Full Title: Quantile Elasticity of International Tourism Demand for South Korea using Quantile Autoregressive Distributed Lag Model

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Abstract

This paper investigates international inbound tourism demand for South Korea and its determinants using quantile autoregressive model. In contrast to previous studies which dealt with only conditional mean, we examine effects of covariates at various conditional quantile levels; and therefore, more complete and interesting results are found. For inbound tourism demand, U.S. and Japanese tourism demand are considered. For U.S. tourism demand, costs of living in Korea and competing destinations have moderate significant negative effects only at very high and low quantiles, while income does not have any significant effect to tourism demand. On the other hand, for Japanese tourism demand, income has significantly positive effects at lower quantiles, and living costs in Korea and competing destinations have significant negative effects at higher quantiles. These results address the heterogeneity in the tourism demand analysis.

Key-words: Tourism demand; Quantile autoregression; Elasticity; Response analysis

JEL: C22; L83;

I. INTRODUCTION

Tourism-related companies in Korea increased rapidly (29% of the total number of companies). Moreover, tourism-related income is almost 5% of the total GDP in Korea (annual statistical reports from Korean Tourism Research Institute, 2005). However, tourism balance of payments has been strongly in deficit since 2000 because more Koreans went abroad compared to the number of inbound international tourists. For example, the fact that numbers of inbound and outbound tourists were 6.16 and 11.61 million yields a deficit of 8.49 billion US dollars in 2006 (Korea Tourism Organization, 2007). Because of the above reasons, analyzing inbound tourism demand for South Korea is quite important to evaluate government policies or plans for the tourism industry.

Tourism impact models contribute to our understanding of economic effects of tourism and their measurements (see, Frechtling (1994)). There have been a number of empirical studies for estimating international tourism demand function. For example, Kim and Song (1998), Voget and Wittayakkorn (1998) and Song, Romily and Liu (2000) consider univariate error correction model to estimate international tourism demand. Recent studies extend univariate model to multivariate model such as vector autoregressive model and vector error correction model to take care of relationships among considered variables (see, Lim and McAleer (2001), Dritsakis (2004), Song and Witt (2006), Oh and Ditton (2006), Seo, Park and Yu (2009)). For international tourism demand for Korea, Kim and Song (1998), Song and Witt (2003), Oh (2005) and Oh and Ditton (2006) examined the relationship between tourism demand and other macroeconomic variables. Most of these studies estimated an appropriate conditional mean demand function for international tourism. Although conditional mean function contains some valuable information for determinants of international tourism demand, it might be limited in the sense that only information related with the conditional mean is revealed. Moreover, focusing only on average tendencies of conditional distribution can fail to capture useful information of the inbound tourism demand. For example, if the distribution of inbound tourism demand is highly skewed, the average may not capture the interesting behaviour of the underlying tourism demand. In this paper we estimate inbound international tourism demand and examine its determinants using quantile regression approach.

Quantile regression, first introduced by Koenker and Bassett (1978), estimates a family of conditional quantile functions and provides several summary statistics of the conditional distribution function, rather than one statistic, say, the mean. Analyzing conditional quantile rather than conditional mean function is of great importance for the government and tourism industry managers to adjust policies and plans because the effects of covariates on the lower and upper quantiles may differ. For example, if the government or tourism industry managers are more sensitive to the lower tourism demand than the average level, they might consider conditional lower quantiles to develop their policies or plans. An additional advantage of quantile regression method is that income and price elasticity can be calculated at every quantile level. This is different from the classical log-log linear regression model in which the short-run and long-run elasticity are expressed by single values, the mean elasticity. However, we can estimate various informative elasticity correspond to the conditional quantile levels, that is, quantile elasticity. This is quite useful when one has more interests in higher or lower levels of tourism demand. To the best of our knowledge, no study has used the quantile regression method in the tourism research area even though it is a quite flexible and useful methodology to analyse many economic problems in the tourism studies.

Since most studies for tourism demand consider time series data, one should consider time-dependent structure in the demand function, for example, an autoregressive model. In quantile regression literature, Koenker and Xiao (2006) established the consistency and asymptotic normality of the autoregressive quantiles. However, in their model, a time-series variable is only generated by its predetermined values, i.e., autoregressive process. Since we also consider some exogenous variables as covariates such as price and income variables in the regression model, the model is not a quantile autoregressive (QAR) but a quantile autoregressive distributed lag (QADL) model. The QADL model is an extended version of QAR model in the sense that a dependent time-series variable is explained by not only its previous values but other exogenous variables. QADL model is also more general model to the usual autoregressive distributed lag model which has been frequently used in tourism demand analysis. Galvao, Montes-Rojas and Park (2009) extended the results of Koenker and Xiao (2006) and showed the consistency and asymptotic normality of QADL estimators. In this paper, we apply the results of Galvao, Montes-Rojas and Park (2009), and estimate the quantile income and price elasticity of the international tourism demand for Korea.

For data used in this study, Japanese and U.S. inbound tourists of South Korea are considered from November, 1980 to December, 2005, as proxies for inbound tourism demand. For exogenous variables, the industrial production index, the exchange rate weighted relative price index, and the relative price levels in competing foreign destinations are considered. Since the sample size is relatively small (T=302), the stationary and the moving-blocks bootstrap methods (Politis and Romano (1994), Fitzenberger (1998)) are used instead of estimating the asymptotic variance-covariance matrices of QADL estimator proposed by Galvao, Montes-Rojas and Park (2009).

The empirical results show that there exist asymmetric effects of relative prices and income on tourism demand. For the U.S. tourism demand case, the estimated regression quantile of income is insignificant, but cost of living in Korea and competing destinations have moderate negative effects at the extremes of high and low quantiles. For Japanese tourism demand case, income has significantly positive effects at the [0.02,0.6] quartiles, and living costs in Korea and competing destinations have significant negative effects at [0.5,0.98] and [0.87,0.98] quantiles, respectively. Interestingly, it is found that travelling to South Korea is a luxury good for Japanese tourists who are only in the [0.02, 0.57] conditional quantiles.

The response analysis shows that a positive income shock encourages Japanese tourists who belong to the lower quantiles of conditional distribution of tourism demand to increase their tourism demand. On the other hand, cost shock makes Japanese tourists who belong to the upper quantiles of conditional distribution of tourism demand decrease their tourism demand. For the U.S. case, there are little responses of tourism demand to the shocks of explanatory variables.

Since our empirical results show that the behaviour of each tourism demand for South Korea is different, it can be quite interesting to see how one can distinguish one from the other visitors. As the referees pointed out that, one could apply the decision-tree method (Biggs, deVille and Sue (1991)) and the CHAID program (Chi-squared Automatic Interaction Detection, see Díaz-Pérez, Bethencourt-Cejas and Àlvarez-González (2005) and references therein.)[1] to segment the tourism market. By this method, one can sequentially identify which predictor is most significant in tourism segmentation.

This paper is organised as follows. Section II presents the empirical model. Section III describes the data. Section IV discusses the empirical results. Section V presents the conclusions.

II. THE MODEL

Estimation and inference of the ordinary sample quantiles has been extended to the joint behaviour of many regression quantiles since the works of Koenker and Bassett (1978).[2] In the time-series context, Weiss (1987) and Koul and Mukherjee (1994) consider the linear quantile autoregressive model. Recently, asymptotic behaviours of general autoregression quantile are studied by Koenker and Xiao (2006). Following Koenker and Xiao (2006), consider the p-th order autoregressive process by letting $\{U_t\}$ be a sequence of iid standard uniform random variables,

$$y_t = \theta_0(U_t) + \theta_1(U_t)y_{t-1} + \cdots + \theta_p(U_t)y_{t-p}, \qquad (1)$$

where the θ_j's are unknown function from the interval [0,1] to the real number. If we assume the right hand side of (1) is monotone increasing in the random variable U_t, the τ-th conditional quantile function of y_t can be represented by

$$Q_{y_t}(\tau \mid y_{t-1}, \cdots, y_{t-p}) = \theta_0(\tau) + \theta_1(\tau)y_{t-1} + \cdots + \theta_p(\tau)y_{t-p}, \qquad (2)$$

or more compactly by

$$Q_{y_t}(\tau \mid \Im_{t-1}) = x_t'\theta(\tau), \qquad (3)$$

where $x_t = (1, y_{t-1}, \cdots, y_{t-p})'$, and $\Im_t$ is the information set generated by $\{y_s, s \le t\}$. Most previous theoretical studies for quantile autoregressive model, for example, Weiss (1987) and Koul and Mukherjee (1994), do not consider the effects on conditional scale or shape. However, the quantile autoregression form in (1) and (2) is different from previous studies in that the autoregressive coefficients are τ (quantile)-dependent. Hence, lagged dependent variables can change the location and scale or shape of the conditional distribution.

