MODELLING THE VOLATILITY OF LONG-STAY TOURIST ARRIVALS TO BARBADOS

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ABSTRACT

Although volatility is an important characteristic of tourism economies, it has not received a lot of attention from regional researchers. Volatility in monthly tourist arrivals are primarily due to unanticipated events, such as natural disasters, crime, the threat of terrorism, and business cycles in tourist source countries. This study exploits recent modelling techniques to measure and investigate the volatility in monthly international tourist arrivals for Barbados. The results show that the volatility of tourist arrivals to Barbados is asymmetric: positive shocks have a differential impact on future volatility than negative shocks. There is also some evidence of short-run volatility persistence.

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1. Introduction

Tourism is one of the most important industries in the Barbados economy. At the end of 2003, value-added arising from visitors to the island was estimated at BDS$512.4 million, or about 12 percent of nominal gross domestic product (GDP). In addition, to its contribution to domestic economic activity, tourism is also the leading foreign-exchange earning industry, and makes significant contributions to government revenue, and employment.

As a result of time-varying effects, such as changes in economic fortunes abroad, natural disasters, ethnic conflicts, crime, terrorist incidents, and other exogenous factors, there have been periods of considerable fluctuation in international tourism demand to Barbados. These fluctuations in demand can and do have a significant impact on the solvency of small hotels, employment in the industry and overall economic activity. It is therefore imperative that tourism planners and policymakers have an understanding of volatility and models to forecast volatility of tourist arrivals.

Modelling the volatility of tourism demand is a relatively new area of leisure studies. Nevertheless, there have been some recent attempts in this area, most notably Chan, Lim and McAleer (2005), Chan et al. (2005) and Shareef and McAleer (2005). In Chan, Lim and McAleer (2005), the authors model the conditional mean and conditional variance of the logarithm of the monthly tourist arrivals from the four leading source countries – Japan, New Zealand, UK and USA – to Australia between 1975 and 2000. The main utility of the multivariate volatility models used is that they explicitly take into account volatility correlation between markets. The authors estimate three multivariate constant conditional correlation (CCC) volatility models: the symmetric CCC-MGARCH approach of Bollerslev (1990), the symmetric vector ARMA-GARCH framework of Ling and McAleer (2003) and the asymmetric vector ARMA-AGARCG method of Chan, Hoti and McAleer (2002). Chan, Lim and McAleer find the presence of interdependent effects in the conditional variances between the four leading source countries, and asymmetric effects in arrivals from Japan and New Zealand. The authors report that their estimates are robust to the alternative specifications of the multivariate conditional variance.

Chan et al. (2005) use several techniques to investigate the conditional volatility in monthly international tourist arrivals to Barbados (1973-2002), Cyprus (1976-2002) and Fiji (1968-2002). They estimate a constant volatility linear regression model by OLS as a baseline for comparison with three time-varying conditional volatility models – ARCH, GJR and EGARCH. Overall, the authors report evidence of short run persistence, and occasionally long run persistence, of shocks to international tourist arrivals. Chan et al. (2005) also find evidence of asymmetric effects of shocks for Barbados using the EGARCH specification.

Shareef and McAleer (2005) model both the volatility in monthly international tourist arrivals and the volatility in the growth rate of monthly tourist arrivals for six small island tourist economies: Barbados, Cyprus, Dominica, Fiji, Maldives and Seychelles during the period 1980-2000 using GARCH(1,1) and GJR(1,1). While estimates for the conditional mean and variance in monthly international tourist arrivals for a particular country are similar using both the GARCH(1,1) and GJR(1,1), estimates varied somewhat across countries. A similar result held when the growth rate of monthly tourist arrivals was modelled. Using the log-moment and second moment conditions, they obtain support for the statistical adequacy of the GARCH(1,1) and GJR(1,1) models.

This paper extends the literature surveyed above by estimating seven models of tourism volatility using monthly data for the period 1977-2005 for Barbados. These models allow the authors to investigate asymmetry, threshold effects and mean varying volatility in tourism arrivals. After the introduction, Section 2 discusses the patterns of tourist arrivals to Barbados. Section 3 describes the data used, while the specifications of the volatility models estimated in this study are outlined in Section 4. Section 5 presents the regression estimates and a discussion of the empirical results. Section 6 concludes.

2. Trends and Composition of Tourist Arrivals

In this section the authors analyse the trends in tourist arrivals to Barbados over the period 1977-2005, to provide an initial analysis of the factors that can influence tourism demand volatility. There are many different tourist source countries for which the Barbados Statistical Service maintains data. Of these, the main markets are the United States (US), the United Kingdom (UK), Canada and CARICOM; the remaining source markets are too small relative to the main markets and are hence placed in the category called OTHER. Table 1 gives an overview of the average numbers of tourist arrivals in each period and their shares. The sample is split into two periods, 1977-1990 and 1991-2005, for comparison purposes. Over the entire period, 1977-2005, tourist arrivals from the US rose by 2.2 percent per annum, compared to 7.4 percent for the UK, 3.2 for CARICOM and less than one percent for the OTHER source markets. Canada was the only major market to record an annual decline (down by 2 percent per year).

