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FORECASTING INTERNATIONAL TOURISM DEMAND AND UNCERTAINTY FOR THREE SMALL ISLAND TOURISM ECONOMIES

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ABSTRACT

Volatility in monthly international tourist arrivals is the squared deviation from the mean monthly international tourist arrivals, and is widely used as a measure of risk or uncertainty. Fluctuating variations, or conditional volatility, in international monthly tourist arrivals are typically associated with unanticipated events. The time-varying effects related to many small island tourism economies, such as natural disasters, ethnic conflicts, crime, the threat of terrorism, and business cycles in tourist source countries, can lead to substantive variations in monthly international tourist arrivals. This paper shows how the GARCH model can be used to forecast international tourism demand and uncertainty by modelling the conditional volatility in monthly international tourist arrivals to three small island tourism economies that have extensive monthly observations on international tourist arrivals, namely Barbados, Cyprus and Fiji. The paper demonstrates the importance of modelling conditional volatility in establishing accurate confidence interval forecasts of monthly international tourist arrivals for the three countries.

1 INTRODUCTION

Volatility in monthly international tourist arrivals is the squared deviation from the mean monthly international tourist arrivals, and is widely used as a measure of risk or uncertainty. Monthly international tourist arrivals to each of the three Small Island Tourism Economies (SITEs) analysed in this paper, namely Barbados, Cyprus and Fiji, exhibit distinct patterns and positive trends. However, monthly international tourist arrivals for some SITEs have increased rapidly for extended periods, and stabilised thereafter. Most importantly, there have been increasing variations in monthly international tourist arrivals in SITEs for extended periods, with subsequently dampened variations. Such fluctuating variations in monthly international tourist arrivals, which vary over time, are regarded as the conditional volatility in tourist arrivals, and can be modelled using financial econometric time series techniques. Fluctuating variations, or conditional volatility, in international monthly tourist arrivals are typically associated with unanticipated events. There are time-varying effects related to SITEs, such as natural disasters, ethnic conflicts, crime, the threat of terrorism, and business cycles in tourist source countries, among many others, which can cause variations in monthly international tourist arrivals. Owing to the nature of these events, recovery from variations in tourist arrivals from unanticipated events may take longer for some countries than for others. These time-varying effects may not necessarily exist within SITEs, and hence may be intrinsic to the tourist source countries.

In this paper, we show how the GARCH model can be used to measure the conditional volatility in monthly international tourist arrivals to three SITEs. It is, for example, possible to measure the extent to which the 1991 Gulf War influenced variations in monthly international tourist arrivals to Cyprus, and to what extent the coups d'état of 1987 and 2000 affected subsequent monthly international tourist arrivals to Fiji.

An awareness of the conditional volatility inherent in monthly international tourist arrivals and techniques for modelling such volatility are vital for a critical analysis of SITEs, which depend heavily on tourism for their macroeconomic stability. The information that can be ascertained from these models about the volatility in monthly international tourist arrivals is crucial for policy-makers in the public and private sectors, as such information would enable them to instigate policies regarding income, bilateral exchange rates, employment, government revenue, and so forth. Such information is also crucial for decision makers in the private sector, as it would enable them to alter their marketing and management operations according to fluctuations in volatility.

The GARCH model is well established in the financial economics and econometrics literature. After the development by Engle (1982) and Bollerslev (1986), extensive theoretical developments regarding the structural and statistical properties of the model have evolved (for derivations of the regularity conditions and asymptotic properties of a wide variety of univariate GARCH models, see Ling and McAleer (2002a, 2002b, 2003)). In this paper we extend the concept of conditional volatility and the GARCH model to estimate and forecast monthly international tourist arrivals data. The GARCH model is applied to monthly international tourist arrivals in three SITEs, which rely overwhelmingly on tourism as a primary source of export revenue. Such research would be expected to make a significant contribution to the existing tourism research literature, as tourism research on the volatility of monthly international tourist arrivals would appear to be non-existent.

