

**FORECASTING U.S. TOURISM DEMAND
IN BERMUDA AND THE WEST INDIES**

APPROVED BY SUPERVISORY COMMITTEE:

**FORECASTING U.S. TOURISM DEMAND
IN BERMUDA AND THE WEST INDIES**

A Thesis

**Submitted to the Faculty of Graduate Studies and Research
in Partial Fulfillment of the Requirements**

for the Degree of

Master of Business Administration

in the

College of Commerce

University of Saskatchewan

Saskatoon

by

Ewart David Gerard Archer

July, 1989

ABSTRACT

FORECASTING U.S. TOURISM DEMAND IN BERMUDA AND THE WEST INDIES

Ewart David Gerard Archer

University of Saskatchewan

Co-Supervising Professors: Ashok Patil & Said Elfakhani

This study reviews the literature on the explanation of tourism demand and demonstrates the application of least squares regression, smoothing methods and Box-Jenkins analysis to the problem of estimating future levels of tourism demand in selected Caribbean and Atlantic destination areas.

The results support the conclusion that it is possible to make reasonably accurate one- to three-year forecasts of tourism demand by assuming that there are no significant changes in demand conditions. No single technique generates the most accurate forecast for all of the destinations considered, and some approaches generate less accurate results than can be achieved by the use of a "naive" forecast, in which the most recently observed level of demand is used to predict future levels. However, in part, this latter outcome reflects inadequacies in the data base that must be used for prediction.

ACKNOWLEDGEMENTS

I wish to express my gratitude to Dean Douglas Bicknell for the generous assistance he provided during my two-year stay at the University.

Professors Elfakhani and Patil offered a number of suggestions for improving the initial draft of this thesis, Professor Huq helped me with some technical details of the analysis in Chapter 3, and both Larry Yau and Myrna Ham showed me how to use a computer to get the finished product printed out quickly and cheaply. I thank them all for their time and their patience.

E.D.G.A.

University of Saskatchewan

June, 1989

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1. INTRODUCTION

1.1 Objective of the Study

Recognition of the increasing economic significance of international tourist flows has helped to create a substantial body of work that seeks to describe and explain the demand for tourism services throughout the world. This thesis attempts to apply some of the analytical methods developed in that literature to the problem of constructing short and medium term tourism demand forecasts for islands in the Caribbean and Atlantic, where the travel trade has been growing rapidly during the last three decades, and as such has begun to engage the active attention of economic planners. The quality of much tourism planning depends upon the accuracy of quantitative forecasts of travel demand, which serve as a basis for decisions about the provision of airline capacity, air and sea port facilities, transportation and communication links, hotel accommodation, entertainment and recreational services, and a host of other infrastructural elements which must be provided in a timely fashion if an economy is to take full advantage of its potential for tourism development. Accurate short term forecasts are also essential for annual budgeting and other resource allocation decisions in tourism administration, and are the basis for numerous tactical decisions on the promotion, pricing and packaging

of tourist services (World Tourism Organization, n.d.).

1.2 Defining Tourism

According to Ogilvie (1933), the term 'tourist' refers to a visitor whose stay at a place is temporary and whose travel expenditures are made possible by income or wealth accumulated primarily at the individual's place of usual residence, and not at any of the places visited. This meaning of 'tourist' has been adopted by international agencies such as the United Nations, and its affiliate, the World Tourism Organization, which consider a tourist to be a traveller who visits a place other than his usual place of residence for a period of not less than twenty-four hours and not more than one year, for a purpose other than the pursuit of an occupation remunerated at the destination. Defined primarily in terms of length of stay and source of income, tourist visits can be for any of a broad range of recreational, health, educational, religious, business or family-related activities.

1.3 Organization of the Study

The analysis which follows begins in Chapter 2 with a review of the literature that provides the research context for the present work. Chapters 3 and 4 are devoted to the specification and estimation of causal and time series models of tourism demand, respectively, and the results of these alternative forecasting approaches are summarized and compared in a concluding chapter.

2. REVIEW OF THE LITERATURE

This chapter discusses various approaches to demand forecasting and reviews a number of studies in which quantitative techniques have been applied to the analysis of travel demand.

2.1 Qualitative Methods

Demand forecasts may be based upon qualitative or quantitative procedures. The qualitative approaches typically involve a mechanism for pooling the predictions made by experienced tourism industry professionals. Perhaps the most straightforward method of this type consists of mail or telephone surveys of tour operators, travel agents, airline managers, hoteliers and others active in the tourism business, who are asked for their opinions about expected short term changes in demand levels. A more elaborate procedure, called the Delphi technique, is structured to prevent a team of experts from unduly influencing each other in the forecasts they generate. A questionnaire which asks for tourism demand predictions, and for the rationale underlying such predictions, is circulated to the experts, who provide independently written answers. These answers may describe expected demand levels in terms of numerical probability estimates. Each answer is then reviewed by all members of the group, and the questionnaire is revised for re-submission to the experts, each of whom is

then asked to re-evaluate his initial answers in the light of the responses from the other group members. This process may be repeated through several rounds until enough of a consensus is achieved for the administrative team overseeing the exercise to prepare a final forecast.

As an alternative, a panel of experts may be assembled for the purpose of creating a range of consensus forecasts under various optimistic or pessimistic assumptions regarding the main factors intuitively believed to influence demand. One expression of this approach, known as morphological analysis, has been described as a process guided by normative policy considerations:

Each of the variables is considered in turn and all possible states for each are identified...the actions of each variable are combined to assess their interactions on demand. This indicates various attainable levels of demand under different assumptions about the performance of each of the variables. The most desirable level of demand is then estimated in relation to the variables at work and an assessment is made of how this level might be attained. (Archer, 1980: 10).

2.2 Quantitative Methods

Qualitative methods have been criticized because they can be expensive, time-consuming, and heavily subjective where undue weight is given to the opinions of experts in particular fields (Archer, 1980). If sufficient past data are available, quantitative forecasting methods may be employed instead.

2.2.1 Causal Models

Quantitative approaches are divided into two main categories: causal models and time series models. Causal models attempt to provide a parsimonious explanatory structure for estimating demand levels, and therefore express a particular theory of tourism demand. This method of demand estimation involves the construction of a statistical relationship of the form

$$Y = f (X_1, X_2, \dots, X_n) \quad (2.1)$$

where 'Y' is a measure of travel demand (typically tourist expenditures or arrivals) and the 'X_i' are the 'n' explanatory variables included in the model. Ordinary least squares analysis can be employed to calculate coefficient values for the independent variables which minimize the sum of the squared differences between the actual values of 'Y' and estimates of 'Y' made from the independent variables. If the relationship between 'Y' and the 'X_i' is assumed to be linear, the regression model is

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n + e \quad (2.2)$$

More commonly, the estimating relationship is assumed to be multiplicative so that

$$Y = b_0X_1^{b_1} X_2^{b_2} \dots X_n^{b_n} \quad (2.3)$$

and this relationship can be restated in double logarithmic form as

$$\ln Y = \ln b_0 + b_1 \ln X_1 + b_2 \ln X_2 + \dots + b_n \ln X_n + \ln e \quad (2.4)$$

Under the assumption that the regression parameters do not change in the short or medium term, Equation (2.4) can be used to project future tourism demand. Archer (1980) suggests, however, that regression forecasts should not be made for more than two or three years into the future, since it may not be realistic to assume unchanging relationships between the independent and dependent variables beyond that time.

2.2.2 Time Series Models

Time series models differ from causal models in that they are based upon the identification of a particular historical pattern in a data series. This pattern, whether linear, exponential, or cyclic, is assumed to remain reasonably stable in the short and medium term, and can therefore be extrapolated for predictions. Models of this type are univariate, since they analyze only the variable to be forecast and do not address the role of other variables which may be producing or influencing the observed patterns in the values that are projected into the future.

Perhaps the simplest application of this approach is the use of a bivariate regression equation in which the independent variable is a measure of time, expressed in months, years, or any appropriate interval. More commonly, prediction is based upon the calculation of moving averages

of series values (Makridakis, Wheelwright and McGee, 1983). A moving average of order 'T' is the mean of 'T' consecutive observations in a series. As each new observation becomes available, the oldest data point is discarded and a new mean is calculated. Thus,

$$\bar{Y}_T = \frac{\sum_{t=1+i}^{T+i} Y_t}{T} \quad i = 0, 1, 2, \dots, N \quad (2.5)$$

where $\bar{Y}_T$ is the single moving average of order 'T', and the ' Y_t ' are individual observations. If a moving average for 'T' historical periods is employed as a forecast for period (T+1), the prediction is likely to lag behind the actual data if the observations have a consistent trend. Reducing or removing this lag is possible if a second moving average is calculated and the difference between the two moving averages is used to estimate the trend. Symbolically,

$$b_0 = \bar{Y}_T + (\bar{Y}_T - \bar{Y}_P) \quad (2.6)$$

$$b_1 = \frac{2}{T-1} (\bar{Y}_T - \bar{Y}_P) \quad (2.7)$$

$$F_{T+x} = b_0 + b_1 x \quad (2.8)$$

where ' $\bar{Y}_T$ ' is the T-period moving average, ' $\bar{Y}_P$ ' is the P-period moving average of the T-period moving average, and ' F_{T+x} ' is the forecast for 'x' periods ahead of the most recent observation in the data series.

In the case of this second, double moving average model, there is an unequal weighting of the (T + P) observations used to generate a forecast. The same principle of unequal weighting defines exponential

smoothing models, in which the weights decline exponentially as the observations get older (Makridakis, Wheelwright and McGee, 1983). Exponential smoothing models are of the form

$$F_{t+1} = \alpha Y_t + (1 - \alpha) F_t \quad (2.9)$$

where α is a smoothing parameter selected by trial and error. That is, a forecast is the sum of the weighted values of the most recent observation and the most recent forecast. The right hand side of Equation (2.9) can be expanded by writing ' F_t ' in terms of ' Y_{t-1} ' and ' F_{t-1} '. Repeated substitution of this kind reveals an equation with the following structure

$$F_{t+1} = \alpha Y_t + \alpha(1 - \alpha) Y_{t-1} + \alpha(1 - \alpha)^2 Y_{t-2} + \dots + \alpha(1 - \alpha)^{N-1} Y_{t-(N-1)} + (1 - \alpha)^N F_{t-(N-1)} \quad (2.10)$$

As with single moving average models, forecasts from the single exponential model shown above lag behind the actual data when a trend exists. However, there are double (linear) exponential smoothing methods, corresponding to double moving average models, which adjust for the trend by adding the difference between single and double smoothed values to the single smoothed values. For example, Brown's Linear Exponential Smoothing Method is described by the following equations:

$$F_t^1 = \alpha Y_t + (1 - \alpha) F_{t-1}^1 \quad (2.11)$$

$$F_t^2 = \alpha F_t^1 + (1 - \alpha) F_{t-1}^2 \quad (2.12)$$

$$b_0 = F_t^1 + (F_t^1 - F_t^2) \quad (2.13)$$

$$b_1 = \frac{\alpha}{1-\alpha} (F^1_t - F^2_t) \quad (2.14)$$

$$F_{t+x} = b_0 + b_1x \quad (2.15)$$

where ' F^1 ' and ' F^2 ' are single and double smoothing statistics, respectively.

If actual data are fitted to regression models with the general form

$$Y_t = b_0 + b_1Y_{t-1} + b_2Y_{t-2} + \dots + b_nY_{t-n} \quad (2.16)$$

the procedure is denoted as autoregressive, because the dependent variable is related to previous values of itself, rather than to causal factors or time. As a forecasting procedure, this approach may be compared to the moving average and exponential smoothing models presented earlier, since all involve autoregressive methods in which forecasts are calculated by applying various weights to previous values of a data series. A somewhat different modelling scheme, albeit involving the same general equation structure is

$$Y_t = b_0 + b_1a_{t-1} + b_2a_{t-2} + \dots + b_na_{t-n} \quad (2.17)$$

where a forecast is based upon weighted, time-lagged random errors and is referred to as a moving average model, although this sense of the term 'moving average' must be clearly distinguished from smoothing models of the same name. Box and Jenkins (1970) have provided the most comprehensive account of the theory and application of autoregressive and moving average equations, and they are widely referred to as Box-Jenkins models. The procedures

involved are restricted in their application to time series that are stationary (constant) in the mean and variance. However, since nonstationary series can be made stationary by differencing (to induce stability of the mean), or by the use of logarithm or power transformations (to remove heteroscedasticity), the stationarity assumption is not particularly limiting. To difference a series, a new variable is defined by subtracting from each data value the data value for the previous period. That is, if

$$z_t = Y_t - Y_{t-1} \quad (2.18)$$

series ' z_t ' is called the first differences of ' Y_t '.

First differences of a series are represented by

$(1-B)Y_t$ since

$$\begin{aligned} (1-B)Y_t &= Y_t - BY_t \\ &= Y_t - Y_{t-1} \end{aligned} \quad (2.19)$$

where ' B ' is a backshift operator. More generally, k th order differences are symbolized by $(1-B)^k Y_t$.

When differencing is required to induce stationarity, the Box-Jenkins model is built from the transformed data. Retrieving the original data values is possible by integration, which reverses the effect of the differencing transformation. Hence, Box Jenkins models are referred to as autoregressive integrated moving average (ARIMA) models. The general form of an ARIMA model is

$$\begin{aligned} (1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)(1 - B)^d Y_t &= (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q) a_t + \delta \end{aligned} \quad (2.20)$$

where ϕ_i and θ_i are model coefficients, 'd' is the degree of differencing, ' a_t ' is the random error term, and δ is a constant. The order of the autoregressive process incorporated in Equation (2.20) is the highest lag of ' Y_t ' associated with a ϕ coefficient, and the order of the moving average process is the highest lag of a_t associated with a θ coefficient. A convenient shorthand for model description is ARIMA (p,d,q) where 'p' is the order of the autoregressive process, and 'q' is the order of the moving average process.

Where seasonal variations occur in a time series, Box-Jenkins models become more complex. The need for stationarity of the mean may require seasonal differencing, which involves subtracting from each observation a prior observation occurring 's' time periods before, where 's' is the seasonal span. For monthly data, the seasonal span is typically twelve, and seasonal differencing of the first degree involves defining a new variable ' z'_t ', where

$$z'_{13} = Y_{13} - Y_1$$

$$z'_{14} = Y_{14} - Y_2 \text{ etc.}$$

The number of observations in the time series is thereby reduced by the length of the seasonal span.

Pure seasonal models have the form

$$(1 - \phi'_1 B^s - \phi'_2 B^{2s} - \dots - \phi'_p B^{ps}) z'_t = (1 - \theta'_1 B^s - \theta'_2 B^{2s} - \dots - \theta'_q B^{qs}) a_t \quad (2.21)$$

where ϕ' and θ' are seasonal coefficients of order

1,2,3...P and 1,2,3,...Q, respectively.

In time series data with both nonseasonal and seasonal patterns, the applicable ARIMA model may be multiplicative and of the form

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_P B^P)(1 - \phi'_1 B^S - \phi'_2 B^{2S} - \dots - \phi'_P B^{PS})w_t = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_Q B^Q)(1 - \theta'_1 B^S - \dots - \theta'_2 B^{2S} - \dots - \theta'_Q B^{QS})a_t \quad (2.22)$$

where ' w_t ' is a variable defined from the original time series ' Y_t ' by appropriate seasonal and/or consecutive differencing.

2.3 Explaining Tourism Demand

Causal models of tourism demand have focused on the role of two explanatory variables: income levels in the tourist-generating region, and the prices paid for tourism services. Most researchers have explicitly or implicitly assumed that other variables which may determine demand levels, such as consumer tastes, destination accessibility, and political relationships, are either constant, or changing at a constant rate over the period envisioned for model calibration and forecasting. The supply of tourism services has been routinely assumed to be perfectly elastic, in part because estimation of demand elasticities would otherwise be extremely difficult. Gray (1966: 86) and Artus (1972: 583) have defended this assumption on the grounds that few destination countries ever achieve full utilization of their tourist facilities, and that the prices

of many tourist services are normally determined months ahead of actual sales, and are not usually adjusted thereafter in response to demand conditions.

Modelling efforts have been plagued by serious data problems. The number of tourists may be used as one measure of tourism demand in a destination country, but because of variations among tourists in the length of stay per visit and in the amount of tourist services consumed, most economists regard tourism expenditures as a more satisfactory index (Carey, 1987). Unfortunately, these expenditures are difficult to measure with precision. Estimates are usually made from tourist surveys or from the foreign exchange transactions reported by financial institutions, but the surveys are often too expensive to be carried out with the desired frequency, and not all tourist spending passes through the banking system. The accuracy of data on tourist arrivals is also sometimes suspect, and the worst problems are associated with the use of hotel records for counting tourists. Under this method, a tourist who stays at more than one commercial establishment during a visit to a country is counted more than once, while the tourist staying at a private home is not counted at all. More precise estimates are possible where frontier checks are used and where, as in the Caribbean, the great majority of tourists arrive by air or sea at a limited number of ports of entry, with immigration regulations requiring the

completion of an arrival card for each individual. Even in such cases, the quality of tourism statistics varies from country to country, depending upon the level of expertise and effort applied to their collection. Since figures reported by different governments may not be strictly comparable, there is a great advantage to working with data gathered from a single source.

Researchers have also encountered problems in their efforts to measure transportation costs and tourist prices at the destination. Construction of a meaningful index of transportation expenses has become virtually impossible because of the complexity of fare schedules for long-distance travel, and few destination countries have a reliable index of the prices tourists must pay for the goods and services they consume. Where a deterministic model requires such an index as an input variable, use is usually made of the relevant consumer price index, but in destinations which emphasize luxury tourism, as in the Caribbean, this index may be unreliable, because tourist consumption patterns depart substantially from local norms.

The only price component which can be easily and exactly measured has been the foreign exchange rate of the destination area currency. Gray (1966) has argued that this is actually the most important price element, because at the time the prospective tourist chooses a particular destination over competing alternatives, it is often the

only price information he knows precisely. Partly for this reason, exchange rates were a key consideration in the earliest tourism demand studies. For example, Gerakis (1965) compared spending by foreign tourists in seven destination countries before and after significant changes were made to their exchange rates during the period between 1957 and 1962. He found that there was an acceleration in the growth rate of tourist expenditures in each of the four countries that devalued their currencies in terms of the U.S. dollar, and in most cases a simultaneous deceleration in the growth rate of expenditures in other destinations that were judged to be their closest competitors and that had not implemented corresponding devaluations. Reduced rates of growth in expenditures were recorded by each of the three countries which had increased the value of their currencies relative to the U.S. dollar, and the performance of these countries compared unfavourably to growth rates recorded by those of their keenest competitors which had not revalued.

In his investigation of foreign travel spending by U.S. and Canadian tourists, Gray (1966) discovered a similar relationship between tourism demand and destination country exchange rates, based upon annual data for the period 1950-1963. The other independent variables Gray considered were per capita disposable income in the two generating countries, and transportation costs (airfare). Tourist

expenditures proved to be highly income-elastic, but the transportation cost variable was not statistically significant.

Kwack (1972) used a model similar to Gray's to analyze seasonally adjusted quarterly data on U.S. foreign travel expenditures between 1960 and 1967. These expenditures were related to aggregate U.S. disposable income and the ratio of destination country prices to U.S. prices of goods and services. Tourist spending was found to be both price- and income-elastic. Foreign tourist spending in the U.S. was also investigated and found to have even higher income- and price-elasticities than U.S. expenditures abroad.

In a study by Artus (1972) of the major tourist-generating and receiving countries in North America and western Europe, the effects of destination prices and exchange rates were separately accounted for, and each of these variables was specified both in current terms and with a time lag. Like Gray, Artus specified the income variable as real per capita disposable income. The results showed that, except for U.S. and Canadian expenditures in western Europe, tourism demand was both income- and price-elastic. For the U.S. and Canada, elasticities with respect to destination prices were larger than exchange rate elasticities, but among European countries few destination price elasticities were statistically significant, in contrast to most exchange rate elasticities.

Artus encountered technical problems in coefficient estimation because of near collinearity among the independent variables used in his model. In an attempt to avoid this problem, Jud and Joseph (1974) sought to increase the amount of variability in the independent variables by pooling time series and cross sectional data on tourist flows to 17 Latin American destinations, even though this approach required the sweeping assumption of identical elasticity parameters for each of the destination countries in the analysis. As price variables, both destination prices, relative to the prices of generating countries, and travel costs were considered. The elasticity coefficients of both variables were found to be relatively high, a result different from Gray's earlier finding regarding travel costs. Moreover, the elasticity of income, although greater than unity, was substantially lower than the income elasticities reported in earlier studies, leading the authors to conclude that where a travel cost variable is omitted, there is likely to be some overestimation of the income elasticity of demand. Even so, it is clear that the relationship between tourism demand and income is generally stronger than that between demand and price considerations.

Both income and price effects, however, may be declining over time. Bechdolt (1973) reported such a decrease in both elasticities based upon an examination of U.S. tourist flows to Hawaii between 1961 and 1970. O'Hagan

and Harrison (1984) subsequently reported that some European countries, notably Spain, France, Sweden, Norway, Belgium and the United Kingdom, were enjoying shares of the U.S. tourist market that seemed to be price inelastic, but that price elasticities for Greece, Denmark, Ireland and Portugal remained high.

Other studies of the elasticity of substitution provide mixed evidence on this point. To the extent that tourists are price-responsive, they can be expected to be alert to opportunities to substitute cheaper destinations for more expensive ones when destination prices change relative to one another. Rosensweig (1986) reported evidence of substitution effects when he studied U.S. tourist expenditures in the Caribbean, Mexico, and Mediterranean Europe, but in a parallel analysis of outward tourism from major tourist generating countries in Europe, he found little to suggest substitution between Mexico and the Caribbean. Martin and Witt (1988), in a recent study of outward tourism from the U.S., West Germany, the United Kingdom and France, produced results which neither confirm nor refute the substitution hypothesis.

As noted previously, causal models of tourism demand can be used for prediction, but except for the study by Artus (1972), the literature on these models has been exclusively devoted to discussions of the relative contributions of alternative explanatory variables to

observed variations in demand, and has not concerned itself with the estimation of model-based forecasts. If tourism demand is becoming less responsive to income and price effects, however, model forecasts based upon these variables can be expected to become progressively less satisfactory.

2.4 Extrapolating Historical Trends in Tourism Demand

Few studies have appeared in the tourism literature concerning the application of time series models to the problem of forecasting. However, Guerts and Ibrahim (1975) compared the accuracy of four Box-Jenkins models with that of an exponentially smoothed model in the forecasting of monthly tourist arrivals in Hawaii one month ahead of time. Based upon an initialization period of 24 months, the best of the Box-Jenkins models performed equally well with the exponentially smoothed model. This led the authors to conclude that the latter model was to be preferred, since it was cheaper and less complicated to use. Nonetheless, it was noted that this finding applied only to a particular time series and should not be generalized automatically to other data.

3. FORECASTING TOURISM DEMAND: CAUSAL MODELS

In this chapter, single-equation econometric models of tourism demand are specified and tested for accuracy as forecasting instruments. The models use published data on U.S. tourist expenditures in several English-speaking Caribbean or Atlantic territories selected as a group because they share some of the most tourism-dependent economies in the world, and because they offer similar tourist services. The decision to focus on the U.S. tourist population is justified by the extent of American domination of the overall Caribbean/Atlantic tourist population. In recent decades, U.S. visitors have accounted for just over 60 percent of all tourist arrivals and a similar proportion of tourist expenditures in this region (Caribbean Tourism Research and Development Centre, 1984).

3.1 Model I

U.S. tourist expenditures are related to income and price variables in the following manner

$$T_t = b_0 + b_1 Y_t + b_2 P_t + e_t \quad (3.1)$$

where ' T_t ' denotes U.S. tourist expenditures in the destination area in 1982 dollars during the t th period; ' Y_t ' denotes U.S. per capita disposable income in 1982 dollars; ' P_t ' is an exchange rate adjusted price index for the destination area; and ' e_t ' is a disturbance term.

3.1.1 Data Sources

The dependent variable consists of tourism expenditure estimates published annually by the U.S. Department of Commerce in the Survey of Current Business. Expenditure estimates are available for Bermuda, the Bahamas, Jamaica, and a residual category, Other British West Indies, for the period from 1968 to 1985.

The independent variable, U.S. personal disposable income per capita, is also published in the Survey of Current Business. The other independent variable, exchange rate adjusted prices, combines two separate price components in a single number. Exchange rates are published by the International Monetary Fund in International Financial Statistics and are units of destination currency per U.S. dollar. There is no tourist price index for any of the destination areas, so use is made of the relevant consumer price indexes, which are published for three of the destinations in International Financial Statistics. Because no series is available for Bermuda, price data for the Bahamas are applied to the Bermudian case on the grounds that there is greater similarity between the Bahamian and Bermudian economies than between Bermuda and any other destination. Price indexes are adjusted by dividing them by appropriate exchange rate indexes, which are computed in each case as the ratio of the actual exchange rate for a given year to the corresponding exchange rate in a base

year (1982).