During the first period, 1977-1990, the US was the single largest source market, with a share of 32.8 percent of average tourist arrivals and an annual growth rate of 5.5 percent. Between 1991 and 2005, however, arrivals from the US fell by around 1 percent per annum and as a result the US was replaced by the UK as the leading source market for arrivals to Barbados (the specific year in which annual UK arrivals surpassed US arrivals was 1994). Figure 1 shows that since 1994 UK arrivals have generally trended upwards, while most of the other main markets have been relatively flat. In the second half of the sample, the share of UK tourist arrivals doubled from 16.7 percent 34.4 percent, as a result of average annual growth of 5.1 percent per annum.

The fortunes of the Canadian market also changed significantly in the latter half of the period under review. In the first half of the sample, inbound tourism from Canada accounted for 19.1 percent of average annual tourist arrivals, second only to the US. However, during the latter half of the review period, arrivals from this market fell by 2.85 percent per annum. Consequently, Canada's share of average tourist arrivals plummeted to 11 percent, falling to 5th in the list of the largest source markets to Barbados.

CARICOM, in contrast, performed well in both the first and second halves of the period under review. The average annual growth rate of this market increased from 2 percent between 1977 and 1990 to 4.2 percent during 1991 and 2005. Nevertheless, the share of this market decreased from 19 percent to 15.7 percent, mainly due to the overwhelming increase in the UK's share and to a lesser extent, the increase in OTHER.

Table 1 also reveals that there was an increase in the average numbers of tourists from the OTHER source markets, from 46,317 in 1977-1990 to 70,849 in 1991-2005. Accordingly, there was a corresponding increase in OTHER's share of average tourist arrivals from 12.5 percent to 14.8 percent. Since 1999, however, the annual growth rate of tourist arrivals from OTHER has contracted. In 1999, there was a precipitous 34 percent decline in tourist arrivals from OTHER (mainly due to a falloff in arrivals from Germany) and with the exception of the years 2003 and 2004, tourist arrivals declined from that point onward.

3. Volatility of Tourist Arrivals

The data used to model volatility is the logarithms of deseasonalised total monthly tourist arrivals for the entire sample period under study, 1977-2005. The series is deseasonalised using Census X12, the US Census Bureau seasonal adjustment algorithm. The augmented Dickey-Fuller (ADF) test (1979) and the Phillips-Perron (PP) tests (1988) of the unit root hypothesis, conducted using Eviews 5.0, both suggest the absence of a unit root in the log of the monthly deseasonalised series (see Table 2). These tests are robust to changes in lag length and auxiliary equation specification.

Figure 2 plots the log of the monthly deseasonalised arrival rate to Barbados between 1977 and 2005. The cyclicality in the log deseasonalised arrival rate is very apparent. The peaks in the cycle correspond to the boom in the latter half of the 1970s and the recovery from the recession early in the 1990s, while the troughs correspond to the slowdown caused by the second oil price shock in 1979 and the two Persian Gulf conflicts.

Following Chan, Lim and McAleer (2005), volatility is calculated as the square of the estimated residuals ε_t^2 from an autoregressive moving average process. The correlogram of the log arrival rate suggested that an AR(1) or an AR(2) would be suitable. Diagnostic checking confirmed that the AR(1) with a deterministic time trend is a more suitable description of the process:

$$\log(TA_t) = AR(1) + \varphi time + \varepsilon_t \tag{1}$$

$$Vol(\varepsilon_t) = \varepsilon_t^2 \tag{2}$$

where *TA* is the total monthly international tourist arrivals at time *t* and *time* = 1,…,*T*, where *T* = 348.

Figure 3, which plots the estimated volatility series, shows that tourist arrivals volatility is characterised by volatility clustering: a shock is likely to be followed by other (smaller) shocks. These volatility clusters correspond to the peaks and troughs of the cycles described previously. The figure also shows that monthly tourist arrivals are also more volatile in the first half of the sample. This finding corresponds to the Butler (1980) lifecycle model, which predicts that in the early stages of a destination's lifecycle, growth is likely to be positive, but volatile.

4. Volatility Models

All the volatility models used in the paper are provided in Table 3. The RiskMetrics (1996) volatility model is a popular tool employed to measure risk. The framework has two main advantages: (1) it is fairly simple, and; (2) it only requires a small number of observations. The RiskMetrics volatility is calculated as follows:

$$\sigma_t^2 = (1-b)r_t^2 + b\sigma_{t-1}^2 \tag{3}$$

where σ_t^2 is the volatility at time t and r_t^2 is the squared return at time (month-on-month change in arrivals). The weighting parameter (b), using the RiskMetrics approach is set at 0.97 for monthly data.

The RiskMetrics approach is a special case of a generalised autoregressive conditional heteroskedasticity (GARCH) model. GARCH models, introduced by Engle (1982) and generalised by Bollerslev (1986) and Taylor (1986), are specifically designed to model and forecast conditional variances. Volatility is modelled as a function of past values of the dependent variable and independent or exogenous variables.