This paper shows how variations of the GARCH model can be used to forecast international tourism demand and uncertainty by modelling the conditional volatility in monthly international tourist arrivals to Barbados, Cyprus and Fiji. The sample periods for these three SITEs are as follows: Barbados, January 1973 to December 2002 (Barbados Tourism Authority); Cyprus, January 1976 to December 2002 (Cyprus Tourism Organization and Statistics Service of Cyprus); and Fiji, January 1968 to December 2002 (Fiji Islands Bureau of Statistics). In the case of Cyprus, monthly tourist arrivals data were not available for 1995, so the mean monthly tourist arrivals for 1993, 1994, 1996 and 1997 were used to construct the data for 1995 in estimating the trends and volatilities in international tourist arrivals.

The main contributions of this paper are as follows. First, the importance of conditional volatility in monthly international tourist arrivals is examined and modelled, and the macroeconomic implications for SITEs are appraised. Second, the conditional volatilities are estimated and an economic interpretation is provided. Third, the conditional volatilities are used in obtaining more precise forecast confidence intervals. In achieving these objectives, we examine the existing literature on the impact of tourism in small island economies in relation to their gross domestic product, balance of payments, employment, and foreign direct investment, among other factors.

As the effects of positive and negative shocks in international tourism arrivals may have different effects on tourism demand volatility, it is also useful to examine two asymmetric models of conditional volatility. For this reason, two popular univariate models of conditional volatility, namely the asymmetric GJR model of Glosten, Jagannathan and Runkle (1992) and the exponential GARCH (or EGARCH) model of Nelson (1991), are estimated and discussed. Some concluding remarks on the outcome of this research are also provided.

2 SMALL ISLAND TOURISM ECONOMIES

A small island tourism economy (SITE) can best be defined by examining its three main properties, which are its (relatively) small size, its nature as an island, and its reliance on tourism receipts. These three aspects of SITEs are discussed in Shareef (2003).

This paper examines three SITEs for which monthly international tourist arrivals data are available. In Table 1, the common size measures show that these three SITES account for more than 1.8 million people. Their populations range in size for a mini-economy like Barbados, with a population of 260,000, and Cyprus and Fiji, which have populations of around 700,000. Each of these economies is a former British colony, which gained independence during the latter half of the last century. All of these SITEs have relatively large per capita GDP figures. These SITEs are in three geographic regions of the world, with one of them in the Caribbean, one in the Pacific Ocean, and one in the Mediterranean.

Table 1. Common Size Measures of SITEs

SITEs	Mean 1980-2000		2000		Surface Area (km^2)
	Pop. (m)	GDP per capita (USD)	Pop. (m)	GDP per capita (USD)	
Barbados	0.26	7,100	0.27	8,300	430
Cyprus	0.69	10,000	0.76	14,100	9,240
Fiji	0.73	2,300	0.81	2,400	18,270
Mean	**0.56**	**6,467**	**0.61**	**8,267**	**9,313**

The SITEs analysed in this paper are sovereign island economies because of their geophysical nature. Most of them are archipelagic, have risen from the ocean through volcanic activity, and lie along the weaker parts of the earth's crust. Tourists typically reach these countries by air, and freight is usually carried by sea. These island economies are consistently threatened by natural disasters as well as the effects of environmental damage and have inherited the world's most delicate ecosystems. Armstrong and Read (2002, p. 438) reiterate that 'both internal and external communication and trade may be very costly and implications for their internal political and social cohesiveness as well as competitiveness.' These SITEs are in regions of the world where they are frequently faced with unsympathetic climatic conditions, and usually affect all economic activity and the population.

In all of these SITEs, tourism is the mainstay of the economy and earnings from it account for a significant proportion of the value added in their national product. The fundamental aim of tourism development in SITEs is to increase foreign exchange earnings to finance imports. Due to limited natural resource base, these SITEs have an overwhelming reliance on service industries (including value added in wholesale and retail trade (including hotels and restaurants), transport, government, financial, professional, and personal services such as education, health care and real estate services), of which tourism accounts for the highest proportion in foreign exchange earnings. During the period 1980 to 2000, the average earnings from tourism as a proportion of gross export earnings account for 51 percent in Barbados, 37 percent in Cyprus, and 25 percent in Fiji (World Development Indicators (WDI) 2002, The World Bank, 2002). In economic planning, tourism has a predominant emphasis in SITEs where the climate is well suited for tourism development and the islands are strategically located.

