Confidence Intervals for Tourism Demand Elasticity

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Abstract

Long-run tourism demand elasticities are important policy indicators for tourism product providers. Past tourism demand studies have mainly focused on the point estimates of demand elasticities. Although such estimates have some policymaking value, their information content is limited, as their associated sampling variability is unknown. Moreover, point estimates and their standard errors may be subject to small sample deficiencies, such as estimation biases and non-normality, which renders statistical inference for elasticity problematic. This paper presents a new statistical method called the bias-corrected bootstrap, which has been proved to provide accurate and reliable confidence intervals for demand elasticities. The method is herein employed to analyze the demand for Hong Kong tourism.

Keywords: Tourism demand, elasticity, bias-corrected bootstrap.

INTRODUCTION

Researchers and practitioners are interested in tourism demand elasticities for two main reasons. First, these elasticities reflect the way in which tourists respond to changes in the influencing factors of tourism demand in terms of direction and magnitude. Second, they provide useful information for tourism policy formulations, as tourism providers can manipulate such determinants as the tourism price and marketing expenditure to increase demand for the tourism product/service under consideration. Tourism demand elasticities provide "unit-free" measures of the sensitivity of an explanatory variable to tourism demand, given a pre-specified functional relationship. Economic theory suggests that, subject to budgetary constraints, tourists choose to purchase particular tourism products/services from among a set of all available such products/services to maximize their utility (Song and Witt, 2000). When the price of a tourism product/service changes, tourists' real income also changes. In addition, the price of the product/service in question, relative to the alternatives, also changes. These changes are called income and substitution effects, respectively. Thus, the income and price elasticity values derived from the demand function include both of these effects.

Numerous empirical studies on tourism demand elasticity have been published since the early 1970s, including those carried out by Crouch (1995), Li, Song and Witt (2005), and Lim (1997). Table 1 presents a list of all those published since 2000. The general findings of these studies indicate that the income elasticities of tourism demand, especially the demand for international tourism, are generally greater than one, thus indicating that tourism is a luxury. The own price elasticity is normally negative, but the magnitudes vary considerably depending on the type of tourism (long or short haul) and the time span of the demand under consideration (long-run versus short-run). However, these studies report point estimates only. Point estimation gives a single value as an estimate of the parameter of interest, but provides no information about the degree of variability associated with it. Hence, such estimates are substantially less informative than confidence intervals. Another drawback is that point estimation provides a biased estimate of true elasticity, as elasticity is often a non-linear function of other model parameters.

*please insert Table 1 about here

In addition, the sampling distribution of a point elasticity estimator is likely to follow a non-normal distribution, which renders conventional statistical inference based on normal approximation problematic. Hence, with point estimates alone, it is difficult to assess whether an elasticity estimate is statistically significant or whether it truly represents elastic demand. Therefore, a confidence interval that is robust to small sample biases and non-normality and that has a prescribed level of confidence is more useful for decision-makers. The main purpose of this study is to estimate demand elasticity intervals using the bootstrapping method with a view to overcoming the problems associated with point demand elasticity estimates. The empirical analysis of these intervals is based on a dataset relevant to the demand for Hong Kong tourism. More specifically, we estimate the confidence intervals for the long-run elasticities of the demand for inbound tourism to Hong Kong with respect to its main economic determinants: income, own price and substitute price.

We consider nine major inbound markets: Australia, mainland China (China), Japan, Korea, the Philippines, Singapore, Taiwan, the United Kingdom (U.K.) and the United States (U.S.). Our analysis is based on the autoregressive distributed lag (ARDL) model, which is applied to each market. We employ the ARDL bounds test proposed by Pesaran, Shin and Smith (2001) to determine the existence of a long-run relationship between tourism demand and its determinants. Once the presence of such a relationship is established, we estimate the long-run elasticities using the ARDL model. For interval estimation, we employ the bias-corrected bootstrap method developed by Kilian (1998), which Li and Maddala (1999) found to be the best means of constructing confidence intervals for long-run elasticities. It is designed to overcome the aforementioned problems of bias and non-normality in relation to elasticity estimation. This study is closely related to that carried out by Song, Wong and Chon (2003), who modeled the demand for Hong Kong tourism and employed the ARDL model to examine the influence of income and price on the number of international tourists arriving from 16 major origin countries/regions.

Although both the current study and that carried out by Song et al. (2003) provide estimates of long-run elasticities, there are two key differences between them. First, whereas the earlier study employed annual data from 1973 to 2000 to estimate the demand models, our study makes use of quarterly data from 1985 to 2006. An updated dataset with higher sampling frequency yields richer information content, which can lead to better-quality, more accurate estimation. Seasonality is an important factor when quarterly data are used. However, demand elasticity is determined by such economic fundamentals as income and price. Hence, our ARDL model includes seasonal dummy variables and a long autoregressive (AR) term to control for both deterministic and stochastic seasonality. We thus obtain elasticity estimates free from the effects of seasonality. Second, Song et al. (2003) were concerned with point estimates, whereas the main focus of the present study is interval estimation.

Our main finding is that source market income is the most important determining factor for the demand for Hong Kong tourism in the long run. Demand from long-haul markets (Australia, the U.K. and the U.S.) and growing economies (China and Korea) is found to be particularly income-elastic. Overall, however, we find that this demand is not sensitive to the own and substitute prices in the long run, although there is a strong tendency in short-haul markets (Japan, Korea and the Philippines) for price to be statistically significant and often elastic. That is, the demand from Australia, Japan and Korea is inelastic to the price of Hong Kong tourism, although that from Korea and the Philippines is highly elastic to the tourism price of substitute destinations. The remainder of the paper is organized as follows. The next section presents the methodology employed in the study. Section 3 presents the background to tourism in Hong Kong, a description of the data, and the empirical results, and the final section concludes the paper.

METHODOLOGY

According to Song and Witt (2000), the tourism demand for a particular destination can be defined as the quantity of a tourism product (i.e., a combination of tourism goods and services) that consumers are willing to purchase during a specified period under a given set of conditions. Most frequently, this time period is a month, a quarter or a year. Although some researchers use cross-sectional household data to examine the demand for tourism, the majority of related studies use time series data, as does the current study. The conditions related to the quantity of a tourism product demanded include the tourism prices in the destination (tourists' living costs in the destination and their travel costs to it); the tourism prices in competing (substitute) destinations; potential consumers' income levels; and other social, cultural, geographic and political factors. The demand function for a tourism product in a particular destination by the residents of an origin country is given by

$$Q_t = f(PT_t, PS_t, Y_t) + u_t, \qquad (1)$$

where Q_t is the quantity of the tourism product demanded at time t;

PT_t is the price of the tourism product/service at time t;

PS_t is the price for substitute destinations at time t;

Y_t is tourists' level of income at time t; and

u_t is the disturbance term that captures all of the other factors that may influence the quantity of the tourism product demanded at time t.

