exchange rate index from the origin country/region i, respectively. It measures the cost of tourism in Beijing relative to that in the origin country/region adjusted by the corresponding exchange rates. The substitute price variable P_{st} is calculated as a weighted index of CPIs of five substitute markets according to their market shares of international tourist arrivals at time t, that is, $P_{st} = \sum_{j=1}^{5} (CPI_{jt}/EX_{jt})w^i_{jt}$ ($j = 1, 2, \ldots, 5$, representing Hong Kong, South Korea, Japan, Singapore, and Taiwan, respectively), where w^i_{jt} is calculated as $TTA^i_{jt}/(\sum_{j=1}^{5} TTA^i_{jt})$, indicating the share of international tourist arrivals for country/region j at time t, and TTA^i_{jt} is the tourist arrivals of substitute destination j from origin country/region i at time t. These five destinations were chosen after considering the geographical proximity and cultural dimensions.

The inclusion of the lagged-dependent variable on the right-hand side of the demand model according to Song et al. (2003) assists in capturing the tourists' expectations and habits that tend to persist in terms of behavioral patterns and hence need to be incorporated in tourism demand models. Moreover, consumer behavior research has proven that once people have been on holiday to a particular destination and liked it, they tend to be loyal to that destination because of less uncertainty associated with that destination compared with traveling to a completely new one (Choi & Chu, 2001; Hui, Wan, & Ho, 2007). Furthermore, information about the destination visited spreads as people share their holiday experiences through different means with friends and relatives, and it minimizes the risk for potential visitors to that country. Song et al. (2003) alluded to the fact that the "word of mouth" recommendation may play a more important role in destination selection than commercial advertising. They further argued that the number of people selecting a given destination in any year depended on the number of people who selected it in the previous years as another defense for the inclusion of lagged variables in the model.

A further note should be made that in Eq. (2) coefficients β_1, β_2, and β_3 are demand elasticities while α_i ($i = 2, 3, 4$) in Eq. (3) are not. To find demand elasticities from Eq. (3), it is necessary to make algebraic manipulations to get the long-run demand function as compared to short-run dynamic specifications depicted in Eq. (4).

$$\ln Q_{it} = \frac{\alpha_0}{1 - \sum_{j=1}^{p_1} \alpha_{1j}} + \frac{\sum_{j=0}^{q_2} \alpha_{2j}}{1 - \sum_{j=1}^{q_1} \alpha_{1j}} \times \ln Y_{it} + \frac{\sum_{j=0}^{q_3} \alpha_{3j}}{1 - \sum_{j=1}^{q_1} \alpha_{1j}} \times \ln P_{it} + \frac{\sum_{j=0}^{q_4} \alpha_{4j}}{1 - \sum_{j=1}^{q_1} \alpha_{1j}} \times \ln P_{st} \quad (4)$$

where $\frac{\sum_{j=0}^{q_2} \alpha_{2j}}{1-\sum_{j=1}^{q_1} \alpha_{1j}}$, $\frac{\sum_{j=0}^{q_3} \alpha_{3j}}{1-\sum_{j=1}^{q_1} \alpha_{1j}}$, and $\frac{\sum_{j=0}^{q_4} \alpha_{4j}}{1-\sum_{j=1}^{q_1} \alpha_{1j}}$ are income elasticity, own price elasticity, and cross price elasticity, respectively.

A maximum of eight lags ($q = 8$) were used in the models following Song et al.'s (2003) assertion that more time lags can be included in the model if quarterly and monthly data are used for model estimation. For a variable to be accepted in the model, its estimated coefficients should have correct signs as anticipated by the economic theory. The general-to-specific method as suggested by Song and Witt (2003) was carried out and proceeded through a simplification process to make the model more interpretable and a certainly more parsimonious characterization of the data (Song et al., 2009). The test procedure followed specific steps as outlined in Song et al. (2009). Firstly, Eq. (3) was estimated using OLS to establish whether all the variables were statistically significant. This was followed by elimination of variables with statistically insignificant t values one by one from the initial specification, starting with the least significant ones (or highest p values). Once all of the insignificant variables and variables that have wrong signs were eliminated from the specification, the model was tested by a series of diagnostic statistics in order to check if the model suffered any misspecification. These included the tests for autocorrelation, heteroscedasticity, normality, and functional form.

