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# Quantile elasticity of international tourism demand for South Korea using the quantile autoregressive distributed lag model

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Using the quantile autoregressive model, this paper investigates international inbound tourism demand for South Korea and its determinants. In contrast to previous studies which have dealt with the conditional mean only, the authors examine the effects of covariates at various conditional quantile levels. US and Japanese tourism demand are considered for inbound tourism demand. For US tourism demand, the costs of living in Korea and competing destinations have moderately significant negative effects at very high and low quantiles only, while income does not have any significant effect on tourism demand. On the other hand, for Japanese tourism demand, income has significant 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 tourism demand analysis.

*Keywords*: tourism demand; quantile autoregression; elasticity; response analysis

*JEL classification*: C22; L83

There has been a rapid increase of tourism-related companies in Korea (they constitute, at the time of writing, 29% of the total number of companies). Moreover, tourism-related income is almost 5% of the total GDP in Korea (annual statistical reports from the Korean Tourism Research Institute, 2005).

However, the tourism balance of payments has been strongly in deficit since 2000, because more Koreans have travelled abroad than there have been inbound international tourists. For example, the fact that numbers of inbound and outbound tourists were 6.16 and 11.61 million in 2006 yielded a deficit of US$8.49 billion (Korea Tourism Organization, 2007). Analysing inbound tourism demand for South Korea is therefore important for the evaluation of government policies or plans for the tourism industry.

Tourism impact models contribute to our understanding of the 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 Wittayakorn (1998) and Song *et al* (2000) consider the univariate error correction model to estimate international tourism demand. Recent studies extend the univariate model to a multivariate model such as the vector autoregressive model and the vector error correction model to take care of relationships among considered variables (see Lim and McAleer, 2001; Dritsakis, 2004; Oh and Ditton, 2006; Song and Witt, 2006; Seo *et al*, 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 the conditional mean function contains some valuable information for the determinants of international tourism demand, it is limited in the sense that only information related to the conditional mean is revealed. Moreover, focusing only on the average tendencies of conditional distribution can fail to capture useful information about 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 international inbound tourism demand and examine its determinants using the 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. Analysing the conditional quantile rather than the conditional mean function is of great importance for government and tourism industry managers in adjusting policies and plans, because the effects of covariates on the lower and upper quantiles may differ. For example, if government or tourism industry managers are more sensitive to lower tourism demand than the average level, they might consider conditional lower quantiles to develop their policies or plans. An additional advantage of the 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- and long-run elasticities are expressed by single values, the mean elasticity. However, we can estimate various informative elasticities corresponding to the conditional quantile levels – that is, quantile elasticity. This is useful in examining 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 flexible and useful methodology for analysing many economic problems in tourism studies.

Since most studies of tourism demand consider time-series data, one should consider a time-dependent structure in the demand function – for example, an autoregressive model. In the 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 generated only by its predetermined values (that is, an 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 the QAR model in the sense that a dependent time-series variable is explained not only by its previous values but also by other exogenous variables. The QADL model is also a more general model than the usual autoregressive distributed lag model which has been frequently used in tourism demand analysis. Galvao *et al* (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 *et al* (2009) and estimate the quantile income and price elasticity of the international tourism demand for Korea.

For the data used in this study, Japanese and US 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 the QADL estimator proposed by Galvao *et al* (2009).

The empirical results show that there are asymmetric effects of relative prices and income on tourism demand. For the US tourism demand case, the estimated regression quantile of income is insignificant, but the cost of living in Korea and competing destinations has moderate negative effects at the extremes of high and low quantiles. For the Japanese tourism demand case, income has significantly positive effects at the [0.02, 0.6] quantiles, and living costs in Korea and competing destinations have significant negative effects at the [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 the 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 the conditional distribution of tourism demand decrease their tourism demand. For the US case, there are little responses of tourism demand to the shocks of explanatory variables.

Since our empirical results show that the behaviour of each country's tourism demand for South Korea is different, it is interesting to see how one can distinguish one set of visitors from the other. One could apply the decision-tree method (Biggs *et al*, 1991) and the CHAID programme (chi-squared automatic interaction detection; see Díaz-Pérez *et al*, 2005, and references

therein)[1] to segment the tourism market. By this method, one can identify sequentially which predictor is most significant in tourism segmentation.

This paper is organized as follows. The next section presents the empirical model. The subsequent two sections describe the data and discuss the empirical results. The final section sets out our conclusions.

## 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, the asymptotic behaviour of the general autoregression quantile has been 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,

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

where the $\theta_j$s are an 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 $\tau$th conditional quantile function of $y_t$ can be represented by

$$Q_{y_t}(\tau | y_{t-1},\ldots,y_{t-p}) = \theta_0(\tau) + \theta_1(\tau)y_{t-1} + \ldots + \theta_p(\tau)y_{t-p}, \tag{2}$$

or more compactly by

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

where $x_t = (1, y_{t-1},\ldots,y_{t-p})'$ and $\Im_t$ is the information set generated by $\{y_s, s \leq t\}$. Most previous theoretical studies of the 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 $\tau$ (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, $\Sigma_{t=1}^{T}(y_t - x_t'\theta)^2$. 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:

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

where $\rho_\tau(u) = u(\tau - I(u < 0))$ denotes the check function (or loss function) and $I(\bullet)$ is the indicator function, $I(\bullet) = 1$ 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 asymmetric loss function if $\tau \neq 0.5$. When $\tau = 0.5$, it leads to