Equation (1) is a general statement of demand function that suggests that the demand for tourism is determined by its influencing factors, such as income, the own price of tourism and the substitute price. Other variables, such as advertising expenditure and the size of the population from which tourists are drawn, may also be entered into the equation. However, for simplicity's sake, we include only the most relevant variables that have been tested empirically in the demand function. We do not include the transportation cost, mainly due to its high degree of collinearity with income; that is, the information content of transportation cost is virtually identical to that of income, as noted by Lim (1999). Another reason for the exclusion of transportation cost from the model is that no reliable data for it are available. Previous studies have used average economy class air fares as a proxy for transportation cost, but this has been found unreliable, as the average of different such fares tends to cancel out the correlation between travel cost and the demand for travel (Li et al., 2005).

In practice, Equation (1) is estimated using a linear functional form with all of the variables transformed to a natural logarithm. This is because the demand elasticities can be obtained directly when the log-linear demand model is estimated using the ordinary least squares approach (see, for example, Song and Witt, 2000, pp. 10-12). The traditional demand model is usually specified as

$$\log(Q_t) = \alpha_0 + \alpha_1 \log(Y_t) + \alpha_2 \log(PT_t) + \alpha_3 \log(PS_t) + u_t \,, \tag{2}$$

where log(.) represents the natural logarithm. By construction, the coefficients α_1, α_2, and α_3 are income, price, and the substitute elasticities of demand, respectively. For example, $\alpha_1 = \dfrac{\Delta \log(Q)}{\Delta \log(Y)}$ represents the percentage change in demand with respect to a 1% change in income. Equation (2) is a static demand function in which current demand is determined by the current values of the explanatory variables. In reality, the demand for tourism is a dynamic process, and the general form of a dynamic demand function can be written as the following ARDL model.

$$\begin{aligned} \log(Q_t) = \gamma_0 + \sum_{i=1}^{p_1} \gamma_i \log(Q_{t-i}) + \sum_{i=0}^{p_2} \beta_{Y,i} \log(Y_{t-i}) + \\ \sum_{i=0}^{p_3} \beta_{PT,i} \log(PT_{t-i}) + \sum_{i=0}^{p_4} \beta_{PS,i} \log(PS_{t-i}) + u_t \end{aligned} \,. \tag{3}$$

The definitions of the variables in the foregoing equation are the same as those in Equation (1). The error term, u_t, is assumed to be independently and identically distributed (*i.i.d.*). Note that the error term need not follow a normal distribution, as the bootstrap method adopted in this study provides a valid statistical inference under non-normality. This is one of the advantages of the bootstrap method over conventional statistical methods based on normal approximation. The model (3) also contains deterministic terms, such as a linear time trend and seasonal dummy variables, but these are not explicitly included in Equation (3) for the sake of simplicity. Hence, the model (3) captures the effects of income and prices on tourism demand, netting out the effects of seasonal variations. The full details of the data, including the variable descriptions and time plots, are provided in the data section of the paper.

Testing for a long-run relationship

To test for the existence of a long-run relationship between tourism demand and its determinants, we adopt the ARDL bounds tests proposed by Pesaran et al. (2001). One advantage of this procedure, which is often adopted in tourism studies (Mervar and Payne, 2007; Narayan, 2004), is that the tests can be conducted irrespective of whether the time series of interest is stationary (integrated of order zero) or non-stationary (integrated of order one). We re-write model (3) in error-correction model form as

$$\begin{aligned}\Delta\log(Q_t) = \gamma_0 + \sum_{i=1}^{m_1}\psi_{Q,i}\Delta\log(Q_{t-i}) + \sum_{i=1}^{m_2}\psi_{Y,i}\Delta\log(Y_{t-i}) + \\ \sum_{i=1}^{m_3}\psi_{PT,i}\Delta\log(PT_{t-i}) + \sum_{i=1}^{m_4}\psi_{PS,i}\Delta\log(PS_{t-i}) + \\ \pi_1\log(Q_{t-1}) + \pi_2\log(Y_{t-1}) + \pi_3\log(PT_{t-1}) + \pi_4\log(PS_{t-1}) + u_t,\end{aligned} \tag{4}$$

where Δ is the difference operator (i.e., $\Delta X_t = X_t - X_{t-1}$). This equation describes the short-run dynamic interactions between tourism demand and its determinants and their long-run relationship using π coefficients. If the values of π are zero, then no long-run relationship exists. Pesaran et al. (2001) proposed two tests for the null hypothesis of no long-run relationship: an F-test for H_0: $\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$ against the alternative that at least one π is non-zero; and a t-test for H_0: $\pi_1 = 0$. They tabulated the lower- and upper-bound critical values for these tests. The former assume that all of the variables are integrated of order zero, whereas the latter assume they are integrated of order one. If the statistic falls outside the upper-bound critical value, then the null hypothesis is rejected at a prescribed level of significance. If it falls below the lower-bound critical value, then the null hypothesis cannot be rejected. The test is inconclusive if the statistic falls inside these bounds.

Point estimation of long-run elasticity

The long-run elasticities of tourism demand can be obtained from the coefficients of model (3) as

$$\theta \equiv \left(\theta_Y, \theta_{PT}, \theta_{PS}\right) \equiv \left(\frac{\sum_{i=0}^{p_2} \beta_{Yi}}{1-\lambda}, \frac{\sum_{i=0}^{p_3} \beta_{PT,i}}{1-\lambda}, \frac{\sum_{i=0}^{p_4} \beta_{PS,i}}{1-\lambda} \right), \tag{5}$$

where $\lambda = \sum_{i=1}^{p_1} \gamma_i$. θ_Y, θ_{PT} and θ_{PS} represent the long-run elasticities of tourism demand with respect to income, own price and substitute price, respectively. The unknown orders (p_1,…, p_4) are estimated using Akaike's information criterion, and the estimated values are denoted as $(\hat{p}_1,...,\hat{p}_4)$. The least-squares method is used to estimate the parameters of Equation (3). The least squares estimators for

$$\alpha \equiv (\gamma_0, \gamma_1, ..., \gamma_{\hat{p}_1}, \beta_{Y,0}, ..., \beta_{Y,\hat{p}_2}, \beta_{PT,0}, ..., \beta_{PT,\hat{p}_3}, \beta_{PS,0}, ..., \beta_{PS,\hat{p}_4})$$

are denoted as

$$\hat{\alpha} \equiv (\hat{\gamma}_0, \hat{\gamma}_1, ..., \hat{\gamma}_{\hat{p}_1}, \hat{\beta}_{Y,0}, ..., \hat{\beta}_{Y,\hat{p}_2}, \hat{\beta}_{PT,0}, ..., \hat{\beta}_{PT,\hat{p}_3}, \hat{\beta}_{PS,0}, ..., \hat{\beta}_{PS,\hat{p}_4}), \tag{6}$$

and $\{\hat{u}_t\}_{t=p_1+1}^{n}$ represents the least squares residuals. The point estimator for θ is obtained by replacing the unknown parameters with their estimators, that is,

$$\hat{\theta} \equiv \left(\hat{\theta}_Y, \hat{\theta}_{PT}, \hat{\theta}_{PS}\right) \equiv \left(\frac{\sum_{i=0}^{\hat{p}_2} \hat{\beta}_{Yi}}{1-\hat{\lambda}}, \frac{\sum_{i=0}^{\hat{p}_3} \hat{\beta}_{PT,i}}{1-\hat{\lambda}}, \frac{\sum_{i=0}^{\hat{p}_4} \hat{\beta}_{PS,i}}{1-\hat{\lambda}} \right), \tag{7}$$

where $\hat{\lambda} = \sum_{i=1}^{\hat{p}_1} \hat{\gamma}_i$.