Basically, the ordinary least squares (OLS) estimator is obtained by minimizing the sum of the squared errors, $\sum_{t=1}^{T}(y_t - x_t'\theta)^2$. Similarly, for any $\tau \in (0,1)$, the estimator $\hat{\theta}(\tau)$ of the quantile autoregression model is the solution of the following minimization problem

$$\min_{\theta \in \Re^{p+1}} \sum_{t=1}^{T} \rho_\tau (y_t - x_t{}'\theta), \qquad (4)$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ denotes the check function (or loss function) and $I(\cdot)$ is the indicator function, $I(\cdot) = 1$ if $u < 0$ and 0 otherwise. Figure 1 represents the check function, $\rho_\tau(u)$. It is clear from Figure 1 that the check function is an asy mmetric loss function if $\tau \neq 0.5$. When $\tau = 0.5$, it leads to a symmetric loss functio n and the corresponding estimator $\hat{\theta}(\tau)$ is the conditional median estimator, i.e., $\hat{\theta}(\tau)$ minimizes $\sum_{t=1}^{T} | y_t - x_t'\theta |$.

[Figure 1]

The τ -th conditional quantile function of y_t could be estimated by

$$\hat{Q}_{y_t}(\tau \mid x_t) = x_t{}'\hat{\theta}(\tau). \qquad (5)$$

For a given τ, Koenker and Xiao (2006) showed that $\sqrt{T}(\hat{\theta}(\tau) - \theta(\tau))$ is asymptotically normal under some regularity conditions.

Based on above quantile autoregressive model, we include additional appropriate exogenous variables in (1) to explain determinants of international tourism demand. Most empirical studies in the tourism demand estimation literature choose some macroeconomic variables such as the disposable income per capita, exchange rate weighted relative price index, transportation costs and exchange rate weighted relative price index in the competing destinations. Among those explanatory variables, we consider three explanatory variables in the quantile autoregressive model.[3] The τ-th conditional quantile function of y_t, (3), can be modified to include the set of information on macroeconomic variables as follows:

$$Q_{y_t}(\tau \mid x_t, z_t) = x_t{}'\theta(\tau) + z_t{}'\beta(\tau), \tag{6}$$

where $z_t = (z_{1t}, z_{2t})$ denoting $z_{1t} = (v_{1t}, v_{2t}, v_{3t})$ is 1 × 3 vector of exogenous macroeconomic variables and z_{2t} consists of $1\times q_1$, $1\times q_2$ and $1\times q_3$ vectors of lagged variables of v_{1t}, v_{2t} and v_{3t}, respectively. $\theta(\tau)$ and $\beta(\tau)$ can be estimated by solving the minimization problem (4). The equation (6) enables us to study the effects of various covariates, such as, the lagged dependent variable $x_t = (1, y_{t-1}, \cdots, y_{t-p})'$ and other exogenous macroeconomic variables z_t, on the different levels of quantiles of y_t in an unifying framework. The statistical and asymptotic properties, such as, the consistency and asymptotic normality, of the above estimator have been established by Galvao, Montes-Rojas and Park (2009). In the empirical section, we estimate variance-covariance matrices using the stationary bootstrap (Politis and Romana (1994)) and the moving-blocks bootstrap methods. Fitzenberger (1998) shows that the moving-blocks bootstrap covariance estimator provides the heteroskedasticity and autocorrelation consistent standard errors for the quantile regression coefficient estimators.

Once the τ-th conditional quantile function of y_t is estimated, the conditional density of y_t can be estimated by the difference quotients,

$$\hat{f}_{y_t}(\tau \mid x_{t-1}, z_{t-1}) = (\tau_i - \tau_{i-1}) / (\hat{Q}_{y_t}(\tau_i \mid x_{t-1}, z_{t-1}) - \hat{Q}_{y_t}(\tau_{i-1} \mid x_{t-1}, z_{t-1})) \qquad (7)$$

for some appropriately chosen sequence of τ's. Intuitively, the density function of y_t conditional on x_{t-1} and z_{t-1} can be estimated non-parametrically using estimates of conditional quantile function, $\hat{Q}_{y_t}(\tau \mid \cdot)$, since the conditional quantile function can be consistently estimated at the sequence of $\tau = (\tau_1, \cdots, \tau_N)$. Equation (7) is quite useful to analyse determinants of international tourism demand. Comparing to the usual conditional expectation model which gives only one predicted number in response to an exogenous shock, the conditional quantile model predicts the entire conditional distribution of y_t. Moreover, when (6) is a conventional log-linear demand equation, $\hat{\beta}(\tau)$ can be interpreted as the elasticity (income and price elasticity). Thus, one can estimate (short-run or long-run) income and price elasticity at every τ-th quantile, which may provide more complete picture for tourism demand analysis.

III. DATA

For estimating international tourism demand, the monthly data from November, 1980 to December, 2005 (a total of 302 observations), are used. We consider two major sources, numbers of U.S. and Japanese tourist arrivals to South Korea, as proxies of inbound tourism demand. Although recent summary statistics for inbound tourist arrivals to South Korea shows that Chinese and other Asian tourist arrivals are increasing rapidly, U.S. and Japanese tourists still represent 50.71% of the total number of inbound tourist arrivals in

January, 2005. Thus, it is reasonable to choose two representative countries to analyse inbound tourism demand. It is also interesting to see the difference of determinants between these two countries since tourist from these two countries may have different behaviours due to physical distances and cultural backgrounds.

All variables are taken in the natural logarithm. For explanatory variables z_{1t} in (6) we consider the logarithm of industrial production index for origin country i, $IPI_{i,t}$, the logarithm of exchange rate adjusted relative price level (real exchange rate) between Korea and origin country i, $P_{i,t}$, and a composite price index representing the logarithm of weighted sum of exchange rate adjusted relative price levels between competing foreign destinations and origin country i, $PS_{i,t}$, as proxies of the income variable, costs of living at country i and living costs at the competing destinations, respectively. For competing destinations we choose four Asian countries, Hong Kong, Singapore, Thailand and Philippines. Other variables can be used as explanatory variables, for example, transportation costs and specific dummy variables. However, Kim and Song (1998) takes airfares as proxy of transportation costs and reports airfares do not have significant effects to tourism demand for South Korea. The results of Song and Witt (2003) shows that dummy variable which takes care of the 1988 Seoul Olympic Games is not statistically significant for U.S. and Japanese tourists. Since quantile regression is a robust method, estimators are not affected much by outliers. Moreover, near-extreme events can be explained by high or low conditional quantile within the model. With the above reasons, we do not include transportation costs and dummy variables as explanatory variables.

Effective price, $P_{i,t}$ and $PS_{i,t}$, can be written as

$$P_{i,t} = \log\{(CPI_{KR,t} / CPI_{i,t}) / ER_{i,t}\}, \tag{8}$$

$$PS_{i,t} = \log\{\sum_{j=1}^{4} \omega_j (CPI_{j,t} / CPI_{i,t}) / ERS_{i,t}\}, \tag{9}$$

where $CPI_{i,t}$ and $CPI_{KR,t}$ are the consumer price index for origin country i and South Korea, respectively, $ER_{i,t}$ denotes the nominal exchange rate between South Korea and origin country i defined by the number of currency unit of Korea per unit of origin country i, $ERS_{i,t}$ denotes the nominal exchange rate between competing country j and origin country i, and ω_j is the market shares of tourist arrivals for j country among the competing destinations.

Numbers of tourist arrivals and industrial production index (IPI) are seasonally adjusted by X12-ARIMA filter and also detrended using deterministic linear trend.[4] Since we use an autoregressive model U.S. and Japan tourist arrivals series have to be stationary. The use of an autoregressive model for non-stationary time-series data is highly unsuitable. Table 1 shows the summary statistics and the results of unit root tests for U.S. and Japan tourist arrival series.

