Managing Daily Tourism Tax Revenue Risk for the Maldives

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EXTENDED ABSTRACT

International tourism is widely regarded as the principal economic activity in Small Island Tourism Economies (SITEs) (see Shareef (2004) for a comprehensive discussion). Historically, SITEs have been dependent on international tourism for economic development, employment, and foreign exchange, among other economic indicators. A unique SITE is the Maldives, an archipelago of 1190 islands in the Indian Ocean, of which 202 are inhabited by the indigenous population of 261,000 and 89 islands are designated for self-contained tourist resorts. The Maldivian economy depends entirely on tourism, and accounts directly for nearly 38 per cent of real GDP. Employment in tourism accounts for 20 per cent of the working population and 65 per cent of foreign exchange earnings.

Any shock that adversely affects international tourist arrivals to the Maldives also affects earnings from tourism dramatically, and have disastrous ramifications for the economy. An excellent example is the impact of the 2004 Boxing Day Tsunami, which sustained extensive damage to the tourism-based economy of the Maldives and reduced dramatically the number of tourist arrivals in the post-Tsunami period. Therefore, it is vital for the government of the Maldives, multilateral development agencies such as the World Bank and the Asian Development Bank who are assisting Maldives in the Tsunami recovery effort, and the industry stakeholders, namely the resort owners and tour operators, to obtain accurate estimates of international tourist arrivals and their variability. Such accurate estimates would provide vital information for government policy formulation, international development aid, profitability and marketing.

A significant proportion of research in the literature on empirical tourism demand has been based on annual data (see Shareef (2004)), but such analyses are useful only for long-term development planning. An early attempt to improve the short-term analysis of tourism was undertaken by Shareef and McAleer (2005), who modelled the volatility (or predictable uncertainty) in monthly international tourist arrivals to the Maldives. Univariate and multivariate time series models of conditional volatility were estimated and tested. The conditional correlations were estimated to ascertain whether there was specialisation, diversification or segmentation in the international tourism demand shocks from the major tourism source countries to the Maldives. In a similar vein, Chan et al. (2005) modelled the time-varying means, conditional variances and (constant) conditional correlations of the logarithms of the monthly arrival rate for the four leading tourism source countries to Australia.

Daily international arrivals to the Maldives and the number of tourist in residence are analyzed for the period 1994-2003. In the literature, there does not seem to have been any empirical research using daily tourism arrivals data. One advantage of using daily data is that it avoids stochastic seasonality that is prevalent in monthly or quarterly time series data. In the absence of stochastic seasonality, we observe volatility clusterings in the number of international tourist arrivals and their associated growth rates. Therefore, it is useful to analyse daily tourism arrivals data, much like financial data, in terms of the time series patterns, since such an analysis would provide policy makers and the industry stakeholders with accurate indicators of their short-term objectives.

In virtually all SITEs, and particularly the Maldives, tourist arrivals or growth in tourist arrivals translates directly into a financial asset. In the Maldives, every international tourist is required to pay USD 10 for every tourist bed-night spent in the Maldives. This levy is called a ‘tourism tax’ and comprises over 60% of government revenue. Hence, tourism tax revenue is a principal determinant of development expenditure. As a significant financial asset to the economy of SITEs, and particularly so in the case of the Maldives, the volatility in tourist arrivals and their growth rate is identical conceptually to the volatility in financial returns, otherwise known as financial risk.

1. INTRODUCTION

International tourism is the principal economic activity for Small Island Tourism Economies (SITEs). There is a strongly predictable component of international tourism, specifically the government revenue received from taxes on international tourists, but it is difficult to predict the number of international tourist arrivals which, in turn, determines the magnitude of tax revenue receipts. A framework is presented for risk management of daily tourist tax revenues for the Maldives, which is a unique SITE because it relies entirely on tourism for its economic and social development. As these receipts from international tourism are significant financial assets to the economies of SITEs, the time-varying volatility of international tourist arrivals and their growth rate is analogous to the volatility (or dynamic risk) in financial returns. In this paper, the volatility in the levels and growth rates of daily international tourist arrivals are investigated.

