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"Modelling the Volatility in Short and Long Haul

Japanese Tourist Arrivals to New Zealand and Taiwan"

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Modelling the Volatility in Short and Long Haul

Japanese Tourist Arrivals to New Zealand and Taiwan*

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Abstract

This paper estimates the effects of short and long haul volatility (or risk) in monthly Japanese tourist arrivals to Taiwan and New Zealand, respectively. In order to model appropriately the volatilities of international tourist arrivals, we use symmetric and asymmetric conditional volatility models that are commonly used in financial econometrics, namely the GARCH (1,1), GJR (1,1) and EGARCH (1,1) models. The data series are for the period January 1997 to December 2007. The volatility estimates for the monthly growth in Japanese tourists to New Zealand and Taiwan are different, and indicate that the former has an asymmetric effect on risk from positive and negative shocks of equal magnitude, while the latter has no asymmetric effect. Moreover, there is a leverage effect in the monthly growth rate of Japanese tourists to New Zealand, whereby negative shocks increase volatility but positive shocks of similar magnitude decrease volatility. These empirical results seem to be similar to a wide range of financial stock market prices, so that the models used in financial economics, and hence the issues related to risk and leverage effects, are also applicable to international tourism flows.

Keywords: Tourist arrivals, long haul, short haul, risk, conditional volatility, asymmetric effect, leverage.

JEL Classifications: C22, G32, L83.

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1. Introduction

As a tourism source, Japan is a significant supplier of tourists to many countries, including New Zealand and Taiwan. Japan is New Zealand's largest Asian tourist source market. Tourist arrivals from Japan had been increasing by about 15% per annum from 1980 to 1996. After 1996, New Zealand started to experience a decline in the Japanese market when the annual growth rate dramatically decreased by 2.4%, on average. Various events have contributed to the sharp decline in the Japanese market. They include the 1997/1998 Asian economic and financial crises, a continuing economic slowdown in the Japanese economy since the mid-1990s, SARS and the appreciation of the New Zealand dollar (Lim et al, 2007).

Modelling of volatility has been undertaken by many applied economists and policy analysts. If the volatility of international tourism arrivals and/or growth behave like those in financial markets, there will be a risk interpretation for international tourism flows along the lines of financial assets, namely that the variations in international tourist arrivals are essentially equivalent to the prices of financial assets if the rate of growth in tourism spending is constant. Hence, an analysis of the volatility associated with international tourist arrivals is important for tourism management and informed policy decision-making. In this paper, we will examine the short and long haul volatility (or risk) in Japanese outbound tourism to Taiwan and New Zealand, respectively.

According to the international visitor surveys conducted in 2005, most Japanese visitors to New Zealand were package travellers, and very few were repeat tourists. As a long haul destination, New Zealand is a popular destination for older Japanese tourists, with 37% of all visitors aged 55 years and above. The surveys also indicated that shopping and eating out were the most popular activities engaged in by Japanese tourists (Tourism New Zealand 2006). Auckland (in the North Island), followed by Canterbury and Queenstown (in the South Island), were the most popular regions in New Zealand for Japanese tourists. Not surprisingly, hotels were the dominant type of accommodation used by these visitors.

On the other hand, as a short haul tourist destination, Japan is Taiwan's largest Asian tourist source market, which accounted for over 30% of all international tourists in Taiwan, and has increased by more than 4% annually between 1981 and 2005 (Taiwan Tourism Bureau, 2006).

Taiwan was a colony of Japan from 1895 to 1945, prior to the Kuomintang Party's flight to Taiwan from China to exercise its sovereignty (see, for example, Lim et al. (2007)). During that time, only the Japanese language and education were allowed to be spoken and learned by the island residents. Thus, Taiwan's lifestyle has been heavily influenced by the Japanese culture. It is striking that Taiwanese and Japanese enjoy similar leisure activities, such as shopping, dining, and soaking in hot springs all year round.

Japanese tourist arrivals to Taiwan, on average, are 12 times larger than to New Zealand from 1980 to 1996, and more than 6 times the number from 1996 to 2007. The annual growth rate of Japanese tourists to New Zealand during the period 1996 to 2007 was around 3.7%.

According to a survey conducted by the Taiwan Tourism Bureau (2006), about 50% of Japanese travelled to Taiwan for pleasure, followed by business (30%), and visiting relatives and friends (3%). On average, the duration of stay among Japanese short-term tourists was 5 days, compared with 7 days on average for all short-term visitor arrivals. The survey found that Tienhsiang, Taroko Gorge (located on the eastern side of Taiwan) and the night markets in Taipei were the major scenic spots for Japanese tourists. Additionally, cuisine and historical relics were the major attractions for most Japanese tourists.

