A MODEL FOR CARIBBEAN TOURISM DEMAND VOLATILITY

1 Introduction

This paper attempts to model the volatility of Caribbean tourism demand and determine if shocks in demand in one market affects demand in other markets. A comparative analysis of the forecasts from various conditional variance models is undertaken, as well as a critical review of the empirical literature.

The empirical literature on the volatility of tourism demand has been receiving increasing attention, with emphasis being placed on modelling volatility attributed to changes in economic activity, climate, natural and man-made disasters (Shareef and McAleer 2005a). Some researchers (Chan et al. 2005; Hoti et al. 2005) used univariate autoregressive conditional heteroskedastic (ARCH) and generalised autoregressive conditional heteroskedastic (GARCH) processes to determine the conditional variances of tourist demand, while others such as (Chan et al. 2005) utilised multivariate GARCH (MGARCH) models. Limited evidence exists in the literature where GARCH is employed as a forecasting tool for tourist arrivals (Lorde and Moore 2008). Though (Browne et al. 2009) applied the conditional variance Markov regime switching (MS) model to determine the recovery process after a shock for 19 small island tourist economies (SITES), no forecasting estimates were provided.

For the Caribbean, the research has followed the same basic direction. (Grosvenor 2010; Browne et al. 2009; Lorde and Moore 2008a, b; Chan et al. 2005 and Shareef and McAleer 2005a) have examined the volatility of tourism demand to determine its co-movement and whether there are spill-over effects among destinations or regions. However, all of these authors did not include any analysis of multiple crises, events or the impact of return visitors on arrivals to these markets.

The primary limitations found in the literature on the Caribbean are: (i) No use of GARCH or MS processes to forecast long stay arrivals; (ii) Models did not include any analysis on return visitors, special events or multiple crises in determining the co-movement of tourist arrivals; (iii) Models did not factor the influence of qualitative variables on tourist flows, and; (iv) Lack of adequate comparative forecasting performances of conditional volatility models such as ARCH, GARCH, MS, MGARCH and MS-VAR processes. These weaknesses in the forecast literature will provide less help to practitioners as they undertake short-term, medium and long-term business planning and resource allocation and less assistance to policy makers who are engaged in the development and execution of national plans for tourism as they attempt to better understand the changes that occur in the demand for tourism services and how these factors will affect local, social and institutional capital.

This essay, in an attempt to address the major weaknesses outlined above, focuses on the application of ARCH, GARCH, and MGARCH processes (see Engle 1982; Bollerslev 1986) to the integrative model developed in Appendix. In essence, the study will derive the time varying movement of demand amongst the markets, as well as the cross volatility spill-over effects. This approach has the following advantages over the alternative MS and MS-VAR conditional variance models expounded by (Hamilton 1989) which are also estimated and forecasted for comparative purposes: (i) more accurate confidence intervals can be derived, and (ii) more efficient estimators can be obtained if heteroskedasticity in the errors are handled properly. In summary, the empirical conditional variance models will assess, as in, the impact of repeat or return visitors on current tourism demand, the effect of seasonal and multiple crises/special events on tourism flows, the influence of qualitative factors, a wide cross section of countries or markets with a history of differing cultural influences, plus the forecasting performances of the various conditional variance models.

In summary, the ARCH and MGARCH models with the lowest Theil inequality coefficient were found to be the most efficient in explaining and forecasting tourist arrivals when compared to the other univariate and multivariate models, respectively. The countries showing the highest own market volatility were the Dominican Republic, The Bahamas, and Saint Vincent and the Grenadines followed by Grenada. On the other hand, Antigua and Barbuda, Anguilla, Aruba, The Cayman Islands and Jamaica had the highest long-run volatility persistence after an unexpected shock. Using asymmetric models process, the essay found that with most markets negative shocks increase volatility, and have a greater impact than positive shocks.

After this introduction, methodology and data are described in section 2. The results from estimating the various univariate conditional variance models along with their forecasting performances are discussed in section 3. Following that section, the multivariate conditional variance models and their forecasted outturns are presented with concluding remarks in the final section.

2. Models, Methodology and Data

2.1 Demand Volatility Models

The most frequently used models that measure conditional and unconditional volatility are the univariate Markov switching process (Hamilton 1989), as well as the ARCH and GARCH specifications (Hoti et al. 2005). This study will consider these models along with their multivariate counterparts - MS-VAR and MGARCH processes - to determine which set up fits the data best.

<u>Univariate Models</u>

(i) The ARCH model (Engle 1982):

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-i}^2$$

where α represents the short-run persistence, σ_t^2 is the variance for the forecast error made for the time t forecast, ε is the forecast error made at time t and ω is a constant.

(ii) The simple GARCH (1,1) (Bollerslev 1986) specification:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where the conditional variance $\sigma_t^2 > 0$. The parameter α represents the ARCH effect, while β is the GARCH impact. The necessary and sufficient condition for the existence of stationarity is $\alpha + \beta < 1$ (Nelson 1991). A value of $(\alpha + \beta)$ close to 1 indicates that volatility shocks are quite persistent.

(iii) (Glosten et al. 1993) developed the asymmetric (or threshold) GARCH (TGARCH) specification:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-i}^2 + \beta\sigma_{t-i}^2 + \gamma\varepsilon_{t-i}^2\tau_{t-i}$$

with $\alpha + \beta + \gamma / 2 < 1$ being the stationarity condition. The persistence of a negative shock is given by $\alpha + \gamma$. In this model, positive and negative shocks have differential effects on the conditional variance: negative shocks increase volatility if $\gamma > 0$, and $\gamma < 0$ implies positive shocks which expand volatility; while shocks are symmetric if $\gamma = 0$. The average short-run persistence of shocks is $\alpha + \gamma / 2$ and the contribution of shocks to average long-run persistence is $\alpha + \lambda / 2 + \beta$.

(iv) (Nelson 1990) propounded the exponential GARCH model (EGARCH). The specification is given by:

$$\sigma_t^2 = \omega + \beta\sigma_{t-i}^2 + \alpha\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$$

The model is asymmetric as long as $\alpha \neq 0$. When $\gamma < 0$, then positive shocks generate less volatility than negative shocks.

(v) Using a GARCH (1,1) model, the component GARCH (CGARCH) (Ding et al. 1993) can be expressed as:

$$m_t = \omega + \rho(m_{t-i} - \omega) + \phi(\varepsilon_{t-i}^2 - \sigma_{t-i}^2)$$

This model is ideal when policies are used to reduce volatility. The speed of mean reversion to equilibrium is ρ and a value close to 1 indicates a rapid speed of adjustment after a shock and m_t is the time varying long run volatility.

(vi) The Markov Switching (MS) dynamic regression model (Hamilton 1989) follows the form:

$$\mathrm{TA}_t = \nu(s_t) + \alpha TA_{t-1} + X_t^{'}\beta + \varepsilon_t, \varepsilon_t \sim N\left[0, \sigma^2\right]$$

TA is tourist arrivals, where s_t is a random variable following a Markov chain, and X is a vector of explanatory variables, with ε the forecast errors which are normally distributed. If TA_{t-1} exceeds some threshold value, the system is in regime one; otherwise, the system is in regime two (Enders 2004). (Hamilton 1989) posits that regime switches are exogenous. The transitional probabilities are estimated along with the coefficients of the two autoregressive process (Enders 2004).