Interval estimation of long-run elasticity

The interval (or variance) estimation of θ given in (5) constitutes a difficult task, because θ is a non-linear function of the other parameters in ratio form. Interval estimation requires knowledge of both the variance of $\hat{\theta}$ and the percentiles of its sampling distribution, which are completely unknown in this case. In practical applications, the sampling distribution of $\hat{\theta}$, denoted as $\{\hat{\theta}\}$, is approximated, conventionally using a normal distribution. That is, the conventional 90% confidence interval for θ is constructed as [$\hat{\theta}$ - 1.645se($\hat{\theta}$), $\hat{\theta}$ + 1.645se($\hat{\theta}$)], where 1.645 is the 5% critical value from the standard normal distribution, and se($\hat{\theta}$) is the standard error of $\hat{\theta}$ calculated by Taylor's series approximation (called the delta method). This interval is symmetric around $\hat{\theta}$ and depends heavily on the assumption of normal distribution, which is unlikely to hold in practice. In addition, se($\hat{\theta}$) based on the delta method may not adequately capture the true sampling variability of $\hat{\theta}$ (for more details, see Li and Maddala, 1999).

An alternative way of approximating $\{\hat{\theta}\}$ is Efron's (1979) bootstrap method, which is a re-sampling method for observed data. Li and Maddala (1999) compared the properties of alternative methods of variance estimation and confidence intervals for long-run elasticity. Based on their Monte Carlo findings, they proposed that Efron's (1979) bootstrap method be used in practice, because such popular conventional methods as the delta method have been found to be far inferior. Li and Maddala (1999) found Kilian's (1998) bias-corrected bootstrap method to be the most effective, and thus it is adopted in this paper. The bootstrap method is a computer-intensive means of approximating the unknown sampling distribution of a statistic. A typical bootstrap procedure involves the generation of a large number of artificial datasets via the repetitive re-sampling of the observed data. These artificial datasets ensure that the statistical properties of the observed dataset can be effectively replicated. The collection of statistics calculated from them (known as the bootstrap distribution) is then used for statistical inference as an approximation of the true sampling distribution of the statistic.

This method is widely used in economics and has proved to be a superior alternative to conventional methods of statistical inference (Berkowitz & Kilian, 2000; Li & Maddala, 1996; MacKinnon, 2002). In the ARDL context, artificial datasets are generated using the estimated coefficients and re-sampled residuals, following the model structure being estimated. ARDL models, however, involve lagged dependent variables, and the estimated coefficients are biased in small samples (Kiviet and Phillips, 1994). Such bias can undermine the accuracy of the bootstrap distribution and result in misleading inferential outcomes. Kilian's (1998) bias-corrected bootstrap method is designed to adjust for these adverse effects. In this study, we adopt the bootstrap method, both with and without bias-correction. For simplicity of exposition, the full technical details of the bootstrap procedures are omitted here. Interested readers are directed to Kilian (1998) and Li and Maddala (1999), and a written description can be obtained from the corresponding author upon request.

EMPIRICAL RESULTS

Background to Tourism in Hong Kong

Hong Kong is one of the most popular destinations in Asia, partly thanks to its unique culture, which combines a Western lifestyle with Chinese traditions. Over the past three decades, Hong Kong has attracted numerous international tourists (Song et al., 2003) and, according to a World Economic Forum report (2007), was ranked sixth in the world in terms of competitiveness as an international destination and considered to have the most attractive travel and tourism environment in Asia. International tourist arrivals in Hong Kong increased from 6.79 million in 1991 to 25.25 million in 2006, for an average annual growth rate of about 9%. By the end of 2006, the average occupancy rate of hotels was 87%, and the average length of overnight stays was 3.5 nights. Total tourist expenditures accounted for around 7% of Hong Kong's gross domestic product (GDP) that year (Hong Kong Tourism Board, 2006). In the last two decades of the 20th century, however, the Hong Kong tourism industry was affected by two major events. The first, the Asian financial crisis, saw total arrivals decline by 13.1% in 1997 and by 21.7% in 1998, compared to 1996.

The second, the SARS outbreak in March 2003, had a catastrophic impact on Hong Kong tourism, with total arrivals declining by 90% in the second quarter of that year. Although the tourism industry was one of the most severely affected, it has experienced sustained growth since 2004, mainly due to the implementation of the Global Tourism Revival Campaign and a series of new initiatives orchestrated by the Hong Kong government in collaboration with the private sector. For example, the Individual Visit Scheme, which makes it easier for tourists from mainland China to visit Hong Kong, was introduced in the wake of the SARS outbreak. According to the Hong Kong Tourism Board (2006), these tourists accounted for more than 50% of those visiting in 2005, followed by Taiwan (9.1%), Japan (5.2%) and the U.S. (4.9%). The mainland's market share is predicted to increase to more than 60% in 2009 (Turner & Witt, 2008). Given the importance of tourism to economic growth and employment in Hong Kong, it is crucial that businesses and policymakers understand how tourism demand is determined by economic factors in the long run.

Data description

This section describes the variables used in the demand equation (Equation (3)) and provides details of the data. As previously mentioned, tourism demand is measured by the number of international tourist arrivals. Q_t is tourism demand, measured by tourist arrivals to Hong Kong from a particular source market at time t (= 1, …,n), Y_t is the income variable of the source market, measured by the real GDP of the origin, PT_t is the own price of tourism in Hong Kong, and PS_t is the price of tourism in substitute destinations. The own price (PT) is measured by the real cost of living for tourists in Hong Kong and is calculated as the consumer price index of Hong Kong relative to that of the source market, adjusted by the relevant exchange rate. The substitute price (PS) measures tourists' cost of living in substitute destinations selected on the basis of their geographic and cultural characteristics: China, Taiwan, Singapore, Malaysia, Thailand and South Korea. We calculate a single PS index, based on an average of the consumer price indices of these destinations.