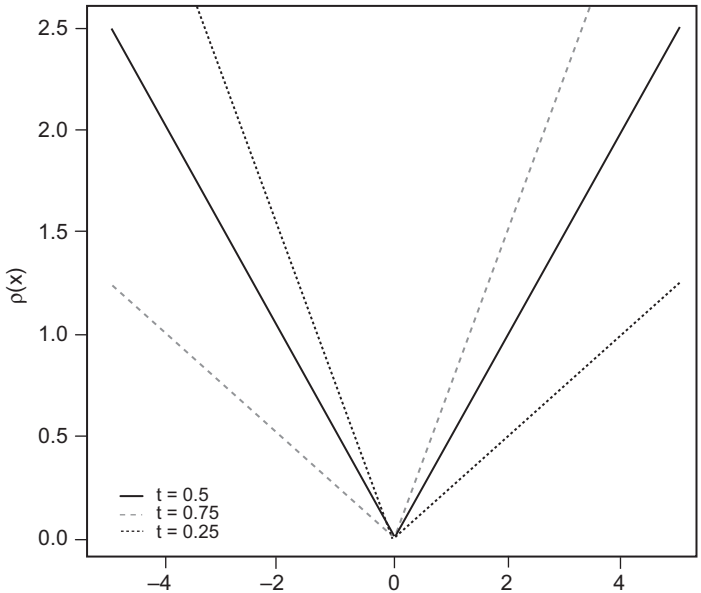


**Figure 1.** Quantile regression: $\rho$ function.

a symmetric loss function and the corresponding estimator $\theta(\tau)$ is the conditional median estimator; that is, $\theta(\tau)$ minimizes $\Sigma_{t=1}^{T} \left| y_t - x_t'\theta \right|$.

The $\tau$th conditional quantile function of $y_t$ could be estimated by

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

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

Based on the above quantile autoregressive model, we include additional appropriate exogenous variables in (1) to explain the determinants of international tourism demand. Most empirical studies in the tourism demand estimation literature choose some macroeconomic variables such as disposable income per capita, exchange rate weighted relative price index, transportation costs and exchange rate weighted relative price index in competing destinations. We consider three of those explanatory variables in the quantile autoregressive model.[3] The $\tau$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 a $1 \times 3$ 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). Equation (6) enables us to study the effects of various covariates, such as the lagged dependent variable $x_t =$

$(1, y_{t-1},\ldots,y_{t-p})'$ and other exogenous macroeconomic variables $z_t$, on the different levels of quantiles of $y_t$ in a unifying framework. The statistical and asymptotic properties, such as the consistency and asymptotic normality, of the above estimator have been established by Galvao *et al* (2009). In the empirical section, we estimate variance–covariance matrices using the stationary bootstrap (Politis and Romano, 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 $\tau$th conditional quantile function of $y_t$ is estimated, the conditional density of $y_t$ can be estimated by the difference quotients,

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

for some appropriately chosen sequence of $\tau$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, $\hat{Q}_{y_t}(\tau|\bullet)$, since the conditional quantile function can be estimated consistently at the sequence of $\tau = (\tau_1,\ldots,\tau_N)$. Equation (7) is useful in analysing the determinants of international tourism demand. Compared 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 $\tau$th quantile, which may provide a more complete picture for tourism demand analysis.

## Data

For estimating international tourism demand, monthly data from November 1980 to December 2005 (302 observations) are used. We consider two major sources, the numbers of US and Japanese tourist arrivals in South Korea, as proxies of inbound tourism demand. Although recent summary statistics for tourist arrivals in South Korea show that Chinese and other Asian tourist arrivals are increasing rapidly, US 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 the tourists may have different behaviours due to physical distance and cultural background.

All variables are taken in the natural logarithm. For explanatory variables $z_{1t}$ in (6), we consider the logarithm of the industrial production index for origin country $i$, $IPI_{i,t}$, the logarithm of the 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 in country $i$

and living costs in competing destinations, respectively. For the competing destinations, we chose four Asian countries: Hong Kong, Singapore, Thailand and the Philippines. Other variables can be used as explanatory variables; for example, transportation costs and specific dummy variables. However, Kim and Song (1998) take airfares as a proxy of transportation costs and report that airfares do not have significant effects on tourism demand for South Korea. The results of Song and Witt (2003) show that the dummy variable which takes care of the 1988 Seoul Olympic Games is not statistically significant for US and Japanese tourists. Since quantile regression is a robust method, estimators are not much affected by outliers. Moreover, near-extreme events can be explained by high or low conditional quantiles within the model. For these 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 Korean currency units per unit of origin country $i$; $ERS_{i,t}$ denotes the nominal exchange rate between competing country $j$ and origin country $i$; and $\omega_j$ is the market share of tourist arrivals for country $j$ among the competing destinations.

The numbers of tourist arrivals and the industrial production index (*IPI*) are seasonally adjusted by the X12-ARIMA filter and are also detrended using the deterministic linear trend.[4] Since we use an autoregressive model, US and Japanese 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 US and Japanese tourist arrivals series.

For the 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 US and Japanese tourism demand are plotted in Figures 2 and 3, respectively. One may expect that 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 the US case. *IPI* achieves the highest value around 2000, but US tourist arrivals keep decreasing around 2000. One notable exception is the relationship between tourist arrivals and *P* during 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*.

**Table 1. Summary statistics and unit root tests.**

| | US arrivals | Japanese 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 the ADF and PP tests are selected by the Schwarz Bayesian criterion and the Newey–West automatic bandwidth, respectively. * and ** denote statistical significance at the 5% and 1% level, respectively.

