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Modelling and Forecasting the Volatility of Long-Stay Tourist Arrivals to Barbados

by

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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 international tourist arrivals is defined as the squared deviation from mean monthly international tourist arrivals and is akin to the standard deviation, which is a common measure of financial risk. Conditional 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 volatility modelling techniques to measure and investigate the implications of conditional volatility in monthly international tourist arrivals from major tourism source markets.

1. Introduction

In recent times, there has been a rekindling of interest in the livelihood of small islands with small populations, which overwhelmingly rely on tourism as a source of income. In these islands, commonly referred to as small island tourism economies (SITEs), tourism accounts for a substantial proportion of foreign exchange earnings. These earnings enable importation of consumer as well as capital goods for economic development, are a significant share of government revenue, are a key determinant of development expenditure, and provide employment for a considerable proportion of the workforce.

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 SITEs. These fluctuations in demand can and do have a significant impact on the solvency of small hotels, employment in the industry and the economies of SITEs in general. It is therefore imperative that tourism planners and policymakers have an understanding of volatility and models to forecast volatility of tourist arrivals.

Although international tourism is presently the fastest growing and most important tradable sector in the world economy, this important sector has often been ignored and consequently there is only a limited literature on the significance of tourism in SITEs and the attendant economic implications. Consequently, little is known about the relationship between tourism and economic performance, particularly with respect to SITEs. We hope to help assuage this neglect by analysing the fluctuations and volatility in tourist arrivals to a representative SITE, Barbados.

Since Barbados depends primarily on tourism earnings as a source of foreign exchange and employment, a careful examination of the volatility of tourist arrivals is important to formulate macroeconomic policy, as well as decision-making in the public and private sectors. This paper provides estimates of univariate symmetric and asymmetric models of the logarithm of and log-difference of monthly long-stay tourist arrivals to Barbados for the period 1977-2005. We also examine the associated volatilities of monthly long-stay tourist arrivals.

The only cases where variations in international tourism demand, particularly the conditional variance in international tourist arrivals, have been investigated in tourism literature are in 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 arrival rate from the 4 leading source countries – Japan, New Zealand, UK and USA – to Australia using monthly data from July 1975 to July 2000 using three multivariate constant conditional correlation (CCC) volatility models, specifically the symmetric CCC-MGARCH model of Bollerslev (1990), the symmetric vector ARMA-GARCH model of Ling and McAleer (2003) and the asymmetric vector ARMA-AGARCG model of Chan, Hoti and McAleer (2002). They find the presence of interdependent effects in the conditional variances between the four leading countries, and asymmetric effects in Japan and New Zealand. They also find 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, they find evidence of short run persistence, and occasionally long run persistence, of shocks to international tourist arrivals. They also find report evidence of asymmetric effects of shocks for Barbados using the EGARCH specification. Using the RMSE, MAE, MAPE and FSE criteria, Chan et al. determine that the optimal forecasting models for Barbados, Cyprus and Fiji are the EGARCH(1,1) EARCH(1) and GARCH(1,1) respectively.

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 SITEs, 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 were 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 found support for the statistical adequacy of the GARCH(1,1) and GJR(1,1) models.

The following section discusses the patterns of tourist arrivals to Barbados. Section 3 describes the data used, namely the logarithm of monthly tourist arrivals. Specifications of the volatility models used in this study are described in Section 4. Section 5 presents the estimates and discussion of the empirical results and the Section 6 presents concluding remarks.

2. Trends and Composition of Tourist Arrivals

In this section we analyse the trends in tourist arrivals to Barbados over the period 1977-2005. Table 1 gives an overview of the average numbers of tourist arrivals in each period respectively and their respective shares. The sample is split into two halves, 1977-1990 and 1991-2005, for further comparison.

There are many different tourist source countries for which the Barbados Statistical Service maintains data. Of these, the main markets are the US, the 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. Over the entire period, 1977-2005, tourist arrivals showed an annual growth rate of 2.22 percent from US, 7.41 percent from the UK, 3.15 from the CARICOM and 0.70 percent from OTHER. With an annual growth rate of -2.01 percent, Canada was the only major market to record an annual decline.

In the period 1977-1990, the US was the single biggest tourist source with a share of 32.76 percent of average tourist arrivals and an annual growth rate of 5.47 percent. Over this period arrivals averaged 121,081 tourists. Over the period 1991-2005, the US lost its dominance to the UK – the specific year in which annual UK arrivals surpassed US arrivals was 1994. The share of average tourist arrivals declined by 33 percent to 24.08 percent and the annual growth rate plunged to -0.60 percent. Tourist arrivals fell to an average of 112,713 over this latter period.

Tourists from the UK have been keen visitors to Barbados over the period 1977-2005. An analysis of UK tourist arrival figures in Figure 1 illustrates an increasing trend over the entire sample period. For the period 1977-1990, UK tourist arrivals grew at 10.11 percent per annum with a corresponding share of 16.69 percent of tourist arrivals. In the second half of the sample, the UK dominated every category. Tourist arrivals averaged 164,549, up 167 percent over the first half of the sample, the share of tourist arrivals doubled from 16.69 percent 34.43 percent and while the growth rate actually fell to 5.06 percent from 10.11 percent, it was still the strongest annual growth rate recorded by any source market.