Using monthly data, Lim et al. (2008) examine the dynamic relationship between travel demand and real income in Japan, using linear and nonlinear models, to distinguish between international travel demand to Taiwan and New Zealand, which are two important short and long haul markets for Japan, respectively. Their empirical results show that New Zealand has a higher income elasticity of demand than does

Taiwan. An extension of their analysis is to model the short and long haul volatility of Japanese tourist arrivals to Taiwan and New Zealand, respectively.

The analysis of volatility is still relatively new to tourism research, with few studies to date having analysed international tourism demand volatility (see, for example, Chan et al. (2005), and Shareef and McAleer (2007, 2008)). Since volatility is not constant, and hence needs to be modelled, it is necessary to use daily or monthly data to estimate time-varying volatility. Monthly data were used in past studies which examined the volatility in international tourist arrivals to Australia, Maldives and Seychelles. These studies examined between four and eight major source markets, which comprised short and long haul travel from Oceania, Asia, Europe and the USA.

The purpose of the paper is to model the short and long haul volatility (or risk) in Japanese tourist arrivals to Taiwan and New Zealand, respectively, from January 1997 to December 2007. The remainder of the paper is organized as follows. Section 2 presents the data for monthly Japanese tourist arrivals to New Zealand and Taiwan and discusses time varying volatility. Section 3 performs unit root tests on the levels, logarithms and growth rates of monthly tourist arrivals. Section 4 discusses the econometric methodology, which presents symmetric and asymmetric conditional volatility models for tourist arrivals. The empirical results are discussed in Section 5. Finally, some concluding remarks are given in Section 6.

2. Data

The data set comprises monthly Japanese tourist arrivals to New Zealand and Taiwan from January 1997 to December 2007, giving a total of 348 observations for each data. The data were obtained from the New Zealand Department of Statistics and the Taiwan Tourism Bureau.

Figures 1 and 2 show the trends and volatility in monthly Japanese tourist arrivals (TA) to New Zealand and Taiwan, respectively. Figures 3 and 4 plot the logarithm of monthly Japanese tourist arrivals, L(TA), to New Zealand and to Taiwan, respectively.

Figures 5 and 6 plot the log difference (or growth rate) of monthly Japanese tourist arrivals, DL(TA), to New Zealand and Taiwan, respectively. Volatility is defined as the squared deviation of TA from the sample mean.

As shown in Figures 1 and 3, monthly Japanese tourist arrivals, as well as the log monthly Japanese tourist arrivals series, show a significant increase before the period 1997, level off during the period 1997 to 2003, and then decrease after 1997. On the other hand, as shown in Figures 2 and 4, monthly Taiwanese tourist arrivals, as well as the log monthly Taiwanese tourist arrivals series, show a slight increase, with an outlier in around 2003 because of SARS. In this case, the two outliers from Japan to Taiwan are omitted from the sample.

Furthermore, the series from both tourism sources in levels and logarithms might be stationary or non-stationary, but the log difference series is clearly stationary. As shown in Figures 5 and 6, there is clear volatility clustering in monthly Japanese tourist arrivals to New Zealand and Taiwan for the log difference series. However, the volatility would seem to be greater for Japanese tourism to New Zealand than to Taiwan.

Although it appears from the figures that both levels and logarithms are non-stationary, there is the possibility of obtaining apparently significant regression results from apparently unrelated data when non-stationary series are used in regression analysis. In the next section, we will show that the data are non-stationary by using formal unit root tests of the series in levels, logarithms and log differences (or growth rates) in the respective series before modelling the time-varying volatility.

Finally, time series observed at monthly frequencies often exhibit seasonality. Lim and McAleer (2001) highlighted seasonality in tourism time series data. In order to extract the underlying trend component of the time series, the multiplicative moving average method technique was used to remove seasonal movements in the data of Japanese tourist arrivals.

Table 1 gives the summary statistics for Japanese tourist arrivals to New Zealand and Taiwan from January 1997 to December 2007. As described above, two outliers arising from SARS in the data from Japan to Taiwan are omitted from the sample. Finally, we have a total of 348 observations from Japan to New Zealand and 346 observations from Japan to Taiwan.

3. Unit Root Tests

It is well known that traditional unit root tests, primarily those based on the classic methods of Dickey and Fuller (1979, 1981), suffer from low power and size distortions. However, these shortcomings have been overcome by modifications to the testing procedures, such as the methods proposed by Perron and Ng (1996), Elliott, Rothenberg and Stock (1996), and Ng and Perron (2001).