3.1.2 Estimation Procedure

Using the ordinary least squares technique, Model I is separately estimated for each of the four destination areas using data for the sub-period 1968-1982. This interval covers a growth phase in U.S. tourism to the study area that lasted for five years after 1968 before being halted by the effects of the global oil price increases of 1973 and 1974. By 1976, tourism in much of the study area had recovered at least some of its earlier growth momentum, but there were subsequent temporary reductions in demand associated with a second round of oil price increases in 1979, and with the U.S. recession of 1982.

Scatter plots of the dependent variable against each of the independent variables offer only limited evidence of well-defined linear relationships (see as examples Figures A.1 and A.2 in Appendix A), and natural logarithms of the data are taken to improve the fit of the regression equations (see Figures A.3 and A.4 for scatter plots of transformed data). The revised model (Model I*) is

$$\ln T_t = \ln b_0 + b_1 \ln Y_t + b_2 \ln P_t + \ln e_t \quad (3.2)$$

Coefficient estimates for Equation (3.2) are shown in Table 3.1. The regression model is expected to have a statistically significant overall 'F' statistic; model coefficients that are statistically significant and positive in the case of the income variable, and statistically

TABLE 3.1
TOURISM DEMAND REGRESSIONS: MODEL I

N = 15

Dependent Variable = Natural logarithms of U.S. tourist expenditures ($\ln T_t$).
Independent Variables = Natural logarithms of U.S. personal disposable income per capita ($\ln Y_t$).
Natural logarithms of the exchange rate adjusted destination price index ($\ln P_t$).

(1) <u>Destination</u>	(2) <u>Constant</u> (b_0)	(3) <u>$\ln Y_t$</u> (b_1)	(4) <u>$\ln P_t$</u> (b_2)	(5) <u>F</u>	(6) <u>R^2</u>	(7) <u>D.W.</u> ¹
Bermuda	11.77	0.61 (0.76)	0.41 (2.04)	34.2*	.85	1.31
The Bahamas	29.55	-1.24 (-1.38)	0.30 (1.35)	1.0	.14	2.24
Jamaica	25.19	-0.53 (-1.04)	-0.34 (-2.99)*	18.9*	.76	1.09
Other British West Indies	-21.54	4.48 (4.74)*	-0.08 (-0.63)	79.8*	.93	2.33

¹D.W. denotes the Durbin Watson Statistic.

Values of the t statistic are shown with regression coefficients in parentheses.

*Indicates statistic is significant at the 5 per cent level.

significant and negative in the case of the price variable; a high coefficient of determination (R^2); a Durbin-Watson statistic indicating no evidence of positive or negative autocorrelation in the residuals; and residual patterns consistent with the assumptions of homoscedasticity and (approximate) normality. Scatter plots of the residuals on the predicted values, and the form of residual histograms suggest that the latter assumptions are satisfied. However, examination of Table 3.1 shows that, although 'F' scores are significant and values of ' R^2 ' are high for all destinations except the Bahamas, the income variable is significant in the presence of the price variable in only one equation (Other British West Indies), and does not have the expected sign in two others (the Bahamas and Jamaica). Similarly, the price index is significant in the presence of the income variable in only one equation (Jamaica), and does not have the hypothesized sign in two others (Bermuda and the Bahamas).

The measurement of price effects in Model I* may be modified in one of two ways. Instead of describing destination price levels, the price variable may be operationalized as the annual percentage change in exchange rate adjusted prices. However, like the original price specification, this formulation fails to achieve statistical significance. A further revision of the variable is based on the grounds that if the destination choices of a tourist

are made well in advance of actual travel, the most appropriate price information is that which is available up to one year before a trip. However, when this idea is tested by introducing a one-year lag to the price level data, the re-estimated regression coefficients for this variable still lack statistical significance.

3.2 Model II

One of the problems with Equation (3.2) is the relatively high correlation between the independent variables: the value of ' R^2 ' for the regression of the income variable on the price index is 0.61 for Jamaica, and 0.89 for the other destinations. In Model II this problem is less severe because the price variable is re-specified as a relative index. The model is

$$\ln T_t = \ln b_0 + b_1 \ln Y_t + b_2 \ln (P_d/P_o)_t + \ln e_t \quad (3.3)$$

where $(P_d/P_o)_t$ is a price relative constructed as the ratio of each destination's exchange rate adjusted consumer price index to the unweighted average of the exchange rate adjusted price indexes for the other destinations in the study area. Model II therefore hypothesizes that the destinations are all substitutes for one another and that relative, rather than absolute price levels play a key role in the destination choices of price-sensitive tourists. In calculating the price-relative, the usual practice is to construct the composite price index in the denominator by

weighting the price index for each competitor destination by its share of total tourist expenditures (or arrivals) in a region (see Uysal and Crompton, 1985; Witt and Martin, 1987). In this study, however, the composite index is an unweighted (or equally weighted) average, because it is assumed that price-sensitive tourists give equal consideration to each destination alternative when evaluating a particular destination.

When income is regressed on the relative price index, the value of ' R^2 ' falls to 0.24 for Bermuda and the Bahamas, and to 0.35 for Jamaica, but increases marginally to 0.91 for the Other British West Indies. For this latter destination, Model II produces results (see Table 3.2) that are similar to Model I. Both models have similar values of ' R^2 ', significant income coefficients, and the coefficient signs expected from economic theory. For Bermuda, however, Model II generates results closer to theoretical expectations than Model I, since for the first time the income variable is significant in the presence of the price variable, and both coefficients have the expected signs. Model II explains even less of demand variation in the Bahamas and Jamaica than Model I, but neither model generates results that conform to economic theory. For the Bahamas, the income coefficient in Model II has the expected sign, but none of the independent variables achieves statistical significance. Serial correlation in the

TABLE 3.2
TOURISM DEMAND REGRESSIONS: MODEL II

N = 15

Dependent Variable = Natural logarithms of real U.S. tourist expenditures ($\ln T_t$).

Independent Variables = Natural logarithms of U.S. personal disposable income per capita ($\ln Y_t$).

Natural logarithms of the ratio of the exchange rate adjusted destination price index to the average of the exchange rate adjusted price indexes for alternative destinations ($\ln(P_d/P_o)_t$).

(1) Destination	(2) Constant (b ₀)	(3) $\ln Y_t$ (b ₁)	(4) $\ln(P_d/P_o)_t$ (b ₂)	(5) F	(6) R^2	(7) D.W.*
Bermuda	0.86	2.00 (5.78)**	-0.17 (0.98)	26.2**	.81	1.56
The Bahamas	18.73	0.07 (0.22)	0.18 (1.04)	0.6	.09	1.89
Jamaica***	38.77	-2.17 (-4.52)**	-0.31 (-1.57)	11.2**	.65	0.84
Other British West Indies	-25.94	4.92 (4.98)**	-0.33 (-1.06)	84.9**	.93	2.45

*D.W. denotes the Durbin Watson Statistic.

Values of the t statistic are shown with regression coefficients in parentheses.

**Indicates statistic is significant at the 5 per cent level.

***If the Jamaica equation is re-estimated using the transformed variables

$$\ln T'_t = \ln T_t - r \ln T_{t-1}$$

$$\ln Y'_t = \ln Y_t - r \ln Y_{t-1}$$

$$\ln (P_d/P_o)'_t = \ln (P_d/P_o)_t - r \ln (P_d/P_o)_{t-1}$$

where 'r' is an estimate of the correlation between e_t and e_{t-1} , the revised regression equation is:

$$\ln T'_t = 37.14 - 1.99 \ln Y'_t - 0.15 \ln (P_d/P_o)'_t + e'_t$$

with ' R^2 ' equal to 0.36, 'F' equal to 3.03, and 'D.W.' equal to 1.70. None of the coefficients is significant at the 5 per cent level.

residuals is evident in the Jamaica equations, but re-estimation of the coefficients to remove this problem does not resolve the disparity between the empirical evidence and theory.

Experimentation with alternatives to the price formulations in Equations (3.2) and (3.3) failed to produce statistically significant price coefficients for any of the destinations. The same result occurs when the price relative is re-conceptualized as a ratio of destination prices to U.S. prices.

The weak effect of the price factor for all destinations may be explained in a number of different ways. One possibility is that the consumer price indexes are poor proxies for tourist prices. Exchange rate indexes can be adopted as the only price measure, but this change does not improve model quality: in a model with income as the other independent variable, exchange rates fail to achieve statistical significance for any of the destination areas. Another possibility is that U.S. tourism demand has become relatively price-inelastic within the range of prices encountered in the Caribbean, a conclusion that depends for its plausibility on extrapolation of the trend toward decreased price sensitivity previously reported for U.S. tourists by Bechdolt (1973) and O'Hagan and Harrison (1984).

For the Bahamas, the lack of a linear relationship between tourism demand and income may reflect the fact that

this is the destination which is closest to the U.S. and offers some of the cheapest foreign vacations available to Americans. If, throughout the survey period, most Americans interested in travel to the West Indies were able to afford Bahamian vacations, increases in U.S. income levels might produce no significant expansion in tourism demand. Also, tourist preferences have been assumed constant, but they could in fact be changing in ways which lead a significant number of the more affluent U.S. tourists to seek out destination alternatives that are regarded as more exclusive or exotic than the Bahamas.

The unexpected negative relationship between income and tourism for Jamaica may indicate that economic factors have been overshadowed by other variables not included in either model. In Jamaica, U.S. tourist expenditures, measured in 1982 dollars, started to decline in 1974 and did not begin to recover until 1981. The decline may be linked to the election in 1972 of a left-of-centre government on the island under the leadership of Michael Manley. The Manley government aroused the ire of successive U.S. administrations by embracing anti-imperialist policies and rhetoric, and by establishing close ties with the Cuban regime of Fidel Castro. Negative press coverage of Jamaica in U.S. media during the 1970s and a formal U.S. State Department notice in 1976 declaring the island a hardship post for U.S. diplomats, appear to have had a significant

impact on the travel trade (Cuthbert and Sparkes, 1978).

If the price variable is deleted altogether from Equation (3.3), the coefficients of the reduced model are as shown in Table 3.3. Forecasts for Bermuda and the Other British West Indies generated by both the full form and the reduced form of Model II are given in Table 3.4. No predictions are attempted for the Bahamas or Jamaica because of the problems noted in the equations for these destinations. Model forecasts are for the period 1983-1985 and are computed using actual values of the independent variables for these years. The results can be compared with actual tourist expenditures during the forecasting period. For Bermuda, predictions from the full form of Model II for the three years have a mean absolute error of 14.4 percent, whereas forecasts from the reduced form have a slightly higher mean error of 17 percent. In the case of the Other British West Indies, however, this pattern is reversed and full form model forecasts have a mean error of 14.8 percent, compared to 14.2 percent for forecasts from the reduced form model. Since the two versions of the model show similar degrees of accuracy, a good case can be made for adopting the more parsimonious structure of the reduced form equation.

TABLE 3.3
TOURISM DEMAND REGRESSIONS: REDUCED FORM OF MODEL II

N = 15

Dependent Variable = Natural logarithms of real U.S. tourist expenditures ($\ln T_t$).

Independent Variable = Natural logarithms of U.S. personal disposable income per capita ($\ln Y_t$).

(1) <u>Destination</u>	(2) <u>Constant</u> (b_0)	(3) <u>$\ln Y_t$</u> (b_1)	(4) <u>F</u>	(5) <u>R^2</u>	(6) <u>D.W.</u> ¹
Bermuda	-0.67	2.16 (7.19)*	51.63*	.80	1.45
The Bahamas	20.40	-0.10 (-0.33)	0.11	.01	2.01
Jamaica	34.69	-1.72 (-4.23)*	17.93*	.58	0.76
Other British West Indies	-16.73	3.92 (12.92)*	166.95*	.93	2.33

¹D.W. denotes the Durbin Watson Statistic.

Values of the t statistic are shown with regression coefficients in parentheses.

* Indicates statistic is significant at the 5 per cent level.

TABLE 3.4
 ACTUAL AND PREDICTED TOURIST EXPENDITURES
 FOR BERMUDA AND OTHER BRITISH WEST INDIES, 1983-1985

Year	Actual	Predicted	Expenditures	Percent Error	
	Expenditures	Model II Full Form	Model II Reduced Form	Model II Full Form	Model II Reduced Form
(1982 U.S. Dollars)					
Bermuda:					
1983	\$ 194,950,688	\$ 224,003,000	221,415,000	14.9	13.6
1984	200,845,952	238,197,000	245,649,000	18.6	22.3
1985	222,782,848	244,466,000	256,104,000	9.7	15.0
			MAPE*	14.4	17.0
Other British West Indies:					
1983	\$ 209,355,904	\$ 246,412,000	249,104,000	17.7	19.0
1984	369,297,410	294,951,000	300,737,000	-20.1	-18.6
1985	341,779,300	319,073,000	324,350,000	-6.6	-5.1
			MAPE*	14.8	14.2

*Denotes mean absolute percentage error.

FORECASTING TOURISM DEMAND: TIME SERIES MODELS

4.1 Time Series Regression

The first time series regression model considered is

$$T_t = b_0 + b_1 X_t + e_t \quad (4.1)$$

where ' X_t ' represents time, expressed in years. Table 4.1 contains the coefficients for Equation (4.1) generated by data on 1982 U.S. tourist expenditures during the period 1968-1982 in each of the four destination areas covered by this study. There are statistically significant time trends during the sample period for Bermuda, Jamaica and the Other British West Indies, although in the case of Jamaica, the trend is negative rather than positive, presumably for the political reasons explained in Chapter 3. For the fourth destination area, the Bahamas, the regression slope coefficient is not statistically significant, and the coefficient of determination is nearly zero, indicating the absence of a linear relationship between tourism demand and time.

The Bahamas is therefore dropped from this part of the analysis and the trends defined for the other three destination areas are extrapolated to produce forecasts for the 1983-1985 forecasting period. Extrapolations of this kind are commonly made in forecasting practice, even though they are difficult to justify theoretically.

TABLE 4.1
TOURISM EXPENDITURES: THE TIME TREND, 1968-1982

N = 15

Dependent Variable = 1982 U.S. tourist expenditures (T_t).

Independent Variable = Time, in years (X_t)

(1) Destination	(2) Constant (b_0)	(3) (X_t) (b_1)	(4) R^2
Bermuda	131,576,300	6,993,556 (8.00)*	.83
The Bahamas	281,991,100	192,179 (0.12)	.001
Jamaica	227,350,100	-6,167,993 (-5.49)*	.70
Other British West Indies	99,438,270	10,786,190 (7.22)*	.80

Values of the t statistic are shown with regression coefficients in parentheses.

*Indicates statistic is significant at the 5 per cent level.

As Table 4.2 shows, however, none of the resulting time trend forecasts is an accurate estimate of the actual values for this period. The greatest forecasting errors are found in the Jamaican case, where the three predictions have a mean absolute percentage error of 24.7 percent.

Some improvement in model accuracy can be expected if a piecewise linear regression is substituted for a simple time trend. Piecewise regression partitions the relationship between the dependent variable and the independent variable into two or more discrete segments, each of which has a different slope. In this way, trends which emerge late in the model calibration period can be separately estimated and described. In the present case, the definition of trend segments is based upon a priori expectations that would have been widely shared among tourism industry professionals at the time demand predictions would have been made. For example, aggregate U.S. tourism demand grew at a vigorous pace between 1968 and 1972, averaging an 8.8 percent increase per year for this period (see Table 4.3). The world oil price increases of 1973 and 1974 interrupted this expansion by making long distance travel more expensive, so that during 1974 and 1975 U.S. tourist expenditures fell, by 2.1 percent and 0.7 percent, respectively. In 1976, however, the decline was halted and reversed, apparently because gains in money income had diminished the impact of travel price increases,

TABLE 4.2
ACTUAL AND PREDICTED TOURIST EXPENDITURES
FOR THREE DESTINATION AREAS, 1983-1985: THE TIME TREND MODEL

	Actual	Predicted	Percent
Year	Expenditures	Expenditures	Error
(1982 U.S. Dollars)			
Bermuda:			
1983	\$ 194,950,688	\$ 243,473,000	24.9
1984	200,845,952	250,467,000	24.7
1985	222,782,848	257,460,000	<u>15.6</u>
		MAPE*	21.7
Jamaica:			
1983	\$ 173,823,024	\$ 134,830,000	-22.4
1984	171,228,112	128,662,000	-24.9
1985	167,310,816	122,494,000	<u>-26.8</u>
		MAPE	24.7
Other British West Indies:			
1983	\$ 209,355,904	\$ 272,017,000	29.9
1984	369,297,410	282,804,000	-23.4
1985	341,779,300	293,590,000	<u>-14.1</u>
		MAPE	22.5

*Denotes mean absolute percentage error.

TABLE 4.3
 AGGREGATE U.S. TOURIST EXPENDITURES:
 VARIATIONS IN ANNUAL GROWTH RATES, 1968-1982

Year	Actual Tourist Expenditures (Millions of 1982 dollars)	Annual Percentage Change
1968	7,710	-
1969	8,300	7.7
1970	9,279	11.8
1971	9,731	4.9
1972	10,792	10.9
1973	11,151	3.3
1974	10,922	-2.1
1975	10,847	-0.7
1976	10,951	1.0
1977	11,162	1.9
1978	11,840	6.1
1979	12,044	1.7
1980	12,003	-0.3
1981	12,132	10.7
1982	12,394	2.2

Source: U.S. Department of Commerce, Survey of Current Business, various issues.

and an annual average growth rate of 3.3 percent was recorded for expenditures between 1976 and 1982.

From these broad trends, U.S. tourism demand in the Caribbean would have been expected to form a pattern that can be described by three slope segments, for 1968-1973, 1974-1975 and 1976-1982, respectively. The applicable three-piecewise model is

$$T_t = b_0 + b_1 X_{1t} + b_2 (X_{1t} - 5)X_2 + b_3 (X_{1t} - 8)X_3 \quad (4.2)$$

$$X_2 = \begin{cases} 1 & \text{if } X_1 > 5 \\ 0 & \text{otherwise} \end{cases}$$

$$X_3 = \begin{cases} 1 & \text{if } X_1 > 8 \\ 0 & \text{otherwise} \end{cases}$$

where ' X_1 ' denotes time in years. The year 1968 is coded as 0, 1972 is coded as 5, and 1975 is coded as 8. ' X_2 ' and ' X_3 ' are indicator variables. The regression slope for the 1968-1973 sub-period is given by ' b_1 '; the slope for the 1974-1975 sub-period is given by the sum of ' b_1 ' and ' b_2 '; and the slope for 1976-82 is given by the sum of ' b_1 ', ' b_2 ' and ' b_3 '.

Table 4.4 displays the regression coefficients for Equation (4.2) in respect of each destination area. All coefficients are significant in the Jamaica equation, but for Bermuda and the Other British West Indies, the ' b_2 ' and ' b_3 ' coefficients lack significance, and for the Bahamas, no coefficient is significant. Moreover, the piecewise relationships do not, in any given instance, reproduce the trend combinations that characterized aggregate U.S. tourist expenditures, nor are they consistent from one destination

TABLE 4.4
TOURISM EXPENDITURES: PIECEWISE REGRESSION, 1968-1982

N = 15

Dependent Variable = 1982 U.S. tourist expenditures (T_t).

Independent Variables = Time, in years (X_{1t}).

Indicator variables (X_2), (X_3).

(1) Destination	(2) Constant (b_0)	(3) X_{1t} - (b_1)	(4) X_2 (b_2)	(5) X_3 (b_3)	(6) F	(7) R^2
Bermuda	125,409,000	8,248,493 (2.69)*	3,155,626 (0.46)	-8,631,514 (-1.38)	25.2*	.87
The Bahamas	291,032,100	-636,011 (-0.12)	-10,919,650 (-0.91)	21,082,370 (1.91)	1.8	.33
Jamaica	199,730,000	5,723,950 (2.22)*	-24,891,890 (-4.35)*	13,608,700 (2.59)*	33.9*	.90
Other British West Indies	86,169,290	14,280,360 (2.70)*	1,847,795 (0.16)	-11,952,570 (-1.11)	20.2*	.85

Values of the t statistic are shown with regression coefficients in parentheses.

*Indicates statistic is significant at the 5 per cent level.

to another. For Bermuda and the Other British West Indies, the model pattern is one of increasingly vigorous growth in the first two sub-periods, followed by a reduced growth rate in the final segment. For the Bahamas, the regression slope becomes increasingly negative with movement from the first to the second line segment, but becomes positive in the final sub-period; and for Jamaica, the slope of the regression line is positive in the first sub-period, sharply negative in the second, and negative, but to a much lesser degree, in the third. Despite these departures from the expectations generated by aggregate expenditures, it is noteworthy that for each destination the piecewise model accounts for a substantially higher proportion of the variation in tourism demand than does the bivariate model. The difference between the two models is particularly significant for the Bahamas and Jamaica. Some 33 percent of the variance in the dependent variable is explained by the piecewise model for the Bahamas (compared to nearly zero percent for the simple time trend), and the resulting forecasts for 1983-85 are of good quality, falling within 10 percent of actual values (see Table 4.5). Piecewise forecasts for Bermuda achieve a similar degree of precision. For the remaining two destinations, however, there is no demonstrable benefit to the use of the piecewise model for prediction as against the simple time trend.

TABLE 4.5
ACTUAL AND PREDICTED TOURIST EXPENDITURES
FOR FOUR DESTINATION AREAS, 1983-1985
THE PIECEWISE MODEL

Year	Actual Expenditures	Predicted Expenditures	Percent Error
(1982 U.S. Dollars)			
Bermuda:			
1983	\$ 194,950,688	\$ 220,272,000	13.0
1984	200,845,952	223,045,000	11.1
1985	222,782,848	225,817,000	<u>1.4</u>
		MAPE*	8.5
The Bahamas:			
1983	\$ 352,447,810	\$ 319,872,000	-9.2
1984	363,744,060	329,399,000	-9.4
1985	373,094,180	338,925,440	<u>-9.2</u>
		MAPE	9.3
Jamaica:			
1983	\$ 173,823,024	\$ 131,931,000	-24.1
1984	171,228,112	126,372,000	-26.2
1985	167,310,816	120,813,000	<u>-27.8</u>
		MAPE	26.0
Other British West Indies:			
1983	\$ 209,355,904	\$ 235,185,000	12.3
1984	369,297,410	239,360,000	-35.2
1985	341,779,300	243,536,000	<u>-28.7</u>
		MAPE	25.4

*Denotes mean absolute percentage error.

4.2 Smoothing Methods

Like time series regression, smoothing methods are noted for their simplicity and low cost. Linear or double moving average models are appropriately applied to forecasting Caribbean tourism demand since the data series for three of the destinations show time trends (see previous Section). Table 4.6 presents forecasts for each destination calculated from Equations (2.6), (2.7) and (2.8), using three-by-three moving averages. The number of observations included in the calculation of the moving average is determined by trial-and-error.

The results show that for the forecasting period of 1983-1985, the moving average model offers roughly the same degree of precision as the piecewise regression. The only exception is the case of the Other British West Indies, where the the moving average prediction is of little accuracy, possibly because of large fluctuations in the data in the years immediately preceding the forecast origin. The most precise forecasts are for the relatively flat Bahamas series, and this result suggests that even linear moving averages do not adjust fully and rapidly to the changing trends in the data.

One alternative to the linear moving average is the use of the double exponential smoothing model. Again, this procedure lacks clear theoretical justification and its value is measured entirely in terms of its forecasting

TABLE 4.6
ACTUAL AND PREDICTED TOURIST
EXPENDITURES FOR FOUR DESTINATION AREAS,
1983-1985: THE LINEAR MOVING AVERAGE MODEL

<u>Year</u>	<u>Actual</u> <u>Expenditures</u> (1982 U.S. Dollars)	<u>Predicted</u> <u>Expenditures</u>	<u>Percent</u> <u>Error</u>
Bermuda:			
1983	\$ 194,950,688	229,645,000	17.8
1984	200,845,952	235,561,000	17.3
1985	222,782,848	241,478,000	8.4
		MAPE*	14.5
The Bahamas:			
1983	\$ 352,447,810	319,101,000	-9.5
1984	363,744,060	328,767,000	-9.6
1985	373,094,180	338,433,000	-9.2
		MAPE	9.4
Jamaica:			
1983	\$ 173,823,024	132,969,000	-23.5
1984	171,228,112	128,878,000	-24.7
1985	167,310,816	124,786,000	-25.4
		MAPE	24.5
Other British West Indies:			
1983	\$ 209,355,904	211,376,000	0.9
1984	369,297,410	204,974,000	-44.5
1985	341,779,300	198,571,000	-41.9
		MAPE	29.1

*Denotes mean absolute percentage error.

accuracy, its simplicity and its relatively undemanding data requirements. Table 4.7 shows forecasts calculated for each destination from Equations (2.11), (2.12), (2.13), (2.14), and (2.15). The smoothing parameter, α , is selected by trial-and-error from the range of values between 0 and 1.

For the Bahamas and Jamaica, the results improve upon the accuracy achieved from use of the linear moving average technique, but this improvement is substantial only for the Bahamas, where forecast errors have a mean of only 3.2 percent, compared with a mean of 9.4 percent for the corresponding forecasts from the three-by-three moving average model. For the other two destinations, forecasts from the exponential model are actually less accurate than moving average forecasts, but the differences are very small.