In the first half of the sample, inbound tourism from Canada recorded a 19.07 percent share of average tourist arrivals, second only to the share recorded by the US. However, over this period, there was a decline of 2.85 percent per annum in Canadian tourist arrivals. In the second half, Canada's share of average tourist arrivals plummeted by 42 percent to 11 percent, falling to 5^{th} in the list of the largest tourist source markets to Barbados. Despite this sharp decline in Canada's share of tourist arrivals, there was a slowdown in the decline in annual tourist arrivals to 1.29 percent per annum.

There was a generally increasing trend in visitor arrivals from CARICOM over the entire sample 1977-2005 during which CARICOM was the third largest tourist source market. Although average annual tourist arrivals from CARICOM increased in number from 70,475 in 1977-1990 to 74,882 in 1991-2005, their share decreased from 18.95 percent to 15.67 percent. This was mainly due to the overwhelming increase in the UK's share and to a much lesser extent, the increase in OTHER's share. Nevertheless, the annual growth rate increased from by 109 percent from 1.99 percent to 4.16 percent over the two periods respectively.

As recorded in Table 1, there was an increase in the average numbers of tourists from OTHER, from 46,317 in 1977-1990 to 70,849 in 1991-2005. There was a corresponding increase in OTHER's share of average tourist arrivals from 12.53 percent to 14.82 percent. Despite these increasing trends, however, the annual growth rate of tourist arrivals from OTHER plummeted from 4.38 percent per annum to -2.50 percent per annum. Further analysis shows that the reason for the higher average number of tourist arrivals in 1991-2003 over 1977-1990 was due to very large numbers of tourist arrivals over the period 1991-1998 when tourist arrivals averaged 85,903 and the annual growth rate was 2.23%. In 1999, there was a precipitous 34 percent decline in tourist arrivals from OTHER and with the exception of the years 2003 and 2004, tourist arrivals declined from that point onward.

When we analyse the overall numbers, we find that the average annual number of tourists was 29 percent higher in the 1991-2005 period than in the 1977-1990 period. This increase occurred even though the US, Canada and OTHER each recorded negative annual growth (-1.46 percent as a group) in tourist arrivals during the period 1991-2005. The reason why the average number overall increased was because of the positive annual growth in tourist arrivals from the UK and CARICOM (4.61 percent as a group) quadrupled the negative growth rate of the previous group; in fact, the positive growth in the UK market (5.06 percent) was enough to outstrip the negative rate of the US, Canada and OTHER combined. While there is a clear upward trend in total tourist arrivals (see Figure 2), the annual growth rate of total tourist arrivals fell by 57 percent, from 3.64 percent during 1977-1990 to 1.58 percent during 1991-2005. This is not surprising, since annual growth rates of tourist arrivals from all source markets, except CARICOM, declined by an average of 93 percent in the period 1991-2005 when compared with the period 1977-1990.

3. Characteristics of Monthly Tourist Arrivals

For the analysis in this section, the authors use logarithms of total monthly tourist arrivals for the entire sample period under study, 1977-2005. The primary reason for using the logarithm of monthly arrivals was as a result of the presence of a unit root in the level of the series. The data are deseasonalised using Census X12, the US Census Bureau seasonal adjustment algorithm. The augmented Dickey-Fuller (ADF) test (1979, 1981) and the Phillips-Perron (PP) tests 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 3 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 recession caused by the second oil price shock in 1979 and the recession of the early 1990s.

Figure 4 gives the volatility of the log arrival rate. 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 ARMA(1,1) or an AR(2) would be suitable. Diagnostic checking confirmed that the ARMA(1,1) with a deterministic time trend was a more suitable description of the process:

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

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

where *TA* is the total monthly international tourist arrivals at time *t* and *time* = 1,…,*T*, where *T* = 324.

Volatility in tourist arrivals is characterised by clustering mainly over the first half of the sample, 1977-1990, with little evidence thereafter. These volatility clusters correspond to the peaks and troughs of the cycles described previously. Monthly tourist arrivals are also more volatile in the first half of the sample.

4. Volatility Models

The RiskMetrics 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). Usually, the weighting parameter (b) 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.

[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.

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 $\gamma_j = 0$.

Ding et. al. (1993) also introduced the Power ARCH 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 $\delta > 0$, $| \gamma_j | \le 1$ for $j = 1, \ldots, r$, $\gamma_j = 0$ for all $j > r$, and $r \le p$. As in the previous models, shocks are asymmetric if $\gamma_j \ne 0$.

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

All models are estimated for the period 1977Q2 to 2005Q12 and the results are presented in Table x. All specifications are estimated by maximum likelihood in the econometric programme EViews 5.0. Additionally, 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 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 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 the persistence in volatility is not too high. 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 author also estimate three models that allow for asymmetry. In the EGARCH(1,1,1) 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 economic 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.

This surprising asymmetric result is also obtained when the Thr.-GARCH(1,1,1) model is employed. In this model when $\gamma < 0$ (-0.325) and 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 a new market. 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 x, ρ has a value of 0.688, which suggest a fairly rapid speed of mean reversion.

To compare the alternative volatility models, Figure 5 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 6. 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 are also having a similar distribution to that of the estimated volatility.

5. Conclusions

This study estimates various models of tourism volatility using monthly data from 1977 to 2005. The models used include the popular RiskMetrics, ARCH, GARCH, exponential GARCH, Threshold GARCH, power GARCH and component GARCH. Each model allows the author to examine a particular aspect of tourism volatility. The ARCH and GARCH models suggest that there is some degree of volatility persistence in monthly tourist arrivals to Barbados, but it is not very large.

The Threshold GARCH, Power GARCH and Exponential GARCH all indicate some degree of 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.