In general form the GARCH(*p*,*q*) model can be written as:

$$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{4}$$

where Equation (4) states that the conditional variance of tourist arrivals depends on a constant (ϖ), the previous period's squared random component of tourist arrivals (referred to as ARCH effects or the short-run persistence of shocks) and the previous period's variance (the contribution of shocks to long-run persistence, $\alpha+\beta$). Non-negativity of σ_t^2 requires that ϖ, α and β are non-negative, while stationarity requires that $\alpha+\beta<1$.[1] A value of $\alpha+\beta$ close to zero therefore implies that the persistence in volatility is high. The GARCH model is suitable when large changes in returns are likely to be followed by further large changes.

The GARCH model assumes that negative shocks have the same impact on future volatility (symmetry) as a big positive shock of the same magnitude, i.e. a terrorist attack on the tourist destination would have the same impact on volatility as hosting a major sporting event. To allow for asymmetry (negative shocks have a larger impact on future volatility than positive shocks), one can use Nelson's (1990) exponential GARCH model (EGARCH). The model is given by:

$$\log(\sigma_t^2) = \varpi + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{j=1}^{p} \alpha_j \left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right| + \sum_{j=1}^{r} \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \tag{5}$$

The EGARCH model is asymmetric as long as $\sum_j \alpha_j \neq 0$ when $\sum_j \gamma_j < 0$, then positive shocks generate less volatility than negative shocks.

One can also account for asymmetry using the threshold GARCH (Thr.-GARCH) model introduced independently by Zakoïan (1994) and Glosten, Jaganathan and Runkle (1993). The specification for the conditional variance is given by:

$$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{r} \gamma_j \varepsilon_{t-j}^2 \Gamma_{t-j} \tag{6}$$

where $\Gamma_{t-k} = 1$ if $\varepsilon_t < 0$ and 0 otherwise. In this model, positive and negative shocks have differential effects on the conditional variance: negative shocks increase volatility, if $\gamma_j > 0$, while shocks are symmetric if $\gamma_j = 0$.

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[1] It is also possible to consider so-called integrated GARCH models where $\alpha+\beta=1$. However, in these models volatility shocks have permanent effects (see Engle and Bollerslev, 1986), which is not likely to be the case for tourist arrivals.

Ding, Granger and Engle (1993) also introduced the Power GARCH specification to deal with asymmetry. In the PARCH model the power parameter δ is estimated rather than imposed, and optional parameters are added to capture asymmetry:

$$\sigma_t^{\delta} = \varpi + \sum_{j=1}^{p} \alpha_j (|\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} \tag{7}$$

where $\delta > 0$, $|\gamma_j| \leq 1$ for $j = 1, \ldots, r$, $\gamma_j = 0$ for all $j > r$, and $r \leq p$. As in the previous models, shocks are asymmetric if $\gamma_j \neq 0$.

Rather than assume that the conditional variance shows mean reversion to ϖ, which is constant for all t, one can estimate a model that allows mean reversion to a varying level, m_t. Using a GARCH(1,1) model, the component GARCH model (CGARCH) can be expressed as:

$$\begin{aligned} \sigma_t^2 - m_t &= \varpi + \alpha(\varepsilon_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi) \\ m_t &= \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \end{aligned} \tag{8}$$

The CGARCH model would be appropriate if policies implemented by tourism officials can result in reduced volatility in the industry.

5. Empirical Results

Volatility models are estimated for the level and log change in arrivals. All models are obtained using maximum likelihood in the econometric programme Eviews 5.0 for the period 1977Q2 to 2005Q12. The Thr.-GARCH model is estimated assuming that the errors have a generalised error distribution, while all the remaining models assume that the conditional distribution of the errors is normal.

The results for the levels approach are presented first. The ARCH(4) specification shows that with the exception of the second lag (which is insignificant), all the lags have a positive effect. Moreover, the coefficients on the lags do not appear to decrease to zero very quickly, suggesting that a shock to tourist arrivals in the current month can have significant (but not too large) effects on volatility of arrivals four months ahead. The ARCH test suggests that the inclusion of the four ARCH terms is enough to remove these effects from the residuals of the mean equation.

For the GARCH(1,1) model all the coefficients are positive and significant at classical levels of testing. The estimated value of $\alpha + \beta$ is 0.544, which implies that the residuals are stationary. Moreover, since the value of $\alpha + \beta$ is not close to unity, it implies that there is short-run, but not long-run volatility persistence. Like the ARCH model, the GARCH(1,1) removes all of the ARCH effects from the residuals in the mean equation. However, the GARCH(1,1) model only requires the estimation of three unknowns, compared five in the case of the ARCH specification.

To allow the effects of positive and negative shocks to differ, the authors also estimate three models that allow for asymmetry. In the EGARCH(1,1) model, the GARCH term is now insignificant at normal levels of testing. The results do, however, suggest that there is some asymmetry in the response of tourist arrivals volatility to shocks, since $\sum_j \alpha_j \neq 0$, but not in the direction originally anticipated. Surprisingly, γ is positive which suggests that positive shocks tend to have a larger effect on tourism volatility than negative shocks. The authors investigated the robustness of this result by using different selection criteria (Schwarz, Akaike and Adjusted R-squared), but the results did not change appreciably. Chan et al. (2005) also finds similar results for Barbados.