4.3 Box-Jenkins Models

The preceding analyses are based upon annual expenditure data which are available for only the last two decades. Such a short time series is inadequate for the use of Box-Jenkins models, which require about fifty observations to generate reliable results (Vandaele, 1983).

One way around this problem is to use an alternative measure of U.S. tourism demand. Since 1975, the U.S. Department of Transportation has published monthly counts of passenger departures on commercial flights leaving U.S.

TABLE 4.7
ACTUAL AND PREDICTED TOURIST
EXPENDITURES FOR FOUR DESTINATION AREAS,
1983-1985: THE EXPONENTIAL SMOOTHING MODEL

	<u>Year</u>	<u>Actual Expenditures</u> (1982 U.S. Dollars)	<u>Predicted Expenditures</u>	<u>Percent Error</u>
Bermuda:				
($\alpha=0.4$)	1983 \$	194,950,688	230,101,000	18.0
	1984	200,845,952	236,053,000	17.5
	1985	222,782,848	242,005,000	8.6
			MAPE*	14.7
The Bahamas:				
($\alpha=0.5$)	1983 \$	352,447,810	336,521,000	-4.5
	1984	363,744,060	351,518,000	-3.4
	1985	373,094,180	366,515,000	-1.8
			MAPE	3.2
Jamaica:				
($\alpha=0.4$)	1983 \$	173,823,024	138,268,000	-20.5
	1984	171,228,112	134,022,000	-21.7
	1985	167,310,816	129,778,000	-22.4
			MAPE	21.5
Other				
British				
West				
Indies:				
($\alpha=0.5$)	1983 \$	209,355,904	202,061,000	-3.5
	1984	369,297,410	195,111,000	-47.2
	1985	341,779,300	188,162,000	-44.9
			MAPE	31.1

*Denotes mean absolute percentage error.

airports for foreign destinations. These passenger figures include travellers who do not meet the accepted definition of a 'tourist' (see Section 1.2), but the non-tourist component on flights headed for the Caribbean consist largely of Caribbean nationals returning home from trips to the U.S. Since the data distinguish between passengers who are U.S. citizens, and those who are not, a reasonable estimate of the tourist flows can be made by excluding all U.S. noncitizens in the traffic from consideration. In this way, estimates of arrivals are derived for analysis of the period from February 1977 to January 1985, giving a span of eight years and 96 observations.

Forecasting from these data requires specification of an appropriate ARIMA model, which is identified by a close correspondence between the form of the model's theoretical autocorrelation and partial autocorrelation functions, and the corresponding autocorrelation functions estimated from the data itself. A 'good' ARIMA model is parsimonious and invertible, has uncorrelated residuals, and fits the initialization data set closely. A model is parsimonious if it uses the smallest number of autoregressive or moving average parameters to describe a data series, and tests of statistical significance are applied to decisions regarding the inclusion or exclusion of model coefficients. Coefficients are of high quality if they are considerably larger than their standard errors, and absolute t-values

greater than 2 are preferred. In addition, the correlations between the predictor variables should not be too large, since the coefficient estimates then become unstable.

Invertibility implies that progressively smaller weights are attached to lagged values as their lag increases, and is an assumption checked by noting whether the moving average coefficients satisfy certain conditions. For a multiplicative seasonal moving average model, the relevant conditions are

$$\begin{aligned} |\theta_1| &< 1 \\ |\theta'_1| &< 1 \end{aligned}$$

Finally, a statistically adequate ARIMA model has an error term that is independently distributed, and accordingly the residuals generated by the application of the model must pass a test of serial independence.

The analysis which follows covers five destinations. Unadjusted monthly U.S. arrivals are shown for Bermuda (Appendix B, Figure B.1), the Bahamas (Figure B.2), Jamaica (Figure B.3), Barbados (Figure B.4) and Antigua (Figure B.5). Barbados and Antigua are the two principal islands of the group described as Other British West Indies in earlier sections of this analysis.

The data for Bermuda show a regular pattern of seasonal variation from year to year, with arrivals peaking during the months of April, May or June, and again in

August, followed by a well-defined low season during December and January. After 1981, however, there is a downshift in the overall number of arrivals, and this is expressed by the lengthening of the low season, which now extends into February, and by a shift from a bimodal peak season, spanning Spring and Summer, to a unimodal distribution of arrivals built around a single peak month in May.

Bermuda is primarily a Spring and Summer destination because it lies well outside the tropics, and its cool temperatures in December and January inhibit tourism. The situation is different in all the other destinations, which lie closer to the Equator and have their main tourist season between December and March. For these islands, there is also a Summer high season, during July and August, but it is of secondary importance. The traditional low period comes in September and October, three months earlier in the year than in Bermuda. In Antigua, there are two low periods in the typical year, since May and June are also off-season months.

Two other secular trends are of note. In Barbados and Antigua, arrivals are substantially higher in 1983 and 1984 than in prior years, and in Jamaica there is a rise in arrivals after 1981. There is no clear secular trend for the Bahamas.

The existence of secular and seasonal variations in

the data means that appropriate transformation of each series is required to ensure at least approximate stationarity of the mean and variance. Consecutive differencing of order 1, and seasonal differencing of order 1 with a span of 12, are applied to each series except that for the Bahamas, which receives seasonal differencing only, because of the absence of a clear trend in arrivals. The data are transformed prior to differencing in order to induce stationarity of the variance, and the closest approximation to homoscedasticity is achieved with logarithms of the original data for the Bahamas, Jamaica and Barbados, and with square roots of the original data for Bermuda and Antigua. The transformed series are shown as Figures B.6, B.7, B.8, B.9, and B.10 for Bermuda, the Bahamas, Jamaica, Barbados and Antigua, respectively.

The adequacy of these transformations is attested to by the form of the autocorrelation functions calculated for each of the transformed series. Stationarity can be assumed if the autocorrelations for a series decay to zero within the first few lags, and if additional spikes occur only at lags that are multiples of the seasonal span, and diminish in magnitude after the first occurrence. The standard error of the sampling distribution of autocorrelations can be estimated at each lag of the autocorrelation function, so it is possible to determine the statistical significance of any non-zero autocorrelation estimates. Figure B.11 gives a plot

of the sample autocorrelation function for Bermuda, and shows confidence limits equal to two standard errors, the most widely utilized confidence interval in Box-Jenkins analysis. For any autocorrelation estimate falling within these confidence limits, the null hypothesis that the true (population) value of the autocorrelation is zero can not be rejected. The Bermuda estimates show one statistically significant autocorrelation at lag 1, and additional statistically significant autocorrelations at lags 11, 12, 13, 24, 25 and 36. This result is consistent with the assumption of stationarity.

For the Bahamas (Figure B.12), the evidence for stationarity is only slightly less unequivocal. The autocorrelations decay toward zero after five lags. However, additional spikes in the autocorrelation function occur not only at lag 12 and lag 36, but also at lags 21, 22, 30, 31, 32, 33, 34 and 35. Moreover, the spikes at high lags are longer than expected. The transformed series is therefore re-examined by splitting the sample into two equal parts and calculating separate means and variances for each half. Although both the mean and the variance of the first subsample of 42 observations are fractionally larger than the corresponding statistics for the remaining 42 observations, neither of these differences is statistically significant when standard tests for differences of the mean and variance are applied. As a result, no new adjustments

are made to this data series.

None of the remaining autocorrelation functions shows any departures from expected patterns as far as the stationarity assumption is concerned. The Jamaica function (Figure B.13) shows spikes only at lags 1 and 12, and the Barbados function (Figure B.14) at lags 1, 11, 12, 24 and 36 only. The Antigua function (Figure B.15), like that for Jamaica, has prominent spikes at lags 1 and 12 only.

4.3.1 Model Identification and Estimation

Two models are selected to represent the five series. The model fitted to every series except the Bahamas is a multiplicative moving average model, composed of a regular moving average parameter of order 1 and a seasonal moving average parameter of order 1 with a seasonal span of 12. This model is

$$w_t = (1 - \theta B) (1 - \theta' B^{12}) a_t \quad (4.3)$$

In Figure B.16, the two theoretical autocorrelation functions shown for this model assume model coefficients with positive values set equal to 0.8. The autocorrelation function consists of a negative spike at lag 1 and symmetrical positive spikes bracketing a prominent negative spike at a lag equivalent to the seasonal span. The theoretical partial autocorrelation function is composed of a series of negative spikes which decay gradually to zero, followed by a positive spike at a lag equivalent to the seasonal span. This pattern is repeated in dampened form at

higher lags.

The model fitted to the series for the Bahamas is a multiplicative autoregressive seasonal model, made up of a regular autoregressive parameter of order 1, and a seasonal autoregressive parameter of order 1 with a span of 12. The symbolic form is

$$(1 - \phi B) (1 - \phi' B^{12}) w_t = a_t \quad (4.4)$$

When the regular autoregressive parameter is positive and the seasonal parameter is negative, the theoretical autocorrelation function assumes the form indicated in Figure B.17, in which positive spikes at low lags decay to zero and are replaced by negative spikes at lags equivalent to the seasonal span. This pattern of alternating positive and negative autocorrelations may persist for a large number of lags. The pattern for the partial autocorrelation function consists of one significant positive spike at lag 1 followed by a series of negative spikes of increasing magnitude. The series terminates in a prominent spike at the lag equivalent to the seasonal span, and then the pattern begins again.

The sample autocorrelation function for Bermuda mirrors the theoretical form of the moving average model in its essentials, with statistically significant values of the correct sign at the key lags: 1, 11, 12 and 13. As expected, the autocorrelations from lags 2 to 10 are not statistically significant. The correlations at lags 14 to

22 also conform to the theoretical pattern, although the bracketed spike expected at lag 24 occurs instead at lag 25. The Jamaica sample autocorrelation also agrees with the theoretical pattern, except that the autocorrelations at lags 11 and 13 are not significant. The Barbados sample function also fails to show a significant spike at lag 13, and the Antigua function shows no significant spike at either lag 11 or lag 13. In each of these cases, however, the estimated autocorrelations are of the correct sign. For the Bahamas, the spikes at low lags and at lag 12 are in the expected directions, but the significant spikes which occur in the sample function at lags 21 and 22 are predicted by theory for lag 24.

Figures B.18, B.19, B.20, B.21 and B.22 give the partial autocorrelation estimates for the five destinations, and while the functions for Bermuda, Jamaica, Barbados and Antigua are fully consistent with theory, some discrepancies may be noted for the Bahamas. The partial autocorrelations at lags 2, 3, 4 and 9 are of the wrong sign, even though none is significantly different from zero, and the partial at lag 13 has the expected sign but is not significant.

None of these disparities between theory and the sample data is sufficiently serious to invalidate the use of the selected models, however. In Tables 4.8 to 4.12, which present parameter estimates for each data series, every

TABLE 4.8
ESTIMATES OF MODEL PARAMETERS, INTERCORRELATIONS OF
PARAMETER ESTIMATES, AND RESIDUAL DIAGNOSTICS FOR
BERMUDA

Series

Square Roots of Monthly U.S. Arrivals (February 1977 to January 1985), with Consecutive Differencing of Order 1, and Seasonal Differencing of Order 1 with a Span of 12.

Model

$$w_t = (1 - 0.8B)(1 - 0.1B^{12})a_t$$

Parameter Estimates:

<u>Parameter</u>	<u>Estimate</u>	<u>Standard Error</u>	<u>T Ratio</u>
MA (1)	0.675	0.081	8.35
SMA (1)	0.559	0.099	5.62

Correlation Matrix of Parameter Estimates

	MA (1)
SMA (1)	-0.01

Chi-Square Statistics for Residuals

	<u>P-Value</u>
Q(12) = 8.02	0.63
Q(24) = 20.52	0.55
Q(36) = 33.98	0.47

TABLE 4.9
ESTIMATES OF MODEL PARAMETERS, INTERCORRELATIONS OF
PARAMETER ESTIMATES, AND RESIDUAL DIAGNOSTICS FOR
THE BAHAMAS

Series

Logarithms of Monthly U.S. Arrivals (February 1977 to January 1985 Seasonal Differencing of Order 1 with a Span of 12.

Model

$$(1 - \phi B) (1 - \phi' B^{12}) w_t = a_t$$

Parameter Estimates:

<u>Parameter</u>	<u>Estimate</u>	<u>Standard Error</u>	<u>T Ratio</u>
CONSTANT	0.022	0.009	2.49
AR (1)	0.495	0.103	4.79
SAR (1)	-0.342	0.109	-3.14

Correlation Matrix of Parameter Estimates

	AR (1)	CONSTANT
CONSTANT	-0.51	
SAR (1)	-0.08	-0.02

Chi-Square Statistics for Residuals

	<u>P-Value</u>
Q(12) = 7.02	0.60
Q(24) = 22.63	0.36
Q(36) = 33.98	0.42

TABLE 4.10
ESTIMATES OF MODEL PARAMETERS, INTERCORRELATIONS OF
PARAMETER ESTIMATES, AND RESIDUAL DIAGNOSTICS FOR
JAMAICA

Series

Logarithms of Monthly U.S. Arrivals (February 1977 to January 1985, with Consecutive Differencing of Order 1, and Seasonal Differencing of Order 1 with a Span of 12.

Model

$$w_t = (1 - \theta B) (1 - \theta' B^{12}) a_t$$

Parameter Estimates:

<u>Parameter</u>	<u>Estimate</u>	<u>Standard Error</u>	<u>T Ratio</u>
MA (1)	0.303	0.107	2.82
SMA (1)	0.559	0.106	5.29

Correlation Matrix of Parameter Estimates

	MA (1)
SMA (1)	-0.15

Chi-Square Statistics for Residuals

	<u>P-Value</u>
Q(12) = 5.91	0.82
Q(24) = 12.15	0.95
Q(36) = 19.64	0.98

TABLE 4.11
ESTIMATES OF MODEL PARAMETERS, INTERCORRELATIONS OF
PARAMETER ESTIMATES, AND RESIDUAL DIAGNOSTICS FOR
BARBADOS

Series

Logarithms of Monthly U.S. Arrivals (February 1977 to January 1985, with Consecutive Differencing of Order 1, and Seasonal Differencing of Order 1 with a Span of 12.

Model

$$w_t = (1 - \theta B) (1 - \theta' B^{12}) a_t$$

Parameter Estimates:

<u>Parameter</u>	<u>Estimate</u>	<u>Standard Error</u>	<u>T Ratio</u>
MA (1)	0.272	0.108	2.51
SMA (1)	0.621	0.100	6.21

Correlation Matrix of Parameter Estimates

	MA (1)
SMA (1)	-0.20

Chi-Square Statistics for Residuals

	<u>P-Value</u>
Q(12) = 11.22	0.34
Q(24) = 26.42	0.23
Q(36) = 35.18	0.41

TABLE 4.12
ESTIMATES OF MODEL PARAMETERS, INTERCORRELATIONS OF
PARAMETER ESTIMATES, AND RESIDUAL DIAGNOSTICS FOR
ANTIGUA

Series

Square Roots of Monthly U.S. Arrivals (February 1977 to January 1985, with Consecutive Differencing of Order 1, and Seasonal Differencing of Order 1 with a Span of 12.

Model

$$w_t = (1 - \theta B)(1 - \theta' B^{12})a_t$$

Parameter Estimates:

<u>Parameter</u>	<u>Estimate</u>	<u>Standard Error</u>	<u>T Ratio</u>
MA (1)	0.325	0.109	2.98
SMA (1)	0.683	0.103	6.62

Correlation Matrix of Parameter Estimates

	MA (1)
SMA (1)	0.03

Chi-Square Statistics for Residuals

	<u>P-Value</u>
Q(12) = 3.84	0.95
Q(24) = 23.76	0.36
Q(36) = 33.41	0.50

parameter has the expected sign, and as the t-ratios indicate, all are statistically significant. Since the highest correlation coefficient between moving average parameters or between autoregressive parameters is only -0.2, it is clear that the models express the principle of parsimony. Model adequacy is verified by examination of the residuals, which should form a random "white noise" process with a mean of zero. Serial correlation in the residuals is measured by the Ljung-Box Q statistic, which has a distribution that approximates a Chi-Square variable, and the probabilities shown as p-values in each table allow a test of the null hypothesis of serial independence at the 5 percent level. For example, in Table 4.8, on the basis of residual autocorrelations for the Bermuda series for lags 1 to 36, there is a 47 percent probability that the residuals are uncorrelated. Using a smaller number of autocorrelations (such as 12 or 24), the probability of serial independence is even higher. Therefore, we cannot reject the null hypothesis of independence. This finding is repeated for every other model application.

Residual autocorrelation functions should have no values different from zero, and visual inspection of the functions for each destination (Figures 4.1 to 4.5) generally confirms this expectation. Where nonzero residual estimates are found, as at lag 24 for Bermuda (Figure 4.1), lag 24 for the Bahamas (Figure 4.2), lag 18 for Barbados

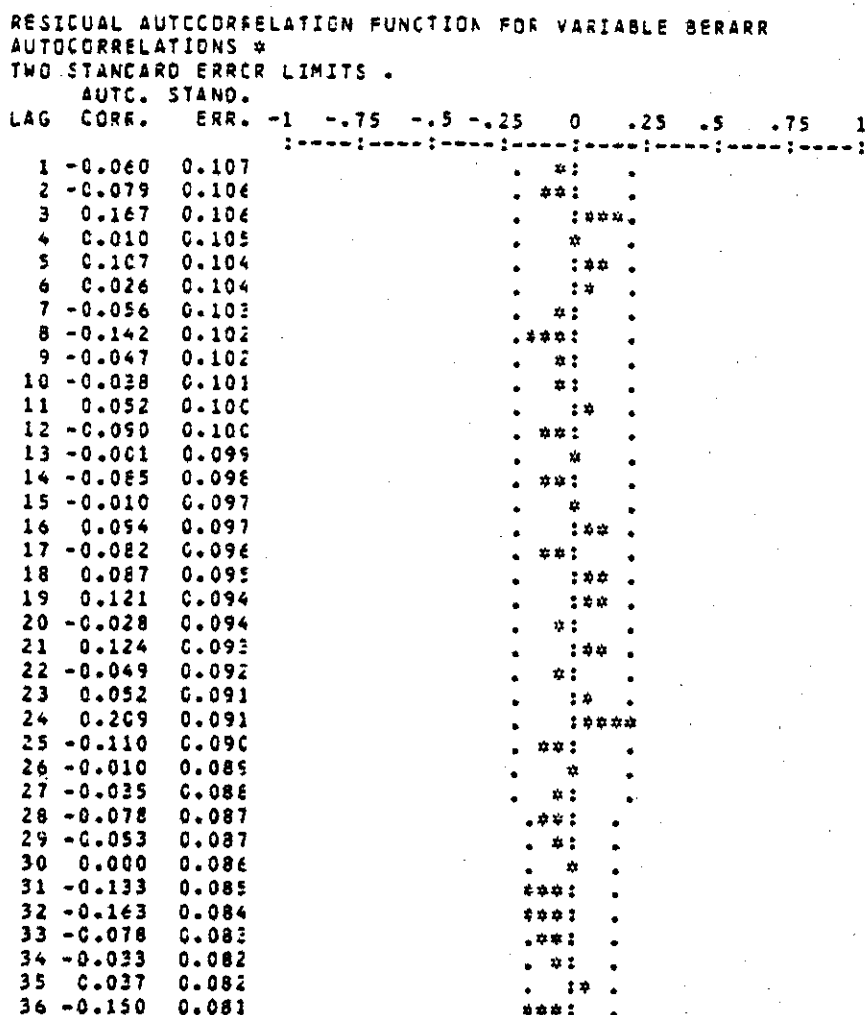


FIGURE 4.1 RESIDUAL AUTOCORRELATION FUNCTION FOR
 BERMUDA

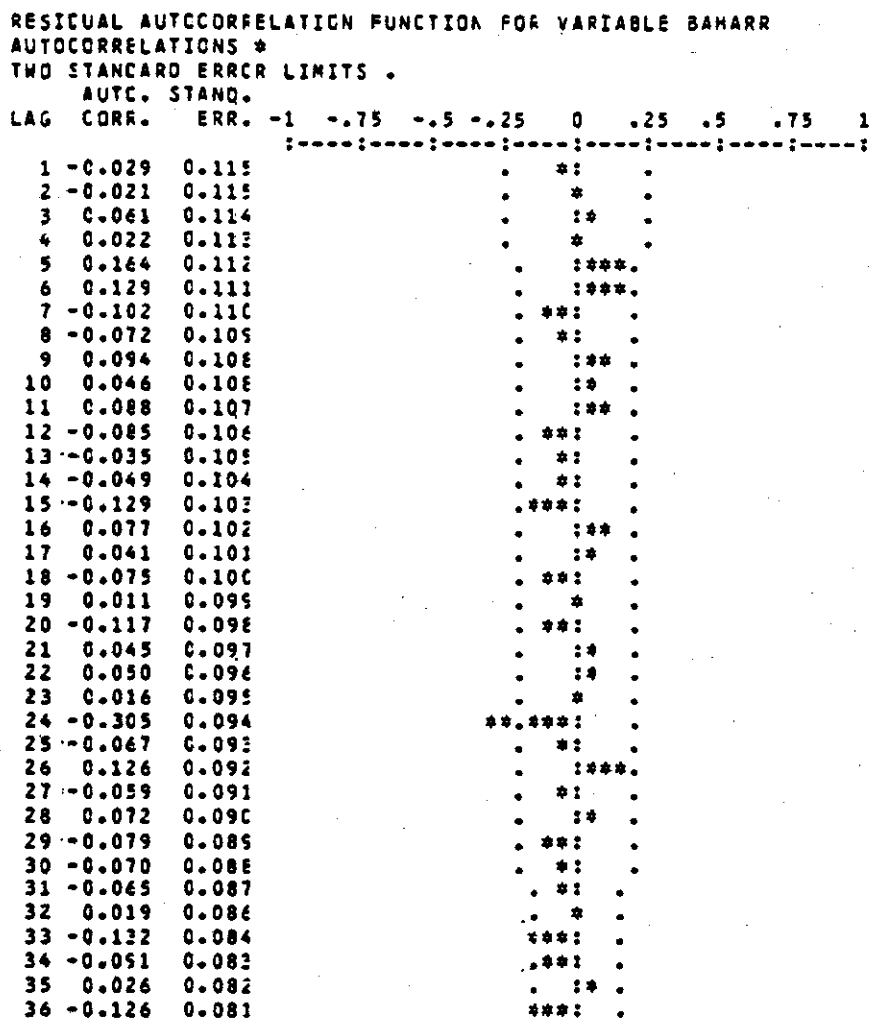


FIGURE 4.2 RESIDUAL AUTOCORRELATION FUNCTION FOR THE
 BAHAMAS

RESIDUAL AUTOCORRELATION FUNCTION FOR VARIABLE JCARR
 AUTOCORRELATIONS *

TWO STANDARD ERROR LIMITS .

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
			:-----:-----:-----:-----:-----:-----:-----:-----:-----:								
1	0.024	0.107					*				
2	-0.051	0.106					**				
3	0.045	0.106					*				
4	-0.073	0.105					*				
5	0.012	0.104					*				
6	0.038	0.104					*				
7	-0.081	0.102					**				
8	-0.061	0.102					*				
9	-0.084	0.102					**				
10	0.085	0.101					*	**			
11	0.140	0.100					*	***			
12	-0.031	0.100					*				
13	0.113	0.099					*	**			
14	-0.120	0.098					**				
15	-0.080	0.097					**				
16	0.005	0.097					*				
17	0.016	0.096					*				
18	-0.110	0.095					**				
19	-0.070	0.094					*				
20	0.008	0.094					*				
21	-0.055	0.093					*				
22	0.026	0.092					*	*			
23	0.058	0.091					*	*			
24	0.031	0.091					*	*			
25	0.163	0.090					*	***			
26	-0.010	0.089					*				
27	-0.125	0.088					**				
28	-0.019	0.087					*				
29	0.007	0.087					*				
30	0.029	0.086					*	*			
31	0.019	0.085					*				
32	-0.060	0.084					*				
33	-0.004	0.083					*				
34	-0.096	0.082					**				
35	-0.033	0.082					*				
36	-0.006	0.081					*				

FIGURE 4.3 RESIDUAL AUTOCORRELATION FUNCTION FOR
 JAMAICA

RESIDUAL AUTOCORRELATION FUNCTION FOR VARIABLE BARBARR
 AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .
 AUTOC. STAND.

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
			:-----:-----:-----:-----:-----:-----:-----:-----:-----:								
1	0.013	0.107					*				
2	-0.067	0.106					*				
3	-0.122	0.106					**				
4	-0.060	0.105					**				
5	0.013	0.104					*				
6	0.005	0.104					*				
7	0.096	0.103						**			
8	-0.175	0.102						**			
9	-0.125	0.102						**			
10	-0.021	0.101					*				
11	0.150	0.100						****			
12	0.033	0.100					*				
13	0.077	0.099						**			
14	0.020	0.098					*				
15	0.043	0.097					*				
16	0.151	0.097						****			
17	-0.067	0.096					*				
18	-0.225	0.095					****				
19	-0.150	0.094					****				
20	-0.007	0.094					*				
21	0.027	0.093						*			
22	0.066	0.092					*				
23	0.040	0.091					*				
24	-0.151	0.091					****				
25	0.015	0.090					*				
26	-0.030	0.089					*				
27	0.128	0.088						****			
28	0.020	0.087					*				
29	-0.059	0.087					*				
30	-0.153	0.086					****				
31	-0.052	0.085					*				
32	0.017	0.084					*				
33	-0.019	0.083					*				
34	-0.024	0.082					*				
35	-0.049	0.082					*				
36	0.116	0.081						***			

FIGURE 4.4 RESIDUAL AUTOCORRELATION FUNCTION FOR
 BARBADOS

RESIDUAL AUTOCORRELATION FUNCTION FOR VARIABLE ANTARR
 AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .
 AUTO. STAND.