Multivariate Models

(i) The specification of the MGARCH model is:

$$\mathrm{H}_t = \mathrm{C} + \mathrm{A}^* \varepsilon_{t-i}\ \varepsilon_{t-i} + \mathrm{B}^*\mathrm{H}_{t-i}$$

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. The parameters are subject to the positivity conditions and co-variance stationarity is required.

As mentioned earlier the MGARCH set up can be affected by the size of the variance – covariance matrix. This matrix usually increases as the number of variables in the model expand, generally making the model difficult to estimate. To reduce the computational burden, a diagonal Vector GARCH (DVEC), a diagonal (Baba, Engle, Kraft and Kroner 1995) (DBEKK) and a constant conditional correlation (CCC) framework were developed to aid in the transformation of the variance–covariance matrix, H_t. In this paper, the DVEC adjustment, which requires that, H_t depends on the square and cross products of the innovations, ε_t and lagged volatility H_{t-i}, is preferred to the DBEKK and CCC models.

The DVEC model developed by (Bollerslev et al. 1988) captures both the variation in the conditional variance and the spill-over influences while the DBEKK framework ensures a positive conditional variance but does not allow for spill-over effects (Karunanayake et al. 2008). On the other hand, the CCC set up provides for spill-over impacts but does not permit the conditional variance to vary.

(ii) The multivariate MS-VAR model is specified as follows:

$$\mathrm{TA}_t - u(s_t) - x_t^{'}\gamma = p(TA_{t-1} - u(s_{t-1}) - x_t^{'}\gamma) + \varepsilon_t \, \varepsilon_t \sim N\left[0, \sigma^2\right]$$

It requires a state vector of dimension N = S $^{(1+p)}$ to obtain the Markov representation for the likelihood evaluation for S regimes and autoregressive order p. The MS-VAR framework is a general regime switching model where the parameter of the observed time series vector TA_t depends on an unobservable regime variable s_t which refers to the probability of being in a different state (Krolzig 1998).

2.2 Methodology

The first step in the methodology is to deseasonalise the series. In this regard, the TRAMO (Time Series Regression with integrated autoregressive moving average (ARIMA) noise, Missing Observations, and Outliers) and SEATS (Signal Extraction in ARIMA Time Series) programmes developed by (Gomez and Maravall 1996) and found in the EVIEWS 6.1 software is used.

After seasonally adjusting the series, the panel unit root tests are employed to check the properties of the variables. This is followed by utilising the correlogram to investigate the autoregressive characteristics of the variables. Next, applying the Maximum Likelihood method, the conditional variance models discussed earlier are estimated to explore the effects of economic shocks and volatility on the observed mean values of the variables, as well as to test for the presence of persistence of volatility in the variances and to undertake forecasts of volatility. To specify the unknown conditional distributions the unconditional distributions (standardised on their means) are compared with commonly used distributions such as the normal and *t*, employing the quantile plots found in EVIEWS 6.1. This provides a first sense of the nature of the conditional distribution. The distribution of the residuals is tested against the normal, *t*, and other commonly utilised distributions (generalised error distribution), in order to determine the nature of the conditional distribution. When this is done, the integrated series can now be estimated and the volatility modelled. Note a volatility component in the mean equation is included as arrivals displayed changes to unexpected shocks.

2.3 Data

Briefly they cover the quarterly period 1999Q1 to 2009Q4[1] for seventeen developing markets and were obtained from the Caribbean Tourist Organisation Statistical Department in March and September 2010. The dependent variable is tourist arrivals (TA_t) and the independent variables that enters the mean equations are past visitors (TA_{t-1}), return visitors (R_t), relative prices between destination market and primary

[1] A bias correction to the Akaike information criteria (AIC) was derived for the regression series (Hurvich and Tsai 1989)

source markets (CPI_{ij}), per capita GDP (Y_t), international oil prices times distance from major cities of the source markets as a proxy for transportation cost (TC_t), special events or crises represented by dummy variables (DUM_t) and the qualitative factors: population size (source markets) (POP_j), and internet usage – destination market (IU_i) as a measure of communication.

3. Estimation Results

Following the methodology section above, the series are first seasonally adjusted by the TRAMO procedure. The transformed data exhibit similar characteristics as the raw data: skewness, leptokurtosis, non-normality and autoregressiveness. Next, applying the panel unit root tests revealed that all the variables are integrated of order 1, [I (1)], that is, they need to be differenced once to become stationary. The next step is to use the correlogram on these differenced series to check their autoregressive characteristics. This pointed to lags of up to 4 observations in some markets, but the associated probabilities were quite low, especially after the first lag for most of the series. Finally, the conditional variance models are estimated and forecasts of volatility presented.

3.1 Univariate Results: ARCH, GARCH and MS Processes

The findings from estimating the various univariate conditional variance models indicate that in most cases, a significant ARCH (1) and GARCH (1, 1) process with the errors following mainly a generalised error distribution were revealed. The R-square of all the models are reasonably high and the correlogram Q-statistics, using lag lengths of up to 10, indicate no significant amount of serial correlation. The covariance stationarity property is upheld, as judged by the sum of the lagged squared errors and the lagged variance terms being less than one ($\alpha + \beta < 1$). The Bahamas (0.98), Saint Vincent and the Grenadines (0.96), Dominica (0.82) and Trinidad and Tobago (0.80), showed the highest volatility persistence. (Bollerslev 1986) also assumes that the individual coefficients need to be non-negative, but this restriction, while sufficient for the variance to be positive, is not necessary (Bollerslev, Chou and Kroner 1992).

The estimation of the tourism series with the ARCH models and its variants include a set of qualitative and quantitative as well as a volatility component in the mean equation as arrivals displayed changes to unexpected shocks. The own volatility spill-over (ARCH) coefficients are highest for The Bahamas, Barbados, the Dominican Republic, Dominica, Curacao, Grenada and Saint Vincent and the Grenadines, ranging from 0.77 for the Dominican Republic to 0.19 for Curacao. Within the Windward Islands (Grenada (0.24), Saint Vincent and the Grenadines (0.28) and Dominica (0.22)) had relatively large own volatility movements in demand.

Volatility persistence (GARCH) coefficients are of greatest concern to Anguilla, Antigua and Barbuda, Aruba, The Bahamas, the Cayman Islands, Dominica, the Dominican Republic, Saint Maarten, and Jamaica with several markets showing long-run effects after a shock. The coefficients of Anguilla, Aruba, the Cayman Islands and Jamaica were around 0.87 with Antigua and Barbuda having the highest of 0.89 while the lowest was seen in The Bahamas and the Dominican Republic (0.75).

The asymmetric effects from the EGARCH and TGARCH models, which showed that negative shocks increase volatility and have a greater influence than positive shocks, were prominent for Aruba, the Dominican Republic, The Bahamas, Jamaica, Barbados, Bermuda, the Cayman Islands, Grenada, St Maarten and Saint Vincent and the Grenadines. With significant coefficients of -0.34,-0.68 and -0.80 for Aruba, Grenada and the Cayman Islands respectively, this indicates that negative shocks raise volatility in these markets.

In Anguilla, Antigua and Barbuda, Saint Lucia, Dominica, Puerto Rico, Curacao and Trinidad and Tobago, positive shocks advance volatility and these effects on conditional volatility are greater than the negative shocks. Trinidad and Tobago has the highest positive shock coefficient of 2.52, followed by Anguilla, 0.80, and St. Lucia, 0.17, implying that positive events push volatility above the value recorded from negative unexpected shocks.

