THE RESILIENCE OF CARIBBEAN TOURISM TO EXTERNAL SHOCKS

ABSTRACT

As with most industries, tourism is susceptible to external shocks from time to time. A study employed by Browne, Edwards and Moore (2009) suggests that shocks to the Caribbean tourist industry tend to have temporary rather than permanent effects, implying that Caribbean tourism is fairly resilient to these negative influences. This paper further investigates specific shocks, namely GDP and oil prices to test the above hypothesis. The study employs a multivariate GARCH model and utilizes monthly tourism data from 1977 to 2009 for 8 Caribbean countries.

1. INTRODUCTION

The greatest concern for tourism researchers had traditionally been overcoming the problems posed by heteroscedastic error terms and/or serial correlation, which could lead to imprecise estimates of tourism demand and reduced performance of tourism forecasting models. More recently, the focus in the economic literature has shifted towards modeling the volatility in these random disturbances. This interest has been primarily attributed to increased fluctuations in global economic activity, climate change, natural disasters, crime as well as terrorism (Shareef and McAleer 2005a).

Modeling tourism volatility is essential for Caribbean economies since most countries in the region depend heavily on tourism. Such research allows for the facilitation of better decision-making, particularly towards the maintenance of the tourist product and investment necessary to accommodate increased tourist arrivals (Hoti et al 2005).

In recognition, Browne et al (2009) applied non-linear unit root tests to examine the volatility persistence of shocks in tourist arrivals in the Caribbean and found that shocks to tourism in the region tend to have only temporary rather than permanent effects. This research implies resilience of Caribbean tourism to external influences and suggests that the Caribbean maybe a good place for tourism investment.

While the authors approach has its merits, other approaches to modelling tourism volatility have typically utilized univariate GARCH techniques. Lately though, with the development of better software packages, researchers have been utilizing multivariate models, which allow for the analysis of co-volatility movement. Hoti et al. (2005) estimated univariate and multivariate volatility models of international tourist arrivals from 14 source markets to the Canary Islands, Spain. The authors used a GARCH (1,1) model and found it to be most appropriate in both the univariate and multivariate cases. Shareef and McAleer (2005, 2005a) and Hoti et al (2005a) also found this specification to be approapriate for modeling tourism volatility.

Karunanyake, Valadkhani and O'Brien (2008)) note, however, that there are two major issues to consider in the estimation of GARCH models: (1) the assumption of covariance stationarity and (2) the positive semi-definiteness of the variance-covariance matrix. The stationarity assumption requires the ARCH and GARCH coefficients be less than one in modulus, so that values close to unity imply high volatility persistence, whereas the positive semi-definiteness of the variance-covariance matrix ensures a positive conditional variance.

The most commonly used GARCH specifications are the Constant Conditional Correlation (CCC) model of Bollerslev (1990), Vector GARCH (VECH) model of Bollerslev (1988) and the BEKK model of Baba et. al (1990). Due to the high parameterization issue, the majority of studies have used the BEKK model, which ensures the conditional variance and covariance matrices are positive semi definite (Wollongong 2008). However, the diagonal VECH model is more flexible compared to the BEKK model as it allows the conditional variance covariance to vary over time. Additionally, the majority studies use the Berndt, Hall, Hall, and Hausman (BHHH) (1974) algorithm to obtain the estimates, and the Marquardt algorithm where the BHHH algorithm does not converge.

A wide range of other univariate and multivariate conditional volatility models can be used in estimation including the CCC-GARCH, Vector Autoregressive Moving Average GARCH (VARMA-GARCH) of Ling and McAleer (2003) and VARMA Asymmetric GARCH (VARMA-AGARCH) model of Hoti et al (2002).

As shocks to Caribbean tourism stem mainly from changes in source market income and relative prices, this paper employs the DVEC multivariate GARCH formulation to investigate the impact of these specific shocks, which are proxy by growth in U.S industrial production and growth in international crude oil prices. The DVEC specifications allows us to obtain the mean and variance spill over effects of these variables on growth in tourist arrivals, as well as to assess the volatility persistence of such shocks. Our study therefore builds on the work of Browne et al (2009) and ascertains whether shocks to the tourism industry in the Caribbean do in fact only have temporary effects.

The remainder of the paper is structured as follows: the next section provides a description of the data, while section 3 explains the chosen methodology. The results are discussed in section 4 and section 5 gives the conclusion.

