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DOES US STOCK MARKET PERFORMANCE EXPLAIN US ARRIVALS TO ANGUILLA

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Abstract:

This paper examines whether the performance of US stock markets as measured by the S&P500 explain arrivals of US tourist to Anguilla. More specifically this paper test for cointegration between the S&P500 and US stay over arrivals to Anguilla. Evidence for cointegration was found only in the univariate case using the Engle Granger technique. That finding was robust to the choice of US equity market and was also observed in Antigua and Barbuda, Grenada and St. Lucia. Other techniques such as the Johansen showed that oil prices was related to arrivals whiles ARDL bounds test suggested no long run relationships amoung the selected variables.

Key Words: Cointegration, US Stock Market, Stay Over Arrivals.

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Introduction

Prior to tourism becoming the dominant economic sector in many ECCU countries such as St. Kitts and Nevis and Saint Lucia, agriculture served as the main driver of economic activity. The progressive removal however of preferential trade arrangements for bananas and other crops in the late 90's contributed to the decline of agriculture and increased focus on tourism. Anguilla however given its size and topography never had a budding agricultural sector and tourism therefore has consistently been the mainstay of the economy. It is reasonable to assume therefore that the island's product is more 'mature' than it's other ECCU counterparts with the exception perhaps of Antigua and Barbuda which also had no agricultural sector and as such also depended heavily on tourism. The Anguillan tourism product is geared towards high net worth individuals and as such authorities deliberately pursue a low volume high value tourism model, which is clearly evident by the fact that although the island accounts on averages[1] only 4.2 per cent of total ECCU tourist arrivals it is estimated to receive 8.8 per cent of tourism receipts.

Following consistent growth, tourist arrivals peaked in 2006 and then subsequently declined to the extent that 2008 arrivals were lower than that recorded in 2001. Additionally Anguilla has fared among the worst of all ECCU territories with its arrivals declining by 15.2 per cent in 2009 following the global economic recession in comparison to Antigua for instance with a decline of 11.8 and St. Lucia 5.8 per cent. What are the reasons for the severity of this decline? Could it be as a result of the maturity of the Anguillan product? Or could it be a failure of the high end tourism model? Work by Caribbean authors see Whitehall and Greenidge (2001) and Malcolm (2003) have found that the Barbadian and Jamaican markets are mature and as with the 'product life cycle' this maturity results in visitor stagnation and eventual decline in the absence of new policy. In this paper however we focus on whether being a high end destination particularly in the midst of a financial crisis could explain the decline in Anguillan tourist arrivals. The reason for focusing on this issue is the novelty of the concept. To this authors knowledge little empirical work has been done linking tourism performance with the financial performance of key source markets, which intuitively affects consumer wealth and therefore the decision to consume a tourism product. Additionally liaising with Anguillan country officials and reading local newspapers one got the sense that many persons had concerns regarding Anguilla's chosen marketing style. Anecdotally this researcher is also aware that wealthy high net wealth individuals typically invest proportionately more of the wealth in stock

[1] 2005 to 2009 average

markets. If this is the case there should be a significant relationship between the performance of the stock market as measured by various indices and the decision to vacation in Anguilla given that the Anguillan tourism consumer are high net wealth individuals. A casual plotting of the growth rates of the S&P 500 alongside Anguillan tourist arrival growth rates interestingly show that in 2006 US stock market indices saw falling rates of growth in the same time period of Anguillan declining arrivals. Although not an explanation in the slightest it did raise the interest of this author to explore the extent to which a relationship may exist between arrivals and US stock market performance.

The US (Anguilla's largest source market) Survey of Consumer Finances shows that the percentage of Americans households who participate in the US stock market has increased over the last two decades to 51.2 per cent by 2007[2]. Although the rate of increase has slowed post 2001 it represents one of the highest participation rates in the world. Further analysis of this rate showed that participation was an increasing function of wealth, as households in the top (90-100 per cent) income percentile had participation rates of 91 per cent whiles households in the lower 20 per cent income percentile had rates of 13.6 per cent. This finding lends credence to our aforementioned hypothesis. This observation is also intuitive and in-line with the academic literature see Vissing-Jorgencen (2000) who argue that wealthier persons are more likely to hold some portion of their wealth in the US stock market. The literature see Hong et al (2004) posit that participation in the US stock market is an increasing function of wealth, social interaction and education. Another intuitive and relevant observation from the US Consumer Survey was that participation rates were higher among couples with no children, 62.1 per cent, than single households with children 31.3 per cent. Tying these findings together was the work of Poterba (2000) who was able to show that stock market performance did influence the consumption decision of US consumers.

Examining possible explanations of Anguillan tourism performance is a timely exercise as the Government of Anguilla (GoA) in collaboration with the Caribbean Development Bank (CDB) are currently developing a Tourism Master Plan for the island which aims to provide policy advice on the way forward with regards to Anguillan tourism. This author as the country economist for Anguilla at the Eastern Caribbean Central Bank (ECCB) aims to contribute to this process by addressing the extent to which Anguilla's reliance on high net worth individuals may have in any way contributed to the recent performance of the industry. The author will attempt to study this work

[2] The last time the survey was done

within a cointegration framework as little research has been done on ECCU tourism demand models using cointegration techniques see Sahely (2005) and Jack (2009).

This paper is therefore constructed as follows, section one presents the tourism performance of Anguilla, section two reviews the literature on tourism demand modeling particularly in small island developing states, section three presents the methodology employed. Section four presents the results and robustness test while section five concludes with policy recommendations.

Anguillan Tourism Performance

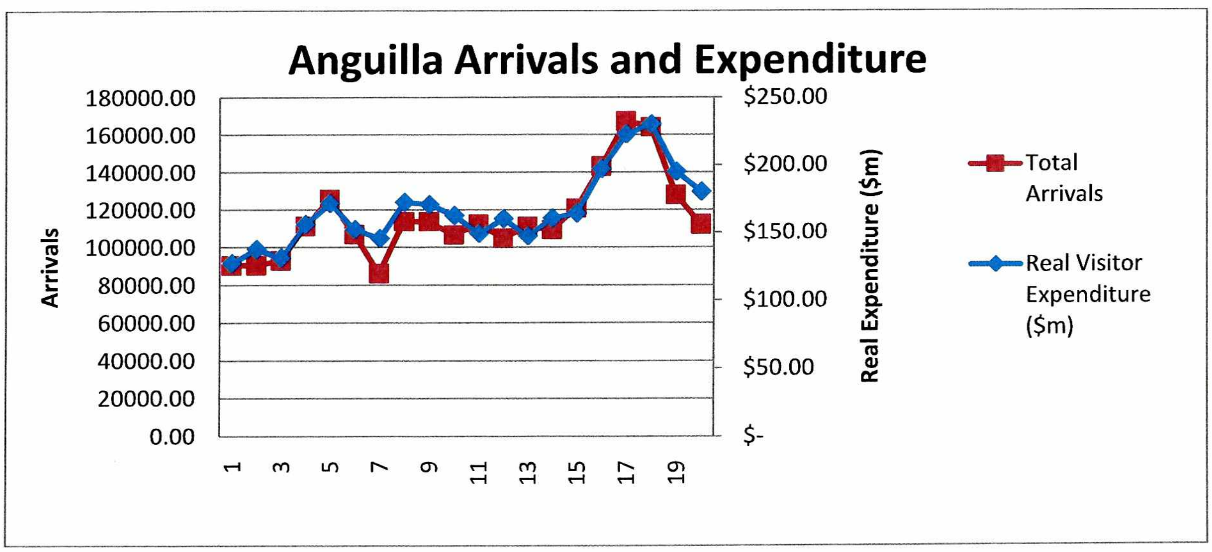
Over the 1990 to 2009 period the number of tourist arrivals to Anguilla increased by 23.8 per cent to 112,115[3]. Growth however over this period has been volatile with rates ranging from a 32.0 per cent increase in 1997 to 19.5 and 22.1 per cent declines in 1996 and 2008 respectively. Most worrying is that tourist arrivals have declined for three consecutive years i.e. 2007 to 2009 with the 2007 to 2008 decline predating the financial crisis. Despite however the volatility and declines in the number of tourist arrivals, real visitor expenditure has been fairly consistent as shown in figure 1 below. Real visitor expenditure averaged $1,449.1 over the 1990 to 2009 period with relatively little deviation observed. This is particularly poignant given that visitor arrivals have been falling. Real visitor expenditure increased 14.1 per cent over the 1990 to 2009 period and 16.7 per cent over the 2005 to 2009 period. Therefore although Anguilla is receiving less visitors, the expenditure per visitor is rising mitigating somewhat the lower arrival levels.

[3] To provide perspective to this discussion Anguillan arrivals accounted for 11 to 12 per cent of ECCU stay over arrivals

Figure 1: Growth Rate of Anguillan Arrivals

Source: ECCB Statistics

Figure 2: Anguillan Arrivals and Real Visitor Expenditure



Source: ECCB Statistics

The largest source market for Anguillan stay over arrivals is the USA. This market at the end of 2009 accounted for 58.9 per cent of visitors, down 8.3 percentage points from a peak of 67.2 per cent of stay over arrivals in 2005. The coinciding of the decline of the US market's contribution to stay over arrivals and the fall in the number of arrivals since 2006 is not missed on this researcher. Over the 2005 to 2009 with the exception of the UK, other source markets such as the Caribbean and Canadian markets saw increases in their contribution to stay over arrivals. The absolute value of these markets however was relatively small and as such couldn't compensate for the slowdown and declining growth in the US market. It is instructive to note however that the Caribbean market is the second largest contributor to stay over arrivals accounting for 22.3 per cent of arrivals in 2009. The growth rate of this market averaged 5.1 per cent over the 1990 to 2009 period.