## Empirical results

### *Estimation results for the 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 *et al* (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 $\hat{\sigma} = n^{-1}\sum_{t=1}^{n}\left|y_t - x_t'\theta(1/2) - z_t'\beta(1/2)\right|$ 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 the US and Japan cases compared to other lag orders.[5] For convenience, the final conditional quantile equation for US and Japanese tourism demand, $y_{US,t}$ and $y_{JP,t}$, respectively, can be written as follows:

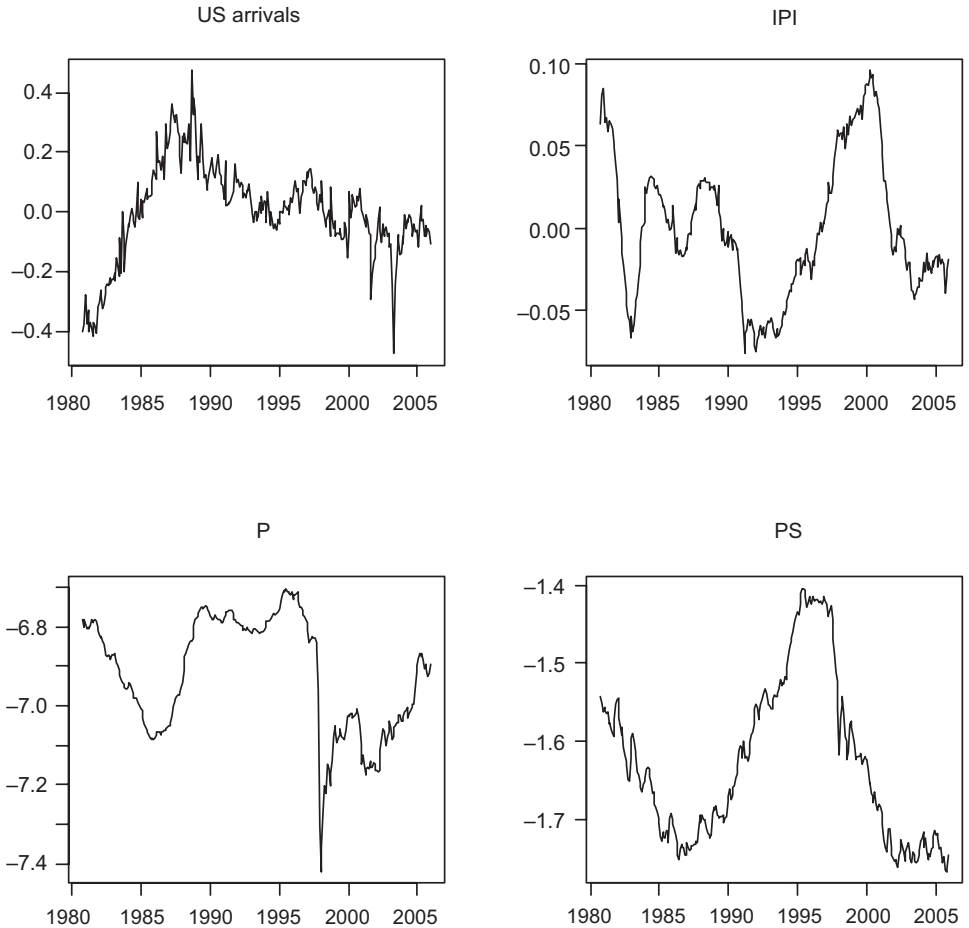


**Figure 2.** US data series.

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

for $i$ = {US, JP}.

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

The estimation results for the tourism demand function of the USA 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 coordinates 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 $\tau$. $\tau$ is taken to have values in [0.02, 0.98]. The shaded area in each plot represents a 95% confidence band.[6]

In Figure 5, the US tourism demand case, $\hat{\theta}_1(\bullet)$ and $\hat{\theta}_2(\bullet)$ are significantly positive but $\hat{\beta}_1(\bullet)$, $\hat{\beta}_2(\bullet)$ and $\hat{\beta}_3(\bullet)$ are not significant for most quantile values.