Using the CGARCH process the following markets are seen to have a fairly rapid speed of adjustment to equilibrium after a shock (approximately two periods): Dominica (0.52) and The Dominican Republic (0.72). The markets that depict the slowest mean reversion speed were Antigua and Barbuda, Puerto Rico, Barbados and Trinidad and Tobago.

For the univariate MS specification, the mean convergences are checked through the closeness of the autoregressive (AR) coefficients to unity, along with the transitional probabilities of the regimes in switching from one state of nature to another. However, false inferences can be drawn once coefficients are poorly estimated if one regime change rarely occurs (Enders 2004). The MS models are further limited as they do not provide adequate explanation on the reasons and timing of regime changes (Enders 2004). Before estimation, serial correlation, heteroskedasticity, parameter constancy and normality tests are undertaken to ensure that the model was well specified.

From the results of the MS model the markets with the highest mean reversion coefficients were the Dominican Republic (0.95), Dominica (0.85), Jamaica (0.70), Anguilla (0.67) and Saint Lucia (0.65), indicating that adjustment to long-run equilibrium will take place within one quarter. These results seem comparable to the CGARCH model which found Dominica and the Dominican Republic with the fastest mean convergence. The lowest adjustment to equilibrium was recorded in The Bahamas (0.32), Aruba (0.35) and Curacao (0.39).

Examining the transitional probabilities which deals with movement from a period of downturn to one of normal growth, Trinidad and Tobago (0.4590) led the way followed by Dominica (0.4078), Puerto Rico (0.3895) and Jamaica (0.3790). The markets with the lowest transit probabilities were The Bahamas (0.0387), Curacao (0.0589) and Grenada (0.0457), implying that policy makers in these markets would need additional efforts and resources to return these markets to normal growth.

3.2 Forecasting Performance of ARCH, GARCH and MS Models

The forecasting performance of the various conditional variance models is assessed with the Theil inequality coefficient, which is considered the best for analysing forecast efficiency on the same variables across different models. The results (see Table 1) show that the ARCH models provided the best within sample forecast, for the majority of markets, followed by CGARCH and the simple GARCH process. The findings from the MS model displayed weaker forecasting performance for most markets except the Bahamas (0.065) and Trinidad and Tobago (0.07). Countries with a higher rate of own volatility (ARCH effects) and volatility persistence (GARCH impacts) performed poorly in the forecast, namely Saint Vincent and the Grenadines, the Cayman Islands, Anguilla, Grenada and Dominica.

Table 1: Forecasting Performances of ARCH, GARCH and MS Models

Country	Models	Root Mean Squared Error (RSME)	Mean Absolute Error (MAE)	Theil Inequality Coefficient	Bias Proportion	Variance Proportion
Anguilla	ARCH(2)	2101.4	1844.7	**0.08**	0.113	0.71
	GARCH(1,1)	9734.3	8482.3	0.30	0.75	0.13
	EGARCH(1,1,1)	5314.6	4740..8	0.191	0.79	0.02
	TGARCH(1,1,1)	4152.6	3686.6	0.155	0.77	0.00
	CGARCH(1,1,1)	2099.490	1843.4	**0.08**	0.075	0.18
	MS	5764.09	5014.89	0.136	0.13	0.45
Antigua and Barbuda	ARCH (1)	5629.6	5022.5	0.063	0.059	0.78
	GARCH(1,1)	4777.1	4016.3	**0.05**	0.001	0.29
	EGARCH(1,1,1)	6376.3	5692.7	0.072	0.138	0.48
	TGARCH(1,1,1)	5632.335	5025.164	0.063	0.059	0.78
	CGARCH(1,1,1)	11649.11	9595.50	0.141	0.46	0.01
	MS	9261	8242.29	0.165	0.52	0.07
Aruba	ARCH (1)	10247.3	8307.1	**0.03**	0.19	0.007
	GARCH(1,1)	24599.9	21654.06	0.092	0.753	0.206
	EGARCH(1,1,1)	22849.4	20038.82	0.085	0.74	0.199
	TGARCH(1,1,1)	13189.79	10983.5	0.047	0.52	0.09
	CGARCH(1,1,1)	13942.57	11695.20	0.05	0.57	0.11
	MS	14903	13264	0.075	0.64	0.12
Bahamas	ARCH(3)	25769.31	20121	**0.03**	0.022	0.75
	GARCH(1,1)	42045	35499	0.060	0.606	0.02
	EGARCH(1,1,1)	60662	53547	0.09	0.733	0.002
	TGARCH(1,1,1)	36478.3	29625.3	0.052	0.516	0.078
	CGARCH(1,1,1)	28436	20042	0.038	0.057	0.8179
	MS	31765	27953.20	0.065	0.652	0.090
Barbados	ARCH(1)	5748.7	4345.6	**0.02**	0.037	0.946
	GARCH(1,1)	15653	13162	0.079	0.59	0.009
	EGARCH(1,1,1)	25352	21601	0.1346	0.70	0.05
	TGARCH(1,1,1)	19856	16772	0.1028	0.655	0.03
	CGARCH(1,1,1)	14101	11799	0.071	0.56	0.002
	MS	21086	18344	0.1176	0.72	0.06
Bermuda	ARCH(2)	8884	7421	0.062	0.29	0.000

	GARCH(1,1)	8885	7422	0.062	0.29	0.000
	EGARCH(1,1,1)	9598	8135	0.066	0.444	0.007
	TGARCH(1,1,1)	12922	9999	0.097	0.299	0.168
	CGARCH(1,1,1)	8356	6897	**0.05**	0.074	0.019
	MS	11905	10595	0.087	0.26	0.145
Cayman	ARCH(1)	15980	10825	0.18	0.27	0.10
	GARCH(1,1)	18113.04	12364	0.12	0.42	0.45
	EGARCH(1,1,1)	23535	18369	0.15	0.588	0.324
	TGARCH(1,1,1)	25675	22453	0.21	0.61	0.005
	CGARCH(1,1,1)	14297	8035	**0.10**	0.14	0.38
	MS	22107	19675	0.135	0.456	0.22
Curacao	ARCH(1)	6695	5865	0.084	0.76	0.13
	GARCH(1,1)	9588	8260	0.11	0.74	0.19
	EGARCH(1,1,1)	2229	1845	**0.03**	0.07	0.363
	TGARCH(1,1,1)	2817	2420	0.037	0.57	0.00
	CGARCH(1,1,1)	9644	8306	0.117	0.74	0.19
	MS	10876	9572	0.13	0.80	0.18
Dom. Republic	ARCH(3)	145462	131451	0.122	0.79	0.156
	GARCH(1,1)	68040	60930	0.053	0.50	0.003
	EGARCH(1,1,1)	61861	50681	**0.04**	0.002	0.197
	TGARCH(1,1,1)	136202	123297	0.11	0.79	0.14
	CGARCH(1,1,1)	124483	112856	0.10	0.78	0.13
	MS	150984	131356	0.145	0.85	0.14
Dominica	ARCH(3)	2031	1579	0.14	0.53	0.049
	GARCH(1,1)	1273	949	0.08	0.288	0.472
	EGARCH(1,1,1)	1343	1141	0.079	0.59	0.004
	TGARCH(1,1,1)	1455	1238	0.085	0.633	0.0001
	CGARCH(1,1,1)	1076	905	**0.06**	0.444	0.075
	MS	2107	1834	0.155	0.60	0.078
Grenada	ARCH(1)	6540	5412	0.145	0.457	0.006
	GARCH(1,1)	4173	3084	**0.10**	0.34	0.02
	EGARCH(1,1,1)	6463	5152	0.15	0.61	0.045
	TGARCH(1,1,1)	5972	5257	0.185	0.69	0.008
	CGARCH(1,1,1)	5335	4133	0.13	0.556	0.144
	MS	6321	5626	0.14	0.62	0.06
Jamaica	ARCH(1)	44273	34043	0.064	0.4111	0.518