Literature Review

Song and Li (2008) in a comprehensive review of 119 post 2000 tourism related studies note that tourism research has grown considerably in the last decade with the bulk of this research focused on developing tourism demand and forecasting models to assist policy makers in adjusting marketing and expenditure proposals. Other reviews, see Crouch (1994) and Lim (1997, 1999) also confirm this trend. In addition to this assessment both Lim (1999) and Song and Li (2008) showed that tourist income, prices of tourist goods and services and transport cost were the key influential tourist demand determinants. Song and Li (2008: pg 12) also added that "*tourist income, tourism prices relative to the origin country, tourism prices in competing destinations and exchanges rates*". The literature also notes that proxies have been established for each of the aforementioned determinants, tourist income is often proxied by real GDP per capita see Lim and McAleer (2001) of the source country whiles relative prices of destination and goods and services is often proxied by consumer price indices adjusted by the exchange rate and use of the real effective exchange rate see Malcolm (2003) and Sahely (2005). Transportation expense is often is proxied by oil prices see Halicioglu (2004). Tourism research in the Caribbean region has also focused on demand modeling see Greenidge 1998, but considerable work is also being done to determine the factors which influence the regions competitiveness see Craigwell and Worrell (2008) and the effects if any of 'maturity' of the Caribbean destination (life cycle phenomena) see Greenidge and Whitehall (2001) and Moore and Whitehall (2005). Sahely (2005) found that real per capita GDP of source markets and the real effective exchange rate positively influenced Anguillan arrivals whiles average oil prices (a proxy for transport cost) negatively influenced arrivals. Craigwell and Worrell (2008) similarly conclude that real GDP growth in source markets, the price of an island's nearest competitor and transportation cost are key determining factors of travel from US and UK markets.

Caribbean authors have also studied the inclusion of proxies for destination maturity in model estimation. Malcolm (2003) citing Butter (1980) highlights that there are six stages of the tourism life cycle namely exploration, involvement, development, consolidation, stagnation and decline[4]. Malcom citing Whitehall and Greenidge (2001) argues that maturity can bring about visible aging of tourism infrastructure, over-crowding, visitor harassment and increased service cost. Whitehall and Greenidge (2001) also examined maturity effects and citing the psychological literature see (Fridgen (1984) and Pearce and Stringer (1991) note that 'image' and 'crowding', are both shaped by the maturity of a destination and lead to negative or disutility of consumption. Where crowding referred to increasing urbanization of a destination whiles image simply referred to visitor perception. To capture maturity effects on tourism demand both of these papers used tourist arrivals in a year divided by the population in that given year.

As aforementioned Song and Li (2008) note that the research literature has grown considerably, with this growth being attributable primarily to the expansion of modeling techniques and methodologies given the general agreement on deterministic factors. Within the literature there are three main types of tourism demand models namely time series, econometric and other quantitative models which include AI and other mathematical approaches. Forecasting using (VECMs) vector error correction models and comparing those with ARIMA and other forecast has also gained prominence.

When referring to time series modeling we refer to the use of ARIMA models as developed by Box and Jenkins (1970) and variations of the Autoregressive Conditional Hetroskedastic (ARCH) espoused by Engle (1982) and further refined by Bollersllev (1986) into GARCH models and GJR (assymentric) models by Glosten et al (1992). ARIMA models suggest that (the present value of a variable is a linear function of its past values and a random error term) while GARCH modeling seeks to estimate the conditional volatility of a series. A particularly relevant study is work by Shareef and McAleer (2005) which used time series analysis to study the conditional volatility of international tourist arrivals to small island economies. These authors found that there is a high degree of persistence in monthly international arrivals to small island developing states (SIDS) such as Barbados and Dominica and that a ARMA (1,1) specification fit international arrival data to SIDS well. Estimates of the conditional mean and variance were close to 1, positive and significant in most SIDS implying that unanticipated shocks to arrivals will reverberate and lead to increased

[4] Parallels to the product life cycle can be drawn

uncertainty for future arrivals. Asymmetric effects however for Dominica was negative indicating that negative shocks to arrivals are not as strong as positive ones. Although these models has be shown to fit the data well given the persistence of tourist arrivals they fail however to provide policy makers with possible factors which can influence arrivals and thus shape policy.

Econometric models include ordinary least squares models, cointegration (error correction models and vector autoregressive models) and time varying parameter models see Song and Li (2008). Of these error correction models are often used as the literature notes that OLS models are inappropriate as they could give rise to spurious regressions and invalidate the analysis drawn. Spurious regression may be estimated given that most macroeconomic time series used in OLS regressions are nonstationary, see Lim and McAleer (2001). Cointegration therefore is often used in the tourism literature to establish whether a long term relationship exist between arrivals or expenditure and certain economic variables. More specifically Engle and Granger (1987) showed that if a stationary, linear combination of two non stationary variables existed that these variables were cointegrated and that a stable long run relationship exist between them. The presence of cointegration also meant that inferences from multivariate regression analysis which include these variables were not subject to the issue of spurious regressions identified by Granger and Newbold (1974). Although a stable long run equilibrium may exist between variables short run disequilbirum may occur and as such Engle and Granger (1987) showed that by transforming a cointegration regression into a error correction model (ECM) that policy makers will obtain information in relation to both the short and long run dynamics of the variables studied. Lim and McAleer (2003) under a cointegration framework analyzed quarterly demand to Australia and found that contigration existed amoung their proxies for incomes, tourism prices and transportation cost and a ECM developed showed[5] that changes in arrivals was linked to income and other factors as shown by Lim(1999). Several approaches exist in determining cointegration see Johansen (1988, 1995), Engle and Granger (1987), Phillips and Perron (1988). Each of these test first plot the variables in question to identify whether particular trends exist after which the order of integration of the variables is determined i.e. determines the presence of a unit root. The different test to determine the presence of one or more conitergrated vectors is conducted and then transformed to an error correction model. Attention is given to selecting the proper lag length and avoiding serial correlation amoung the residuals. Unit root testing is often conducted using the Augmented

[5] Statistically significant results

Dickey-Fuller (ADF) test espoused by Dickey and Fuller (1981). Peseran et al 2001 show a cointegration technique that does not necessarily involve a determination of the stationarity of the underlying variables. This method uses a single equation autoregressive distributed lagged (ARDL) model based on the work of Pesaran et al 2001. Cointegration is established by using a bounds testing procedure to determine the joint significance of lagged explanatory variables within a "univariate error correction model. This significance test is based on *F* and *t* statitcis. Perseran et al 2001 provide upper and lower bounds critical values which are used to test the null that the lagged values of our variables are jointly equal to zero. Failing to reject this null implies that there is no cointegration. In the case where the *F* statistic falls within the upper and lower bounds the test is inconclusive and where the null is rejected then cointegration is said to exist. This upper and lower bound stems from the fact that the model considers the case where all variables in the model are either I (0) or I (1). Use of this technique in a tourism demand setting was exemplified by the work of Halicioglu (2004) who used an ARDL model to examine a tourism demand function for Turkey.

Lastly Song and Li (2008) note that non econometric quantitative tourism models have increasingly been used such as the artificial neural models of Kon and Turner (2005) which attempt to mimic human learning abilities and general algorithms models of Pai et al (2006) where algorithms are constructed with a view of explaining tourism performance. These techniques however are often not intuitive and don't provide policy makers with information about the underlying determinants of demand.

This review has identified that co integration models are the most intuitive and offer policy makers robust and economically interpretable data concerning possible determinants of tourism demand.

3.0 Methodology

A tourism demand model which studies US arrivals to Anguilla, cognizant of the determinants identified in the literature and maturity and stock market proxies will be developed in a cointegration framework. Given the unavailability of data, US expenditure[6] in Anguilla (as a dependent variable) will not be studied. All absolute values will be in logarithmic scale.

3.1 Variable Choice and Construction

In keeping with the literature Anguilla's tourism demand model is defined as;

[6] This would have been a more robust dependent variable choice.

$$A= f\ (T, SM, Y, P, ER, SP, M)$$

Where *A*= the logarithm of US tourist arrivals to Anguilla, *T*= the logarithm of crude oil prices *SM*= return on the S&P 500, *Y*=US GDP per capita, *P*= log (CPI Anguilla/CPI US), *ER*= REER (Real Effective Exchange Rate), *SP*= log(CPI Substitue/CPI US), *M*= log(US tourist arrivals/Anguillan population).

3.2 Unit Root Test

Unit root test are used to determine whether a variable is stationary or not. Currently there are two main groups of such test employed, those which operate under the null hypothesis that the variable has a unit root and those which don't. Most popular amoung the first grouping are the augmented Dickey-Fuller test (1984), the Phillips-Perron (1990) and the Ng-Perron (2001) test. Amoung the later grouping is the Kwiatkowski, Phillips, Schmidt and Shin (1992) test. For this paper unit root results for all four methodologies will be presented to determine the degree to which they converge or whether any conflict between them exist. Perron (1990) argued that the ADF test is restrictive since it assumes no auto-correlation and heteroskedasticty in estimating the residuals. The Perron unit root test therefore relaxes these assumptions. Both the ADF and Perron test have however have low power in case where p (see equations below) is close to but not 1, implying that the test may wrongly suggest that there is a unit root when in fact there isn't. In this regard the KPSS test has an advantage over the aforementioned given its construction i.e. having a null of stationarity. The ADF and Perron test have also been shown (see Schwert 1989) to be biased towards rejecting the null when the series has a "large negative moving average root". The NG- Perron (2001) test build on prior work by Perron use of a modified lag criteria to improve the power of the test results.

The issue of structural breaks in the data is also increasingly coming to the fore. Unit root test, particularly the Dickey-Fuller type, often confuses structural breaks as evidence of non-stationary. Two key unit root test which account for breaks in either the trend or intercept of a series include the Andrews and Zivot (1992) test and the Clemente et al (1998) test. The Clemente et al test is superior to that of the Andrews and Zivot (1992) test as it allows for the possibility of two structural breaks in a series. Results of both will be shown in this paper with the Clemente et al results being the key used. Having conducted the aforementioned test the Clemente et al will be this researchers preferred metric to determine the presence of unit roots.