2. DATA

This study uses monthly data on eight Caribbean countries: Antigua and Barbuda, Aruba, Barbados, Bermuda, Cayman Islands, Curacao, Grenada and Jamaica. Shocks are measured by growth in source market income and relative prices, which are proxy by growth in monthly U.S industrial production and growth in international crude oil prices, respectively. The data for tourism arrivals were obtained from the Caribbean Tourism Organisation (CTO) Statistical Database (online edition), while the data on shocks were obtained from the International Monetary Fund (IMF) International Financial Statistics (IFS) database.

Table 1 provides summary statistics for the monthly long-stay arrivals between 1997M1 and 2007M12, while Figure 1 plots monthly arrivals for the Caribbean countries under investigation.

Summary Statistics

Table 1

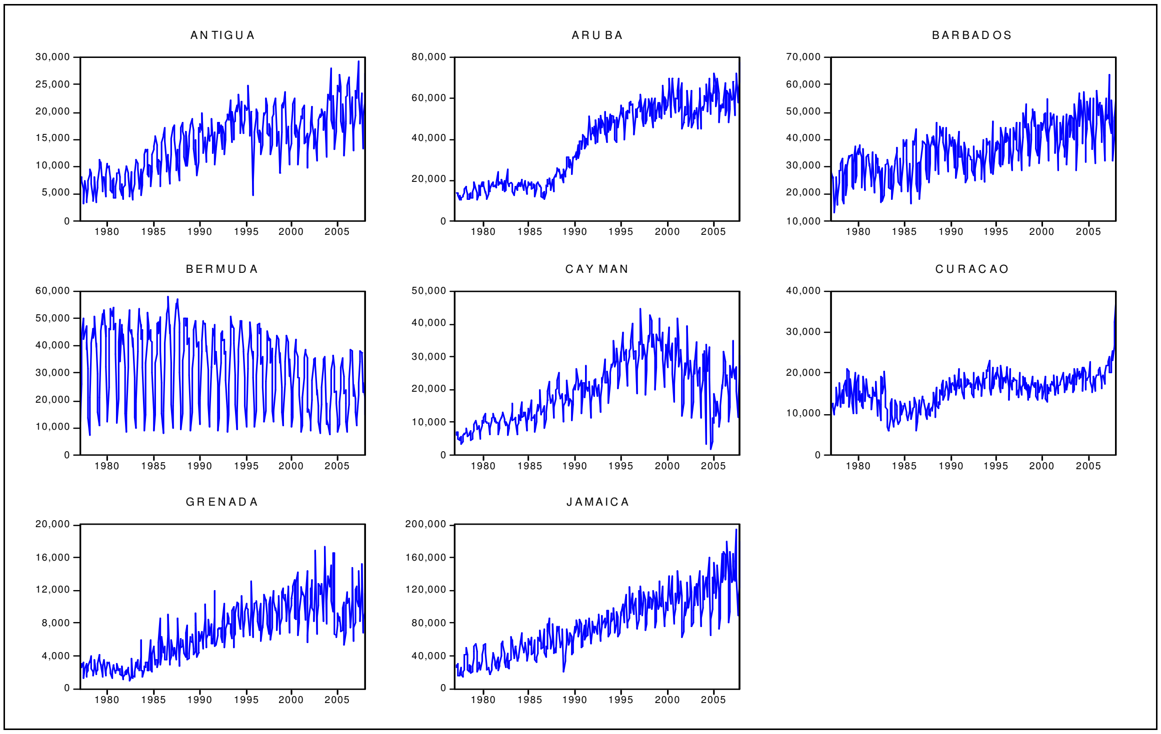
	Tourist Arrivals						
Statistics	**Antigua**	**Barbados**	**Bermuda**	**Cayman**	**Curacao**	**Grenada**	**Jamaica**
Mean	14504.71	36236.46	31981.81	19762.77	15978.19	6919.341	77592.66
Median	15404	36325	34505	19304.5	16447	6788.5	75453
Maximum	29441	63841	58087	44540	37103	17381	195409
Minimum	3272	13260	7312	1968	5946	1047	14782
Std. Dev.	5622.659	9078.467	13586.85	9531.657	3935.425	3698.513	37086.52
Skewness	-0.075639	0.046053	-0.216487	0.27609	0.287954	0.312002	0.424308
Kurtosis	2.253208	2.705787	1.78569	2.089724	5.27957	2.262087	2.616364
Jarque-Bera	8.999046	1.473194	25.76125	17.56931	85.68568	14.47539	13.44355
Probability	0.011114	0.47874	0.000003	0.000153	0	0.000719	0.001204
Sum	5395753	13479964	11897235	7351749	5943887	2573995	28864469
Sum Sq. Dev.	1.17E+10	3.06E+10	6.85E+10	3.37E+10	5.75E+09	5.07E+09	5.10E+11
Observations	372	372	372	372	372	372	372