The ADF unit root test, ADF^{GLS}, was applied to the time series of monthly Japanese tourist arrivals to New Zealand and Taiwan. In essence, ADF^{GL} test uses the modified Akaike information criterion (MAIC) to select the optimal truncation lag. The asymptotic critical values for the ADF tests are given in Dickey and Fuller (1981).

The results of the unit root tests are obtained from the econometric software package EViews. Table 2 shows the results of the unit root tests for Japanese tourists to New Zealand and Taiwan. As shown in Table 2, the null hypothesis of a unit root is not rejected for the levels of Japanese tourist arrivals to New Zealand and Taiwan in the models with a constant and with a constant and trend as the deterministic terms. A similar result holds for the logarithm of monthly Japanese tourist arrivals to each country, where the ADF tests do not reject the null hypothesis of a unit root for the models with a constant and with a constant and trend for Japanese tourism to New Zealand. However, for the series in log differences (or growth rates) for Japanese tourists to New Zealand and Japanese tourists to Taiwan, the null hypothesis of a unit root is rejected by the ADF.

As shown in the unit root tests, the empirical results strongly suggest the use of growth rates in monthly Japanese tourist arrivals to estimate alternative univariate conditional mean and conditional volatility models simultaneously. For this reason, conditional mean and conditional volatility models will be estimated in Section 4 using only the growth rates of Japanese tourist arrivals.

4. Econometric Methodology

The alternative time series models to be estimated for the conditional means of the monthly international tourist arrivals, as well as their respective conditional volatilities, are discussed below. As Figures 1-6 illustrate, monthly Japanese tourist arrivals to New Zealand and Taiwan, the levels and logarithmic series do not show persistence in volatility, whereas the first differences (that is, the log difference or growth rate) of Japanese tourist arrivals show periods of persistent volatility in the sample period. One implication of this persistent time-varying volatility is that the assumption of conditionally homoskedastic residuals would seem to be inappropriate for sensible empirical analysis.

For a wide range of financial data series, time-varying conditional variances can be explained empirically through the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982). When the time-varying conditional variance has both autoregressive and moving average components, this leads to the generalized ARCH(p,q), or GARCH(p,q), model of Bollerslev (1986). The lag structure of the appropriate GARCH model can be chosen by information criteria, such as those of Akaike and Schwarz, although it is very common to impose the widely estimated GARCH(1,1) specification in advance as it typically captures both short and long run volatility persistence adequately.

In the selected conditional volatility model, the residual series should follow a white noise process. Bollerslev et al. (1992) document the adequacy of the GARCH(1,1) specification. Li et al. (2002) provide an extensive review of recent theoretical results for univariate and multivariate time series models with conditional volatility errors.

McAleer (2005) reviews a wide range of univariate and multivariate, conditional and stochastic, models of financial volatility. McAleer et al. (2007) discuss recent developments in modeling univariate asymmetric volatility, while McAleer et al. (2008) develop the regularity conditions and establish the asymptotic properties of a general model of time-varying conditional correlations. As shown in Figures 5 and 6, the log difference monthly tourist arrivals display time-varying volatility persistence, so it is natural to estimate alternative conditional volatility models.

Consider the stationary AR(1)-GARCH(1,1) model for tourist arrivals (or their growth rates, as appropriate), y_t (see, for example, McAleer (2005)):

$$y_t = \phi_1 + \phi_2 y_{t-1} + \varepsilon_t, \qquad |\phi_2| < 1 \tag{1}$$

for $t = 1,...,n$, where the shocks (or movements in monthly tourist arrivals, or growth rates, as appropriate) are given by:

$$\begin{aligned} \varepsilon_t &= \eta_t \sqrt{h_t}, \quad \eta_t \sim iid\,(0,1) \\ h_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \end{aligned} \tag{2}$$

and $w > 0, \alpha \geq 0, \beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. The AR(1) model in equation (1) can easily be extended to univariate or multivariate ARMA(p,q) processes (for further details, see Ling and McAleer (2003a)). In equation (2), the ARCH (or α) effect indicates the short run persistence of shocks, while the GARCH (or β) effect indicates the contribution of shocks to long run persistence (namely, $\alpha + \beta$). The stationary AR(1)-GARCH(1,1) model can be modified to incorporate a non-stationary ARMA(p,q) conditional mean and a stationary GARCH(r,s) conditional variance, as in Ling and McAleer (2003b).