A large proportion of tourism earnings leaves the economy instantaneously to finance imports to sustain the tourism industry. As given in the Commonwealth Secretariat/World Bank Joint Task Force on Small States (2000), imports to service the tourism industry are comprised mostly of non-indigenous goods. For instance, meat and dairy products feature heavily in the Caribbean. Due to scarcity of labour in some SITEs, it is also imported for employment in tourism and results in substantial foreign exchange outflows.

The tourism establishment in SITEs are mostly co-operative developments isolated from the core economy. Hence, the desired effects to the economy are sometimes limited. Tourism requires careful planning in order to maintain sustainability and to limit environmental damage. While tourism has contributed to economic development in many SITEs, they need to be managed responsibly in order to secure their long-term sustainability. Further discussions of the above characteristic features of SITEs are given in Shareef (2003).

The volatility of the GDP growth rate is defined as the square of the deviation from its mean. In SITEs, the volatility of GDP growth rate tends to be very high. In Shareef (2003a), the volatility of the real GDP growth rates for 20 SITEs are given. The lowest mean volatility of real GDP growth rate was recorded for Malta in the Mediterranean for the period 1980-2002, while St. Lucia in the Caribbean Sea recorded the highest mean volatility of 56.9 for the same period.

The Commonwealth Secretariat/World Bank Joint Task Force on Small States (2000) reports that the high volatility in the GDP growth rate recorded among SITEs is due to three main reasons. First, SITEs are more susceptible to changes in the international market conditions since they are highly open to the rest-of-the-world and due to their narrow productive base. Moreover, SITEs produce a limited range of uncompetitive exports, they operate under the same rules and regulations as other countries and have fewer options to hedge against any losses. Finally, SITEs are frequently affected by natural disasters, which adversely affect all the sectors in their economies. The significance of the above varies significantly among SITEs as smallness is associated with relatively high levels of specialisation in production and trade.

These vulnerability factors make the economic management of SITEs difficult and sensitive to the information delivered about changes in the key flows of resources into and out of the economy. For countries that are dominated by tourism, one of the most important factors is the variability in international tourist arrivals. It is critical, therefore, that policy makers in these countries have the most accurate estimate of tourist arrivals, and preferably as far in advance as possible, so that appropriate actions can be taken. Policy areas where data on fluctuations in international tourist arrivals have the greatest impact include the following:

(1) Fiscal policy:

Tourism taxes and other tourism-related income, such as service charges, make direct contributions to government revenue. Any adverse effects on tourist arrivals would affect fiscal policy adversely, and economic development would also be hampered. Therefore, tourism has a direct effect on sustainable development, and hence on the optimal management of development expenditures.

(2) Balance of payments**:**

An adverse effect on tourism numbers will lead to a decline in the overall balance, so that foreign exchange reserves will also decline. This could lead to an exchange rate devaluation, which will make imports more expensive. Such an outcome is crucial to the management of foreign reserves in SITEs, which rely heavily on imports.

(3) Employment in the tourism sector:

As tourism is one of the most important sectors in the economies in SITEs, any shocks that affect the patterns of tourism will affect the sustainability of employment.

(4) Tourism in SITEs has substantial multiplier effects:

Although the agricultural sector in SITEs is typically insignificant, the output of the agriculture sector can be fully absorbed by the tourism sector. Therefore, sustainable tourism can have positive effects on other sectors. Moreover, the construction sector depends highly on the tourism sector for upgrading tourism infrastructure and developing new construction projects. With an increase in the number of international tourists worldwide, tourist destinations need to increase their capacity significantly.

Therefore, due to the nature of SITEs and the implications of being a SITE, as described above, it is clear that tourism sustainability is necessary for SITEs to sustain their economic development. Consequently, it is imperative that forecasts of inbound international tourism demand to these SITEs are obtained accurately.

3 DATA

This paper models the conditional volatility of international tourist arrivals in three SITEs, and also provides forecasts of international tourist arrivals. For these SITEs, the frequency of the data is monthly, and the samples are as follows: Barbados, January 1973 to December 2002; Cyprus, January 1976 to December 2002; and Fiji, January 1968 to December 2002.