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
			:-----:-----:-----:-----:-----:-----:-----:-----:-----:								
1	0.032	0.107									
2	-0.110	0.106									
3	-0.024	0.106									
4	0.049	0.105									
5	0.018	0.104									
6	-0.148	0.104									
7	-0.032	0.103									
8	0.027	0.102									
9	0.009	0.102									
10	0.006	0.101									
11	0.025	0.100									
12	-0.037	0.100									
13	0.082	0.095									
14	-0.072	0.095									
15	-0.125	0.097									
16	0.137	0.097									
17	0.033	0.096									
18	-0.057	0.095									
19	-0.209	0.094									
20	-0.078	0.094									
21	0.153	0.093									
22	-0.151	0.092									
23	-0.143	0.091									
24	0.077	0.091									
25	0.196	0.090									
26	0.072	0.085									
27	-0.076	0.085									
28	0.005	0.087									
29	-0.068	0.087									
30	-0.003	0.086									
31	-0.085	0.085									
32	-0.088	0.084									
33	-0.011	0.083									
34	0.037	0.082									
35	-0.049	0.082									
36	-0.049	0.081									

FIGURE 4.5 RESIDUAL AUTOCORRELATION FUNCTION FOR
 ANTIGUA

(Figure 4.4), and lags 19 and 25 for Antigua (Figure 4.5), the fitting of additional parameters is considered. In no case, however, do these additional coefficients achieve statistical significance. As a result, the original model structures are retained for forecasting.

4.3.2 The Forecasting Process

In addition to the 96 observations used in each destination series for estimating the various models, some 35 observations covering the period February 1985 to December 1987 are used to test the accuracy of model forecasts over various time horizons in the same period. The forecasts are shown alongside actual observations in Tables 4.13 to 4.17. For Bermuda (Table 4.13), the moving average model tends to overestimate the number of monthly arrivals, but error percentages for forecasts cover a considerable range, from two-fifths of one percent (for June, 1986) to just over 54 percent (for April, 1986). Forecasts for the Bahamas (Table 4.14) are more accurate, and the errors vary from one-fifth of one percent (August, 1986) to 14.8 percent (March, 1985). The forecasts for Jamaica (Table 4.15) and Barbados (Table 4.16) also tend to overestimate actual arrivals, and in the latter case all forecast errors are positive. For Antigua, there is the opposite problem that most forecasts are too low, and 23 of the 35 monthly predictions are underestimates.

TABLE 4.13
ACTUAL AND PREDICTED MONTHLY
U.S. ARRIVALS IN BERMUDA

Period	U.S. ARRIVALS		
	Actual	Forecast	Percent Error
1985:			
February	14,192	14,342	1.1
March	31,124	31,581	1.5
April	31,485	37,305	18.5
May	42,740	40,542	-5.1
June	42,590	42,287	-0.7
July	39,410	37,887	-3.9
August	45,982	39,604	-13.9
September	35,264	36,534	3.6
October	35,012	37,464	7.0
November	25,919	26,217	1.1
December	18,414	16,652	-9.6
1986:			
January	11,430	11,732	2.6
February	17,360	14,479	-16.6
March	23,239	31,748	36.8
April	24,337	37,526	54.2
May	36,024	40,773	13.2
June	42,353	42,523	0.4
July	39,015	38,110	-2.3
August	41,503	39,832	-4.0
September	33,194	36,753	10.7
October	27,562	37,685	36.7
November	21,712	26,402	21.6
December	14,269	16,800	17.7
1987:			
January	11,211	11,856	5.8
February	13,760	14,617	6.2
March	22,449	31,988	42.5
April	32,355	37,748	16.7
May	35,578	41,004	15.3
June	32,026	42,759	33.5
July	36,088	38,333	6.2
August	42,760	40,060	-6.3
September	34,561	36,973	7.0
October	28,142	37,908	34.7
November	19,967	26,588	33.2
December	13,861	16,948	22.3

TABLE 4.14
ACTUAL AND PREDICTED MONTHLY
U.S. ARRIVALS IN THE BAHAMAS

Period	U.S. ARRIVALS		
	Actual	Forecast	Percent Error
1985:			
February	70,570	77,035	9.2
March	110,297	94,022	-14.8
April	93,164	82,411	-11.5
May	84,714	72,844	-14.0
June	82,304	70,468	-14.4
July	83,300	86,252	3.5
August	92,268	82,554	-10.5
September	49,070	52,721	7.4
October	57,859	56,272	-2.7
November	74,105	72,116	-2.7
December	73,759	69,630	-5.6
1986:			
January	69,833	68,641	-1.7
February	85,023	79,888	-6.0
March	104,866	99,638	-5.0
April	81,130	86,476	6.6
May	85,373	77,237	-9.5
June	71,250	74,402	4.4
July	83,012	89,103	7.3
August	86,463	86,282	-0.2
September	53,952	54,676	1.3
October	58,122	58,450	0.6
November	81,921	76,356	-6.8
December	77,984	72,492	-7.0
1987:			
January	77,046	71,899	-6.7
February	82,753	83,626	1.1
March	106,596	103,530	-2.9
April	92,440	90,158	-2.5
May	76,211	80,240	5.3
June	79,893	77,407	-3.1
July	86,205	93,396	8.3
August	94,420	90,079	-4.6
September	62,065	57,234	-7.8
October	71,474	61,151	-14.4
November	70,227	79,363	13.0
December	75,247	75,782	0.7

TABLE 4.15
ACTUAL AND PREDICTED MONTHLY
U.S. ARRIVALS IN JAMAICA

Period	U.S. ARRIVALS		
	Actual	Forecast	Percent Error
1985:			
February	37,266	47,356	27.1
March	41,171	46,815	13.7
April	36,809	42,190	14.6
May	34,085	35,600	4.4
June	41,833	46,678	11.6
July	47,393	58,819	24.1
August	48,981	54,248	10.8
September	29,816	33,356	11.9
October	29,260	34,581	18.2
November	37,651	49,085	30.4
December	53,617	58,700	9.5
1986:			
January	42,609	44,154	3.6
February	48,074	53,660	11.6
March	58,367	53,046	-9.1
April	47,625	47,806	0.4
May	45,143	40,339	-10.6
June	45,043	52,891	17.4
July	57,570	66,648	15.8
August	62,660	61,470	-1.9
September	36,272	37,796	4.2
October	35,906	39,184	9.1
November	52,768	55,619	5.4
December	64,765	66,514	2.7
1987:			
January	55,606	50,031	-10.0
February	55,385	60,803	9.8
March	68,122	60,107	-11.8
April	59,471	54,170	-8.9
May	48,398	45,708	-5.6
June	51,944	59,932	15.4
July	59,423	75,520	27.1
August	67,169	69,652	3.7
September	42,239	42,828	1.4
October	44,360	44,400	0.1
November	47,734	63,023	32.0
December	62,024	75,368	21.5

TABLE 4.16
ACTUAL AND PREDICTED MONTHLY
U.S. ARRIVALS IN BARBADOS

Period	U.S. ARRIVALS		
	Actual	Forecast	Percent Error
1985:			
February	16,676	20,820	24.9
March	16,518	17,949	8.7
April	14,227	16,803	18.1
May	10,744	13,923	29.6
June	11,731	15,492	32.1
July	14,884	20,596	38.4
August	15,259	20,495	34.3
September	7,976	11,121	39.4
October	8,858	14,150	59.7
November	13,049	18,843	44.4
December	17,552	20,158	14.8
1986:			
January	18,282	20,039	9.6
February	18,275	26,231	43.5
March	18,307	22,614	23.5
April	14,573	21,169	45.3
May	12,739	17,541	37.7
June	10,818	19,518	80.4
July	14,927	25,948	73.8
August	14,831	25,821	74.1
September	9,229	14,011	51.8
October	10,730	17,827	66.1
November	13,436	23,740	76.7
December	15,461	25,397	64.3
1987:			
January	16,077	25,247	57.0
February	17,065	33,047	93.7
March	19,450	28,491	46.5
April	16,697	26,671	59.7
May	12,701	22,099	74.0
June	13,176	24,591	86.6
July	19,055	32,691	71.6
August	15,765	32,532	106.4
September	9,927	17,652	77.8
October	12,382	22,460	81.4
November	13,434	29,910	122.6
December	17,874	31,996	79.0

TABLE 4.17
ACTUAL AND PREDICTED MONTHLY
U.S. ARRIVALS IN ANTIGUA

Period	U.S. ARRIVALS		
	Actual	Forecast	Percent Error
1985:			
February	6,158	7,757	26.0
March	7,203	6,963	-3.3
April	5,314	5,804	9.2
May	4,555	4,285	-5.9
June	5,156	4,527	-12.2
July	5,050	6,430	27.3
August	4,693	4,765	1.5
September	2,859	3,613	26.4
October	4,422	4,600	4.0
November	6,018	6,290	4.5
December	9,502	6,154	-35.2
1986:			
January	8,943	6,770	-24.3
February	11,180	8,069	-27.8
March	10,617	7,259	-31.6
April	8,441	6,074	-28.0
May	6,170	4,518	-26.8
June	5,775	4,767	-17.5
July	8,215	6,818	-17.0
August	7,507	5,011	-33.2
September	3,221	3,827	18.8
October	4,779	4,841	1.3
November	6,112	6,572	7.5
December	9,720	6,433	-33.8
1987:			
January	11,778	7,062	-40.0
February	12,872	8,388	-34.8
March	11,124	7,562	-32.0
April	10,610	6,351	-40.1
May	7,298	4,757	-34.8
June	5,766	5,012	-13.1
July	10,228	7,112	-30.5
August	8,939	5,263	-41.1
September	4,713	4,048	-14.1
October	4,785	5,089	6.4
November	5,804	6,860	18.2
December	7,596	6,718	-11.6

If the monthly forecasts are grouped by year (Table 4.18), absolute forecast errors average 10.4 percent in 1985, 18.2 percent in 1986, and 25.8 percent in 1987. There is therefore a measurable tendency for predictions to become less accurate as the forecast horizon lengthens. This appears to reflect the difficulty of prediction for destinations like Barbados and Antigua, where the tourist industry is still relatively young, and growth rates vary considerably from year to year. In the Bahamas, on the other hand, tourism has the low-growth profile of a mature industry, and the shorter term forecasts are actually less accurate than the longer term predictions.

TABLE 4.18
ACTUAL AND PREDICTED U.S. ARRIVALS
IN FIVE DESTINATION AREAS, 1985-1987

<u>U.S. Arrivals (1985)*</u>			
Destination	Actual	Forecast	Percent Error
Bermuda	362,132	360,415	-0.5
The Bahamas	871,410	816,325	-6.3
Jamaica	437,882	507,428	15.9
Barbados	147,474	190,350	29.1
Antigua	60,930	61,188	0.4
		MAPE**	10.4
<u>U.S. Arrivals (1986)</u>			
	Actual	Forecast	Percent Error
Bermuda	331,998	374,399	12.8
The Bahamas	938,929	923,641	-1.6
Jamaica	596,802	619,127	3.7
Barbados	171,608	259,856	51.4
Antigua	90,680	70,959	-21.7
		MAPE	18.2
<u>U.S. Arrivals (1987)</u>			
	Actual	Forecast	Percent Error
Bermuda	322,758	376,782	16.7
The Bahamas	974,577	963,865	-1.1
Jamaica	661,875	701,542	6.0
Barbados	183,603	327,387	78.3
Antigua	101,513	74,222	-26.9
		MAPE	25.8

*Data and calculations for 1985 cover an eleven month period from February to December.

**Denotes mean absolute percentage error.

5. CONCLUSION

This study has demonstrated the application of a comprehensive array of forecasting techniques to the problem of predicting U.S. tourism demand at selected Caribbean and Atlantic destinations. An evaluation of the results of this exercise can be attempted by considering Table 5.1, which presents a comparison of forecast errors for 1983-1985 generated by the regression and smoothing models, and the errors that would occur from the use of a "naive" forecast, in which observed tourism expenditures during 1982 (the forecast origin) are used to predict demand in each of the three years in the forecasting period of 1983-1985.

In the case of the Other British West Indies, most models improve on the naive forecast, but for Bermuda, only the piecewise regression model performs better, and for the Bahamas, only the exponential smoothing model is superior. For Jamaica, none of the models performs as well as the naive forecast.

More consistently superior results are achieved with the forecasting of tourism arrivals between 1985 and 1987 using the Box-Jenkins technique. For annual arrivals (see Table 5.2), the technique performs substantially better than the naive forecast for the Bahamas and Jamaica, and only in the case of Barbados is it clearly outperformed by the naive forecast.

TABLE 5.1
A COMPARISON OF FORECAST ERRORS
FOR TOURIST EXPENDITURES, 1983-1985

	Naive Forecast	Model II Reduced Form	Time Trend	Piecewise Regression	Linear Moving Average	Exponential Smoothing
Bermuda:						
1983	18.0	13.6	24.9	13.0	17.8	18.0
1984	14.5	22.3	24.7	11.1	17.3	17.5
1985	<u>3.2</u>	<u>15.0</u>	<u>15.6</u>	<u>1.4</u>	<u>8.4</u>	<u>8.6</u>
MAPE*	11.9	17.0	21.7	8.5	14.5	14.7
The Bahamas:						
1983	-3.5	N.A	N.A	-9.2	-9.5	-4.5
1984	-6.5	N.A	N.A	-9.4	-9.6	-3.4
1985	<u>-8.9</u>	<u>N.A</u>	<u>N.A</u>	<u>-9.2</u>	<u>-9.2</u>	<u>-1.8</u>
MAPE	6.3			9.3	9.4	3.2
Jamaica:						
1983	-12.0	N.A	-22.4	-24.1	-23.5	-20.5
1984	-10.6	N.A	-24.9	-26.2	-24.7	-21.7
1985	<u>-8.6</u>	<u>N.A</u>	<u>-26.8</u>	<u>-27.8</u>	<u>-25.4</u>	<u>-22.4</u>
MAPE	10.4		24.7	26.0	24.5	21.5
Other British West Indies:						
1983	-10.2	19.0	29.9	12.3	0.9	-3.5
1984	-49.1	-18.6	-23.4	-35.2	-44.5	-47.2
1985	<u>-45.0</u>	<u>-5.1</u>	<u>-14.1</u>	<u>-28.7</u>	<u>-41.9</u>	<u>-44.9</u>
MAPE	34.8	14.2	22.5	25.4	29.1	31.9

*Denotes mean absolute percentage error.

TABLE 5.2
A COMPARISON OF FORECAST ERRORS
FOR TOURIST ARRIVALS, 1985-1987

	Naive Forecast	Box-Jenkins Forecast
Bermuda:		
1985	-1.1	-0.5
1986	11.6	12.8
1987	<u>14.8</u>	<u>16.7</u>
MAPE*	9.2	10.0
 The Bahamas:		
1985	-9.5	-6.3
1986	-9.4	-1.6
1987	<u>-12.7</u>	<u>-1.1</u>
MAPE	10.5	3.0
 Jamaica:		
1985	6.9	15.9
1986	-15.6	3.7
1987	<u>-28.2</u>	<u>6.0</u>
MAPE	16.9	8.5
 Barbados:		
1985	3.8	29.1
1986	-4.4	51.4
1987	<u>-10.7</u>	<u>78.9</u>
MAPE	6.3	53.1
 Antigua:		
1985	30.5	0.4
1986	-1.8	-21.7
1987	<u>-12.3</u>	<u>-26.9</u>
MAPE	14.9	16.3

*Denotes mean absolute percentage error.

5.1 Limitations of the Study

These findings support the conclusion that, if selected predictor variables can be correctly forecast, or if stability can be assumed in existing demand conditions, it should be possible to make reasonably accurate one- to three-year forecasts of tourism demand from available data. It is important, however, to recognize some of the basic shortcomings of this study. The accuracy of the data sets that have been used cannot be ascertained with great precision, and the substitution of consumer price indexes for tourist prices may have introduced measurement error into the price variables. Moreover, the regression models of Chapters 3 and 4 are estimated from only 15 observations in each case. Partly because of the limited data available for model calibration, only income and price variables have been utilized as predictors in the causal models (Chapter 3). As a consequence, the resulting forecasting structures are highly simplified, and there can be no assurance that the model coefficients specified will remain substantially unchanged beyond the 1983-1985 forecasting period.

Given the assumptions made in model construction, and the failure of any of the price variables to achieve statistical significance, short-run changes in tourism demand have been linked to predictors, such as income in the tourist-generating country, or past random demand "shocks", that are beyond the control of policymakers at the

destination. Most of the prediction equations, therefore, cannot function as devices for actively manipulating tourism demand, and their main value lies in the signals they provide to planners and policymakers about the desirability of making upward or downward adjustments in the resources that are made available to the tourist sector.

5.2 Directions for Future Research

An important challenge facing researchers is to develop and apply demand models that abandon some of the restrictive assumptions that are presently adopted. If the assumption of constant consumer tastes is relaxed, for example, advertising effort, the attractiveness of a destination's image to particular groups in the tourist population, the specific mix and quality of destination services, and the destination choices supported or promoted by tour operators and travel agencies become important factors accounting for variations in tourism demand. While there has been some basic research on these factors for many years (see Hunt, 1975; Goodrich, 1977), incorporating them into causal models still poses difficult data problems, since the periodic measurements required do not now exist, and in most cases would be expensive to make. The most easily measured of these factors is advertising expenditures, but published estimates of these outlays are available for only a few years and a few destinations, and

grossly underestimate actual values, because only a fraction of the advertising media is surveyed. Even if this deficiency could be overcome, the need for comparable time series of other independent variables is not as easily satisfied. There is no single approach to the measurement of the quality of tourist services or the attractiveness of destination images, for example, but even if a single method were consistently used in each case, it would likely be of such complexity as to make its regular application infeasible for less developed destinations.

Another potentially fruitful research direction involves narrowing the focus of prediction equations to particular demographic or behavioural groups. In planning the provision of tourist services, especially hotel and recreational facilities, there is much to be gained by anticipating demand variations for particular life-cycle, income or life-style segments of the tourist population, rather than, or in addition to, forecasting the demand behaviour of nationality groups in the aggregate. As with the application of causal models with less restrictive assumptions, however, this is a forecasting refinement which requires the kind of data base that is now not usually available for most destinations.

APPENDIX A
DATA AND DIAGNOSTIC AIDS
FOR REGRESSION MODELS

TABLE A.1
U.S. TOURIST EXPENDITURES AT
FOUR DESTINATION AREAS, 1968-1985

	Destination Areas			
	BERMUDA	THE BAHAMAS	JAMAICA	OTHER BRITISH WEST INDIES
(Expenditures in Millions of Current U.S. Dollars)				
1968	50	105	78	38
1969	56	132	85	42
1970	63	127	95	44
1971	62	120	90	56
1972	69	144	105	60
1973	80	136	109	95
1974	110	151	122	87
1975	118	161	118	103
1976	133	168	109	125
1977	123	158	100	144
1978	136	198	118	153
1979	164	224	122	190
1980	191	262	118	189
1981	192	243	127	252
1982	230	340	153	188
1983	203	367	181	218
1984	217	393	185	399
1985	249	417	187	382

Source: U.S. Department of Commerce, Survey of Current Business, various issues.

TABLE A.2
U.S. PERSONAL DISPOSABLE
PER CAPITA, 1968-1985

YEAR	Per Capita Disposable Income (U.S. Dollars)
1968	3,037
1969	3,239
1970	3,489
1971	3,740
1972	4,000
1973	4,481
1974	4,855
1975	5,291
1976	5,744
1977	6,262
1978	6,968
1979	7,682
1980	8,421
1981	9,243
1982	9,725
1983	10,340
1984	11,257
1985	11,872

Source: U.S. Department of Commerce, Survey of Current Business,
various issues.

TABLE A.3
IMPLICIT PRICE DEFLATOR
U.S. PERSONAL CONSUMPTION EXPENDITURES

YEAR	U.S. Implicit Price Deflator
1968	0.39299
1969	0.41047
1970	0.42894
1971	0.44941
1972	0.46718
1973	0.49558
1974	0.54754
1975	0.59157
1976	0.62605
1977	0.66752
1978	0.71577
1979	0.78156
1980	0.86618
1981	0.94616
1982	1.00000
1983	1.04129
1984	1.08043
1985	1.11768

Source: U.S Department of Commerce, Survey of Current Business, various issues.

TABLE A.4
EXCHANGE RATE INDEXES
FOR FOUR DESTINATION AREAS
1968-1985

Destination Areas			
YEAR	THE BAHAMAS	JAMAICA	OTHER BRITISH WEST INDIES
1968	102.0	23.4	99.4
1969	102.0	46.8	99.4
1970	100.2	46.8	99.4
1971	100.0	46.1	98.2
1972	100.0	44.9	95.5
1973	100.0	51.0	97.4
1974	100.0	51.0	102.1
1975	100.0	51.0	100.4
1976	100.0	51.0	99.6
1977	100.0	51.0	99.8
1978	100.0	80.6	100.0
1979	100.0	99.2	100.0
1980	100.0	100.0	100.0
1981	100.0	100.0	100.0
1982	100.0	100.0	100.0
1983	100.0	108.5	100.0
1984	100.0	221.3	100.0
1985	100.0	312.0	100.0

Source: Calculated by the author. Exchange rate index (I_t) is calculated as:

$$I_t = \frac{\text{Exchange rate}_t}{\text{Exchange rate}_{1982}}$$

Exchange rates are taken from: International Monetary Fund, International Financial Statistics, various issues.

TABLE A.5
UNADJUSTED CONSUMER PRICE INDEXES
FOR THREE DESTINATION AREAS, 1968-1985

Destination Areas			
YEAR	THE BAHAMAS	JAMAICA	OTHER BRITISH WEST INDIES
1968	35.8	13.5	18.6
1969	39.0	14.4	19.7
1970	41.4	15.8	21.1
1971	43.3	16.8	22.7
1972	46.3	17.6	24.3
1973	48.8	21.1	28.4
1974	55.2	26.2	39.4
1975	60.8	30.8	47.5
1976	63.4	33.8	49.8
1977	65.4	37.7	54.0
1980	84.9	83.3	79.1
1981	94.3	93.8	90.7
1982	100.0	100.0	100.0
1983	104.1	111.6	105.2
1984	108.1	142.6	110.1
1985	113.1	179.3	114.5

Source: International Monetary Fund, International Financial Statistics, various issues.