In equations (1) and (2), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the

absence of normality of η_t, the conditional shocks (or standardized residuals). The conditional log-likelihood function is given as follows:

$$\sum_{t=1}^{n} l_t = -\frac{1}{2} \sum_{t=1}^{n} \left(\log h_t + \frac{\varepsilon_t^2}{h_t} \right).$$

The QMLE is efficient only if η_t is normal, in which case it is the MLE. When η_t is not normal, adaptive estimation can be used to obtain efficient estimators, although this can be computationally intensive. Ling and McAleer (2003b) investigated the properties of adaptive estimators for univariate non-stationary ARMA models with GARCH(r,s) errors. The extension to multivariate processes is rather complicated.

The GARCH process in equation (2) is a function of the unconditional shocks, so the moments of ε_t need to be investigated. Ling and McAleer (2003a) showed that the QMLE for GARCH(p,q) is consistent if the second moment of ε_t is finite. For GARCH(p,q), Ling and Li (1997) demonstrated that the local QMLE is asymptotically normal if the fourth moment of ε_t is finite, while Ling and McAleer (2003a) proved that the global QMLE is asymptotically normal if the sixth moment of ε_t is finite. The well known necessary and sufficient condition for the existence of the second moment of ε_t for GARCH(1,1) is $\alpha + \beta < 1$.

As discussed in McAleer et al. (2007), Elie and Jeantheau (1995) and Jeantheau (1998) established that the log-moment condition was sufficient for consistency of the QMLE of a univariate GARCH(p,q) process (see Lee and Hansen (1994) for the proof in the case of GARCH(1,1)), while Boussama (2000) showed that the log-moment condition was sufficient for asymptotic normality. Based on these theoretical developments, a sufficient condition for the QMLE of GARCH(1,1) to be consistent and asymptotically normal is given by the log-moment condition, namely

$$E(\log(\alpha\eta_t^2 + \beta)) < 0. \tag{3}$$

The log-moment condition for the GARCH(1,1) model involves the expectation of a function of a random variable and unknown parameters. Although the sufficient

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moment conditions for consistency and asymptotic normality of the QMLE for the univariate GARCH(1,1) model are stronger than their log-moment counterparts, the second moment condition is more straightforward to check. In practice, the log-moment condition in equation (3) would be estimated by the sample mean, with the parameters α and β, and the standardized residual, η_t, being replaced by their QMLE counterparts.

The standard GARCH model treats the effects of positive shocks (or upward movements in monthly tourist arrivals) on the conditional variance, h_t, are the same as negative shocks (or downward movements in monthly tourist arrivals) of a similar magnitude. However, the effects of positive and negative effects may have asymmetric effects on volatility. In order to accommodate asymmetric behaviour, Glosten, Jagannathan and Runkle (1992) proposed the GJR model, for which GJR(1,1) is defined as follows:

$$h_t = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{4}$$

where $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0, \beta \geq 0$ are sufficient conditions for $h_t > 0$, and $I(\eta_t)$ is an indicator variable that is defined by

$$I(\eta_t) = \begin{cases} 1, & \varepsilon_t < 0 \\ 0, & \varepsilon_t \geq 0 \end{cases}$$

as η_t has the same sign as ε_t. The indicator variable differentiates between positive and negative shocks of equal magnitude, so that asymmetric effects in the data are captured by the coefficient γ. For financial data, it is expected that $\gamma \geq 0$ because negative shocks increase risk by increasing the debt to equity ratio, although this interpretation may not hold for tourism data in the absence of an equivalent interpretation in terms of risk. The asymmetric effect, γ, measures the contribution

of shocks to both short run persistence, $\alpha + \dfrac{\gamma}{2}$, and to long run persistence,

$$\alpha + \beta + \frac{\gamma}{2}.$$

Ling and McAleer (2002a) showed that the regularity condition for the existence of the second moment for GJR(1,1) under symmetry of η_t is given by:

$$\alpha + \beta + \frac{1}{2}\gamma < 1, \qquad (5)$$

while McAleer et al. (2007) showed that the weaker log-moment condition for GJR(1,1) was given by:

$$E(\ln[(\alpha + \gamma I(\eta_t))\eta_t^2 + \beta]) < 0, \qquad (6)$$

which involves the expectation of a function of a random variable and unknown parameters.

An alternative model to capture asymmetric behaviour in the conditional variance is the Exponential GARCH (EGARCH(1,1)) model of Nelson (1991), namely:

$$\log h_t = \omega + \alpha \mid \eta_{t-1} \mid + \gamma \eta_{t-1} + \beta \log h_{t-1}, \quad \mid \beta \mid < 1 \quad (7)$$

where the parameters α, β and γ have different interpretations from those in the GARCH(1,1) and GJR(1,1) models.