	GARCH(1,1)	24962	20281	**0.03**	0.080	0.56
	EGARCH(1,1,1)	88958	70571	0.138	0.611	0.285
	TGARCH(1,1,1)	56172	43512	0.0836	0.498	0.472
	CGARCH(1,1,1)	41245	31645	0.060	0.37	0.53
	MS	74213	64565	0.115	0.578	0.342
Puerto Rico	ARCH(3)	37351	31960	**0.06**	0.37	0.178
	GARCH(1,1)	54719	49185	0.099	0.72	0.23
	EGARCH(1,1,1)	60210	54280	0.11	0.74	0.24
	TGARCH(1,1,1)	38239	32652	**0.06**	0.59	0.18
	CGARCH(1,1,1)	43185	37732	0.076	0.65	0.20
	MS	62109	55277	0.125	0.72	0.21
St Lucia	ARCH(1)	4495	3644	**0.04**	0.058	0.19
	GARCH(1,1)	9170	7701	0.081	0.57	0.03
	EGARCH(1,1,1)	6051	4954	0.055	0.37	0.003
	TGARCH(1,1,1)	7858	6954	0.078	0.49	0.34
	CGARCH(1,1,1)	7478	6188	0.067	0.50	0.007
	MS	9513	8276	0.095	0.62	0.10
St. Maarten	ARCH(1)	10130.74	7323	**0.05**	0.400	0.160
	GARCH(1,1)	18658	17533	0.0949	0.88	0.002
	EGARCH(1,1,1)	14079	12601	0.073	0.80	0.08
	TGARCH(1,1,1)	10359	7679	**0.05**	0.455	0.49
	CGARCH(1,1,1)	19238	18142	0.09	0.88	0.001
	MS	21009	18487	0.125	0.86	0.05
St. Vincent &	ARCH(1)	5814	4925	0.19	0.403	0.0477
Grenadines	GARCH(1,1)	2662	1636	**0.10**	0.03	0.12
	EGARCH(1,1,1)	2891	1966	**0.10**	0.017	0.11
	TGARCH(1,1,1)	4989	4184	0.17	0.34	0.021
	CGARCH(1,1,1)	3947	3158	0.1725	0.60	0.218
	MS	5102	4438.74	0.18	0.37	0.067
Trinidad &	ARCH(1)	4345	3418	**0.03**	0.034	0.16
Tobago	GARCH(1,1)	4199	3299	**0.029**	0.01	0.11
	EGARCH(1,1,1)	5621	4510	0.04	0.28	0.40
	TGARCH(1,1,1)	5213	4329	0.08	0.18	0.05
	CGARCH(1,1,1)	4287	3369	**0.03**	0.05	0.06
	MS	5589	4975	0.07	0.16	0.08

Now using a dynamic forecast of various time horizons (4, 6 and 8) the Theil inequality coefficients were compared across the different models per markets. These results are displayed in Table 2 and 3 with the forecasting rank in brackets. The ARCH model gave the best within sample forecast results followed by the GARCH and EGARCH specifications while horizon 4 provided the most accurate result.

Table 2: Ex-ante or Post sample Forecasting Comparison

Forecasting Comparison (Theil Inequality Coefficient) with rank in brackets				
Forecasting Periods/Horizons				
Country	Models	2010 (4)	2011 (8)	2012 (12)
Anguilla	ARCH(2)	0.0829 (1)	0.087 (1)	0.09507 (1)
	GARCH(1,1)	0.37 (6)	0.3753 (6)	0.3905 (5)
	EGARCH(1,1,1)	0.22 (5)	0.221 (5)	0.253 (4)
	TGARCH(1,1,1)	0.175 (4)	0.1853 (4)	0.205 (3)
	CGARCH(1,1,1)	0.086 (2)	0.099 (2)	0.0975 (2)
	MS	0.153 (3)	0.1651 (3)	0.205 (3)
Antigua and Barbuda	ARCH (1)	0.0675 (2)	0.0725 (2)	0.0775 (2)
	GARCH(1,1)	0.0553 (1)	0.063 (1)	0.0658 (1)
	EGARCH(1,1,1)	0.0758 (3)	0.084 (4)	0.0825 (3)
	TGARCH(1,1,1)	0.0758 (3)	0.0775 (3)	0.0825 (3)
	CGARCH(1,1,1)	0.154 (4)	0.173 (5)	0.1854 (4)
	MS	0.184 (5)	0.202 (6)	0.2256(5)
Aruba	ARCH (1)	0.0353 (1)	0.0490 (1)	0.0575 (1)
	GARCH(1,1)	0.103 (6)	0.1151 (5)	0.1254 (6)
	EGARCH(1,1,1)	0.0925 (5)	0.0975 (4)	0.1025 (5)
	TGARCH(1,1,1)	0.052 (2)	0.0575 (2)	0.0650 (3)
	CGARCH(1,1,1)	0.0525 (3)	0.0575 (2)	0.0625 (2)
	MS	0.088 (4)	0.0956 (3)	0.1017 (4)
Bahamas	ARCH(3)	0.035 (1)	0.040 (1)	0.0451 (1)
	GARCH(1,1)	0.0625 (4)	0.0675 (3)	0.0736 (3)
	EGARCH(1,1,1)	0.0955 (6)	0.1025 (5)	0.1075 (6)
	TGARCH(1,1,1)	0.0619 (3)	0.0675 (3)	0.0750 (4)
	CGARCH(1,1,1)	0.0425 (2)	0.0567 (2)	0.0557 (2)
	MS	0.0793 (5)	0.0858 (4)	0.0912 (5)
Barbados	ARCH(1)	0.025 (1)	0.0325 (1)	0.0375 (1)
	GARCH(1,1)	0.085 (3)	0.095 (3)	0.10 (3)
	EGARCH(1,1,1)	0.145 (6)	0.155 (6)	0.17 (5)
	TGARCH(1,1,1)	0.125 (4)	0.1325 (4)	0.1375 (4)
	CGARCH(1,1,1)	0.0775 (2)	0.0825 (2)	0.09 (2)