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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/%**
1.US	121,081	32.76	5.47	**1.UK**	164,549	34.43	5.06
2.Canada	70,475	19.07	-2.85	**2.US**	115,062	24.08	-0.60
3.CARICOM	70,046	18.95	1.99	**3.CARICOM**	74,882	15.67	4.16
4.UK	61,702	16.69	10.11	**4.OTHER**	70,849	14.82	-2.50
5.OTHER	46,317	12.53	4.38	**5.Canada**	52,575	11.00	-1.29
Total	369,621	100	3.64	**Total**	466,905	100	1.58

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]

Notes: p-value given in square parenthesis.

Table 3: List of Volatility Models

Naïve	$\sigma_t^2 = \varpi$
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	$\sigma_t^2 = \varpi + \sum_{j=1}^{p}\alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^2$
Taylor/Schwert	$\sigma_t^2 = \varpi + \sum_{j=1}^{p}\alpha_j \mid \varepsilon_{t-j} \mid + \sum_{j=1}^{q}\beta_j \sigma_{t-j}$
A-GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p}\left[\alpha_j \varepsilon_{t-j}^2 + \gamma_i \varepsilon_{t-j}\right] + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^2$
Thr.-GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p}\alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^2 + \sum_{j=1}^{r}\gamma_j \varepsilon_{t-j}^2 \Gamma_{t-j}$
GJR-GARCH	$\sigma_t^2 = \varpi + \sum_{j=1}^{p}\left[\alpha_j + \gamma_i I_{\{\varepsilon_{t-1}>0\}}\right]\varepsilon_{t-j}^2 + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^2$
Log-GARCH	$\log(\sigma_t) = \varpi + \sum_{j=1}^{p}\alpha_j \mid \varepsilon_{t-j} \mid + \sum_{j=1}^{q}\beta_j \log(\sigma_{t-j})$
EGARCH	$\log(\sigma_t^2) = \varpi + \sum_{j=1}^{q}\beta_j \log(\sigma_{t-j}^2) + \sum_{j=1}^{p}\alpha_j \left\lvert \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right\rvert + \sum_{j=1}^{r}\gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}}$
NGARCH	$\sigma_t^\delta = \varpi + \sum_{j=1}^{p}\alpha_j \mid \varepsilon_{t-j} \mid^\delta + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^\delta$
A-PARCH	$\sigma_t^\delta = \varpi + \sum_{j=1}^{p}\alpha_j (\mid \varepsilon_{t-j} \mid - \gamma_j \varepsilon_{t-j})^\delta + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^\delta$
CGARCH(1,1)[a]	$\sigma_t^2 - m_t = \varpi + \alpha(\varepsilon_{t-1}^2 - \varpi) + \beta(\sigma_{t-1}^2 - \varpi)$ $m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$

[a] Model also estimated with threshold.

Table 4: Out-of-Sample Forecasting Accuracy

	Forecast Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
MSE1	1	3	6	12	24	1	3	6	12	24	Average
VOLF_AGARCH	2.726	0.896	1.116	0.736	0.757	12	10	11	9	6	9.6
VOLF_APARCH	1.688	1.097	1.067	0.821	0.862	11	13	10	10	12	11.2
VOLF_ARCH	0.718	0.628	0.763	0.602	0.676	8	4	2	1	1	3.2
VOLF_CGARCH	0.122	0.627	0.772	0.629	0.720	3	3	3	4	4	3.4
VOLF_CGARCHT	0.065	0.551	0.778	0.625	0.728	2	1	4	3	5	3
VOLF_EGARCH	0.677	0.601	0.815	0.623	0.684	7	2	6	2	2	3.8
VOLF_GARCH	0.343	0.688	0.825	0.692	0.763	4	7	7	5	7	6
VOLF_GJRGARCH	0.367	0.696	0.733	0.708	0.774	5	8	1	7	9	6
VOLF_LOGGARCH	0.395	0.701	0.778	0.720	0.778	6	9	5	8	10	7.6
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	9	11	8	14	13	11
VOLF_PARCH	1.146	0.668	1.034	0.693	0.716	10	6	9	6	3	6.8
VOLF_RSK	0.023	0.644	1.372	0.939	1.110	1	5	13	13	14	9.2
VOLF_TAYLOR	4.684	1.199	1.331	0.836	0.837	14	14	12	11	11	12.4
VOLF_TRGARCH	3.354	1.042	1.482	0.855	0.769	13	12	14	12	8	11.8
MSE2	1	3	6	12	24	1	3	6	12	24	
VOLF_AGARCH	3.182	0.909	0.509	0.255	0.048	12	10	10	8	8	9.6
VOLF_APARCH	1.816	1.321	0.674	0.379	0.130	11	13	11	12	11	11.6
VOLF_ARCH	0.692	0.446	0.184	0.168	0.024	8	5	4	3	3	4.6
VOLF_CGARCH	0.103	0.376	0.164	0.178	0.044	3	3	2	5	7	4