This surprising asymmetric result is also obtained when the Thr.-GARCH(1,1) model is employed. In this model when $\gamma < 0$ (-0.325) it suggests that positive shocks increase the volatility of tourist arrivals. A similar estimate for the asymmetric term is also obtained when the PGARCH(1,1,1) model is used. Again alternative selection criteria are employed, but the results did not vary significantly.

The asymmetric response to economic shocks found in this paper, although surprising, can be attributed to the tourist area life cycle concept (see Moore and Whitehall, 2005 for evidence of this phenomena in Barbados). This response may be due to the ebbs and flows of attracting new airlift capacity in a mature tourist destination like Barbados. A larger number of flights coming to Barbados, provided there is enough demand, should lead to greater tourist arrivals. However, it is a difficult task to build up demand in new markets. Butler (1980) suggests that a tourist market goes through six key phases: exploration, involvement, development, consolidation, stagnation, and decline and/or rejuvenation. In the first two stages growth in arrivals is likely to be positive but slow and volatile.

The final volatility model considered is the CGARCH model which allows mean reversion to varying levels of volatility. Since $0 < \rho < 1$, this implies that Equation (8) has an unconditional value of $\omega/(1-\rho)$, or that shocks affecting the conditional variance decay exponentially, with a speed of mean reversion governed by ρ. In Table 4, ρ has a value of 0.688, which suggest a fairly rapid speed of mean reversion.

To compare the alternative volatility models, Figure 4 plots the estimated variances as implied by the parameter estimates. In order to minimise the impact of initial conditions and to appreciate the differences across models the authors present the results for two years after 9/11. The figure shows that the RiskMetrics, ARCH, CGARCH, GARCH all capture the large spike in volatility. In addition, the volatility implied by the ARCH, EGARCH, PARCH and Thr.-GARCH are all less smooth than that obtained from the RiskMetrics, CGARCH and GARCH specifications

The authors also compare the implied volatility obtained from the models outlined above to the estimated volatility using quantile-quantile (QQ)-plots. The results are shown in Figure 5. The QQ figures plot the quantiles of the chosen series against the quantiles of another series. If the two distributions are the same, the QQ-plot should lie on a straight line. If the QQ-plot does not lie on a straight line, the two distributions differ along some dimension. The pattern of deviation from linearity provides an indication of the nature of the mismatch. One will notice that most of the points on the QQ-plot for the CGARCH are on the straight line. The implied variances from the GARCH model also have a similar distribution to that of the estimated volatility.

To evaluate the robustness of these results, the authors, rather than modelling the levels of tourist arrivals, also attempt to model the growth in tourist arrivals. The results from this approach are provided in Table 5. Most of the findings from this approach are quite similar to those obtained earlier. The estimated value of $\alpha + \beta$ from the GARCH model is 0.586, compared to 0.544 for the model using levels. Additionally, the EGARCH, Thr-GARCH and PGARCH specifications all suggest that the growth in tourist arrivals is asymmetric.

The empirical quantile-quantile plots for the volatility models of tourism growth are presented in Figure 6. Again the CGARCH and GARCH models seem to provide the best models of tourism volatility. One change from the previous regressions, however, is that the ARCH model also seems to provide a reasonable specification of tourism volatility in Barbados.

5. Conclusions

This study estimates various models of tourism volatility using monthly data from 1977 to 2005. The models used include the popular RiskMetrics approach, as well as ARCH, GARCH, exponential GARCH, Threshold GARCH, power GARCH and component GARCH specifications. Each model allows the authors to examine a particular aspect of tourism volatility. The ARCH and GARCH models suggest that there is short-run volatility persistence in monthly tourist arrivals to Barbados.

The Threshold GARCH, Power GARCH and Exponential GARCH all indicate asymmetry in the volatility of tourism arrivals: positive shocks have a differential impact on future volatility than negative shocks. The authors attribute these findings to the tourist area life cycle, where new markets tend to add to growth in arrivals, but are also likely to be more volatile. The Component GARCH model also finds evidence of mean reversion to varying levels of volatility.

The models are then evaluated by comparing the implied volatilities as well as with QQ-plots. The results show that the CGARCH and GARCH models tend to capture most of the volatility persistence in the tourism arrivals to Barbados, and also have a similar distribution to that of the estimated volatility.

The asymmetry in tourist arrivals found in this and other studies (that positive shocks have a greater impact on future volatility than negative shocks) could suggest that the destination is not capitalising as best as it could on exploiting positive events (cricket tour, good news, etc). This therefore suggests that greater effort may be needed by players in the industry to maximise the benefits arising from positive shocks. This could be accomplished by using schemes or programmes that reward repeat visitors. Thus, an individual that visits the island for a one-off event has a greater incentive to return.

There are many useful possible topics for future research tourism demand volatility research. Policymakers, for example, would also be interested in forecasting tourism volatility. Therefore a study that evaluates the performance of possible volatility forecasting models would be useful. Another important avenue of research is in the area of volatility correlation between the source markets. If business cycles in the major source markets are correlated, it is likely that volatility in each of these markets should be correlated.