Once the model passed all diagnostic tests as specified and all coefficients in the models had correct signs, then the final step was to calculate the demand elasticities and forecast tourist arrivals from each source market. For this study, Holt-Winters exponential smoothing method, which considers three parameters (level, trend, and seasonality), was used to produce forecasts for all independent variables. According to Song et al. (2009), the exponential smoothing approach is appropriate because it is capable of producing reliable forecasts for the explanatory variables in the tourism demand models. Lastly, since variables in the demand models were in logarithm, the forecasted values of tourist arrivals had to be transformed back through the anti-logarithm computation to natural numbers.

The Data

Quarterly time series data from three long-haul source markets (i.e., Canada, the United Kingdom, and the United States) for the period 2000Q1–2010Q2 was used. Tourist arrival data was collected from the official website of the Beijing Tourism Administration (http://www.bjta.gov.cnt), and Beijing's CPI data was obtained from Beijing Statistical Bureau (http://www.bjstats.gov.cn). The real GDP index (2005 = 100), CPI (2005 = 100), and exchange rate index (2005 = 100) for all source markets were obtained from the International Financial Statistics (IFS) released by the International Monetary Fund (IMF, 2012). Five competitive destinations of Beijing, including Hong Kong, South Korea, Japan, Singapore, and Taiwan, were selected to calculate the substitute price. The inbound tourist arrivals of three selected markets to these five destinations were respectively collected from the official websites of Hong Kong Tourism Board (HKTB, 2011), Korea Tourism Organization (2011), Japan National Tourist Organization (2011), Singapore Tourism Board (2011), Tourism Bureau Ministry of Transportation and Communication in Taiwan (2011).

Discussions of Results

Three models (the United States, the United Kingdom, and Canada) were first estimated with a full lag of 8, and the general-to-specific procedure was followed to achieve final models. Table 1 presents the parsimonious models.

Validity of Models

From Table 1, all the three models have a high goodness-of-fit value as suggested by high adjusted R^2 values (0.969, 0.961, and 0.988 respectively for the United States, the United Kingdom, and Canada). Thus, about 96.9%, 96.1%, and 98.8% of the variations in tourist arrivals from the United States, the United Kingodm, and Canada, respectively, over 2000Q1–2010Q2 period is explained by the regressors in the models. The diagnostic test results indicate that the model for the demand from the United Kingdom passed all tests. The Canada model failed the autocorrelation and functional form test while the United States model failed only the functional form test. The autocorrelation problem is not rare when a lagged dependent variable is included as an explanatory variable in the model because it probably would be highly correlated with the lagged demand (Morley, 2009). The Jarque-Bera statistic for testing normality of the residual for the estimated model is 2.256 ($p = 0.323$), 0.344 ($p = 0.842$), and 0.974 ($p = 0.614$) for the models of the United States, the United Kingdom, and Canada, which were all greater than 5%, thus, the normality assumption was not rejected. All three models are found to be free of heteroscedasticity problems as they all pass the White test and the ARCH test. Overall, these three models are valid due to the satisfactory diagnostic testing results and are reliable for further analysis.

Estimates of the Models

The signs and magnitudes of the coefficients of the independent variables included in the models appear as expected and do not deviate from predictions of theory. The coefficients are also statistically significant in all cases, indicating that the variables considered are significant determinants of demand for Beijing tourism. It is of interest to note, in addition, that the lagged dependent variables are highly significant in all three models. This is evidence that demand for Beijing tourism is highly dependent on previous visits. Consistent with findings from Song et al. (2003) and Ayeh and Lin (2011), this result implies that international tourism demand in Beijing is highly influenced by the “word of mouth” effect and/or consumer persistence (or repeat visits). The implication here, therefore, is that Beijing would have to provide high quality service in order to attract new tourists and tourists to come back.