International tourist arrivals to each of these SITEs exhibit distinct seasonal patterns and positive trends. For Barbados, there are some cyclical effects, which coincide with the business cycles in the US economy. These business cycles are the boom period in the latter half of the 1970s, the slump due to the second oil price shock of 1979, and the recession in the early 1990s. In Cyprus, the only visible change in monthly international tourist arrivals is the outlier of the 1991 Gulf War. For Fiji, the coups of 1987 and 2000 are quite noticeable.

The volatility of the deseasonalised and detrended monthly tourist arrivals can be calculated from the square of the estimated residuals using non-linear least squares. The most visible cases of volatility clusterings of monthly international tourism demand are Barbados and Cyprus. In Barbados, in the first third of the sample, monthly international tourism arrivals have been highly volatile owing to the economic cycles in the US economy. For Cyprus, there is volatility clustering in the late-1970s to mid-1980s due to the second oil price shock. For Fiji, volatility clusterings are virtually non-existent.

The volatility of the growth rate of deseasonalised monthly international tourist arrivals can be calculated from the square of the estimated residuals using non-linear least squares (the data and figures are available on request). For Barbados, there is clear evidence of volatility clustering during the early 1970s and in the mid-1980s, after which there is little evidence of volatility clustering. Volatility clustering is visible for Cyprus in the mid-1970s. The volatility structure of Fiji resembles that of a financial time series, with volatility clustering not so profound, except for outliers, which signify the coups d'état of 1987 and 2000.

The volatility in monthly international tourist arrivals to the three SITEs show similar behavioural patterns, but there are visible differences in the magnitudes of the calculated volatility, particularly for Barbados and Fiji. This is plausible for monthly international tourist arrivals to these SITEs, so there would seem to be a strong case for estimating both symmetric and asymmetric conditional volatility models.

4 UNIVARIATE MODELS OF TOURISM DEMAND

This section discusses alternative models of the volatility of international tourist arrivals using the Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by Engle (1982), as well as subsequent developments in Bollerslev (1986), Bollerslev et al. (1992), Bollerslev et al. (1994), and Li et al. (2003), among others. The most widely used variation for symmetric shocks is the generalised ARCH (GARCH) model of Bollerslev (1986). In the presence of asymmetric behaviour between positive and negative shocks, the GJR model of Glosten et al. (1992) and the EGARCH model of Nelson (1991) are also widely used. Ling and McAleer (2002a, 2002b, 2003) have made further theoretical advances in both the univariate and multivariate frameworks.

4.1 Symmetric GARCH(1,1)

The uncertainty or risk (h_t) in the ARMA(1,1)-GARCH(1,1) model for monthly international tourist arrivals is given in Table 2, and the unconditional shocks for monthly international tourist arrivals are given by ε_t^2, where $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. The ARCH (or α) effect captures the short-run persistence of shocks to international tourist arrivals, while the GARCH (or β) effect measures the contribution of shocks to long-run persistence of shocks, $\alpha + \beta$. The parameters are typically estimated by maximum likelihood to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the absence of normality of the standardised shocks, η_t.

It has been shown in Ling and McAleer (2003) that the QMLE of GARCH (*p*,*q*) is consistent if the second moment 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, which is also sufficient for consistency of the QMLE. Jeantheau (1998) showed that the weaker log-moment condition is sufficient for consistency of the QMLE for the univariate GARCH (*p,q)* model. Hence, a sufficient condition for the QMLE of GARCH(1,1) to be consistent and asymptotically normal is given by the log-moment condition (see Table 2). McAleer et al. (2003) argue that this conclusion is not straightforward to check in practice as it involves the expectation of an unknown random variable and unknown parameters. Moreover, the second moment condition is far more straightforward to check in practice, although it is a stronger condition.

4.2 Asymmetric GJR(1,1) and EGARCH(1,1)

The effects of positive shocks on the conditional variance h_t are assumed to be the same as negative shocks in the symmetric GARCH model. Asymmetric behaviour is captured in the GJR model, as defined in Table 2, where $\omega > 0$, $\alpha \geq 0$, $\alpha + \gamma \geq 0$ and $\beta \geq 0$ are sufficient conditions for $h_t > 0$, and $I(\eta_t)$ is an indicator variable (see Table 2). The indicator variable distinguishes between positive and negative shocks such that asymmetric effects are captured by γ, with $\gamma > 0$. In the GJR model, the asymmetric effect, γ, measures the contribution of shocks to both short run persistence, $\alpha + \gamma / 2$, and long run persistence, $\alpha + \beta + \gamma / 2$. The necessary and sufficient condition for the existence of the second moment of GJR(1,1) under symmetry of η_t is given in Table 2 (see Ling and McAleer (2002b)). The weaker sufficient log-moment condition for GJR(1,1) is also given in Table 2. McAleer et al. (2003) demonstrated that the QMLE of the parameters are consistent and asymptotically normal if the log-normal condition is satisfied.