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Table 1: Mean of Tourist Arrivals and Shares 1977-2005

1977-1990				1991-2005			
Source	Head Count	Share/%	Growth %	Source	Head Count	Share %	Growth %
US	121,081	32.76	5.47	UK	164,549	34.43	5.06
Canada	70,475	19.07	-2.85	US	115,062	24.08	-0.60
CARICOM	70,046	18.95	1.99	CARICOM	74,882	15.67	4.16
UK	61,702	16.69	10.11	OTHER	70,849	14.82	-2.50
OTHER	46,317	12.53	4.38	Canada	52,575	11.00	-1.29
Total	369,621	100	3.64	Total	466,905	100	1.58

Source: Barbados Statistical Service

Table 2: Descriptive Statistics and Unit Root Tests of Log of Monthly Deseasonalised Tourist Arrivals

Statistic	Value
Mean	10.457
Maximum	10.471
Minimum	9.879
St. Dev	0.197
Skewness	-0.366
Kurtosis	2.546
Jarque-Bera	10.777
	[0.004]
Observations	348
ARCH test (F-statistic)	5.827
	[0.016]
ADF test	-4.542
	[0.002]
PP test	-6.740
	[0.000]

Note: P-value given in square parenthesis

Table 3: List of Volatility Models

Model	Specification
RiskMetrics	$\sigma_t^2 = (1-b)r_t^2 + b\sigma_{t-1}^2$
ARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 +$
GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$
EGARCH	$\log(\sigma_t^2) = \varpi + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{j=1}^{p} \alpha_j \left\| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right\| + \sum_{j=1}^{r} \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}}$
Thr.-GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{r} \gamma_j \varepsilon_{t-j}^2 \Gamma_{t-j}$
PGARCH	$\sigma_t^\delta = \varpi + \sum_{j=1}^{p} \alpha_j (\lvert \varepsilon_{t-j} \rvert - \gamma_j \varepsilon_{t-j})^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta$
CGARCH(1,1)[a]	$\sigma_t^2 - m_t = \varpi + \alpha(\varepsilon_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi)$ $m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$

Table 4: Estimated Results for Volatility Models (Levels)

	$ARCH(4)$		$GARCH(1,1)$		$EGARCH(1,1,1)$		$Thr.-GARCH(1,1,1)$		$PGARCH(1,1,1)$		$CGARCH(1,1)$
c	0.002	c	0.002	c	-4.319	c	0.001	c	0.000	c	0.003
	(0.000)**		(0.001)**		(1.147)**		(0.001)*		(0.000)		(0.000)**
ε_{t-1}^2	0.226	ε_{t-1}^2	0.171	$\left\lvert \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\rvert$	0.600	ε_{t-1}^2	0.396	δ	3.305	$(\varepsilon_{t-1}^2 - \varpi)$	0.152
	(0.083)**		(0.059)**		(0.117)**		(0.177)**		(1.873)*		(0.086)*
ε_{t-2}^2	-0.031	σ_{t-1}^2	0.373	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	0.176	σ_{t-1}^2	0.438	$\lvert\varepsilon_{t-1}\rvert$	0.139	$(\sigma_{t-1}^2 - \varpi)$	-0.489
	(0.034)		(0.185)**		(0.082)**		(0.218)**		(0.102)		(0.250)*
ε_{t-3}^2	0.089			σ_{t-1}^2	0.077	$\varepsilon_{t-1}^2\Gamma_{t-1}$	-0.325	ε_{t-1}	-0.434	ρ	0.688
	(0.044)**				(0.196)		(0.185)*		(0.179)**		(0.237)**
ε_{t-4}^2	0.088			σ_{t-2}^2	0.256			σ_{t-1}^2	0.461		
	(0.071)				(0.147)*				(0.164)**		
ARCH Test	0.157		0.659		0.025		0.648		0.710		0.188
(F-statistic)	[0.693]		[0.417]		[0.875]		[0.421]		[0.400]		[0.665]
Observations	347		347		347		347		347		347

Notes: (1) Standard errors are provided in (parentheses) below coefficients, while p-values are given in square parentheses [.].