The structure of the paper is as follows. In Section 2, the economy of the Maldives is described. This is followed in Section 3 by an assessment of the impact of the 2004 Boxing Day Tsunami on tourism in the Maldives. The concept of Value-at-Risk (VaR) is analysed in Section 4, the data are discussed in Section 5, the models of volatility are presented in Section 6, the empirical results are examined in Section 7, forecasting is undertaken in Section 8, and some concluding remarks are given in Section 9

2. THE TOURISM ECONOMY OF THE MALDIVES

An archipelago in the Indian Ocean, the Maldives comprises 1,190 islands, of which 200 are inhabited. It was a former British protectorate, which became independent in 1965. The Exclusive Economic Zone of the Maldives is 859,000 square kilometres, and the aggregated land area is roughly 290 square kilometres. In the 2000 census, the total population was 270,101, and is estimated to have grown at 2.4 percent per annum over the period 1990-2000.

The Maldives has shown an impressive economic growth record, with an average growth rate of 7 per cent per annum over the last two decades. This record economic performance has been achieved largely due to the growing tourism demand to the Maldives. Furthermore, economic growth has enabled Maldivians to enjoy an estimated real per capita GDP of USD 2,261 in 2003, which is considerably above average for small island developing countries, with an average per capita GDP of USD 1,500. The engine of growth in the Maldives has been the tourism industry, accounting for 37 percent of GDP, more than one-third of fiscal revenue, and two-thirds of gross foreign exchange earnings in recent years. The fisheries sector remains the largest sector in terms of employment, accounting for about one-quarter of the labour force, and is still an important source of foreign exchange earnings. Due to the high salinity content in the soil, agriculture continues to play a minor role. The government, which employs about 20 percent of the labour force, plays a dominant role in the economy, both in the production process and through its regulation of the economy.

Tourism in the Maldives has a direct impact on fiscal policy, which determines development expenditure. More than one-fifth of government revenue arises from tourism-related levies. The most important tourism-related revenues are the tourism tax, the resort lease rents, resort land rents, and royalties. Except for the tourism tax, the other sources of tourism-related revenues are based on contractual agreements with the government of the Maldives. Tourism tax is levied on every occupied bed night from all tourist establishments, such as hotels, tourist resorts, guest houses and safari yachts. Initially, this tax was levied at USD 3 in 1981, and was then doubled to USD 6 in 1988. After 16 years with no change in the tax rate, from 1 November 2004 the tax rate was increased to USD 10. This tax is regressive as it does not take into account the profitability of the tourist establishments. Furthermore, it fails to take account of inflation, such that the tax yield has eroded over time.

Tourism tax is collected by the tourist establishments and is deposited at the Inland Revenue Department at the end of every month. This current revenue is used directly to finance the government budget on a monthly basis. Since the tax is levied directly on the tourist, any uncertainty that surrounds international tourist arrivals will affect tax receipts, and hence fiscal policy. Any adverse affect on international tourist arrivals may also result in the suspension of planned development expenditures.

The nature of tourist resorts in the Maldives is distinctive as they are built on islands that have been set aside for tourism development. Tourism development is the greatest challenge in the history of Maldives, and has led to the creation of distinctive resort islands. These islands are deserted and uninhabited, but have been converted into ‘one-island-one-hotel’ schemes. The building of physical and social infrastructure of the resort islands has had to abide by strict standards to protect the flora, fauna and the marine environment of the islands, while basic facilities for sustainability of the resort have to be maintained. The architectural design of the resort islands in the Maldives varies profoundly in their character and individuality. Only twenty percent of the land area of any given island is allowed to be developed, which is imposed to restrict the capacity of tourists on every island. All tourist accommodation must face a beach front area of five metres. In most island resorts, bungalows are built as single or double units. Recently, there has been an extensive development of water bungalows on stilts along the reefs adjacent to the beaches. All the conveniences for tourists are available on each island, and are provided by the onshore staff.

3. IMPACT OF THE 2004 TSUNAMI ON TOURISM IN THE MALDIVES

As the biggest ever national disaster in the history of the Maldives, the 2004 Boxing Day Tsunami caused widespread damage to the infrastructure on almost all the islands. The World Bank, jointly with the Asian Development Bank (World Bank (2005)), declared that the total damage of the Tsunami disaster was USD 420 million, which is 62 per cent of the annual GDP. In the short run, the Maldives will need approximately USD 304 million to recover fully from the disaster to the pre-tsunami state.

A major part of the damage was to housing and tourism infrastructure, with education and fisheries sectors also severely affected. Moreover, the World Bank damage assessment highlighted that significant losses were sustained in water supply and sanitation, power, transportation and communications. Apart from tourism, the largest damage was sustained by the housing sector, with losses close to USD 65 million. Approximately, 1,700 houses were destroyed, another 3,000 were partially damaged, 15,000 inhabitants were fully displaced, and 19 of the 202 inhabited islands were declared uninhabitable.