	MS	0.13 (5)	0.15 (5)	0.17 (5)
Bermuda	ARCH(2)	0.0675 (3)	0.075 (3)	0.0775 (2)
	GARCH(1,1)	0.0650 (2)	0.07 (2)	0.0775 (2)
	EGARCH(1,1,1)	0.0725 (4)	0.075 (3)	0.0850 (3)
	TGARCH(1,1,1)	0.1025 (6)	0.12 (5)	0.125 (5)
	CGARCH(1,1,1)	0.055 (1)	0.06 (1)	0.065 (1)
	MS	0.095 (5)	0.1025 (4)	0.115 (4)
Cayman	ARCH(1)	0.19 (5)	0.2075 (5)	0.22 (4)
	GARCH(1,1)	0.135 (2)	0.145 (2)	0.155 (1)
	EGARCH(1,1,1)	0.17 (4)	0.185 (4)	0.1975 (3)
	TGARCH(1,1,1)	0.23 (6)	0.255 (6)	0.27 (5)
	CGARCH(1,1,1)	0.115 (1)	0.125 (1)	0.155 (1)
	MS	0.145 (3)	0.165 (3)	0.18 (2)
Curacao	ARCH(1)	0.0875 (3)	0.0950 (2)	0.0975 (3)
	GARCH(1,1)	0.125 (4)	0.14 (3)	0.155 (4)
	EGARCH(1,1,1)	0.0425 (1)	0.0475(1)	0.0525 (1)
	TGARCH(1,1,1)	0.045 (2)	0.0475 (1)	0.055 (2)
	CGARCH(1,1,1)	0.13 (5)	0.15 (4)	0.1625 (5)
	MS	0.15 (6)	0.1625 (5)	0.17 (6)
Dom. Republic	ARCH(3)	0.14 (5)	0.1475 (4)	0.155 (3)
	GARCH(1,1)	0.06 (2)	0.065 (2)	0.0725 (1)
	EGARCH(1,1,1)	0.055 (1)	0.0625 (1)	0.075 (2)
	TGARCH(1,1,1)	0.13 (4)	0.145 (3)	0.155 (3)
	CGARCH(1,1,1)	0.125 (3)	0.145 (3)	0.155 (3)
	MS	0.17 (6)	0.19 (5)	0.1975 (4)
Dominica	ARCH(3)	0.155 (4)	0.17 (4)	0.175 (5)
	GARCH(1,1)	0.095 (3)	0.1025 (3)	0.12 (4)
	EGARCH(1,1,1)	0.09 (2)	0.0975 (2)	0.1075 (2)
	TGARCH(1,1,1)	0.095 (3)	0.1025 (3)	0.115 (3)
	CGARCH(1,1,1)	0.065 (1)	0.075 (1)	0.0825 (1)
	MS	0.17 (5)	0.185 (5)	0.20 (6)
Grenada	ARCH(1)	0.155 (4)	0.16 (4)	0.165 (4)
	GARCH(1,1)	0.1075 (1)	0.11(1)	0.1125 (1)
	EGARCH(1,1,1)	0.155 (4)	0.16 (4)	0.1625 (3)
	TGARCH(1,1,1)	0.19 (5)	0.1975 (5)	0.2050 (5)
	CGARCH(1,1,1)	0.1375 (2)	0.1405 (2)	0.1475 (2)

	MS	0.1475 (3)	0.1550 (3)	0.1625 (3)
Jamaica	ARCH(1)	0.070 (3)	0.075 (2)	0.08 (2)
	GARCH(1,1)	0.0355 (1)	0.0425 (1)	0.05 (1)
	EGARCH(1,1,1)	0.155 (6)	0.165(5)	0.1775 (6)
	TGARCH(1,1,1)	0.09 (4)	0.0975 (3)	0.1050 (4)
	CGARCH(1,1,1)	0.065 (2)	0.075 (2)	0.0825 (3)
	MS	0.125 (5)	0.14 (4)	0.1475 (5)
Puerto Rico	ARCH(3)	0.065 (1)	0.07 (1)	0.0775 (1)
	GARCH(1,1)	0.105 (4)	0.11 (4)	0.1175 (3)
	EGARCH(1,1,1)	0.12 (5)	0.1275 (5)	0.1350 (4)
	TGARCH(1,1,1)	0.0675 (2)	0.0725 (2)	0.0775 (1)
	CGARCH(1,1,1)	0.085 (3)	0.09 (3)	0.0975 (2)
	MS	0.14 (6)	0.1525 (6)	0.1650 (5)
St Lucia	ARCH(1)	0.05 (1)	0.055 (1)	0.0625 (1)
	GARCH(1,1)	0.085 (5)	0.09 (4)	0.0925 (3)
	EGARCH(1,1,1)	0.06 (2)	0.0625 (2)	0.0675 (2)
	TGARCH(1,1,1)	0.0825 (4)	0.09 (4)	0.0925 (3)
	CGARCH(1,1,1)	0.075 (3)	0.085 (3)	0.0925 (3)
	MS	0.10 (6)	0.105 (5)	0.11 (4)
St. Maarten	ARCH(1)	0.0525 (1)	0.06 (1)	0.065 (1)
	GARCH(1,1)	0.1025 (5)	0.11 (3)	0.1175 (4)
	EGARCH(1,1,1)	0.08 (3)	0.085 (2)	0.0925 (3)
	TGARCH(1,1,1)	0.055 (2)	0.06 (1)	0.065 (1)
	CGARCH(1,1,1)	0.10 (4)	0.115 (4)	0.1175 (4)
	MS	0.1325 (6)	0.14 (5)	0.145(5)
St. Vincent and	ARCH(1)	0.20 (6)	0.205 (6)	0.21(5)
Grenadines	GARCH(1,1)	0.115 (2)	0.1225 (2)	0.1275 (2)
	EGARCH(1,1,1)	0.11 (1)	0.115 (1)	0.12 (1)
	TGARCH(1,1,1)	0.18 (3)	0.1875 (3)	0.1897 (3)
	CGARCH(1,1,1)	0.19 (4)	0.1925 (4)	0.1955 (4)
	MS	0.195 (5)	0.20 (5)	0.21(5)
Trinidad & Tobago	ARCH(1)	0.035 (1)	0.04 (1)	0.045 (1)
	GARCH(1,1)	0.0425 (2)	0.05 (2)	0.055 (2)
	EGARCH(1,1,1)	0.05 (3)	0.055 (3)	0.06 (3)
	TGARCH(1,1,1)	0.0875 (5)	0.0925 (5)	0.095 (5)
	CGARCH(1,1,1)	0.035 (1)	0.04 (1)	0.045 (1)

	MS	0.0775 (4)	0.08 (4)	0.085 (4)

Table 3: Ex-post and Ex-Ante Forecasting Comparison (Theil Inequality Coefficient)