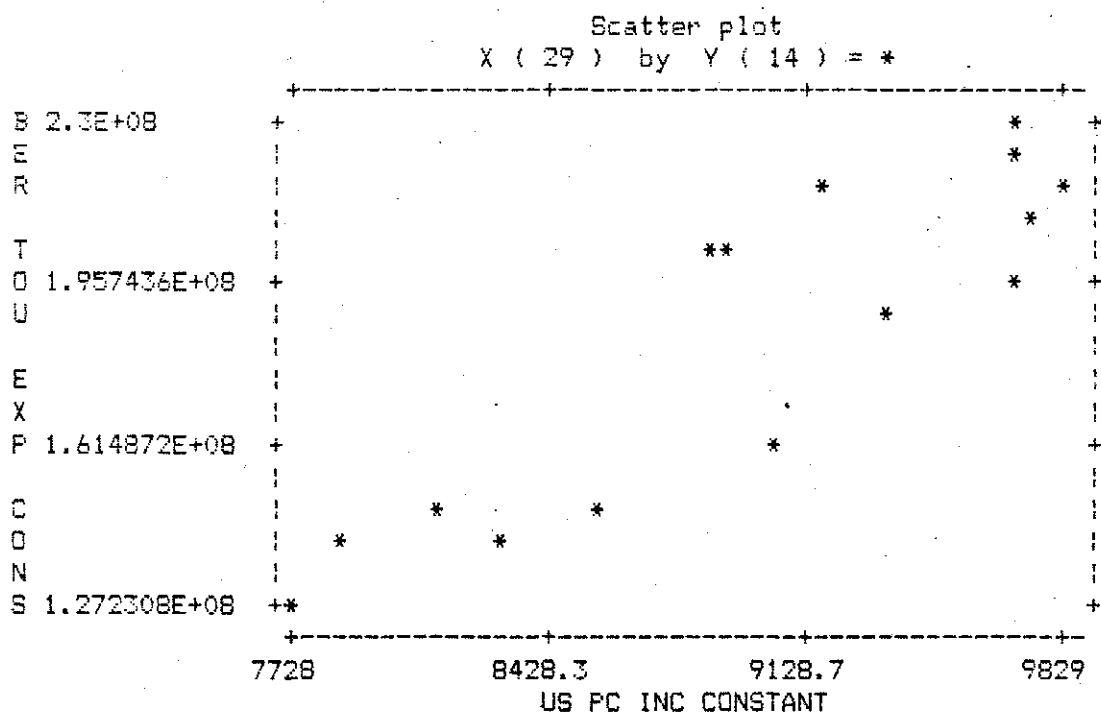
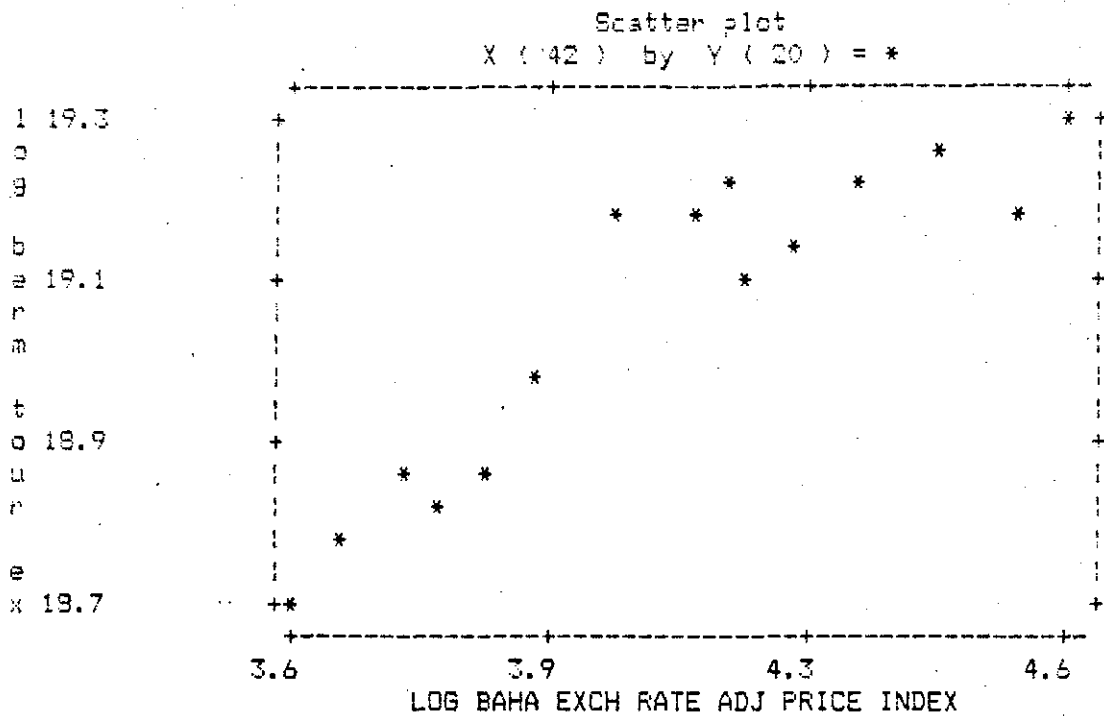


FIGURE A.1 SCATTER PLOT OF U.S. TOURIST EXPENDITURES
IN BERMUDA ON U.S. PERSONAL DISPOSABLE
INCOME PER CAPITA, 1968-1982.



**FIGURE A.2 SCATTER PLOT OF U.S. TOURIST EXPENDITURES
IN BERMUDA ON AN EXCHANGE RATE ADJUSTED
PRICE INDEX FOR THE BAHAMAS, 1968-1982**

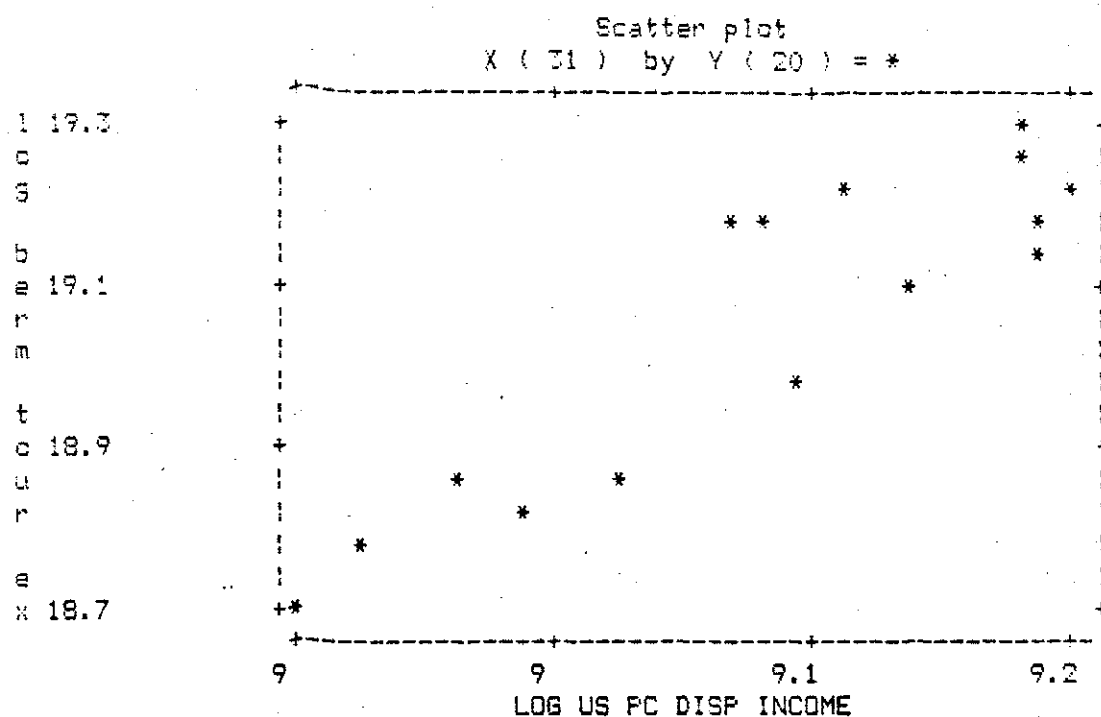


FIGURE A.3 SCATTER PLOT OF LOGARITHMS OF U.S. TOURIST EXPENDITURES IN BERMUDA ON LOGARITHMS OF U.S. PERSONAL DISPOSABLE INCOME PER CAPITA, 1968-1982.

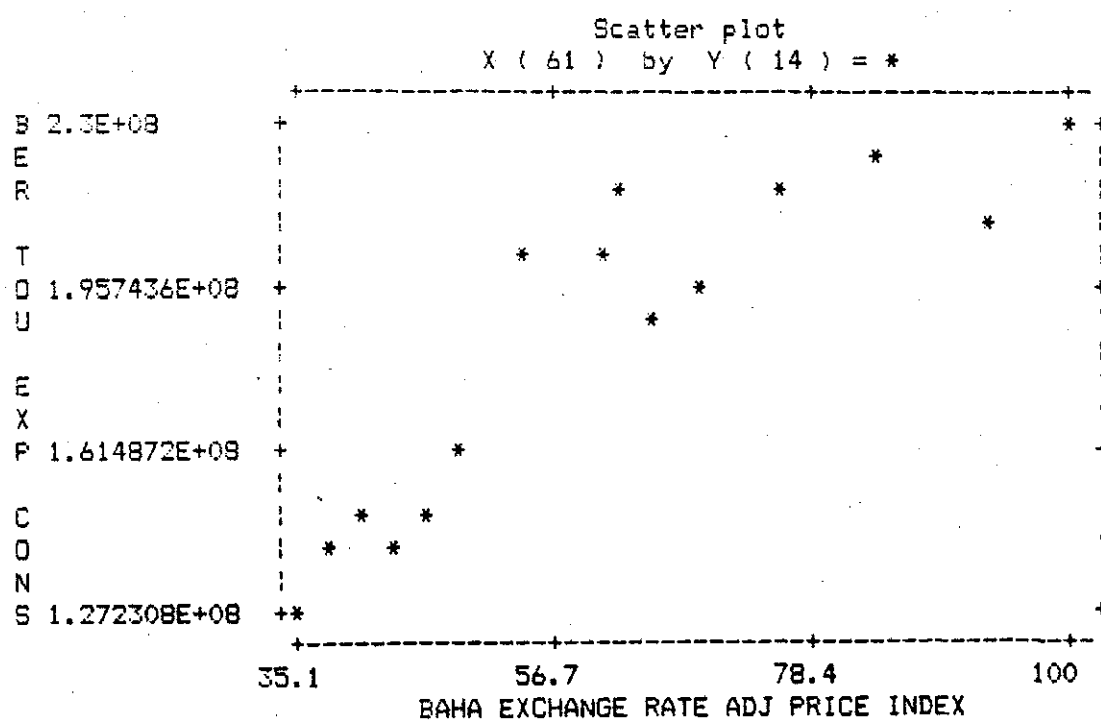


FIGURE A.4 SCATTER PLOT OF LOGARITHMS OF U.S. TOURIST EXPENDITURES IN BERMUDA ON LOGARITHMS OF AN EXCHANGE RATE ADJUSTED PRICE INDEX FOR THE BAHAMAS, 1968-1982.

APPENDIX B
DATA AND DIAGNOSTIC AIDS
FOR BOX-JENKINS MODELS

GRAPHIC DISPLAY OF SERIES FOR VARIABLE BERARR

DATA - *

MEAN - .

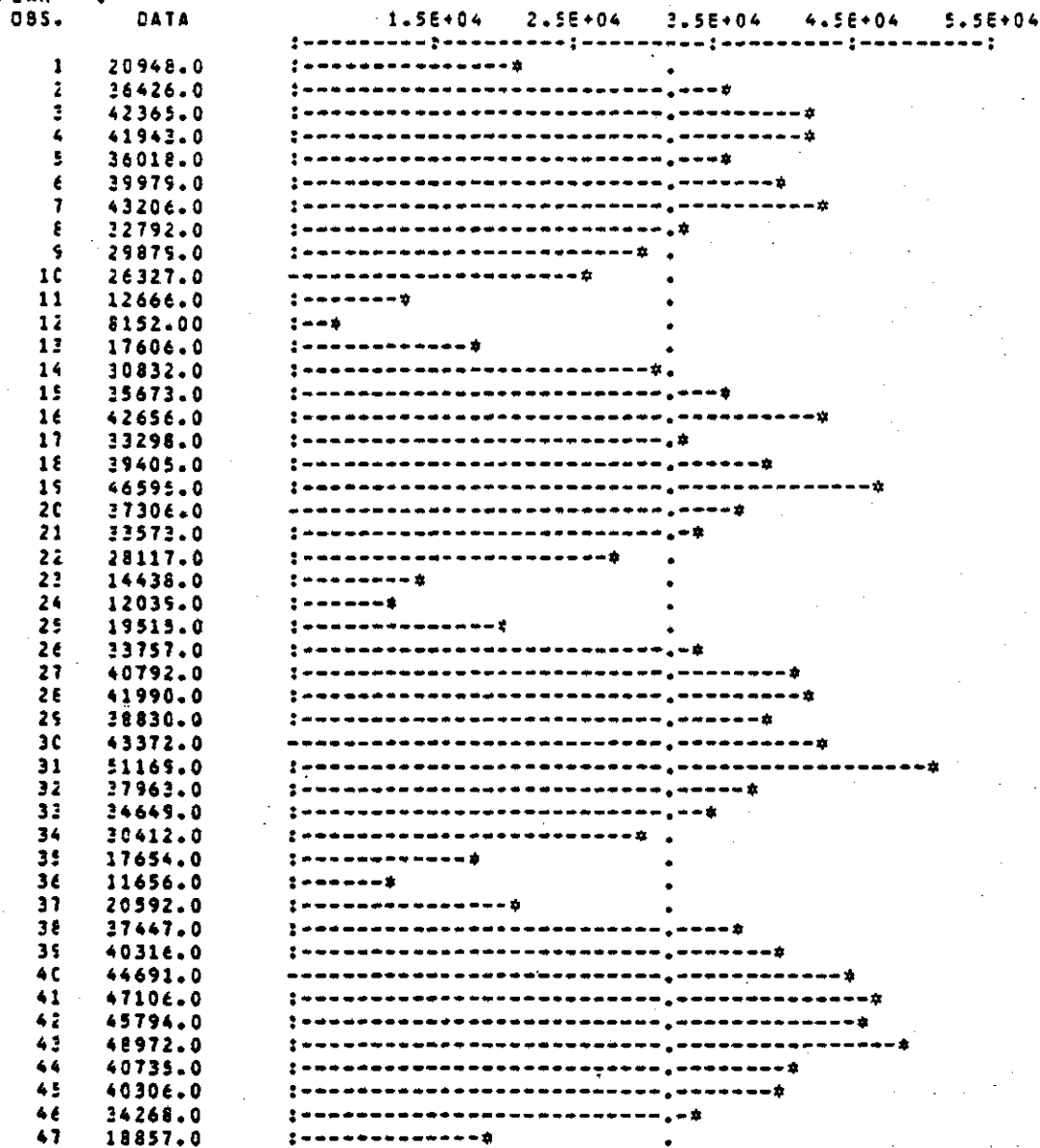


FIGURE B.1 UNADJUSTED MONTHLY U.S. ARRIVALS IN
BERMUDA, FEBRUARY 1977-JANUARY 1985

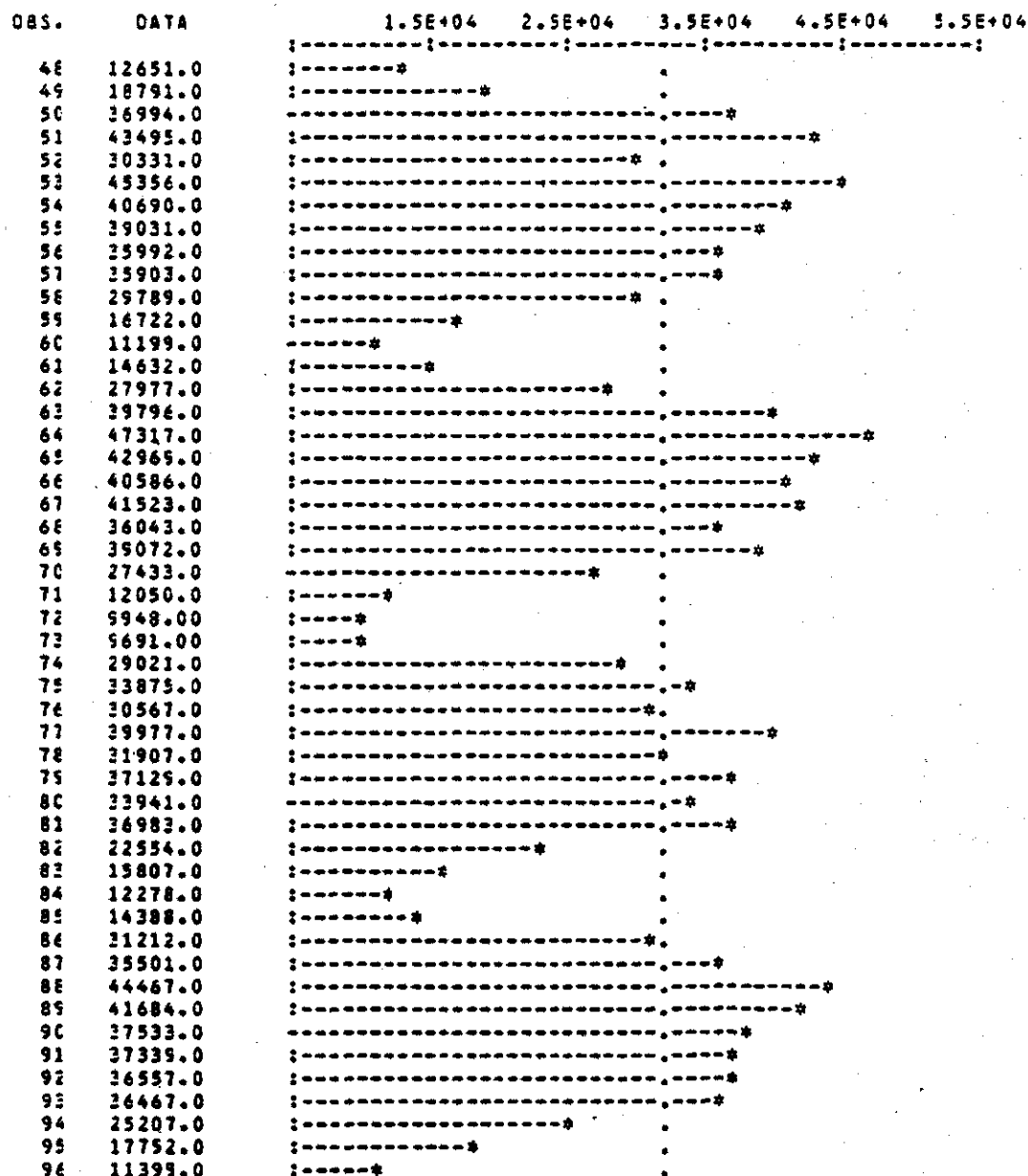


FIGURE B.1 UNADJUSTED MONTHLY U.S. ARRIVALS IN
(contd.) BERMUDA, FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF SERIES FOR VARIABLE BAHARR

DATA - *

MEAN - .

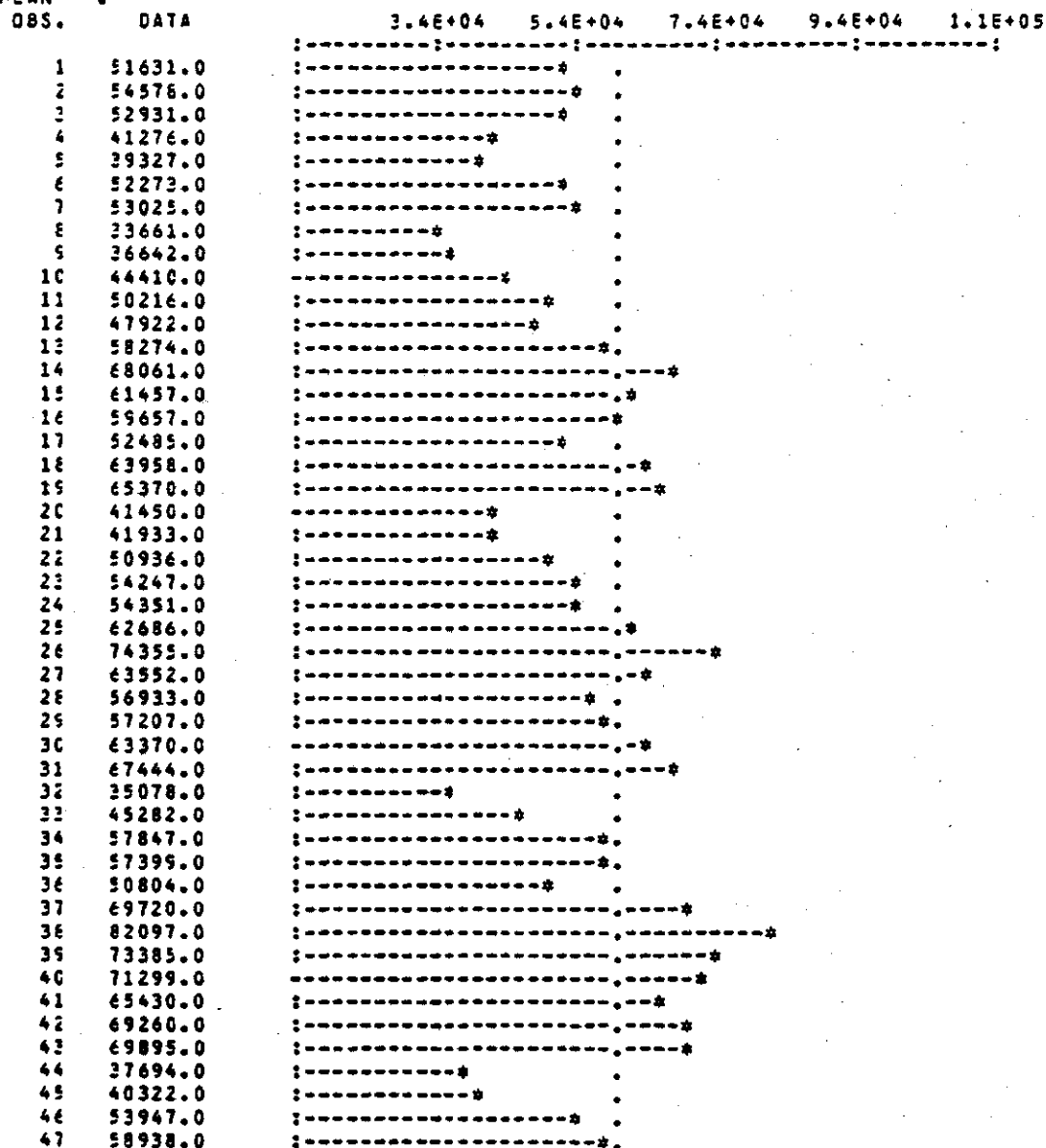


FIGURE B.2 UNADJUSTED MONTHLY U.S. ARRIVALS IN
THE BAHAMAS, FEBRUARY 1977-JANUARY 1985

OBS.	DATA	3.4E+04	5.4E+04	7.4E+04	9.4E+04	1.1E+05
48	52647.0	:	:	:	:	:
49	60776.0	:	:	:	:	:
50	74132.0	:	:	:	:	:
51	63491.0	:	:	:	:	:
52	68583.0	:	:	:	:	:
53	56897.0	:	:	:	:	:
54	59745.0	:	:	:	:	:
55	57510.0	:	:	:	:	:
56	37064.0	:	:	:	:	:
57	42172.0	:	:	:	:	:
58	51376.0	:	:	:	:	:
59	56297.0	:	:	:	:	:
60	52201.0	:	:	:	:	:
61	67748.0	:	:	:	:	:
62	80803.0	:	:	:	:	:
63	77126.0	:	:	:	:	:
64	66103.0	:	:	:	:	:
65	57964.0	:	:	:	:	:
66	70867.0	:	:	:	:	:
67	67058.0	:	:	:	:	:
68	47041.0	:	:	:	:	:
69	53112.0	:	:	:	:	:
70	58388.0	:	:	:	:	:
71	51449.0	:	:	:	:	:
72	54310.0	:	:	:	:	:
73	67775.0	:	:	:	:	:
74	76289.0	:	:	:	:	:
75	72120.0	:	:	:	:	:
76	60725.0	:	:	:	:	:
77	60457.0	:	:	:	:	:
78	83847.0	:	:	:	:	:
79	75260.0	:	:	:	:	:
80	50237.0	:	:	:	:	:
81	53163.0	:	:	:	:	:
82	61192.0	:	:	:	:	:
83	64955.0	:	:	:	:	:
84	61879.0	:	:	:	:	:
85	72276.0	:	:	:	:	:
86	53977.0	:	:	:	:	:
87	80029.0	:	:	:	:	:
88	72926.0	:	:	:	:	:
89	69680.0	:	:	:	:	:
90	80022.0	:	:	:	:	:
91	79243.0	:	:	:	:	:
92	49471.0	:	:	:	:	:
93	53046.0	:	:	:	:	:
94	71896.0	:	:	:	:	:
95	66081.0	:	:	:	:	:
96	66313.0	:	:	:	:	:

FIGURE B.2 UNADJUSTED MONTHLY U.S. ARRIVALS IN
(contd.) THE BAHAMAS, FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF SERIES FOR VARIABLE JCARR

DATA - *

MEAN - .