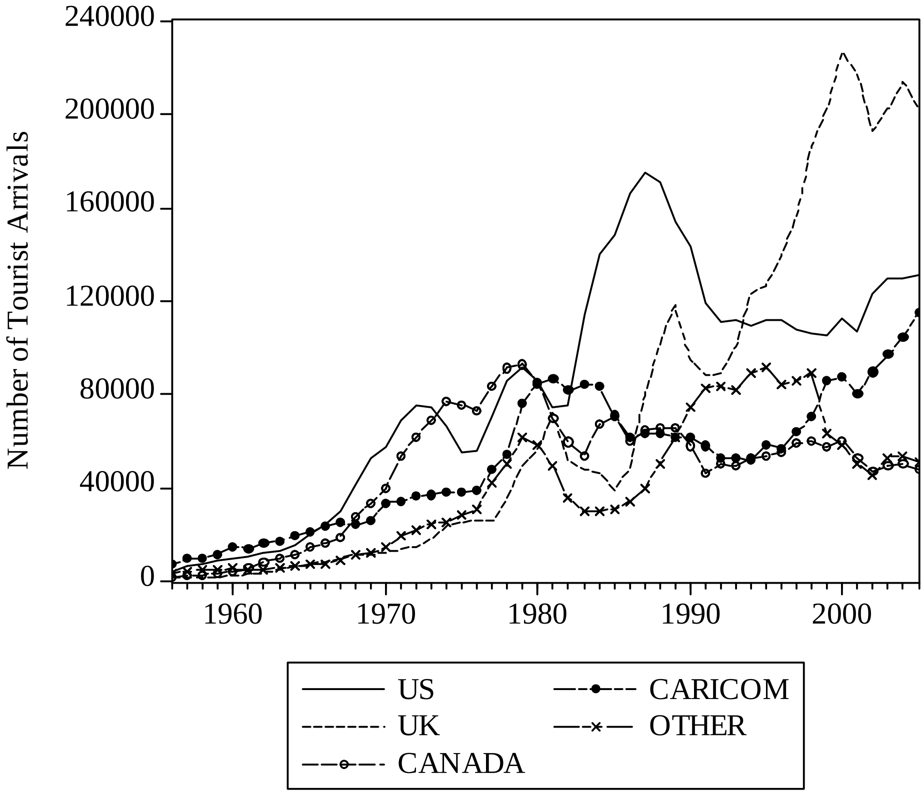
(2) * and ** indicates significance at the 10 and 5 percent level of significance, respectively.

Table 5: Estimated Results for Volatility Models (Growth)

	$ARCH(4)$		$GARCH(1,1)$		$EGARCH(1,1,1)$		$Thr.-GARCH(1,1,1)$		$PGARCH(1,1,1)$		$CGARCH(1,1)$
c	0.000	c	0.000	c	-12.565	c	0.000	c	0.000	c	0.000
	(0.000)**		(0.000)**		(1.882)**		(0.000)*		(0.000)		(0.000)
ε_{t-1}^2	0.427	ε_{t-1}^2	0.413	$\left\lvert \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\rvert$	0.739	ε_{t-1}^2	0.652	δ	1.658	$(\varepsilon_{t-1}^2 - \varpi)$	0.168
	(0.106)**		(0.099)**		(0.127)**		(0.229)**		(0.869)*		(0.129)
ε_{t-2}^2	-0.006	σ_{t-1}^2	0.173	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	0.162	σ_{t-1}^2	0.015	$\lvert \varepsilon_{t-1} \rvert$	0.382	$(\sigma_{t-1}^2 - \varpi)$	-0.257
	(0.037)		(0.090)*		(0.080)**		(0.081)		(0.092)**		(0.326)
ε_{t-3}^2	0.087			σ_{t-1}^2	-0.152	$\varepsilon_{t-1}^2 \Gamma_{t-1}$	-0.479	ε_{t-1}	-0.300	ρ	0.762
	(0.054)				(0.184)		(0.248)*		(0.151)**		(0.153)**
ε_{t-4}^2	0.083							σ_{t-1}^2	0.275		
	(0.066)								(0.131)**		
ARCH Test	0.553		1.092		0.048		1.858		1.805		0.473
(F-statistic)	[0.458]		[0.298]		[0.828]		[0.174]		[0.180]		[0.492]
Observations	347		347		347		347		347		347

Notes: (1) Standard errors are provided in (parentheses) below coefficients, while p-values are given in square parentheses [.].
(2) * and ** indicates significance at the 10 and 5 percent level of significance, respectively.