Country	Models	2008	2008 Forecast	2009	2009 Forecast	2010	2011	2012
Anguilla	ARCH(2)	0.0451	0.0512	0.0578	0.0667	0.0829 (1)	0.087 (1)	0.09507 (1)
	GARCH(1,1)	0.33	0.345	0.35	0.365	0.37 (6)	0.3753 (6)	0.3905 (5)
	EGARCH(1,1,1)	0.19	0.195	0.205	0.215	0.22 (5)	0.221 (5)	0.253 (4)
	TGARCH(1,1,1)	0.155	0.16	0.165	0.01675	0.175 (4)	0.1853 (4)	0.205 (3)
	CGARCH(1,1,1)	0.04	0.0425	0.055	0.065	0.086 (2)	0.099 (2)	0.0975 (2)
	MS	0.085	0.09	0.115	0.13	0.153 (3)	0.1651 (3)	0.205 (3)
Antigua and Barbuda	ARCH (1)	0.0355	0.0350	0.055	0.0575	0.0675 (2)	0.0725 (2)	0.0775 (2)
	GARCH(1,1)	0.03	0.0325	0.05	0.055	0.0553 (1)	0.063 (1)	0.0658 (1)
	EGARCH(1,1,1)	0.045	0.045	0.055	0.0575	0.0758 (3)	0.084 (4)	0.0825 (3)
	TGARCH(1,1,1)	0.05	0.0475	0.055	0.0625	0.0758 (3)	0.0775 (3)	0.0825 (3)
	CGARCH(1,1,1)	0.10	0.13	0.14	0.15	0.154 (4)	0.173 (5)	0.1854 (4)
	MS	0.14	0.155	0.165	0.175	0.184 (5)	0.202 (6)	0.2256(5)
Aruba	ARCH (1)	0.025	0.03	0.035	0.035	0.0353 (1)	0.0490 (1)	0.0575 (1)
	GARCH(1,1)	0.075	0.08	0.09	0.095	0.103 (6)	0.1151 (5)	0.1254 (6)
	EGARCH(1,1,1)	0.065	0.07	0.075	0.075	0.0925 (5)	0.0975 (4)	0.1025 (5)
	TGARCH(1,1,1)	0.025	0.03	0.035	0.035	0.052 (2)	0.0575 (2)	0.0650 (3)
	CGARCH(1,1,1)	0.015	0.025	0.03	0.035	0.0525 (3)	0.0575 (2)	0.0625 (2)
	MS	0.05	0.055	0.065	0.075	0.088 (4)	0.0956 (3)	0.1017 (4)
Bahamas	ARCH(3)	0.015	0.0175	0.025	0.0275	0.035 (1)	0.040 (1)	0.0451 (1)
	GARCH(1,1)	0.035	0.065	0.045	0.060	0.0625 (4)	0.0675 (3)	0.0736 (3)
	EGARCH(1,1,1)	0.075	0.08	0.075	0.085	0.0955 (6)	0.1025 (5)	0.1075 (6)
	TGARCH(1,1,1)	0.025	0.035	0.04	0.045	0.0619 (3)	0.0675 (3)	0.0750 (4)
	CGARCH(1,1,1)	0.035	0.045	0.045	0.0475	0.0425 (2)	0.0567 (2)	0.0557 (2)
	MS	0.055	0.065	0.0675	0.075	0.0793 (5)	0.0858 (4)	0.0912 (5)
Barbados	ARCH(1)	0.015	0.02	0.025	0.0275	0.025 (1)	0.0325 (1)	0.0375 (1)
	GARCH(1,1)	0.045	0.055	0.065	0.075	0.085 (3)	0.095 (3)	0.10 (3)
	EGARCH(1,1,1)	0.10	0.125	0.135	0.145	0.145 (6)	0.155 (6)	0.17 (5)
	TGARCH(1,1,1)	0.087	0.09	0.10	0.125	0.125 (4)	0.1325 (4)	0.1375 (4)
	CGARCH(1,1,1)	0.055	0.065	0.065	0.07	0.0775 (2)	0.0825 (2)	0.09 (2)
	MS	0.085	0.095	0.010	0.102	0.13 (5)	0.15 (5)	0.17 (5)
Bermuda	ARCH(2)	0.045	0.055	0.06	0.0625	0.0675 (3)	0.075 (3)	0.0775 (2)
	GARCH(1,1)	0.045	0.0575	0.065	0.065	0.0650 (2)	0.07 (2)	0.0775 (2)
	EGARCH(1,1,1)	0.04	0.045	0.055	0.065	0.0725 (4)	0.075 (3)	0.0850 (3)
	TGARCH(1,1,1)	0.075	0.080	0.085	0.095	0.1025 (6)	0.12 (5)	0.125 (5)
	CGARCH(1,1,1)	0.025	0.035	0.045	0.055	0.055 (1)	0.06 (1)	0.065 (1)
	MS	0.075	0.0775	0.085	0.09	0.095 (5)	0.1025 (4)	0.115 (4)
Cayman	ARCH(1)	0.10	0.135	0.15	0.155	0.19 (5)	0.2075 (5)	0.22 (4)
	GARCH(1,1)	0.085	0.095	0.10	0.125	0.135 (2)	0.145 (2)	0.155 (1)

	EGARCH(1,1,1)	0.095	0.10	0.125	0.14	0.17 (4)	0.185 (4)	0.1975 (3)
	TGARCH(1,1,1)	0.15	0.175	0.185	0.20	0.23 (6)	0.255 (6)	0.27 (5)
	CGARCH(1,1,1)	0.075	0.095	0.10	0.11	0.115 (1)	0.125 (1)	0.155 (1)
	MS	0.065	0.075	0.085	0.085	0.145 (3)	0.165 (3)	0.18 (2)
Curacao	ARCH(1)	0.045	0.055	0.055	0.075	0.0875 (3)	0.0950 (2)	0.0975 (3)
	GARCH(1,1)	0.075	0.085	0.095	0.10	0.125 (4)	0.14 (3)	0.155 (4)
	EGARCH(1,1,1)	0.01	0.015	0.025	0.03	0.0425 (1)	0.0475(1)	0.0525 (1)
	TGARCH(1,1,1)	0.015	0.015	0.02	0.025	0.045 (2)	0.0475 (1)	0.055 (2)
	CGARCH(1,1,1)	0.10	0.11	0.125	0.13	0.13 (5)	0.15 (4)	0.1625 (5)
	MS	0.10	0.13	0.14	0.145	0.15 (6)	0.1625 (5)	0.17 (6)
Dom.	ARCH(3)	0.095	0.10	0.105	0.12	0.14 (5)	0.1475 (4)	0.155 (3)
Republic	GARCH(1,1)	0.025	0.035	0.05	0.055	0.06 (2)	0.065 (2)	0.0725 (1)
	EGARCH(1,1,1)	0.025	0.045	0.05	0.0575	0.055 (1)	0.0625 (1)	0.075 (2)
	TGARCH(1,1,1)	0.085	0.095	0.12	0.125	0.13 (4)	0.145 (3)	0.155 (3)
	CGARCH(1,1,1)	0.065	0.075	0.075	0.10	0.125 (3)	0.145 (3)	0.155 (3)
	MS	0.125	0.145	0.155	0.165	0.17 (6)	0.19 (5)	0.1975 (4)
Dominica	ARCH(3)	0.095	0.125	0.13	0.145	0.155 (4)	0.17 (4)	0.175 (5)
	GARCH(1,1)	0.055	0.075	0.085	0.09	0.095 (3)	0.1025 (3)	0.12 (4)
	EGARCH(1,1,1)	0.065	0.0675	0.075	0.085	0.09 (2)	0.0975 (2)	0.1075 (2)
	TGARCH(1,1,1)	0.055	0.075	0.065	0.075	0.095 (3)	0.1025 (3)	0.115 (3)
	CGARCH(1,1,1)	0.035	0.045	0.055	0.06	0.065 (1)	0.075 (1)	0.0825 (1)
	MS	0.10	0.125	0.135	0.145	0.17 (5)	0.185 (5)	0.20 (6)
Grenada	ARCH(1)	0.095	0.10	0.125	0.145	0.155 (4)	0.16 (4)	0.165 (4)
	GARCH(1,1)	0.055	0.065	0.075	0.085	0.1075 (1)	0.11(1)	0.1125 (1)
	EGARCH(1,1,1)	0.087	0.098	0.12	0.15	0.155 (4)	0.16 (4)	0.1625 (3)
	TGARCH(1,1,1)	0.14	0.165	0.175	0.185	0.19 (5)	0.1975 (5)	0.2050 (5)
	CGARCH(1,1,1)	0.055	0.065	0.095	0.10	0.1375 (2)	0.1405 (2)	0.1475 (2)
	MS	0.12	0.13	0.14	0.145	0.1475 (3)	0.1550 (3)	0.1625 (3)
Jamaica	ARCH(1)	0.025	0.035	0.04	0.045	0.070 (3)	0.075 (2)	0.08 (2)
	GARCH(1,1)	0.01	0.01	0.015	0.025	0.0355 (1)	0.0425 (1)	0.05 (1)
	EGARCH(1,1,1)	0.10	0.125	0.125	0.145	0.155 (6)	0.165(5)	0.1775 (6)
	TGARCH(1,1,1)	0.05	0.065	0.07	0.08	0.09 (4)	0.0975 (3)	0.1050 (4)
	CGARCH(1,1,1)	0.015	0.02	0.02	0.035	0.065 (2)	0.075 (2)	0.0825 (3)
	MS	0.08	0.095	0.10	0.125	0.125 (5)	0.14 (4)	0.1475 (5)
Puerto Rico	ARCH(3)	0.015	0.025	0.035	0.045	0.065 (1)	0.07 (1)	0.0775 (1)
	GARCH(1,1)	0.065	0.075	0.085	0.095	0.105 (4)	0.11 (4)	0.1175 (3)
	EGARCH(1,1,1)	0.055	0.065	0.075	0.095	0.12 (5)	0.1275 (5)	0.1350 (4)
	TGARCH(1,1,1)	0.025	0.045	0.055	0.065	0.0675 (2)	0.0725 (2)	0.0775 (1)
	CGARCH(1,1,1)	0.025	0.035	0.045	0.055	0.085 (3)	0.09 (3)	0.0975 (2)
	MS	0.10	0.105	0.11	0.12	0.14 (6)	0.1525 (6)	0.1650 (5)
St Lucia	ARCH(1)	0.01	0.015	0.025	0.035	0.05 (1)	0.055 (1)	0.0625 (1)
	GARCH(1,1)	0.055	0.065	0.07	0.08	0.085 (5)	0.09 (4)	0.0925 (3)
	EGARCH(1,1,1)	0.035	0.045	0.055	0.055	0.06 (2)	0.0625 (2)	0.0675 (2)
	TGARCH(1,1,1)	0.025	0.035	0.045	0.045	0.0825 (4)	0.09 (4)	0.0925 (3)
	CGARCH(1,1,1)	0.03	0.045	0.055	0.065	0.075 (3)	0.085 (3)	0.0925 (3)
	MS	0.04	0.045	0.065	0.075	0.10 (6)	0.105 (5)	0.11 (4)
St. Maarten	ARCH(1)	0.015	0.025	0.025	0.035	0.0525 (1)	0.06 (1)	0.065 (1)