The World Bank also stated that the tourism industry would remain a major engine of the economy, and that the recovery of this sector would be vital for the Maldives to return to higher rates of economic growth, full employment and stable government revenue. In the Asian Development Bank report, similar reactions were highlighted by stating that it would be vitally important to bring tourists back in full force, as tourism is the most significant contribution to GDP. In fact, tourism means everything to the Maldivian economy.

In the initial macroeconomic impact assessment undertaken by the World Bank, the focus was only on 2005. The real GDP growth rate was revised downward from 7 per cent to 1 per cent, consumer prices were expected to rise by 7 per cent, the current account balance was to double to 25 per cent of GDP, and the fiscal deficit was to widen to 11 per cent of GDP, which is unsustainable, unless the government were to implement prudent fiscal measures.

The 2004 Boxing Day Tsunami also caused widespread destruction and damage to countries such as Indonesia, India and Sri Lanka. Compared with the damage caused to the Maldives, the destruction which occurred in these other countries is substantially different in terms of its scale and nature. In India, widespread socioeconomic and environmental destruction was caused in the eastern coast affecting the states of Andhra Pradesh, Kerala and Tamil Nadu, and the Union Territory (UT) of Pondicherry. The Tsunami struck with 3- to 10-metre waves and penetrated as far as 3 kilometres inland, affecting 2,260 kilometres of coastline (World Bank (2005)). Nearly 11,000 people died in India. The tsunami also adversely affected the earning capacity of some 645,000 people whose principal economic activity is fisheries.

According to the damage assessment report published in World Bank (2005)), nearly 110,000 lives were lost in Indonesia, 700,000 people were displaced, and many children were orphaned. The total estimate of damages and losses from the catastrophe amounted to USD 4.45 billion, of which 66 per cent constituted damages, while 34 per cent constituted losses in terms of income flows to the economy. Furthermore, total damages and losses amounted to 97 per cent of Aceh's GDP. Although Aceh's GDP derives primarily from oil and gas, which were not affected, and most livelihoods rely primarily on fisheries and agriculture, this was still a catastrophic event.

In Sri Lanka, the human costs of the disaster were also phenomenal, with more than 31,000 people killed, nearly 100,000 homes destroyed, and 443,000 people remaining displaced. The economic cost amounted to USD 1.5 billion dollars, which is approximately 7 per cent of annual GDP (World Bank (2005)). As in India, Indonesia and the Maldives, the tsunami affected the poorest Sri Lankans, who work in the fisheries industry, and some 200,000 people lost their employment in the tourism industry.

Compared with all the tsunami-stricken countries, the Maldives was affected entirely as a result of its geophysical nature. When the tsunami struck, the

Maldives was, for a moment, wiped off the face of the earth.

4. VALUE-AT-RISK AND TOURISM

Value-at-Risk (VaR) is a procedure designed to forecast the maximum expected negative return over a target horizon, given a (statistical) confidence limit, (see Jorion (2000) for a discussion). Put simply, VaR measures an extraordinary loss on an ordinary or typical day. VaR is used widely to manage the risk exposure of financial institutions and is a requirement of the Basel Capital Accord. The central idea underlying VaR is that, by forecasting the worst possible return for each day, institutions can be prepared for the worst case scenario. In the case of the banking industry, or authorized deposit-taking institutions, more generally, such an insurance policy can help avoid bank runs, which can be devastating to the economy if they result in widespread bank failures. In the case of SITEs such as the Maldives, where tourism revenue is a major source of income and foreign exchange reserves, it is important to understand the risks associated with this particular source of income, and to implement adequate risk management policies to ensure economic stability and sustained growth. Forecasted VaR figures can be used to estimate the level of reserves required to sustain desired long term government projects and foreign exchange reserves. Furthermore, an understanding of the variability of tourist arrivals, and hence tourism related revenue, is critical for any investor planning to invest in or lend funds to SITEs.