The ADF and Perron test are widely used and will be described below. The augmented Dickey-Fuller and Perron test are based on the regressions below.

$$\Delta y_t = \alpha + \delta t + (\rho - 1)y_{t-1} + \sum_{i=1}^{k} \gamma \Delta y_{t-1} + u_t$$

Where;

$$H_o: (\rho - 1) = 0 \text{ and } H_1: (\rho - 1) < 0$$

The lag length in equ 1 is often chosen based on the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). The KPSS test statistic is defined as;

$$LM = \sum_{t=1}^{T} \frac{S_t^2}{\sigma_\varepsilon^2}$$

And is based on;

$$y_t = \alpha + \beta T + \varepsilon$$

In unit root testing the decision to include or exclude an intercept, or a trend is material and for the purposes of this paper plotting of the respective variables and economic theory will be used to guide this decision.

3.3 Cointegration Test

For the purposes of this paper (three) cointegration test will be employed, namely the Engle-Granger two step approach, the Johansen maximum likelihood approach and the ARDL model. The Engle-Granger two step approach is a residual based test. It requires first that the long run relationship between the variables be estimated as;

$$Y_t = \alpha + X_t + \varepsilon$$

Having done this the first difference of the residual from this equation are regressed on their lagged value.

$$\Delta \epsilon = \beta \varepsilon_{t-1} + \varphi$$

The residuals capture divergences between the variables from an assumed equilibrium. The test statistic of the of the lagged residual is then compared against the MacKinnon (1990, 2010) critical values. The EG operates under the null that no cointegration exist, rejection of the EG null signifies cointegration and therefore implies that the residuals are mean reverting i.e. stationary. This signifies cointegration as the divergencies between X and Y are stochastic. In this paper EG test will be conducted on a uni and multivariate case i.e. between arrivals and equity indices alone and between arrivals, equity indices and other I (1) macroeconomic variables. Different equity indices will also be used to determine which are or are not cointegrated with arrivals. This will be important for policy makers to isolate which index should be studied.

If a cointegration relationship is found then an Error Correction Mechanism (ECM) can be established. If two variables are cointegrated they move together over time, a shock however to one variable may disturb this equilibrium. These (ECM) models estimate the speed at which our dependent variable returns to equilibrium given a change in the independent variable i.e. "speed of adjustment". In doing this these models show the short and long run dynamics between cointegrated variables. Such models are defined as

$$\Delta Y_t = \alpha + \beta_1 \Delta X_{t-1} + \beta_2 \varepsilon_{t-1}$$

The coefficient of β_2 is the "speed of adjustment". This coefficient should be negative and significant to validate our ECM model.

The second test is the Johansen maximum likelihood approach. This is based on a vector autoregressive (VAR) approach and therefore allows for each variable to be exogenous and endogenous in the system. The VAR framework used in Johansen can be defined as

$$y_t = A_1 y_{t-1} + \cdots + A_k y_{t-p} + \varepsilon$$

Where y_t is a n × 1 vector of I(1) variables and A_1 is an n × n matrix of unknown parameters. This VAR can be written as a vector error correction mechanism (VECM) defined below

$$\Delta y_t = \boldsymbol{\pi}\, y_{t-1} + \sum_{i=1}^{p-1} \vartheta_i \Delta y_{t-1} + \gamma + \delta t + \varepsilon_t$$

where Π refers to the 'rank' of the model implying the number of cointegrating vector if any which exist. Π can further be defined as Π=αβ where α is a matrix representing the number of cointegrating vectors and β a matrix of weighting factors. Determining the 'rank' of a matrix is done using a log likelihood test.

The third model is the ARDL approach of Peraran 2001 which is a two stage one. First a model defined as[7];

$$\Delta lnA = a + \sum_{i=1}^{m} a_1 \Delta \ln A_{t-i} + \sum_{i=1}^{m} a_2\ \Delta lnSM_{t-i} \sum_{i=1}^{m} a_3\ \Delta lnER_{t-i} + \sum_{i=1}^{m} a_4\ \Delta lnT_{t-i}$$
$$+ \sum_{i=1}^{m} a_5\, \Delta lnP_{t-i} + a_6 lnA_{t-1} + a_7 lnSM_{t-1} + a_8 lnER_{t-1} + a_9 lnT_{t-1}$$
$$+ a_{10} lnP_{t-1}$$

is executed with a lag length of four[8] to determine whether a long run relationship exist between our variables. This relationship is proved by testing the hypothesis below having executed the equation above.

$$Ho\text{: } a_6 = a_7 = a_8 = a_9 = a_{10} = 0$$

The joint hypothesis that the lagged coefficients are zero is tested and compared against the upper and lower bounds of Pesaran et al 2001. Should our F statistic fall below the lower bound articulated by Pesaran et al 2001 then no cointegration exist. If a long run relationship does exist then test will be done to ensure that other variables are at a minimum weakly exogenous. Each variable will therefore be placed on the left hand side of the equation. Once this has been established a model defined as

$$\Delta lnA = a + \sum_{i=1}^{m} a_1 \Delta \ln A_{t-i} + \sum_{i=1}^{m} a_2\ \Delta lnSM_{t-i} \sum_{i=1}^{m} a_3\ \Delta lnER_{t-i} + \sum_{i=1}^{m} a_4\ \Delta lnT_{t-i} + \sum_{i=1}^{m} a_5\, \Delta lnP_{t-i} + \lambda EC_{t-1} + u_t$$

Is used to obtain coefficients for our "error correction" and other variables. The appropriate lag specification will be based on AIC and SBC selection criteria.

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7 A refers to arrivals SM the stock market ER the real effective exchange rate, T oil prices and P our cpi metric

8 Given that quarterly data is used , 3 and 2 lag lengths also used

4.0 Results

4.1 Unit Root Test

Plotting the variables and levels and differences yield the following. As shown in the charts below most of the variables follow a clearly upward or downward trend. Variables appear mean reverting in differences. The arrivals and the density metrics exhibit high levels of seasonality as expected.