Figure 1: Annual Tourist Arrivals by Source Market



Source: Barbados Statistical Service

Figure 2: Logarithm of Monthly Deseasonalised Tourist Arrivals

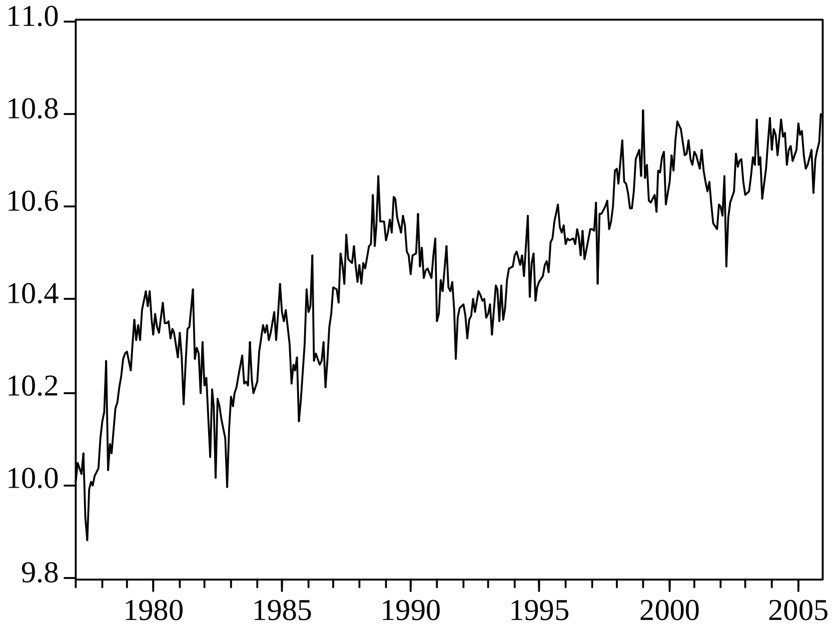


Figure 3: Volatility of Monthly Tourist Arrivals