	Forecast Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
VOLF_CGARCHT	0.053	0.283	0.167	0.169	0.024	2	1	3	4	2	2.4
VOLF_EGARCH	0.647	0.308	0.112	0.144	0.031	7	2	1	2	4	3.2
VOLF_GARCH	0.309	0.471	0.214	0.226	0.077	4	6	5	7	10	6.4
VOLF_GJRGARCH	0.332	0.420	0.217	0.329	0.189	5	4	6	10	13	7.6
VOLF_LOGGARCH	0.360	0.524	0.337	0.327	0.167	6	8	8	9	12	8.6
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	9	12	12	14	14	12.2
VOLF_PARCH	1.166	0.506	0.324	0.182	0.003	10	7	7	6	1	6.2
VOLF_RSK	0.017	0.543	0.444	0.112	0.033	1	9	9	1	5	5
VOLF_TAYLOR	6.127	1.674	1.037	0.352	0.061	14	14	14	11	9	12.4
VOLF_TRGARCH	4.078	0.936	1.034	0.380	0.037	13	11	13	13	6	11.2
R2LOG	1	3	6	12	24	1	3	6	12	24	
VOLF_AGARCH	2.368	0.983	0.997	0.910	0.881	12	10	10	9	8	9.8
VOLF_APARCH	1.579	1.005	1.001	0.941	0.919	11	12	12	13	13	12.2
VOLF_ARCH	0.744	0.933	0.929	0.858	0.836	8	4	2	1	3	3.6
VOLF_CGARCH	0.143	0.932	0.929	0.877	0.865	3	3	3	3	6	3.6
VOLF_CGARCHT	0.078	0.915	0.920	0.861	0.855	2	2	1	2	5	2.4
VOLF_EGARCH	0.705	0.938	0.940	0.884	0.872	7	5	4	5	7	5.6
VOLF_GARCH	0.379	0.947	0.945	0.906	0.895	4	8	7	8	10	7.4
VOLF_GJRGARCH	0.403	0.958	0.944	0.924	0.919	5	9	6	11	12	8.6
VOLF_LOGGARCH	0.432	0.945	0.941	0.905	0.891	6	7	5	7	9	6.8
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	9	11	11	14	14	11.8

	Forecast Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
VOLF_PARCH	1.128	0.943	0.964	0.882	0.851	10	6	9	4	4	6.6
VOLF_RSK	0.031	0.818	0.958	0.914	0.821	1	1	8	10	1	4.2
VOLF_TAYLOR	3.678	1.018	1.033	0.929	0.896	14	14	13	12	11	12.8
VOLF_TRGARCH	2.809	1.015	1.049	0.884	0.836	13	13	14	6	2	9.6
QLIKE	1	3	6	12	24	1	3	6	12	24	
VOLF_AGARCH	1.006	1.007	0.906	0.967	0.929	13	6	3	2	6	6
VOLF_APARCH	1.004	0.999	0.963	0.977	0.892	11	2	7	5	3	5.6
VOLF_ARCH	0.997	1.014	0.973	1.001	0.949	8	13	11	11	9	10.4
VOLF_CGARCH	0.980	1.009	0.971	0.996	0.942	3	9	10	9	7	7.6
VOLF_CGARCHT	0.975	1.011	0.969	0.994	0.905	2	11	9	8	4	6.8
VOLF_EGARCH	0.996	1.008	0.937	0.984	0.974	7	7	6	6	11	7.4
VOLF_GARCH	0.989	1.009	0.963	0.986	0.944	4	8	8	7	8	7
VOLF_GJRGARCH	0.990	1.006	0.991	1.004	0.986	5	5	12	13	12	9.4
VOLF_LOGGARCH	0.991	1.009	0.999	1.001	0.972	6	10	13	12	10	10.2
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	9	4	14	10	13	10
VOLF_PARCH	1.001	1.013	0.913	0.971	0.889	10	12	5	3	2	6.4
VOLF_RSK	0.946	1.017	0.882	1.056	1.072	1	14	1	14	14	8.8
VOLF_TAYLOR	1.006	0.999	0.913	0.957	0.869	12	3	4	1	1	4.2
VOLF_TRGARCH	1.007	0.994	0.903	0.974	0.919	14	1	2	4	5	5.2
MAE1	1	3	6	12	24	1	3	6	12	24	
VOLF_AGARCH	1.651	0.955	1.050	0.871	0.796	12	11	11	9	7	10

	Forecast Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
VOLF_APARCH	1.299	1.090	1.020	0.917	0.873	11	13	10	12	12	11.6
VOLF_ARCH	0.848	0.774	0.859	0.790	0.764	8	6	6	1	3	4.8
VOLF_CGARCH	0.350	0.738	0.847	0.803	0.788	3	3	2	3	5	3.2
VOLF_CGARCHT	0.254	0.677	0.851	0.803	0.792	2	1	3	4	6	3.2
VOLF_EGARCH	0.823	0.679	0.857	0.791	0.764	7	2	5	2	2	3.6
VOLF_GARCH	0.586	0.791	0.888	0.847	0.818	4	7	7	6	8	6.4
VOLF_GJRGARCH	0.606	0.761	0.835	0.847	0.843	5	4	1	7	10	5.4
VOLF_LOGGARCH	0.629	0.817	0.854	0.854	0.834	6	9	4	8	9	7.2
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	9	12	9	14	14	11.6
VOLF_PARCH	1.071	0.801	0.977	0.827	0.762	10	8	8	5	1	6.4
VOLF_RSK	0.151	0.768	1.074	0.873	0.886	1	5	12	10	13	8.2
VOLF_TAYLOR	2.164	1.163	1.149	0.920	0.845	14	14	14	13	11	13.2
VOLF_TRGARCH	1.831	0.926	1.116	0.878	0.784	13	10	13	11	4	10.2
MAE2	1	3	6	12	24	1	3	6	12	24	
VOLF_AGARCH	1.784	0.953	1.072	0.829	0.755	12	10	11	9	6	9.6
VOLF_APARCH	1.347	1.149	1.054	0.898	0.849	11	13	10	11	12	11.4
VOLF_ARCH	0.832	0.668	0.815	0.714	0.716	8	5	6	2	3	4.8
VOLF_CGARCH	0.322	0.613	0.798	0.722	0.739	3	3	2	3	5	3.2
VOLF_CGARCHT	0.231	0.532	0.802	0.723	0.738	2	1	3	4	4	2.8
VOLF_EGARCH	0.804	0.555	0.812	0.708	0.708	7	2	4	1	1	3
VOLF_GARCH	0.556	0.686	0.848	0.776	0.770	4	6	7	7	7	6.2