Figure 3: Oil and S&P 500 Logs and Differences

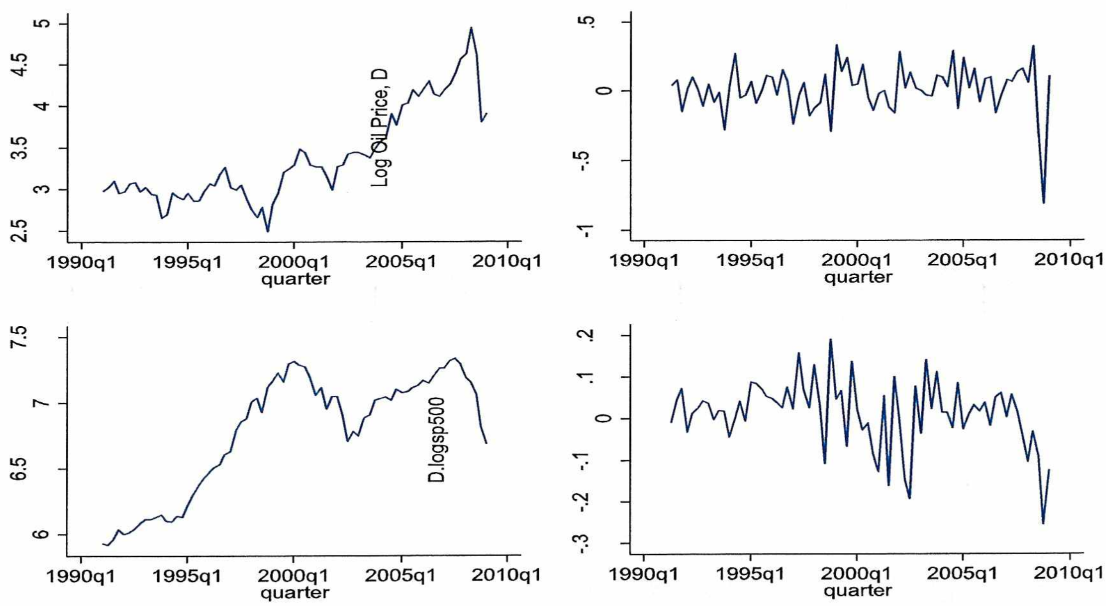


Figure 4: GDP per Capita and CPI Logs and Differences

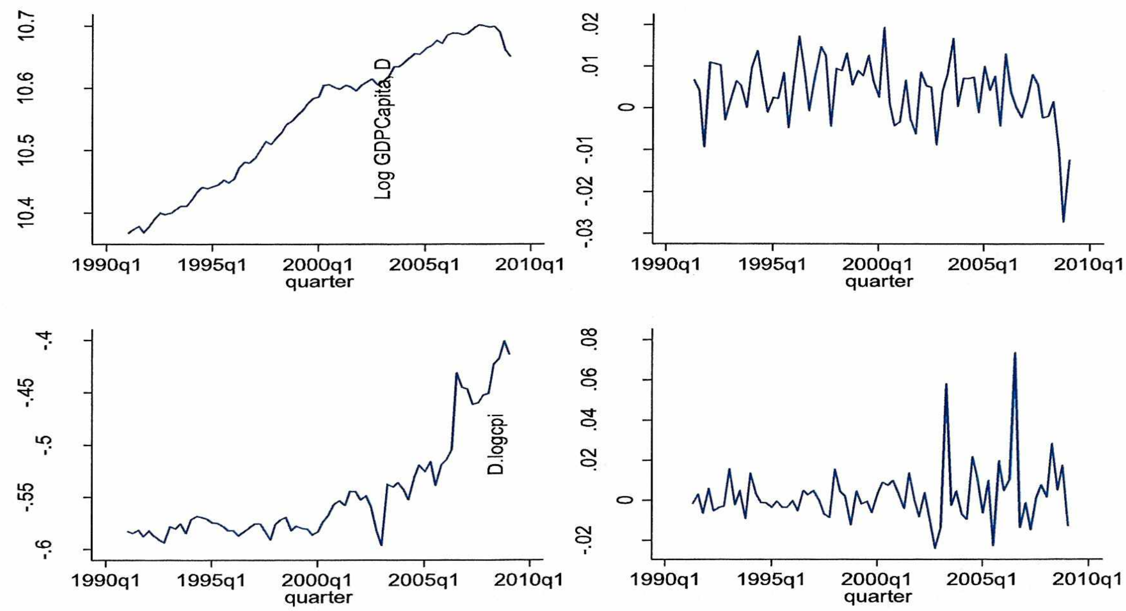


Figure 5: Arrivals and Density Logs and Differences

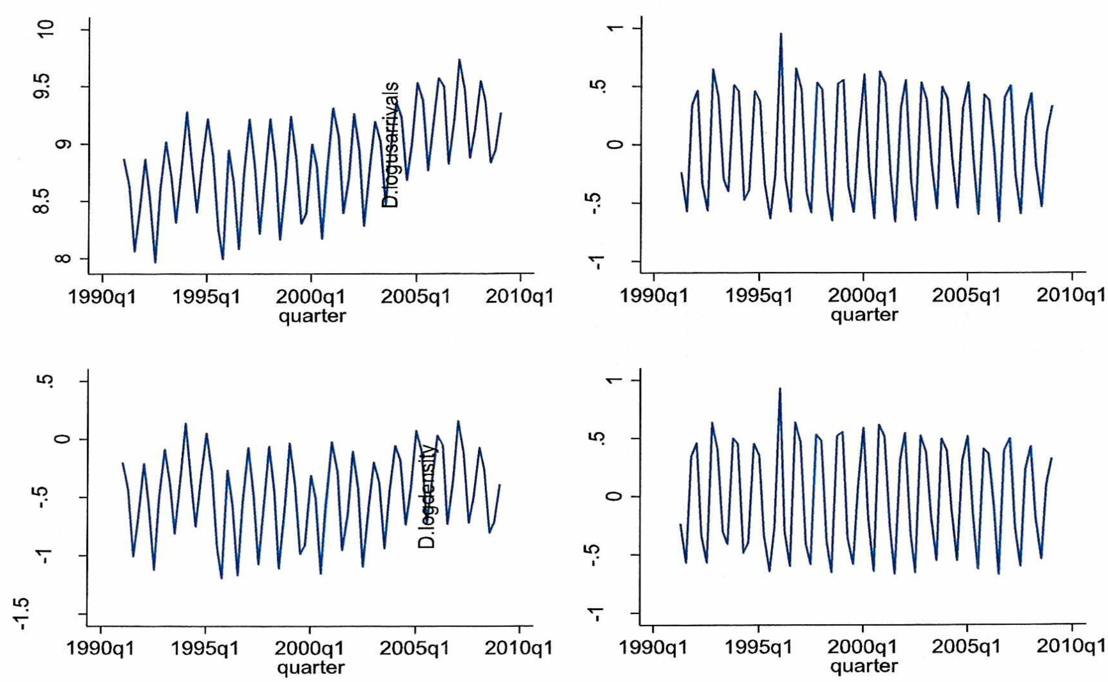
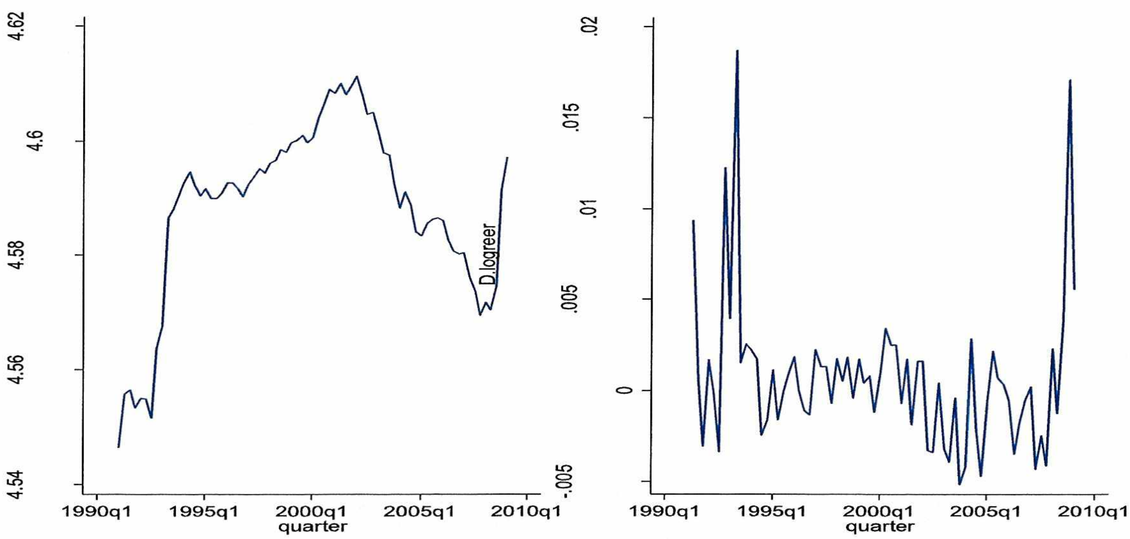


Figure 6: REER and Difference



Empirical unit root test results[9] are presented in the tables below. Under the ADF test all variables are I(1) except GDP per Capita which is I(2). The Phillips-Perron test show that with the exception of Arrivals and Density which have no unit root all variables are I(1). The KPSS test confirm the ADF results in that all variables are I(1) except GDP per capita which is I(2). Results from the NG-Perron test were conflicting and are not presented here. Structural break test show that most series had at least two structural breaks except density and arrivals which had only one. The structural break test did show however that all variables had a unit root. When testing the Density variables with one structural break however the null of a unit root being present was rejected at the 5 per cent significance level.

[9] Trend and intercept

Table 1: ADF, Philips Perron and KPSS Results

Unit Root Results 1991-2009 (Trend and Intercept)			
	ADF	**PP**	**KPSS#**
Oil	-8.249*** *0.00*	-8.249*** *0.00*	0.062***
GDP	-1.334 *0.87*	-6.5*** *0.00*	0.211072
	-12.298*** *0.00*		
CPI	-9.609*** *0.00*	-12.119*** *0.00*	0.112***
Arrivals	-4.836*** *0.00*	No unit root	0.097***
Density	-13.48*** *0.00*	No unit root	0.098***
REER	-6.488*** *0.00*	-6.63*** *0.00*	0.113***
S&P 500	-3.94** *0.0153*	-7.613*** *0.00*	0.087***

Note: ADF,PP and KPSS figures are for the differenced series. P values in *italics*

#Note:KPSS null is stationarity. Test statictics shown, critical values at the 1,5,10% are .216,.146,.119

Table 2: Clemente Reyes Structural Break Unit Root Test

Unit Root Results 1991-2009 (Clemente-Montanes-Reyes Structural Break Test)			
	Break One	**Break Two**	**Unit Root Test**
	1998q2	2004q4	
Oil	5.139***	12.568***	-4.643**
	0.00	*0.00*	
	1997q3	2003q3	
GDP	16.132***	9.056***	-3.358**
	0.00	*0.00*	
	2002q3	2005q4	
CPI	5.43***	12.163***	-1.862**
	0.00	*0.00*	
	2001q1	2004q1	
Arrivals	1.68	3.0***	-3.194**
	0.10	0.00	
	1995q4	2003q3	
Density	-0.656	2.287**	-0.497***
	0.52	0.03	
	1992q1	2003q4	
REER	7.818***	-4.149***	-0.678***
	0.00	*0.00*	
	1996q3	2005q4	
S&P 500	17.37***	2.213**	-2.653**
	0.00	*0.03*	

Note: P values show in *italics* . Critical value for unit root test at the 5% level is -5.490

Table 3: Zivot Andrews Structural Break Test

Unit Root Results 1991-2009 (Zivot-Andrews Structural Break Test)		
	Test Statistics	**Time**
Oil	-3.505***	1997q1
GDP	-1.432***	2006q2
CPI	-5.334***	2002q4
Arrivals	-5.053***	1995q3
Density	-5.155***	1995q3
REER	-2.295***	1995q1
S&P 500	-2.46***	1998q1
Note: Null hypothesis is the presence of a unit root against an alternative of a one time break. 1 and 5% critical values are -5.57 and -5.08		

4.2 Cointegration Results

4.2.1 Engle-Granger

The two step Engle Granger co integration test was conducted under bivariate and multivariate models for all the ECCU islands, using three US equity indices namely the S&P 500, the Dow Jones and the Nasdaq. The aim of doing so was to determine whether our main hypothesis was true for other islands and if so whether it would hold only in similarly marketed destinations i.e. those which aim at servicing high net worth individuals. Ascertaining this fact strengthen our hypothesis as it would prove that cointegration between arrivals and the indices is unique only to high end destinations. To add robustness to the findings and to provide the Government of Anguilla with targeted policy advice, three indices were used. It would be instructive to policy makers to clarify which if any of the indices US arrivals were co integrated with and the nature of this relationship via an error correction model.

Residual analysis to ensure no serial correlation was conducted using the Breusch-Godfrey LM test. The appropriate number of lags to achieve this was five. Bivariate analysis showed that all three equity indices were cointegrated with US arrivals to Anguilla at the 10 and 5 per cent significance levels. This finding was unique to Anguilla lending credence to our hypothesis that a long term relationship exist between US arrivals and the US equity indices. The Breush- Godfrey LM statistic averaged 0.55 signifying a non rejection of the null of no serial correlation amoung the residuals. With reference to the other islands Grenada's US arrivals was cointegrated with all three indices but only at the 10 per cent significance level. Similarly the St. Lucian US arrivals was cointegration with all three indices but only at the 10 per cent significance level. Antiguan US arrivals were cointegrated with the Dow Jones index at the 10 per cent significance level. Despite the arrivals being significant at the 5 and 10 percent level for Anguilla and 10 per cent for the other islands in all they cases they were marginally so. This can possible be attributed to the relatively small sample size (72 observations) utilized in this study.

Multivariate analyses lead to no cointegration being observed in any island using any of the equity indices. This is in stark contrast to the observations in the bivariate case.