Formally, a VaR threshold is the lower bound of a confidence interval in terms of the mean. For example, suppose interest lies in modelling the random variable Y_t, which can be decomposed as $Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t$. This decomposition suggests that Y_t is comprised of a predictable component, $E(Y_t \mid F_{t-1})$, which is the conditional mean, and a random component, ε_t. The variability of Y_t, and hence its distribution, is determined entirely by the variability of ε_t. If it is assumed that ε_t follows a distribution such that $\varepsilon_t : D(\mu_t, \sigma_t)$ where μ_t and σ_t are the unconditional mean and standard deviation of ε_t, respectively, these can be estimated using numerous parametric and/or non-parametric procedures. The procedure used in this paper is discussed in Section 6. Therefore, the VaR threshold for Y_t can be calculated as $VaR_t = \mu_t - \alpha\sigma_t$ where α is the critical value from the distribution of ε_t that gives the correct confidence level. Alternatively, σ_t can be replaced by alternative estimates of the variance (see Section 6 below). For further details, see McAleer et al. (2005) for a formal development, specifically the Sustainable Tourism@Risk (or ST@R) model.

5. DATA ISSUES

The data used in this paper are total daily international tourist arrivals from 1 January 1994 to 31 December 2003, and were obtained from the Ministry of Tourism of the Maldives. As can be seen in Table 1, there were over four million tourists during this period, with Italy being the largest tourist source country. Tourists from Western Europe accounted for more than 80 per cent of tourists to the Maldives, with Russia as the biggest emerging market.

A distinct advantage of using daily data is that it avoids stochastic seasonality that is prevalent in monthly or quarterly time series data. However, for weekly data, there is evidence of strong seasonality, where the peak tourist season corresponding to the European winter months and weaker seasonality evident in the European summer months. In the absence of stochastic seasonality, volatility clustering can be observed in the number of international tourist arrivals and their associated growth rates.

There exists a direct relationship between the daily total number of tourists in residence and the daily tourism tax revenue. Modelling the variability of daily arrivals can be problematic as institutional factors, such as predetermined weekly flight schedules, lead to excessive variability and significant day-of-the-week effects. This problem can be resolved in one of two ways. Weekly tourist arrivals could be examined, as this approach removes both the excess variability inherent in daily total arrivals and day-of-the-week effects. However, this approach is problematic as it leads to substantially fewer observations being available for estimation and forecasting. A second solution, and one that is adopted in this paper, is to calculate the daily tourists in residence. This daily total is of paramount importance to the Government of the Maldives as it has a direct effect on the tourism tax revenue received. The tourists in residence series are calculated as the seven-day rolling sum of the daily tourist arrivals series, which assumes that tourists stay in the Maldives for seven days, on average. This is a reasonable assumption as the typical tourist stays in the Maldives for approximately 7 days, according to the Ministry of Tourism of the Maldives.

The graphs for daily tourist arrivals, weekly tourist arrivals and tourists in residence are given in Figures 1-3, respectively. All three series display high degrees of variability and seasonality, as would be expected of tourist arrivals data. As would be expected, the highest levels of tourism arrivals in the Maldives occur during the European winters, while the lowest levels occur during the European summers. The descriptive statistics for each series are given in Table 2. The daily tourist arrivals series display the greatest variability, with a mean of 1,122 arrivals per day, a maximum of 4,118 arrivals per day, and a rather low minimum of 23 arrivals per day. Furthermore, the daily arrivals series have a coefficient of variation (CoV) of 0.559, which is nearly twice the CoV of the other two series. The weekly arrivals and tourists in residence series are remarkably similar, with virtually identical CoV values of 0.3 and 0.298, respectively.

As the focus of this paper is on managing the risk associated with the variability in tourist arrivals and tourist tax revenues, the paper focuses on modelling the growth rates, namely the returns in both total tourist arrivals and total tourists in residence. The graphs for the returns in total daily tourist arrivals, total weekly tourist arrivals and total daily tourists in residence are given in Figures 4-6, respectively. The descriptive statistics for the growth rates of the three series are given in Table 3. Daily tourist arrivals display the greatest variability, with a standard deviation of 81.19, a maximum of 368.23%, and a minimum of -412.57%. Each of the series is found to be non-normally distributed, based on the Jarque-Bera Lagrange multiplier statistic for normality.

6. VOLATILITY MODELS

The primary inputs required for calculating a VaR threshold are the forecasted variance, which is typically given as a conditional volatility, and the critical value of the distribution for a given level of significance. Several models are available for measuring and forecasting the conditional volatility. In this paper, the symmetric Generalized Autoregressive Conditional Heteroskedastcity (GARCH) model of Bollerslev (1986), and the asymmetric GJR model of Glosten, Jagannathan and Runkle (1992), which discriminates between positive and negative shocks to the tourist arrivals series, will be used to forecast the required conditional volatilities.