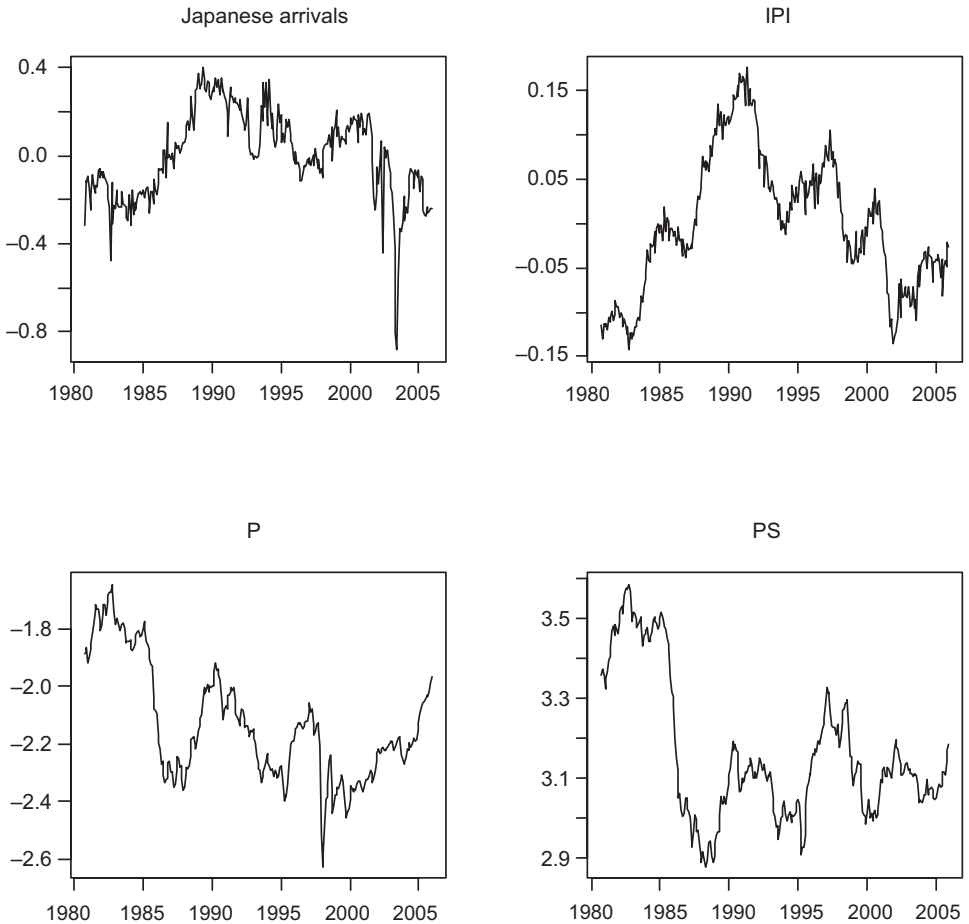


**Figure 3.** Japanese data series.

This implies *IPI*, *P* and *PS* variables rarely affect US tourism demand. Since $\hat{\theta}_1(\bullet)$ is significantly positive and decreasing for all $\tau$ values, we can say that one month's previous US tourism demand has much more impact at lower quantiles than at higher quantiles. For quantile range [0.22, 0.80], $\hat{\theta}_1(\bullet)$ is quite stable around 0.63, which is similar to the OLS estimate, 0.66. Since $\hat{\theta}_1(\bullet)+\hat{\theta}_2(\bullet)<1$ for the whole quantile region, we can say that US tourism demand is stationary for all $\tau$ values. $\hat{\beta}_1(\bullet)$ is negative for most quantile values. This is different from the initial expectation that higher income has positive effects on tourism demand. However, $\hat{\beta}_1(\bullet)$ is not significant for the whole quantile range and $\hat{\beta}_2(\bullet)$ is significantly positive at [0.12 0.18] and negative at [0.9, 0.98]. Thus, when the cost of living in South Korea increases, US tourism demand increases slightly at lower quantiles but decreases sharply at higher quantiles. Although

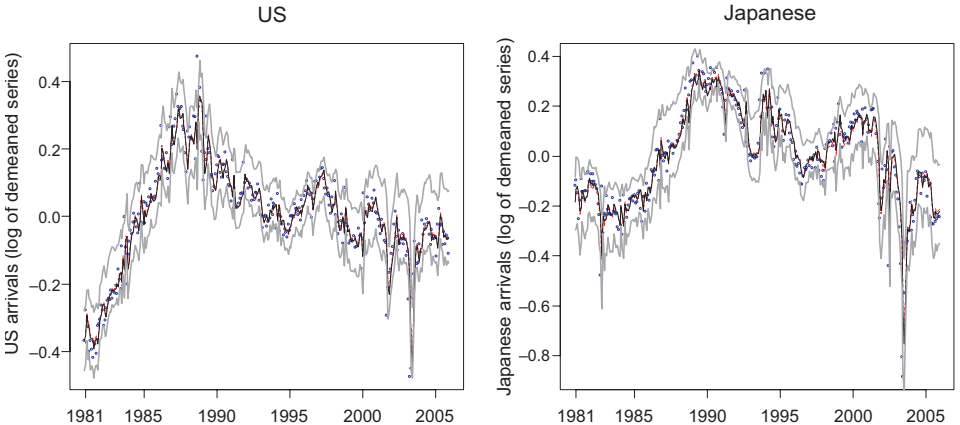


**Figure 4.** Quantile autoregression process for US and Japanese tourist arrivals. *Notes*: The figure shows a scatterplot of US and Japanese tourist arrivals. Superimposed on the plot are {0.05, 0.95} quantile regression lines in grey and the median fit is the solid line.

this is inconsistent with our initial expectations, it could be explained by the different objectives of tourists. For example, US tourism demand at higher quantiles may be due to the vacation objective, while the business objective may be the main reason for tourism demand at lower quantiles. This kind of heterogeneity may help to explain the contradicting effects of $\hat{\beta}_2(\bullet)$. In the conditional mean model, the OLS coefficient of $\beta_2$ is –0.0095 and not significant. The minus sign of the 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 regions, 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 US tourism demand.