Table 4: Engle Granger Bivariate Results for Anguilla (S&P 500)

```
. egranger  logusarrivals logsp500, trend lag(5)
(3 missing values generated)
Replacing variable _egresid...

Augmented Engle-Granger test for cointegration         N (1st step)  =        73
Number of lags   =  5                                  N (test)      =        67
1st step includes linear trend
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.514	-4.090	-3.473	-3.164

```
Critical values from MacKinnon (1990, 2010)

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

lags(*p*)	chi2	df	Prob > chi2
1	0.462	1	0.4968

H0: no serial correlation

Table 5: Engle Granger Multivariate Results for Anguilla (S&P 500)

```
. egranger logusarrivals logsp500  logreer logcpi logoilprice, trend lags(5)
(75 missing values generated)
Replacing variable _egresid...

Augmented Engle-Granger test for cointegration        N (1st step)  =        73
Number of lags   =  5                                 N (test)      =        67
1st step includes linear trend
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.932	-5.291	-4.635	-4.304

```
Critical values from MacKinnon (1990, 2010)

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

lags(*p*)	chi2	df	Prob > chi2
1	1.171	1	0.2792

H0: no serial correlation

Following the evidence of cointegration (in the bivariate case) in Anguilla, Antigua and Barbuda, Grenada and St. Lucia an error correction model (ECM) was used to determine the exact nature of the relationship. However in order for valid inferences to be made from ECM model is necessary that the coefficient of the lagged residual which serves as the 'speed of adjustment parameter' is significant and its coefficient negative. Mathematically deviations from equilibrium between two variables can only be corrected if our cointegrating vector is negative. The ECM models constructed for the aforementioned islands were all valid based on the aforementioned criteria. In Anguilla's case current changes in arrivals is not affected by current changes in the equity index. Changes in arrivals are however positively affected by the level of arrivals in the preceding fourth and fifth quarters. Interestingly current changes were not affected by the preceding three quarter levels of arrivals. This is evidence of the high degree of seasonality in the data. Certain times of year exhibit specific arrivals profiles. By way of example a change in the first quarter of the year would be positively related by a factor of .4 with the arrivals of the first quarter in the preceding year. In the case of the S&P 500 and Nasdaq a current change in arrivals was positively related to the level of the respective index by a factor of .6 and .3 respectively, signifying that there is a yearlong lag between arrivals and the respective indices. The coefficient on the adjustment factor indicates that in each quarter 67 per cent of any disequilibrium between the two variables is corrected. This was observed in all three indices.

Table 6: Engle Granger ECM's Results for Anguilla (S&P 500)

```
. egranger logusarrivals logsp500, ecm trend lags(5)
(3 missing values generated)
Replacing variable _egresid...

Engle-Granger 2-step ECM estimation                   N (1st step)  =        73
Number of lags   =  5                                 N (2nd step)  =        67
1st step includes linear trend

Engle-Granger 2-step ECM
------------------------------------------------------------------------------
D.           |
logusarriv~s |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    _egresid |
         L1. |  -.6749073   .1971646    -3.42   0.001    -1.070198   -.2796162
             |
    logsp500 |
         D1. |   .1534149   .2936713     0.52   0.604    -.4353606    .7421904
             |
logusarriv~s |
         LD. |   .1368791   .1949419     0.70   0.486    -.2539558    .5277141
        L2D. |  -.1224174    .197187    -0.62   0.537    -.5177534    .2729187
        L3D. |   .1115666    .180425     0.62   0.539    -.2501637     .473297
        L4D. |   .4753804   .1411963     3.37   0.001     .1922988     .758462
        L5D. |   .3087195   .1346335     2.29   0.026     .0387956    .5786434
             |
    logsp500 |
         LD. |   .0502862   .2939231     0.17   0.865     -.538994    .6395665
        L2D. |   .0065898   .3218237     0.02   0.984    -.6386278    .6518074
        L3D. |  -.1756854   .3206625    -0.55   0.586     -.818575    .4672041
        L4D. |   .5774042   .3161692     1.83   0.073    -.0564769    1.211285
        L5D. |  -.1466973   .3207819    -0.46   0.649    -.7898263    .4964317
             |
       _cons |  -.0066886    .024388    -0.27   0.785    -.0555835    .0422063
------------------------------------------------------------------------------

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
---------------------------------------------------------------------------
    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |          0.220               1                   0.6393
---------------------------------------------------------------------------
                        H0: no serial correlation
```

4.2.2 Johansen Cointegration Test

As an alternative to the EG analysis above bivariate and multivariate Johansen cointegration test was also conducted for Anguilla and the other ECCU countries particularly in cases which the EG test showed that cointegration existed. Additionally for robustness as with the EG test we separately test our main hypothesis using the Dow Jones and Nasdaq equity indices. Johansen (1995) showed that five specifications of his cointegration test can be applied. These specifications center on the restricting of trends and or constants in the model specification (see below). For completeness all five models were used to determine which best fitted the data. The subsequent analysis would be based on the best model.

- Model One: specifies an unrestricted constant and assumes that the in level form the data does not have quadratic trends. This model restricts the cointegrating equations (CE) to center around a constant mean, with a linear time trend.
- Model Two: specifies a restricted constant and assumes no linear time trend nor quadratic trends, it only allows for the CE to center around a constant mean.
- Model Three: allows for a quadratic trend in the level form of the data and a linear trend in the cointegrating equations.
- Model Four: similar to model three but allows for a linear and not quadratic trend in the level data.
- Model Five: assumes no trends in the data.

The data used in this study with the exception of GDP per capita does not appear to follow a consistently linear trend. As shown in figures (3 to 5) there is a fair amount of volatility in the data and as such this researcher expected either model one or five to fit the data best. For the purposes of this paper the model specification choice will be based on graphical analysis of the predicted cointegrating equations and AIC and HQIC model fit statistics. If the specification fitted the data well then our predicted cointegration equations should be mean reverting and its goodness of fit statistic in this case the (AIC) should be lowest. To determine whether cointegration exist in either the bivariate or multivariate case the "varsoc" Stata command which utiltizes the lag length selection methodology of Tray (1984) and Nielsen (2001) was used when determining the number of cointegrating vectors. A lag length of four was used based on the AIC, HQIC and SBIC values.

Table 7: Anguilla Bivariate Lag Length Selection

```
. varsoc logusarrivals logsp500

  Selection-order criteria
  Sample:  1992q1 - 2009q1                     Number of obs     =       69
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-69.7581				.027439	2.07994	2.10564	2.1447
1	48.5485	236.61	4	0.000	.000999	-1.23329	-1.15622	-1.03902
2	61.1249	25.153	4	0.000	.000779	-1.48188	-1.35342	-1.1581
3	96.5158	70.782	4	0.000	.000314	-2.39176	-2.21192	-1.93847
4	107.56	22.089*	4	0.000	.000256*	-2.59594*	-2.36472*	-2.01313*

```
  Endogenous:  logusarrivals logsp500
   Exogenous:  _cons
```

This lag length was also selected in constructing the VECM's to ensure that there was no serial correlation in the residuals. In this paper we use the BG test to assess the presence of serial correlation.

As articulated above when using Johansen's methodology it is first necessary to determine the number of cointegrating vectors in our bivariate and multivariate cases. In the terminology of Johansen this would mean establishing the rank of the matrix Π in equation 7 above. When seeking to establish a cointegrating vector amoung "n" variables at most one expects "n-1" cointegrating vectors. In the biriviate model therefore at most one coinegrating vector was expected. In the bivariate case, test for cointegration using a lag length of four lead to the non rejection of a maximum rank 0 at the 5 per cent significance level in all specifications. In each case there was strong support of the null with trace statistics of 4 to 5 and critical values of 18 to 25. Table 8 presents the case of the unrestricted trend which is typical for the other specifications.

Table 8: Anguilla Johansen Cointegration Test (Unrestricted Trend)

```
. vecrank logusarrivals logsp500, trend(trend) lags(4)

                      Johansen tests for cointegration
Trend: trend                                             Number of obs =       69
Sample:  1992q1 - 2009q1                                          Lags =        4
```

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	16	106.18362	.	5.1088*	18.17
1	19	108.60102	0.06767	0.2740	3.74
2	20	108.73803	0.00396		

Given that in the bivariate case cointegration was not shown to exist we tried in the case of different indices and different islands. In the case of the other equity indices and countries we find similar results.

Table 9: St. Lucia Johansen Cointegration Test (Unrestricted Trend)

```
. vecrank logslu lognasdaq, trend(trend) lags(4)

                    Johansen tests for cointegration
Trend: trend                                       Number of obs =      65
Sample:  1993q1 - 2009q1                                   Lags =       4
-------------------------------------------------------------------------
                                                          5%
maximum                                       trace    critical
  rank    parms      LL       eigenvalue  statistic    value
    0      16    87.768185         .        11.1520*   18.17
    1      19     91.17094     0.09941      4.3465      3.74
    2      20    93.344168     0.06468
-------------------------------------------------------------------------
```

Having failed to establish cointegration in a bivariate case we proceed to determine whether in a multivariate case there is cointegration. Determining the number of cointegrating vectors was done in a manner similar to the bivariate case. First as with the bivariate case the Stata 11 "varsoc" command was utilized and showed that a four lag specification was best. This lag length was used for all five specifications and the result was that there was one cointegrating vector in most specifications. Using the Dow Jones index no cointegrating vectors were found in any specification. Similarly in the Nadaq index no cointegrating vectors were found except in the case of no trend. Multivariate analysis using the indices showed similar evidence in St. Lucia and Antigua and Barbuda but none in Grenada.

Table 10: Anguilla Johansen Multivariate Cointegration Test (Unrestricted Constant).