	Forecast Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
VOLF_GJRGARCH	0.576	0.648	0.779	0.772	0.793	5	4	1	5	9	4.8
VOLF_LOGGARCH	0.600	0.724	0.813	0.796	0.799	6	8	5	8	10	7.4
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	9	12	9	14	14	11.6
VOLF_PARCH	1.080	0.711	0.979	0.774	0.713	10	7	8	6	2	6.6
VOLF_RSK	0.130	0.786	1.160	0.885	0.963	1	9	12	10	13	9
VOLF_TAYLOR	2.475	1.294	1.245	0.924	0.824	14	14	13	13	11	13
VOLF_TRGARCH	2.019	0.967	1.245	0.905	0.770	13	11	14	12	8	11.6

Table 5: Out-of-Sample Forecasting Accuracy (Combination Models)

	Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
MSE1	1	3	6	12	24	1	3	6	12	24	Average
VOLF_COMB1	0.252	0.596	0.938	0.698	0.811	4	1	4	4	5	3.6
VOLF_COMB2	0.139	0.597	0.907	0.681	0.798	1	2	2	2	3	2
VOLF_COMB3	3.063	0.766	1.254	0.728	0.776	7	5	7	5	1	5
VOLF_COMB4	0.182	0.598	0.913	0.692	0.805	2	3	3	3	4	3
VOLF_COMB5	0.406	0.616	0.875	0.655	0.778	5	4	1	1	2	2.6
VOLF_COMB6	0.191	1.163	1.038	1.031	1.016	3	7	6	7	7	6
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	6	6	5	6	6	5.8
MSE2	1	3	6	12	24	1	3	6	12	24	
VOLF_COMB1	0.222	0.395	0.432	0.265	0.056	4	3	3	4	4	3.6
VOLF_COMB2	0.118	0.373	0.357	0.237	0.050	1	1	2	2	3	1.8
VOLF_COMB3	3.657	0.686	0.697	0.243	0.039	7	5	5	3	1	4.2
VOLF_COMB4	0.157	0.386	0.437	0.286	0.074	2	2	4	5	5	3.6
VOLF_COMB5	0.371	0.405	0.320	0.217	0.041	5	4	1	1	2	2.6
VOLF_COMB6	0.166	1.211	1.026	1.091	0.971	3	7	7	7	6	6
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	6	6	6	6	7	6.2
R2LOG	1	3	6	12	24	1	3	6	12	24	
VOLF_COMB1	0.284	0.919	0.941	0.855	0.854	4	2	3	2	4	3
VOLF_COMB2	0.161	0.920	0.937	0.860	0.858	1	3	1	4	5	2.8
VOLF_COMB3	2.608	0.958	0.994	0.860	0.843	7	5	5	5	1	4.6
VOLF_COMB4	0.209	0.919	0.938	0.854	0.852	2	1	2	1	2	1.6

	Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
VOLF_COMB5	0.443	0.931	0.942	0.858	0.852	5	4	4	3	3	3.8
VOLF_COMB6	0.219	1.011	0.997	1.007	1.005	3	7	6	7	7	6
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	6	6	7	6	6	6.2
QLIKE	1	3	6	12	24	1	3	6	12	24	
VOLF_COMB1	0.986	1.013	0.971	0.994	0.819	4	7	3	3	1	3.6
VOLF_COMB2	0.981	1.011	0.969	0.993	0.839	1	4	2	2	2	2.2
VOLF_COMB3	1.007	1.010	0.905	0.972	0.896	7	3	1	1	5	3.4
VOLF_COMB4	0.983	1.012	0.978	1.001	0.855	2	5	5	7	4	4.6
VOLF_COMB5	0.991	1.013	0.972	0.997	0.852	5	6	4	4	3	4.4
VOLF_COMB6	0.984	0.989	0.994	1.000	0.996	3	1	6	5	6	4.2
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	6	2	7	6	7	5.6
MAE1	1	3	6	12	24	1	3	6	12	24	
VOLF_COMB1	0.502	0.747	0.947	0.848	0.844	4	3	4	5	5	4.2
VOLF_COMB2	0.372	0.734	0.925	0.838	0.837	1	1	2	2	4	2
VOLF_COMB3	1.750	0.854	1.075	0.847	0.798	7	5	7	4	1	4.8
VOLF_COMB4	0.427	0.742	0.932	0.842	0.837	2	2	3	3	3	2.6
VOLF_COMB5	0.638	0.754	0.912	0.822	0.827	5	4	1	1	2	2.6
VOLF_COMB6	0.437	1.048	1.011	0.998	0.980	3	7	6	6	6	5.6
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	6	6	5	7	7	6.2
MAE2	1	3	6	12	24	1	3	6	12	24	
VOLF_COMB1	0.471	0.628	0.936	0.800	0.806	4	3	4	4	5	4