[Table 1]

For unit-root test, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are performed. The optimal truncation lags and bandwidths are selected by the Schwarz Bayesian Criterion (SBC) and Newey-West automatic bandwidth for ADF and PP tests, respectively. For both series, we reject the null hypothesis that the series have a unit-root at the 5% significance level. The data series for U.S. and Japan tourism demand are plotted in

Figure 2 and 3, respectively. One can expect tourist arrivals have a positive correlation with IPI, a negative correlation with P (costs of living in Korea) and a positive correlation with PS (costs of living in competing destinations). In Figure 2, it is hard to observe such relationships for U.S. case. IPI achieves the highest value around 2000 but U.S. tourist arrivals keep decreasing around 2000. One notable exception is the relationship between tourist arrivals and P around 1981-1987. On the other hand, in Figure 3, Japanese tourist arrivals have positive and negative relationships with IPI and P, respectively. However, it seems there is little positive relationship between tourist arrivals and PS.

[Figure 2]

[Figure 3]

IV. EMPIRICAL RESULTS

Estimation results for quantile autoregression model

The selection of the lag order of the autoregressive model is of importance, and can be implemented by some useful information criteria. Galvao, Montes-Rojas and Park (2009) suggested the Bayesian information criteria (BIC) along the lines suggested by Machado (1993). When one considers the conditional median regression, BIC can be written by

$$BIC = n\log\hat{\sigma} + \frac{1 + p + (1 + q_1 + q_2 + q_2)\cdot\dim(z_{2t})}{2}\log n,$$

where $\hat{\sigma} = n^{-1}\sum_{t=1}^{n}| y_t - x_t'\theta(1/2) - z_t'\beta(1/2)|$ and $\dim(z_{2t})$ denotes the dimension of z_{2t}.

For other quantiles, the obvious asymmetric modification of the above equation can be used. After examining various combinations of lag orders $l = (p, q_1, q_2, q_3)$ in (6),

$l = (2,0,0,0)$ is selected for both U.S. and Japan cases compared to other lag orders.[5] For convenience, the final conditional quantile equation for the U.S. and Japanese tourism demand, $y_{US,t}$ and $y_{JP,t}$, respectively, can be written as follows:

$$Q_{y_{i,t}}(\tau \mid y_{i,t-1}, z_{1,t}) = \theta_{i,0}(\tau) + \theta_{i,1}(\tau) y_{i,t-1} + \theta_{i,2}(\tau) y_{i,t-2} + \beta_{i,1}(\tau) IPI_{i,t} + \beta_{i,2}(\tau) P_{i,t} + \beta_{i,3}(\tau) PS_{i.t}, \quad (10)$$

for i ={US, JP}.

Figure 4 shows fitted conditional quantiles at $\tau = 0.05$, 0.5 and 0.95 for U.S. and Japanese inbound tourism demand. 0.05 and 0.95 conditional quantiles are plotted with gray lines. It is worthwhile mentioning that fitted 0.05 and 0.95 conditional quantiles explain near-extreme events, for example, Severe Acute Respiratory Syndrome (SARS) in 2003, very well.

[Figure 4]

The estimation results for tourism demand function of U.S. and Japan are summarized in Figures 5 and 6, respectively. For brevity, we chose to present the results in a graphical form. Each panel in Figures 5 and 6 plots on coordinate of the parameter vector $(\theta_{i,0}(\tau), \theta_{i,1}(\tau), \theta_{i,2}(\tau), \beta_{i,1}(\tau), \beta_{i,2}(\tau), \beta_{i,3}(\tau))'$ as a function of τ. τ is taken to have values in [0.02, 0.98]. The shaded area in each plot represents a 95 percent confident band.[6]

In Figure 5, U.S. tourism demand case, $\hat{\theta}_1(\cdot)$ and $\hat{\theta}_2(\cdot)$ are significantly positive but other $\hat{\beta}_1(\cdot)$, $\hat{\beta}_2(\cdot)$ and $\hat{\beta}_3(\cdot)$ are not significant for the most quantile values. This implies IPI, P and PS variables rarely affect U.S. tourism demand. Since $\hat{\theta}_1(\cdot)$ is significantly positive and decreasing for all τ values we can say that one month previous

U.S. tourism demand has much more impacts at lower quantiles than higher quantiles. For quantile range [0.22, 0.80], $\hat{\theta}_1(\cdot)$ is quite stable around 0.63 which is similar to OLS estimate, 0.66. Since $\hat{\theta}_1(\cdot)+\hat{\theta}_2(\cdot)<1$ for the whole quantile region, we can say U.S. tourism demand is stationary for all τ values. $\hat{\beta}_1(\cdot)$ is negative for most quantile values. This is different from initial expectation that higher income gives positive effects to tourism demand. However, $\hat{\beta}_1(\cdot)$ is not significant for whole quantile range and $\hat{\beta}_2(\cdot)$ is significantly positive at [0.12 0.18] and negative at [0.9, 0.98]. Thus, when cost of living in South Korea increases, U.S. tourism demand increases slightly at lower quantiles but decreases sharply at higher quantiles. Although this is inconsistent with our initial expectations, it could be explained by different objective of tourists. For example, U.S. tourism demand at higher quantiles can be due to the vacation objective while the business objective can be main reason for tourism demand at lower quantiles. This kind of heterogeneity may help to explain the contradicting effects of $\hat{\beta}_2(\cdot)$. In the conditional mean model, OLS coefficient of β_2 is -0.0095 and not significant. The minus sign of OLS coefficient may be due to large negative values of $\hat{\beta}_2(\tau)$ for $\tau \in [0.90, 0.98]$. $\hat{\beta}_3(\tau)$ is not significant for most quantile region except around 0.18 and 0.92 quantiles. Negatively significant values at $\tau \in [0.92, 0.98]$ of $\hat{\beta}_3(\tau)$ imply that four competing destinations are not substitutes but complements at higher quantiles for U.S. tourism demand.

[Figure 5]

In Figure 6, Japan tourism demand case, $\hat{\theta}_1(\cdot)$ and $\hat{\theta}_2(\cdot)$ are significantly positive for most quantile values and quite similar to those of U.S. case. $\hat{\beta}_1(\cdot)$, $\hat{\beta}_2(\cdot)$ and $\hat{\beta}_3(\cdot)$ show overall decreasing pattern over τ. $\hat{\beta}_1(\cdot)$ is significantly positive around [0.02, 0.6], whereas $\hat{\beta}_2(\cdot)$ is significantly negative around [0.5, 0.98]. These imply that income and costs of living in Korea do not have distinct effects to tourism demand at [0.6, 0.98] and [0.02, 0.5], respectively. These results could be important for government and tourism-related industry managers to evaluate their policies and plans. If they are pessimistic about future Japanese tourism demand so that they decide to consider that at lower conditional quantiles, income levels of Japanese tourists should be considered rather than cost of living in Korea. In the similar manner, if they are interested in tourism demand at higher conditional quantiles, cost of living should be more weighted than income levels. Since $\hat{\beta}_3(\cdot)$ is significantly negative at high quantile values, [0.87, 0.98], four competing destinations are not substitutes but complements for Japanese tourists. This is a similar result to U.S. case.

[Figure 6]

Estimation results for the long-run elasticities

Since we consider the log-linear model, the long-run elasticity of income, relative price in South Korea and relative price in competing destinations can be easily obtained from the estimated regression quantiles. The long-run elasticities of explanatory variables are given by $\varepsilon_I(\tau) = \beta_{i,1}(\tau)/(1-\theta_{i,1}(\tau)-\theta_{i,2}(\tau))$, $\varepsilon_P(\tau) = \beta_{i,2}(\tau)/(1-\theta_{i,1}(\tau)-\theta_{i,2}(\tau))$ and $\varepsilon_{PS}(\tau) = \beta_{i,3}(\tau)/(1-\theta_{i,1}(\tau)-\theta_{i,2}(\tau))$ for income (IPI), relative price in South Korea (P) and relative price in competing destinations (PS), respectively. The estimated long-run elasticities are plotted in Figure 7. The 95 percent bootstrapped confidence interval is illustrated by gray lines, and dashed horizontal lines represent elasticity computed by OLS coefficients.