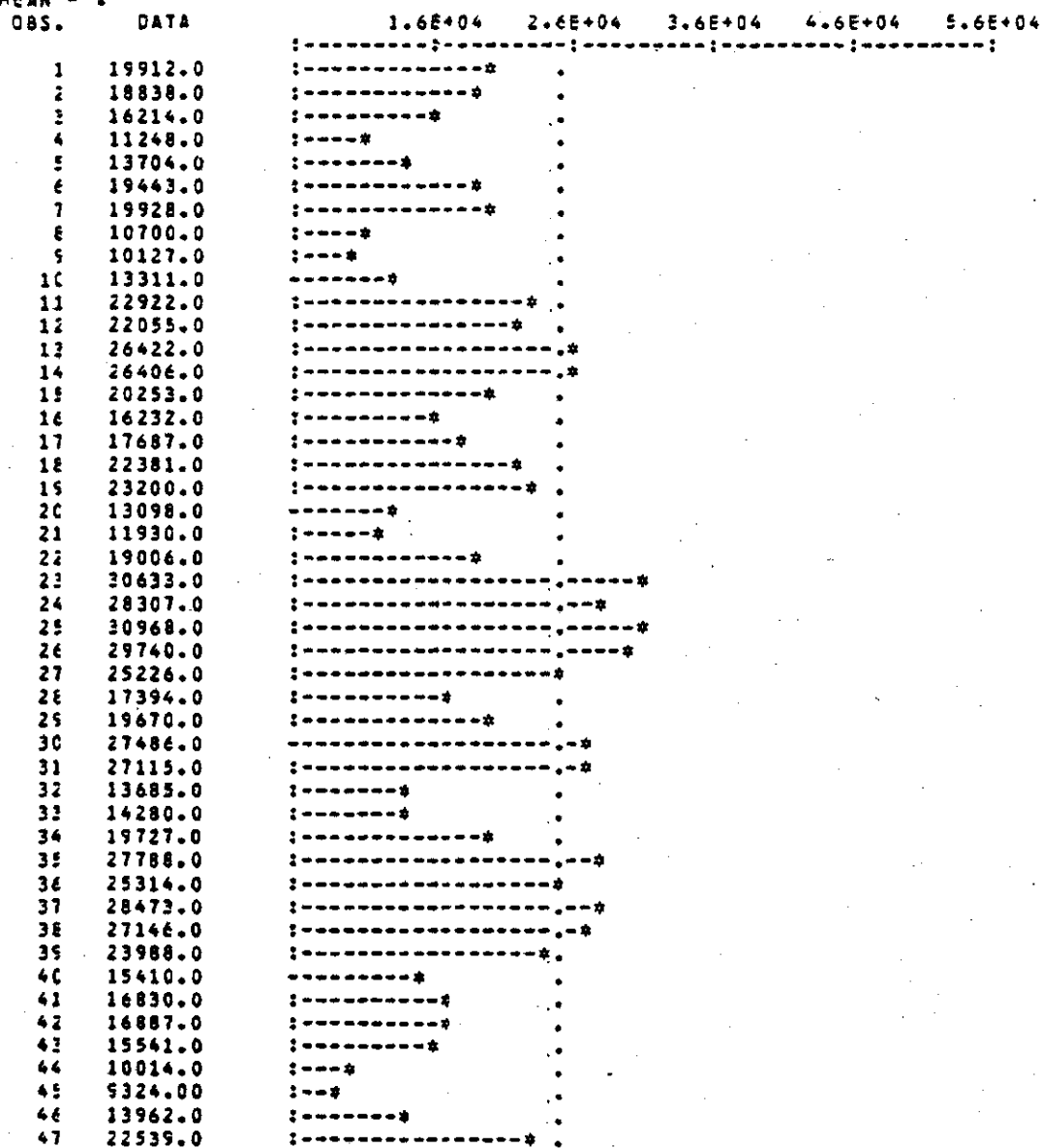


FIGURE B.3 UNADJUSTED MONTHLY U.S. ARRIVALS IN
JAMAICA, FEBRUARY 1977-JANUARY 1985

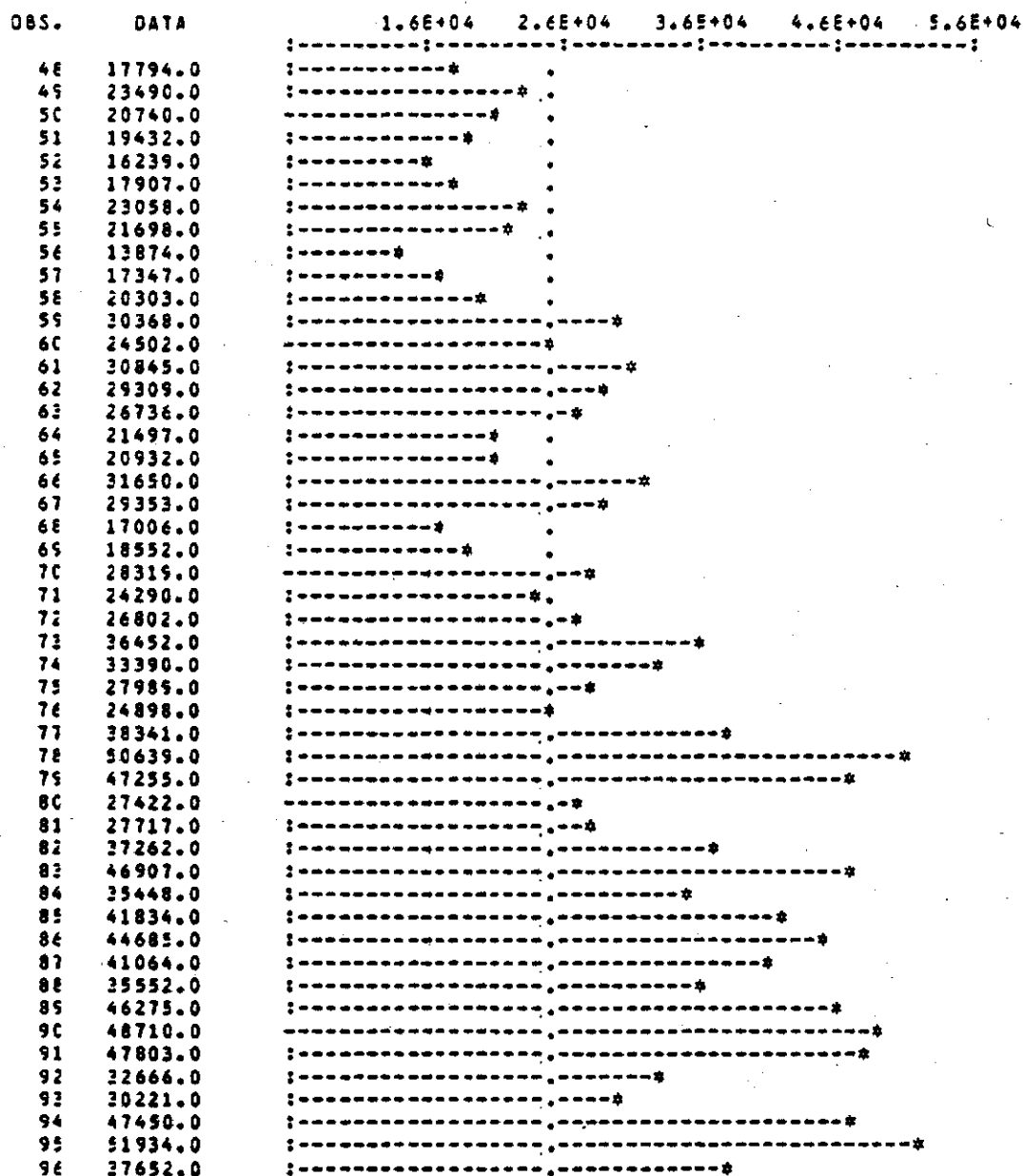


FIGURE B.3 UNADJUSTED U.S. MONTHLY ARRIVALS IN
(contd.) JAMAICA, FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF SERIES FOR VARIABLE BARBARR

DATA - *

MEAN - .

OBS.	DATA	3.0E+03	8.0E+03	1.3E+04	1.8E+04	2.3E+04
1	8146.00	:	:	:	:	:
2	7069.00	:	:	:	:	:
3	5792.00	:	:	:	:	:
4	4253.00	:	:	:	:	:
5	4053.00	:	:	:	:	:
6	5021.00	:	:	:	:	:
7	6513.00	:	:	:	:	:
8	3480.00	:	:	:	:	:
9	4904.00	:	:	:	:	:
10	6313.00	:	:	:	:	:
11	7337.00	:	:	:	:	:
12	7736.00	:	:	:	:	:
13	7114.00	:	:	:	:	:
14	7041.00	:	:	:	:	:
15	5612.00	:	:	:	:	:
16	4440.00	:	:	:	:	:
17	4433.00	:	:	:	:	:
18	6378.00	:	:	:	:	:
19	7494.00	:	:	:	:	:
20	4080.00	:	:	:	:	:
21	5213.00	:	:	:	:	:
22	7973.00	:	:	:	:	:
23	8620.00	:	:	:	:	:
24	9012.00	:	:	:	:	:
25	5555.00	:	:	:	:	:
26	8394.00	:	:	:	:	:
27	7386.00	:	:	:	:	:
28	5630.00	:	:	:	:	:
29	5957.00	:	:	:	:	:
30	7515.00	:	:	:	:	:
31	5052.00	:	:	:	:	:
32	4325.00	:	:	:	:	:
33	5752.00	:	:	:	:	:
34	9007.00	:	:	:	:	:
35	8197.00	:	:	:	:	:
36	9030.00	:	:	:	:	:
37	9631.00	:	:	:	:	:
38	8556.00	:	:	:	:	:
39	7151.00	:	:	:	:	:
40	5549.00	:	:	:	:	:
41	6477.00	:	:	:	:	:
42	7761.00	:	:	:	:	:
43	7977.00	:	:	:	:	:
44	3564.00	:	:	:	:	:
45	5598.00	:	:	:	:	:
46	6547.00	:	:	:	:	:
47	8821.00	:	:	:	:	:

FIGURE B.4 UNADJUSTED MONTHLY U.S. ARRIVALS IN
BARBADOS, FEBRUARY 1977-JANUARY 1985

OBS.	DATA	3.0E+02	8.0E+02	1.3E+04	1.8E+04	2.3E+04
48	7965.00	:	:	:	:	:
49	8855.00	:	:	:	:	:
50	6800.00	:	:	:	:	:
51	6319.00	:	:	:	:	:
52	5549.00	:	:	:	:	:
53	6131.00	:	:	:	:	:
54	7789.00	:	:	:	:	:
55	5463.00	:	:	:	:	:
56	2662.00	:	:	:	:	:
57	4145.00	:	:	:	:	:
58	5932.00	:	:	:	:	:
59	7942.00	:	:	:	:	:
60	7454.00	:	:	:	:	:
61	8197.00	:	:	:	:	:
62	6201.00	:	:	:	:	:
63	5794.00	:	:	:	:	:
64	5238.00	:	:	:	:	:
65	4633.00	:	:	:	:	:
66	6525.00	:	:	:	:	:
67	6301.00	:	:	:	:	:
68	3062.00	:	:	:	:	:
69	4430.00	:	:	:	:	:
70	6490.00	:	:	:	:	:
71	4868.00	:	:	:	:	:
72	6838.00	:	:	:	:	:
73	11154.0	:	:	:	:	:
74	10117.0	:	:	:	:	:
75	9930.00	:	:	:	:	:
76	7592.00	:	:	:	:	:
77	9602.00	:	:	:	:	:
78	10865.0	:	:	:	:	:
79	11873.0	:	:	:	:	:
80	7638.00	:	:	:	:	:
81	9605.00	:	:	:	:	:
82	10227.0	:	:	:	:	:
83	11678.0	:	:	:	:	:
84	10877.0	:	:	:	:	:
85	14816.0	:	:	:	:	:
86	13186.0	:	:	:	:	:
87	12555.0	:	:	:	:	:
88	10765.0	:	:	:	:	:
89	12330.0	:	:	:	:	:
90	18316.0	:	:	:	:	:
91	17873.0	:	:	:	:	:
92	9740.00	:	:	:	:	:
93	10821.0	:	:	:	:	:
94	15681.0	:	:	:	:	:
95	17027.0	:	:	:	:	:
96	15585.0	:	:	:	:	:

FIGURE B.4 UNADJUSTED MONTHLY U.S. ARRIVALS IN
(contd.) BARBADOS, FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF SERIES FOR VARIABLE ANTARR

DATA - *

MEAN - .

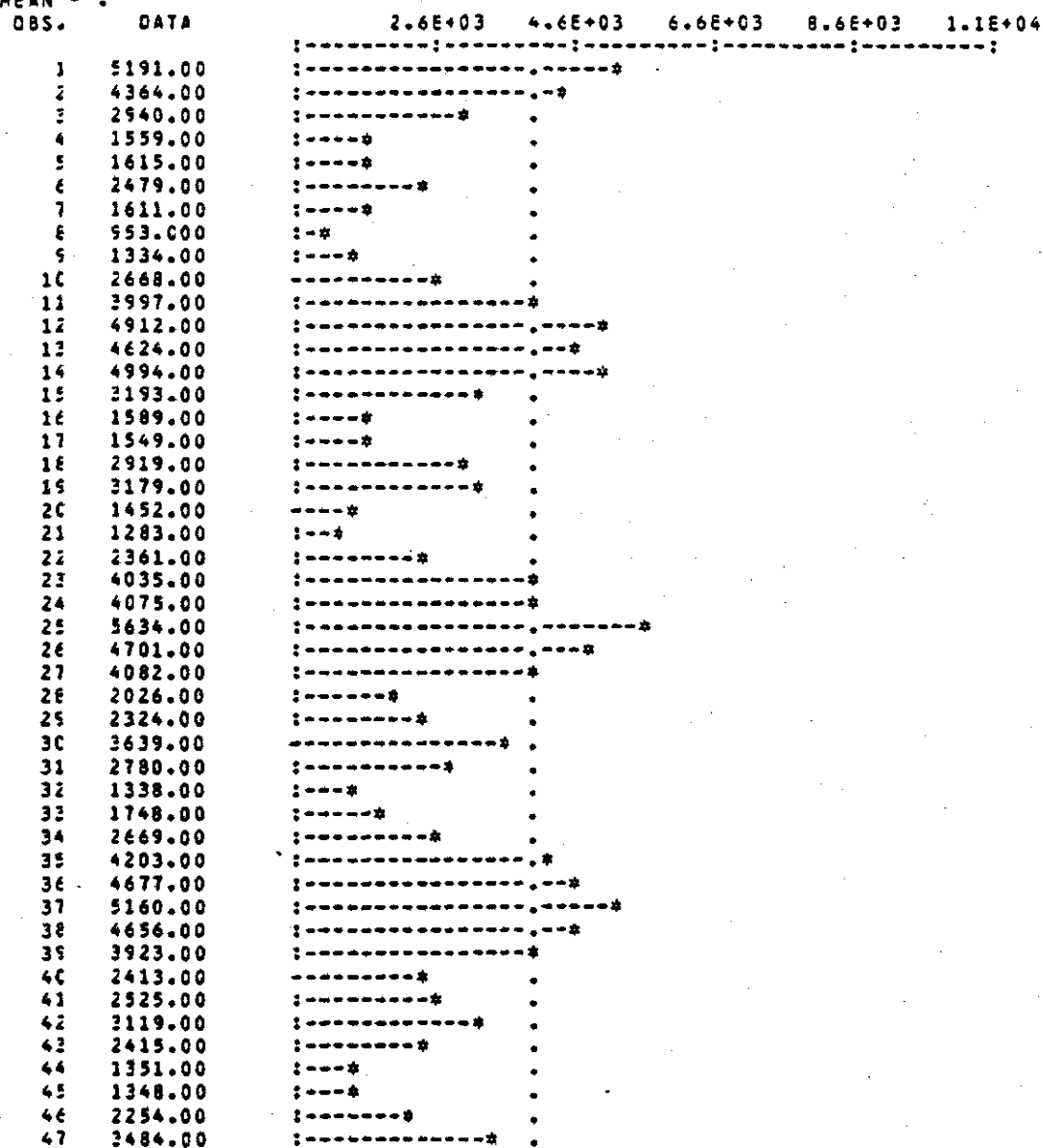


FIGURE B.5 UNADJUSTED MONTHLY U.S. ARRIVALS IN
ANTIGUA, FEBRUARY 1977-JANUARY 1985

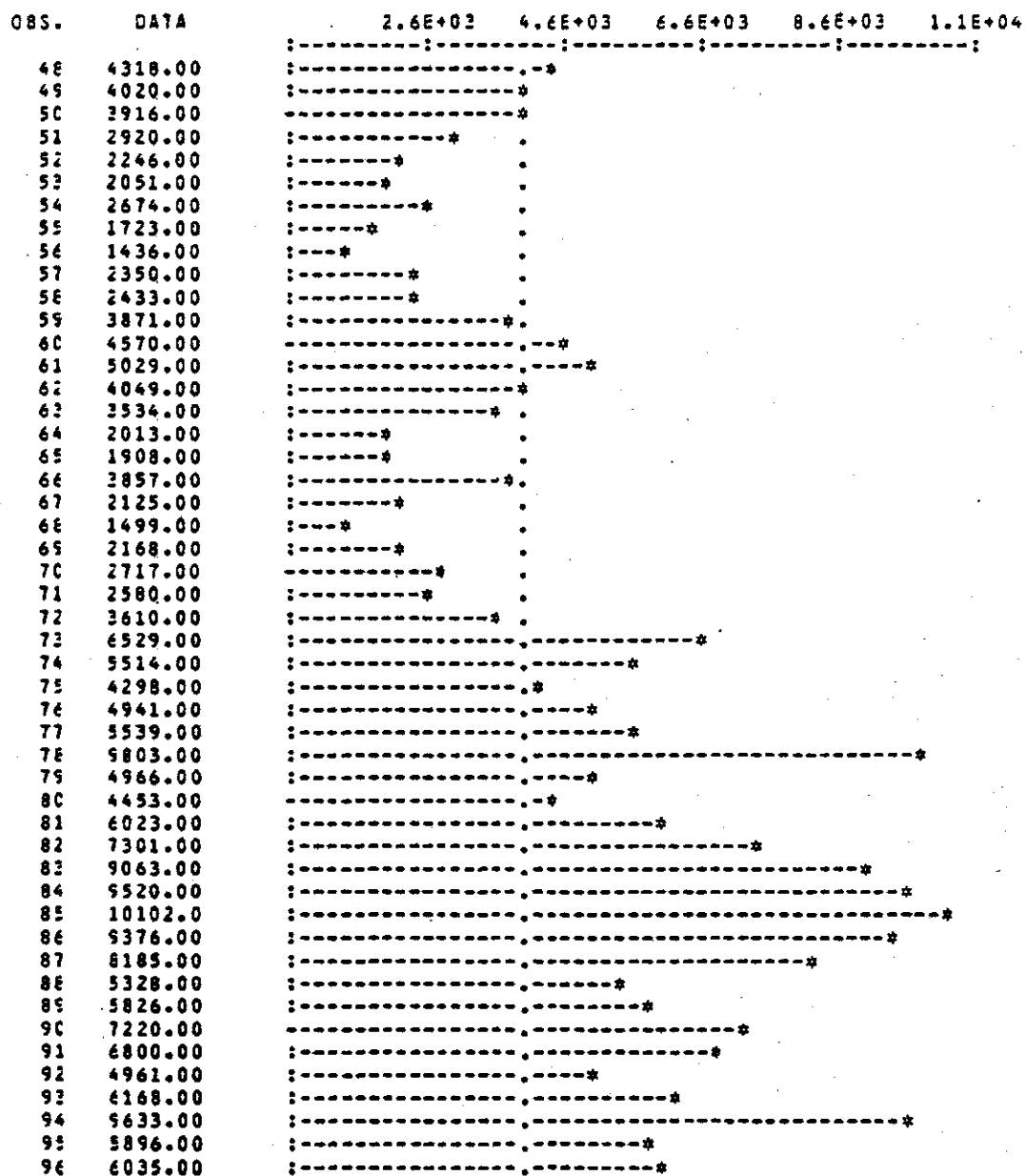


FIGURE B.5 UNADJUSTED MONTHLY U.S. ARRIVALS IN
(contd.) ANTIGUA, FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF DIFFERENCED SERIES FOR VARIABLE BERARR
 DEGREE OF NONSEASONAL DIFFERENCING - 1 DEGREE OF SEASONAL DIFFERENCING - 1
 DATA - *
 MEAN - .

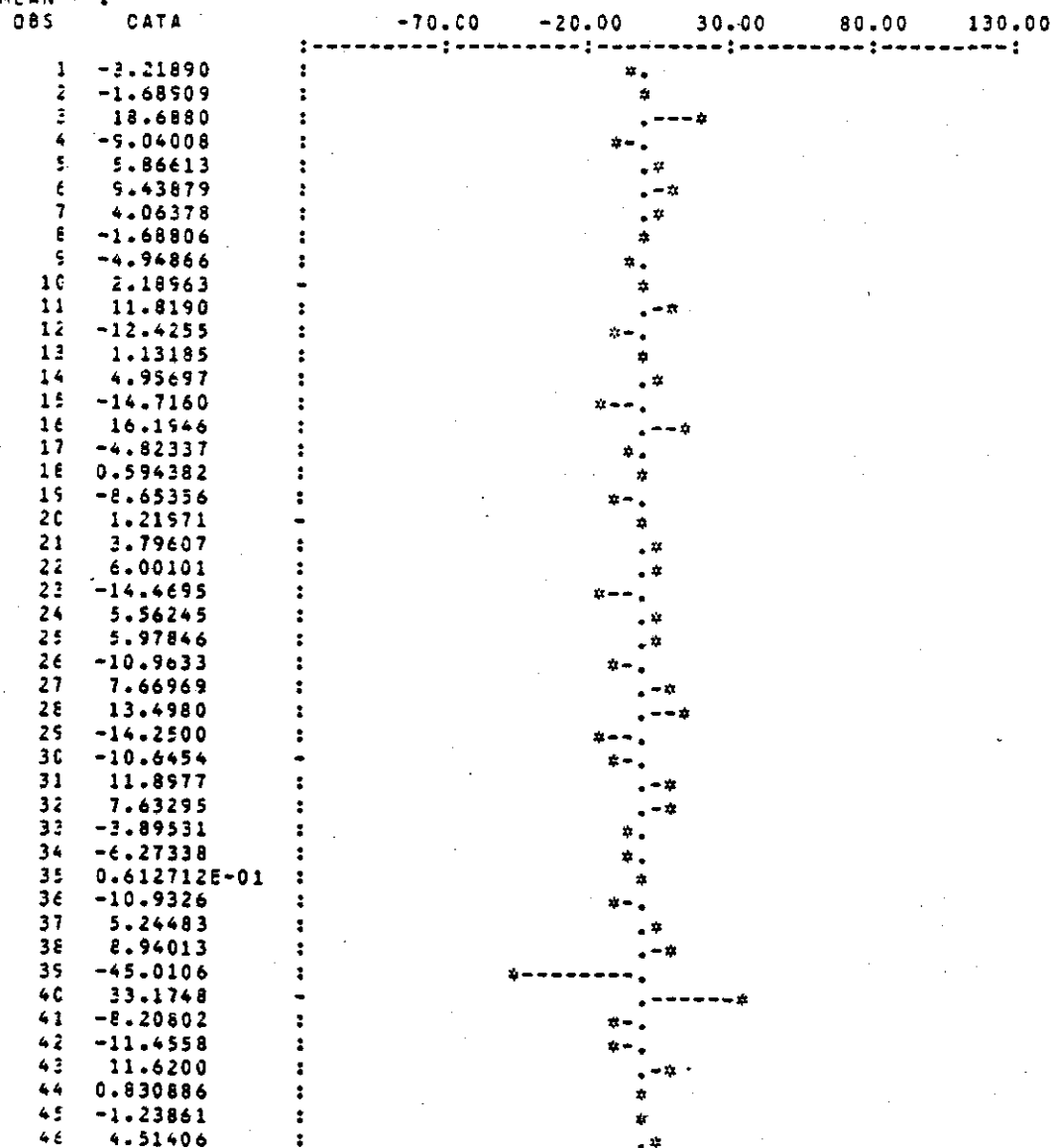


FIGURE B.6 CONSECUTIVELY AND SEASONALLY DIFFERENCED
 SQUARE ROOTS OF MONTHLY U.S. ARRIVALS IN
 BERMUDA, FEBRUARY 1977-JANUARY 1985

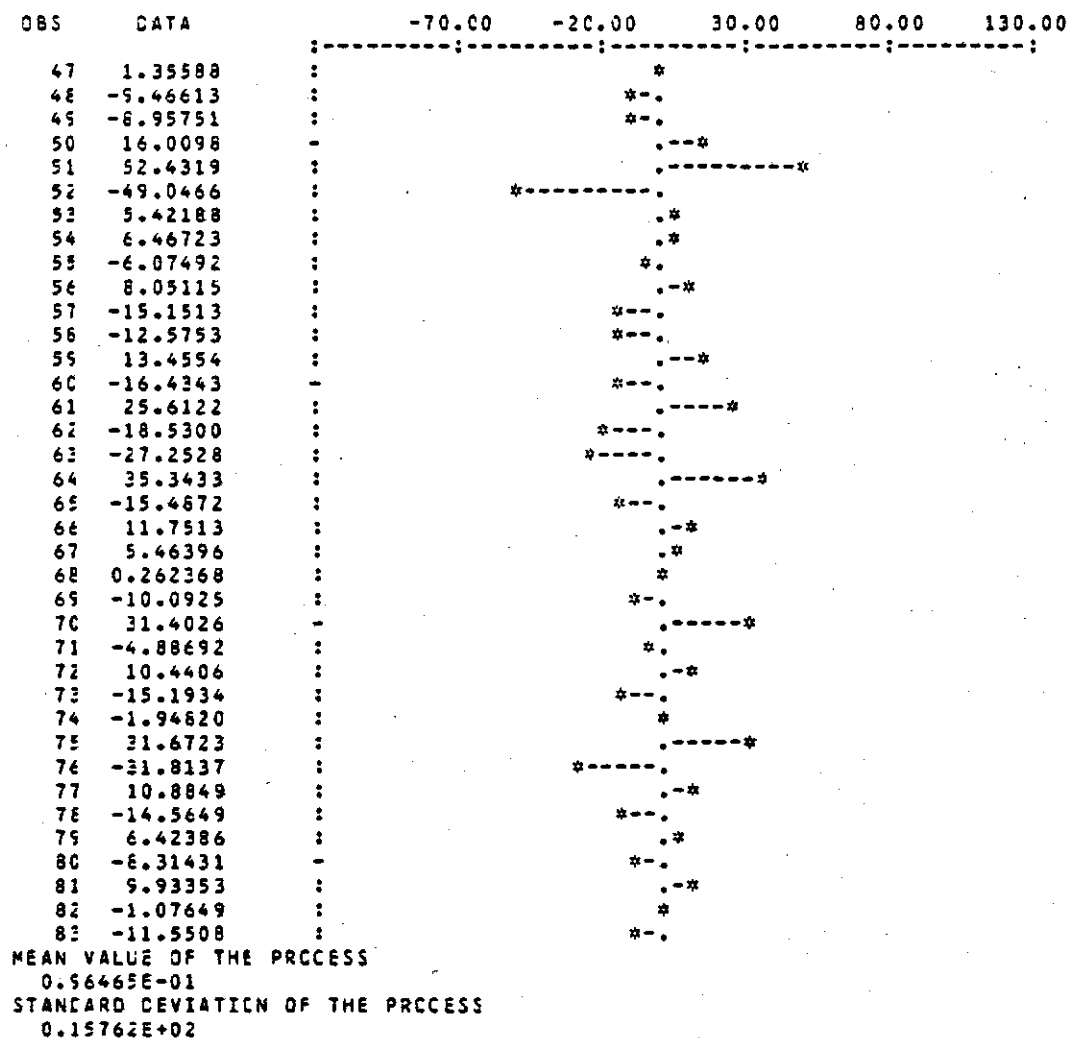


FIGURE B.6 CONSECUTIVELY AND SEASONALLY DIFFERENCED
SQUARE ROOTS OF MONTHLY U.S. ARRIVALS IN
(contd.) BERMUDA, FEBRUARY 1977-January 1985