The GJR(p,q) model is given as $Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t$, where $\varepsilon_t = h_t^{1/2}\eta_t$,

$$h_{it} = \omega_i + \sum_{l=1}^{p} (\alpha_i \varepsilon_{i,t-l}^2 + \gamma_i I(\eta_{i,t})\varepsilon_{i,t-l}^2) + \sum_{l=1}^{q} \beta_i h_{i,t-l}$$

$$I(\eta_{i,t}) = \begin{cases} 1, \varepsilon_{i,t} \le 0 \\ 0, \varepsilon_{i,t} > 0 \end{cases}$$

where F_t is the information set available to time *t*, and $\eta : iid(0,1)$. The four equations in the model state the following: (i) the growth in tourist arrivals depends on its own past values; (ii) the shock to tourist arrivals has a predictable conditional variance component, h_t, and an unpredictable component, η_t; (iii) the conditional variance depends on its own past values and the recent shocks to the growth in the tourist arrivals series; and (iv) the conditional variance is affected differently by positive and negative shocks to the growth in tourist arrivals.

In this paper, $Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t$ is modelled as a simple AR(1) process. For the case $p = q = 1$, $\omega > 0,\ \alpha_1 \ge 0,\ \alpha_1 + \gamma_1 \ge 0,\ \beta_1 \ge 0$ are sufficient conditions to ensure a strictly positive conditional variance, $h_t > 0$. The ARCH (or $\alpha_1 + \frac{1}{2}\gamma_1$) effect captures the short run persistence of shocks (namely, an indication of the strength of the shocks in the short run), and the GARCH (or β_1) effect indicates the contribution of shocks to long run persistence ($\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1$) (namely, an indication of the strength of the shocks in the long run). For the GJR(1,1) model, $\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1$ is a sufficient condition for the existence of the second moment, which is necessary for sensible empirical analysis. Restricting $\gamma_1 = 0$ in the GJR(1,1) model leads to the GARCH(1,1) model of Bollerslev (1986). For the GARCH(1,1) model, the second moment condition is given by $\alpha_1 + \beta_1 < 1$.

In the GJR and GARCH models, the parameters are typically estimated using the maximum likelihood estimation (MLE) method. In the absence of normality of the standardized residuals, η_t, the parameters are estimated by the Quasi-Maximum Likelihood Estimation (QMLE) method (for further details see, for example, Li, Ling and McAleer (2002) and McAleer (2005)). The second moment conditions are also sufficient for the consistency and asymptotic normality of the QMLE of the respective models.

7. EMPIRICAL RESULTS

The variable of interest for the Maldivian Government is the number of tourists in residence at any given day as this figure is directly related to tourism revenue. In this section, the tourists in residence series are used to estimate the GARCH(1,1) and GJR(1,1) models described in Section 6. All estimation was conducted using the EViews 5 econometric software package, though similar results were obtained using the RATS package. The models are estimated using QMLE for the case p=q=1.

The estimated GJR(1,1) equation for the tourists in residence series for the full sample is given as follows:

$$Y_t = \underset{(0.0541)}{0.001} + \underset{(0.0169)}{0.1561} Y_{t-1}$$

$$h_t = \underset{(0.058)}{0.592} + \underset{(0.011)}{0.121} \varepsilon_{t-1}^2 + \underset{(0.015)}{0.048} I \varepsilon_{t-1}^2 + \underset{(0.012)}{0.803} h_{t-1},$$

where the figures in parentheses are standard errors. All the parameters are estimated to be positive and significant, which indicates that the model provides an adequate fit to the data. As γ_1 is estimated to be positive and significant, it appears that volatility is affected asymmetrically by positive and negative shocks, with previous negative shocks having a greater impact on volatility than previous positive shocks of a similar magnitude.

The estimated GARCH(1,1) equation for the tourists in residence series for the full sample is given as follows:

$$Y_t = \underset{(0.0541)}{0.001} + \underset{(0.0169)}{0.1561} Y_{t-1}$$

$$h_t = \underset{(0.058)}{0.598} + \underset{(0.009)}{0.149} \varepsilon_{t-1}^2 + \underset{(0.012)}{0.799} h_{t-1}.$$

Furthermore, as the respective estimates of the second moment conditions, $\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1$ for GJR(1,1) and $\alpha_1 + \beta_1 < 1$ for GARCH(1,1), are satisfied, the QMLE are consistent and asymptotically normal. This means that the estimates are statistically adequate and sensible for purposes of interpretation.