The income variable measured by the real GDP index is found to be significant in respect to travel from all three countries, confirming the hypothesis that income, which reflects the affluence and development of a country, has an important impact on tourism demand. The price of Beijing’s tourism product/service has the expected

Table 1. Estimates of Demand Models: The Depend Variable is $\ln Q_{it}$.

Variable	USA	UK	Canada
Intercept	–7.072	–1.364	–4.5
	(–4.149)***	(-1.047)	(–2.879)***
$\ln Q_{t-1}$	0.405		0.43
	(8.221)***		(11.848)***
$\ln Q_{t-2}$		0.41	
		(7.550)***	
$\ln Q_{t-3}$			0.104
			(2.673)**
$\ln Q_{t-4}$		0.154	
		(3.003)***	
$\ln Y_t$	2.147	0.639	
	(5.497)***	(2.027)*	
$\ln Y_{t-7}$			1.349
			(3.753)***
$\ln P_t$			–0.388
			(–3.092)***
$\ln P_{st-7}$	0.835		
	(2.521)**		
$\ln P_{st-8}$			0.911
			(2.263)**
D_1	–0.316	–0.334	–0.526
	(–7.646)***	(-8.527)***	(–17.872)***
D_2	0.41	0.097	0.037
	(8.746)***	(3.002)***	(1.068)
D_3	0.086	0.32	–0.184
	(2.024)*	(7.829)***	(–5.256)***
D2001q1fmd		–0.317	
		(-4.179)***	
D03SARS	–1.682	–0.886	–1.601
	(–18.210)***	(–11.879)***	(–24.955)***
D03birdflu		–0.971	
		(–13.009)***	
D08oly			0.202
			(2.355)**
D08visa	–0.115		–0.174
	(–1.743)*		(–2.820)***
D08fin	–0.166		
	(–1.841)*		
R^2	0.977	0.971	0.992
Adjusted R^2	0.969	0.961	0.988
F-statistic	119.799***	102.919***	244.346***
Akaike info criterion	–1.889	–2.308	–2.640
Schwarz criterion	–1.445	–1.877	–2.102
Durbin-Watson stat.	2.332	1.713	2.548

(*Continued*)

Table 1. Continued.

Variable	USA	UK	Canada
Jarque-Bera stat.	2.256	0.344	0.974
LM test	10.431	2.026	17.025**
White test	8.897	5.372	6.736
ARCH	0.308	0.643	0.032
Ramsey RESET test	5.741**	0.460	5.109**

Note: (1) The figures in parenthesis are *t* statistics. (2) ***, **, and * represent 1%, 5%, and 10% significant levels, respectively. (3) The Breusch-Godfrey LM test is used for testing serial correlation. The Jarque-Bera test is used for testing normality. The White test and ARCH test are used for testing heteroscedasticity. The Ramsey's Regression Equation Error Test (or Ramsey RESET test) is used to test functional form.

negative sign and is significant in the Canada model. This is consistent with the hypothesis that higher prices reduce arrivals, in particular from Canada to Beijing. Substitute price is significant in two of the three markets (i.e. the United States and Canada), suggesting that the cost of tourism in the substitute destinations for Beijing is another important determinant.

Noteworthy, from Table 1, the very high significance of the seasonal dummies in all three models suggests that seasonal variation is an important feature in the demand for Beijing's tourism. It implies that Beijing's tourism industry needs to innovatively diversify its tourism resources to attract more tourists in the low seasons in order to avoid redundancies. As expected, the dummy variable of SARS epidemic (D03SARS) has a negative sign and is significant in all source markets. This confirms the UNWTO records and the Beijing statistics that the SARS outbreak did have a negative impact on tourism to Beijing. Also, it is found that the Beijing Olympic Games (D08oly) has a positive sign in the case of the Canadian model, crediting the positive effects of the 2008 Beijing Olympics (see Table 1). Our results show that the visa restriction policy in 2008 significantly reduced tourist arrivals from both the United States and Canada, which is consistent with the findings in Song et al. (2012). They found that visa regulations before and during the Olympic Games did result in a significant loss in tourists across ten origin countries, particularly for Western countries. Other events such as the foot-and-mouth outbreak in the U and the bird flu in 2003 negatively impacted British tourists' travel to Beijing.