An alternative model to capture asymmetric behaviour in the conditional variance is the EGARCH(1,1) model of Nelson (1991). When β = 0, EGARCH(1,1) becomes EARCH(1). There are some distinct differences between EGARCH, on the one hand, and GARCH(1,1) and GJR(1,1), 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) Nelson (1991) showed that $|\beta| < 1$ ensures stationarity and ergodicity for EGARCH(1,1); (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 conditional (or standardized) shocks appear in equation (4), McAleer et al. (2003) observed that is likely $|\beta| < 1$ is a sufficient condition for the existence of all moments, and hence also sufficient for asymptotic normality of the QMLE of EGARCH(1,1).

5 EMPIRICAL ESTIMATES AND FORECASTS

This section models the monthly international tourist arrivals to Barbados, Cyprus and Fiji for the periods 1973(1)-2001(12), 1976(1)-2001(12) and 1968(1)-2001(12), respectively, using a variety of models, namely: (i) OLS constant variance (or non-time-varying volatility) model; and (ii) various time-varying conditional volatility models, namely the ARCH(1), GJR(1,0), EARCH(1), GARCH(1,1), GJR(1,1) and EGARCH(1,1) models. The GJR(1,0) model is also known as the asymmetric ARCH(1) model.

For each country, the empirical results obtained from the conditional volatility models are compared with their OLS counterparts. The conditional mean specifications for the three countries are given as follows:

$$BRB_t = \phi BRB_{t-1} + \sum_{i=1}^{2} \tau_i t^i + \sum_{i=1}^{12} \delta_i D_i + \theta \varepsilon_{t-1} + \varepsilon_t \quad (1)$$

$$CYP_t = \phi CYP_{t-1} + \sum_{i=1}^{12} \delta_i D_i t + \varepsilon_t \quad (2)$$

$$FJI_t = \phi FJI_{t-1} + \sum_{i=1}^{2} \tau_i t_i + \sum_{i=1}^{12} \delta_i D_i + \theta \varepsilon_{t-1} + \varepsilon_t \quad (3)$$

$$t_1 = \begin{cases} t, \; t = 1,...,88 \\ 0, \; t = 89,...,T \end{cases}$$

$$t_2 = \begin{cases} t, \; t = 89,...,T \\ 0, \; t = 1,...,88 \end{cases}$$

where BRB_t, CYP_t and FJI_t are the total monthly international tourist arrivals at time t for Barbados, Cyprus and Fiji, respectively; D_i (= 1 in month $i = 1, 2, ..., 12$, and = 0 elsewhere) denotes 12 seasonal dummy variables; and $t = 1,...,T$, where T = 347, 311 and 407 for Barbados, Cyprus and Fiji, respectively.

Autoregressive (AR(1)) specifications were used for each country, but there was no evidence of unit roots in any of the three international tourist arrivals series. Different deterministic time trends were used for each of the three SITEs according to their respective empirical regularities. The time trend is the simplest for Cyprus, but are more complicated for Barbados and Fiji, with each of the latter having breaking trends and moving average (MA(1)) error processes.

There is a distinct seasonal pattern in each tourist arrivals series. Although there are several alternative methods for modelling seasonality, twelve seasonal dummy variables are included for simplicity in the respective tourist arrivals models. The empirical estimates are discussed only for the constant volatility linear regression model and three conditional volatility models. The three optimal time-varying conditional volatility specifications for each country, namely ARCH(1), GJR(1,0) and EGARCH(1,1) for Barbados, ARCH(1), GJR(1,0) and EARCH(1) for Cyprus, and GARCH(1,1), GJR(1,1) and EGARCH(1,1) for Fiji, are selected on the basis of the significance of their parameter estimates and on their overall forecast accuracy performance.