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

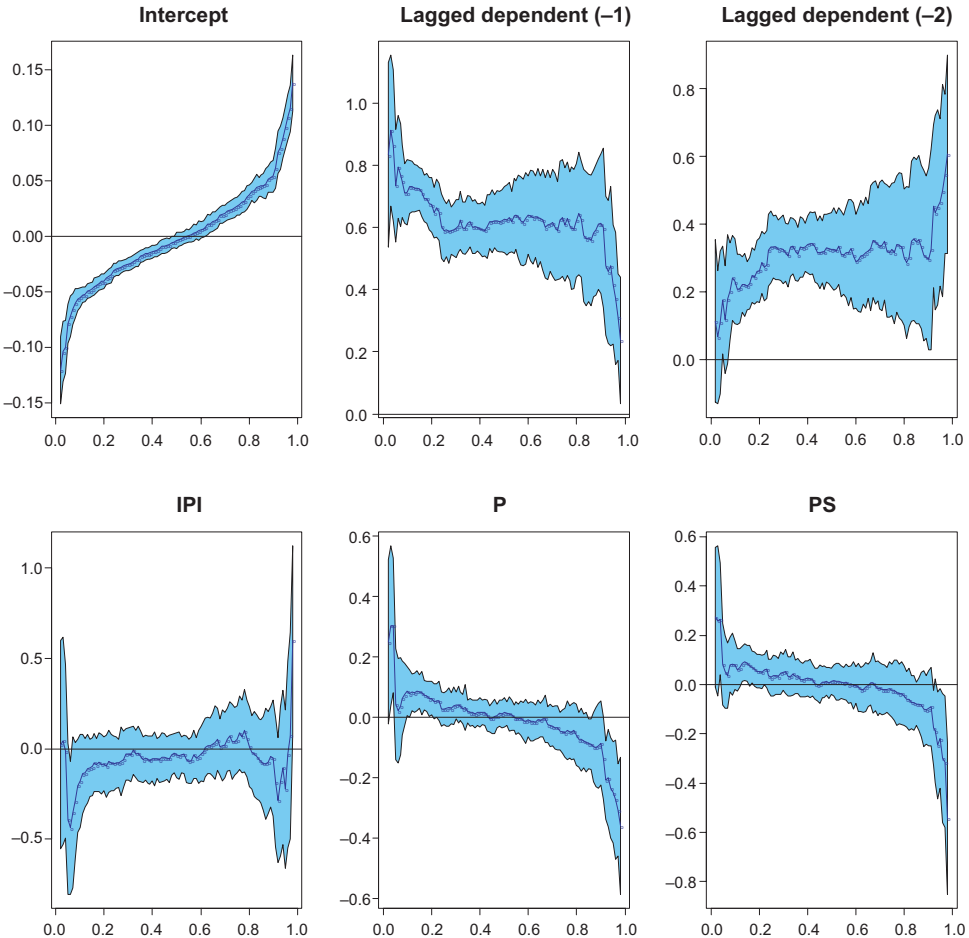


**Figure 5.** Quantile autoregression process for US tourism demand.
*Notes*: The shaded region illustrates a 95% confidence band for the estimated effects. The standard errors for the regression quantile are estimated by the stationary bootstrap method.

### *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 obtained easily 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% bootstrapped confidence interval is illustrated by grey lines, and dashed horizontal lines represent elasticity computed by OLS coefficients.

The long-run elasticities have quite similar shapes to the corresponding regression quantile processes in Figures 5 and 6. $\hat{\varepsilon}_I(\bullet)$, $\hat{\varepsilon}_P(\bullet)$ and $\hat{\varepsilon}_{PS}(\bullet)$ for the

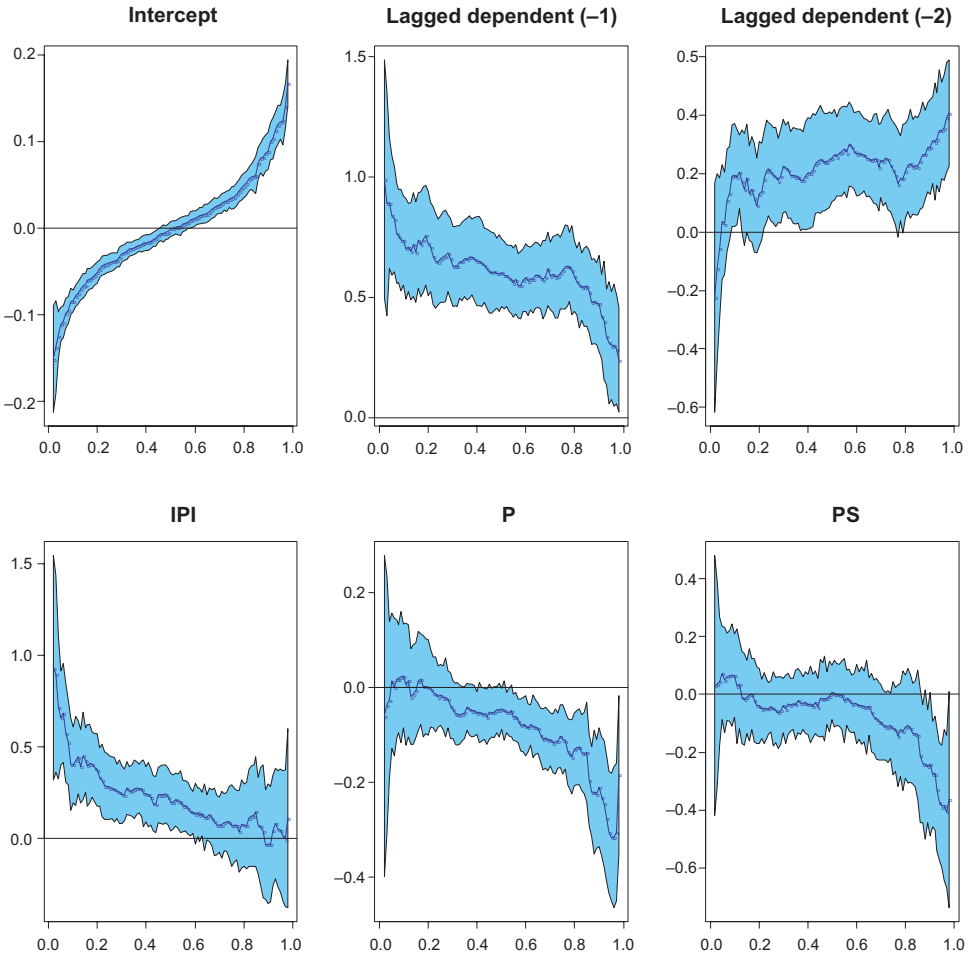


**Figure 6.** Quantile autoregression process for Japanese tourism demand.
*Notes*: The shaded region illustrates a 95% confidence band for the estimated effects. The standard errors for the regression quantile are estimated by the stationary bootstrap method.