	GARCH(1,1)	0.065	0.075	0.095	0.10	0.1025 (5)	0.11 (3)	0.1175 (4)
	EGARCH(1,1,1)	0.015	0.045	0.055	0.075	0.08 (3)	0.085 (2)	0.0925 (3)
	TGARCH(1,1,1)	0.01	0.035	0.045	0.05	0.055 (2)	0.06 (1)	0.065 (1)
	CGARCH(1,1,1)	0.025	0.025	0.045	0.065	0.10 (4)	0.115 (4)	0.1175 (4)
	MS	0.10	0.12	0.125	0.13	0.1325 (6)	0.14 (5)	0.145(5)
St. Vincent	ARCH(1)	0.10	0.12	0.14	0.18	0.20 (6)	0.205 (6)	0.21(5)
and	GARCH(1,1)	0.075	0.085	0.09	0.10	0.115 (2)	0.1225 (2)	0.1275 (2)
Grenadines	EGARCH(1,1,1)	0.09	0.10	0.12	0.125	0.11 (1)	0.115 (1)	0.12 (1)
	TGARCH(1,1,1)	0.125	0.135	0.145	0.15	0.18 (3)	0.1875 (3)	0.1897 (3)
	CGARCH(1,1,1)	0.14	0.155	0.165	0.175	0.19 (4)	0.1925 (4)	0.1955 (4)
	MS	0.155	0.165	0.175	0.19	0.195 (5)	0.20 (5)	0.21(5)
Trinidad &	ARCH(1)	0.01	0.015	0.025	0.03	0.035 (1)	0.04 (1)	0.045 (1)
Tobago	GARCH(1,1)	0.015	0.025	0.0375	0.045	0.0425 (2)	0.05 (2)	0.055 (2)
	EGARCH(1,1,1)	0.025	0.035	0.035	0.045	0.05 (3)	0.055 (3)	0.06 (3)
	TGARCH(1,1,1)	0.045	0.055	0.065	0.075	0.0875 (5)	0.0925 (5)	0.095 (5)
	CGARCH(1,1,1)	0.01	0.015	0.025	0.03	0.035 (1)	0.04 (1)	0.045 (1)
	MS	0.03	0.05	0.065	0.075	0.0775 (4)	0.08 (4)	0.085 (4)

3.3 The MGARCH and MS-VAR Models: Estimation Performance

To appropriately model the conditional variance and the covariance of the error terms across markets in an autoregressive form, the MGARCH and MS-VAR models are utilised. The error distribution of the series is tested against either the multivariate normal or student's t distribution of the residuals, in order to determine the nature of the conditional distribution, after completing the preliminary steps in the estimation procedure.

In most cases the estimation procedure revealed a significant MGARCH process with the errors following mostly a multivariate normal distribution. The covariance stationarity property is satisfied, as evidenced by the sum of the lagged squared errors and the lagged variance terms being less than one. The R-square of all the models are quite reasonable along with the Portmanteau tests which indicate no significant amount of autocorrelation.

Note due to the relatively small degrees of freedom the complete seventeen MGARCH equations could not be estimated, so the tests were done in groups, that is, the markets were categorised according to proximity (Grosvenor 2010), colonial affiliation, language and cultural associations:

(A) The Bahamas, Barbados, The Cayman Islands and Jamaica (the largest English speaking destination markets)

(B) Dominica, St. Vincent and the Grenadines, St. Lucia, Grenada (Windward Islands markets (a))

(C) Barbados, St. Lucia and Grenada (Windward Islands markets (b))

(D) Anguilla, Antigua and Barbuda and Bermuda (Leeward Islands markets)

(E) Aruba, Curacao and St. Maarten (Dutch Islands markets)

(F) Dominican Republic and Puerto Rico (Spanish Islands markets)

The results of the groups showed evidence of own volatility (ARCH) and volatility persistence (GARCH), confirming the previous results above. However there was no support for short-run cross over spill-over effects among the markets in Group A, but The Bahamas, The Cayman Islands and Jamaica all displayed statistically significant cross over spill-over influences in the long-run. The findings from Group B revealed statistically significant short and long-run cross spill-over impacts between Dominica and Saint Vincent and the Grenadines, thus indicating that shocks to arrivals in one market affects the other market.

There was significant short-run cross spill-over effects between Barbados and Grenada in Group B, and long-run cross spill-over influences in all three markets - Barbados, Grenada and Saint Lucia - in Group C, while Anguilla, Antigua and Barbuda, Bermuda, Aruba, Curacao, and Saint Maarten revealed similar long-run impacts in Groups D and E. For group F, there was no evidence of short and long-run cross over spill-over impacts.

Using the MS-VAR model, which was well specified with residual tests showing no evidence of serial correlation, heteroskedasticity, parameter constancy and non-normality, checks were done on the recovery process of the 17 Caribbean markets by allowing the growth rate in arrivals in a downturn to be different from a normal period. The results of the transitional probabilities showed how the model will move from one state of nature to another. To determine the mean reversion speed after a shock the sum of the autoregressive (AR) coefficients was examined, the closer they are to unity the faster is mean convergence. The results (see Tables 4 and 5) showed that there is a 9.8% probability to move from normal growth into downturn, but it was difficult to get out of a downturn with a probability of less than 15% (0.148%) each quarter. Implications from this finding are that additional efforts and resources will be required to move the economy back to normal growth after a downturn. The sum of the autoregressive (AR) coefficients revealed strong evidence of mean convergence (0.723). This result while similar to previous findings for the Dominican Republic and Dominica, indicate that Jamaica, Saint Lucia and Anguilla have high AR coefficients.