Demand Elasticity Analysis

Elasticity analysis has its theoretical foundation in demand theory and interprets tourism demand from an economic perspective. Such analysis is often carried out to directly benefit policy and decision making. Elasticity measures the responsiveness of tourism demand (i.e. tourist arrivals) from the United States, the United Kingdom, and Canada resulting from a change in one determinant. For example, price elasticity has a direct impact on total revenues; thus it is critical for the suppliers of tourism products and services. When the tourism product is price elastic (i.e. the absolute value being greater than one), total tourism revenue (TTR, i.e. a product of average price of the tourism products/services [*P*] and total quantity demanded [*Q*]) increases with a

Table 2. Estimated Demand Elasticities.

Country	Income elasticity	Price elasticity	Cross price elasticity
USA	3.608	—	1.404
UK	1.468	—	—
Canada	2.895	–0.832	1.956

decrease in price. Retrospectively, TTR will decrease when price reduces if the tourism product is price inelastic (i.e., the absolute value being less than one). This is because the percentage change in quantity is less than the percentage decrease in price. Consideration of the estimated models leads to the generation of the demand elasticities, which are examined by the results shown in Table 2.

Income elasticity value indicates the responsiveness of the tourism demand to the change in the income levels in the origin country (Song et al., 2009). Table 2 shows that the lowest income elasticity of demand is 1.468 for the United Kingdom model while the highest is 3.608 for the United States model. All three long-haul markets' income elasticities are greater than one, indicating that tourists from the United States, the United Kingdom, and Canada regard foreign travel to Beijing as a luxury product. This is consistent with most findings in the tourism demand literature (Li, 2009; Song, Kim, & Yang, 2010). Our results imply that a rise in income of the British, Canadians, and Americans would probably lead to a more than proportionate rise in tourism demand in Beijing. On the contrary, economic downturn in those three destinations is also likely to have a much greater negative impact on tourism demand in Beijing. Results in Table 2 reveal that the price elasticity of demand for Beijing tourism by tourists from Canada is inelastic. Results show that a 1% increase in the relative price of Beijing tourism would lead to a 0.832% decrease in arrivals from Canada. To some extent, this elasticity figure implies that Canadian arrivals in Beijing are not very responsive to relative price fluctuations when choosing Beijing as a holiday destination.

The cross price elasticities of the Canada and the United States model are found to be positive with a value of 1.956 and 1.404, respectively. This suggests that tourists from Canada and the United States are very much aware of the costs of tourism in the five competitive destinations of Beijing (i.e. Hong Kong, South Korea, Japan, Singapore, and Taiwan), and a change in the cost of holiday traveling in the competing destinations will have a big impact on the demand for Beijing tourism by Canadian tourists. Therefore, there is a need to launch more aggressive destination image branding campaigns while reinforcing all readily held images to shape the experiences to this target group of audience. This is consistent with the finding from Song and Fei (2007) who concluded that tourists from Canada were aware of the prices of tourism in the substitute destinations (substitute effect).

Forecasts and Evaluation

Forecasts

The demand models estimated in Table 1 were used to forecast tourist arrivals for the period 2010Q3–2015Q4. As indicated previously, the independent variables that we needed to conduct forecasts were income (Y_{it}), own price (P_{it}), and substitute price (P_{st}).