[Figure 7]

The long-run elasticities have quite similar shapes to corresponding regression quantile processes in Figures 5 and 6. $\hat{\varepsilon}_I(\cdot)$, $\hat{\varepsilon}_P(\cdot)$ and $\hat{\varepsilon}_{PS}(\cdot)$ for U.S. are not significant although regression quantile $\hat{\beta}_1(\cdot)$ and $\hat{\beta}_2(\cdot)$ are significant over some intervals in (0, 1). These are due to uncertainties in the autoregression quantiles $\hat{\theta}_1(\cdot)$ and $\hat{\theta}_2(\cdot)$. For Japan case, $\hat{\varepsilon}_I(\tau)$ is significantly positive for $\tau \in [0.02, 0.7]$ and has overall decreasing pattern. Significant $\hat{\varepsilon}_I(\tau)$ values vary from 0.4 ($\tau = 0.57$) to 5.8 ($\tau = 0.1$). Since $\hat{\varepsilon}_I(\tau) = 1$ at $\tau = 0.57$, we can say that travelling to South Korea is a luxury good for Japanese tourists who belong to 0 to 0.57 conditional quantiles, while it is not a luxury good for $\tau \in [0.57, 0.7]$. $\hat{\varepsilon}_P(\tau)$ are significantly negative for $\tau \in [0.3, 0.98]$ and decreasing in overall, and its varying range is given by [-0.17,-0.97], whereas $\hat{\varepsilon}_{PS}(\tau)$ is only significant at upper quantiles. At the high quantiles, say $\tau \in [0.9, 0.98]$, $\hat{\varepsilon}_{PS}(\tau)$ is larger than $\hat{\varepsilon}_P(\tau)$ in absolute value. This implies Japanese tourists who belong to high quantiles are more sensitive to cost of living in competing destinations than that in South Korea.

We compare our estimates $\hat{\varepsilon}_I(\cdot)$, $\hat{\varepsilon}_P(\cdot)$ and $\hat{\varepsilon}_{PS}(\cdot)$ with corresponding estimates reported by previous studies. As the following information shows, our estimates of these elasticities are quite different from those in the previous studies for U.S. tourism demand. However, this difference is moderate for Japan tourism demand. These dissimilarities can be due to usage of different time horizon or time frequency or explanatory variables.

Using annual time-series data from 1961 to 1995, Kim and Song (1998) estimated inbound tourism demand in South Korea. They used error correction model and analysed tourism demand by four major tourist-generating countries: Germany, Japan, U.K. and U.S. Their estimated long-run income elasticities for U.S. and Japan are 2.998 and 2.536, respectively, and significant at the 1% significance level. The elasticity of relative living price in Korea for U.S. case is -0.544, but it is not significant at the 5 percent level. Price variable for Japan case is excluded from estimation procedure because it yielded very insignificant estimate. For competing destinations, it turns out that Malaysia and China are substitutes whereas Singapore and Thailand are complements. Recently, Song and Witt (2003) used the general-to-specific procedure to select the best tourism forecasting model. They used such procedures to estimate tourism demand in South Korea using annual time-series data from 1962 to 1994. Since they do not report estimated elasticities, we calculate the long-run elasticities of income, relative price, and relative price in competing destinations based on their reported estimates. Unfortunately, autoregressive coefficient, AR(1), for Japan tourism demand is explosive, i.e., greater than 1, and therefore, we do not calculate elasticities for Japan case. The elasticities for U.S. case are $\hat{\varepsilon}_I = 1.23$, $\hat{\varepsilon}_P = -4.17$ and $\hat{\varepsilon}_{PS} = 1.26$. The major difference between our results and those of previous studies are of U.S. tourism demand case. While our estimated elasticities are insignificant at all quantile values, $\hat{\varepsilon}_I$ and $\hat{\varepsilon}_{PS}$ in Kim and Song (1998) are significant and have distinct values. The same is for $\hat{\varepsilon}_P$ and $\hat{\varepsilon}_{PS}$ in Song and Witt (2003). For Japan case, the above inconsistencies between our estimates and those of previous studies seem to be shrunken. Income elasticity in Kim and Song (1998) , 2.536, is in the range of our estimates, $\hat{\varepsilon}_I(\tau) \in [0.4, 5.8]$. Since we consider Hong Kong, Singapore, Thailand and Philippines as major competing destinations, significant negative $\hat{\varepsilon}_{PS}(\cdot)$ in upper quantiles support Kim and Song (1998)'s results. However, while both Kim and Song (1998) and Song and Witt (2003) reported that relative price coefficients are insignificant, $\hat{\varepsilon}_P(\tau)$ is significantly negative for $\tau \in [0.3, 0.98]$.

Response of conditional tourism demand to an exogenous shock

Finally, responses of tourism demand to particular shocks are analysed using estimated models. Suppose for a moment that $\xi_i(\cdot)$ for some $i > 0$ and $\tau \in (0,1)$ in conditional quantile function, $Q_{y_t}(\tau \mid X_t) = \xi_0(\tau) + \sum_{i=1}^{n} \xi_i(\tau) X_{i,t}$, is strictly positive and monotone decreasing. When a positive shock is given to $X_{i,t}$, a positive (negative) coefficient associated with $X_{i,t}$ generates higher (lower) values of $Q_{y_t}(\tau \mid X_t)$ given that other elements of $X_{i,t}$, $i = 1, 2, \cdots, n$ are the same. Thus, $\xi_i(\cdot) > 0$ ensures upward (downward) shift of $Q_{y_t}(\tau \mid X_t)$ at point τ with respect to a positive (negative) shock. Moreover, since $\xi_i(\cdot)$ is monotone decreasing such a upward (downward) shift is distinct at lower conditional quantiles. The above effects can be directly illustrated by comparing two densities, for example, pre-shock and post-shock conditional densities. Conditional density can be estimated using (7).[7] Figures 8 and 9 show responses of U.S. and Japan tourism demand to one standard deviation shock, respectively.[8]

In Figure 8, since $\hat{\theta}_1(\cdot)$ is positive and decreasing left tail parts shift to the right considerably more than right tail parts do. In the same manner, positive and increasing $\hat{\theta}_2(\cdot)$ leads to more positive shift of right tail than left tail. Since $\hat{\beta}_1(\cdot)$, $\hat{\beta}_2(\cdot)$ and $\hat{\beta}_3(\cdot)$ are closed to 0 there are no distinct changes for those conditional densities.

[Figure 8]

For Japan case (Figure 9), responses of conditional tourism demand for AR(1) and AR(2) are very similar to those of U.S. case. When a shock is given to income, only lower tail part shift to the right without having changes in upper tail part. This implies that a positive shock to income encourages Japanese tourists who have relatively lower tourism demand. On the other hand, positive shocks to living costs in South Korea and competing destinations (P and PS) make upper tails move to the left without particular changes in lower tails. This suggests Japanese tourists who have relatively higher tourism demand are disappointed with positive living cost shocks.

[Figure 9]

V. CONCLUSION

This paper examines tourism demand and its determinants of inbound tourism demand in South Korea using quantile autoregressive distributed lag model. We consider the U.S. and Japanese tourist arrivals as proxies for tourism demand. For U.S. tourism demand case, autoregressive quantiles of order two are significant over the whole quantile region. The estimated regression quantile of income is insignificant over the whole quantile region. Costs of living in Korea and competing destinations have moderate negative effects only at the very high and low quantiles. On the other hand, for Japan tourism demand, income has significantly positive effect at [0.02, 0.6] quantile, and living costs in Korea and competing destinations have significant negative effects at [0.5, 0.98] and [0.87, 0.98], respectively. The estimated long-run elasticities of three explanatory variables are similar to estimated regression quantiles. One interesting finding compared to previous studies is that travelling to South Korea is a luxury good for Japanese tourists who are only in the (0, 0.57) conditional quantiles. The effects of income and cost shock on the tourism demands are also studied by the response analysis. The results show that a positive income and cost shock have different effects on the Japan tourism demand. Specifically, a positi ve income shock encourages Japanese tourists who are in the lower quantiles of conditional distribution of tourism demand to increase their tourism demand. On the other hand, cost shock makes Japanese tourists who are in the upper quantiles of conditional distribution of tourism demand decrease their tourism demand. For the U.S. case, there are little responses of tourism demand to the shocks of explanatory variables.

The empirical results of this study show that there exists the country specific heterogeneity in the tourism demand. For the U.S. case, most covariates turned out to be statistically insignificant. However, Japanese tourism demand for South Korea can be explained by chosen independent variables quite well. This different behaviours of two in-bound tourism demands is due to the different individual characteristics of two countries, for example, location of a country, physical distance from the origin, individual budget constraint, the neighborhood of the origin, among others. Thus identifying the different characteristics of demands is of importance for developing tourism market strategies and government policies.