The average monthly arrivals are highest for Jamaica at around 77,593 visitors followed by Barbados, which has average monthly arrivals of 36,237. Average arrivals for the other islands in the sample range between 31981 and 6919 visitors. Jamaica achieved the maximum amount of arrivals during the period 1977M1 to 2007M12 with 19,5409 visitors, while Grenada attracted the least with an average of 1047 visitors.

The most volatile of the Caribbean tourism destinations appears to be Jamaica and Bermuda, which have the highest standard deviations. With the exception of Antigua, all of the other countries exhibit similar levels of tourism volatility. The general distribution of the tourism data is slightly skewed to the right with an average skewness of around 0.2. In fact, only two of the eight distributions show negative skewness. In terms of the kurtosis, only the distribution of arrivals to Curacao seems to exhibit fat like tails. The rest of the distribution has kurtosis of less than 3, implying relatively small tails.

Tourist Arrivals (Raw form)

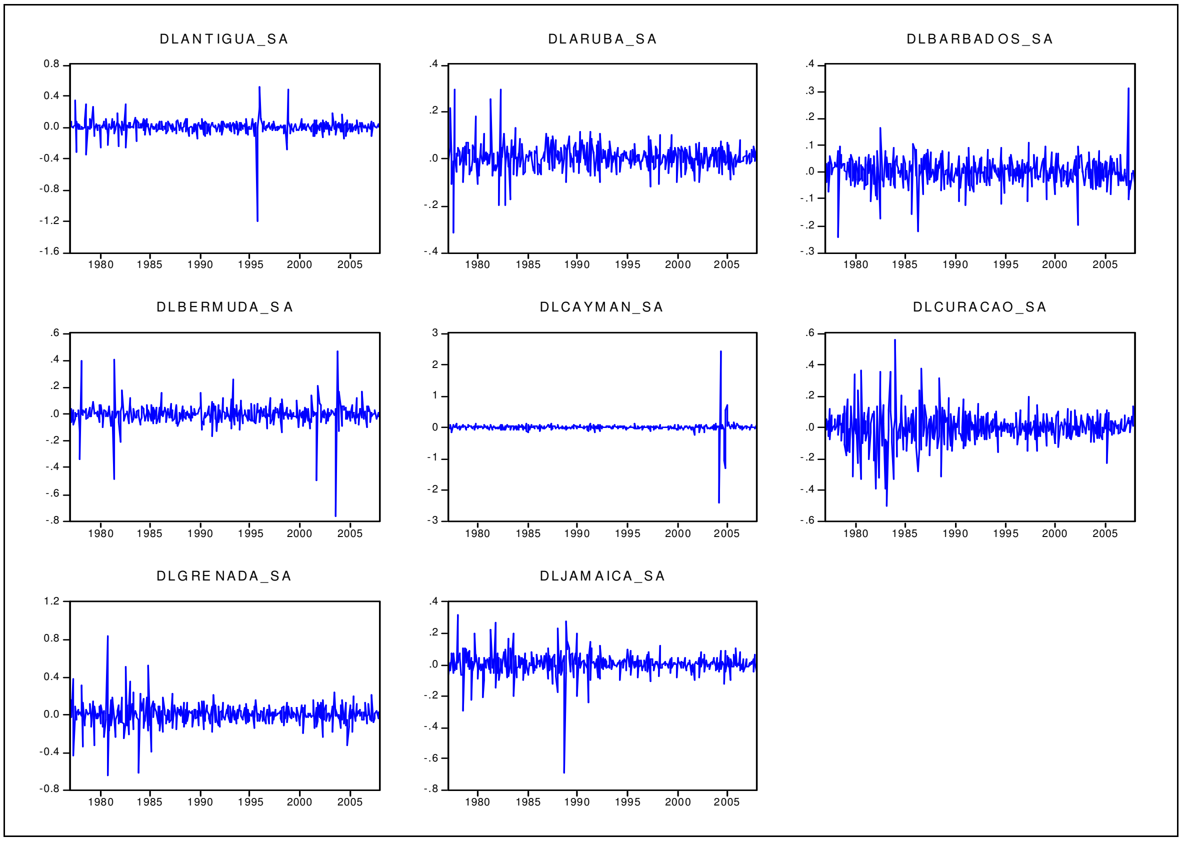
Figure 1



Most of the arrivals for each country show an increasing trend over the review period. Bermuda arrivals, however, show a fairly stationary arrival pattern. Arrivals to the Cayman Island increased rapidly between 1977 and 2000 but declined thereafter, only to pick up again in 2006. A visual inspection of figure 1, implies a high presence of seasonality in each of the eight tourism series.

Tourism Arrivals (Seasonally Adjusted Growth Rates)

Figure 2



The figure above shows the growth in the deseasonalised tourism series for each of the eight countries. There is clear evidence of volatility clustering, particularly in Aruba, Bermuda, Curacao, Grenada and Jamaica.

3. METHODOLOGY

Conditional volatility or uncertainty models are particularly useful for modeling time varying correlations as they allow for a distinction between long run and short run persistence. Such models are frequently used in finance to analyse risk, asymmetric shocks and leverage effects. Engle's (1982) Autoregressive Conditional Heteroscedasticity (ARCH) model and the subsequent generalized ARCH model developed by Bollerslev (1986) are the most popular for modeling volatility. However, the GARCH model is especially known for its superior estimation power. Bollerslev (1986) GARCH model states that the error variance of any series *y* at time *t* depends on the squared error terms from previous periods as well as past variances, where the ARCH effect (the coefficient on the past squared error terms) captures the short-run persistence of innovations (an indication of the strength of the shocks in the short run) and the GARCH effect (the coefficient on the past variances) measures the contribution of these innovations to long run persistence.