The data on tourist arrivals from the nine aforementioned source markets are collected from the Hong Kong Tourism Board's monthly Visitor Arrivals Statistics. Real GDP, consumer price index and exchange rate date are obtained from the International Monetary Fund's International Financial Statistics Online Service website. We use quarterly data covering the 1985:Q1 to 2006:Q4 period for all series, except for Korea, the Philippines, Singapore and Taiwan, whose starting periods are 1990:Q1, 1991:Q1, 1991:Q1 and 1989:Q1, respectively. Several dummy variables capture the deterministic shifts in tourism demand due to unexpected events: permission for private visits to China (1987:Q4-2006:Q4, Taiwan only), the Tiananmen Square incident (1989, the U.S. only), the Asian financial crisis (1997-1998), Hong Kong's return to China (1997:Q3), the 9/11 terrorist attacks (2001:Q4, the U.S. only) and the SARS epidemic (2003:Q2). Quarterly seasonal dummy variables capture seasonality. Time plots of the data for two representative source markets, Australia and China, are presented in Figure 1. Tourist arrivals from the former show a mild upward trend and strong seasonality, with SARS having a significant impact. Those from China show a strong linear trend and mild seasonality, with real income exhibiting strong upward trend.

*please insert Figure 1 about here

Test for long-run relationship and point estimates of elasticity

As previously mentioned, the orders of the ARDL model (3) are selected using Akaike's information criterion, following a simple-to-general modeling strategy. The estimated orders and p-values of the residual diagnostics are reported in Table 2. According to the Breusch-Godfrey LM test for autocorrelation, all of the estimated models have residuals with no evidence of autocorrelation at the 1% level of significance. Only the Chinese and U.S. markets have significant autocorrelation at the 5% level. According to White's test for heteroskedasticity, only the Taiwanese and U.S. markets show evidence of it at the 1% level of significance. The Ramsey Regression Equation Specification Error Test shows evidence of model misspecification, but only for the Philippines market. There is evidence of a non-normal error term for the ARDL models of the Australian, Korean and U.K. markets; the bootstrap procedure adopted in this paper, however, is valid even under non-normality. These results show that, overall, the estimated ARDL models are statistically adequate.

*please insert Table 2 about here

Table 3 reports the ARDL bounds (F and t) test results. Following Pesaran et al. (2001), the lag lengths (m's) in (4) are chosen as the orders implied by the underlying vector autoregressive model. The F and t statistics reported in Table 3 indicate the rejection of the null hypothesis at the 5% level of significance in all cases, which is evidence in favor of the presence of a long-run relationship for all of the source markets. Table 4 also reports the point estimates of income, own-price and cross-price elasticities. Their mean values are 1.32, -0.10 and 0.39, respectively, which are, on average, indicative of elastic demand to income and inelastic demand to own and substitute prices. However, the point estimates alone are of limited usefulness, and their statistical significance should be properly evaluated using confidence intervals. For example, the point income elasticity of demand from Australia is 1.35. In relation to this outcome, there are two economic questions to be answered.

*please insert Tables 3 and 4 about here

The first is whether point estimate 1.35 is significantly different from zero. If the associated confidence interval does not cover zero, then this would indicate that this point estimate is different from zero at a given level of confidence. The second question is whether the point estimate is statistically greater than one, which would be evidence of elastic demand to income. If the associated confidence interval does not cover one, then this would be evidence that the point estimate is statistically different from one. Table 4 shows several cases in which the point elasticity estimates have the wrong signs. Again, confidence intervals are required to properly evaluate the statistical significance of this outcome. For example, the point estimate for the own price elasticity of China is 0.37, which is inconsistent with the law of demand. A key question is whether this estimate is statistically different from zero. If the confidence interval covers zero, then the estimate is in fact an estimate of zero at a given level of confidence. As we shall see in the next section, we decide that the own-price elasticity of demand from China is statistically no different from zero, as the associated confidence interval covers zero.

Before turning to our discussion of the interval estimation results, we here provide an illustration to highlight the usefulness of the bootstrap method. Figure 2 provides a density estimate of the bootstrap approximation to $\{\hat{\theta}\}$ for the income elasticity of

Australia. Point estimate 1.35 in Table 4 may be regarded as the expected value of this distribution. The plot provides a useful visual impression of the sampling variability associated with this estimation. It can be seen that the shape of the distribution is far different from that of a normal distribution; this departure from normality is clear in the Q-Q plot presented in Figure 3, as the plot deviates from the 45° line. It is right-skewed with a higher probability mass on the right-hand side of the distribution. The 90% confidence interval calculated is [1.02, 1.78], where 1.02 and 1.78 are the 5th and 95th percentiles of the plotted distribution. This interval represents well the degree of variability observed in the plotted distribution and also captures its asymmetry; that is, the distribution is asymmetric around point estimate 1.35. Conventional confidence intervals based on normal approximation provide a symmetric interval around the point estimate and are associated with a substantial underestimation of variability (for further details, see Li and Maddala, 1999).

*please insert Figures 2 and 3 about here

Confidence intervals for long-run elasticity

Table 5 reports the 90% confidence intervals for long-run elasticities, based on a number of alternative methods, including normal approximation, bootstrap with bias-correction and bootstrap without bias correction. Although the results are not overly sensitive to the use of two different methods, they do show a certain degree of variation. Overall, the two bootstrap methods provide consistent inferential results, whereas the conventional intervals approach often provides outcomes that are in conflict with its bootstrap counterparts. For example, Taiwan's income elasticity is found to be unitary elastic based on the conventional interval of [0.15, 1.09], whereas both of the bootstrap intervals indicate inelastic income elasticity, as they do not cover the value of one. According to the conventional interval, the own price elasticity of Japan is statistically zero, whereas both bootstrap intervals indicate negative and inelastic elasticity. Similarly, the cross-price elasticity of the U.K. is statistically zero according to the conventional interval, whereas both bootstrap intervals indicate positive and inelastic cross-elasticity. These examples clearly demonstrate that the bootstrap intervals provide more economically sensible inferential outcomes.

*please insert Table 5 about here

We prefer the bootstrap intervals with bias-correction to those without, on the basis of the Monte Carlo results presented by Li and Maddala (1999), who found the latter to be too optimistic and to under-report the true value. We therefore use bias-corrected bootstrap intervals for our subsequent analysis, although the two bootstrap methods provide qualitatively similar results in most cases. We begin with the overall statistical significance of elasticities by looking at the mean confidence intervals based on the bias-corrected bootstrap. The mean confidence interval for income elasticity is [0.81, 1.86], which indicates that demand is, on average, sensitive to income. Income elasticity is statistically significant for all of the markets, except for the Philippines. The own and cross-price elasticities are, on average, statistically insignificant, as the mean confidence intervals cover zero in both cases. Three markets (Australia, Korea and Japan) have statistically significant own-price elasticities, and three (Korea, Japan and the U.K.) statistically significant cross-price elasticities.