8. FORECASTING

A rolling window is used to forecast the 1-day ahead conditional variances and VaR thresholds for the tourists in residence, with the sample ranging from 7 January 1994 to 31 December 2003. In order to strike a balance between efficiency in estimation and a viable number of rolling regressions, the rolling window size is set at 1,000, which leads to a forecasting period from 3 May 1997 to 31 December 2003. Using the notation developed in the previous sections, the VaR threshold forecast for the growth rate of tourists in residence at any given time t is given by, $VaR_t = E(Y_t \mid F_{t-1}) - \alpha\sqrt{h_t}$, where $E(Y_t \mid F_{t-1})$ is the forecasted expected growth rate of total tourists in residence, and h_t is the forecasted conditional variance of the growth rate in total tourist arrivals.

The forecasted variances for both models are quite similar, with a correlation coefficient of 0.98. The forecasted VaR thresholds represent the maximum expected negative growth rate that could be expected given a specific confidence level. As is standard in the finance literature, where many of these techniques were developed, this paper uses a 1% level to calculate the VaR. In other words, growth rates smaller than the forecasted VaR should only be observed in 1% of all forecasts, which is referred to as the correct "conditional coverage". The results show that, in using the GJR (GARCH) model, we observe 32 (30) instances where the actual daily growth rate is smaller than the forecasted VaR threshold. Based on a Likelihood Ratio test, both models display the correct conditional coverage. In addition the second moment conditions for each rolling window of both models is satisfied for every rolling window which provides greater confidence in the statistical adequacy of the two estimated models. Finally, both models lead to the same average VaR at -6.59%, which means that, on average, the lowest possible daily growth rate in tourists in residence, and hence in tourist tax revenues, is -6.59%, given a 99% level of significance

9. CONCLUSION

Daily international arrivals to the Maldives and their associated growth rates were analyzed for the period 1994-2003. This seems to be the first analysis of daily tourism arrivals and growth rates data in the tourism research literature. The primary purpose for analyzing volatility was to model and forecast the Value-at-Risk (VaR) thresholds for the number of tourist arrivals and their growth rates. This would also seem to be the first paper in the tourism research literature to have applied the VaR portfolio approach to manage the risks associated with tourism revenues.

The empirical results based on two widely-used conditional volatility models showed that volatility was affected asymmetrically by positive and negative shocks, with previous negative shocks to the growth in tourist arrivals having a greater impact on volatility than previous positive shocks of a similar magnitude. The forecasted VaR threshold represented the maximum expected negative growth rate that could be expected given a specific confidence level. Both conditional volatility models led to the same average VaR at -6.59%, which meant that, on average, the lowest possible growth rate in tourists in residence, and hence in tourist tax revenues, was -6.59%. This should be useful information for both private and public tourist providers in the Maldives.

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Table 1. Composition of Tourist Arrivals, 1994-2003

Source Country	Head Count	%
1. Italy	852,389	20.78
2. Germany	730,453	17.81
3. UK	603,501	14.72
4. Japan	381,374	9.30
5. France	238,638	5.82
6. Switzerland	237,245	5.79
7. Austria	118,324	2.89
8. The Netherlands	60,011	1.46
Total International Tourist Arrivals	4,101,028	100

Table 2: Descriptive Statistics

Statistics	Daily Arrivals	Weekly Arrivals	Tourists in Residence
Mean	1,122	7,833	7,699
Median	1,007	7,510	7,430
Maximum	4,118	14,942	15,517
Minimum	23	3,316	3,145
Std. Dev.	627	2,351	2,293
Skewness	1.087	0.535	0.593
Kurtosis	4.436	2.784	2.981
CoV	0.559	0.300	0.298
Jarque-Bera	1033	25.808	201.597

Table 3: Descriptive Statistics for Growth Rates

Statistics	Daily Arrivals	Weekly Arrivals	Tourists in Residence
Mean	0.010	0.163	5.24e-12
Median	-7.66	-0.027	-0.039
Maximum	368.23	50.37	26.34
Minimum	-412.57	-38.45	-20.64
Std. Dev.	81.19	11.66	3.21
Skewness	0.143	0.344	0.283
Kurtosis	3.01	4.95	8.76
CoV	8,119	71.53	6.12e11
Jarque-Bera	12.44	92.61	4,799.9