The first forecast was done for the United States in 2010Q3, and on the basis of this, forecasts for other quarters up to 2015Q4 were made as shown below:

$$\begin{aligned}\ln Q_{2010Q3} = & -7.072 + 0.405 \times \ln Q_{2010Q2} + 2.147 \times \ln Y_{2010Q3} + 0.835 \\ & \times \ln P_{S2008Q4} - 0.316 \times 0 + 0.41 \times 0 + 0.086 \times 1 = 5.237\end{aligned} \tag{5}$$

The value of 5.237 from the above equation is in logarithm and has to be transformed using the following formula to get the final forecast as a natural number giving the first forecast as 188,131.

$$Q_{2010Q3} = \mathrm{EXP}\left(\ln Q_{2010Q3}\right) \tag{6}$$

Following the same procedure, the model used to forecast tourist arrivals for Canada and the United Kingdom are shown in Eq. (7) and Eq. (8), respectively.

$$\begin{aligned}\ln Q_{2010Q3} = & -4.500 + 0.430 \times \ln Q_{2010Q2} + 0.104 \times \ln Q_{2009Q4} + 1.349 \\ & \times \ln Y_{2008Q4} - 0.388 \times \ln P_{2010Q3} + 0.911 \times \ln P_{S2008Q3} - 0.526 \\ & \times 0 + 0.037 \times 0 - 0.184 \times 1 = 3.667\end{aligned} \tag{7}$$

$$\begin{aligned}\ln Q_{2010Q3} = & -1.364 + 0.41 \times \ln Q_{2010Q1} + 0.154 \times \ln Q_{2009Q3} + 0.639 \\ & \times \ln Y_{2010Q3} - 0.334 \times 0 + 0.097 \times 0 + 0.32 \times 1 = 3.907\end{aligned} \tag{8}$$

Table 3 shows the final forecasts of tourist arrivals in Beijing by country of origin from 2010Q3–2015Q4. As shown in Table 3 and Figure 1, tourist arrivals to Beijing from all the markets are expected to have positive growth rates over the period 2010–2015. It is found that the first quarter is the season with lowest visits from all three long-haul markets.

Results show that compared to the other two countries, Canada will be the fastest growing market for Beijing tourism with an average annual growth rate of 9.17% over 2010–2015. It is noteworthy that tourist arrivals from Canada will have a dramatic increase starting from 2010 and continue on a strong upward trend till 2015. Strong growth in tourism demand to Beijing is expected to continue throughout the forecast period with tourist arrivals rising from 0.15 million in 2010 to 0.23 million in 2015, and therefore the market share is likely to increase accordingly.

The number of tourist arrivals from the United States to Beijing is expected to increase steadily with an average annual growth rate of 6.39% since 2010, increasing from 0.69 million in 2010 to 0.93 million in 2015. Although the average annual growth rate of the United States is not as strong as that of Canada, still, the U.S. market is likely to remain the largest market in tourism arrivals among the three origin markets in the near future. For the United Kingdom, tourist arrivals are projected to grow by 5.89% per annum over the forecasting period.

Evaluation of Forecasting Accuracy

The models were estimated using the data from 2000Q1–2010Q2, and the period 2010Q3–2011Q4 was selected to conduct forecasting evaluation. A group of error measures were used to evaluate forecasting performance of three models, such as mean absolute percentage error (MAPE), root mean square percentage error

Table 3. Forecasts of Tourist Arrivals in Beijing by Country of Origin ('000).