Our overall results can be compared with the findings of meta-analytic reviews of tourism demand, such as those published by Crouch (1995, 1996) and Lim (1997, 1999). Crouch (1995, p. 112) reported that demand is, in general, highly elastic to income: about 70% of the income elasticity (point) estimates reported in past studies indicate an elastic demand to income. According to Crouch (1996, p. 118), the normal range of income elasticity according to conventional wisdom lies between 1.0 and 2.0, which is largely compatible with our mean confidence interval for this elasticity. Lim (1999, Table 4), however, reports that less than 50% of the own-price elasticity (point) estimates reported in past studies are statistically significant, which indicates that the overall statistical insignificance of our price elasticity estimates is not a surprising outcome. Indeed, there is evidence to show that price elasticity (point) estimates are highly varied (Crouch, 1996, p. 119) and can be situation-specific (Crouch, 1995, p. 116). Moreover, demand is becoming more income-sensitive, with long-haul tourists less aware of prices in far-off lands (Crouch, 1996, p. 133).

We now turn to the bias-corrected confidence intervals for individual markets. For Australia, the 90% confidence interval for income elasticity is [1.02, 1.78], which is indicative of more than the unitary elastic demand with respect to income. That for own-price elasticity is [-0.86, -0.32], thus indicating that demand is inelastic to own price. Cross-price elasticity is statistically insignificant for this market, as the interval covers zero. For China, demand is highly elastic to income, with a 90% confidence interval [1.39, 2.43], whereas both the own and substitute price elasticities are statistically insignificant. For Japan, the interval [0.24, 3.84] for income elasticity indicates statistical significance, but it appears to be too wide to allow any meaningful interpretations. The 90% confidence interval for price elasticity in this market is [-0.94, -0.09], which is indicative of inelastic demand to own price, and cross-price elasticity is statistically insignificant. For Korea, demand is highly elastic to income, inelastic to own-price and highly elastic to substitute price.

Demand from the Philippines shows a statistically significant response only to substitute price, thus indicating highly elastic cross-price elasticity. For Singapore and Taiwan, only income elasticity is statistically significant, with the former exhibiting elastic income demand and the latter inelastic. Income elasticity for the U.K. is found to be significant and highly elastic, although cross-price elasticity is significant but inelastic. Finally, for the U.S., only income elasticity is significant, with roughly unitary elastic demand to income. These results suggest that the income levels of source markets are the main drivers of tourism demand for Hong Kong in the long run. It is found that demand from long-haul markets (Australia, the U.K. and the U.S.) and growing economies (China and Korea) is highly income-elastic. Overall, price elasticities are found to be statistically insignificant, although there is a strong tendency for short-haul markets to react to own and substitute prices with statistical significance.

CONCLUSION

The elasticities of demand for tourism are important measures for both academics and practitioners, as they are useful for policymaking and long-term planning. A large number of studies have estimated income and price elasticities, but their primary focus has been on point estimation, with interval estimation completely neglected. Point estimation alone is not informative, because the completely unknown sampling variability renders statistical inference about elasticity impossible. It is also well known that conventional methods of variance estimation for long-run elasticity are inaccurate and unreliable. Based on these failings, the bias-corrected bootstrap method proposed by Li and Maddala (1999) was adopted in this study, as it has been found to be the best means of constructing confidence intervals. Our analysis is based on the ARDL model, which belongs to a general class of dynamic linear models widely used in tourism demand studies. We establish the presence of a long-run relationship and then estimate long-run income and price elasticities. We find strong evidence of a long-run relationship among demand, income and prices for all nine of the source markets considered. The bias-corrected bootstrap confidence intervals obtained show that the income levels of source markets are the most important determinant of Hong Kong tourism demand in the long run.

Demand from long-haul markets (Australia, the U.K. and the U.S.) and growing economies (China and Korea) demonstrates a particularly high degree of elasticity to income. Overall, such demand is found not to be sensitive to the own and substitute prices of Hong Kong tourism, although we observe a strong tendency for short-haul markets to react sensitively to these prices. The results presented in this paper also clearly demonstrate that the use of the conventional confidence interval approach can provide misleading inferential outcomes on the long-run elasticity of demand. The bootstrap method provides more economically sensible results, as they are not dependent on a restrictive model or distributional assumptions. The ranges of possible income and price elasticities in the tourism literature have been obtained through meta-analysis alone; that is, they represent the collective evaluation of the point estimates reported in accumulated prior studies. Although meta-analytic results offer interesting insights, they provide no indication of whether economically sensible interval estimates of tourism demand elasticities can be obtained from an observed dataset. By adopting the bias-corrected bootstrap as a means of statistical inference, this paper represents the first attempt to provide such estimates.

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Table 1
Published Tourism Demand Elasticities

Author(s)	Source Market	Destination	Measured by	Elasticity		
				Income	**Price**	**Sub. Price**
Song, Romilly and Liu (2000)	U.K.	Australia	Arrivals	2.721	-2.086	---
	U.K.	Belgium/Luxembourg	Arrivals	2.162		---
	U.K.	France	Arrivals	2.123	-1.079	---
	U.K.	Germany	Arrivals	2.263	-1.251	---
	U.K.	Italy	Arrivals	1.739	-1.013	---
	U.K.	Netherlands	Arrivals	2.488	-0.23	---
	U.K.	Greece	Arrivals	2.174	-0.21	---
	U.K.	Spain	Arrivals	2.199	-0.496	---
	U.K.	Irish Republic	Arrivals	2.655	0.947	---
	U.K.	Switzerland	Arrivals	2.028	-0.146	---
	U.K.	U.S.	Arrivals	2.003	0.16	---
Vanegas and Croes (2000)	U.S.	Aruba	Arrivals	1.512	-0.114	---
	U.S.	Aruba	Arrivals	1.485	---	---
	U.S.	Aruba	Arrivals	1.494	-0.123	---
	U.S.	Aruba	Arrivals	1.702	-0.198	---
	U.S.	Aruba	Arrivals	1.384	---	---
Kulendran and Witt (2001)	U.K.	Germany	Arrivals	0.541	-4.001	-0.714
	U.K.	Greece	Arrivals	0.608	-9.9	---
	U.K.	Netherlands	Arrivals	0.727	---	---
	U.K.	Portugal	Arrivals	1.821	-0.921	---
	U.K.	Spain	Arrivals	0.928	-2.988	---
	U.K.	U.S.	Arrivals	1.697	---	-3.567
Greenidge (2001)	U.S.	Barbados	Arrivals	2.268	---	---
	U.K.	Barbados	Arrivals	1.512	---	---
	Canada	Barbados	Arrivals	3.1342	-0.184	---
Song, Witt and Li (2003)	Australia	Thailand	Arrivals	3.518	-3.582	4.102
	Japan	Thailand	Arrivals	---	-0.709	0.772
	South Korea	Thailand	Arrivals	2.046	---	-2.902
	Singapore	Thailand	Arrivals	---	-5.745	4
	Malaysia	Thailand	Arrivals	---	---	4.238
	U.K.	Thailand	Arrivals	4.922	-0.414	0.559
	U.S.	Thailand	Arrivals	---	-1.619	-0.367
Song and Witt (2003)	Germany	South Korea	Arrivals	---	---	0.75
	Japan	South Korea	Arrivals	-4.715	-0.281	3.43
	U.K.	South Korea	Arrivals	3.273	-0.018	0.642
	U.S.	South Korea	Arrivals	---	-8.776	3.362
Song , Wong and Chon (2003)	Australia	Hong Kong	Arrivals	---	-0.583	0.552
	Canada	Hong Kong	Arrivals	3.322	-1.012	---
	Mainland China	Hong Kong	Arrivals	1.521	-0.402	1.248
	France	Hong Kong	Arrivals	2.616	-0.436	0.663
	Germany	Hong Kong	Arrivals	3.62	-1.389	---
	Indonesia	Hong Kong	Arrivals	1.484	-2.885	---
	India	Hong Kong	Arrivals	1.459	-1.059	1.209
	Japan	Hong Kong	Arrivals	2.53	---	---