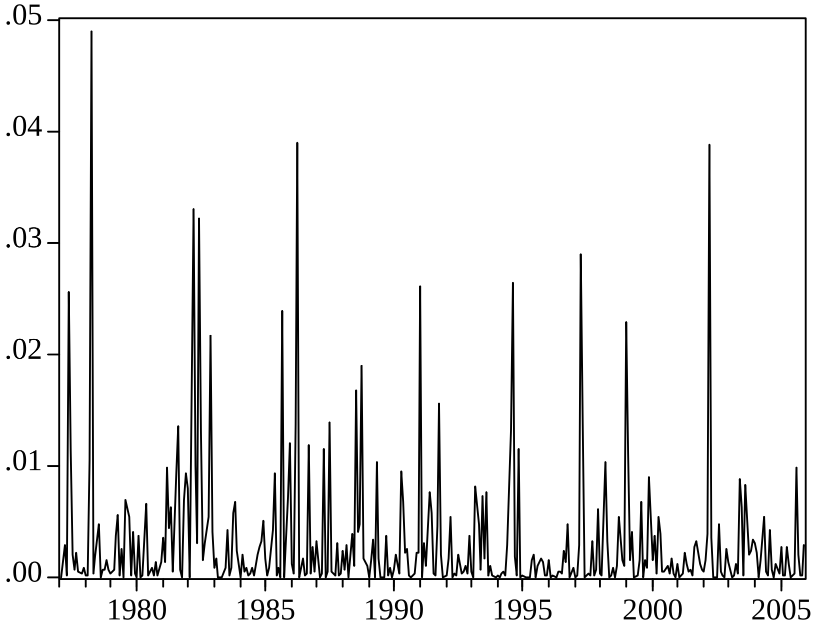


Figure 4: Performance of Volatility Models Post 9/11

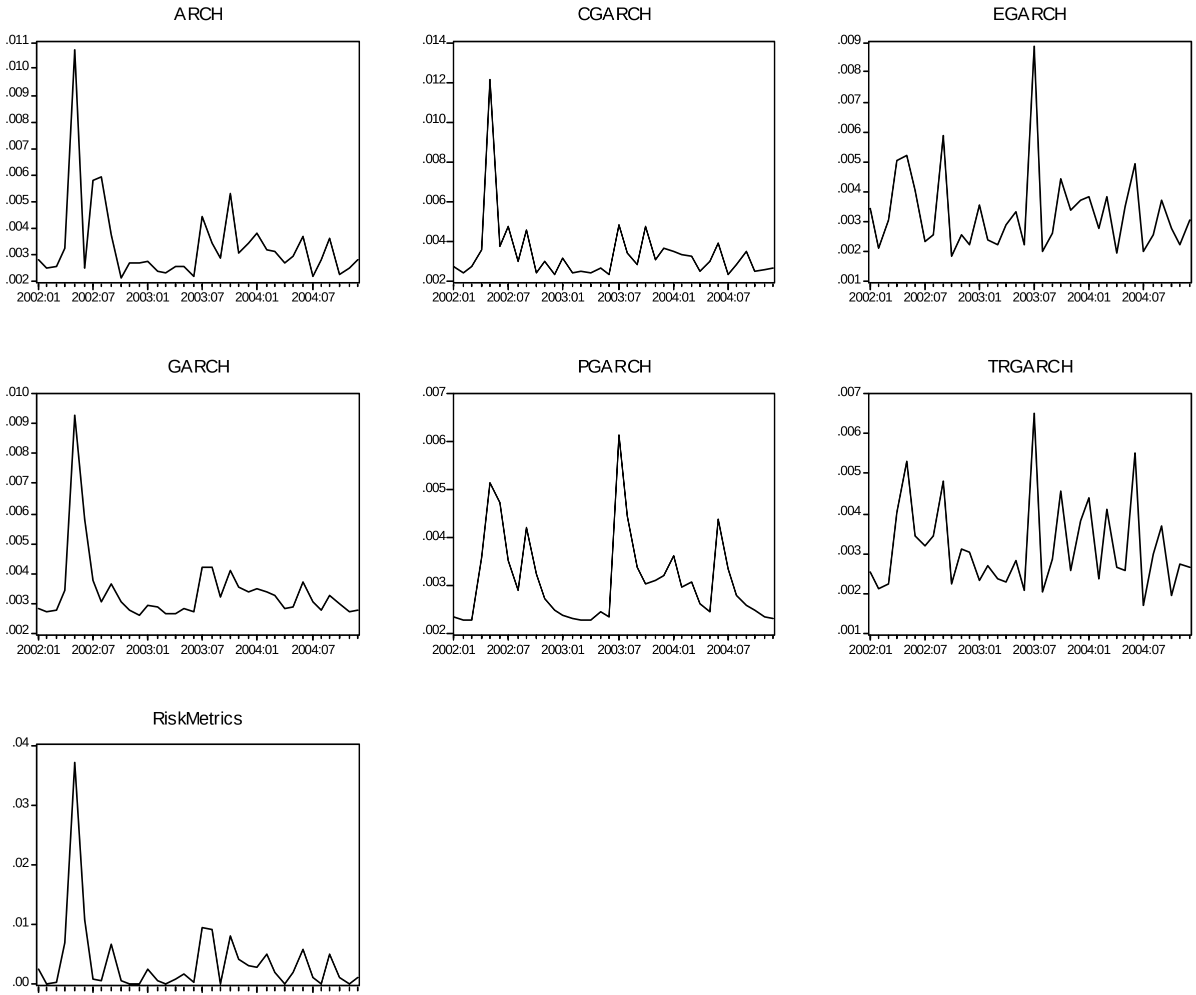


Figure 5: Empirical Quantile-Quantile Plots (Levels)

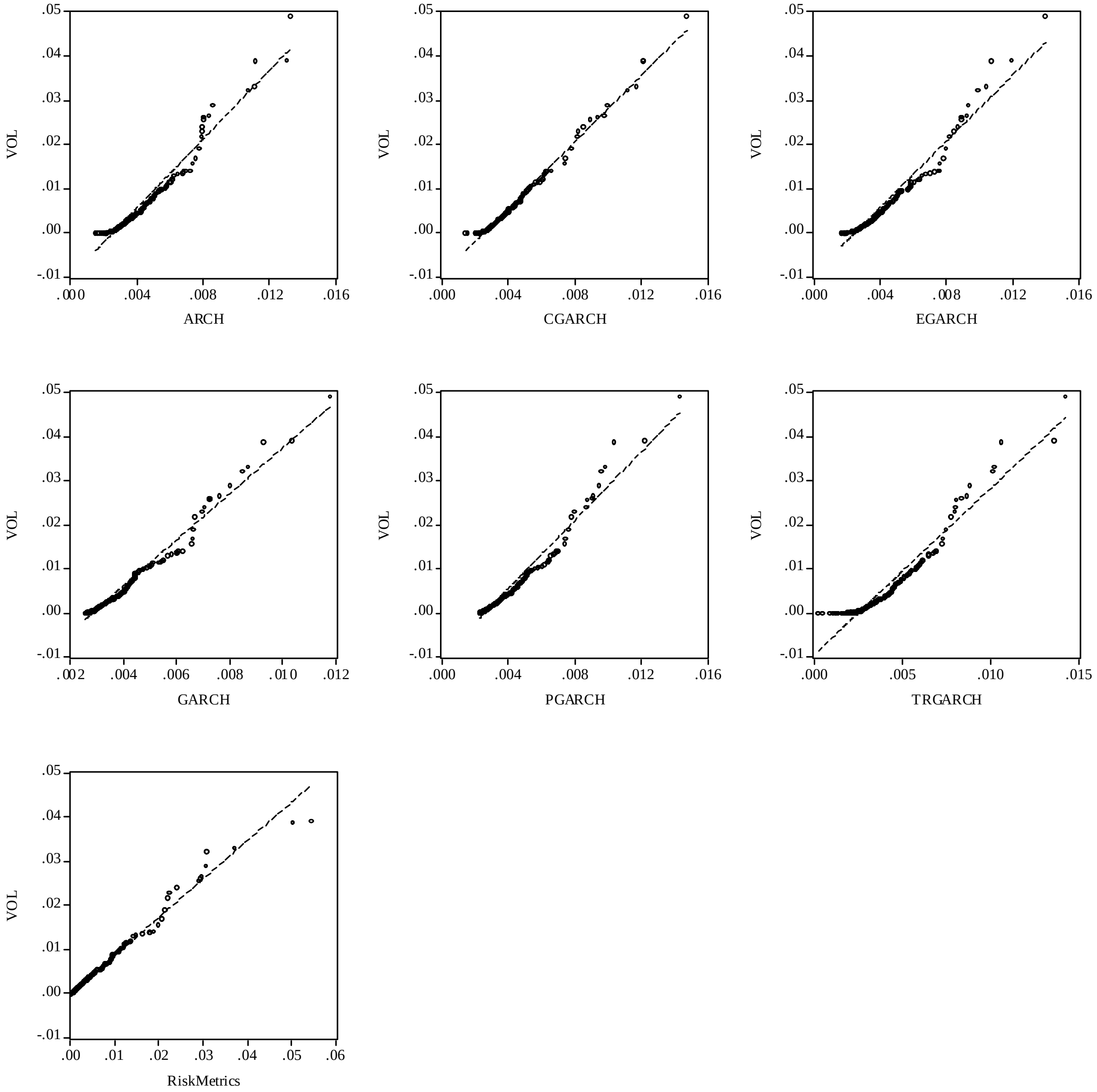


Figure 6: Empirical Quantile-Quantile Plots (Growth)