	Comparison Criteria					Rank					
	Forecasting Horizon					Forecasting Horizon					
VOLF_COMB2	0.343	0.610	0.906	0.781	0.797	1	1	2	2	3	1.8
VOLF_COMB3	1.912	0.828	1.142	0.828	0.773	7	5	7	5	1	5
VOLF_COMB4	0.396	0.622	0.916	0.793	0.803	2	2	3	3	4	2.8
VOLF_COMB5	0.609	0.636	0.885	0.760	0.786	5	4	1	1	2	2.6
VOLF_COMB6	0.407	1.100	1.037	1.013	0.989	3	7	6	7	6	5.8
VOLF_NAIVE	1.000	1.000	1.000	1.000	1.000	6	6	5	6	7	6

Table 6: Superior Predictive Ability Tests

	Naïve	SPA_l	SPA_c	SPA_u
Benchmark: RiskMetrics				
MSE1	0.149	0.222	0.222	0.222
MSE2	0.049	0.068	0.068	0.068
QLIKE	0.010	0.010	0.010	0.010
R2LOG	0.576	0.569	0.648	0.668
MAE1	0.164	0.243	0.243	0.254
MAE2	0.151	0.213	0.213	0.222
Benchmark: GARCH(1,1)				
MSE1	0.003	0.007	0.008	0.009
MSE2	0.005	0.010	0.010	0.012
QLIKE	0.004	0.008	0.009	0.011
R2LOG	0.232	0.011	0.011	0.012
MAE1	0.047	0.016	0.019	0.022
MAE2	0.065	0.018	0.018	0.026
Benchmark: CGARCHT(1,1)				
MSE1	0.031	0.085	0.089	0.158
MSE2	0.037	0.084	0.090	0.147
QLIKE	0.026	0.065	0.070	0.092
R2LOG	0.357	0.142	0.142	0.257
MAE1	0.200	0.150	0.150	0.263
MAE2	0.228	0.208	0.212	0.314

Figure 1:

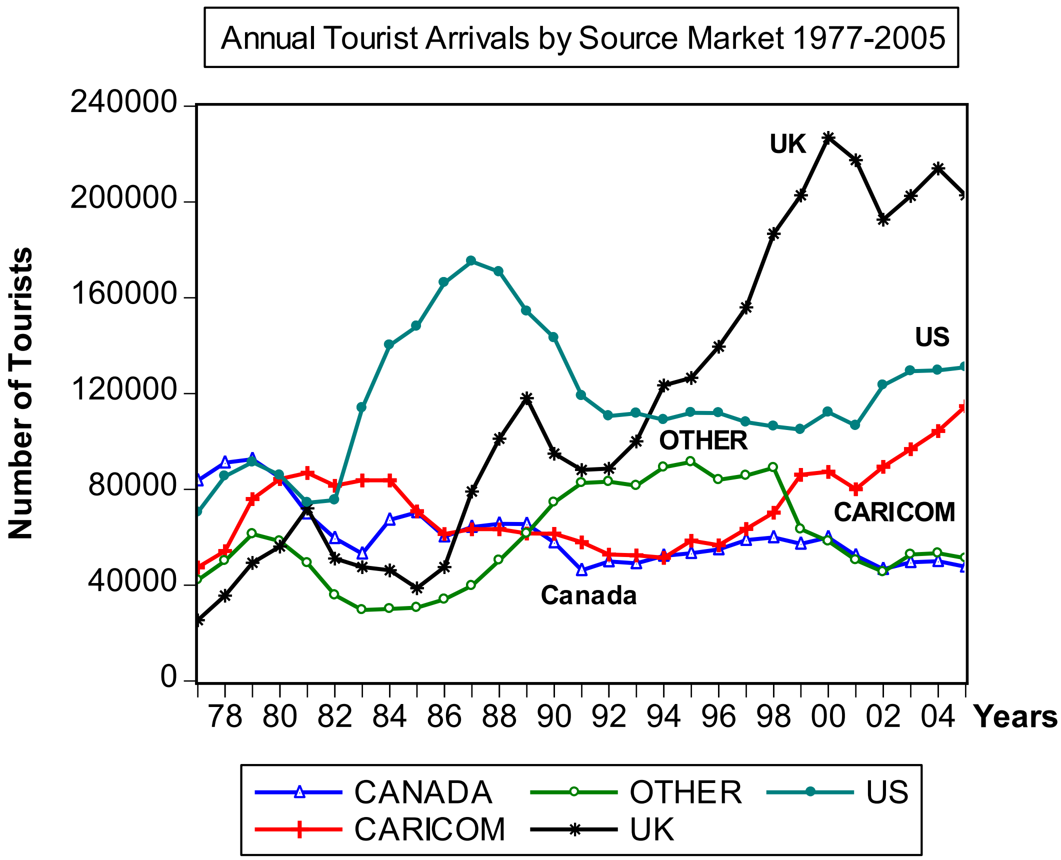
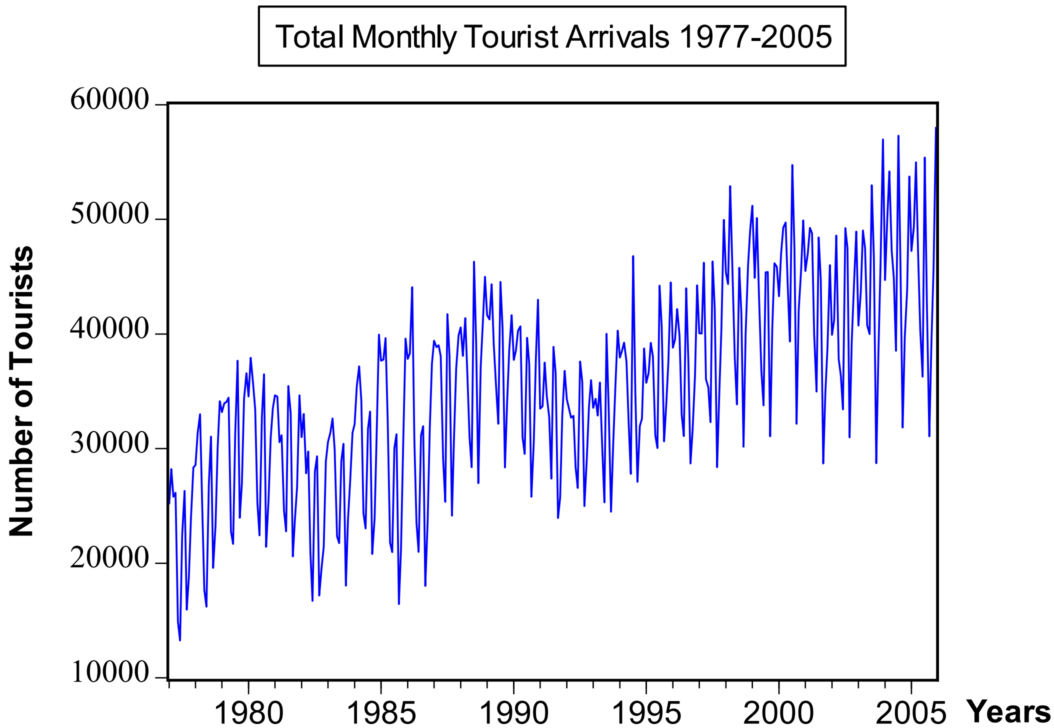