(Table 1 Continued)

Author(s)	Source Market	Destination	Measured by	Elasticity		
				Income	Price	Sub. Price
Song, Wong and Chon (2003)	South Korea	Hong Kong	Arrivals	1.704	---	---
	Malaysia	Hong Kong	Arrivals	1.02	-0.206	---
	Philippines	Hong Kong	Arrivals	---	---	1.657
	Singapore	Hong Kong	Arrivals	1.316	-1.223	---
	Taiwan	Hong Kong	Arrivals	2.14	-1.729	---
	Thailand	Hong Kong	Arrivals	0.944	-0.911	---
	U.K.	Hong Kong	Arrivals	2.096	-0.492	0.643
	U.S.	Hong Kong	Arrivals	1.499	-1.004	0.463
Song and Wong (2003)	Australia	Hong Kong	Arrivals	0.233	-0.421	0.308
	Canada	Hong Kong	Arrivals	2.907	-0.799	0.524
	France	Hong Kong	Arrivals	2.211	-0.364	0.822
	Germany	Hong Kong	Arrivals	1.182	-0.175	1.173
	U.K.	Hong Kong	Arrivals	2.079	-0.537	0.563
	U.S.	Hong Kong	Arrivals	2.907	-1.013	0.301
Dritsakis (2004)	U.K.	Greece	Arrivals	6.0268	---	---
	Germany	Greece	Arrivals	2.1592	---	---
Lim (2004)	South Korea	Australia	Arrivals	19.194	-19.68	---
Croes and Vanegas (2005)	U.S.	Aruba	Arrivals	2.66	-0.22	---
	Venezuela	Aruba	Arrivals	3.86	-1.62	---
	Netherlands	Aruba	Arrivals	6.75	-0.044	---
Li, Wong, Song and Witt (2006)	U.K.	France	Expenditure	2.817	-1.163	0.997
	U.K.	Greece	Expenditure	1.834	-1.959	0.506
	U.K.	Italy	Expenditure	1.935	-1.184	-0.502
	U.K.	Portugal	Expenditure	1.779	-0.161	-0.725
	U.K.	Spain	Expenditure	2.22	-1.23	-0.478
Mervar and Payne (2007)	15 EUM [a]	Croatia	Arrivals	4.8	---	---
	15 EUM	Croatia	Arrivals	4.91	---	---
	members of EZ [b]	Croatia	Arrivals	3.88	---	---
	members of EZ	Croatia	Arrivals	4.29	---	---
	25 EUM	Croatia	Arrivals	5	---	---
	25 EUM	Croatia	Arrivals	5.1	---	---
Muňoz (2007)	Germany	Spain	Arrivals	5.4	-2.16	---
Lim, McAleer and Min (2008)	Japan	Taiwan	Arrivals	2.19	---	---
	Japan	New Zealand	Arrivals	1.4	---	---
	Japan	New Zealand	Arrivals	0.81	---	---
Ouerfelli (2008)	Germany	Tunisia	Arrivals	3.71	-7.47	0.43
	France	Tunisia	Arrivals	2.77	-2.71	0.3
	Italy	Tunisia	Arrivals	2.17	-2.43	-0.15
	Italy	Tunisia	Arrivals	1.81	-2.39	---
	U.K.	Tunisia	Arrivals	1.44	-0.93	0.003
	U.K.	Tunisia	Arrivals	0.48	-0.41	0.06
Lim, Min and McAleer (2008)	Japan	New Zealand	Arrivals	1.4	---	---
	Japan	New Zealand	Arrivals	1.193	---	---
	Japan	Taiwan	Arrivals	0.4	---	---

Notes: [a]: “old” European Union members; [b]: European Zone.

Table 2

ARDL Model Selection Results and p-values of Residual Diagnostic Tests

	Orders	Hetero	Auto	JB	RESET
Australia	(4,0,2,1)	0.08	0.43	0.00*	0.38
China	(2,0,0,0)	0.47	0.03	0.54	0.95
Japan	(2,0,0,0)	0.24	0.77	0.39	0.92
Korea	(2,0,2,2)	0.21	0.25	0.03	0.05
Philippines	(2,0,1,0)	0.99	0.16	0.79	0.00*
Singapore	(2,0,0,0)	0.14	0.05	0.77	0.55
Taiwan	(2,0,0,0)	0.00*	0.05	0.21	0.07
U.K.	(2,1,0,2)	0.45	0.08	0.03	0.88
U.S.	(2,1,0,1)	0.00*	0.05	0.16	0.06

Notes: (1) Orders: ARDL orders; Hetero: White's heteroskedasticity test with no cross product terms; Auto: Breusch-Godfrey LM test for serial correlation at lag 8; JB: Jarque-Bera test for normality; RESET: Ramsey's Regression Equation Specification Error Test with one augmentation term. (2) All entries for the tests are the p-values. The starred entries indicate significance at the 1% level.

Table 3

ARDL Bounds Test Statistics

	Australia	China	Japan	Korea	Philippines
F-statistic	37.01*	5.56**	36.14*	24.93*	71.00*
t-statistic	-11.76*	-3.83**	-11.74*	-9.97*	-16.71*
	Singapore	Taiwan	U.K.	U.S.	
F-statistic	53.75*	27.29*	114.13*	84.83*	
t-statistic	-14.6*	-10.21*	-17.92*	-18.14*	

Notes: (1) * and ** represent 1% and 5% significance levels, respectively. (2) The critical values of the bounds test (F-statistics) are from Pesaran et al. (2001:300; Table CI (iii)): 1% 4.29 to 5.61 and 5% 3.23 to 4.35; the critical values of the t-statistics were also obtained from Pesaran et al. (2001:303, Table CI(iii)): 1% -3.43 to -4.37 and 5% -2.86 to -3.78.