Endnotes

1. We are very grateful to the referees for pointing out this method and providing related literature to us.

2. See Koenker (2005) for excellent survey of quantile regression.

3. Three explanatory variables are discussed in the section III.

4. The X-12-ARIMA seasonal adjustment method was developed by the Census Bureau in the United States and has been frequently used for seasonal adjustment. For more detailed discussion on the X-12-ARIMA seasonal adjustment method (see, Findley, Monsell, Bell, Otto and Chen (1998)). The linear detrending series of IPI can be obtained from the regression of IPI on linear time trend variable with constant.

5. When lagged explanatory variables in addition to the level variables are added to (6), the estimated $\hat{\beta}(\tau)$ corresponds to those variables are not significant over all τ. When only lagged explanatory variables are added to (6), the corresponding $\hat{\beta}(\tau)$ are not significant over all τ. The same is for AR(3) term.

6. Variance-covariance matrices are estimated using the stationary bootstrap method proposed by Politis and Romana (1994). We also estimated variance-covariance matrices using the moving-blocks bootstrap method. Since the moving-blocks bootstrap method yields very similar 95 percent confident band the results for the moving-blocks bootstrap are not reported.

7. Chernozhukov and Umantsev (2001) used similar approach for conditional value-at-risk analysis.

8. Responses of conditional tourism demand to negative shocks are also estimated. Since they have mirror images of positive shock case, the corresponding results are not reported in this paper.

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TABLES

Table 1. Summary statistics and unit root tests

	U.S. arrivals	Japan arrivals
Mean	0.0013	0.0011
Median	0.0052	0.0016
Max	0.4746	0.4000
Min	-0.4750	-0.8845
Std. Dev.	0.1604	0.1977
Skewness	-0.3582	-0.5055
Kurtosis	3.6274	4.1386
J-B	11.41**	29.17**
(p-value)	0.0033	(0.0000)
	Unit root test	
ADF	-2.9769**	-2.8796**
(lag)	(1)	(1)
(p-value)	(0.0030)	(0.0040)
PP	-3.2015**	-3.4751**
(bandwidth)	(9)	(2)
(p-value)	(0.0014)	(0.0006)

Notes: J-B denotes the Jarque and Bera test for normality defined as T[skewness^2/6 +(kurtosis- 3)^2/24] which is asymptotically distributed as $\chi^2(2)$. (lag) and (bandwidth) for ADF and PP test are selected by Schwarz Bayesian Criterion and Newey-West automatic bandwidth, respectively. * and ** denote statistical significance at the 5% and 1% level, respectively.