US case are not significant, although regression quantiles $\hat{\beta}_1(\cdot)$ 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 the Japananese case, $\hat{\varepsilon}_I(\tau)$ is significantly positive for $\tau \in [0.02, 0.7]$ and has an overall decreasing pattern. Significant $\hat{\varepsilon}_I(\tau)$ values vary from 0.4 ($\tau$ = 0.57) to 5.8 ($\tau$ = 0.1). Since $\hat{\varepsilon}_I(\tau)$ at $\tau$ = 0.57, we can say that travelling to South Korea is a luxury good for Japanese tourists who belong to the 0–0.57 conditional quantiles, while it is not a luxury good for $\tau \in [0.57, 0.7]$. $\hat{\varepsilon}_P(\tau)$ is significantly negative for $\tau \in [0.3, 0.98]$ and decreasing overall, and its varying range is given by [–0.17, –0.97], whereas $\hat{\varepsilon}_{PS}(\tau)$ is only significant at the 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 that Japanese tourists who belong to high quantiles are more sensitive to the cost of living in competing destinations than that in South Korea.

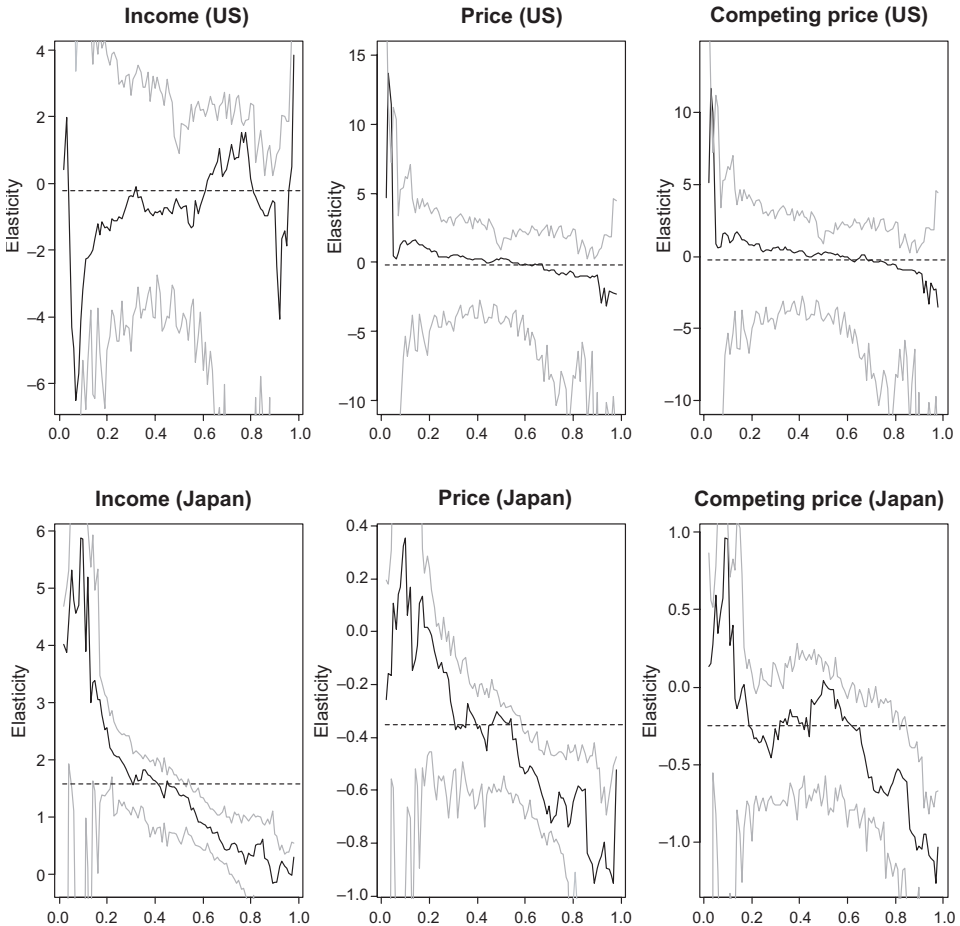


**Figure 7.** Long-run elasticities.
*Notes*: The grey lines illustrate a 95% bootstrap confidence band for the estimated long-run elasticities. The dashed horizontal lines denote the long-run elasticities estimated by the OLS method.