```
. vecrank logusarrivals logsp500 logoil logreer logcpi , trend(constant) lags(4)

                       Johansen tests for cointegration
Trend: constant                                        Number of obs =      69
Sample:  1992q1 - 2009q1                                        Lags =       4
-------------------------------------------------------------------------------
                                                        5%
maximum                                     trace    critical
  rank    parms      LL       eigenvalue  statistic    value
    0      80    652.58528         .       72.0392     68.52
    1      89    665.93626      0.32090    45.3372*    47.21
    2      96    676.08376      0.25482    25.0422     29.68
    3      101   683.78096      0.19997     9.6478     15.41
    4      104   687.68543      0.10700     1.8389      3.76
    5      105   688.60486      0.02630
-------------------------------------------------------------------------------
```

The evidence of at least one cointegrating vector in some specifications of the S&P500 index then lead to the development of VECMs. VECM's provides coefficients of the short run dynamics among the variables, the coefficients of the adjustment parameters and the strength of the relationship between current changes and lagged value of a variable (beta). In order to formally determine which model best fits the data the AIC selection criteria is utilized. Based on this criteria the no trend model was chosen and as such the result interpretation will be based on this specification. Plots of the predicted cointegration equations over the period under review are also displayed.

In the table 11 below the coefficients of the lagged arrivals are highly significant and negative up to three lags. The negative signing of the coefficients could reflect the high seasonality of the data with some quarters recording strong growth and others declines. It was also observed that the current change in arrivals was not significantly affected by any lagged changes of the S&P 500. Intuitively if a long run relationship exists between the variables it was expected that there would be a negative relationship between them. When a normalizing restriction is placed on the beta of the arrivals CE, the log oil price beta coefficient is highly significant and negative indicating that oil prices have a significant long run impact in the tourism demand framework.

Table 11: Anguilla Johansen Multivariate VECM Results (No Trend)

```
. vec logusarrivals logsp500 logoil logreer logcpi , trend(none) lags(4)

Vector error-correction model

Sample:  1992q1 - 2009q1                          No. of obs      =        69
                                                  AIC             = -16.78703
Log likelihood =  663.1525                        HQIC            =   -15.708
Det(Sigma_ml)  =  3.09e-15                        SBIC            = -14.06725
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_logusarrivals	16	.187567	0.8777	380.3612	0.0000
D_logsp500	16	.076815	0.3075	23.53394	0.1002
D_logoilprice	16	.164197	0.3038	23.12551	0.1104
D_logreer	16	.003973	0.2808	20.68862	0.1908
D_logcpi	16	.014076	0.3059	23.36289	0.1044

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_logusarr~s						
_ce1						
L1.	-.1774188	.1015523	-1.75	0.081	-.3764577	.0216201
logusarriv~s						
LD.	-.4245578	.1313897	-3.23	0.001	-.682077	-.1670386
L2D.	-.8242556	.0705117	-11.69	0.000	-.962456	-.6860551
L3D.	-.5061387	.1182396	-4.28	0.000	-.737884	-.2743934
logsp500						
LD.	.2010374	.3303949	0.61	0.543	-.4465246	.8485995
L2D.	-.0336228	.3357598	-0.10	0.920	-.6916998	.6244542
L3D.	-.1896763	.3444884	-0.55	0.582	-.8648612	.4855087
logoilprice						
LD.	-.0097878	.183755	-0.05	0.958	-.369941	.3503655
L2D.	-.1993858	.2180861	-0.91	0.361	-.6268267	.2280552
L3D.	-.0279603	.2087074	-0.13	0.893	-.4370193	.3810987
logreer						
LD.	-5.697709	6.850864	-0.83	0.406	-19.12516	7.729738
L2D.	9.079329	7.094064	1.28	0.201	-4.82478	22.98344
L3D.	13.94629	7.221244	1.93	0.053	-.2070862	28.09967
logcpi						
LD.	.6278543	1.665573	0.38	0.706	-2.636609	3.892317
L2D.	2.272607	1.660879	1.37	0.171	-.9826561	5.527871
L3D.	.5698628	1.685359	0.34	0.735	-2.733379	3.873105

Other output omitted

Table 12: (contd) Anguilla Johansen Multivariate VECM Results (No Trend)

Cointegrating equations

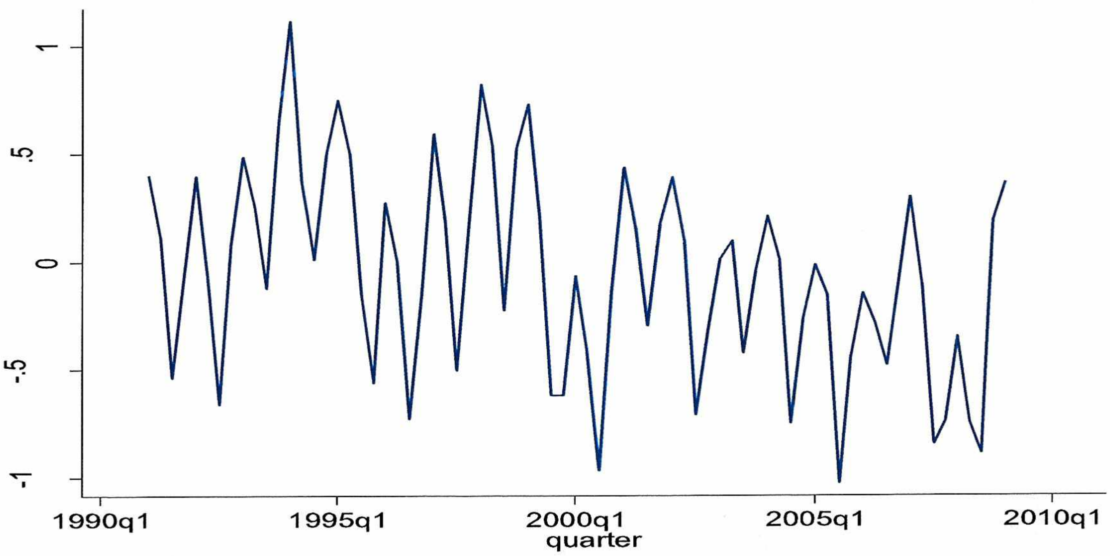
Equation	Parms	chi2	P>chi2
_ce1	4	24226.04	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_ce1						
logusarriv~s	1	.	.	.	.	.
logsp500	-.1707037	.1413796	-1.21	0.227	-.4478026	.1063952
logoilprice	-1.067464	.24682	-4.32	0.000	-1.551222	-.5837058
logreer	-.4024266	.5652343	-0.71	0.476	-1.510265	.7054123
logcpi	4.196971	2.922048	1.44	0.151	-1.530137	9.92408

Figure 7: Anguilla Predicted Cointegration Equation (No Trend)



Based on table 11-12 and equation 7 our estimates can be highlighted as follows.

$$\Delta y_t = \boldsymbol{\pi}\, y_{t-1} + \sum_{i=1}^{p-1} \vartheta_i \Delta y_{t-1} + \gamma + \delta t + \varepsilon_t$$

$$\Pi=\alpha\beta$$

Figure 8: Anguilla Johansen Multivariate Parameter Estimates (No Trend)

Johansen Results: Unrestricted Trend (Extract)					
Parameters	**Arrivals**	**S&P 500**	**Log Oil Price**	**Log Reer**	**Log CPI**
α=	-0.177	0.078	-0.137	-0.0014	-0.0204
	-1.75	*1.89*	*1.5*	*-0.65*	*-2.69*
β=	1	-0.1707	-1.067	-0.4024	4.196
	.	*-1.21*	*-4.32*	*-0.71*	*1.44*

The, α, coefficients and their signings provide us with an idea as to how the variables adjust in an equilibrium setting over time. The coefficients and signing of the β coefficients meanwhile provide us with information on the long run equilibrium relationship among the variables. The coefficients of the other short run parameters are shown in the appendices. The high significance of the beta value of the oil variable and its marginal alpha significance (12.2 per cent) suggest that this variable in responsible for the one cointegrating vector noted above. This specification had no constant or trend variable.

Lastly the model defined above is used to construct dynamic forecast of Anguillan arrivals. Comparing these forecasts to actual arrivals will allow us to gauge the strength of the model. For the purpose of this paper forecast of the next seven quarters of US arrivals were done. Table 13 shows the dynamic forecast, their standard errors and compares forecasted to the actual log arrivals for that period.

Table 13: 2009q1 to 2010q3 Forecast and Standard Errors vs. Actual

Year	Logusarrivals	Logusarrivals_SE	Logusarrivals_LB	Logusarrivals_UB
2009q2	9.631	0.187	9.261	9.999
2009q3	9.247	0.209	8.836	9.659
2009q4	8.845	0.214	8.424	9.266
2010q1	9.184	0.223	8.745	9.623
2010q2	9.430	0.275	8.896	9.964

Year	Logusarrivals	Forecast % Change	Actual Log Arrivals	Actual % Change
2009q1	9.271		9.271	
2009q2	9.631	36.022	9.085	-18.578
2009q3	9.247	-38.400	8.665	-42.000
2009q4	8.845	-40.200	9.085	42.000
2010q1	9.184	33.900	9.419	33.400
2010q2	9.430	24.600	9.613	19.400

We can see that with time the standard errors of the forecast increase. The model correctly predicts the seasonality effects of arrivals in three out of the five quarters. Fig 9 below shows illustrates comparisons between arrivals forecast and actual.