Quarters	USA	UK	Canada
2010Q1	*119.579*	*29.484*	*26.813*
2010Q2	*203.37*	*44.786*	*39.691*
2010Q3	188.131	49.732	39.106
2010Q4	169.393	42.293	41.368
2011Q1	113.326	30.128	25.575
2011Q2	207.668	46.865	38.123
2011Q3	203.069	51.938	38.412
2011Q4	190.374	44.655	43.874
2012Q1	127.945	31.646	28.947
2012Q2	231.708	49.629	44.412
2012Q3	220.025	54.867	44.981
2012Q4	202.477	47.412	49.836
2013Q1	135.675	33.539	32.387
2013Q2	245.410	52.773	49.578
2013Q3	232.922	58.278	50.006
2013Q4	214.304	50.468	55.218
2014Q1	143.588	35.674	35.824
2014Q2	259.715	56.211	54.777
2014Q3	246.496	62.045	55.204
2014Q4	226.792	53.779	60.925
2015Q1	151.955	38.003	39.513
2015Q2	274.848	59.915	60.403
2015Q3	260.859	66.120	60.863
2015Q4	240.006	57.333	67.164
2010	680.473	166.296	146.979
2011	714.437	173.586	145.985
2012	782.154	183.554	168.176
2013	828.311	195.058	187.188
2014	876.591	207.709	206.729
2015	927.669	221.371	227.943
Growth rates			
Q1	4.91%	5.21%	8.06%
Q2	6.21%	5.99%	8.76%
Q3	6.76%	5.86%	9.25%
Q4	7.22%	6.27%	10.18%
2012	9.48%	5.74%	15.20%
2013	5.90%	6.27%	11.30%
2014	5.83%	6.49%	10.44%
2015	5.83%	6.58%	10.26%
AAGR (%)	6.39%	5.89%	9.17%

Note: (1) AAGR denotes the average annual growth rate over 2010–2015 calculated by $(\sqrt[5]{Q_{2015}/Q_{2010}} - 1)$. (2) Figures in italic are actual tourist arrivals.

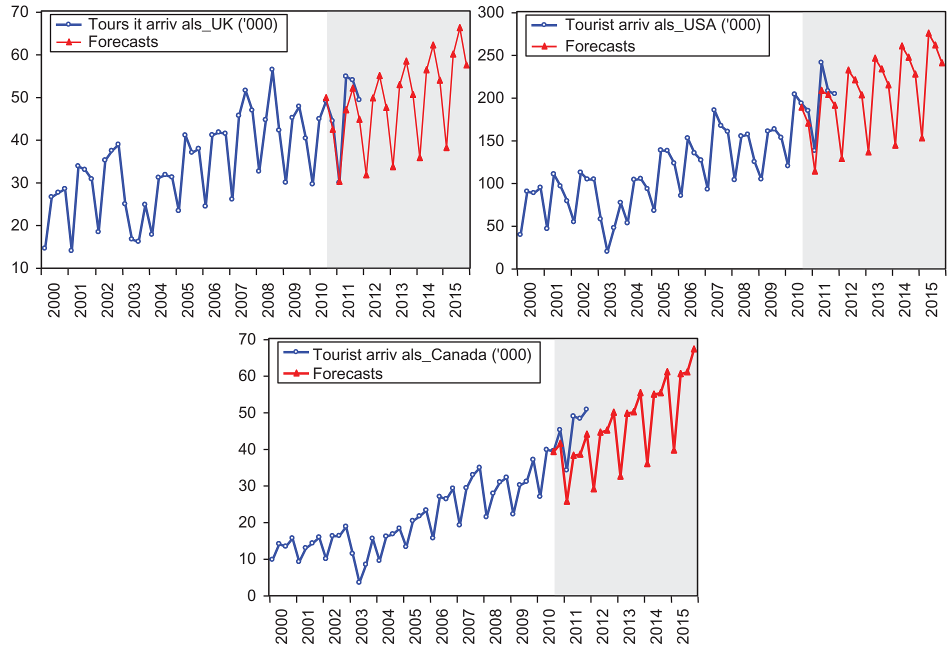

Figure 1. Forecasts of Tourist Arrivals from the United Kingdom, the United States, and Canada to Beijing (‘000), 2000Q1–2015Q4 (color figure available online).