FIGURES

Figure 1. Quantile regression: ρ function

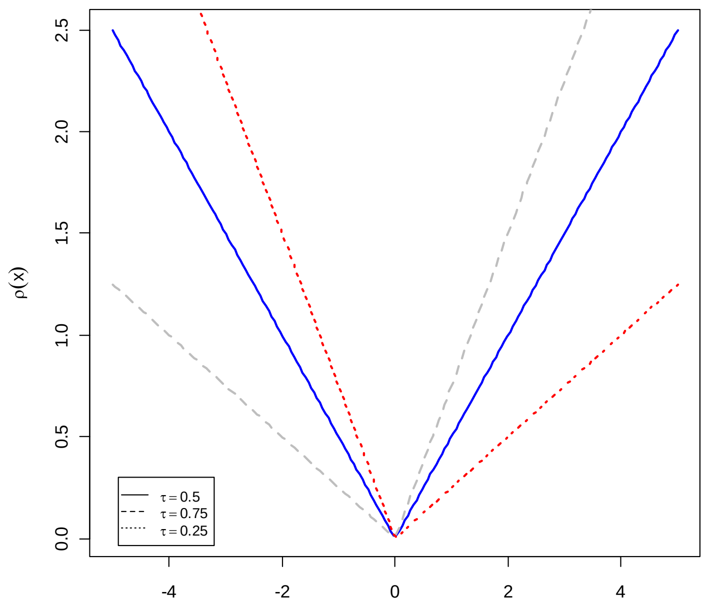


Figure 2. U.S. data series

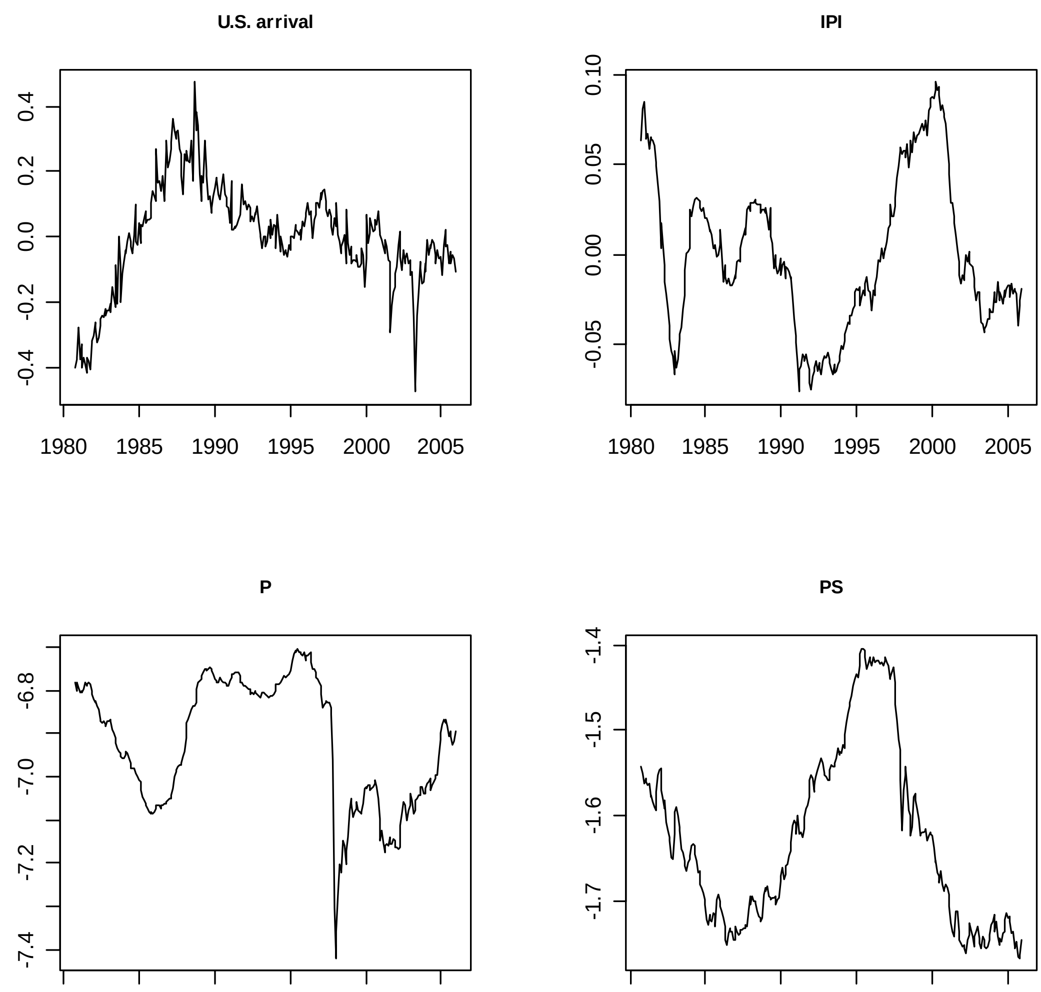


Figure 3. Japan data series

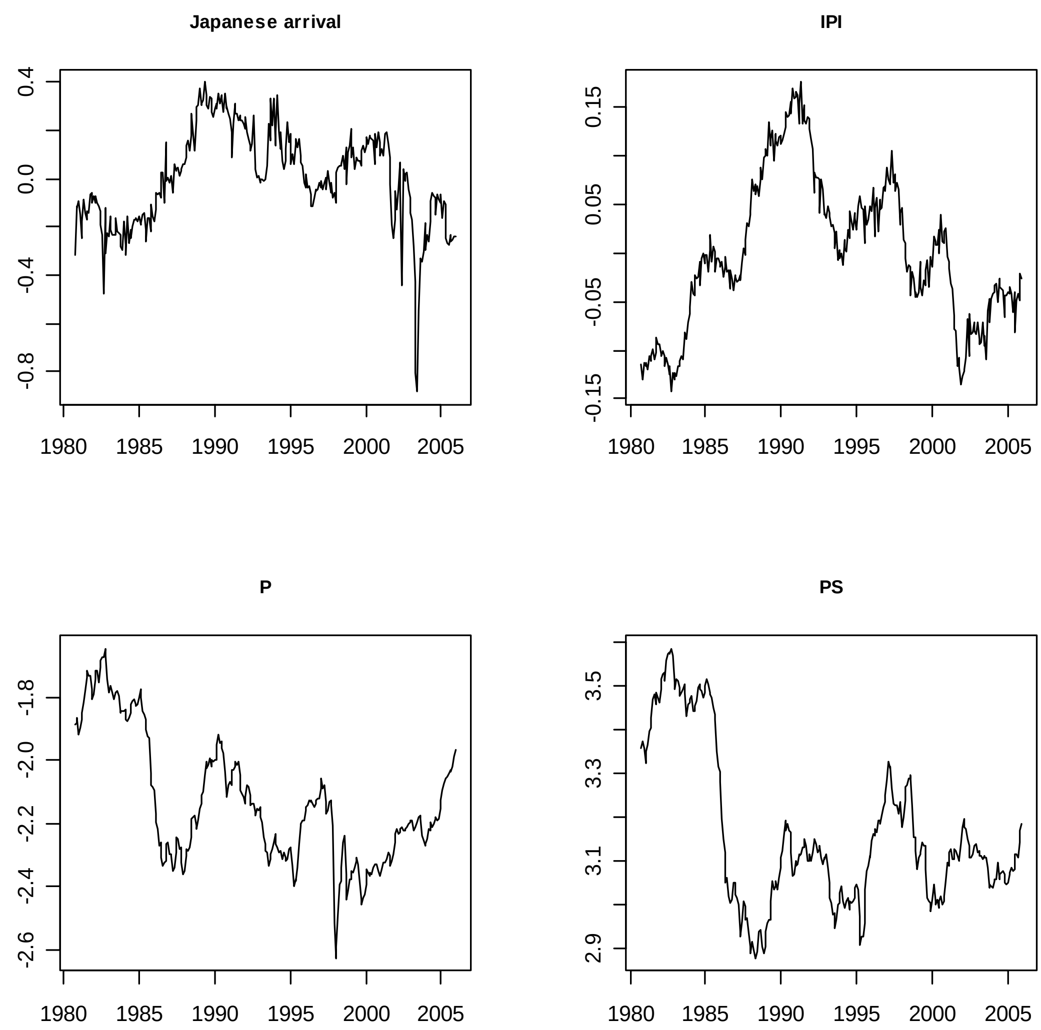
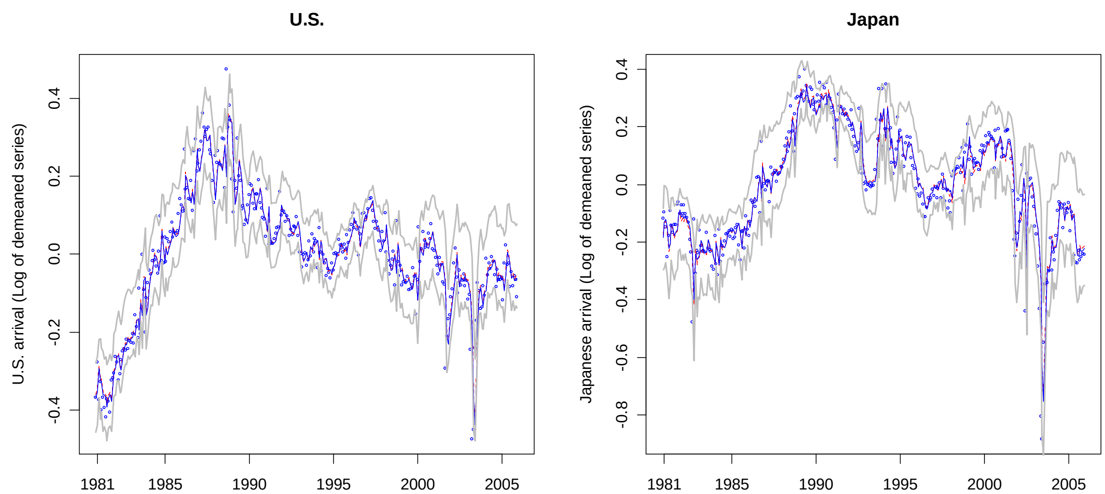
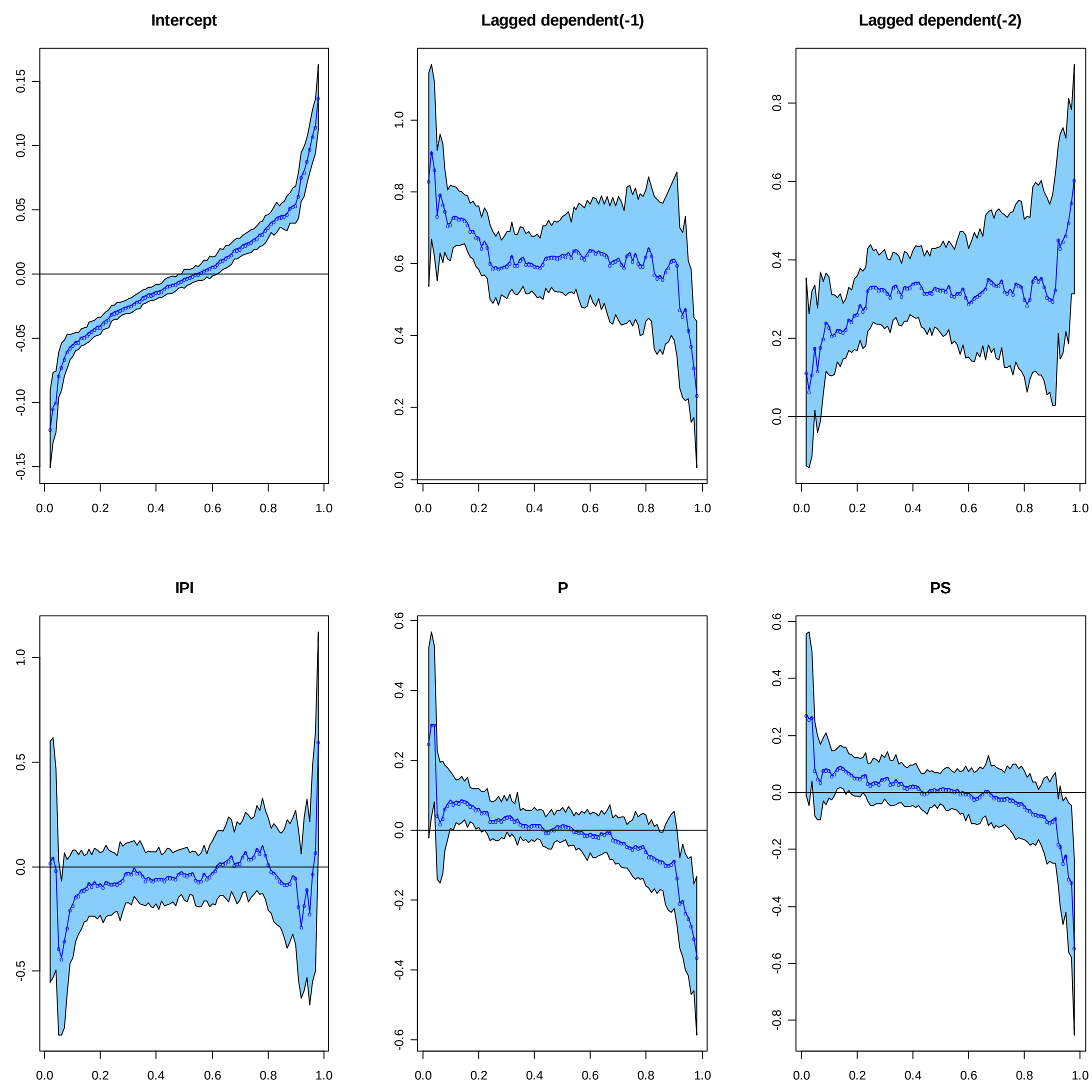