Table 4

Long-run Elasticity Point Estimates

	Income	Own Price	Cross Price
Australia	1.35	-0.56	0.34
China	1.89	0.37	-0.71
Japan	1.89	-0.50	-0.14
Korea	1.35	-0.41	1.83
Philippines	0.48	0.25	2.48
Singapore	1.01	-0.35	0.06
Taiwan	0.62	0.32	-0.38
U.K.	2.08	0.07	0.37
U.S.	1.19	-0.11	-0.31
Mean	1.32	-0.10	0.39

Table 5

90% Confidence Intervals for Long-run Elasticities

Normal approximation based on the delta method

	Income elasticity		Price elasticity		Cross elasticity	
Australia	0.94	1.75	-0.88	-0.24	-0.19	0.87
China	1.61	2.17	-0.45	1.19	-2.12	0.70
Japan	1.61	2.17	-1.31	0.32	-1.55	1.27
Korea	1.10	1.59	-0.69	-0.13	0.91	2.75
Philippines	-0.19	1.14	-0.54	1.04	1.04	3.91
Singapore	0.34	1.68	-0.14	0.44	-1.37	1.49
Taiwan	0.15	1.09	-0.07	0.71	-1.32	0.56
U.K.	1.67	2.49	-0.25	0.39	-0.16	0.90
U.S.	0.58	1.80	-0.57	0.35	-1.13	0.51
Mean	0.87	1.76	-0.54	0.45	-0.65	1.44

Bootstrap with no bias correction

	Income elasticity		Price elasticity		Cross elasticity	
Australia	0.98	1.69	-0.81	-0.31	-0.01	0.67
China	1.63	2.17	-0.42	1.03	-1.98	0.45
Japan	0.37	3.23	-0.88	-0.16	-1.00	0.80
Korea	1.20	1.52	-0.53	-0.12	1.52	2.70
Philippines	0.18	0.83	-0.9	0.57	1.68	2.99
Singapore	0.85	1.16	-0.82	0.10	-0.35	0.44
Taiwan	0.37	0.86	0.07	0.67	-0.96	0.17
U.K.	1.56	2.55	-0.08	0.20	0.08	0.70
U.S.	0.93	1.42	-0.38	0.16	-0.70	0.09
Mean	0.90	1.71	-0.53	0.24	-0.19	1.00

Bias-corrected bootstrap

	Income elasticity		Price elasticity		Cross elasticity	
Australia	1.02	1.78	-0.86	-0.32	-0.11	0.85
China	1.39	2.43	-0.63	2.24	-3.94	0.94
Japan	0.24	3.84	-0.94	-0.09	-1.32	0.92
Korea	1.13	1.56	-0.57	-0.03	1.45	2.98
Philippines	-0.05	0.90	-0.32	0.77	1.59	3.52
Singapore	0.84	1.20	-0.97	0.15	-0.51	0.55
Taiwan	0.33	0.90	-0.00	0.70	-1.17	0.24
U.K.	1.47	2.59	-0.10	0.23	0.03	0.75
U.S.	0.88	1.56	-0.50	0.24	-0.83	0.23
Mean	0.81	1.86	-0.54	0.43	-0.53	1.22

Income elasticity: lower and upper bounds of 90% confidence interval for income elasticity

Price elasticity: lower and upper bounds of 90% confidence interval for own-price elasticity

Cross elasticity: lower and upper bounds of 90% confidence interval for cross-price elasticity

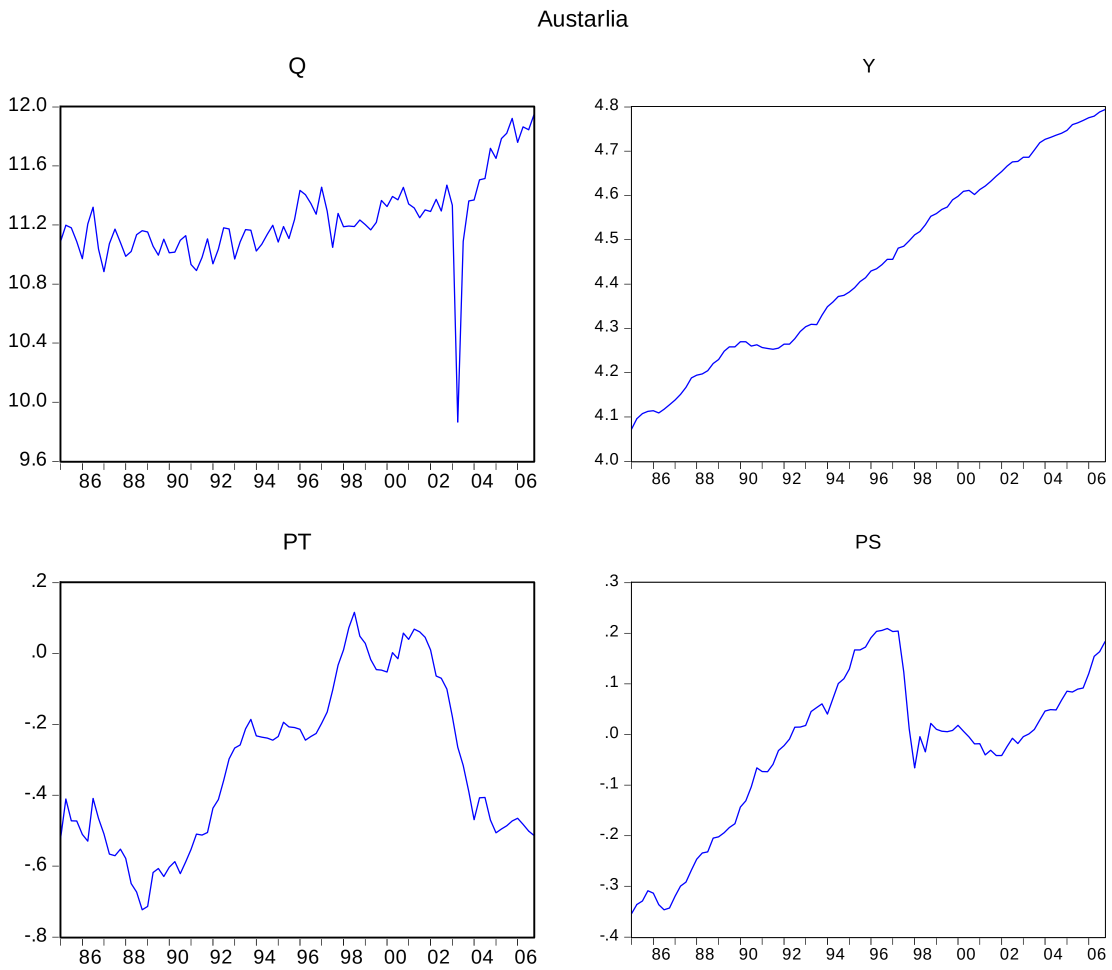

Figure 1. Plots of Selected Time Series

Q: the number of tourist arrivals from a source market;
Y: real GDP of the source market;
PT: price level (CPI) of Hong Kong tourism relative to that of the source market, adjusted with exchange rates;
PS: price level of substitute destinations.
All variables are measured at a quarterly frequency in natural logarithm