Figure 9: Actual vs. Forecast

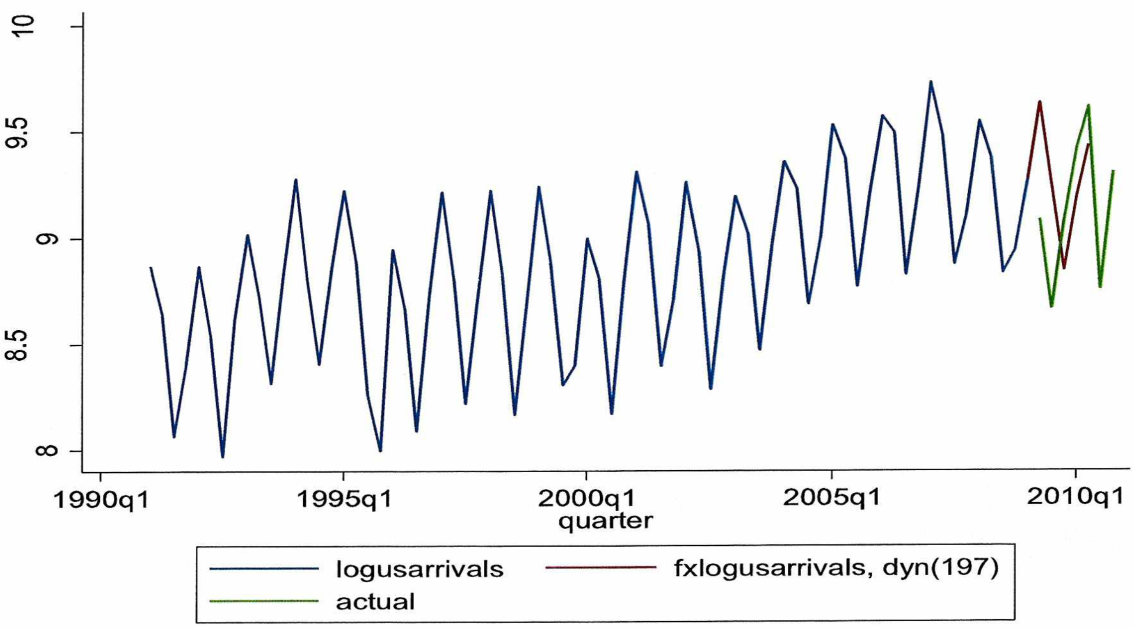
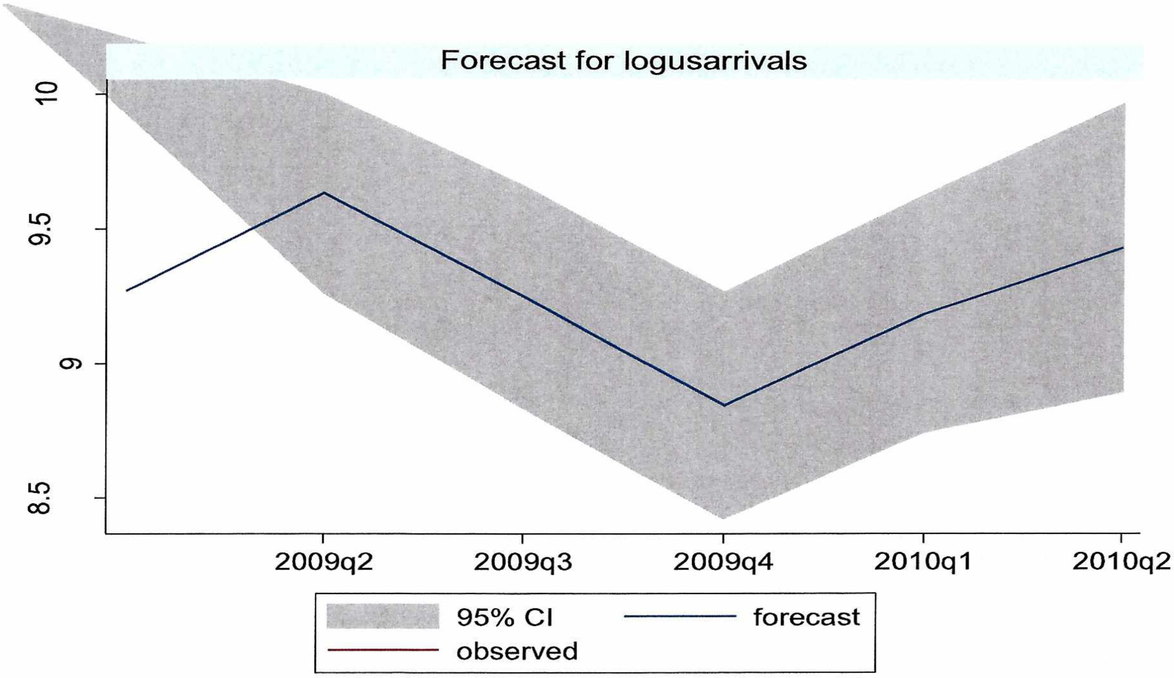


Figure 10: Standard Error of Forecast



4.2.3 ARDL Test

The results of the ARDL test in both the bivariate and multivariate cases showed that there was no long run relationship amoung the variables selected. This assessment is based on the F statistics obtained during the first stage of the ARDL. The first stage of the technique required that lagged changes and lagged level form of our variables be regressed. Given that quarterly data was used an initial lag length of four was used selected. This was then reduced to 2 lags as shown in table 16. The results are presented below. Joint hypothesis test in line with equation 11 show that our F statistic was below the lower bound of 2.86 implying that the null of the lagged coefficients being jointly equal to zero could not be rejected. F statistics for 2 and 3 lags also show a non rejection of the null.

Table 14: Stage One ARDL Results (4 lags)

```
. reg D.logusarrivals L1.D.logusarrivals L2.D.logusarrivals L3.D.logusarrivals L4.D. logusarrivals L1.D.logsp500 L2.D.logsp500
> L3.D.logsp500 L4.D.logsp500  L1.D.logreer L2.D.logreer L3.D.logreer L4.D. logreer  L1.D.logoilprice L2.D.logoilprice L3.D.log
> oilprice L4.D. logoilprice  L1.D.logcpi L2.D.logcpi L3.D.logcpi L4.D. logcpi L.logusarrivals L.logsp500 L.logreer L.logoilpri
> ce L.logcpi

      Source |       SS       df       MS              Number of obs =      68
-------------+------------------------------           F( 25,    42) =   15.69
       Model |   13.577399    25  .543095959           Prob > F      =  0.0000
    Residual |  1.45370201    42  .034611953           R-squared     =  0.9033
-------------+------------------------------           Adj R-squared =  0.8457
       Total |   15.031101    67  .224344791           Root MSE      =  .18604

------------------------------------------------------------------------------
D.           |
logusarriv~s |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
logusarriv~s |
         LD. |  -.1576907    .278193    -0.57   0.574    -.7191069    .4037255
        L2D. |  -.5374333     .24375    -2.20   0.033    -1.029341   -.0455258
        L3D. |  -.3538315   .1780443    -1.99   0.053    -.7131394    .0054764
        L4D. |    .200416   .1577067     1.27   0.211     -.117849     .518681
             |
    logsp500 |
         LD. |   .1112104   .4139019     0.27   0.789    -.7240775    .9464983
        L2D. |  -.1878791   .3835197    -0.49   0.627    -.9618531    .5860949
        L3D. |  -.1880313   .3832986    -0.49   0.626    -.9615591    .5854966
        L4D. |   .2621179    .405051     0.65   0.521    -.5553082    1.079544
             |
     logreer |
         LD. |  -5.872832   7.735776    -0.76   0.452    -21.48426    9.738597
        L2D. |   1.736403   7.674313     0.23   0.822    -13.75099    17.22379
        L3D. |    8.92336   7.989818     1.12   0.270    -7.200745    25.04746
        L4D. |   1.246215   8.205217     0.15   0.880    -15.31258    17.80501
             |
 logoilprice |
         LD. |  -.1792637   .2100769    -0.85   0.398    -.6032159    .2446886
        L2D. |  -.3004905   .2346129    -1.28   0.207    -.7739585    .1729776
        L3D. |  -.1760758   .2409429    -0.73   0.469    -.6623182    .3101666
        L4D. |  -.1349533   .2371137    -0.57   0.572    -.6134682    .3435615
             |
      logcpi |
         LD. |   2.719107   2.380586     1.14   0.260     -2.08511    7.523323
        L2D. |   3.570241    2.13767     1.67   0.102    -.7437529    7.884235
        L3D. |   2.043261    2.08608     0.98   0.333    -2.166618     6.25314
        L4D. |   2.481669   1.980896     1.25   0.217     -1.51594    6.479278
             |
logusarriv~s |
         L1. |  -.4146356   .2700053    -1.54   0.132    -.9595282    .1302571
             |
    logsp500 |
         L1. |  -.0087965   .1102987    -0.08   0.937    -.2313883    .2137953
             |
     logreer |
         L1. |    1.01988   3.354641     0.30   0.763     -5.75006     7.78982
             |
 logoilprice |
         L1. |   .3926817    .171373     2.29   0.027     .0468369    .7385264
             |
      logcpi |
         L1. |  -2.847472   2.052672    -1.39   0.173    -6.989932    1.294987
             |
       _cons |  -3.825502   14.14449    -0.27   0.788    -32.37024    24.71924
------------------------------------------------------------------------------
```

Table 15: Example of Joint Hypothesis Test

```
. test ( L.logsp500 L.logreer L.logcpi L.logusarrivals L.logoilprice)

 ( 1)  L.logsp500 = 0
 ( 2)  L.logreer = 0
 ( 3)  L.logcpi = 0
 ( 4)  L.logusarrivals = 0
 ( 5)  L.logoilprice = 0

       F(  5,    42) =    2.01
            Prob > F =    0.0969
```

Table 16: ARDL Results Using Varying Lag Lengths

Order of Lag	F-Statistic
2	$F(5,54)= 2.51$
3	$F(5,48)= 1.55$
4	$F(5,42)= 2.01$
Note at the 90% sig. level CV bounds are 2.45-3.52	

5.0 Policy Recommendations

The tourism industry is the key driver of economic activity in Anguilla. This fact is particularly poignant given that there is little agricultural or manufacturing activity on the island to supplement and/or strengthen via linkages with tourism. Additionally policy makers in an environment of fiscal austerity and growing debt must carefully determine how their limited tourism budget can be spent. The findings of this paper suggest that developing a profile of the typical target visitor will be beneficial to the GoA. High net wealth individuals have several characteristics, one of which is that they invest a proportionally larger amount of their wealth in US stock markets. In order to show that as a direct consequence, stock market performance can be used as a predictor of Anguillan tourist arrivals, three cointegration techniques were used to test for long run relationships within our demand framework. The EG suggested cointegration but only in the univariate case i.e. between arrivals and the S&P500. In the case of the Johansen technique univariate test showed no long run relationships whiles multivariate result suggested that oil prices was the source of the cointegrating vector noted in the chosen specification. The ARDL test showed that cointegration did not exist in either uni or multivariate cases. These results paint a mixed and somewhat inconclusive picture regarding the hypothesis of the paper.

Nonetheless policy makers need to develop a holistic framework of who the targeted Anguillan tourist is and thereby focus their efforts on how particular 'characteristics' can be empirically studied with a view of facilitating informed marketing decisions. An additional characteristic for instance which policy makers may find useful is that high net wealth individuals with children have lower stock market participation rates than those with children. Although this paper did not find conclusive evidence linking equity market performance with arrivals the authorities may still wish to diversify the target market to include both types of visitors to mitigate the 'risk' any one segment may pose re the stability of visitor arrivals.