As noted in McAleer et al. (2007), there are some important differences between EGARCH, on the one hand, and GARCH and GJR, on the other, as follows: (i) EGARCH is a model of the logarithm of the conditional variance, which implies that no restrictions on the parameters are required to ensure $h_t > 0$; (ii) moment conditions are required for the GARCH and GJR models as they are dependent on lagged unconditional shocks, whereas EGARCH does not require moment conditions to be established as it depends on lagged conditional shocks (or standardized

residuals); (iii) Shephard (1996) observed that $|\beta| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1); (iv) as the standardized residuals appear in equation (7), $|\beta| < 1$ would seem to be a sufficient condition for the existence of moments; and (v) in addition to being a sufficient condition for consistency, $|\beta| < 1$ is also likely to be sufficient for asymptotic normality of the QMLE of EGARCH(1,1).

Furthermore, EGARCH captures asymmetries differently from GJR. The parameters α and γ in EGARCH(1,1) represent the magnitude (or size) and sign effects of the standardized residuals, respectively, on the conditional variance, whereas α and $\alpha + \gamma$ represent the effects of positive and negative shocks, respectively, on the conditional variance in GJR(1,1). Asymmetric effects are captured by the coefficient, γ, though in a different manner, in the EGARCH and GJR models.

The EGARCH model is also capable of capturing leverage through the debt to equity ratio, whereby negative shocks increase volatility but positive shocks of a similar order of magnitude decrease volatility. As in financial markets, asymmetry and leverage may also be found in tourism markets. When a negative shock affects a tourist destination, tourism will suffer and enter a turbulent phase so that volatility will increase, whereas a positive shock on volatility may be smaller or even in the opposite direction, so that the market may enter a period of tranquility.

5. Empirical Results

It is well known that the estimates of volatility will depend on the adequacy of the specification of the conditional mean equation, which yields the standardized residuals. Both the asymptotic standard errors, as well as the robust standard errors of Bollerslev and Wooldridge (1992), are presented. In virtually all cases, the asymptotic standard errors are smaller than their robust counterparts.

As described in Section 4, we use three specifications, GARCH(1,1), GJR(1,1) and EGARCH(1,1), to estimate conditional mean and conditional volatility models for

Japanese tourists to New Zealand and Taiwan. The estimates are given in Tables 3 and 4. As shown in the unit root tests, which are given in Table 2, the results suggest the use of growth rates in monthly tourist arrivals to estimate alternative univariate conditional mean and conditional volatility models simultaneously.

Table 3 presents the empirical results of the growth rates of monthly Japanese tourist arrivals to New Zealand. These empirical results are supported by the estimates of the lagged dependent variables in the estimates of equation (1), with all the coefficients of the lagged dependent variable being less than one in each of the estimated three models for the growth rates of monthly Japanese tourist arrivals to New Zealand. This is consistent with the empirical finding that the log difference (or growth rate) is stationary.

As shown in the second column of Table 3, the GARCH(1,1) estimates for the log difference (or growth rate) of monthly Japanese tourist arrivals to New Zealand suggest that the short run persistence of shocks is 0.009, while the long run persistence is 0.955. As the second moment condition, $\alpha + \beta < 1$, is satisfied, the log-moment condition is also satisfied. Thus, the regularity conditions are satisfied, the QMLE are consistent and asymptotically normal, and inferences are valid. Therefore, the symmetric GARCH(1,1) estimates are statistically significant.

If positive and negative news of a similar magnitude to monthly Japanese tourist to New Zealand are treated asymmetrically, this can be evaluated using the GJR(1,1) model. The result of GJR (1,1) are shown in the third column of Table 3. The asymmetry coefficient is found to be positive and significant for monthly Japanese tourist to New Zealand, namely 0.325, which indicates the negative shocks increase risk (or volatility). Moreover, the short run persistence of positive and negative shocks are estimated to be -0.092 and 0.260, respectively, and the long run persistence of shocks is estimated to be 0.977 for the log difference in daily prices of hogs.

As described in section 4, an alternative model to examine asymmetric behaviour is the EGARCH model. As shown in the last column of Table 3, each of the EGARCH(1,1) estimates is statistically significant. The coefficient of the absolute

lagged dependent variable, $|\beta|$, is estimated to be 0.967 and is significant, which suggests that all moments exist, with the estimates likely to be consistent and asymptotically normal. Overall, the size effect of the standardized residuals, α, have a negative but insignificant impact on the conditional variances. The sign effect of the standardized residuals, γ, is negative and significant, which evident asymmetry. Furthermore, the absolute vale of γ (0.291) is higher than for the corresponding α estimates (0.029), which suggest that the sign effects have larger impacts than the size effects on the conditional variances. Finally, there is a leverage effect in the case of the monthly growth of Japanese tourist to New Zealand, whereby negative shocks increase volatility but positive shocks of a similar magnitude decrease volatility. These empirical results are similar to a wide range of financial stock market prices, so that the theory of finance, including an analysis of risk is directly applicable to international tourist arrivals.