GRAPHIC DISPLAY OF DIFFERENCED SERIES FOR VARIABLE BAHARR
 DEGREE OF NONSEASONAL DIFFERENCING - 0 DEGREE OF SEASONAL DIFFERENCING - 1
 DATA - *

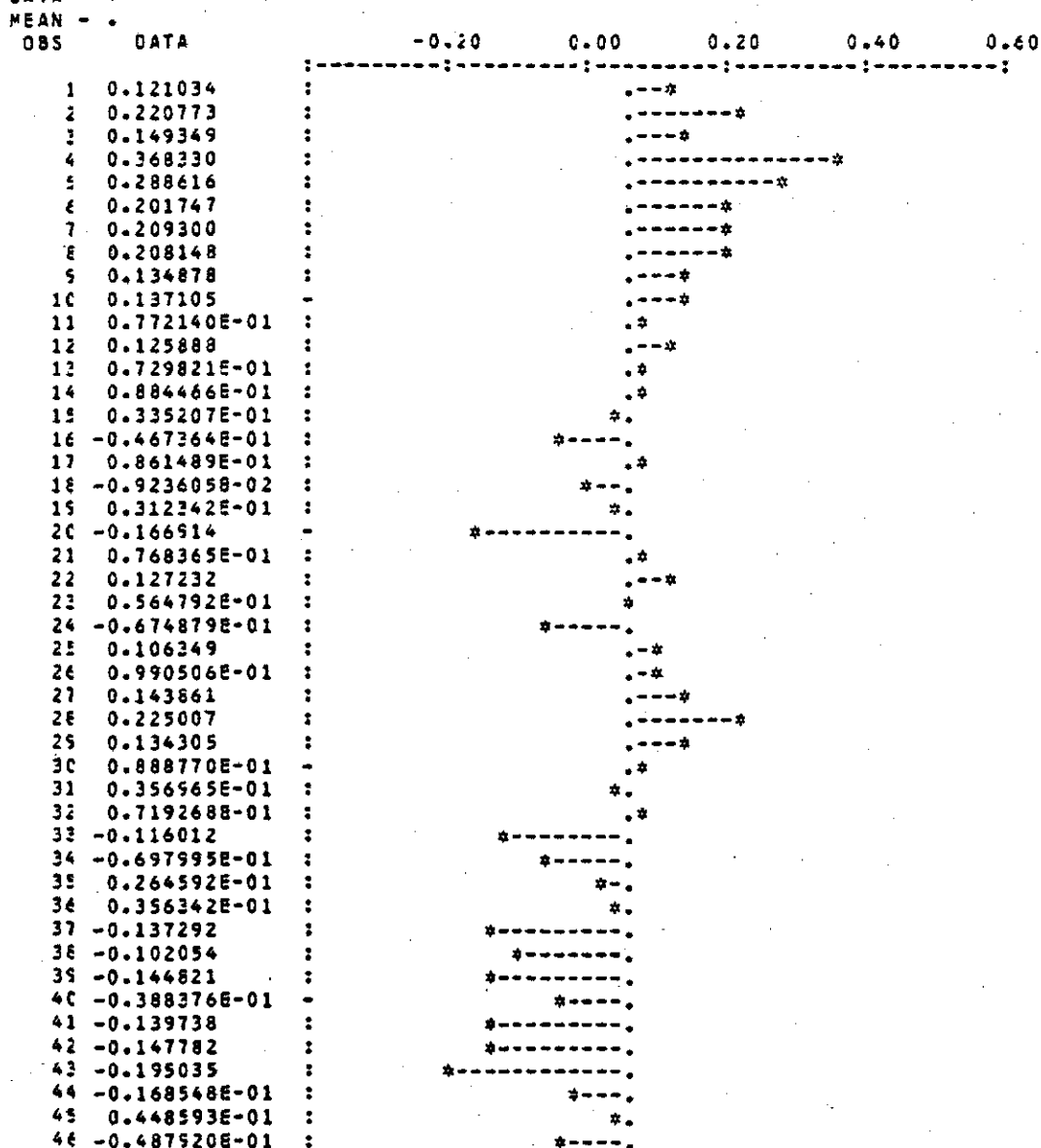


FIGURE B.7 SEASONALLY DIFFERENCED LOGARITHMS OF
 MONTHLY U.S. ARRIVALS IN THE BAHAMAS,
 FEBRUARY 1977-JANUARY 1985

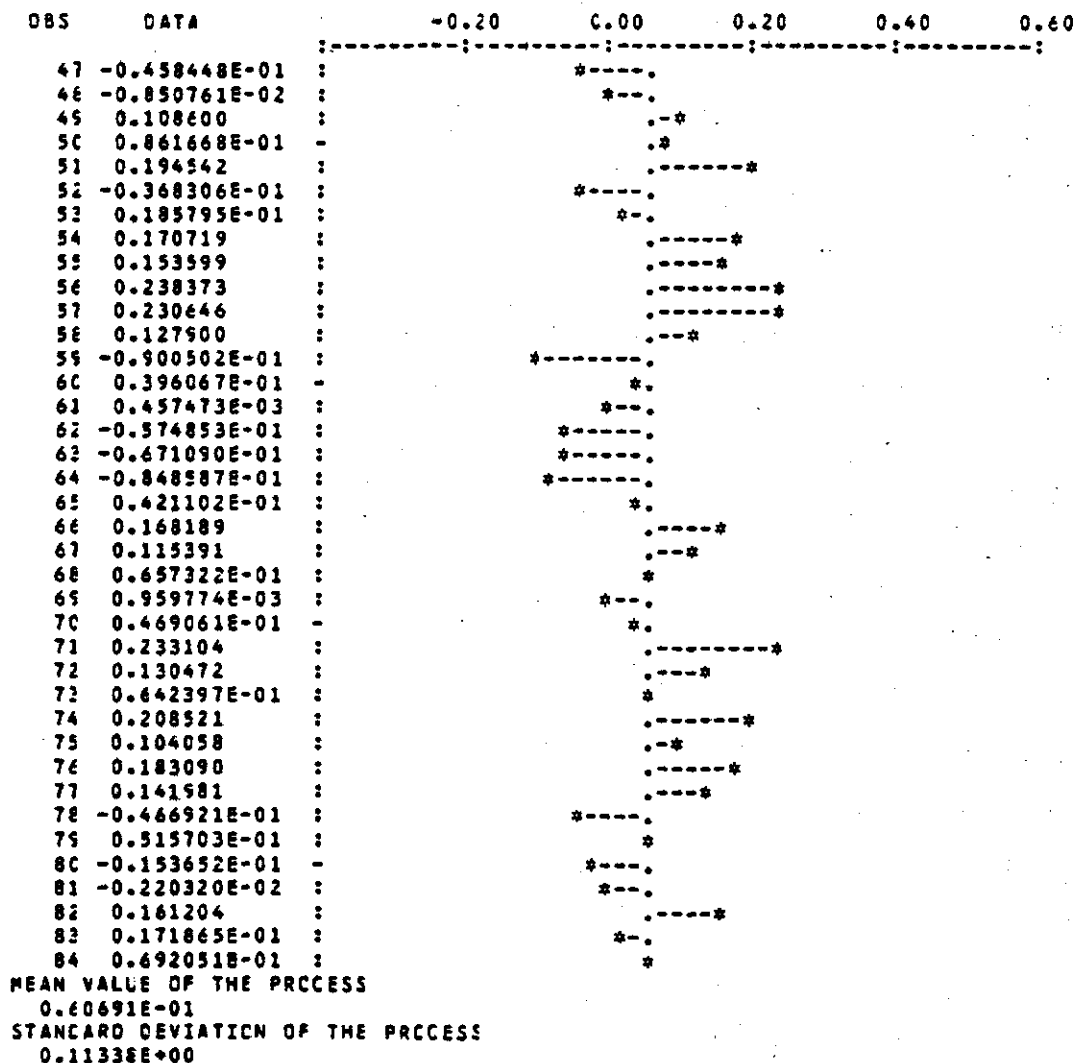


FIGURE B.7 SEASONALLY DIFFERENCED LOGARITHMS OF
MONTHLY U.S. ARRIVALS IN THE BAHAMAS,
(contd.) FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF DIFFERENCED SERIES FOR VARIABLE JCARR
 DEGREE OF NONSEASONAL DIFFERENCING - 1 DEGREE OF SEASONAL DIFFERENCING - 1
 DATA - *
 MEAN - .

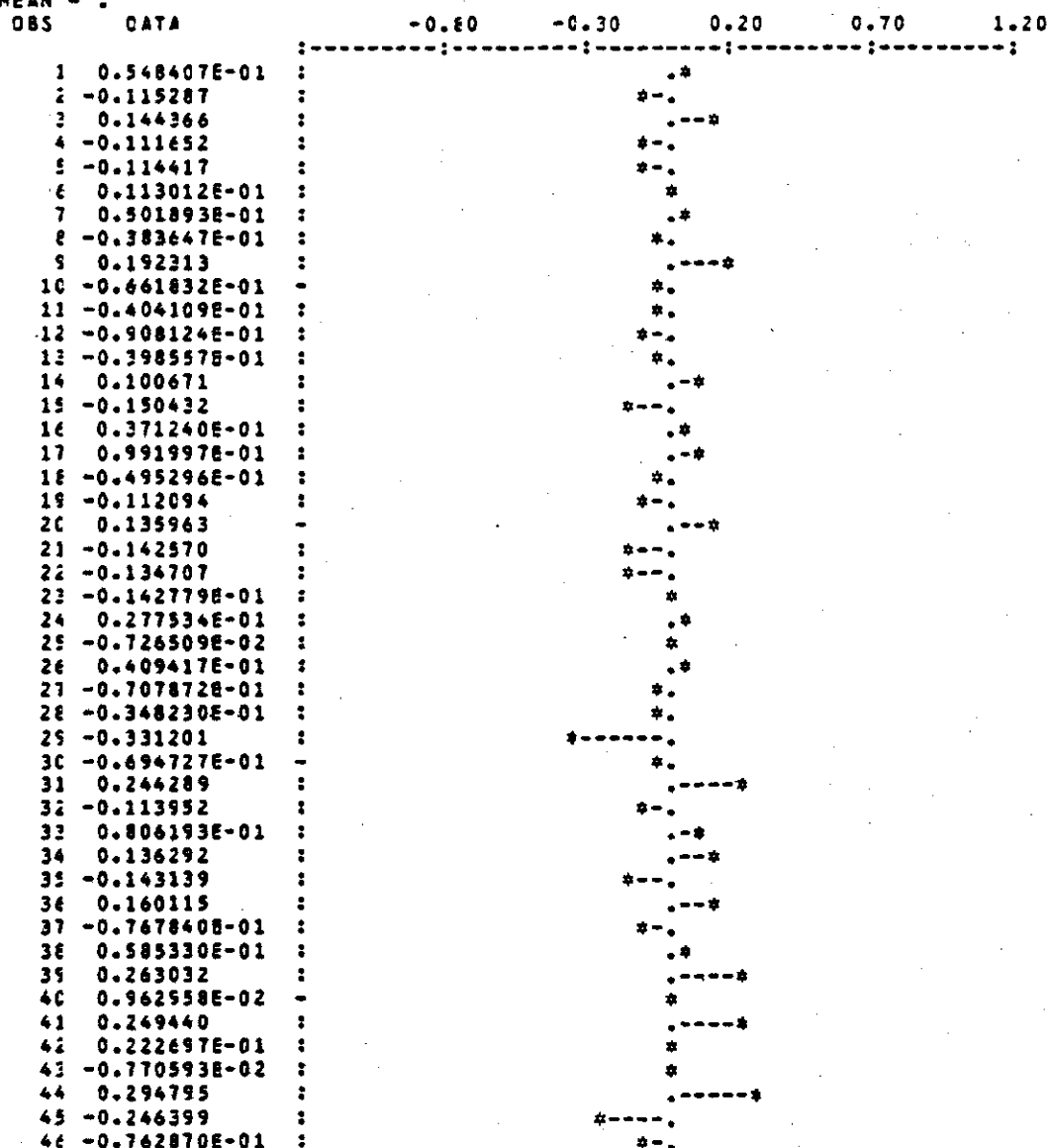


FIGURE B.8 CONSECUTIVELY AND SEASONALLY DIFFERENCED
 LOGARITHMS OF MONTHLY U.S. ARRIVALS IN
 JAMAICA, FEBRUARY 1977-JANUARY 1985

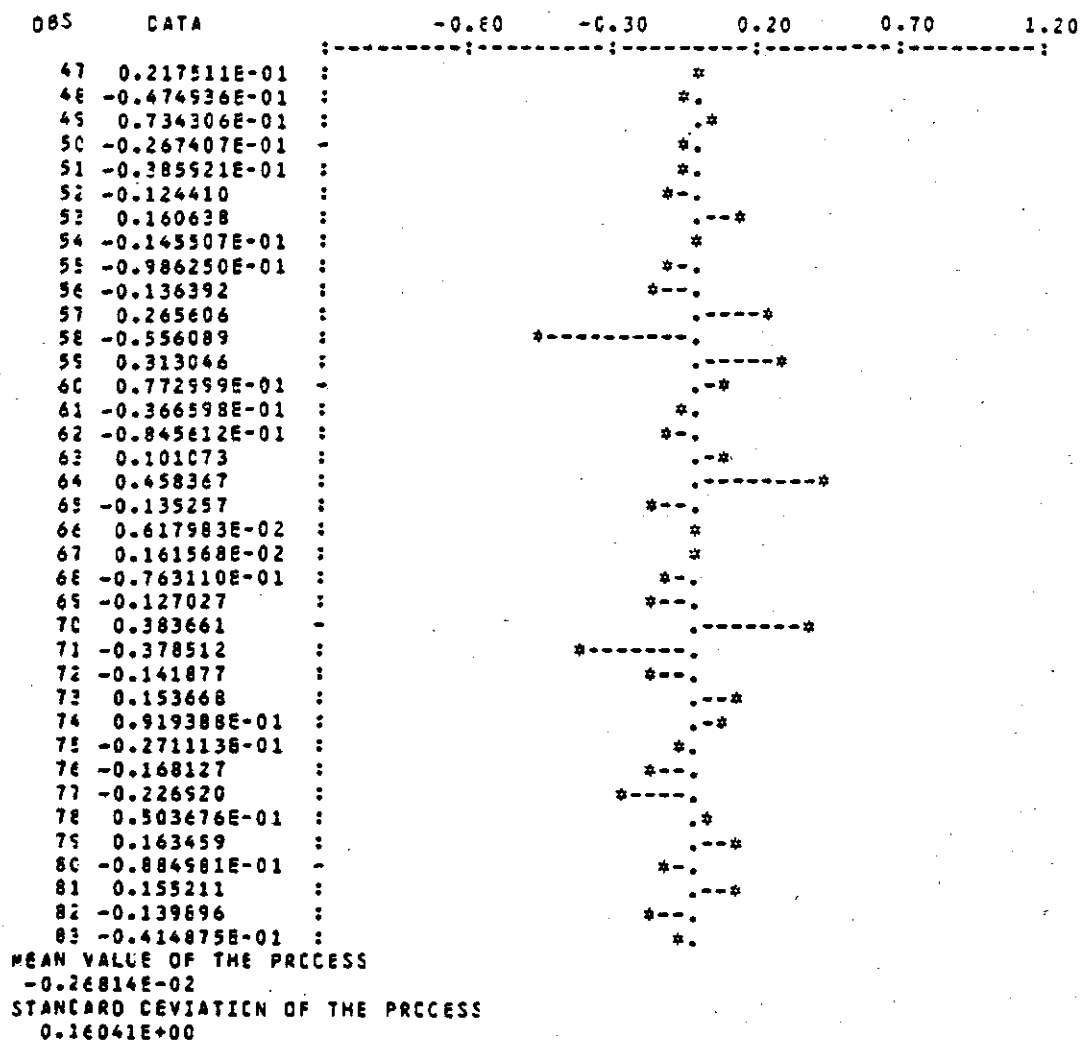


FIGURE B.8 CONSECUTIVELY AND SEASONALLY DIFFERENCED
LOGARITHMS OF MONTHLY U.S. ARRIVALS IN
(contd.) JAMAICA, FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF DIFFERENCED SERIES FOR VARIABLE BARBARR
 DEGREE OF NONSEASONAL DIFFERENCING - 1 DEGREE OF SEASONAL DIFFERENCING - 1
 DATA - *

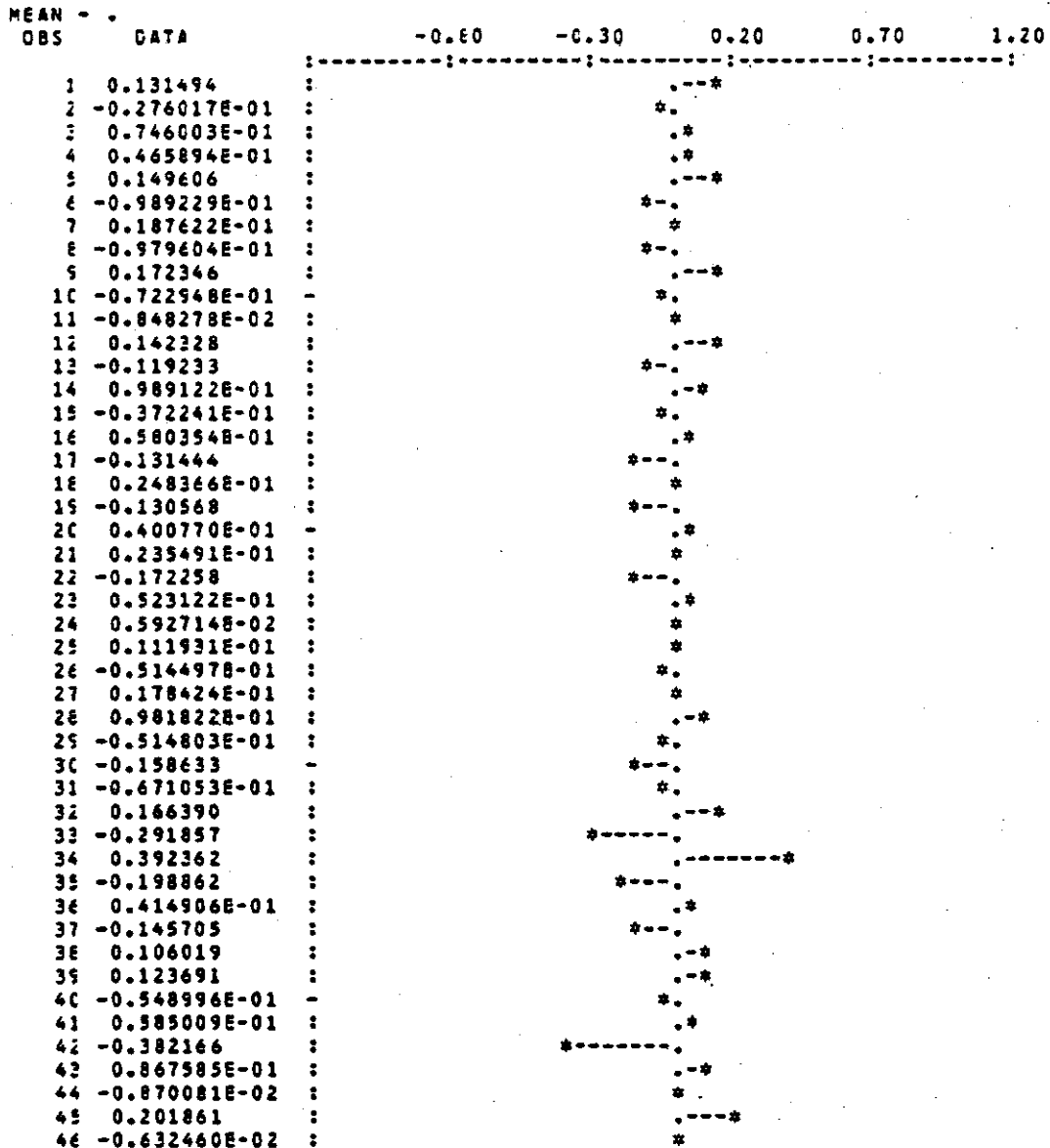


FIGURE B.9 CONSECUTIVELY AND SEASONALLY DIFFERENCED
 LOGARITHMS OF MONTHLY U.S. ARRIVALS IN
 BARBADOS, FEBRUARY 1977-JANUARY 1985

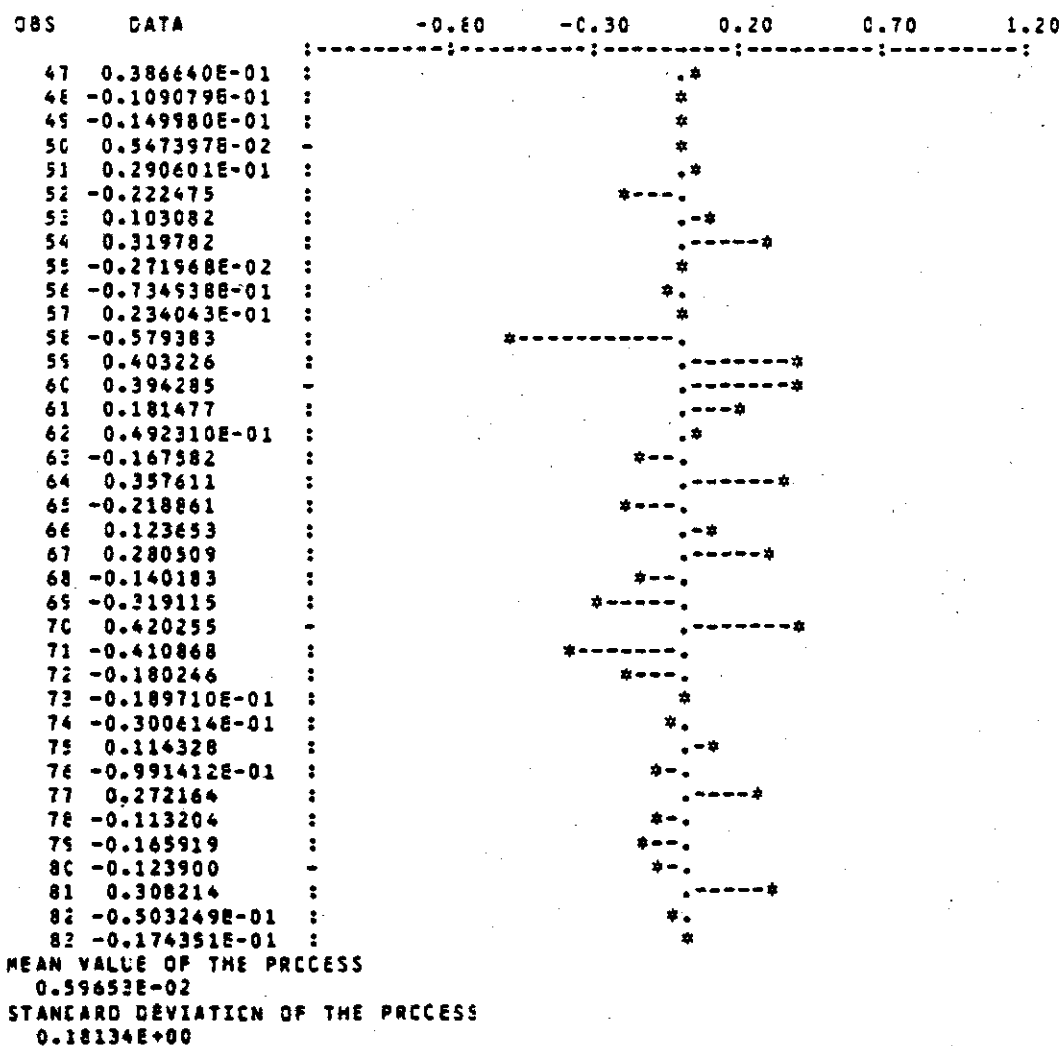


FIGURE B.9 CONSECUTIVELY AND SEASONALLY DIFFERENCED
LOGARITHMS OF MONTHLY U.S. ARRIVALS IN
(contd.) BARBADOS, FEBRUARY 1977-JANUARY 1985