We compare our estimates $\hat{\varepsilon}_I(\bullet)$, $\hat{\varepsilon}_P(\bullet)$ and $\hat{\varepsilon}_{PS}(\bullet)$ 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 US tourism demand. However, this difference is moderate for Japanese tourism demand. These dissimilarities may be due to the use of a 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 an error correction model and analysed tourism demand by four major tourist-generating countries: Germany, Japan, the UK and the USA. Their estimated long-run income elasticities for the USA and Japan are 2.998 and 2.536, respectively, and significant at the 1% significance level. The elasticity of the relative living

price in Korea for the US case is –0.544, but it is not significant at the 5% level. The price variable for the Japanese case is excluded from the estimation procedure because it yields a 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, the autoregressive coefficient, AR(1), for Japanese tourism demand is explosive (that is, greater than 1) and, therefore, we do not calculate elasticities for the case of Japan. The elasticities for the US 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 relates to the US 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 true for $\hat{\varepsilon}_P$ and $\hat{\varepsilon}_{PS}$ in Song and Witt (2003). For the Japanese case, the above inconsistencies between our estimates and those of previous studies seem to be reduced. 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 the Philippines as major competing destinations, significant negative $\hat{\varepsilon}_{PS}(\bullet)$ in upper quantiles support Kim and Song's (1998) results. However, while both Kim and Song (1998) and Song and Witt (2003) reported that relative price coefficients were insignificant, $\hat{\varepsilon}_P(\tau)$ was significantly negative for $\tau \in [0.3, 0.98]$.

### *Response of conditional tourism demand to an exogenous shock*

Finally, the responses of tourism demand to particular shocks are analysed using estimated models. Suppose for a moment that $\xi_i(\bullet)$ for some $i > 0$ and $\tau \in (0,1)$ in conditional quantile function, $Q_{y_t}(\tau | X_t) = \xi_0(\tau) + \Sigma_{i=1}^{n} \xi_i(\tau) X_{i,t}$, 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 $Q_{y_t}(\tau | X_t)$ given that other elements of $X_{i,t}$, $i = 1,2,\ldots,n$ are the same. Thus, $\xi_i(\bullet) > 0$ ensures an upward (downward) shift of $Q_{y_t}(\tau | X_t)$ at point $\tau$ with respect to a positive (negative) shock. Moreover, since $\xi_i(\bullet)$ is monotone decreasing, such an upward (downward) shift is distinct at lower conditional quantiles. The above effects can be illustrated directly 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 the responses of US and Japanese tourism demand to one standard deviation shock, respectively.[8]

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

For the Japanese case (Figure 9), the responses of conditional tourism demand for AR(1) and AR(2) are very similar to those of the US case. When a shock is given to income, only the lower tail part shifts to the right, with no changes

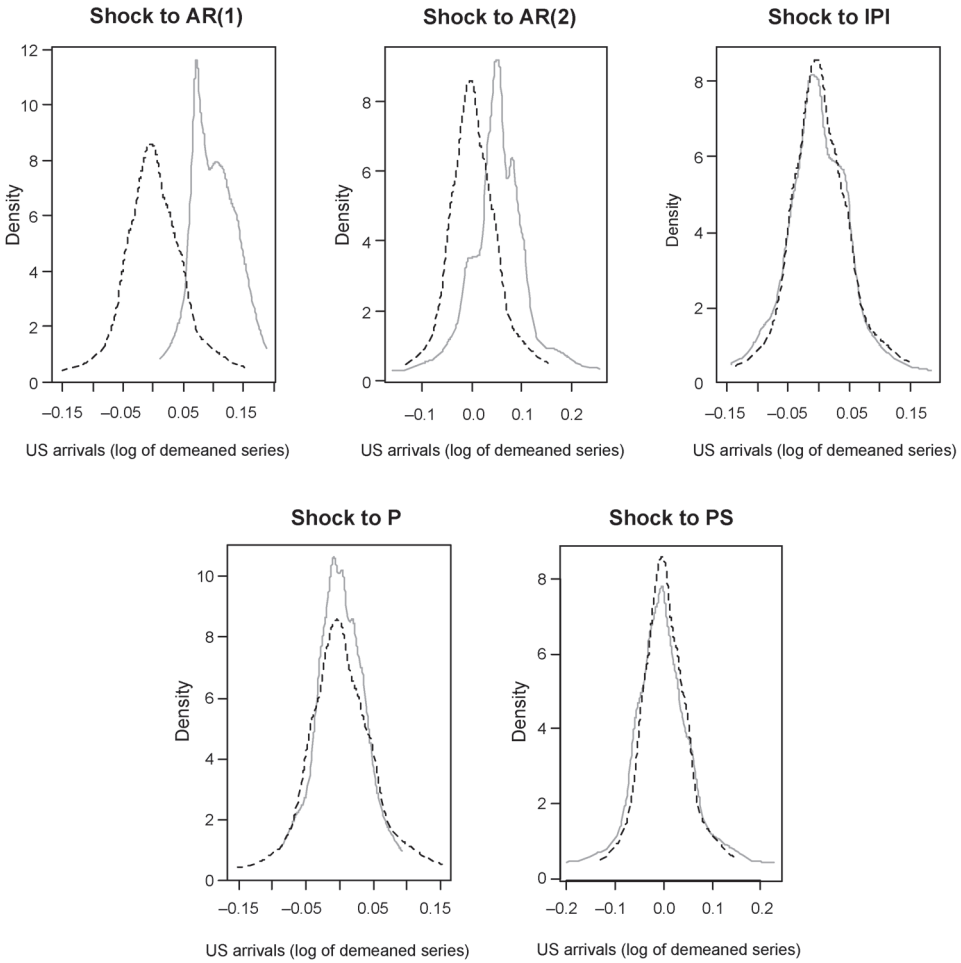


**Figure 8.** Local effects on the density of US tourism demand of positive shocks. *Notes*: The conditional density of tourist demand for the pre-shock and post-shock cases are illustrated with dashed and grey lines, respectively.

in the 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 that Japanese tourists who have a relatively higher tourism demand are disappointed with positive living cost shocks.

## Conclusion

This paper examines tourism demand and the determinants of inbound tourism demand in South Korea using the quantile autoregressive distributed lag model.