Table 4: Autoregressive coefficients (MS-VAR model)

Variable	Coefficient	T-Statistics	T-probability
P(0/0) Downturn	0.705	350	0.0000***
P(0/1) Normal	0.018	1.85	0.065*

Notes: *, ** and *** indicates significance at the 10, 5 and 1% level respectively.
Descriptive statistics for residuals: Normality test = 0.8654**, ARCH test = 0.3321**, Portmanteau test= 0.9853** and Chow test =0.4586**

Table 5: Transitional probabilities

	Downturn (Regime 0, t)	Normal Growth (Regime 1, t)
Downturn (Regime 0, t+1)	0.852	0.098
Normal Growth (Regime 1, t+1)	0.148	0.902

3.4 Forecasting Performance: MGARCH and MS-VAR models

Using OxMetrics 6, the multivariate model was forecasted to obtain the Theil inequality coefficient for the six groups. The results (see Table 6) showed that Group E (Aruba, Curacao and St. Maarten) had the best forecast of 0.038, followed by Group A (The Bahamas, Barbados, The Cayman Islands and Jamaica) of 0.0495, Group F (Dominican Republic and Puerto Rico) and Group C (Barbados, St Lucia and Grenada). Comparing the generated Theil inequality to the MS-VAR and simple average individual forecast coefficient, the MGARCH was found to be the most efficient estimator with more accurate forecasts.

Table 6: MGARCH and MS-VAR Forecasting Performance

	2008			2009			2010			2011			2012		
Markets	Actual	MGARCH	MSVAR	Actual	MGARCH	MSVAR	MGARCH	Average	MS-VAR	MGARCH	Average	MS-VAR	MGARCH	Average	MS-VAR
Group A	0.025	0.035	0.085	0.025	0.04	0.095	0.0495 (2)	0.0525 (2)	**0.108 (1)**	0.0525 (2)	0.06 (2)	0.12 (1)	0.075 (2)	0.072 (3)	0.14 (1)
Group B	0.035	0.055	0.12	0.045	0.075	0.135	0.082 (6)	0.0875 (6)	0.142 (5)	0.098 (6)	0.088 (6)	0.155 (4)	0.1050 (4)	0.094(5)	0.17 (5)
Group C	0.015	0.03	0.07	0.02	0.035	0.10	0.0590 (4)	0.0625 (4)	0.12 (2)	0.0625 (4)	0.065 (3)	0.135 (2)	0.075 (2)	0.070 (2)	0.145 (2)
Group D	0.01	0.025	0.045	0.01	0.03	0.085	0.071 (5)	0.075 (5)	0.13 (3)	0.08 (5)	0.07 (5)	0.145 (3)	0.095 (3)	0.075 (4)	0.15 (4)
Group E	**0.01**	**0.015**	**0.075**	**0.005**	**0.02**	**0.095**	**0.038 (1)**	**0.0395 (1)**	**0.11 (1)**	0.041 (1)	0.052 (1)	0.12 (1)	0.06 (1)	0.058(1)	0.14 (1)
Group F	0.015	0.02	0.065	0.015	0.025	0.09	0.0525 (3)	0.0555 (3)	0.135 (4)	0.055 (3)	0.066 (4)	0.145 (3)	0.06 (1)	0.075 (4)	0.155 (3)

Conclusion

This essay critically evaluates the literature on the volatility of tourism demand, especially as it pertains to the Caribbean region with the objective of producing models and forecasts that rectify the major problems highlighted in the literature. ARCH, GARCH, MS, MS-VAR and MGARCH processes are estimated to derive short-run estimates of own market volatility, volatility persistence in the long-run, and cross spill-over short and long-run effects in the markets. The results showed the markets displaying the highest own market volatility are Dominican Republic (0.77), The Bahamas (0.36), and Saint Vincent and the Grenadines (0.28), followed by Grenada (0.24). Antigua and Barbuda (0.89), and Anguilla, Aruba, The Cayman Islands and Jamaica (all 0.87) revealed the highest long-run volatility persistence after an unexpected shock.

In assessing the asymmetric models using EGARCH and TGARCH processes, the chapter found that with most markets negative shocks increase volatility, and had a greater impact than positive shocks. For Anguilla, Antigua and Barbuda, Dominica, Puerto Rico, Saint Lucia, Curacao and Trinidad and Tobago positive shocks were greater than negative shocks and they increased volatility in these markets.

There was similarity of results between the MS model and CGARCH as Dominica and the Dominican Republic had the fastest mean convergence results. In addition to these markets the MS model found Jamaica (0.70), Anguilla (0.67) and Saint Lucia (0.65) with autoregressive coefficients close to unity. The transitional probabilities showed that Trinidad and Tobago (0.4590) and Dominica (0.4078) were the quickest markets to switch to normal growth after a downturn within a quarter.

The forecasting performance of the conditional variance models are compared to each other using several selection criteria. ARCH models were found to be the most efficient in forecasting, while markets with high levels of volatility persistence provided the weakest forecast accuracy. The forecasting performance of the multivariate models (MGARCH and MS-VAR) were compared and with a Theil inequality coefficient of 0.038 (Aruba, Curacao and St. Maarten) had the best forecast. The cross spill-over effects of the markets were assessed with the MGARCH models, which provided short and long-run effects.

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Appendix:

Table A: Error Correcting Model of Tourist Arrivals - PDOLS

$$\Delta TA_t = 276.09 + 1.78\,\Delta R + 5.525\,\Delta GDPUS + 2.2589\,\Delta GDPEUR + 5.619\,\Delta GDPCAN$$
(3.54***) (14.64***) (3.46***) (4.48***) (4.25***)

$$-3.11500\,\Delta TC + 2.7526\,\Delta IUUS + 5.1082\,\Delta IUEUR + 3.1811\,\Delta IUCAN + 1.04\,\Delta TA_{t-1}$$
(-7.89***) (2.85***) (1.97**) (2.10**) (2.75***)

$$-1.13\,\Delta CPIJUS - 0.86\,\Delta CPIJEUR - 2.15\,\Delta CPIJCAN + 4.9404\,DUM - 0.4807\,ECT_{t-1}$$
(-2.08**) (-1.90*) (-1.67*) (2.37***) (-15.25***)

Diagnostic Tests

R^2 = 0.86 $\overline{R}^2$ = 0.845 F = 86 DW = 1.96 NORM = 4.228 CHOW= 0.4519
AR = 0.75 ARCH = 0.14 HET = 0.118 RESET = 1.10 DMW = 0.0810

Note: t- statistics of regressors are shown in parentheses.. ***, ** and * indicates significance at the 1, 5 and 10% level of testing, respectively. However, all diagnostics tests are performed at the 5% level of testing. Δ is the first difference operator. R^2 is the coefficient of determination, $\overline{R}^2$ is the coefficient of determination adjusted for degrees of freedom, F is the F-Statistic for the joint significance of the explanatory variables. DW is the Durbin Watson statistic and the NORM is the test for normality of the residuals based on the Jarque- Bera test statistics. AR is the Lagrange multiplier test for residual autocorrelation and ARCH is the autoregressive conditional heteroskedasticity. HET is the unconditional heteroskedasticity test based on the regression of squared residuals. Finally, RESET = Ramsey test for functional form mis-specification. Chow Test examines the parameter constancy between the forecast error variance and model variance. Diebold Mariano West test (DMW) implies that the models are equally accurate on average for predicting future values.