In this paper, we employ the multivariate GARCH model to analyse the mean and volatility spill over effects from growth in U.S industrial output and international crude oil prices on growth in tourism arrivals in the Caribbean. Volatility (or uncertainty) here refers to the changes in the variability of shocks to tourism growth rates, U.S industrial output expansion and appreciation in international crude oil prices. This is defined as the squared deviation of each observation from the respective sample mean.
Consider the following specification for tourism growth, U.S industrial output expansion and appreciation in oil prices, measured in logged differences, y_t:

$$y_t = E(y_t \mid \mathrm{I}_{t-1}) + \varepsilon_t, \qquad t = 1, \ldots., n$$
$$\varepsilon_t \sim N(0, H) \qquad (1)$$

Where, y_t is a $mx1$ vector containing growth rates for tourism, U.S industrial production and international crude oil prices, while I_t is an mxm matrix of historical information available at time t. ε_t is a $mx1$ vector, which is independently and identically distributed (iid) with mean 0 and variance H_t.

$$H_t = \omega + \alpha * \varepsilon^2{}_{t-1} + \beta * H_{t-1}$$
where $\omega > 0, \alpha > 0$ *and* $\beta > 0$ $\qquad (2)$

Assuming that H_t follows a multivariate GARCH process, the volatility and co-volatility in tourism, U.S industrial production and international oil price growth can be modelled using equation 2. Here α represents a mxm matrix of constants, α is a mxm matrix of coefficients measuring ARCH effects, while β is a mxm matrix capturing GARCH effects or volatility spill over.

The problem with the general MGARCH model outlined above is that the size of the variance-covariance matrix H_t increases exponentially as we increase the number of variables in the model, making the general model extremely difficult to estimate. As a result, a number of approaches have been developed to reduce the computational burden of GARCH modelling. The three main approaches are the diagonal VEC (DVEC), diagonal BEKK (DBEKK) and the constant conditional correlation (CCC) transformations of H_t. Of the three, the BEKK and the CCC are normally preferred for reduction of the variance-covariance parameters. However, because of the objective this paper we choose to employ the DVEC approach.