All the estimates are obtained using the Berndt, Hall, Hall and Hausman (BHHH) (1974) algorithm in the EViews 4 econometric software package. Virtually identical estimates were obtained using the RATS program. Several different sets of initial values have been used in each case, but do not lead to substantial differences in the estimates.

Estimates of the parameters of both the international tourist arrivals and conditional volatility models for the univariate OLS linear regression model and various univariate GARCH models for Barbados, Cyprus and Fiji are presented in Tables 3-5, respectively. Asymptotic t-ratios are reported under each corresponding parameter estimate. The tourist arrivals estimates for the linear regression constant volatility model and the three time-varying conditional volatility models vary across the three countries, as well as total international tourist arrivals. There is highly significant seasonality in international tourist arrivals for each country and for each month. The lagged effects of monthly international tourist arrivals is highly significant for all three countries, and especially so for Barbados.

The constant volatility linear regression model estimated by OLS is compared with the three optimal time-varying conditional volatility models for Barbados, namely ARCH(1), GJR(1,0) and EGARCH(1,1). Asymmetric effects are not significant for GJR(1,0) but are significant for EGARCH(1,1). The contribution of shocks to long run persistence is not significant for either ARCH(1) or GJR(1,0). For Cyprus, the constant volatility linear regression model estimated by OLS is compared with the three optimal time-varying conditional volatility models, namely ARCH(1), GJR(1,0) and EARCH(1). Asymmetric effects are not significant for either GJR(1,0) or EGARCH(1,1). The contribution of shocks to long run persistence is not significant for any of the three time-varying conditional volatility models. Finally, the constant volatility linear regression model estimated by OLS is compared with the three optimal time-varying conditional volatility models for Fiji, namely GARCH(1,1), GJR(1,1) and EGARCH(1,1). Asymmetric effects are not significant for either GJR(1,0) or EGARCH(1,1). The contribution of shocks to long run persistence is significant for each of the three time-varying conditional volatility models.

Overall, the results show that the parameter estimates for the short run persistence of shocks to international tourist arrivals, and occasionally also the long run persistence of shocks to international tourist arrivals, are significant. The asymmetric effects of shocks in some of the GARCH, GJR and EGARCH specifications are also significant. These results show that the OLS linear regression model with constant variance (that is, non-time-varying volatility) is not the optimal specification for modelling international tourist arrivals to Barbados, Cyprus and Fiji.

The descriptive statistics of monthly international tourist arrivals and volatility are given in Table 6, while the graphs of the respective series are given in Figures 1 and 2. It is not surprising that the volatilities of monthly international tourist arrivals to each of the three SITEs is positively skewed.

The constant volatility OLS linear regression model and the three optimal time-varying conditional volatility models for each country are used to forecast the final 12 observations in the sample. The four criteria used to evaluate the respective forecast performance of the models for each country are as follows:

1. Root Mean Square Error:

$$RMSE = \sqrt{\frac{\sum_{\tau=T+1}^{T+m} (\hat{y}_\tau - y_\tau)^2}{m+1}}$$

2. Mean Absolute Error:

$$MAE = \frac{1}{(m+1)} \sum_{\tau=T+1}^{T+m} \left| \hat{y}_\tau - y_\tau \right|$$

3. Mean Absolute Percentage Error:

$$MAPE = \frac{1}{(m+1)} \sum_{\tau=T+1}^{T+m} \left| \frac{\hat{y}_\tau - y_\tau}{y_\tau} \right|$$

4. Forecast Standard Error:

$$\sqrt{\hat{\mathrm{Var}}(\hat{y}_\tau - y_\tau \mid x_\tau)} = \hat{h}_\tau^{\frac{1}{2}} \left(1 + \frac{1}{T} + \frac{(x_\tau - \bar{x})^2}{\sum_{t=1}^{T} (x_t - \bar{x})^2} \right)^{\frac{1}{2}}$$

where $y_t = E(y_t \mid x_t) + \varepsilon_t$, m denotes the size of the forecast horizon, T denotes the sample size used for within sample parameter estimation, and $\hat{h}_\tau$ denotes the estimated conditional variance for time τ.