Figure 4. Quantile autoregression process for U.S. and Japan tourism arrivals



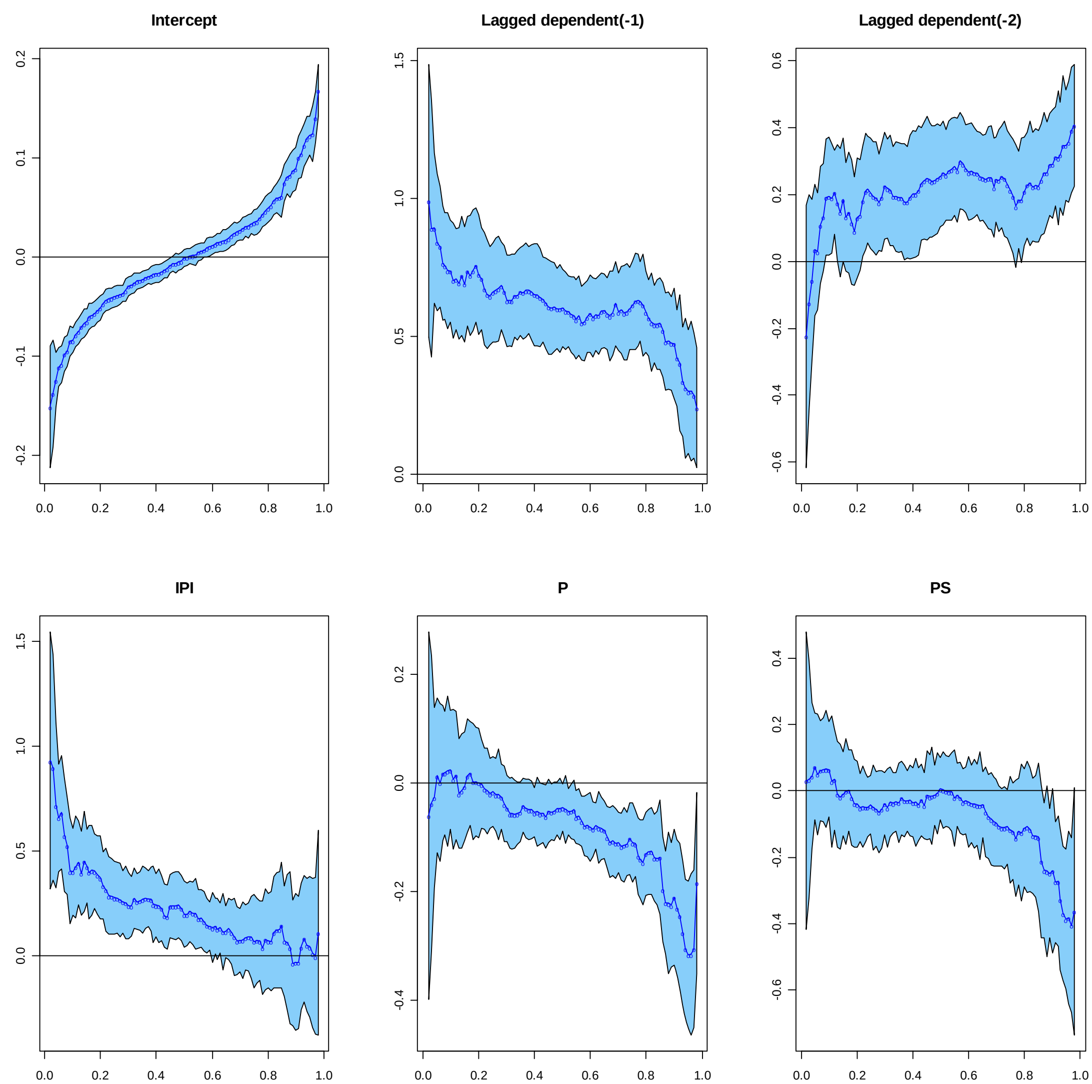
Notes: The plot shows a scatter plot of U.S. and Japan tourist arrivals. Superimposed on the plot are {0.05, 0.95} quantile regression lines in gray and the median fit in solid line.

Figure 5. Quantile autoregression process for U.S. tourism demand



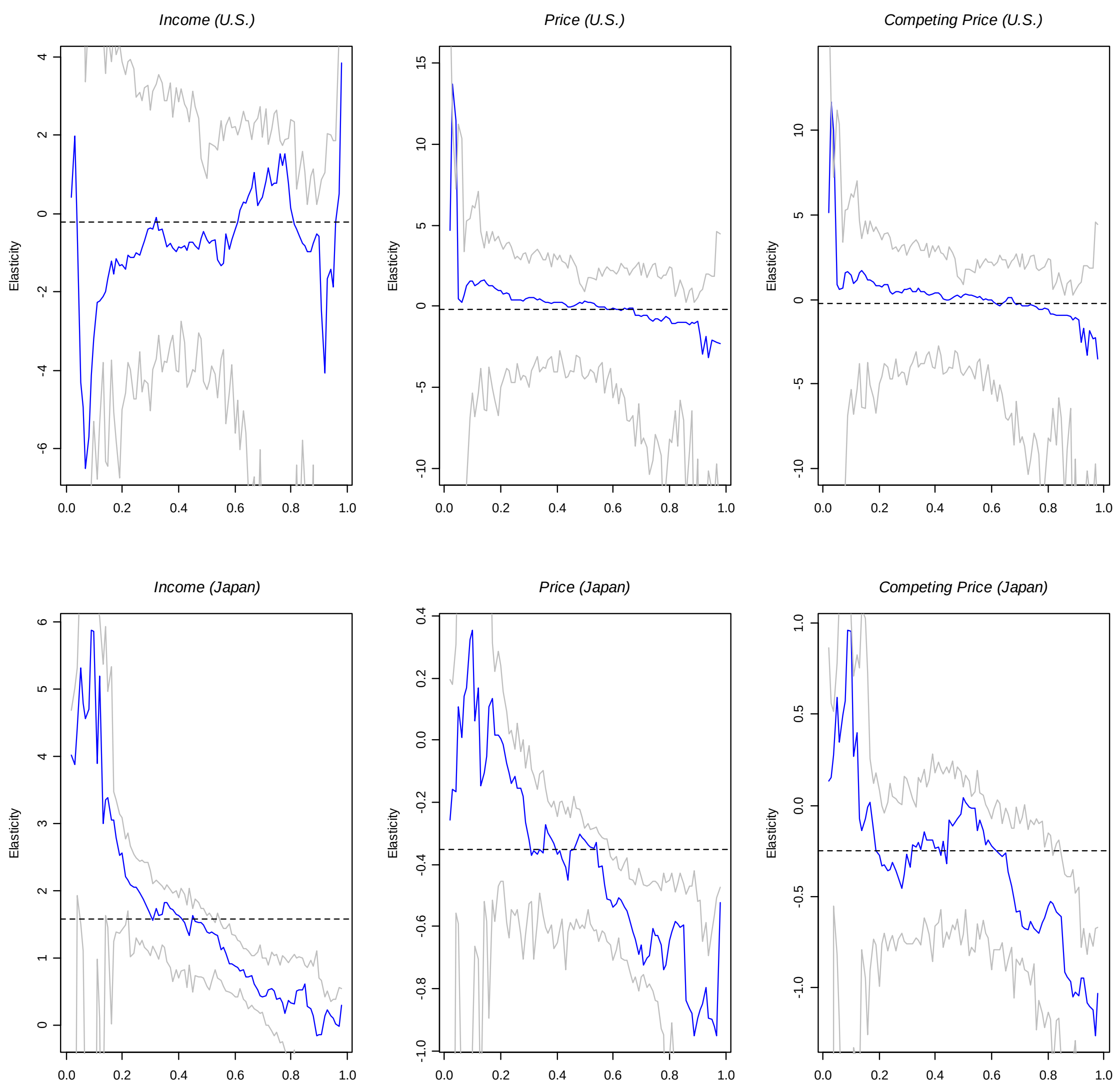
Notes: The shaded region illustrates a 95% confidence band for the estimated effects. The standard errors for regression quantile are estimated by the stationary bootstrap method.