There is no reason to believe that the conditional variance of tourist arrivals would be constant over time and therefore we want (1) a model that allows the conditional variance to vary with $t = 1,....,n$. Additionally, (2) we would like a model that enables us to assess the spill over effects from changes in crude oil price volatility and volatility on U.S industrial production on tourism volatility in the Caribbean. The DVEC model allows for the investigation of both (1) and (2), while the DBEKK specification allows for (1) and not (2) and the CCC model allows for (2) but not (1).

The DVEC transformation requires that H_t depend on the squares and cross products of innovations, ε_t and lagged volatility H_{t-1}.

$$H_t = C + A * \varepsilon_{t-1}\varepsilon_{t-1} + B * H_{t-1} \quad (3)$$

VEC is the operator that stacks the lower triangle of the variance-covariance matrix. A is a *mxm* matrix of ARCH terms and B is a *mxm* matrix of GARCH terms measuring own volatility and cross volatility spill over. As in the unrestricted VEC model in equation 2, the parameters are subjected to the positivity conditions imposed on the MGARCH process and co-variance stationarity is required. In this paper, equation 3 is estimated in the Eviews programme version 6.0 using both the BHHH and Marquandt algorithms, depending on which is able to achieve convergence.

4. RESULTS

Table 2 of the appendix presents the mean, own and spillover volatility effects from the model estimated in equation 3. The results suggest that there are significant own volatility and cross-volatility spillover effects in growth of tourist arrivals, US industrial production and oil prices among the eight Caribbean territories investigated, while little support is found for significant mean effects.

With the exception of Barbados, own-volatility spillover effects were significant in each case at the 5% level, with parameter estimates ranging from 0.01 to 3.31. Volatility spillovers from growth are significant for all countries except for Barbados, suggesting the absence of ARCH effects in the Barbados tourism data. The results are similar for spill over effects from oil prices. The equations for all countries other than Barbados show evidence of significant volatility spill over effects from growth in oil prices, at least at the 5% level of significance. The coefficient on the cross-product variance of tourism and income was highest for Cayman both under co-volatility spillover effects from income and oil prices. Similarly, the results from the Grenada model suggests that the presence of co-volatility between changes in tourism and changes in crude oil prices are lowest for that country.

In terms of persistence, Aruba, Grenada and Curacao have GARCH coefficients of 0.98, 0.97 and 0.90, respectively, implying high tourism volatility persistence in these countries. Volatility persistence is low for Cayman (0.285), Bermuda (0.169) and Antigua (0.168). Moreover, there is virtually no volatility persistence for Barbados and Jamaica.

4. CONCLUSION

This paper set out to model tourism volatility in the Caribbean using data on eight Caribbean countries and the DVEC specification of the multivariate GARCH approach, which has recently been applied to model tourism volatility for other popular tourism destinations. Our results support the results by Browne *et al.* (2009) that tourism shocks to the Caribbean tourism industry generally have transitory rather than permanent effects. Three out of eight of the countries in the chosen sample show high persistence to shocks from changes in source market income and relative prices but persistence in the other six countries appears to be relatively low or non-existent.

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APPENDIX

Table 2

Tourist Destination	Mean Effects			CONDITIONAL VARIANCE					
				Volatility Spillover Effects			Volatility Persistence		
	β_{ta}	β_{gdp}	β_{ops}	β_{ta}	β_{gdp}	β_{ops}	β_{ta}	β_{gdp}	β_{ops}
Antigua	-0.482**	-0.927	0.087*	0.718**	0.180**	0.655**	0.168**	0.328**	0.333**
Aruba	-0.314**	-0.092	0.021	0.000	0.004	0.008	0.979**	0.599**	0.794**
Barbados	-0.394**	0.202	-0.039	0.064*	-0.093**	-0.190**	0.093	0.177	0.246
Bermuda	-0.303**	-0.007	-0.007	0.154**	0.148**	0.293**	0.169	-0.257**	-0.331**
Cayman	-0.539**	-0.580	-0.083**	3.313**	0.585**	1.638**	0.285**	0.344**	0.402*
Curacao	-0.428**	-0.433	-0.051	0.088**	0.053**	0.225**	0.902**	-0.905**	0.758**
Grenada	-0.382**	0.403	-0.045	0.014**	-0.041**	-0.086**	0.970**	0.622**	0.793**
Jamaica	-0.509**	0.253	0.022	0.541**	0.248**	0.558**	0.000	0.002	0.002

SHOCKS

Table 3