With no restrictions on the parameters required to ensure that volatility, $h_t > 0$, this seems to suggest that the asymmetric EGARCH (1,1) model is better than the asymmetric GJR (1,1) model.

Table 4 shows the statistical results for the GARCH(1,1), GJR(1,1) and EGARCH(1,1) models for the monthly growth of Japanese tourist to Taiwan. For the conditional mean estimates, all the coefficients of the lagged dependent variable are less than one in each of the estimated three models for the growth rates of monthly Japanese tourist arrivals to Taiwan. This is supported by the estimates of the lagged dependent variables in equation (1), and suggests that the log difference (or growth rate) is stationary.

Regarding the conditional volatility estimates, the second column of Table 4 shows a relative low time-varying persistence in the monthly growth of Japanese tourist to Taiwan, with an estimated short run persistence of shocks of 0.034 and estimated long run persistence of shocks of 0.392 for the symmetric GARCH (1,1) model. However, the estimated coefficient α is insignificant while β is significant at the 10% level. As the second moment condition, $\alpha + \beta < 1$, is satisfied, the log-moment condition is

also satisfied. This is slightly different from the estimates for the monthly growth of Japanese tourists to New Zealand, in which the variance, in the long run has a much smaller time variation in the monthly growth rate of Japanese tourists to Taiwan.

For the GJR(1,1) model, both the second moment and log-moment conditions are satisfied. The asymptotic t-ratio for the γ estimate is positive but is not significant, suggesting that a negative shock will not affect risk (or volatility) any differently from a positive shock of equal magnitude. Again, the short run persistence of positive shocks is not positive, which suggests the GJR (1,1) model may not ensure a positive variance.

As shown in the last column of Table 4, each of the EGARCH(1,1) estimates is statistically significant, except the coefficient γ. The absolute value of the coefficient of lagged log volatility, $|\beta|$, is estimated to be 0.701 and is significant, which suggests that all moments exist, with the estimates likely to be consistent and asymptotically normal. Overall, the size effects of the standardized residuals, α, have positive and significant impacts on the conditional variances, and the sign effect of the standardized residuals, γ, is positive but is not significant. However, the insignificant sign effect, γ, suggests that there is no asymmetric differences between positive and negative shocks for monthly growth in Japanese tourists to Taiwan. This result is different from the case of monthly growth in Japanese tourists to New Zealand.

6. Concluding Remarks

The primary purpose of the paper was to estimate the long and short haul volatility in monthly Japanese tourists to New Zealand and Taiwan, respectively. Estimation of volatility in international tourist arrivals is important for tourism management because the patterns of risk have important implications for tourism policy. The model of conditional volatility can provide useful insights to understand and predict the risk to

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the policy maker of fluctuations in tourism demand and guaranteeing tourism revenues.

Following standard econometric unit root tests, our results strongly suggest the use of growth rates in monthly international tourist arrivals to estimate alternative univariate conditional mean and conditional volatility models simultaneously. In order to capture appropriately the volatilities (or risk) in tourist arrivals, we use symmetric and asymmetric conditional volatility models, specifically the widely- used GARCH(1,1), GJR(1,1) and EGARCH(1,1) models, to examine the effects of positive or negative shocks of equal magnitude on the growth rates of Japanese tourists to New Zealand and Taiwan. The monthly data cover the period January 1997 to December 2007.

An important finding was the asymmetric impacts of positive and negative shocks of similar magnitude on the volatility of monthly growth of Japanese tourists to New Zealand. Moreover, the results empirically have also shown that there is a leverage effect in the case of monthly growth of Japanese tourists to New Zealand, whereby negative shocks increase volatility but positive shocks of similar magnitude decrease volatility. These empirical results seem to be similar to a wide range of financial stock market prices, so that the theory of finance is relevant and directly applicable to international tourist arrivals.

In comparison with asymmetric long haul volatility in the monthly growth of Japanese tourists to New Zealand, the results suggest a relatively low time-varying persistence in the monthly growth of Japanese tourists to Taiwan. However, the empirical results also suggest that there were no asymmetric differences between positive and negative shocks. In general, the result is different from the estimates for the monthly growth of Japanese tourists to New Zealand, in which the long run variance has a lower time variation in the monthly growth of Japanese tourists to Taiwan.