Figure 6. Quantile autoregression process for Japan tourism demand



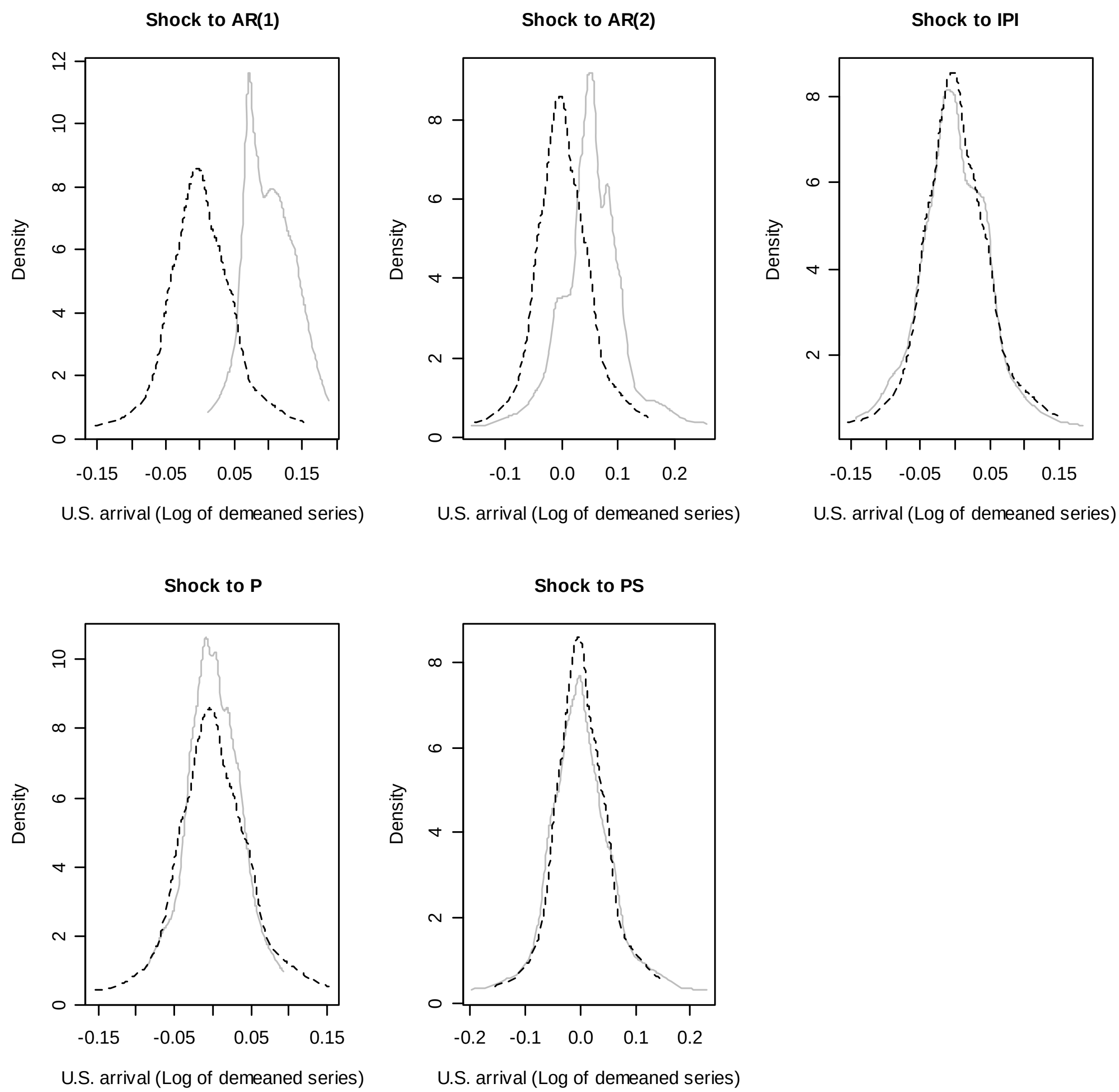
Notes: The shaded region illustrates a 95% confidence band for the estimated effects. The standard errors for regression quantile are estimated by the stationary bootstrap method.

Figure 7. Long-Run Elasticities



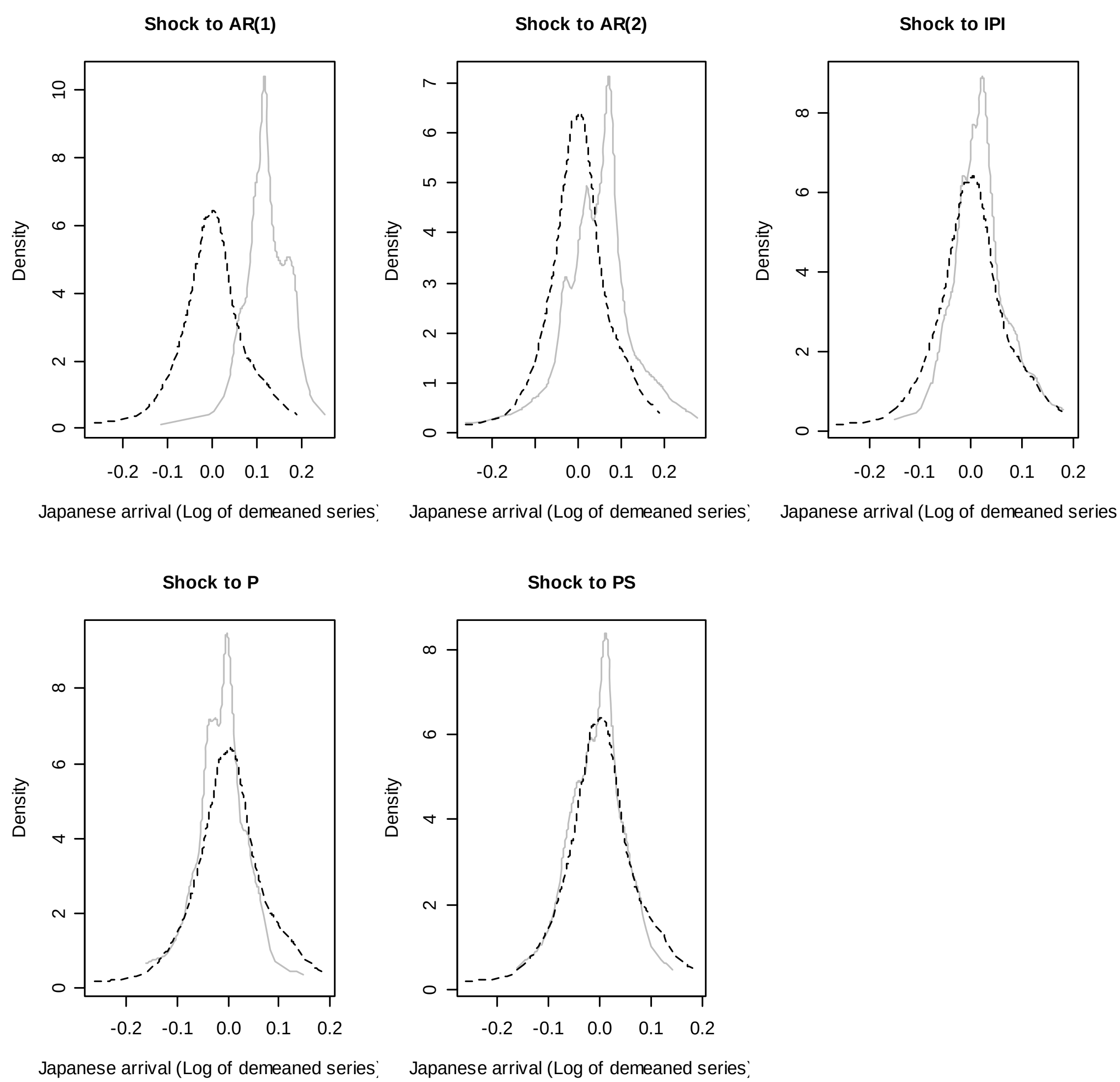
Notes: Gray lines illustrates a 95% bootstrap confident band for the estimated long-run elasticities. Dashed horizontal lines denote the long-run elasticities estimated by OLS method.

Figure 8. Local effects on the density of U.S. tourism demand by positive shocks.



Notes: Conditional density of tourist demand for pre-shock and post-shock cases are illustrated with dashed and gray lines, respectively.

Figure 9. Local effects on the density of Japan tourism demand by positive shocks.



Notes: Conditional density of tourist demand for pre-shock and post-shock cases are illustrated with dashed and gray lines, respectively.