GRAPHIC DISPLAY OF DIFFERENCED SERIES FOR VARIABLE ANTARR
 DEGREE OF NONSEASONAL DIFFERENCING - 1 DEGREE OF SEASONAL DIFFERENCING - 1
 DATA - *

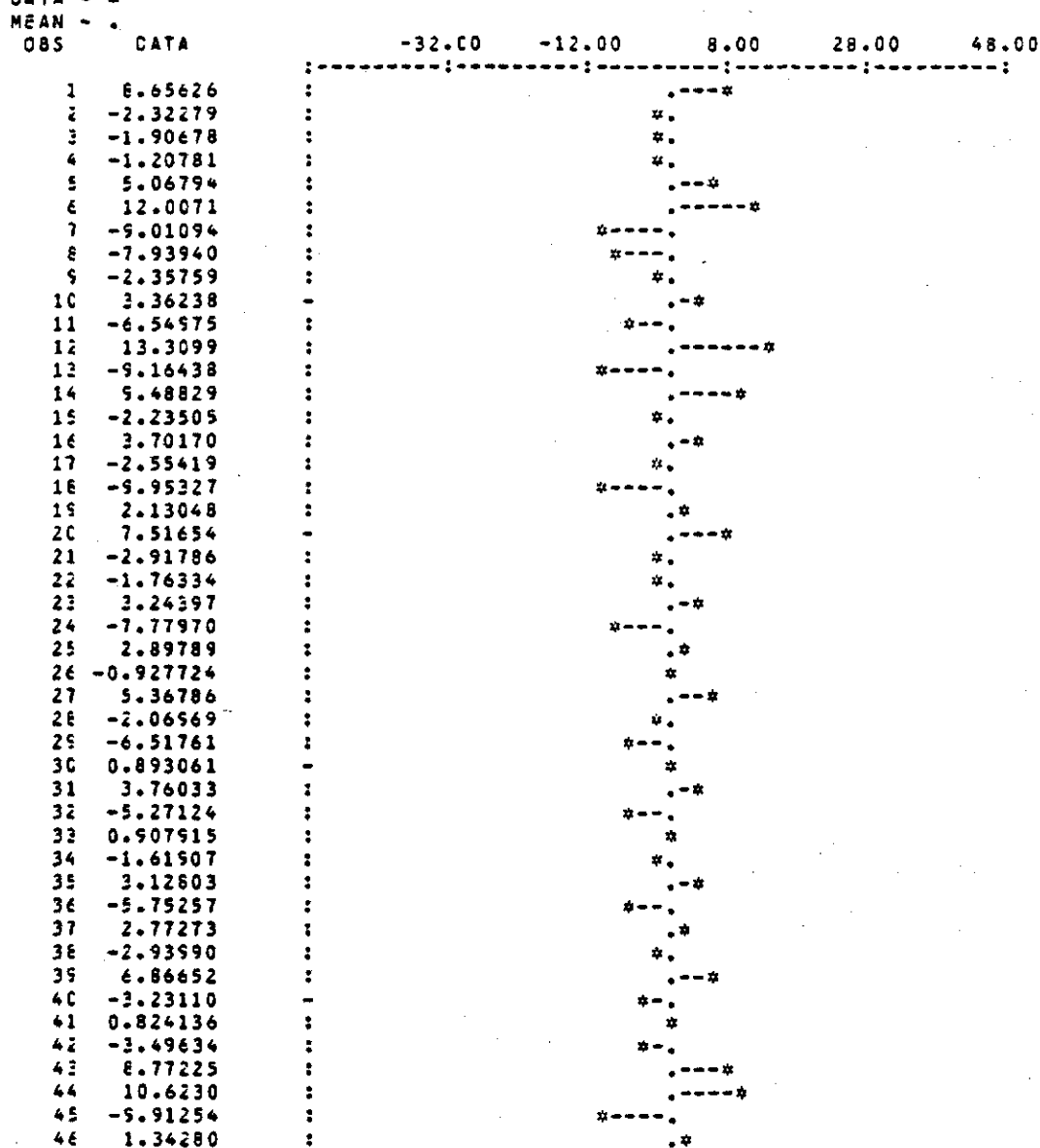


FIGURE B.10 CONSECUTIVELY AND SEASONALLY DIFFERENCED
 SQUARE ROOTS OF MONTHLY U.S. ARRIVALS IN
 ANTIGUA, FEBRUARY 1977-JANUARY 1985

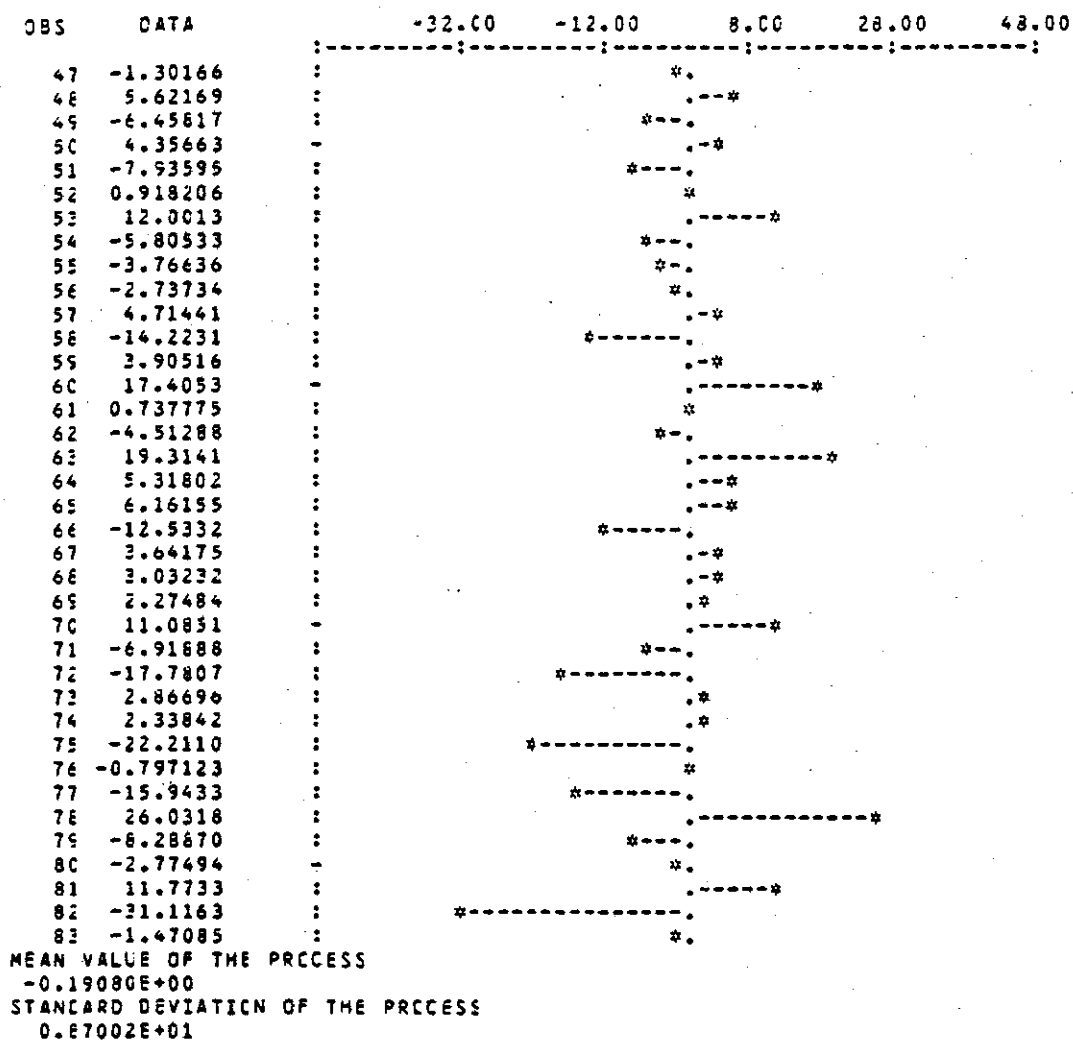


FIGURE B.10 CONSECUTIVELY AND SEASONALLY DIFFERENCED
SQUARE ROOTS OF MONTHLY U.S. ARRIVALS IN
(contd.) ANTIGUA, FEBRUARY 1977-JANUARY 1985

AUTOCORRELATION FUNCTION FOR VARIABLE BERARR
 AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
			:-----:-----:-----:-----:-----:-----:-----:-----:-----:								
1	-0.488	0.107					*****.***:				
2	-0.072	0.106					. *:				
3	0.175	0.106					. :***.				
4	-0.131	0.105					.***:				
5	0.148	0.104					. :***.				
6	-0.009	0.104					. *				
7	-0.090	0.103					. **:.				
8	0.035	0.102					. :*				
9	-0.128	0.102					.***:				
10	0.090	0.101					. :**..				
11	0.250	0.100					. :***.*				
12	-0.543	0.100					*****.***:				
13	0.313	0.099					. :***.**				
14	-0.056	0.098					. *:				
15	-0.086	0.097					. **:.				
16	0.172	0.097					. :***.				
17	-0.142	0.096					.***:				
18	-0.023	0.095					. *				
19	0.141	0.094					. :***.				
20	-0.094	0.094					. **:.				
21	0.145	0.093					. :***.				
22	-0.113	0.092					. **:.				
23	-0.081	0.091					. **:.				
24	0.300	0.091					. :***.**				
25	-0.263	0.090					*.***:				
26	0.133	0.089					. :***.				
27	-0.020	0.088					. *				
28	-0.079	0.087					. **:.				
29	0.046	0.087					. :*				
30	0.062	0.086					. :*				
31	-0.095	0.085					.***:				
32	-0.001	0.084					. *				
33	-0.052	0.083					. *:				
34	0.043	0.082					. :*				
35	0.091	0.082					. :**..				
36	-0.241	0.081					***.***:				

FIGURE B.11 SAMPLE AUTOCORRELATION FUNCTION FOR
 BERMUDA

AUTOCORRELATION FUNCTION FOR VARIABLE SAHARR
 AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .

LAG	AUTOCORR.	STANDARD ERROR	-1	-.75	-.5	-.25	0	.25	.5	.75	1
1	0.551	0.107									
2	0.437	0.106									
3	0.361	0.105									
4	0.316	0.105									
5	0.265	0.104									
6	0.155	0.103									
7	-0.016	0.103									
8	-0.065	0.102									
9	-0.029	0.101									
10	-0.061	0.101									
11	-0.132	0.100									
12	-0.286	0.099									
13	-0.151	0.098									
14	-0.184	0.098									
15	-0.122	0.097									
16	-0.068	0.096									
17	0.048	0.096									
18	0.035	0.095									
19	0.058	0.094									
20	0.122	0.093									
21	0.150	0.093									
22	0.184	0.092									
23	0.145	0.091									
24	0.055	0.090									
25	0.065	0.090									
26	0.115	0.089									
27	0.005	0.088									
28	-0.025	0.087									
29	-0.172	0.086									
30	-0.150	0.086									
31	-0.233	0.085									
32	-0.262	0.084									
33	-0.358	0.083									
34	-0.368	0.082									
35	-0.331	0.082									
36	-0.310	0.081									

FIGURE B.12 SAMPLE AUTOCORRELATION FUNCTION FOR
 THE BAHAMAS

AUTOCORRELATION FUNCTION FOR VARIABLE BARBARR
 AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .
 AUTC. STAND.

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
			:-----:-----:-----:-----:-----:-----:-----:-----:-----:								
1	-0.326	0.107					***.***:				
2	-0.021	0.106					. *				
3	-0.048	0.106					. *:				
4	-0.046	0.105					. *:				
5	-0.010	0.104					. *				
6	0.066	0.104					. :*				
7	0.164	0.103					. :***.				
8	-0.142	0.102					. ***:				
9	-0.051	0.102					. *:				
10	-0.043	0.101					. *:				
11	0.238	0.100					. :***.*				
12	-0.377	0.100					***.***:				
13	0.131	0.099					. :***.				
14	0.037	0.098					. :*				
15	-0.038	0.097					. *:				
16	0.186	0.097					. :****				
17	-0.064	0.096					. *:				
18	-0.120	0.095					. **:				
19	-0.122	0.094					. **:				
20	0.072	0.094					. :*				
21	0.072	0.093					. :*				
22	0.046	0.092					. :*				
23	0.047	0.091					. :*				
24	-0.213	0.091					****:				
25	0.092	0.090					. :***.				
26	-0.096	0.089					. **:				
27	0.133	0.088					. :***.				
28	-0.067	0.087					. *:				
29	0.014	0.087					. *				
30	0.003	0.086					. *				
31	-0.051	0.085					. *:				
32	0.057	0.084					. :*				
33	-0.042	0.083					. *:				
34	0.018	0.082					. *				
35	-0.126	0.082					***:				
36	0.223	0.081					. :***.*				

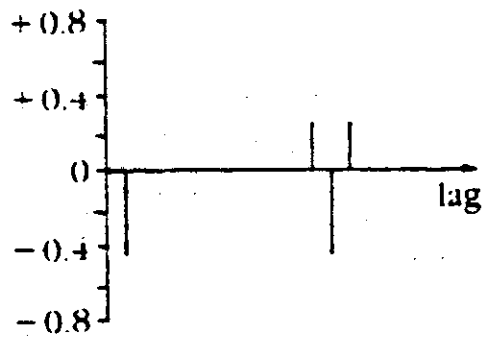
FIGURE B.14 SAMPLE AUTOCORRELATION FUNCTION FOR
 BARBADOS

AUTOCORRELATION FUNCTION FOR VARIABLE ANTARR
 AUTOCORRELATIONS *

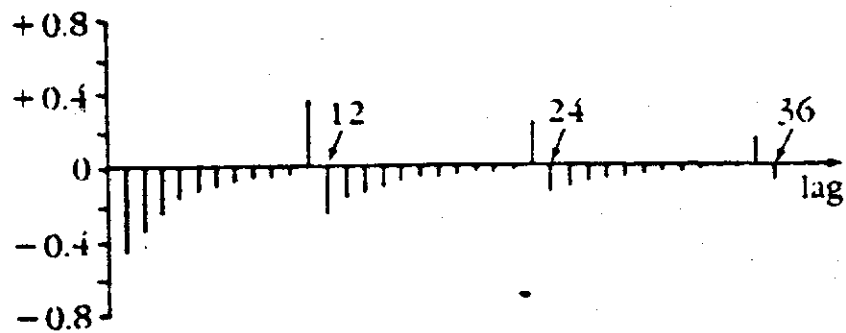
TWO STANDARD ERROR LIMITS .

LAG	CORR.	STAND. ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
			:-----:-----:-----:-----:-----:-----:-----:-----:-----:								
1	-0.285	0.107									
2	-0.041	0.106									
3	0.024	0.106									
4	-0.009	0.105									
5	0.065	0.104									
6	-0.055	0.104									
7	0.084	0.103									
8	-0.004	0.102									
9	-0.060	0.102									
10	0.115	0.101									
11	0.135	0.100									
12	-0.369	0.100									
13	0.058	0.095									
14	-0.040	0.098									
15	-0.050	0.097									
16	0.039	0.097									
17	0.068	0.096									
18	-0.007	0.095									
19	-0.092	0.094									
20	-0.039	0.094									
21	0.178	0.093									
22	-0.140	0.092									
23	-0.068	0.091									
24	0.035	0.091									
25	0.036	0.090									
26	0.055	0.089									
27	-0.028	0.088									
28	0.028	0.087									
29	-0.106	0.087									
30	0.091	0.086									
31	-0.072	0.085									
32	-0.011	0.084									
33	-0.021	0.083									
34	0.058	0.082									
35	-0.050	0.082									
36	-0.073	0.081									

FIGURE B.15 SAMPLE AUTOCORRELATION FUNCTION FOR
 ANTIGUA

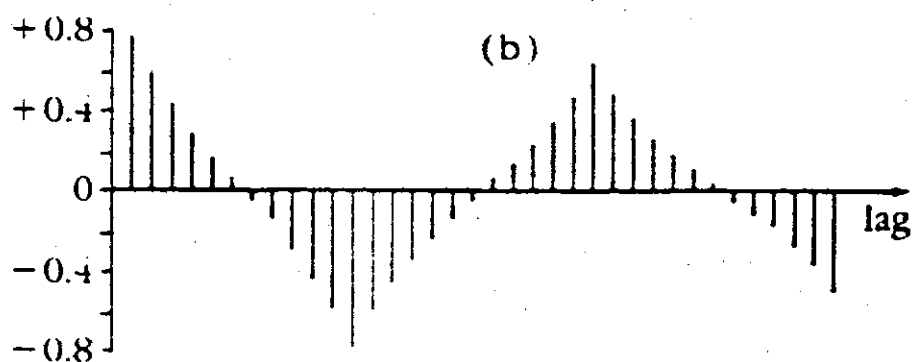


AUTOCORRELATION FUNCTION

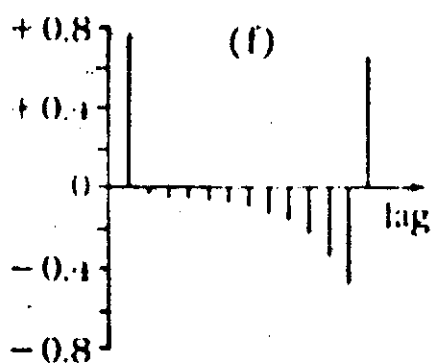


PARTIAL AUTOCORRELATION FUNCTION

FIGURE B.16 THEORETICAL AUTOCORRELATION AND PARTIAL
AUTOCORRELATION FUNCTIONS FOR A MULTI-
PLICATIVE MOVING AVERAGE MODEL



AUTOCORRELATION FUNCTION



PARTIAL AUTOCORRELATION FUNCTION

FIGURE B.17 THEORETICAL AUTOCORRELATION AND PARTIAL
AUTOCORRELATION FUNCTIONS FOR A MULTI-
PLICATIVE AUTOREGRESSIVE SEASONAL MODEL

PARTIAL AUTOCORRELATION FUNCTION FOR VARIABLE BERARR
 PARTIAL AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .
 FR-ALT STAND.

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
1	-0.488	0.110									
2	-0.407	0.110									
3	-0.116	0.110									
4	-0.151	0.110									
5	0.093	0.110									
6	0.162	0.110									
7	0.093	0.110									
8	0.003	0.110									
9	-0.260	0.110									
10	-0.261	0.110									
11	0.250	0.110									
12	-0.296	0.110									
13	-0.080	0.110									
14	-0.183	0.110									
15	-0.131	0.110									
16	-0.058	0.110									
17	0.019	0.110									
18	-0.046	0.110									
19	0.153	0.110									
20	0.038	0.110									
21	0.115	0.110									
22	-0.056	0.110									
23	0.034	0.110									
24	0.032	0.110									
25	-0.014	0.110									
26	-0.014	0.110									
27	-0.088	0.110									
28	0.010	0.110									
29	-0.113	0.110									
30	0.006	0.110									
31	0.081	0.110									
32	-0.039	0.110									
33	0.001	0.110									
34	-0.126	0.110									
35	0.017	0.110									
36	-0.108	0.110									

FIGURE B.18 SAMPLE PARTIAL AUTOCORRELATION FUNCTION FOR
 BERMUDA

PARTIAL AUTOCORRELATION FUNCTION FOR VARIABLE BAHARR
 PARTIAL AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
1	0.551	0.105									
2	0.135	0.105									
3	0.091	0.105									
4	0.068	0.105									
5	0.023	0.105									
6	-0.093	0.105									
7	-0.212	0.105									
8	-0.047	0.105									
9	0.076	0.105									
10	-0.022	0.105									
11	-0.076	0.105									
12	-0.228	0.105									
13	0.140	0.105									
14	-0.056	0.105									
15	0.072	0.105									
16	0.115	0.105									
17	0.237	0.105									
18	-0.075	0.105									
19	-0.032	0.105									
20	-0.016	0.105									
21	0.148	0.105									
22	-0.055	0.105									
23	-0.063	0.105									
24	-0.182	0.105									
25	0.058	0.105									
26	-0.004	0.105									
27	-0.162	0.105									
28	0.051	0.105									
29	-0.058	0.105									
30	-0.090	0.105									
31	-0.151	0.105									
32	-0.037	0.105									
33	-0.002	0.105									
34	-0.086	0.105									
35	-0.010	0.105									
36	-0.126	0.105									

FIGURE B.19 SAMPLE PARTIAL AUTOCORRELATION FUNCTION FOR
 THE BAHAMAS

PARTIAL AUTOCORRELATION FUNCTION FOR VARIABLE JCARR
 PARTIAL AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .
 FR-ALT STAND.

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
1	-0.322	0.110									
2	-0.193	0.110									
3	0.042	0.110									
4	-0.019	0.110									
5	0.004	0.110									
6	0.064	0.110									
7	0.028	0.110									
8	-0.001	0.110									
9	-0.130	0.110									
10	0.016	0.110									
11	0.220	0.110									
12	-0.348	0.110									
13	-0.049	0.110									
14	-0.202	0.110									
15	-0.014	0.110									
16	-0.084	0.110									
17	0.054	0.110									
18	-0.013	0.110									
19	-0.083	0.110									
20	0.000	0.110									
21	-0.112	0.110									
22	0.050	0.110									
23	0.139	0.110									
24	-0.090	0.110									
25	0.141	0.110									
26	0.045	0.110									
27	-0.002	0.110									
28	-0.152	0.110									
29	0.023	0.110									
30	0.010	0.110									
31	-0.007	0.110									
32	-0.055	0.110									
33	-0.050	0.110									
34	0.014	0.110									
35	-0.065	0.110									
36	-0.208	0.110									

FIGURE B.20 SAMPLE PARTIAL AUTOCORRELATION FUNCTION FOR JAMAICA

PARTIAL AUTOCORRELATION FUNCTION FOR VARIABLE BARBARR
 PARTIAL AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .
 PR-ALT STAND.

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
:-----:-----:-----:-----:-----:-----:-----:-----:-----:-----:-----:-----:											
1	-0.326	0.110									
2	-0.143	0.110					***.***:				
3	-0.116	0.110					.***:				
4	-0.123	0.110					.**:				
5	-0.097	0.110					.***:				
6	0.010	0.110					.*				
7	0.207	0.110					.:****				
8	0.001	0.110					.*				
9	-0.075	0.110					.**:				
10	-0.089	0.110					.**:				
11	0.240	0.110					.:****.*				
12	-0.311	0.110					**.***:				
13	-0.159	0.110					.***:				
14	-0.015	0.110					.*				
15	0.028	0.110					.:*				
16	0.223	0.110					.:****				
17	0.036	0.110					.:*				
18	-0.175	0.110					.***:				
19	-0.075	0.110					.**:				
20	-0.036	0.110					.*:				
21	-0.028	0.110					.*:				
22	-0.100	0.110					.**:				
23	0.177	0.110					.:****				
24	-0.252	0.110					*.***:				
25	0.126	0.110					.:****.				
26	-0.044	0.110					.*:				
27	-0.051	0.110					.*:				
28	0.015	0.110					.*				
29	0.064	0.110					.*:				
30	-0.114	0.110					.**:				
31	-0.064	0.110					.*:				
32	-0.051	0.110					.*:				
33	-0.023	0.110					.*				
34	0.018	0.110					.*				
35	0.074	0.110					.:*				
36	-0.088	0.110					.**:				

FIGURE B.21 SAMPLE PARTIAL AUTOCORRELATION FUNCTION FOR
 BARBADOS

PARTIAL AUTOCORRELATION FUNCTION FOR VARIABLE ANTARR
 PARTIAL AUTOCORRELATIONS *
 TWO STANDARD ERROR LIMITS .

LAG	CORR.	ERR.	-1	-.75	-.5	-.25	0	.25	.5	.75	1
1	-0.285	0.110									
2	-0.123	0.110									
3	-0.030	0.110									
4	-0.017	0.110									
5	0.065	0.110									
6	-0.062	0.110									
7	0.052	0.110									
8	0.025	0.110									
9	-0.046	0.110									
10	0.090	0.110									
11	0.220	0.110									
12	-0.303	0.110									
13	-0.076	0.110									
14	-0.096	0.110									
15	-0.137	0.110									
16	-0.010	0.110									
17	0.163	0.110									
18	-0.032	0.110									
19	-0.032	0.110									
20	-0.092	0.110									
21	0.094	0.110									
22	-0.019	0.110									
23	0.020	0.110									
24	-0.150	0.110									
25	-0.044	0.110									
26	0.021	0.110									
27	-0.034	0.110									
28	-0.005	0.110									
29	-0.007	0.110									
30	0.063	0.110									
31	-0.095	0.110									
32	-0.127	0.110									
33	0.041	0.110									
34	0.029	0.110									
35	-0.103	0.110									
36	-0.148	0.110									

FIGURE B.22 SAMPLE PARTIAL AUTOCORRELATION FUNCTION FOR
 ANTIGUA

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