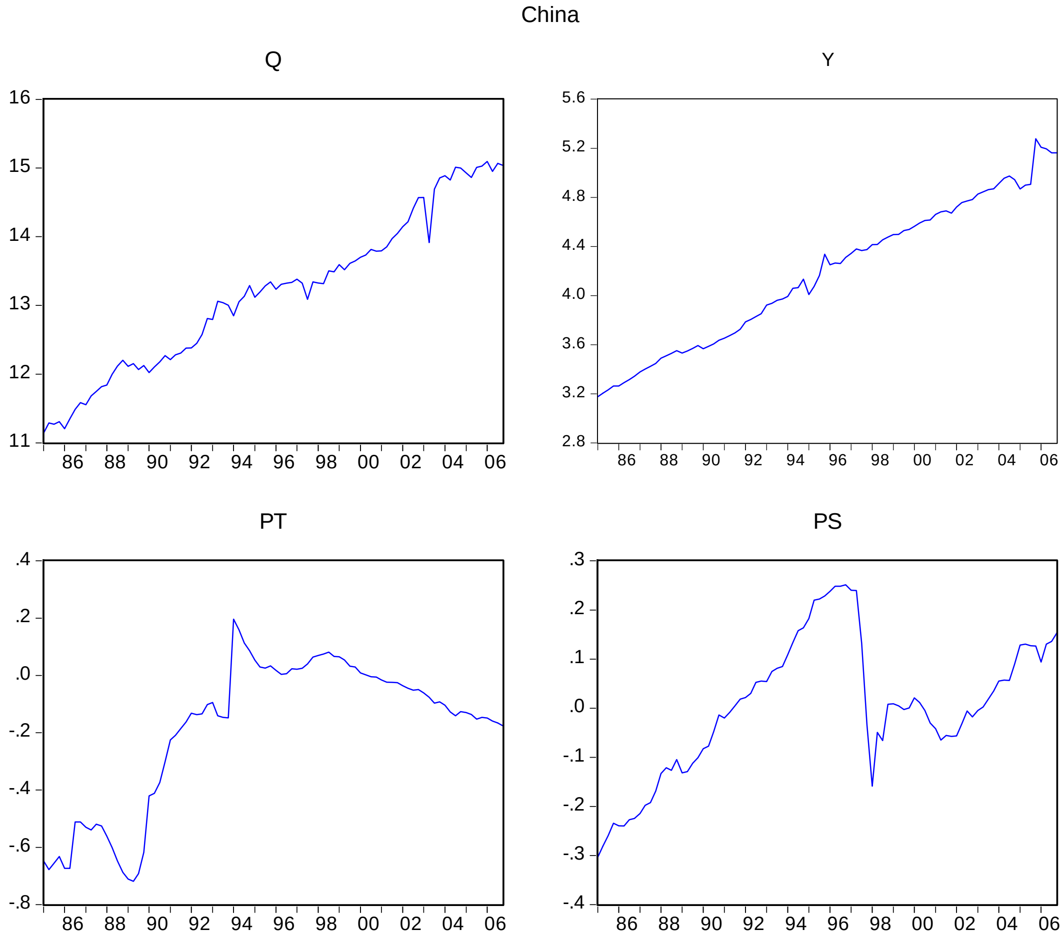

Figure 1. Continued

Q: the number of tourist arrivals from a source market;
Y: real GDP of the source market;
PT: price level (CPI) of Hong Kong tourism relative to that of the source market, adjusted with exchange rates;
PS: price level of substitute destinations.
All variables are measured at a quarterly frequency in natural logarithm

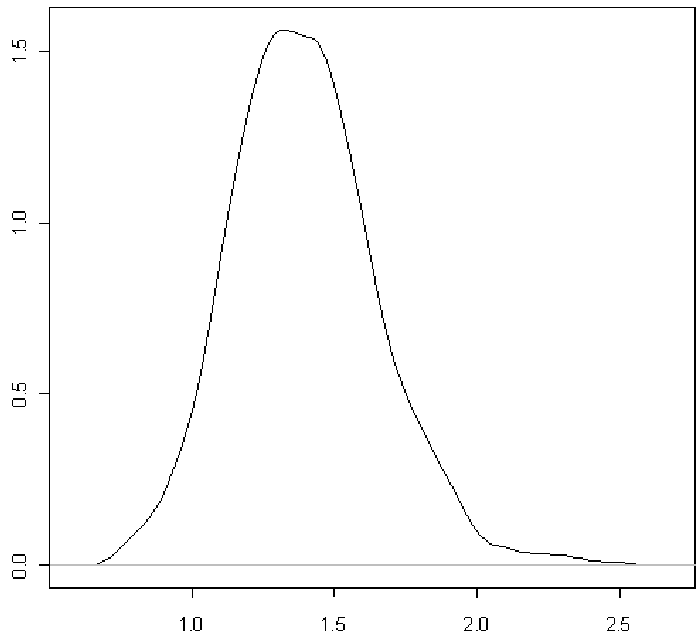

Figure 2. Density Estimate of Bootstrap Distribution of Income Elasticity Estimator (Australia, Bias-corrected Bootstrap).

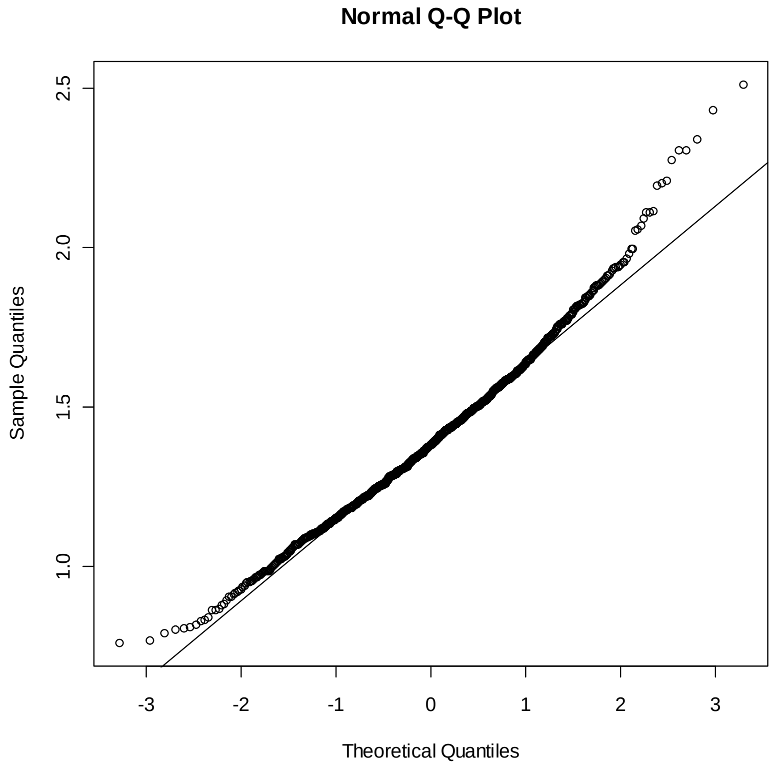

Figure 3. Normal Q-Q Plot for Bootstrap Distribution of Income Elasticity Estimator (Australia, Bias-corrected Bootstrap)