The forecast results are reported in Table 7, with the rankings of the models by forecast standard errors for the 12 months being based on the largest number of accurate monthly forecasts. For Barbados, the optimal forecasting model overall based on the four criteria is EGARCH(1,1), followed by GJR(1,0), so that both asymmetry and the long run persistence of shocks assist in the optimal forecasting of monthly international tourist arrivals. The optimal forecasting model for Cyprus overall based on the four criteria is EARCH(1), followed by ARCH(1), so that asymmetry, but not the long run persistence of shocks, assists in the optimal forecasting of monthly international tourist arrivals. Finally, for Fiji, the optimal forecasting model overall based on the four criteria is GARCH(1,1), followed by GJR(1,1), so that both asymmetry and the long run persistence of shocks assist in the optimal forecasting of monthly international tourist arrivals.

It is instructive that at least two of the three time-varying conditional volatility models is superior to the constant volatility linear regression model estimated by OLS for each of the three countries.

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REFERENCES

Armstrong, H.W. and Read, R. (2002), 'The Phantom of Liberty?: Economic Growth and the Vulnerability of Small States', *Journal of International Development*, 14 (3), 435-458.

Berndt, E.K., Hall, B.H., Hall, R.E. and Hausman, J. (1974), 'Estimation and Inference in Nonlinear Structural Models', *Annals of Economic and Social Measurement*, 3, 653-665.

Bollerslev, T. (1986), 'Generalised Autoregressive Conditional Heteroscedasticity', *Journal of Econometrics*, 31, 307-327.

Bollerslev, T., Chou, R.Y. and Kroner, K.F. (1992), 'ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence', *Journal of Econometrics,* 52, 5-59.

Bollerslev, T., Engle, R.F. and Nelson, D.B. (1994), 'ARCH Models' in R.F Engle and D.L McFadden (eds.), *Handbook of Econometrics*, 4, (North Holland-Amsterdam), pp. 2961-3038.

Bollerslev, T. and Woodridge, J.M. (1992), 'Quasi-maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances', *Econometric Reviews*, 11, 143-173.

Commonwealth Secretariat/World Bank Joint Task Force on Small States (2000), 'Small States: Meeting Challenges in the Global Economy', London: Commonwealth Secretariat/Washington, D.C., The World Bank.

Engle, R.F. (1982), 'Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation', *Econometrica*, 50, 987-1007.

Glosten, L., Jagannathan, R. and Runkle, D. (1992), 'On the Relation Between the Expected Value and Volatility of Nominal Excess Return on Stocks', *Journal of Finance*, 46, 1779-1801.

Jeantheau, T. (1998), 'Strong Consistency of Estimators for Multivariate ARCH Models', *Econometric Theory*, 14, 70-86.

Li, W.K., Ling, S. and McAleer, M. (2002), 'Recent Theoretical Results for Time Series Models with GARCH Errors', *Journal of Economic Surveys*, 16, 245-269. Reprinted in M. McAleer and L. Oxley (eds.), *Contributions to Financial Econometrics: Theoretical and Practical Issues*, Blackwell, Oxford, 2002, 9-33.

Ling, S. and McAleer, M. (2002a), 'Necessary and Sufficient Moment Conditions for GARCH (r,s) and Asymmetric Power of GARCH(r,s) Models', *Econometric Theory,* 18, 722-729.

Ling, S. and McAleer, M. (2002b), 'Stationary and the Existence of Moments of a Family of GARCH Processes', *Journal of Econometrics,* 106, 109-117.

Ling, S. and McAleer, M. (2003), 'Asymptotic Theory for a Vector ARMA-GARCH Model', *Econometric Theory,* 19, 278-308.

McAleer, M., Chan, F. and Marinova, D. (2003), 'An Econometric Analysis of Asymmetric Volatility: Theory and Applications to Patents', to appear in *Journal of Econometrics.*

Nelson, D.B. (1991), 'Conditional Heteroscedasticity in Asset Returns: A New Approach', *Econometrica*, 59, 347-370.

Shareef, R. (2003), 'Small Island Tourism Economies: A Bird's Eye View', in D. Post (ed.), *Proceedings of the International Conference on Modelling and Simulation: Socio-economic Systems,* Townsville, Australia, 3, pp. 1124-1129.