(RMSPE), mean absolute error (MAE), root mean square error (RMSE), and Theil’s U statistic. Lewis (1982, quoted in Frechtling, 2001, p. 26) has suggested the following guidelines of interpreting MAPE values: (1) a model with a MAPE less than 10% indicates a highly accurate forecasting model, (2) a model MAPE equal to between 10%–20% indicates a good forecasting model, (3) a model MAPE equal to between 20%–50% indicates a reasonably accurate forecasting model, and (4) a model MAPE equal to more than 50% is inaccurate forecasting. A smaller value of all measures (except for the Theil’s U statistic) indicates that a better forecasting model produces more accurate values of predictions. The advantage of using Theil’s U statistic lies in the fact that it “allows a relative comparison of formal forecasting methods with naive approaches and also squares the errors involved so that large errors are given much weight than small error” (Makridakis, Wheelwright, & Hyndman, 1998, p. 48). When the value of the U-statistic is less than one ($U < 1$), the forecasting technique being used is better than the naive method, namely, the smaller the U-statistic, the better the forecasting technique is relative to the naive method. When the value of the U-statistic is larger than one, it means that there is no point in using a formal forecasting method, since using a naive method will produce better results. When the U-statistic is equal to one, it indicates that the naive method is as good as the forecasting technique being evaluated.

As presented in Table 4, the three models developed in this study seem to be very competitive in terms of forecasting ability. The MAPE and RMSPE for the models of the United States and the United Kingdom are less than 10%, indicating that they are highly accurate forecasting models. The model for Canada performs relatively poorly

Table 4. Forecast Evaluation Results.

Measure	USA	UK	Canada
MAPE	8.39%	5.73%	14.89%
RMSPE	10.09%	7.42%	17.15%
MAE	15.70	2.91	6.62
RMSE	18.70	3.91	7.56
Theil's U statistic	0.36	0.35	0.87

with its MAPE around 15%, but is still within the range of 10% and 20%, indicating a model of good forecasting. The same results can be reached by checking other two accuracy measures, namely MAE and RMSE. The U-statistic for all three models is less than one, suggesting that the ADLM approach is superior to naive method in respect to the forecasting ability.

Conclusions, Implications, and Directions for Future Research

This paper uses the ADLM approach to model and forecast inbound tourism demand for Beijing with a focus on three international source markets of the United States, the United Kingdom, and Canada. Through general-to-specific modeling approach, a parsimonious model, consistent with economic theory and evaluated in terms of the diagnostic tests, was derived for each origin market.

We find broad support that the income level, the tourism price of Beijing, the price from competing destinations, and the "word of mouth" effect and/or consumer persistence (or repeat visits) are significant determinants of tourism demand for Beijing, at least from the three selected countries. Equally important is seasonality. It is evident that Beijing international tourism demand is remarkably low in the first quarter (January, February, and March), probably due to the bad weather (this time of the year in Beijing is cold and snowy, and occurrences of sandstorms are common). Except for the 2008 Beijing Olympic Games dummy, which is associated with a positive response especially from Canada, the dummies for the outbreak of SARS epidemic in 2003 and the 2008 visa regulation policy each had a significant negative effect on Beijing tourism demand. The SARS epidemic affected arrivals to Beijing from all the three origin markets, while the visa policy affected arrivals from the United States and Canada. Similarly, special one-off events such as the outbreak of foot and mouth disease and the bird flu in 2003 were associated with a negative response from British residents visiting Beijing.

In many ways, our results demonstrate that a good understanding of demand elasticities in a destination is critical for tourism policymakers and planners in that destination. The income elasticity of demand for Beijing tourism is elastic for all three source markets, suggesting it is heavily influenced by the economic conditions in the countries of origin. For the United Kingdom, the real income level of British residents appears to have a large impact on their visits to Beijing whereas the own price and substitute price have little impact. The cross price elasticities show that both Canadian and American tourists are much aware of the prices of tourism in Beijing's competing destinations (i.e. are very sensitive to the price changes in the alternative destinations).

Finally, the forecasts for the three markets are projected to have upward trend over the forecast period of 2012–2015. The evaluation of this also shows sufficient evidence of good forecasting ability of three models by the ADLM approach.