Annual Tourist Arrivals by Source Market 1977-2005
Number of Tourists
240000
200000
160000
120000
80000
40000
0
78
80
82
84
86
88
90
92
94
96
98
00
02
04
Years
UK
US
OTHER
CARICOM
Canada
CANADA
OTHER
US
CARICOM
UK

Figure 2:



Total Monthly Tourist Arrivals 1977-2005
Number of Tourists
60000
50000
40000
30000
20000
10000
1980
1985
1990
1995
2000
2005
Years

Figure 3: Log of Deseasonalised Tourist Arrivals

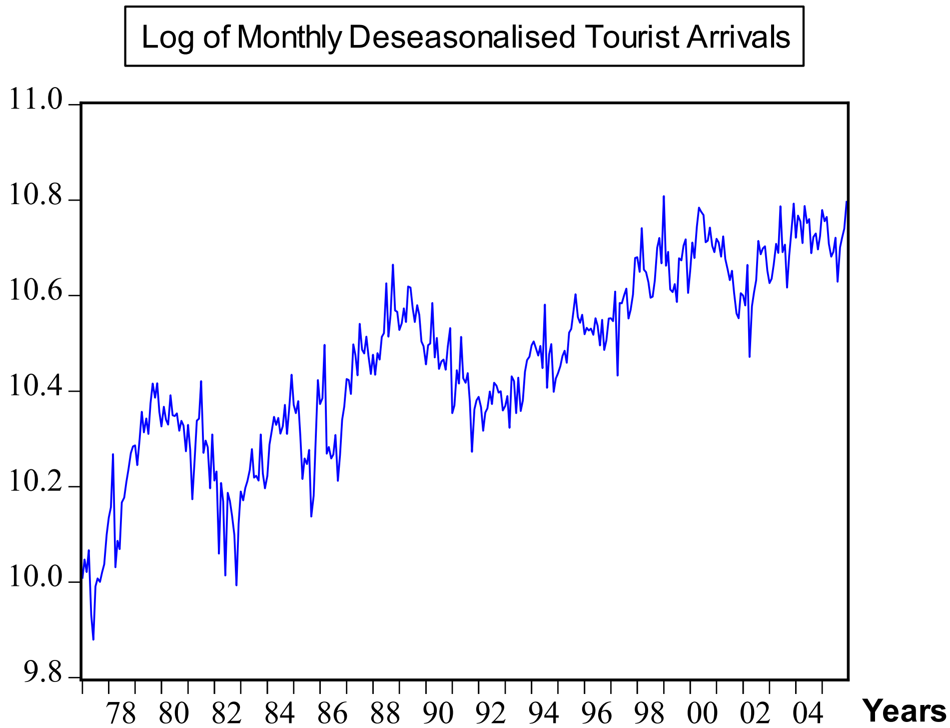


Figure 4: Volatility of Arrivals to Barbados

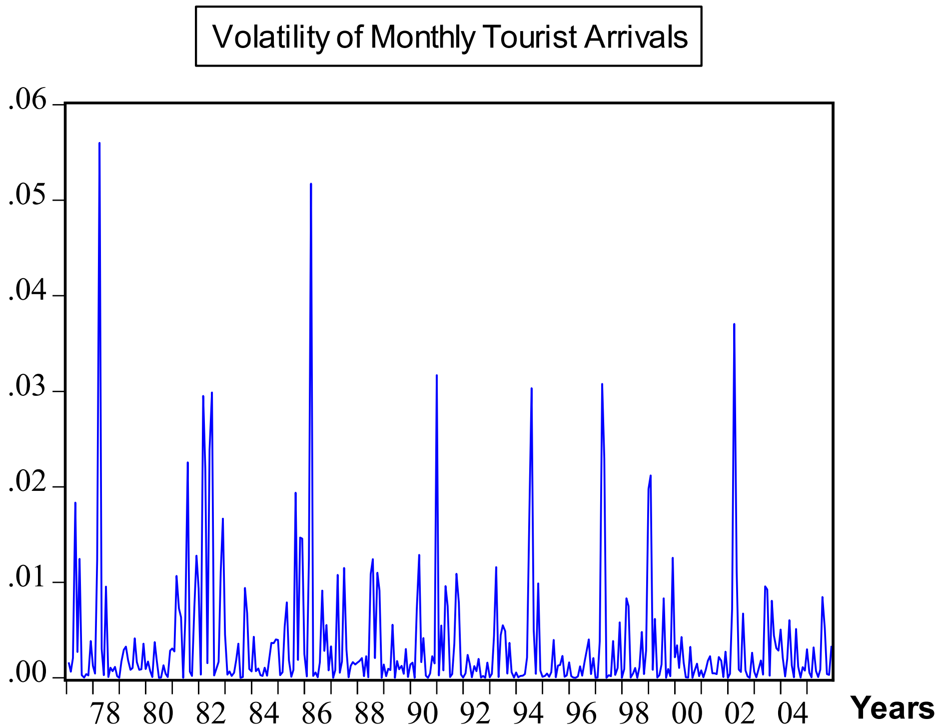


Figure 5: Performance of Volatility Models Post 9/11

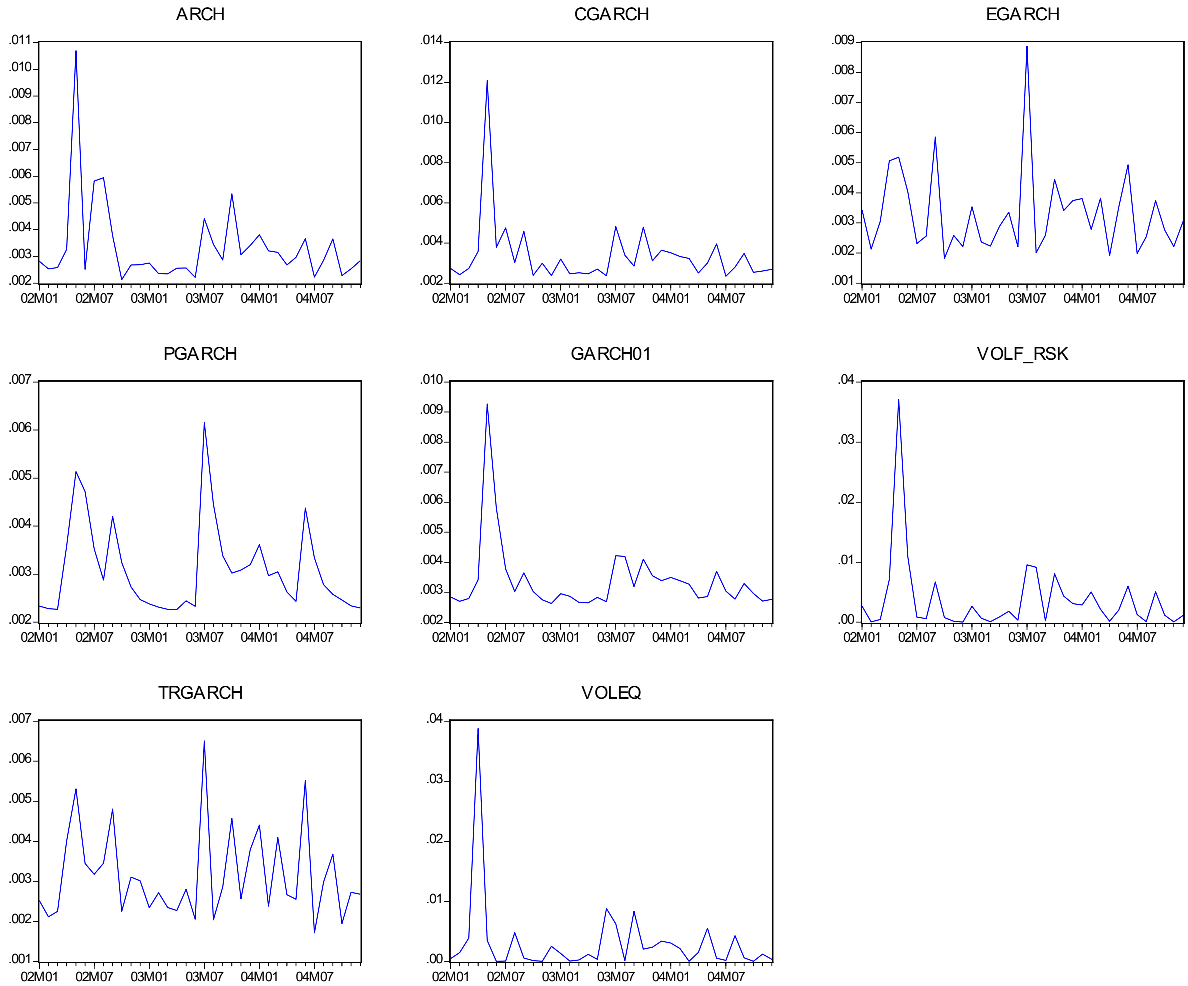


Figure 6: Empirical Quantile-Quantile Plots