Shephard, N. (1996), 'Statistical Aspects of ARCH and Stochastic Volatility', in O.E. Barndorff-Nielsen, D.R. Cox and D.V. Hinkley (eds.), *Statistical Models in Econometrics, Finance and Other Fields,* Chapman & Hall, London, pp. 1-67.

World Bank (2002), 'World Development Indicators', CD-ROM 2002.

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Table 2. GARCH (1,1), GJR(1,1) and EGARCH(1,1) Conditional Volatility Models

Model Specification	**Sufficient Conditions for $h_t > 0$**	**Regularity Conditions**
Symmetric specification **ARMA-GARCH (1,1):** $\varepsilon_t = \eta_t \sqrt{h_t}$, $\eta_t \sim iid\ (0,1)$	$\omega > 0$ $\alpha \geq 0$ $\beta \geq 0$	**Log-Moment:** $E[\log(\alpha\eta_t^2 + \beta)] < 0$ **Second Moment:** $\alpha + \beta < 1$
Asymmetric specifications $\varepsilon_t = \eta_t \sqrt{h_t}$, $\eta_t \sim iid\ (0,1)$ **(1) ARMA-GJR(1,1):** $h_t = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1}$ $I(\eta_t) = \begin{cases} 1, & \eta_t < 0 \\ 0, & \eta_t \geq 0 \end{cases}$	$\omega > 0$ $\alpha \geq 0$ $\alpha + \gamma \geq 0$ $\beta \geq 0$	**Log-Moment:** $E[(\log((\alpha + \gamma I(\eta_t))\eta_t^2 + \beta)] < 0$ **Second Moment:** $\alpha + \beta + \gamma / 2 < 1$
(2) ARMA-EGARCH(1,1): $\log h_t = \omega + \alpha \mid \eta_{t-1} \mid + \gamma\, \eta_{t-1} + \beta \log h_{t-1}$	Not necessary	$\mid \beta \mid < 1$

Table 3. GARCH (1,1), GJR(1,1) and EGARCH(1,1) Conditional Volatility Models

Barbados

Estimates	OLS	ARCH(1)	A-ARCH(1)	EGARCH (1,1)
θ	-0.501 -8.152	-0.500 -7.597	-0.490 -6.772	-0.449 -7.306
ω		5591272.813 10.396	5553966.677 10.526	6.749 1.544
α		0.064 1.028	0.148 1.347	-0.064 -6.230
γ			-0.154 -1.264	0.166 2.127
β				0.570 2.020

Cyprus

Estimates	OLS	ARCH(1)	A-ARCH(1)	EGARCH (1,1)
ω		73620917.673 8.246	74523980.142 8.033	18.025 144.143
α		0.406 1.847	0.494 1.389	0.582 4.825
γ			-0.195 -0.482	0.081 1.045

Fiji

Estimates	OLS	ARCH(1)	A-ARCH(1)	EGARCH (1,1)
θ	0.056 0.765	-0.251 -3.803	-0.260 -9.930	-0.294 -3.546
ω		1499028.575 5.553	1420679.169 4.732	0.538 1.710
α		0.453 3.722	0.394 2.342	0.382 2.602
γ			0.147 0.621	-0.101 -1.539
β		0.295 2.364	0.307 10.585	0.946 43.438

Note: Asymptotic t-ratios are reported under each corresponding parameter estimate.

Table 4. Forecast Results for Monthly International Tourist Arrivals

Barbados	**RMSE**	**MAE**	**MAPE**	**FSE (ranking)**
OLS	2951	2552	6.01	4
ARCH(1)	3013	2612	6.13	2
GJR(1,0)	2931	2513	5.93	3
EGARCH(1,1)	2847	2424	5.8	1
Cyprus	**RMSE**	**MAE**	**MAPE**	**FSE (ranking)**
OLS	24675	17254	9.35	2
ARCH(1)	24089	16582	9.07	4
GJR(1,0)	24475	17415	10.01	3
EARCH(1)	23842	16712	9.35	1
Fiji	**RMSE**	**MAE**	**MAPE**	**FSE (ranking)**
OLS	3404	2595	7.31	3
GARCH(1,1)	3109	2300	6.51	1
GJR(1,1)	3180	2361	6.68	2
EGARCH(1,1)	3201	2575	7.56	4