These results have important policy implications. As the empirics have revealed, the word-of-mouth or the supply constraint factor in Beijing is an important long-run determinant of Beijing tourism demand from the United States, the United Kingdom, and Canada. This necessitates suppliers of tourism products/services in Beijing to continuously aim at improving their service quality and tourist satisfaction as well as promote and upgrade their brand images. In this way, the repeat and potential tourists could be attracted. Furthermore, it is possible that tourists' visiting intension could be increased if Beijing suppliers provide very attractive discounts, and deliberate efforts that address the seasonality problem could also be vital. One such way we suggest is organizing special events (e.g., MICE events) as this has the potential to reduce seasonality-related redundancies that are suffered by the whole tourism industry.

The result for the income elasticity demands that tourism planners in Beijing should closely monitor the economic cycles and the levels of future economic activities in the United States, the United Kingdom, and Canada. It may also be crucial for Beijing tourism planners to sustain the destination competitiveness by paying close attention to its competitors' pricing strategies. Once a competitor launches a new strategy such as a promotion campaign, Beijing should take prompt actions accordingly, but with the exception of arrivals from Canada. Canadian tourists are less responsive to price increase in Beijing's tourism products and services, suggesting that the attraction of this particular market niche is not about a better pricing strategy. Engaging in promotion through non-pricing competition such as direct marketing and image branding would be a great idea (i.e. more proactive strategies may need to be used to boost the tourist arrivals from Canada). Moreover, there is a need for Beijing tourism stakeholders to allocate appropriate resources and manpower to cater to the special needs of these three growing market segments, and strategically design promotional campaigns to sustain this growth in the long run.

This study has adopted the ADLM approach, which can only reflect the long-run equilibrium relationship. To capture the short-run dynamic characteristics of tourism demand, the error correction model (ECM), which has its advantage in the ability to reflect a dynamic self-correcting process of tourism demand behavior towards its long-run steady state, is recommended to model and forecast the tourism demand on a city level as a future research direction. Some studies have made attempts to successfully model and forecast the inbound tourism demand in Hong Kong (e.g., Song, Kim, & Yang, 2010; Song, Lin et al., 2010), mainland China (Song et al., 2012), as well as Asia (Song & Lin, 2010). Other advanced econometric models such as a time varying parameter error correction model proposed by Li, Wong, Song, and Witt (2006), which relaxes the constancy restriction on the parameters to be estimated in a traditional fixed-parameter econometric model to take account of the possibility of parameter changes over time, can be considered as an alternative to model the tourism demand in mainland China, especially at a provincial level or a city level.

As with many studies, some caveats accompany the results of our forecasting models. The accuracy of the final forecasts not only relies on the goodness-of-fit of the final models but also on the projections of independent variables such as GDP, own price, and substitute price. Though the exponential smoothing method adopted in this study has been a popular way to produce forecasts for independent variables, other forecasting techniques (e.g., GDP projections from IMF, state space models for exponential smoothing) could perhaps increase the forecasting accuracy. In addition, any unpredicted event in the near future could affect the forecasting performance of the models as they have not been considered in the forecasting process. So our forecasts should be taken as no more than indicative.

Some fruitful directions of future research are addressed as follows. The first issue is about how to handle seasonality. Tourism in most destinations presents seasonal variations, and Beijing is not an exception as discussed earlier. However, as an emerging market undergoing fast growth, Beijing is most likely to experience changing seasonal patterns. Therefore, seasonality in Beijing should be treated as stochastic rather than deterministic in tourism demand analysis (Li, 2009). A second feasible direction is to produce interval, turning point, and directional change forecasting for the purpose of enhancing the practical value of forecasting exercises rather than point forecasting only. To date, there are limited studies on researching into mainland China (neither at the national level nor at the city level) focusing on this issue. Although point forecasts have their values, their information content may be insufficient, particularly in situations with a high degree of demand uncertainty, such as the ongoing economic crisis (Song, Lin, Witt, & Zhang, 2011).

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