Based on the empirical results presented in the paper, a different pattern of long haul and short haul risk exists between Japanese tourists to New Zealand and to Taiwan. However, Japanese tourists to New Zealand have larger impacts from negative shocks than from positive shocks of a similar magnitude, so that tourism managers can

develop appropriate strategies when the tourism industry is affected by negative shocks.

Analysing volatility effects is important for the tourism industry, in general, and for the airlines, tourist attractions and the lodging sector, in particular. Volatility experienced by this industry has significant implications for capital investment, resource and yield management. The empirical findings of this paper provide useful insights which can be expected to be of interest to the private and public sectors in tourism management policy formulation with regard to short and long haul destinations. It is unusual in empirical tourism research to analyse tourism volatility. Hence, the theoretical and empirical modelling of tourism volatility in this paper should make a significant contribution to the literature.

While volatility has an interpretation of risk in finance, it is also used to construct more precise (that is, accurate) confidence intervals and forecast intervals. With respect to the latter, the use of daily data may be superior to monthly data for computing time-varying standard errors and time-varying forecast standard errors. The potential usefulness of these issues will be considered in future research.

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Table 1

Summary Statistics

Statistics	Japan to New Zealand	Japan to Taiwan
Mean	9077	69699
Median	9329	68665
Maximum	20322	120599
Minimum	376	33558
Skewness	0.04	0.25
Kurtosis	2.04	2.66
Jarque-Bera	13.42	5.28
(probability)	(0.001)	(0.07)
No. observations	348	346

Table 2

Unit Root Tests for Tourist Arrivals

Variables	Japan to New Zealand		Japan to Taiwan	
	ADF^{GLS} Z={1}	ADF^{GLS} Z={1,t}	ADF^{GLS} Z={1}	ADF^{GLS} Z={1,t}
Y	-0.03 (12)	0.03 (12)	-0.05 (15)	-0.21*** (13)
LY	-0.05*** (14)	-0.009 (13)	-0.10 (14)	-0.21*** (14)
DLY	-3.96.*** (13)	-6.26***(12)	-2.94***(12)	-2.95*** (12)

Note: *** denotes the null hypothesis of a unit root is rejected at the 1% level.

Table 3

Conditional Mean and Volatility Models for the Log Difference in

Japanese Tourist Arrivals to New Zealand, 1979/01 - 2007/12

Parameters	Dependent variable: DL(TA)		
	GARCH	GJR	EGARCH
ϕ_1	0.007	-0.019	-0.037
	(0.016)	(0.015)	(0.012)***
	[0.015]	[0.015]	[0.014]***
ϕ_2	-0.037	-0.048	-0.006
	(0.060)	(0.058)	(0.061)
	[0.051]	[0.045]	[0.045]
ω	0.003	0.005	-0.039
	(0.001)***	(0.001)***	(0.030)
	[0.001]*	[0.003]	[0.031]
GARCH/GJR α	0.009	-0.092	
	(0.018))	(0.027)***	--
	[0.015]	[0.043]**	
GJR γ		0.325	
	--	(0.084)***	--
		[0.122]***	
GARCH/GJR β	0.955	0.906	
	(0.025)***	(0.028)***	--
	[0.024]***	[0.011]***	
EGARCH α			-0.029
	--	--	(0.034)
			[0.038]
EGARCH β			0.967
	--	--	(0.007)***
			[0.010]***
EGARCH γ			-0.291
	--	--	(0.052)***
			[0.065]***
Diagnostics			
Second moment	0.964	0.977	-
Log-moment	-0.016	-0.030	-
No. observations	346	346	346

Notes:

DL(TA) is log difference in tourist arrivals.

Numbers in parentheses are asymptotic standard errors, while numbers in brackets are the Bollerslev and Wooldridge (1992) robust standard errors.

*and *** denote significance at the 10% and 1% levels, respectively.

Table 4

Conditional Mean and Volatility Models for the Log Difference

in Japanese Tourist Arrivals to Taiwan, 1979/01 - 2007/12

Parameters	Dependent variable: DL(TA))		
	GARCH	GJR	EGARCH
ϕ_1	0.002	-0.001	0.001
	(0.009)	(0.006)	(0.010)
	[0.008]	[0.008]	[0.008]
ϕ_2	-0.419	-0.446	-0.367
	(0.056)***	(0.065)***	(0.065)***
	[0.053]***	[0.051]***	[0.050]***
ω	0.014	0.013	-6.615
	(0.016)	(0.002)	(0.614)***
	[0.028]	[0.015]	[0.358]***
GARCH/GJR α	0.034	-0.057	
	(0.049)	(0.074)	--
	[0.058]	[0.069]	
GJR γ		0.102	
	--	(0.114)	--
		[0.064]	
GARCH/GJR β	0.358	0.467	
	(0.426)*	(0.399)	--
	[1.162]	[0.673]	
EGARCH α			0.250
	--	--	(0.103)**
			[0.117]**
EGARCH β			-0.701
	--	--	(0.172)***
			[0.101]***
EGARCH γ			0.088
	--	--	(0.068)
			[0.060]
Diagnostics			
Second moment	0.392	0.461	-
Log-moment	-0.412	-0.342	-
No. observation	344	344	344