Anguilla may also wish to collaborate with other ECCU countries such as Antigua and Barbuda and St. Lucia who also target high net worth individuals in an effort to better understand that niche market. The results of this paper show that in these islands there is some evidence of cointegration between US indices and arrivals[10]. Joint monitoring over time of stock market performance and arrivals will be instructive with a view of building a longer data set is also advised. It will also be instructive to ascertain the degree to which other destinations which target high net worth individuals serve as complements or substitutes to the destination. Do increase arrivals to Antigua or St. Baths[11] result in increased arrivals to Anguilla, given that these tourists are in the region and may choose to visit neighboring islands? Answering this and similar minded questions are important particularly given the backdrop of talks to increasingly market the Caribbean region as one destination.

An area of further research centers in the constructing of other forecasting models using GARCH and ARIMA techniques. These can be compared with Johansen and simple linear forecast to determine which methodology provides the best results. On the basis of this work a comprehensive tourism demand forecasting model can be defined and used to assist policy makers.

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[10] Using the univariate EG test
[11] Other high net wealth destinations

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Appendix
Full Johansen Output (Unrestricted Trend)

```
. vec logusarrivals logsp500 logoil logreer logcpi , trend(none) lags(4)

Vector error-correction model

Sample:  1992q1 - 2009q1                        No. of obs      =         69
                                                AIC             =  -16.78703
Log likelihood =  663.1525                      HQIC            =    -15.708
Det(Sigma_ml)  =  3.09e-15                      SBIC            =  -14.06725

Equation           Parms    RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_logusarrivals      16    .187567   0.8777   380.3612   0.0000
D_logsp500           16    .076815   0.3075   23.53394   0.1002
D_logoilprice        16    .164197   0.3038   23.12551   0.1104
D_logreer            16    .003973   0.2808   20.68862   0.1908
D_logcpi             16    .014076   0.3059   23.36289   0.1044
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
D_logusarr~s |
        _ce1 |
         L1. |  -.1774188   .1015523    -1.75   0.081    -.3764577    .0216201
             |
logusarriv~s |
         LD. |  -.4245578   .1313897    -3.23   0.001     -.682077   -.1670386
        L2D. |  -.8242556   .0705117   -11.69   0.000     -.962456   -.6860551
        L3D. |  -.5061387   .1182396    -4.28   0.000     -.737884   -.2743934
             |
    logsp500 |
         LD. |   .2010374   .3303949     0.61   0.543    -.4465246    .8485995
        L2D. |  -.0336228   .3357598    -0.10   0.920    -.6916998    .6244542
        L3D. |  -.1896763   .3444884    -0.55   0.582    -.8648612    .4855087
             |
 logoilprice |
         LD. |  -.0097878    .183755    -0.05   0.958     -.369941    .3503655
        L2D. |  -.1993858   .2180861    -0.91   0.361    -.6268267    .2280552
        L3D. |  -.0279603   .2087074    -0.13   0.893    -.4370193    .3810987
             |
     logreer |
         LD. |  -5.697709   6.850864    -0.83   0.406    -19.12516    7.729738
        L2D. |   9.079329   7.094064     1.28   0.201     -4.82478    22.98344
        L3D. |   13.94629   7.221244     1.93   0.053    -.2070862    28.09967
             |
      logcpi |
         LD. |   .6278543   1.665573     0.38   0.706    -2.636609    3.892317
        L2D. |   2.272607   1.660879     1.37   0.171    -.9826561    5.527871
        L3D. |   .5698628   1.685359     0.34   0.735    -2.733379    3.873105
------------------------------------------------------------------------------
```

D_logsp500						
_ce1						
L1.	.0784121	.0415889	1.89	0.059	-.0031005	.1599248
logusarriv~s						
LD.	-.1144443	.0538082	-2.13	0.033	-.2199064	-.0089822
L2D.	-.051878	.0288768	-1.80	0.072	-.1084754	.0047194
L3D.	-.0612498	.0484228	-1.26	0.206	-.1561567	.0336572
logsp500						
LD.	.1359381	.135307	1.00	0.315	-.1292588	.401135
L2D.	.1856095	.1375041	1.35	0.177	-.0838935	.4551126
L3D.	.2289813	.1410788	1.62	0.105	-.047528	.5054906
logoilprice						
LD.	.0956021	.0752534	1.27	0.204	-.0518919	.2430961
L2D.	-.025918	.0893131	-0.29	0.772	-.2009684	.1491324
L3D.	.1659663	.0854722	1.94	0.052	-.0015561	.3334888
logreer						
LD.	-1.217674	2.805643	-0.43	0.664	-6.716633	4.281285
L2D.	-1.59768	2.905241	-0.55	0.582	-7.291847	4.096487
L3D.	-1.249778	2.957325	-0.42	0.673	-7.046029	4.546472
logcpi						
LD.	-.1416628	.6821042	-0.21	0.835	-1.478562	1.195237
L2D.	-.5968833	.6801819	-0.88	0.380	-1.930015	.7362487
L3D.	.1888524	.690207	0.27	0.784	-1.163928	1.541633
D_logoilpr~e						
_ce1						
L1.	.1375337	.0888994	1.55	0.122	-.0367059	.3117732
logusarriv~s						
LD.	-.0089671	.1150191	-0.08	0.938	-.2344005	.2164663
L2D.	-.0252642	.0617263	-0.41	0.682	-.1462455	.095717
L3D.	-.0173525	.1035074	-0.17	0.867	-.2202233	.1855184
logsp500						
LD.	.1543978	.2892291	0.53	0.593	-.4124808	.7212765
L2D.	-.0341072	.2939255	-0.12	0.908	-.6101907	.5419763
L3D.	.719199	.3015667	2.38	0.017	.1281392	1.310259
logoilprice						
LD.	.0302768	.1608599	0.19	0.851	-.2850029	.3455566
L2D.	-.010562	.1909135	-0.06	0.956	-.3847456	.3636216
L3D.	.2446805	.1827034	1.34	0.180	-.1134115	.6027725
logreer						
LD.	.1391224	5.997276	0.02	0.981	-11.61532	11.89357
L2D.	-12.17402	6.210174	-1.96	0.050	-24.34574	-.0023061
L3D.	-3.890117	6.321509	-0.62	0.538	-16.28005	8.499812
logcpi						
LD.	-1.842737	1.45805	-1.26	0.206	-4.700462	1.014988
L2D.	-.5887673	1.453941	-0.40	0.686	-3.438439	2.260904
L3D.	-.6384862	1.47537	-0.43	0.665	-3.530159	2.253186

D_logreer						
_ce1						
L1.	-.0014012	.0021513	-0.65	0.515	-.0056177	.0028153
logusarriv~s						
LD.	-.0003946	.0027834	-0.14	0.887	-.0058499	.0050607
L2D.	.0004863	.0014937	0.33	0.745	-.0024414	.0034139
L3D.	-.0019992	.0025048	-0.80	0.425	-.0069085	.0029102
logsp500						
LD.	.0010519	.0069991	0.15	0.881	-.0126661	.01477
L2D.	.0034347	.0071128	0.48	0.629	-.0105061	.0173755
L3D.	-.0024676	.0072977	-0.34	0.735	-.0167708	.0118356
logoilprice						
LD.	-.0054847	.0038927	-1.41	0.159	-.0131142	.0021448
L2D.	.0038344	.00462	0.83	0.407	-.0052205	.0128894
L3D.	.0027346	.0044213	0.62	0.536	-.0059309	.0114002
logreer						
LD.	.184671	.1451296	1.27	0.203	-.0997778	.4691197
L2D.	.3769927	.1502816	2.51	0.012	.0824463	.6715391
L3D.	.0056056	.1529758	0.04	0.971	-.2942214	.3054326
logcpi						
LD.	.030961	.0352837	0.88	0.380	-.0381938	.1001158
L2D.	.0241034	.0351843	0.69	0.493	-.0448565	.0930633
L3D.	-.0247048	.0357029	-0.69	0.489	-.0946811	.0452715
D_logcpi						
_ce1						
L1.	-.0204875	.007621	-2.69	0.007	-.0354244	-.0055505
logusarriv~s						
LD.	.026919	.0098602	2.73	0.006	.0075933	.0462446
L2D.	.0157188	.0052916	2.97	0.003	.0053475	.0260902
L3D.	.015549	.0088733	1.75	0.080	-.0018425	.0329404
logsp500						
LD.	.0097575	.0247947	0.39	0.694	-.0388391	.0583541
L2D.	.0508436	.0251973	2.02	0.044	.0014579	.1002293
L3D.	-.0358799	.0258523	-1.39	0.165	-.0865495	.0147897
logoilprice						
LD.	-.0190965	.01379	-1.38	0.166	-.0461244	.0079313
L2D.	.0000246	.0163664	0.00	0.999	-.0320529	.0321021
L3D.	.0003161	.0156626	0.02	0.984	-.0303819	.0310142
logreer						
LD.	-.1231162	.5141266	-0.24	0.811	-1.130786	.8845533
L2D.	.1513715	.5323776	0.28	0.776	-.8920694	1.194812
L3D.	.3706629	.541922	0.68	0.494	-.6914846	1.43281
logcpi						
LD.	-.1371736	.1249938	-1.10	0.272	-.3821569	.1078097
L2D.	-.0637078	.1246415	-0.51	0.609	-.3080007	.1805851
L3D.	-.1033642	.1264786	-0.82	0.414	-.3512577	.1445293

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	4	24226.04	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
logusarriv~s	1	.	.	.	.	.
logsp500	-.1707037	.1413796	-1.21	0.227	-.4478026	.1063952
logoilprice	-1.067464	.24682	-4.32	0.000	-1.551222	-.5837058
logreer	-.4024266	.5652343	-0.71	0.476	-1.510265	.7054123
logcpi	4.196971	2.922048	1.44	0.151	-1.530137	9.92408