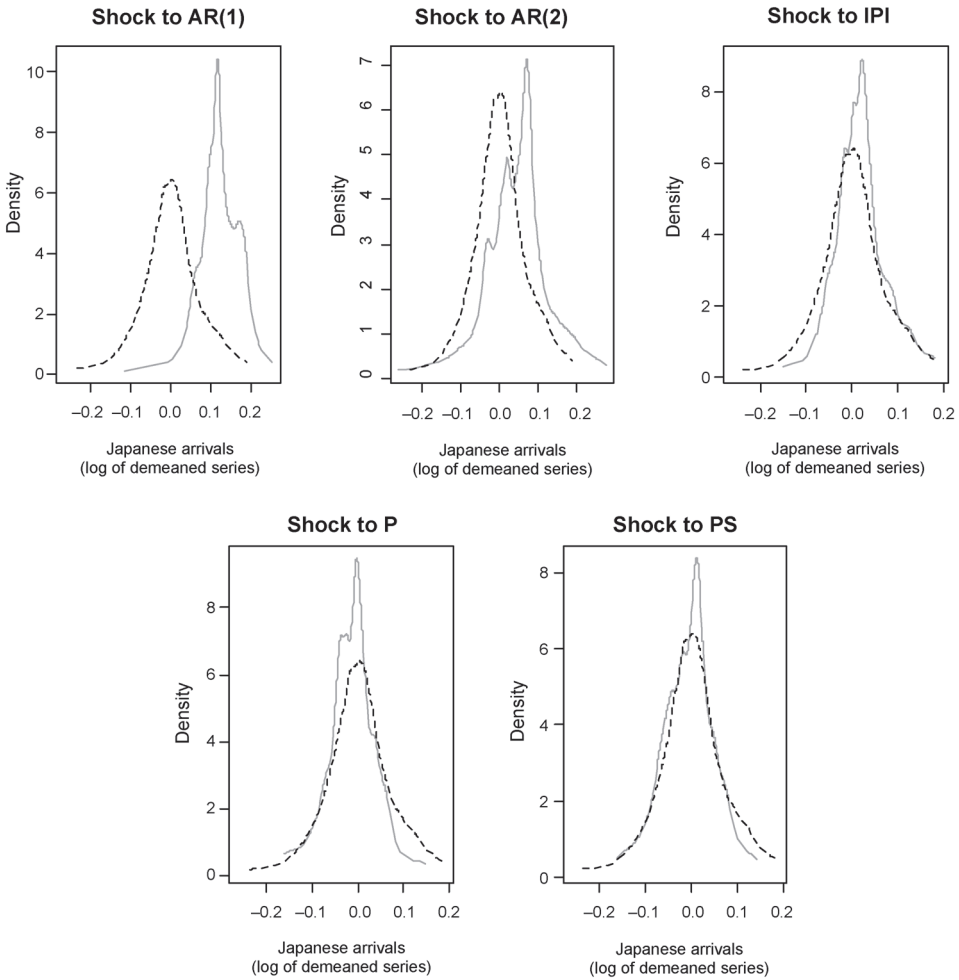


**Figure 9.** Local effects of positive shocks on the density of Japanese tourism demand.

*Notes:* The conditional density of tourist demand for the pre-shock and post-shock cases are illustrated with dashed and grey lines, respectively.

We consider US and Japanese tourist arrivals as proxies for tourism demand. For the US 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. The cost of living in Korea and competing destinations has moderate negative effects only at the very high and low quantiles. On the other hand, for Japanese tourism demand, income has a significantly positive effect at the [0.02, 0.6] quantile, and living cost in Korea and competing destinations has 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 the 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 tourism demand are also studied by the response analysis. The results show that a positive income and cost shock have different effects on Japanese tourism demand. Specifically, a positive income shock encourages Japanese tourists who are in the lower quantiles of the 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 US case, there is little response in tourism demand to the shocks of explanatory variables.

The empirical results of this study show that there is country-specific heterogeneity in tourism demand. For the US case, most covariates turned out to be statistically insignificant. However, Japanese tourism demand for South Korea can be explained quite well by the independent variables chosen. This different behaviour of two sources of inbound tourism demand is due to the different individual characteristics of the two countries: for example, location, physical distance from the origin, individual budget constraints and the neighbourhood of the origin, among others. Thus, identifying the different characteristics of demand is important in the development of tourism market strategies and government policies.

## Endnotes

1. We are very grateful to the anonymous referees for pointing out this method and providing us with relevant literature.
2. See Koenker (2005) for an excellent survey of quantile regression.
3. Three explanatory variables are discussed in the data section.
4. The X-12-ARIMA seasonal adjustment method was developed by the US Census Bureau and has been frequently used for seasonal adjustment. For more detailed discussion on the X-12-ARIMA seasonal adjustment method see Findley *et al* (1998). The linear detrending series of IPI can be obtained from the regression of IPI on the 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 not significant over all $\tau$. When only lagged explanatory variables are added to (6), the corresponding $\hat{\beta}(\tau)$ are not significant over all $\tau$. The same applies to AR(3) term.
6. Variance–covariance matrices are estimated using the stationary bootstrap method proposed by Politis and Romano (1994). We also estimated variance–covariance matrices using the moving-blocks bootstrap method. Since the moving-blocks bootstrap method yields a very similar 95% confidence band, the results for the moving-blocks bootstrap are not reported.
7. Chernozhukov and Umantsev (2001) used a 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 the positive shock case, the corresponding results are not reported in this paper.

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