Notes:

DL(TA) is log difference in tourist arrivals.

Numbers in parentheses are asymptotic standard errors, while numbers in brackets are the Bollerslev and Wooldridge (1992) robust standard errors.

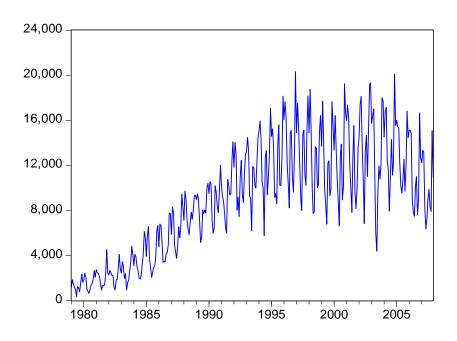*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

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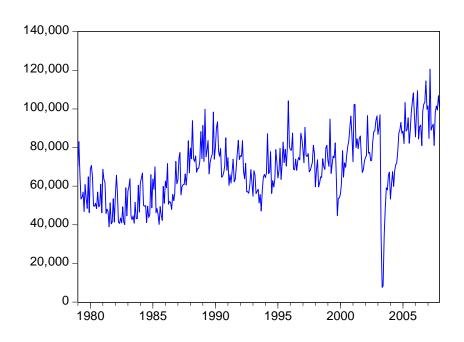**Figure 1. Monthly Tourist Arrivals from Japan to New Zealand**

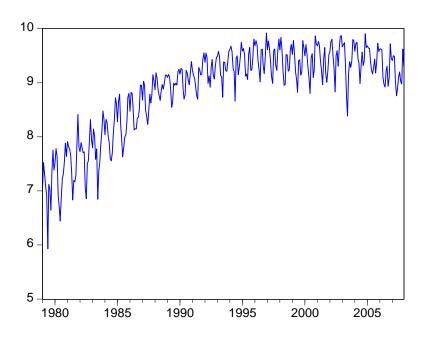**Figure 2. Monthly Tourist Arrivals from Japan to Taiwan**

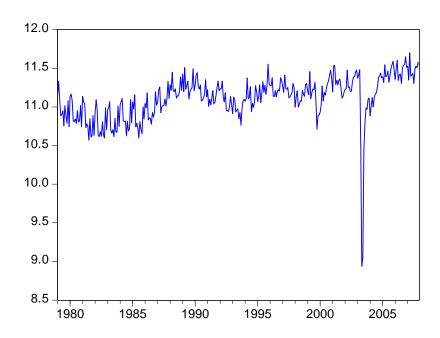**Figure 3. Log Monthly Tourist Arrivals from Japan to New Zealand**

Figure 4. Log Monthly Tourist Arrivals from Japan to Taiwan
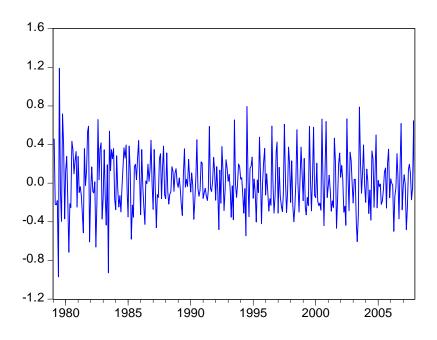
Figure 5. Log difference in Monthly Tourist Arrivals from Japan to New Zealand
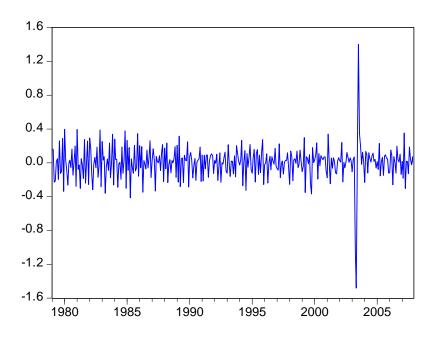
Figure 6. Log difference in Monthly Tourist Arrivals from Japan to Taiwan